Doctoral theses at NTNU, 2022:306

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Theoretical and experimental analysis of methods for enhancing user comfort in dynamic thermal indoor environments

Doctoral thesis

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Norwegian University of Science and Technology
Thesis for the Degree of Philosophiae Doctor
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Trondheim, October 2022

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Preface

This doctoral thesis is submitted to the Norwegian University of Science and Technology (NTNU) as partial fulfilment of the requirements for the degree of Philosophiae Doctor. The work was funded by the Research Council of Norway (Norges Forskingsrådet) through the Research Centre on Zero Emission Neighbourhoods in Smart Cities (FME ZEN, Grant no. 257660). The research was carried out at the Department of Civil and Environmental Engineering (IBM) at NTNU under the supervision of Prof. Salvatore Carlucci (NTNU/The Cyprus Institute) and co-supervised by Dr Igor Sartori (SINTEF Community).

This work is the culmination of a journey that started in September 2018 after deciding to leave the industrial sector for a change. I decided to pursue and get a PhD. I found my PhD path full of little peaks that were not on my radar but were much more rewarding. I would be lying if I said I had not experienced despair, defeat and tiredness in the previous four years. However, I also felt joy, optimism, trust and brotherhood. This journey has never really been a lonely adventure, and I would like to thank everyone who supported me and helped me cross the finish line.

To begin with, I want to thank my supervisors, Salvatore Carlucci and Igor Sartori, for inspiring me to be ambitious, believing in me, and teaching me how to identify and develop good research.

Many thanks to all the researchers involved in the IEA EBC Annex 79 'Occupant-Centric Building Design and Operation' – especially Subtasks 1 & 2 – for the many fruitful and insightful discussions, which undoubtedly boosted my PhD.

I want to express my heartfelt gratitude to all the people around me for their invaluable ongoing support, both personally and professionally and for making the PhD journey a most enjoyable time in my life. Particularly to Siri, Camilla, Shabnam, Therese, Amin, Atle, David, Ali, Carine, Anna, Artur, Mattia, Rosita, Cristobal, Ramya, Oskar, and Tobias. Thanks for the lunch breaks, conversations at the coffee machine, and social events. You made it fun to come to work. I would also like to thank the fantastic IBM administration team for their kind support.

Finally, I am forever thankful to my family, my parents, and my sister Jessica, for their unconditional support, understanding and love.

Trondheim, June 2022

Matteo Favero

Abstract

In the last decades, increasing global energy demand, a foreseen reduction of available fossil fuels and increasing evidence for global warming have shown the urgency to rethink the built environment and promote energy transition. Indeed, in most industrialised nations, the building sector accounts for about 40% of the total energy consumption (space heating and cooling, domestic hot water, ventilation, lighting and appliance use). A significant share of this energy is used to thermal control buildings and provide thermally comfortable indoor environments. However, technical building systems are typically designed and operated considering fixed set-point temperatures based on the ‘one-size-fits-all’ principle – which has been questioned in the last fifty years – assuming universal thermal comfort requirements. Furthermore, the indoor environment frequently changes abruptly across buildings or between various parts within a single building. For instance, manually operating thermostats, windows and solar shades can result in considerable and not systematic changes in the indoor environment. Also, automatic controllers exhibit, to a lesser degree, a similar behaviour. Moreover, individual activity modifies the basal metabolic rate over time, and the addition or removal of clothes affects the heat balance of the human body as well. In other words, the steady-state temperature settings are the exception rather than the rule. Building temperature ranges should instead be based on real-time empirical evidence regarding the needs of its occupants, which is obtained through their feedback (usually on a rating scale). This thesis investigates these topics and relies upon an experimental study to explore the human reaction to dynamic thermal environments.

The general approach utilised in this thesis encompasses a technical/methodological aspect, namely a newer controlled experimental procedure and a robust and replicable methodology for human feedback acquisition, and a statistical aspect, namely an original statistics-enabled occupant-centric modelling. The technical/methodological aspect refers to how thermal comfort data are collected; that is, the specific approach and experimental set-up utilised. The statistical aspect refers to how thermal comfort data are analysed, namely, the specific statistical technique to be adopted and the needed modelling steps.

It was found that the human reaction to dynamic thermal stimuli is asymmetric with respect to heating and cooling processes, and two distinct mechanisms cause discomfort due to overheating and overcooling. Compared to the recommendations regarding temperature cycles, drifts and ramps included in the ASHRAE Standard 55, this result showed that current recommendations underestimate the risk of thermal discomfort during a cooling process while overestimating it during a heating one. Concerning the subjective thermal comfort data analysis, the choice of the statistical method affects the conclusions. While it may seem a trivial consideration, till now, it is common in the thermal comfort field to find studies that use, for example, linear regression on ordinal data following an old approximation used to overcome the lack of statistical tools and computational power (which are not anymore limiting aspects in statistical analysis). Particularly, we showed that applying a linear regression model to ordinal data suggested that there is no difference in means and effect size between genders (female/male). In contrast, an ordinal regression model leaded to the opposite conclusion. This is considered one of the reasons why there is no consensus in the scientific literature on whether gender is an influential factor when assessing the perception of the thermal environment. This result points out that greater attention should be paid to the choice of the statistical method used to analyse subjective data, which should consider the level of measurement used during the data gathering. Furthermore, two different procedures were proposed to facilitate the integration of the occupants and their actual needs into the design and operation of buildings: the former is suitable for a better-informed design phase, where the target is the optimal thermal comfort conditions expressed for an ‘average’ occupant; the other is appropriate for including the human-in-the-control-loop of a building, where satisfying the needs of a specific occupant is the primary goal.

Through this thesis work, new knowledge concerning the human reactions to a dynamic thermal environment was created, which can improve the understanding of the extent to which the indoor environmental conditions can vary both naturally and artificially. Designing and implementing thermally comfortable set-point modulations that consider the occupant feedback capabilities would be beneficial to increase perceived thermal comfort and productivity, potentially reduce energy consumption and significantly support the clean energy transition. In addition, several recommendations for future research are presented.

Sammendrag

I løpet av de siste tiårene har økende global energietterspørsel, en forventet reduksjon av tilgjengelig fossilt brensel og økende bevis for global oppvarming, vist at det haster med å tenke nytt om det bygde miljøet og fremme energiomstilling. I de fleste industrialiserte land står byggesektoren for omtrent 40 % av det totale energiforbruket (oppvarming og kjøling av rom, varmtvann til husholdningsbruk, ventilasjon, belysning og bruk av apparater). En betydelig andel av denne energien brukes til å varmekontrollere bygninger og gi termisk komfortable innendørsmiljøer. Imidlertid er tekniske bygningssystemer vanligvis designet og drevet med tanke på faste settpunkttemperaturer som baserer seg på “one-size-fits-all”-prinsippet – hvilket det de siste femti årene har blitt stilt spørsmål ved– som stiller universelle krav til termisk komfort. Videre endrer innemiljøet seg ofte brått på tvers av bygninger eller mellom ulike deler i bygningen. For eksempel kan manuelt betjente termostater, vinduer og solskjermer resultere i betydelige og ikke-systematiske endringer i innemiljøet. Automatiske kontroller viser i mindre grad en lignende oppførsel. Kroppslig aktivitet endrer dessuten basalstoffskiftet over tid, og tilføyelse eller fjerning av klær påvirker varmebalansen i menneskekroppen. Med andre ord er steady-state temperaturinnstillingene unntaket snarere enn regelen. Temperaturområdet i et bygg bør i stedet være basert på sanntids empiriske bevis angående behovene til brukerne, som er innhentet gjennom deres tilbakemeldinger (vanligvis på en vurderingsskala). Denne oppgaven undersøker disse temaene og baserer seg på en eksperimentell studie for å utforske menneskets reaksjon på dynamiske termiske miljøer.

Den generelle tilnærmingen som benyttes i denne oppgaven omfatter et teknisk/metodologisk aspekt, nemlig en nyere kontrollert eksperimentell prosedyre og en robust samt replikerbar metodikk for innhenting av menneskelig tilbakemelding, og et statistisk aspekt, nemlig en original statistikkaktivert occupant-sentrisk modellering. Det tekniske/metodiske aspektet refererer til hvordan termisk komfordata samles inn;

det vil si den spesifikke tilnærmingen og eksperimentelle oppsettet som benyttes. Det statistiske aspektet refererer til hvordan termisk komfordata analyseres, nemlig den spesifikke statistiske teknikken som skal tas i bruk og de nødvendige modelleringstrinnene.

Det ble funnet at den menneskelige reaksjonen på dynamiske termiske stimuli er asymmetrisk i forhold til oppvarmings- og kjølingsprosesser, og to distinkte mekanismer ble funnet til å forårsake ubehag på grunn av overoppheting og overkjøling. Sammenlignet med anbefalte temperatursykluser, drifter og ramper inkludert i ASHRAE Standard 55, viste dette resultatet at gjeldende anbefalinger undervurderer risikoen for termisk ubehag ved en kjøleprosess mens den overvurderes ved en oppvarmingsprosess. Når det gjelder den subjektive termiske komfordataanalysen, påvirkes konklusjonen av valgt statistisk metode. Selv om det kan virke som en triviell vurdering, er det frem til nå vanlig innen termisk komfort å finne studier som bruker for eksempel lineær regresjon på ordinære data etter en eldre tilnærming brukt for å kompensere for mangelen på statistiske verktøy og beregningskraft (som ikke lenger er begrensende aspekter i statistisk analyse). Spesielt viste vi at bruk av en lineær regresjonsmodell på ordinaldata antydet at det ikke er forskjell i gjennomsnitt og effektstørrelse mellom kjønn (kvinne/mann). Derimot førte en ordinær regresjonsmodell til motsatt konklusjon. Dette anses som en av grunnene til at det ikke er konsensus i vitenskapelig litteratur om hvorvidt kjønn er en påvirkningsfaktor når man vurderer oppfatningen av det termiske miljøet. Dette resultatet peker på at det bør vies større oppmerksomhet til valget av den statistiske metoden som benyttes ved analyse av subjektive data, som bør ta hensyn til målenivået som brukes under datainnsamlingen. Videre ble det foreslått to forskjellige prosedyrer for å lette integreringen av brukerne og deres faktiske behov i design og drift av bygninger: førstnevnte er egnet for en bedre informert designfase, hvor målet er de optimale termiske komforforholdene uttrykt for en “gjennomsnittlig” bruker; sistnevnte er hensiktsmessig for å inkludere mennesket-i-kontroll-sløyfen i en bygning, der det å tilfredsstille behovene til en spesifikk bruker er hovedmålet.

Gjennom denne avhandlingen har det blitt skapt ny kunnskap om menneskets reaksjoner på et dynamisk termisk miljø, som kan forbedre forståelsen av hvilken grad innemiljøforholdene kan variere både naturlig og kunstig. Å designe og implementere termisk komfortable settpunktmodulasjoner som tar hensyn til tilbakemeldingsevnen for beboere vil være fordelaktig for å øke opplevd termisk komfort, og produktivitet, samt potensielt redusere energiforbruket og betydelig støtte overgangen til ren energi. I tillegg presenteres flere anbefalinger for fremtidig forskning.

Sommario

Negli ultimi decenni, l'aumento dei consumi energetici mondiali, la minore disponibilità di combustibili fossili e la crescente evidenza del riscaldamento globale hanno manifestato la necessità di ripensare l'ambiente edificato e promuovere la transizione energetica. Infatti, nella maggior parte dei paesi industrializzati, il settore edile rappresenta circa il 40% del consumo totale di energia (riscaldamento e raffrescamento degli ambienti, acqua calda sanitaria, ventilazione, illuminazione e utilizzo di elettrodomestici). Una quota significativa di questa energia viene utilizzata per il controllo termico degli edifici e per fornire ambienti interni termicamente confortevoli. Tuttavia, i sistemi tecnici per l'edilizia sono generalmente progettati e gestiti considerando temperature di setpoint fisse basate sul principio 'one-size-fits-all' – che è stato messo in discussione negli ultimi cinquant'anni – assumendo requisiti di comfort termico universali. Inoltre, le condizioni ambientali interne possono cambiare bruscamente da un edificio all'altro o tra le varie zone di uno stesso edificio. Ad esempio, il funzionamento manuale di termostati, finestre e tende solari può comportare cambiamenti considerevoli e non sistematici nell'ambiente interno. Inoltre, i controllori automatici mostrano, in misura minore, un comportamento simile. In aggiunta, il metabolismo basale cambia a seconda dell'attività fisica della singola persona, ed indossare o togliere gli indumenti influisce sull'equilibrio termico del corpo umano. In altre parole, considerare la temperatura in regime stazionario è l'eccezione piuttosto che la regola. Gli intervalli di temperatura degli edifici dovrebbero invece essere basati su prove empiriche in tempo reale relative ai bisogni dei suoi occupanti, ottenute attraverso i loro feedback (di solito su una scala di valutazione). La presente tesi analizza questi aspetti proponendo uno studio sperimentale per esplorare la reazione umana agli ambienti termici dinamici.

L'approccio generale utilizzato in questa tesi comprende un aspetto tecnico/metodologico, ovvero una procedura sperimentale innovativa e una

metodologia robusta e replicabile per l'acquisizione del feedback da parte degli utenti, e un aspetto statistico, ovvero una modellazione statistica originale incentrata sull'occupante. L'aspetto tecnico/metodologico si riferisce alle modalità di raccolta dei dati di comfort termico; cioè lo specifico approccio e l'impostazione sperimentale utilizzata. L'aspetto statistico si riferisce al modo in cui i dati sul comfort termico vengono analizzati, ovvero la specifica tecnica statistica da adottare e le fasi di modellazione necessarie.

È stato riscontrato che la reazione umana agli stimoli termici dinamici è asimmetrica rispetto ai processi di riscaldamento e raffreddamento, e che due meccanismi distinti causano disagio da surriscaldamento e sovraraffreddamento. Rispetto alle raccomandazioni relative a "temperature cycles, drifts and ramps" incluse nello Standard ASHRAE 55, questo risultato ha mostrato che le attuali raccomandazioni sottovalutano il rischio di disagio termico durante il processo di raffreddamento mentre lo sovrastimano durante quello di riscaldamento. Per quanto riguarda l'analisi soggettiva dei dati di comfort termico, la scelta del metodo statistico influisce sulle conclusioni. Anche se può sembrare una considerazione banale, nel campo del comfort termico è comune trovare studi che utilizzino, ad esempio, la regressione lineare su dati ordinali basandosi su una vecchia approssimazione, utilizzata per sopperire alla mancanza di strumenti statistici e potenza computazionale (che non sono più aspetti limitanti nell'analisi statistica). In particolare, abbiamo mostrato che l'applicazione di un modello di regressione lineare su dati ordinali suggerisce che non vi è alcuna differenza nella media e nell'ampiezza dell'effetto tra i sessi (femmina/maschio). Al contrario, un modello di regressione ordinale ha portato alla conclusione opposta. Questo è considerato uno dei motivi per cui non c'è consenso nella letteratura scientifica sul fatto che il sesso sia un fattore influente nella valutazione della percezione dell'ambiente termico. Tale risultato evidenzia la necessità di porre una maggiore attenzione nella scelta del metodo statistico utilizzato per l'analisi dei dati soggettivi, il quale dovrebbe considerare la scala di misura utilizzata durante la raccolta dei dati. Inoltre, sono state proposte due diverse procedure per facilitare l'integrazione degli occupanti e le loro effettive esigenze nella progettazione e nel funzionamento degli edifici: la prima è utile per informare una fase progettuale più consapevole, dove l'obiettivo sono le condizioni ottimali di comfort termico espresse per un occupante 'medio'; l'altra procedura è adatta per includere l’essere umano nel circuito di controllo dell’ edificio, dove soddisfare i bisogni di uno specifico occupante è l’obiettivo primario.

Attraverso questo lavoro di tesi è stata creata nuova conoscenza riguardante la reazione umana ad un ambiente termico dinamico, la quale può migliorare la comprensione dell’entità con cui le condizioni ambientali interne possono variare sia naturalmente che artificialmente. Progettare e implementare modulazioni termicamente confortevoli del setpoint, che tengano conto delle capacità di feedback degli occupanti, sarebbe utile per aumentare il comfort termico e la produttività, ridurre potenzialmente il consumo di energia e supportare in modo significativo la transizione verso l’utilizzo sostenibile di fonti energetiche rinnovabili. Infine, vengono presentate alcune raccomandazioni per la ricerca futura.

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Glossary

Beta mixed-effects model — A mixed-effect model which assume a beta distribution for the conditional distribution of the response variable.

Central tendency — A measure of a central or typical value for a probability distribution. Mean, median, and mode are examples of possible measures of central tendency.

Cluster-specific procedure — An approach used to handle the group-level residual (i.e., group-level random effect) during the prediction. The probabilities calculated with this approach have a cluster-specific interpretation (i.e., describe only the unit belonging to the specific cluster).

Cumulative probit model — A cumulative link model (belonging to the broad class of ordinal regression models) in which the link function is the probit.

Dispersion — A measure of variability of a distribution, usually around its central tendency. Variance, standard deviation, and interquartile range are example of possible measures of dispersion.

Logit — Sometimes called log-odds, it is the inverse of the cumulative distribution function of the standard logistic distribution. It is a type of function that maps probability values from (0,1) to real numbers in $(-\infty, +\infty)$.

Mixed-effects model — A synonym of multilevel model. See multilevel model.

Multilevel model — A statistical technique suitable to model the relationship between the dependent(s) and independent(s) variables when there is a correlation between observations (e.g., whenever the data are clustered and/or nested) [1].

Ordinal mixed-effect model — A mixed-effect model which assume a multinomial distribution for the conditional distribution of the response variable.

Population-averaged procedure — A simulation-based approach used to handle the group-level residual (i.e., group-level random effect) during the prediction. The probabilities calculated with this approach have a population-averaged interpretation (i.e., averaged across the random effects).

Probability density function — Provides the probability distribution for continuous variables. It allows to determine the probability of an observation being within a set range around a target value [2].

Probability mass function — Provides the probability distribution for discrete variables. It allows to determine the probability of an observation being exactly equal to a target value [2].

Probit — The inverse of the cumulative distribution function of the standard normal distribution. It is a type of function that maps probability values from (0,1) to real numbers in $(-\infty, +\infty)$.

Random effect — A term that refers to the randomness in the probability model for the group-level coefficients of a multilevel model [1].

List of Papers

Main publications

The following journal articles constitutes the main publications of this thesis:

(I) **M. Favero**, I. Sartori, S. Carlucci, Human thermal comfort under dynamic conditions: An experimental study, Building and Environment 204 (2021) 108144. doi:10.1016/j.buildenv.2021.108144.

Contribution of the PhD candidate: Conceptualisation, Data curation, Formal analysis, Methodology, Software, Validation, Visualisation, Writing – original draft, and Writing – review & editing.

(II) **M. Favero**, A. Luparelli, S. Carlucci, Analysis of subjective thermal comfort data: a statistical point of view [Manuscript submitted for publication] (2022).

Contribution of the PhD candidate: Conceptualisation, Formal analysis, Methodology, Software, Visualisation, Writing – original draft, and Writing – review & editing.

(III) **M. Favero**, J.K. Møller, D. Calì, S. Carlucci, Human-in-the-loop methods for occupant-centric building design and operation, Applied Energy 325 (2022) 119803. doi:10.1016/j.apenergy.2022.119803.

Contribution of the PhD candidate: Conceptualisation, Data curation, Formal analysis, Methodology, Software, Validation, Visualisation, Writing – original draft, and Writing – review & editing.

Supplementary publications

The following journal articles constitutes the supplementary publications of this thesis:

(a) M. Schweiker, E. Ampatzi, M.S. Andargie, R.K. Andersen, E. Azar, V.M. Barthelmes, C. Berger, L. Bourikas, S. Carlucci, G. Chinazzo, L.P. Edappilly, **M. Favero**, S. Gauthier, A. Jamrozik, M. Kane, A. Mahdavi, C. Piselli, A.L. Pisello, A. Roetzel, A. Rysanek, K. Sharma, S. Zhang, Review of multi-domain approaches to indoor environmental perception and behaviour, Building and Environment 176 (2020). doi:10.1016/j.buildenv.2020.106804.

Contribution of the PhD candidate: Data curation, Formal analysis, Writing – original draft, and Writing – review & editing.

(b) A.L. Pisello, I. Pigliautile, M. Andargie, C. Berger, P.M. Bluyssen, S. Carlucci, G. Chinazzo, Z. Deme Belafi, B. Dong, **M. Favero**, A. Ghahramani, G. Havenith, A. Heydarian, D. Kastner, M. Kong, D. Licina, Y. Liu, A. Luna-Navarro, A. Mahdavi, A. Nocente, M. Schweiker, M. Touchie, M. Vellei, F. Vittori, A. Wagner, A. Wang, S. Wei, Test rooms to study human comfort in buildings: A review of controlled experiments and facilities, Renewable & sustainable energy reviews 149 (2021) 111359. doi:10.1016/j.rser.2021.111359.

Contribution of the PhD candidate: Formal analysis, Investigation, and Writing – original draft.

(c) G. Chinazzo, R.K. Andersen, E. Azar, V.M. Barthelmes, C. Becchio, L. Belussi, C. Berger, S. Carlucci, S.P. Corgnati, S. Crosby, L. Danza, L. de Castro, **M. Favero**, S. Gauthier, R.T. Hellwig, Q. Jin, J. Kim, M.S. Khanie, D. Khovalyg, C. Lingua, A. Luna-Navarro, A. Mahdavi, C. Miller, I. Mino-Rodriguez, I. Pigliautile, A.L. Pisello, R.F. Rupp, A. Sadick, F. Salamone, M. Schweiker, M. Syndicus, G. Spigliantini, N.G. Vasquez, D. Vakalis, M. Vellei, S. Wei, Quality criteria for multi-domain studies in the indoor environment: critical review towards research guidelines and recommendations [Manuscript submitted for publication] (2022).

Contribution of the PhD candidate: Conceptualisation, Formal analysis, Visualisation, and Writing – original draft.

(d) S. Carlucci, M. De Simone, S.K. Firth, M.B. Kjærgaard, R. Markovic, M.S. Rahaman, M.K. Annaqeeb, S. Biandrate, A. Das, J.W. Dziedzic, G. Fajilla, **M. Favero**, M. Ferrando, J. Hahn, M. Han, Y. Peng, F. Salim, A. Schlüter, C. van Treeck, Modeling occupant behavior in buildings, Building and environment 174 (2020) 106768. doi:10.1016/j.buildenv.2020.106768.

Contribution of the PhD candidate: Data curation, Investigation, Visualisation, Writing – original draft, and Writing – review & editing.

(e) M. Vellei, E. Azar, K. Bandurski, C. Berger, S. Carlucci, B. Dong, **M. Favero**, A. Mahdavi, M. Schweiker, Documenting occupant models for building performance simulation: A state-of-the-art, Journal of building performance simulation 15 (2022) 634-655. doi:10.1080/19401493.2022.2061050.

Contribution of the PhD candidate: Conceptualisation, Data curation, Formal analysis, Writing – original draft, and Writing – review & editing.

(f) B. Dong, R. Markovic, S. Carlucci, Y. Liu, A. Wagner, A. Liguori, C. van Treeck, D. Oleynikov, E. Azar, G. Fajilla, J. Drgoňa, J. Kim, M. Vellei, M. De Simone, M. Shamsaiee, M. Bavaresco, **M. Favero**, M. Kjaergaard, M. Osman, M. Frahm, S. Dabirian, D. Yan, X. Kang, A guideline to document occupant behavior models for advanced building controls, Building and Environment 219 (2022) 109195. doi:10.1016/j.buildenv.2022.109195.

Contribution of the PhD candidate: Conceptualisation, Investigation, Methodology, and Writing – original draft.

Additional publication

The following article was published during the doctoral research but is not included in the thesis:

(1) A. Mahdavi, C. Berger, H. Amin, E. Ampatzi, R.K. Andersen, E. Azar, V.M.Barthelmes, **M. Favero**, J. Hahn, D. Khovalyg, H.N. Knudsen, A. Luna-Navarro, A. Roetzel, F.C. Sangogboye, M. Schweiker, M. Taheri, D. Teli, M. Touchie, S. Verbruggen, The Role of Occupants in Buildings' Energy Performance Gap: Myth or Reality?, Sustainability (Basel, Switzerland) 13(6) (2021) 3146. doi:10.3390/su13063146.

Introduction

In the last decades, increasing global energy demand, a foreseen reduction of available fossil fuels and increasing evidence for global warming have sparked a surge in promoting the energy transition. In most industrialised nations, buildings energy consumption account for a considerable amount (about 40 % [3]) of total energy consumption and is used for space heating, cooling, ventilation, and lighting of rooms, as well as the generation of domestic hot water and electric appliances used by inhabitants. Typically, space heating and cooling are the most energy-intensive processes. For instance, in 2018, they accounted for almost 40 % of all energy consumed by buildings worldwide [4]. Rethinking how buildings are designed and operated is necessary to reduce their energy consumption. However, the design and operation of buildings have significant implications for people's comfort, well-being, and health, especially considering that humans spend approximately 90 % of their time indoors [5]. Consequently, measures to reduce energy consumption in buildings should be centred on the occupants.

The human sensory system is exposed to a variety of environmental stimuli. In buildings, four ecological factors are identified as the main aspects characterising the indoor environment, namely thermal, visual, auditory, and air quality stimuli. Human senses allow people to perceive these stimuli and subsequently evaluate and respond to them, often through behavioural actions. Although not all interactions between occupants and the built environment are motivated by a reaction to an unpleasant stimulus (i.e., discomfort), perception and behaviour have a strong correlation [6]. Nevertheless, there are few studies linking perception and action. Furthermore, the scientific literature in this field frequently treats these various stimuli separately.

The thermal domain is, to date, the most studied in climatic chamber experiments among the four environmental factors typically considered in buildings. However, most focus is on stationary thermal environments, while the experiments on dynamic conditions mainly involve step-changes. Unsurprisingly, technical building systems are typically designed and operated considering fixed set-point temperatures based on the ‘one-size-fits-all’ principle assuming universal thermal comfort requirements. On the one hand, maintaining a tight temperature range demands more energy than allowing a wider operative temperature shift. On the other, the understanding of the human response to changing thermal environments is still limited. So, to what extent the indoor thermal conditions of buildings can be modulated without sacrificing the thermal comfort perceived by their occupants remains an unresolved research subject.

Therefore, it is evident that indoor environmental monitoring and control strategies play an essential role in the design and operation of a building (both for energy consumption and the thermal comfort of the occupants). Tailoring services such as Heating, Ventilation, and Air Conditioning (HVAC), lighting, and electrical power have the potential to save a significant amount of required energy. In addition to environmental awareness, occupant-aware control schemes have been shown to save between 10–42 %, depending on factors such as outdoor climate and control strategy [7,8]. A more detailed view of the building environment and its occupants opens the door to more energy efficient building services tailored to specific purposes and target groups.

Aims and structure of the thesis

The general aim of this thesis is to investigate how indoor thermal conditions may be modulated while guaranteeing satisfactory thermal comfort conditions. The general approach utilised in this thesis encompasses both a technical/methodological and a statistical point of view. The technical/methodological aspect refers to how thermal comfort data are collected; that is, the specific approach and experimental set-up utilised. On the other, the statistical aspect refers to how thermal comfort data are analysed, namely, the specific statistical technique to be adopted and the needed modelling steps. Both of these aspects are essential and interrelated. They compose the research design – the overall strategy for data collection and analysis – which, in turn, is based on the specific question driving the research.

The introduction provides a brief preface to the context and the aims of the thesis. Chapter 1 offers a more detailed theoretical background for the research. It summarises historical research on ‘static’ thermal comfort, its integration into standards and the most recent development of ‘dynamic’ thermal comfort. An overview of human thermal perception and thermoregulation is also provided with a hint of thermophysiological models. It also describes the individual differences in thermal comfort and briefly introduces the new paradigm of ‘personalised thermal comfort’. In addition, the subjective assessment of the thermal environment and the behaviour of occupants in buildings are discussed. The knowledge gap identified from the theoretical background, as well as the primary research topics addressed in this thesis, are given in Chapter 2. Chapter 3 presents the methodology undertaken in this thesis. The results are presented in Chapter 4 and discussed in Chapter 5. Finally, the conclusions and future developments are presented in Chapter 6.

Chapter 1
Background

Thermal comfort models for the human body have been available for over 40 years as a result of considerable efforts in the 1960s and earlier to develop such models for military and aerospace applications. Currently, the most adopted international thermal comfort standards, ASHRAE 55:2020 [9], ISO 7730:2005 [10] and EN 16798-1:2019 [11] (formerly EN 15251:2007 [12]), propose requirements based on Fanger model (beyond also including other approaches), which solves the heat balance between the human body and its surroundings represented as a uniform environment. Fanger introduced the ‘Predicted Mean Vote’ (PMV) as the index that predicts the mean thermal sensation vote on a standard scale for a large group of persons exposed to a given combination of activity level, clothing insulation and four thermal environmental variables (dry-bulb air temperature, mean radiant temperature, air velocity and relative humidity) [13]. The PMV-model is generally referred to as a static model because it is only suited to predict thermal sensation under steady-state or slowly changing indoor conditions (i.e., rate of change lower than 2.0 K/h) [10]. Based on the PMV, the ‘Predicted Percentage of Dissatisfied’ (PPD) was determined:

$$\mathrm{PPD} = 100 - 95 \cdot e^{(-0.03353 \cdot \mathrm{PMV}^4 - 0.2179 \cdot \mathrm{PMV}^2)} \qquad \text{Eq. (1)}$$

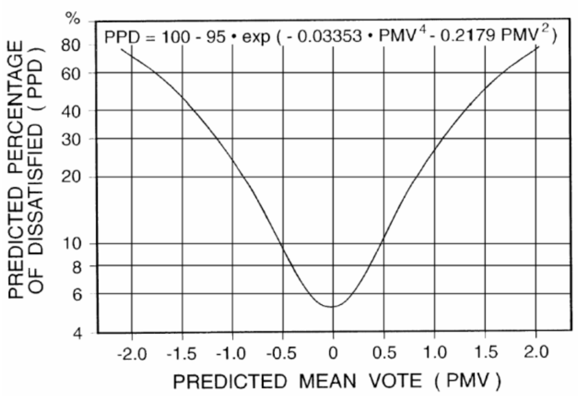


Fig. 1 – Predicted percentage dissatisfied (PPD) as a function of predicted mean vote (PMV). From ASHRAE 55:2020 [9].

In Fig. 1 can be seen that the relationship between PMV and PPD has a minimum of 5% at PMV = 0 – generally referred to in the literature as thermal neutrality. Furthermore, it is also symmetric on the cooler (i.e., for negative PMV values) and the warmer (i.e., for positive PMV values) sides. In this regard, the issue that arises is whether the outcome of Fanger's analysis (specifically, minimum of dissatisfied of 5 % and symmetry of the curve centred at PMV = 0) are correct. Different studies have found other relationships than the one described by Fanger [14-17].

In the 1970s, the same period when Fanger developed his model, Nicol and Humphreys [18] hypothesised the presence of 'control mechanisms' (feedback loops) between the occupants' thermal comfort perception and their behaviour in buildings. They suggested that the building design may concentrate on how to allow for the 'control mechanisms' to operate rather than trying to establish optimum indoor climates. In the first meta-analysis of thermal comfort field studies worldwide, Humphreys [19] compiled data from more than 30 field studies of thermal comfort and shows, with compelling evidence, the disparity between physiological model predictions and empirical field study. In a subsequent reanalysis of the data, Humphreys [20] evaluated the influence of climate and found that the indoor temperature required for thermal comfort is related to the prevailing outdoor mean temperature. Later on, the analysis of the two studies was brought together [21]. It can be said that these papers are the ancestors of what is nowadays known as the adaptive thermal comfort model since they have shaped its development (e.g., see [22-25]). The hypothesis of adaptive thermal comfort predicts that contextual factors and past thermal history modify occupant's thermal expectations and preferences [26]. People in warm climate zones would prefer higher indoor temperatures than people living in cold climate zones, which contrasts with the assumptions underlying comfort standards based on the PMV model [26]. Adaptation is defined as the gradual decrease of the human response to repeated environmental stimulation, and can be both behavioural (e.g., clothing adjustment), physiological (e.g., acclimatisation) as well as psychological (e.g., expectation) [24,26,27]. Therefore, the adaptive model recognises the adaptation of people; however, it focuses on long-term adaptation mechanisms, ignoring short-term ones.

In current standards, Fanger's PMV/PPD model is the prerogative of mechanically heated and/or cooled buildings, while the adaptive thermal comfort model is reserved for free-running buildings. Both are steady-state and whole-body thermal comfort models that predict the mean thermal sensations for a group of people. Therefore, they can account neither for dynamic and non-uniform thermal environments nor for individual differences.

1.1 Dynamic and non-uniform thermal environments

Manually operating thermostats, ventilation fans, windows, and window shades can result in considerable and not systematic changes in the indoor environment. Automatic controllers exhibit, to a lesser degree, a similar behaviour. The indoor environment frequently changes abruptly across buildings or between various parts within a single building. Individual activity modifies the basal metabolic rate over time, and the addition or removal of clothes affects the heat balance as well. In other words, the steady-state temperature settings that define most comfort studies are the exception rather than the rule. In 1981, Rohles [28] stated that 'human response to the thermal environment depends on seven variables' (air temperature, relative humidity, mean radiant temperature, air velocity, clothing, physical activity, and time). He also mentioned that 'even though the thermal conditions to which humans are exposed are never constant for long periods of time, time has received only modest attention as a variable in comfort research' [28]. These days, 'time' continues to be the least understood variable in the field of thermal comfort research.

Nowadays, all thermal comfort standards include definitions of the requirements for indoor thermal conditions in buildings both for design and operational assessment. However, current standards only indicate the maximum variations in operative temperature for non-steady-state thermal environments. ASHRAE 55:2020 [9] and ISO 7730:2005 [10] classify temperature variations as either temperature drifts and ramps or temperature cycles. Drifts and ramps are defined as ‘monotonic, non-cyclic changes in operative temperature’ [9], and their limits during a period are shown in Table 1. Drifts refer to passive temperature changes in an enclosed space, while ramps denote actively controlled ones. In contrast, cycles refer to ‘those situations where the operative temperature repeatedly rises and falls, and the period of these variations is not greater than 15 min’ [9]. For these changes, ASHRAE 55 allows a maximum peak-to-peak cyclic variation in operative temperature of 1.1 K and recommends treating cyclic variations with a period greater than 15 min as drifts or ramps.

Table 1 – Limits on temperature drifts and ramps by ASHRAE 55:2020 [9].

Time period (h)	**Maximum operative temperature to change allowed (K)**
0.25	1.1
0.5	1.7
1	2.2
2	2.8
4	3.3

ISO 7730:2005 [10] provides less detailed indications. For temperature cycles, it sets a maximum peak-to-peak variation of 1 K, whereas, for drifts and ramps with a rate of change lower than 2.0 K/h, it prescribes steady-state methods. These standards also include step-changes, which involve changing the environment (i.e., moving to/from another space) rather than a change within the environment. Consequently, they are not described here because they are out of the scope of this thesis.

The limiting criteria in Table 1 are probably based on early laboratory studies of thermal comfort under transient exposure [29-31]. During the same period (the 1970s and 1980s), other studies were conducted on both cyclical [32,33] and monotonic temperature variations [34-38]. Hensen [39] reviewed these studies meticulously and found inconsistent results. He offered several possible explanations for these dissimilarities, including the different voting scales and acceptability criteria and the distinct experimental conditions, among others. Despite these discrepancies, Hensen argued that the experimental results support a 2.2 K/h constraint for cyclical variations in operative temperature. As no evidence had been found to the contrary, he also concluded that this limit could also apply to temperature drifts and ramps. Since this review, only a handful of studies have been conducted on cyclical [40-42] and monotonic variations [43]. Under cyclical variations, these recent studies indicate a positive effect on occupants' thermal comfort. In contrast, for monotonic variations, different rates of temperature change result in inconsistent effects. As mentioned earlier, different acceptability criteria and voting scales could plausibly be the main source of the discrepant findings. Another factor that might be responsible for these differences involves human thermal perception and thermoregulation.

1.2 Human thermal perception and thermoregulation: a brief overview

The skin, the largest organ in the human body, is an interface that separates the body from the rest of the world. On a daily basis, its surface processes at least hundreds of physical sensations, among them environmental thermal stimuli. These stimuli are detected by the free nerve endings of the primary sensory neurons in the skin. These neurones, located in the dorsal root ganglia, convert the external stimuli into electrical signals that are then transmitted to second-order neurons (namely dorsal horn neurons), which are located in the spinal cord [44]. At this first relay centre, thermal information is further processed before being sent to the brain. This pathway is illustrated in Fig. 2.

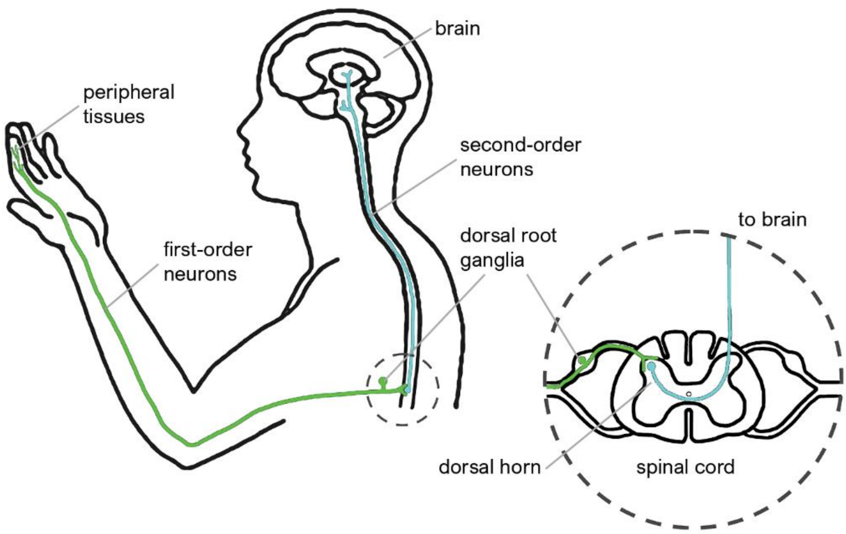


Fig. 2 – Pathways for autonomous thermoregulatory responses and thermal perception from peripheral tissues. Adapted from Ref. [45].

In neurophysiology, significant progress has been made in identifying primary sensory neurons' thermal response profiles [44,46,47]. Researchers have ascertained that the principal detectors of the thermal stimuli in the peripheral nervous system are the ion channels of the transient receptor potential (TRP) family [44]. These thermosensitive TRPs are triggered at specific threshold temperatures and function as dedicated transducers of distinct thermal modes. Among them, TRPM2/TRPV1 and TRPM8 are the primary sensors of hot and cold temperatures, respectively. Conversely, the understanding of spinal cord temperature encoding remained limited until recently, when Ran et al. [48] showed that the representation of heat and cold in the dorsal horn is substantially different from the operation of TRPs. They observed that the response of cold-sensitive spinal neurons is mostly determined by the rate of cooling and rapidly adapts to the steady-state value. Heat-sensitive spinal neurons, on the other hand, respond primarily to absolute temperatures and are not as adaptable. The interested reader is referred to Ref. [45] for a more detail description and further discussions of this topic.

1.2.1 Thermophysiological models

As mentioned previously, Fanger's PMV model predicts thermal responses (i.e., thermal sensation votes) to a given steady-state environment. These predictions are based on formulae obtained from experimental conditions, making this model empirical. However, the environment where humans carry out their everyday tasks is intrinsically dynamic and non-uniform. Furthermore, Fanger's model regards the body as a whole, de facto excluding the human thermoregulatory system. As a consequence, the human being is viewed as a passive recipient of thermal stimuli.

As an alternative to Fanger's steady-state heat balance model, models that include the thermoregulatory system have emerged. These models include a 'passive system' and an 'active system'. The former simulates the human body and its energy transfer physical mechanisms (both within and between the human body and its environment). In contrast, the latter simulates the thermoregulatory mechanisms that regulate the internal body temperature –vasodilation, vasoconstriction, sweating and shivering.

One of the first and well-known examples of these type of models is Gagge two-node thermal model [49], which is a lumped-parameter model. They split the body into two concentric shells, with the inner shell representing internal organs, bone, muscle, and subcutaneous tissue and the outer shell representing the skin layer. As the temperatures of both shells are usually assumed to be uniform, the model thermally consists of two nodes. Human thermoregulation models have evolved in the past 50 years and more advance complex model have been developed (e.g., the Berkeley Comfort Mode [50], Tanabe [51], Fiala [52], ThermoSEM [53] and Takada [54]). According to Fu ([55] cited in [56]), different models can be classified into four categories: (i) one-node thermal models, (ii) two-node thermal models, (iii) multi-node thermal models and (iv) multi-element thermal models. These models either represent the human body as a single segment or divide it into several parts (i.e., multi-segment) (see Fig. 3). The interested reader is referred to Ref. [57] for further discussions on this topic.

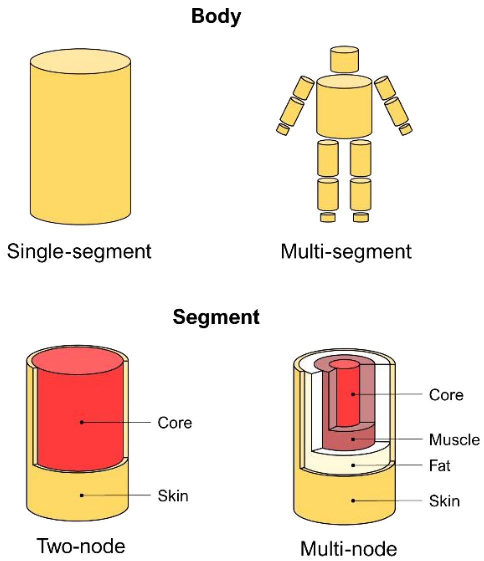


Fig. 3 – Comparison of the model segmentation. Adapted from Ref. [57].

While these models are invaluable to deepen the understanding of dynamic thermal comfort, they require more 'invasive' measurements (e.g., skin temperature sensors) that would make them difficult to be applied directly in everyday control strategies (e.g., temperature control in an office). For this reason, these types of models have been not analysed in this thesis.

1.3 Individual differences

In thermal comfort, individual differences refer to situations where distinct people perceive the same thermal environment differently (i.e., inter-individual differences) and/or when the same individual assesses the same environment differently at different times or in different situations (i.e., intra-individual differences). Humphreys and Nicol [58] suggested that inter-individual differences encompass both temperature differences to be considered neutral and differences in the interpretation of the semantic scale categories. In contrast, intra-individual differences refer to personal judgments that differ from time to time.

In an effort to summarise the factors that in thermal comfort might lead to the individual differences and to assess their significance, Wang et al. [59] reviewed 112 papers (only peer-reviewed conference or journal articles) including both chamber and field studies but presenting them separately. They found out that no consistent conclusions could be drawn on the size and significance of inter-group differences in the preferred/neutral temperature between females and males, nor the young and the elderly. However, it is believed that certain groups of occupants (females and the elderly) are more critical towards the indoor thermal environment, and more sensitive to deviations from an optimal environment, than other sub-populations (males and the young) [60]. Furthermore, numerous contextual factors can also influence occupants' thermal comfort perception, including behavioural and cultural aspects, individual preferences, space layout, architectural features, and adaptive opportunities available [61].

1.3.1 Personal comfort paradigm

Nowadays, all thermal comfort standards are based on models that inherently do not account for individual differences. As a consequence, buildings are designed and operated accordingly. For instance, a traditional, centralized air-conditioning system strives to always maintain an ideal indoor environment with uniformly distributed temperature across the occupied zone. However, because of individual variances in comfort requirements, this 'one-size-fits-all' strategy unavoidably disappoints a considerable portion of building inhabitants. Unsurprisingly, the actual satisfaction percentage of existing building occupants frequently does not reach the ASHRAE Standard's goal satisfaction rate of 80 % [62-64].

To address individual differences, a new modelling approach called personal comfort model was derived [65]. In these models, the unit of analysis is the individual rather than a group of people. Personal comfort models can be used to understand individual occupants' specific needs and desires, potentially specifying a set of variables that would fulfil their thermal comfort in a given environment. In this setting, a valid solution is using personally-owned thermal control devices, such as personal comfort systems (PCSs). PCSs concentrate on conditioning the micro-environment of each occupant rather than the entire volume of space within a given thermal zone of a building. For example, PCS such as heated and cooled chairs can address the individual differences in thermal comfort while providing potential energy savings [66]. In this situation, the centralised system oversees keeping the ambient temperatures within a range that allows the PCS to compensate for each individual's thermal comfort demands. While this approach looks promising, most of these PCSs were tested under controlled conditions, and long-term performance studies from real buildings are lacking. Furthermore, there is a knowledge and tool gap that must be bridged in order for these systems to be extensively used in buildings. For this reason, PCSs have been not used and analysed in this thesis.

1.4 Rating scales for subjective assessment of thermal environments

According to a commonly cited definition, thermal comfort is 'the condition of mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluation' [9]. Regardless the apparent simplicity of this definition, determining such conditions is a complex and partially unsolved matter. In general, capturing the volatile nature of constructs (e.g., thermal comfort) is, to any extent, notoriously difficult. It can be very challenging with just one question or item to consider. However, in thermal comfort research single-item scales are commonly used. The most adopted of which is the ASHRAE 7-point thermal sensation scale, consisting of seven verbal anchors: 'cold', 'cool', 'slightly cool', 'neutral', 'slightly warm', 'warm', and 'hot'. This is a perceptual judgement (single-item) scale [67] and is utilised to measure thermal sensation. Other rating scales are also employed in thermal comfort studies: the most common ones being thermal evaluation, preference, and acceptability. ISO 10551:2019 [67], beyond those already mentioned, also introduces a 'tolerance scale', which is rarely used in the scientific literature. When utilising single-item scales, three significant problematics are commonly expressed: (i) it is improbable that they can capture the construct (poor content validity), (ii) they have fewer discrimination points (low sensitivity), and (iii) they do not have an internal consistency metric (reliability). In 1981, Auliciems [68] specified that the scales of thermal comfort have not been tested for validity and reliability. To our knowledge, thermal comfort scales have not yet been tested. Although the verification of the validity, sensitivity and reliability of the thermal comfort scales is of fundamental importance, it is beyond the scope of this thesis and, therefore, not analysed here. Furthermore, we believe this issue should be addressed with a collaborative effort among researchers within the thermal comfort community and not as a 'single' individual.

Each one of these (single-item) scales used in thermal comfort research can be presented in different formats (e.g., discontinuous versus continuous format) and methods (e.g., paper- versus computer-based). Independently of the format and method used, it is common practice to assign a numerical value to each level (i.e., the verbal anchors) of a scale. For instance, the ASHRAE 7-point thermal sensation scale generally varies from -3 ('cold') to +3 ('hot') with one-unit steps. However, different values can be assigned, such as 1 for 'cold' and 7 for 'hot'. This interchangeability is possible because these numbers are merely placeholders without underlying meaning. Nevertheless, it is common practice to calculate the mean of the thermal sensation votes of a group of people (e.g., [13,26]). The reasoning behind this method is that, while the variable is ordinal in nature, a vote created by averaging different responses is continuous. Furthermore, the averaged votes will result in a more normal-looking distribution and, therefore, statistical methods that assume normality (e.g., linear regression and analysis of variance) can be applied. The origin of this approach can be found in early works to measure attitudes, such as in Thurstone [69] and Likert [70]. However, there are two problems with this approach. Firstly, it is not appropriate to calculate the mean of an ordinal variable because its linearity (i.e., equally spaced divisions) is an arbitrary assumption imposed to the original scale values. This assumption was also recently questioned by Schweiker et al. [71,72]. Secondly, this approach conflates the problem of the level of measurement with that of the distribution of a variable. Averaging ordinal data may improve the degree to which the distribution of votes resembles a normal distribution, but it does not change the nature of the observations from ordinal to interval.

Consequently, in the field of thermal comfort, it is common practice to analyse subjective human thermal responses independently of how they have been measured. That is, the statistical analysis is unrelated to the modalities of the data that have been acquired. For example, even if measured on an ordinal scale, thermal sensation vote (TSV) is generally treated as continuous and analysed with linear regression or other statistical tests that assume (conditional) normality. Since thermal comfort 'is assessed by subjective evaluation' [9], the choice of an appropriate method to analyse these data is essential. As mentioned in Section 1.1, Hensen [39], in his review, assigned to different voting scales and acceptability criteria as one of the possible explanation for the inconsistent results.

Discussion regarding the different types of rating scales employed (e.g., categorical scale, visual analogue scale, and graphic categorical scale), the number of anchors utilised, and the assumptions underlying their usage are outside the scope of this thesis. The interested reader is referred to previous studies such as [71-74] for further discussions of these topics.

1.5 Occupant behaviour

Occupant behaviour is complicated and requires a multidisciplinary approach to be appropriately comprehended (if at all possible). On the one hand, both external elements like culture, economics, and climate and internal factors such as individual comfort preferences, physiology, and psychology influence occupant behaviour. On the other hand, occupant behaviour involves interactions with building systems (e.g., adjusting the thermostat, switching lights, opening/closing windows), which greatly influence building operations and, therefore, energy consumption, costs, and comfort. This, in turn, affects the behaviour of the occupants, establishing a closed-loop.

The field of occupant modelling emerged over 40 years ago (e.g., [75]) but has increased recently – particularly because of Annex 66 'Definition and Simulation of Occupant Behavior in Buildings' (https://annex66.iea-ebc.org/) promoted by the International Energy Agency's Energy in Buildings and Communities Programme (IEA EBC). Experimental research methodologies, modelling strategies and model validation, and occupant simulation were all formalised in this Annex. However, several open questions about occupant comfort and behaviour and the implementation of advanced occupant modelling paved the way for the follow-up IEA EBC Annex 79 'Occupant-Centric Building Design and Operation' (https://annex79.iea-ebc.org/).

While it is not within the objectives of this thesis to develop occupant behaviour models, to design and operate (low energy) buildings, it is essential to have a thorough understanding of occupant behaviour and the ability to analyse and quantify its influence on the use of building technologies.

Chapter 2

Knowledge gap and research questions

As highlighted in Section 1, although thermal comfort models for the human body are available for over four decades, several research gaps (both from a technical/methodological and statistical point of views) affect the understanding of this topic. The following gaps were identified as relevant for investigation in this thesis:

- Some knowledge gaps still affect understanding of the human response to changing thermal environments. Among them, ‘time’ continues to be the least understood variable.
- Despite the fact that thermal comfort is, by definition, ‘assessed by subjective evaluation’ [9], the relevance of the proper use of rating scales for subjective assessment of thermal environments seems to be overlooked. Particularly, the importance of an appropriate processing of these data and model development.
- Nowadays, although not formally considered into standardisation, the presence of individual differences in thermal comfort is a recognised fact. However, its integration (e.g., in the form of human feedback) in both the design and operation of buildings is still lacking.
- There is a little knowledge about occupants’ interactions with building technologies. For example, on thermal comfort-driven actions caused by multiple and interdependent environmental influences. Moreover, there is a lack of guidelines and documentation for applying occupant behaviour models during building design and operation.

2.1 Research questions

This thesis aimed to close these knowledge gaps by investigating how enhancing user comfort in (dynamic) thermal indoor environments with particular emphasis on the technical/methodological perspective (i.e., ‘experimental aspect’) and the subsequent data analysis (i.e., ‘modelling and statistics aspect’). It also aims to provide more occupant-centric design and control strategies for the buildings’ indoor environment (i.e., ‘applicational aspect’). This results in the following research questions:

RQ1. To what extent can the indoor thermal condition be modulated without compromising occupants’ thermal comfort?

RQ2. How are the rating scales analysed for the subjective assessment of thermal environments?

RQ3. How can the description of occupants’ thermal preferences be used to provide more satisfying control strategies?

As shown in Fig. 4, the answers to these research questions are given using the work developed in three peer-reviewed scientific journal articles: Article I, II and III. These articles constitute the ‘main’ publications of this thesis. In addition, six peer-reviewed scientific journal articles are appended as ‘supplementary’ publications: Article a, b, c, d, e and f. These publications constitute the groundwork and points of reflection concerning occupant behaviour and thermal comfort in buildings, used for the different elements analysed in this thesis. More details about the scientific publications are provided in Fig. 5.

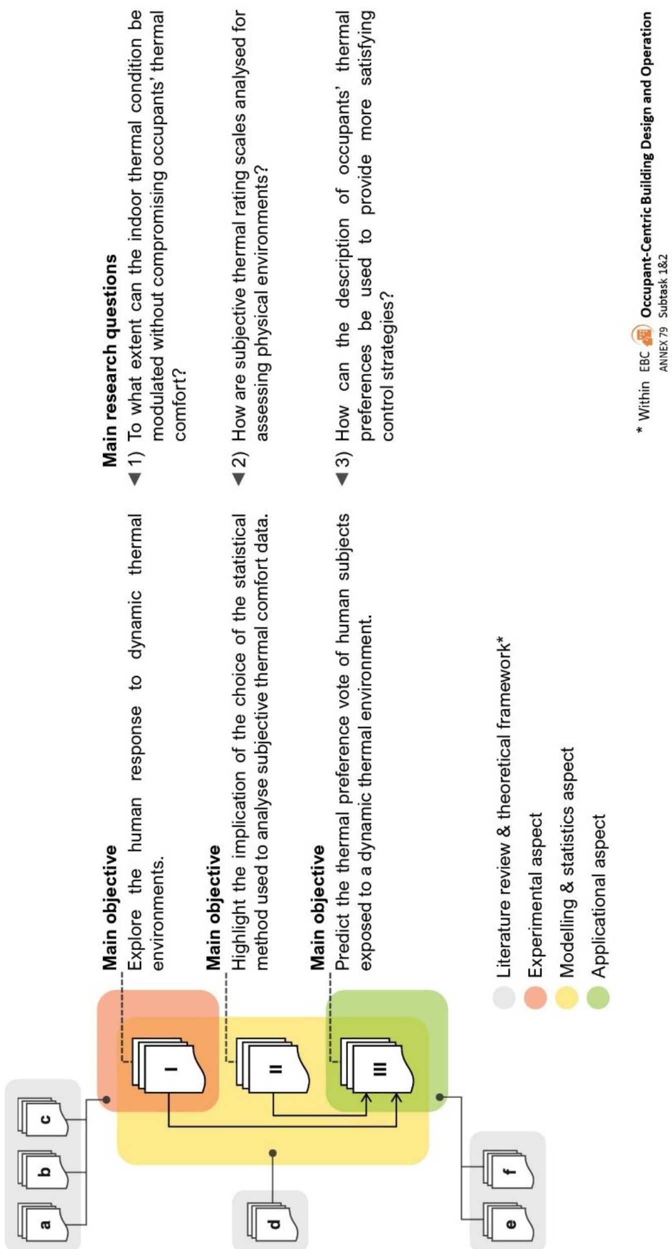
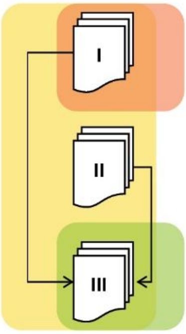


Fig. 4 – Outline of research with main research question, objectives, and research activities.

Main publications

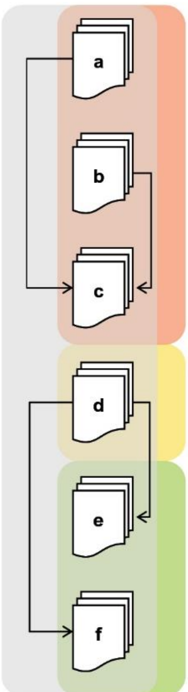


Journal article:
Favero, Matteo; Sartori, Igor; Carlucci, Salvatore. Human thermal comfort under dynamic conditions: An experimental study. *Building and Environment* (2021).

Journal article:
Favero, Matteo; Luparelli, Antonio; Carlucci, Salvatore. Analysis of subjective thermal comfort data: a statistical point of view [Manuscript submitted for publication] (2022).

Journal article:
Favero *et al*. Human-in-the-loop methods for occupant-centric building design and operation. *Applied Energy* (2022).

Supplementary publications



Journal article:
Schweiker *et al*. Review of multi-domain approaches to indoor environmental perception and behaviour. *Building and Environment* (2020).

Journal article:
Pisello *et al*. Test rooms to study human comfort in buildings: A review of controlled experiments and facilities. *Renewable and Sustainable Energy Reviews* (2021).

Journal article:
Chinazzo *et al*. Quality criteria for multi-domain studies in the indoor environment: critical review towards research guidelines and recommendations [Manuscript submitted for publication] (2022).

Journal article:
Carlucci *et al*. Modeling occupant behavior in buildings.
Building and Environment (2020).

Journal article:
Vellei *et al*. Documenting occupant models for building performance simulation: A state-of-the-art. *Journal of Building Performance Simulation* (2022).

Journal article:
Dong *et al*. A Guideline to Document Occupant Behavior Models for Advanced Building Controls. *Building and Environment* (2022).

Literature review & theoretical framework* | Experimental aspect | Modelling & statistics aspect | Applicational aspect

Fig. 5 – Journal publications in this thesis.

Chapter 3
Methods

As mentioned in the Introduction, the general aim of this thesis is to investigate how indoor thermal conditions may be modulated while guaranteeing satisfactory thermal comfort conditions. The general approach utilised in this thesis encompasses both a technical/methodological and a statistical point of view. Both aspects are essential and interrelated since they compose the research design which is based on the specific question driving the research. The research methods used are presented below, arranged by each study.

3.1 Literature review and theoretical framework

These reviews and theoretical frameworks were conducted under the umbrella of the IEA EBC Annex 79 'Occupant-Centric Building Design and Operation' (https://annex79.iea-ebc.org/) and were the result of a collaborative effort of international researchers. These activities were performed to identify current trends, experiences, and outcomes of various aspects related to occupant behaviour in buildings, which constitute the groundwork and point of reflections for the different elements analysed in this thesis (Fig. 4). Specifically, the 'experimental aspect' (Article a, b, and c), 'modelling and statistics aspect' (Article d) and 'applicational aspect' (Article e and f).

3.2 Experimental aspect

The core of this PhD thesis is based on the design and implementation of an exploratory study performed in a climatic chamber furnished like a typical single-office. The experimental study was used to answer RQ1 ('To what extent can the indoor thermal condition be modulated without compromising occupants' thermal comfort?') and benefited from some outcomes of the Article a, b, and c of the 'supplementary publications'.

3.2.1 Experimental set-up

The facility

The experiment was conducted in the ZEB Test Cell Laboratory on the Norwegian University of Science and Technology (NTNU) premises (Trondheim campus) between September 2019 and January 2020. Two identical climatic chambers (Fig. 6), furnished like a typical single office, were used to recreate a change in the environment induced by thermal ramps. Space heating and cooling were provided from a constant air-volume system that supplied 100 % fresh air from outside, distributed by a 2 m-long perforated fabric tube installed at the ceiling. Further details on the facility's experimental equipment can be found in Article I.

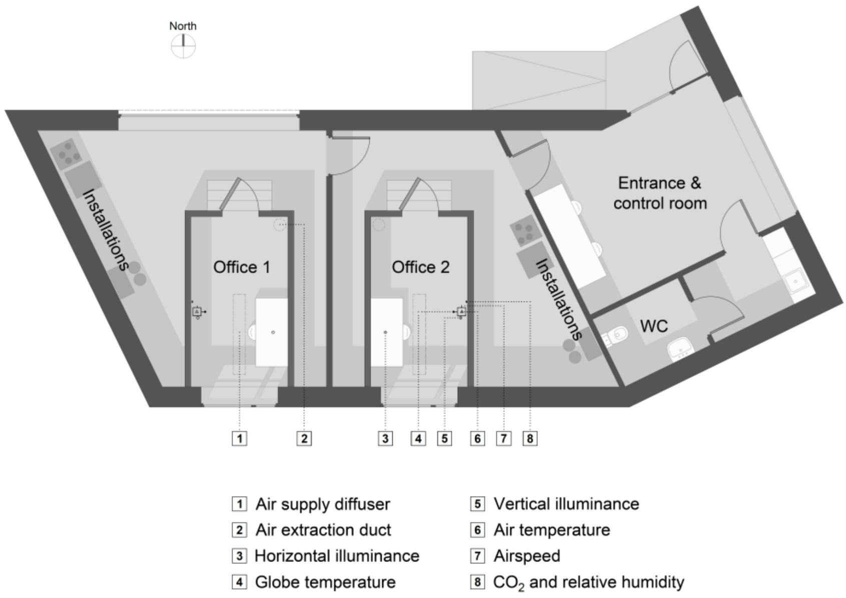


Fig. 6 – Floor plan of the facility.

Participants

Thirty-eight participants (29 females, 9 males) were recruited from the university campus with a targeted age between 20 and 67. Participation in the experiment was voluntary and in agreement with the principles and instructions of the European General Data Protection Regulation (GDPR). To comply with the GDPR, the experiment description was submitted to the Norwegian Centre for Research Data (NSD) and approved with reference code 525790. Further details about the main demographic and anthropometric characteristics of the subjects can be found in Article I.

Experimental conditions

The operative temperature set-point of 22.0 °C ± 1.0 °C was defined in accordance with the thermal comfort limit for winter according to Category A of ISO 7730:2005 [10]. Both space heating and cooling variations were tested within winter conditions. The rates of temperature changes, derived from the limit in ASHRAE 55:2020 [9] (Table 1), were: (i) ±4.4 K/h, (ii) ±3.4 K/h, (iii) ± 2.2 K/h and (iv) ±1.4 K/h. The study's design was a randomised crossover trial, a longitudinal study in which participants received a randomised sequence of thermal ramps. The experimental session was seven and a half hours, including a half-hour lunch break. The day could be split into half days to increase participation, meaning one-morning session (8:00–11:30) and one-afternoon session (12:00–15:30). However, participants were required to attend an even number of morning and afternoon sessions. Further details about the experimental procedure can be found in Article I.

Data collection

The indoor environment was monitored during the experiments by measuring ambient and indoor air temperatures, surface temperatures, globe temperature, relative humidity, airspeed, CO_2 concentration, and horizontal and vertical illuminance every minute throughout every session. The mean radiant temperature (MRT) was calculated according to ISO 7726:1998 [76] based on the surrounding surfaces' measured temperature and the angular factor computed for a seated person in the specific climate chamber. The calculated MRT was combined with the measured air temperature and air velocity to calculate the operative temperature. In addition, a weather station installed in proximity to the southern façade of the ZEB Test Cell measured ambient air temperature, relative humidity, wind speed and direction, global solar irradiance on the horizontal plane and precipitation in 10-minute intervals. Further details about the environmental measurements are given in Article I.

Participants were asked to fill out computer-based questionnaires at different scheduled intervals to evaluate the indoor environment during the experiment. By means of graphic categorical scales (see Fig. 7.a), these questionnaires were used to assess perception, evaluation, preference, and acceptability of the thermal, visual, acoustic and air quality of the environment. It is vital to illustrate how the participants vote and how we acquire this information. Participants could manually draw a diagonal line on the rating scale of the computer-based questionnaire. This questionnaire was an interactive PDF file in which a hidden button allowed, if pressed, to change the scale format into the one shown in Fig. 7.b. This graduated scale allowed us to quantify the vote precisely.

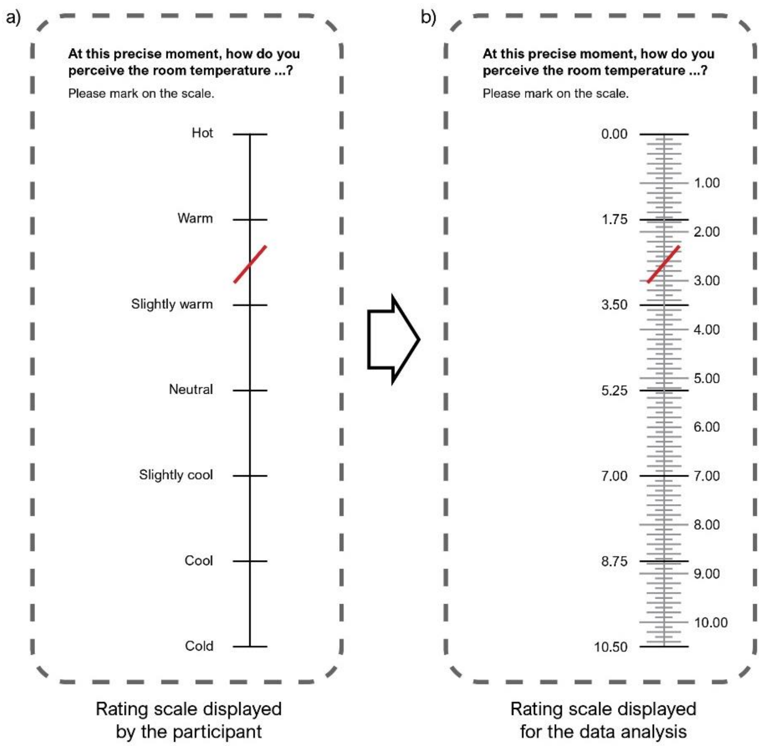


Fig. 7 – Extract from the rating scale used to assess the perception of the room temperature; (a) rating scale displayed by the participant and (b) rating scale displayed for the data analysis.

Furthermore, participants were instructed to press a digital button (see Fig. 8) as soon as they felt uncomfortable. Here uncomfortable was defined as the decision to 'take action to restore a comfort condition' (e.g., if the environment is too warm, then regulate the thermostat or open the window). It is essential to point out that participants could press the button for any source of discomfort related to the indoor environment (e.g., stuffy air, noise from the ventilation system, lack of daylight) and not only for temperature-related discomfort. After pressing the digital button, a computer-based questionnaire appeared on the dedicated laptop. This questionnaire was used to assess the environment and record the source(s) of discomfort through multiple-choice answers.

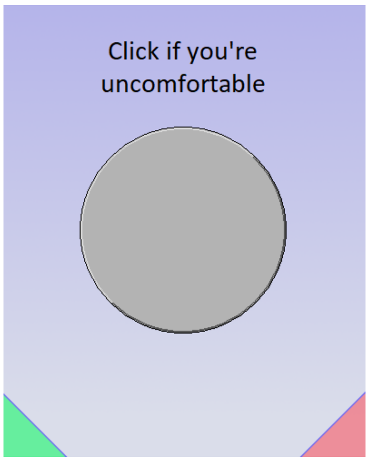


Fig. 8 – Digital interface for the discomfort button.

In addition, there were two other questionnaires, one at the beginning and one at the end of each session. After arrival, participants were asked to fill out a questionnaire related to demographic and anthropometric characteristics, current clothing level and satisfaction with the workplace. At the end of the session, subjects were asked to fill out a questionnaire about their satisfaction with the workplace as a whole, expressed on a Likert scale. All the survey questions and rating scales are given in the appendix of Article I.

3.2.2 Experimental data analysis

Environmental, demographic and anthropometric data were studied using survival analysis. Survival analysis comprises a family of methods that examine and model the time it takes for events to occur. However, its goal is not limited to investigating the effects on the time until the event occurs but also evaluating the relationship of survival time to covariates. Covariates (often referred to interchangeably as predictors or independent/explanatory variables) assess the impact of certain features on the dependent variable. The prototype event is death – hence the name ‘survival analysis’ and much of its terminology – but the range of applications of survival analysis is much broader. For example, the same methods are known as ‘failure-time analysis’ in engineering and ‘event-history analysis’ in sociology. Further details about survival analysis can be found in Article I.

Kaplan-Meier method and Cox regression

Survival analysis is the name for a collection of statistical techniques. These techniques can be summarised into three categories: (i) non-parametric models, (ii) parametric models, and (iii) semi-parametric models. The main difference between the three categories is whether the survival time is assumed to follow a specific distribution. Non-parametric methods are used when no theoretical distribution adequately fits the data; therefore, they are distribution-free. The Kaplan-Meier method is an example of this category. Conversely, in the parametric model, the underlying distribution of the outcome is specified. For survival analysis, several parametric distributions can be used to describe time to event data, such as exponential, Weibull and log-normal distribution, each of which is defined by a different hazard function. Semi-parametric models are a combination of the two previously mentioned categories. Even if these models’ regression parameters (the betas) are known, the outcome’s distribution remains unknown. The Cox proportional hazards (PH) model belongs to this category. Since the survival time distribution is unknown during the analysis, non-parametric and semi-parametric models were utilised, more specifically, the Kaplan-Meier method and Cox regression. The former has been used only to describe and visualise the survival curves at a preliminary stage, while the latter evaluates the relationship of survival time to covariates. Details on the mathematical formulation and assumption underlying the Kaplan-Meier method and Cox regression can be found in Article I.

3.3 Modelling and statistics aspect

This analysis was used to answer the RQ2 ('How are the rating scales analysed for the subjective assessment of thermal environments?') and benefited from some aspects analysed in the Article d of the 'supplementary publications'.

3.3.1 Statistical modelling

One of the goals of thermal comfort research is to establish a relationship between the thermal environment and the human response. In a statistical modelling framework, this is generally achieved through regression analysis. Regression analysis is *'the blanket name for a family of data analysis techniques that examine relationships between variables'* [77], which are categorised into a dependent variable ('outcome' or 'response' variable), Y, and one or more independent variables ('explanatory variables', 'predictors', 'covariates' or 'features'), X. Here, two different modelling strategies to analyse subjective thermal comfort data were compared: the cumulative probit model and the classical linear regression, referred to as gaussian (ordinal-as-metric) model. Further details on the mathematical formulation of these models can be found in Article II.

Bayesian approach

Bayesian approach was used to analyse the data. This approach is not entirely new in thermal comfort studies (e.g., [78-80]); however, it is not an established practice either. Since statistical knowledge in this field generally tends towards 'frequentist' principles, it is essential to explain the Bayesian approach and compare it with the frequentist one. Frequentist statistics have a more recent history than its philosophical adversary, Bayesian statistics. Frequentist statistics were established mostly in the early 20th century and have lately emerged as the dominant paradigm in inferential statistics, whereas Bayesian statistics were invented in the 19th century. Despite this dominance, there is no consensus on whether frequentism or Bayesian statistics are superior. In addition, the statistical nomenclature is not as old as the philosophical interpretations. The modern statistical terminology 'Bayesian' and 'frequentist' consolidated in the second part of the 20th century.

Essentially, the divide between frequentists and Bayesians is in the definition of probability. For frequentists, probabilities are associated with frequencies of events. For

Bayesian, probabilities are related to their own understanding (i.e., certainty or uncertainty) of events. This difference has important implications in the analysis of data. Nevertheless, the aim is neither to go into details about their differences, nor to be a full introduction to either approach. For a more complete treatment, see, for example, [81] and [82]. Furthermore, it is essential to emphasise that we are not advocating that the specific approach used is the best way to analyse subjective thermal comfort data measured on an ordinal scale: the approach presented is merely one of the possible ways to do so. For instance, ordinal models in a frequentist framework provide another valid solution for analysing ordinal data (see *ordinal* package [83]). Statistics is a field that is an art as much as it is a science. Although statistical theory is founded on exact assumptions and conditions, the real world is seldom that straightforward. Consequently, the practice of statistics involves a tremendous number of choices, and the challenge is how to make those choices.

Dataset

The analysis was carried out on Indraganti et al.' study [84] dataset, included in ASHRAE Global Thermal Comfort Database II [85]. This dataset comprised 6048 observations (~27 % female) collected during 14 months from 2787 individuals (all Indian nationals within the age group of 18–48 years). More details regarding the field survey can be found in Indraganti et al. [84]. This dataset was selected because there are no missing values for either thermal sensation votes (i.e., the dependent variable), or gender and air temperature (i.e., the independent variables). Furthermore, the data were collected under a wide range of indoor air temperatures. The analysis was not carried out on the entire ASHRAE Global Thermal Comfort Database II for the following reasons:

- The dependent variable needs to be measured on the ordinal scale. Unfortunately, the Comfort Database II does not distinguish between scales, and ordinal and continuous measurements are mixed.
- There are conspicuous missing values in the Comfort Database II. This issue does not derive from the database itself but originates from the lack of explicit agreement on measuring the 'essential' variables in thermal comfort studies.
- Different datasets composed the Comfort Database II. Even though all these datasets went through a rigorous quality assurance process to harmonise

their contents, it is reasonable to assume that each dataset has some unique peculiarities – different measurement protocols, questionnaires, or instruments. This aspect of the database would require that analysis of the entire database be carried out with an ‘appropriate’ method that considers these peculiarities (e.g., multilevel modelling).

3.4 Applicational aspect

This analysis was used to answer the RQ3 (‘How can the description of occupants’ thermal preferences be used to provide more satisfying control strategies?’) and benefited from some outcomes of the Article e and f of the ‘supplementary publications’.

3.4.1 Statistical modelling

Multilevel models (commonly referred to as mixed or hierarchical models) were used to deal with clustered and nested data. When individuals form groups or clusters, it is reasonable to expect that two randomly selected individuals from the same group will tend to be more alike than two individuals chosen from different groups; for example, on the same floor of the same building, two people sharing an office facing south compared to two people sharing an office facing north. Following similar reasoning, measurements taken on the same individual on different occasions will be more highly correlated than measurements taken from different individuals. Therefore, whenever data are clustered and/or nested, the assumption of independent errors is violated.

The dataset used during the analysis comes from the experimental investigation described in Section 3.2 (all the information about the experimental design can be found in Article I). This experimental study examined a mixture of nested and crossed relationships. As shown in Fig. 9, different measurements on the thermal environment (level 1) are nested within experiment conditions (level 2), which, in turn, are cross-classified by participant and day (level 3). It is essential to mention that the multilevel structure defined here is not the property of a model but rather the property of the experimental/study design, which is then reflected in the data, which the model then encapsulates.

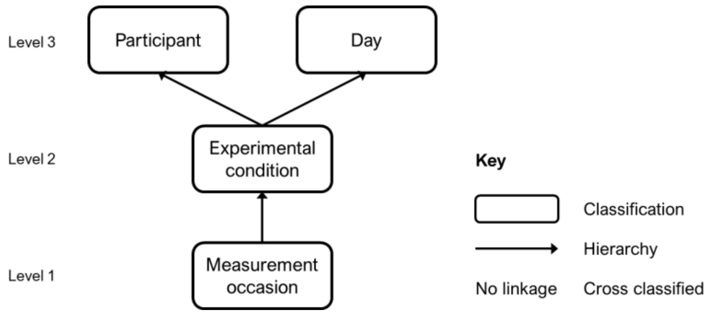


Fig. 9 – Schematic of the three-level hierarchical study: repeated measures within experimental conditions cross-classified by participant and day.

Within the multilevel framework, different modelling strategies can be used. Here, two different modelling strategies were applied: the beta mixed-effects model (a beta model including random effects) and the ordinal mixed-effects model (an ordinal model including random effects). The beta mixed-effects model is a suitable choice when the thermal preference votes are measured on a continuous, but bounded, scale. In contrast, the ordinal mixed-effects model is appropriate when a categorical scale is used. For the sake of clarity and brevity, the beta mixed-effects model and the ordinal mixed-effects model will hereafter be referred to as simply the beta model and ordinal model, respectively. Variable selection was performed with an automated backward elimination employing the Akaike information criterion (AIC) as the selection criterion. Further details about these models can be found in Article III.

Computing predictions suitable for building design and operation

Two different procedures were used to handle the group-level residual during prediction. For the ordinal model, the first procedure consisted of holding the group-level residual at its mean of zero and calculating the probabilities for some specific values of the predictors. Holding the group-residual at zero means considering only a part of the subject, namely the one whose random effect is zero. Random effects allow accounting for heterogeneity in the data, for instance, the inherent differences among peoples. However, fixing the random effects to zero is not a requirement, and a different estimated value for the random effect could be chosen. The response probabilities thus calculated have a cluster-specific (or subject-specific in this case) interpretation. This procedure is appropriate during the building operation phase, where the focus should be on satisfying the needs of the specific occupant or type of occupants (i.e., the specific cluster). The second procedure outlined a simulation-based approach, which resulted in probabilities with a population-averaged interpretation. This interpretation derives from the fact that the calculated probabilities are an average of all simulated random effects (i.e., averaged across experimental conditions, participants and days). This procedure is suitable for the occupant-centric building design phase, where the target is the 'general' occupant whose needs represent those of a large group of typical building users. The same two procedures were applied to the beta model, with the difference that the prediction was not a vector (i.e., probabilities of voting in each category) but rather a single number (i.e., predicted mean). Further details about the two procedures can be found in Article III.

Chapter 4
Results

The results of the main research activities are presented in the following subsections, arranged by each study.

4.1 Human thermal comfort under dynamic environmental conditions

The aim of RQ1 was to explore the human response to dynamic thermal environments. The results are grouped according to (i) general results and observations, (ii) descriptive analysis from the KM method, and (iii) results obtained from the extended Cox model.

4.1.1 General observations

A total of 314 thermal ramps were performed, which led to 223 recorded thermal discomfort events. Fig. 10 presents a time course of the discomfort events during exposure to the different thermal ramps for both the space heating and cooling processes. In this figure, the right-censored observations are also represented (dots without the black outline). Right-censored observations were observed when the experimental session was interrupted because the time available for the session was over. For ease of interpretation, the ASHRAE 55-2020 [9] comfort limit (dark grey X-shaped cross) and a fitted line between this limit (grey dashed line) are also plotted in Fig. 10. It can be clearly seen that the thermal discomfort events are not symmetrical. Participants were more sensitive to a cold variation than a warm one. In fact, 83% of the discomfort events for cold are within the ASHRAE comfort limit, while on the warm side, only 30% are within the comfort limit.

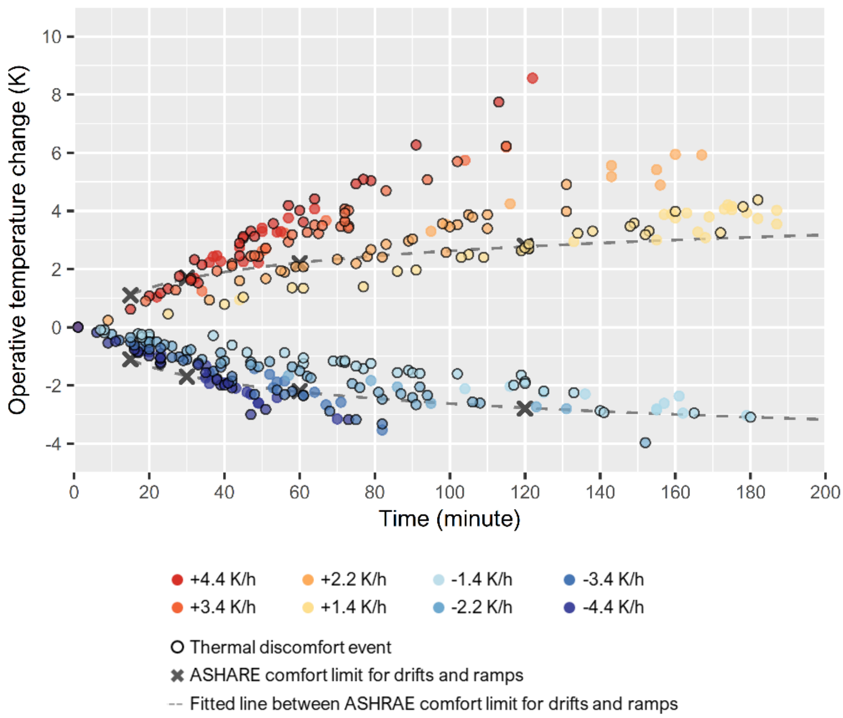


Fig. 10 – Thermal ramps endpoint.

An overview of participants' assessment of perception, evaluation, preference, and acceptability of the thermal environment during the discomfort event is presented in Fig. 11. In this figure, participants' votes on the four previously mentioned rating scales are divided between heating and cooling mode. Particularly:

a) Thermal sensation: Discomfort events are not symmetric. During space heating, thermal behaviours were undertaken mostly when the environment was sensed as 'warm' (+2) with a temperature difference (ΔT) up to 5 K. On the other hand, during space cooling, actions were undertaken when the environment was perceived as 'slightly cool' (-1) and 'cool' (-2). Here the same range of operative temperature change (-3 K) was perceived differently.

b) Thermal comfort: The distribution of discomfort events for space heating and cooling is remarkably similar. Most of the thermal behaviours were undertaken when the environment was judged to be 'slightly uncomfortable' (+1) or ‘uncomfortable’ (+2) for both space heating and cooling processes. This suggests that, indeed, thermal comfort is the driver for thermal behaviour.

c) Thermal preference: Most of the actions were undertaken with a thermal preference vote different from ‘without change’ (0). Reasonably, a participant would initiate a thermal behaviour out of a desire for a higher or lower temperature.

d) Thermal acceptability: For both space heating and cooling processes, discomfort events follow a skewed distribution, specifically a negative skew (or left-skewed) for acceptable environments and a positive skew (or right-skewed) for unacceptable ones. Consequently, most of the actions were undertaken at the boundary between an acceptable and unacceptable environment.

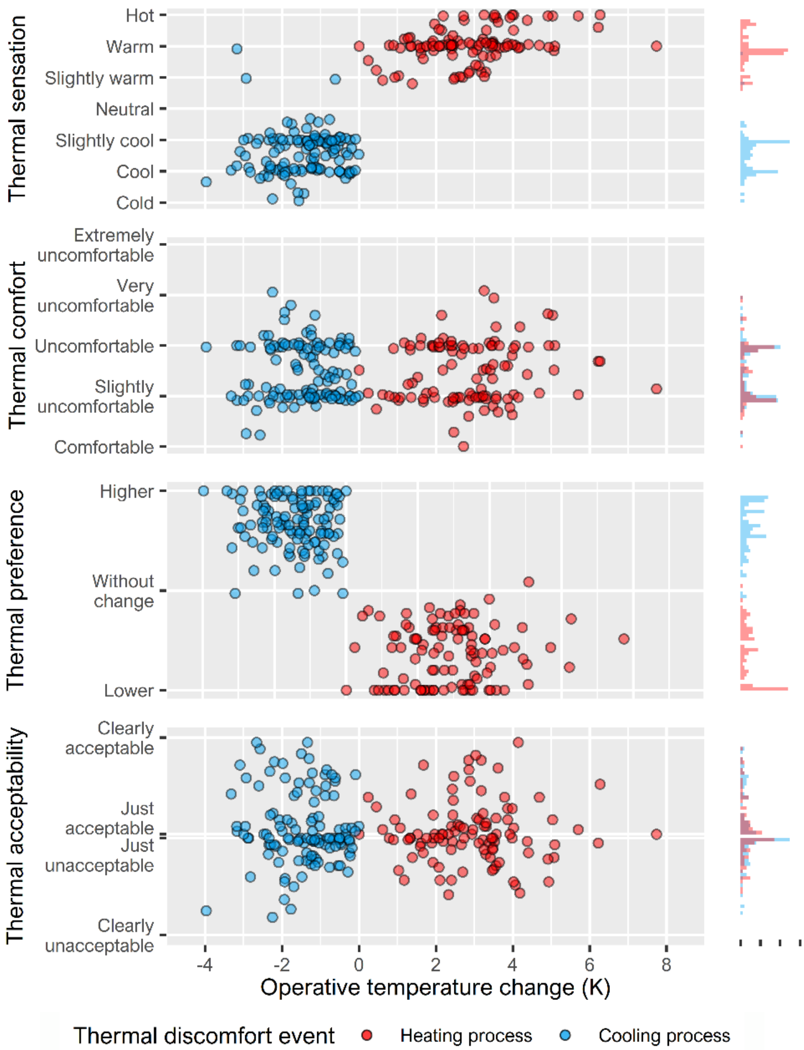


Fig. 11 – Rating scales for thermal discomfort events.
Note. The data shown here represent only the ‘right-here-right-now’ votes on the questionnaire at the moment of the thermal discomfort event (i.e., when the digital button was pressed).

4.1.2 KM survival curves

Fig. 12 shows the KM curves for the various thermal ramps, where the plus symbol represents the right censoring. In this figure, it is noticeable that the survivability for warm variations was higher than for cold ones. Also, for both space heating and cooling processes, slower variations led to longer survival than faster variations.

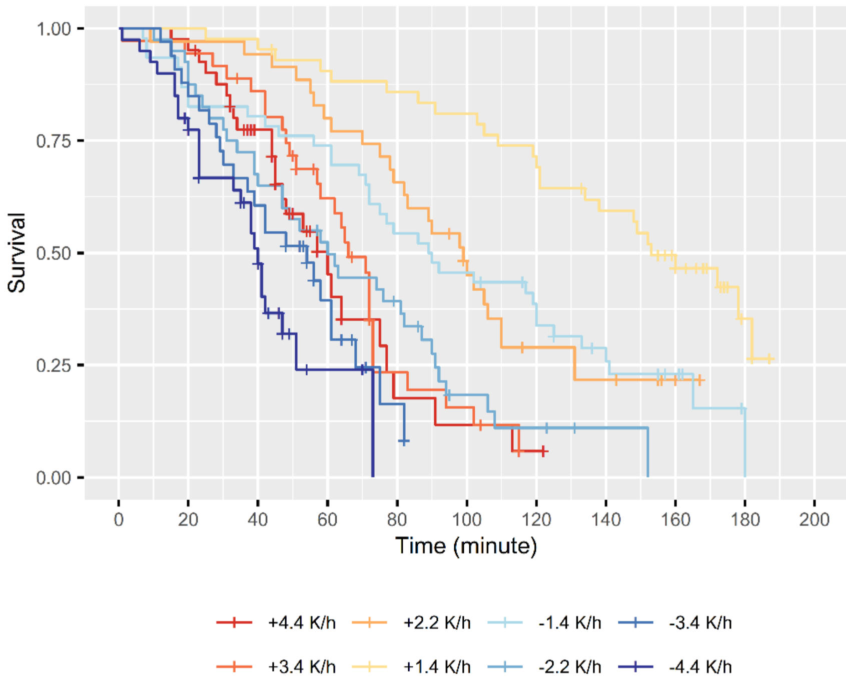


Fig. 12 – KM survival curves for different rates of temperature change.

Fig. 13 shows the log-log plot drawn for each slope (in absolute value). The initial distance between the curves for space heating and cooling processes is greater for a ramp slope of 1.4 K/h than a ramp slope of 4.4 K/h, indicating an effect between the temperature change and the direction of the change (i.e., increase or decrease of the temperature). Moreover, on the whole, all the curves show a divergent-convergent shape: that is the curves initially separate but eventually join up.

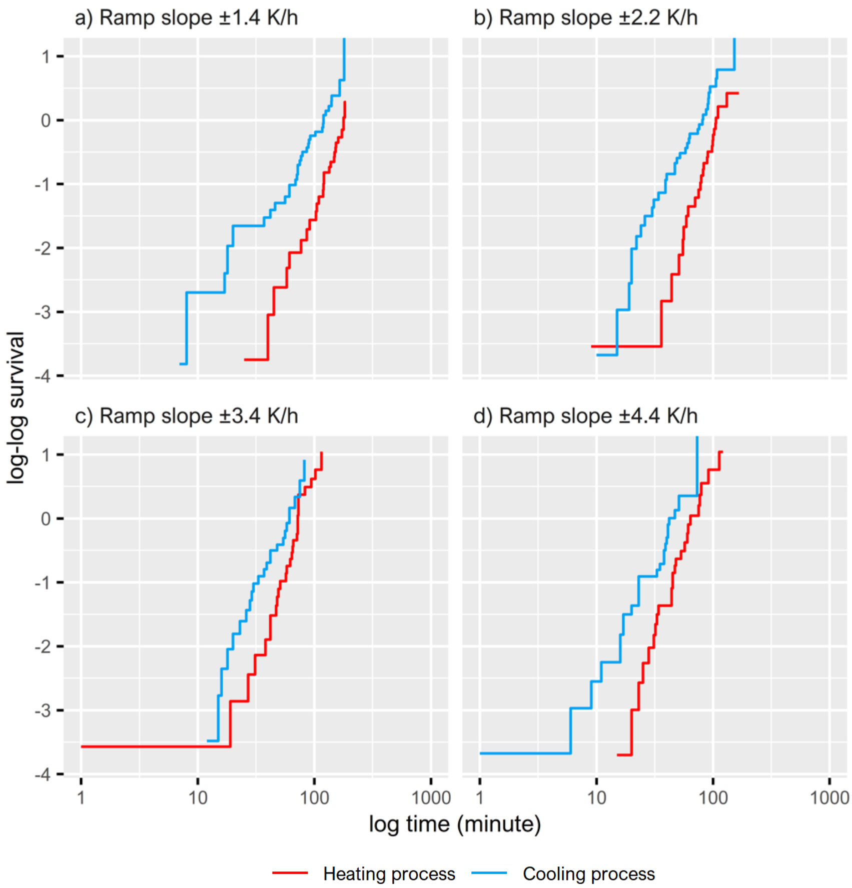


Fig. 13 – Log-log survival chart for heating and cooling based on the rate of temperature changes.

In the context of monotonic temperature variations (thermal ramps), warm changes induce thermal discomfort with some delay compared to cold ones, but this delay progressively wears off. The underlying process, that is, the discomfort from thermal ramps, is delayed on the warm side, or stated analogously, the survival is prolonged temporarily. However, it is important to point out that the number of participants still at risk decreased towards the curve's end. Therefore, caution is generally required not to over-interpret the right side of this part of the plot.

4.1.3 Cox-regression

Two separate models were developed for the space heating and cooling processes. This choice had the advantage of assessing the selected covariates' significant predictors separately for the two models. Table 2 lists all the covariates used in the inference of the heating and cooling models.

Table 2 – List of covariates used in the model for both space heating and cooling processes.

Variable	Code	Type	Unit
Thermal resistance of clothing	*Clothing*	Continuous, time-independent	clo
Gender	*Gender*	Categorical, time-independent	Female (reference) / Male
Age	*Age*	Continuous, time-independent	Years
Body Mass Index	*BMI*	Continuous, time-independent	kg/m^2
Time lived in Norway	*Time.Norway*	Categorical, time-independent	Less than or equal to 3 years (reference) / More than 3 years
Air velocity	*Air.vel*	Continuous, time-dependent	m/s
Time of day	*Time.day*	Categorical, time-independent	Morning (reference) / Afternoon
Vapour pressure	*Vap.pre*	Continuous, time-dependent	N/m^2
Operative temperature change	*Top.delta*	Continuous, time-dependent	K
Initial operative temperature	*Top.start*	Continuous, time-independent	°C
Participant ID-code	*ID.subj*	Categorical, time-independent	—

Before proceeding with the analysis, it is essential to briefly explain how survival analysis evaluates the relationship of survival time to covariates. In survival analysis, the measure of effect is called hazard ratio and is expressed as an exponential of one or more regression coefficients in the model. By taking the logarithm of the hazard on each variable is possible to evaluate if the relationship between each variable and the hazard itself (i.e., the functional form) is linear or not. Further details can be found in Article I.

For spacing heating process four significant predictor were identified (Body Mass Index, time lived in Norway, operative temperature variation and initial operative temperature) all positively associated with increased risk of 'warm discomfort'. Gender, even though was not statistically significant, was still maintained in the model. This because gender was found to be a confounder for BMI. Among the statistically significant predictors, there are three continuous variables. Their functional form (i.e., their relationship with the hazard) were showed in Fig. 14. BMI, formerly called the Quetelet index, is a measure for indicating nutritional status in adults. Fig. 14.a shows that the hazard increases from low BMI to around ‘normal weight’ BMI levels, where it flattens out and then rises slightly in the pre-obesity category, but not significantly. This indicates that participants with lower BMI values have a lower hazard of experiencing ‘warm discomfort’ than participants with normal and pre-obesity BMI values. This result is not completely in line with the literature. While it is true that the underweight population (BMI < 18.5 kg/m^2) is associated with a higher comfortable temperature, the overweight population (i.e., BMI > 25.0 kg/m^2) is associated with a lower comfort temperature. However, BMI does not actually measure body fat nor the proportion of muscle-to-fat. Therefore, it is possible that some of the participants were incorrectly classified in the pre-obesity category. Concerning the initial operative temperature, Fig. 14.b shows that a linear fit is within the confidence interval; therefore, a linear relationship between the log(hazard) and the initial operative temperature is assumed (red line). Fig. 14.c shows that the hazard increases linearly with the increment in operative temperature until about +4 K, where it flattens out. Nevertheless, conceptually, it is hard to believe that the hazard of thermal discomfort associated with a monotonous rise in operative temperature levels off as higher delta temperatures are reached. A more logical fit would be a continuation of the linear relationship before the +4 K increment (the solid green line in Fig. 14.c). A possible explanation for the hazard’s flattening upon reaching higher delta temperatures is that different individuals have different frailty levels. More frail individuals are more likely to experience the discomfort event early. Consequently, over time, the ‘risk set’ has an increasing proportion of less frail individuals, and the hazard flattens out.

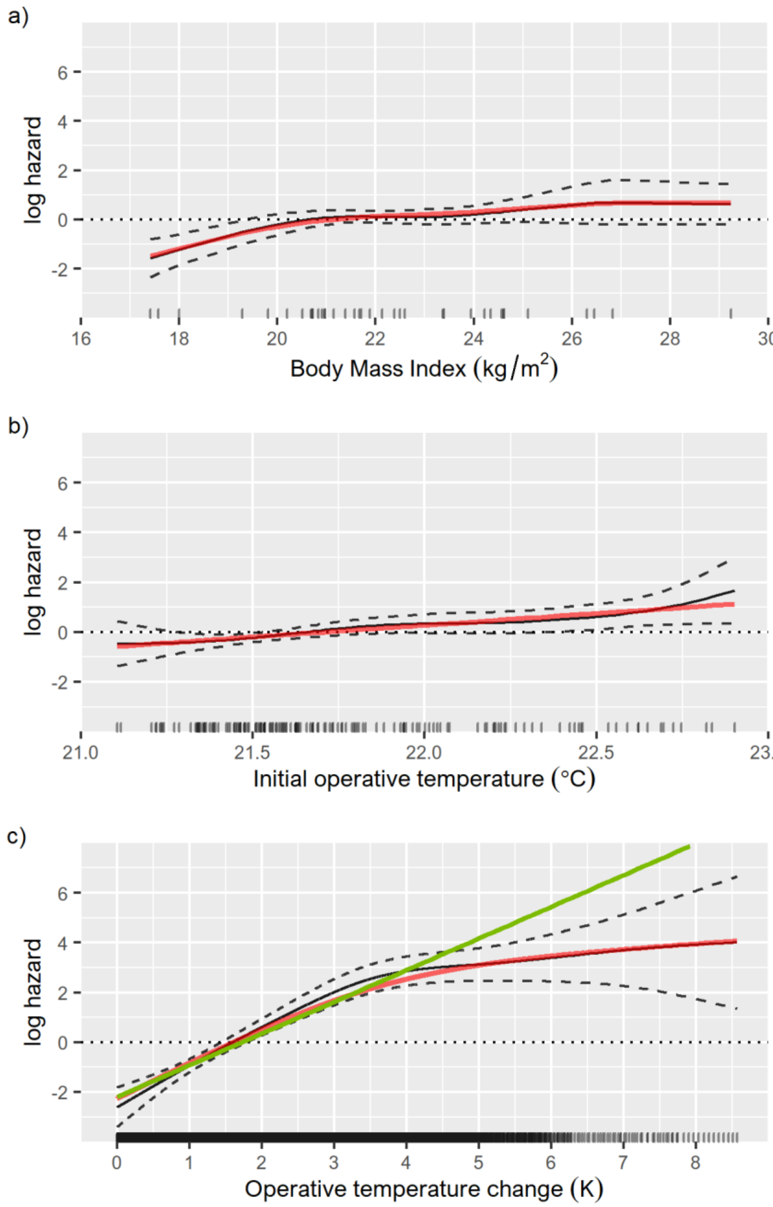


Fig. 14 – Penalised spline fit of (a) Body Mass Index, (b) initial operative temperature and (c) operative temperature change for heating.
Note. The red line is the chosen relationship; the green line is the hypothesized relationship (logical fit); rug plots at the bottom of each plot.

For spacing cooling process three significant predictor were identified (time lived in Norway, time of day and operative temperature variation). Time of day and operative temperature variation were negatively associated with an increased risk of ‘cold discomfort’, while time lived in Norway was positively associated with the same outcome. Gender and thermal resistance of clothing, even though were not statistically significant, were still maintained in the model. In this case, they remained because their presence improved the model’s overall fit compared to the model without them. Fig. 15 showed the relationship between the log(hazard) and the operative temperature variation. Here, the hazard decreases fairly linearly with the decrement in the operative temperature. Therefore, a linear relationship was assumed (red line).

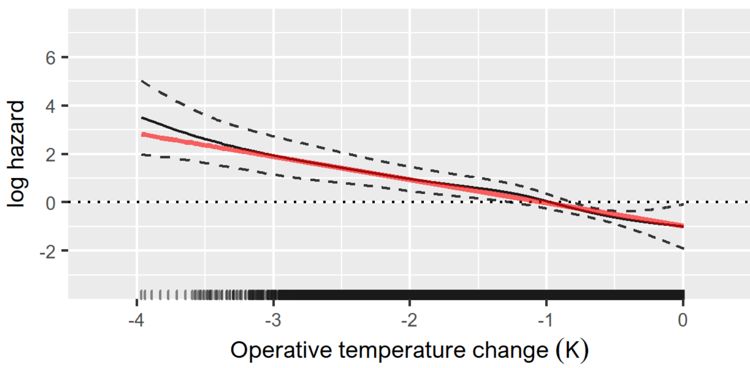


Fig. 15 – Penalised spline fit of operative temperature change for cooling.
Note. The red line is the chosen relationship; rug plots at the bottom of the plot.

4.2 Analysis of subjective thermal comfort data

The aim of RQ2 was to highlight the implication of the choice of the statistical method used to analyse subjective thermal comfort data. In this field, it is common practice to analyse subjective human thermal responses independently of how they have been measured. Subjective thermal comfort data are usually measured on an ordinal scale but then treated as continuous and analysed with linear regression or other statistical tests that assume (conditional) normality. The results comparing the cumulative probit and gaussian (ordinal-as-metric) model are grouped according to the modelling step. It is important to mention that this analysis should be regarded as an indicative example:

as such only two variables (gender and air temperature) were used as covariates during the analysis. Thermal sensation vote (TSV) was selected as dependent variable.

4.2.1 Unconditional model

The goal of a modelling strategy is to try to reproduce or predict an observable phenomenon via the lens of a model. Before incorporating a predictor, the unconditional model can be used to test the ‘goodness’ of the modelling technique. The posterior predictions from the two models are shown in Fig. 16. Here the data generated from the models are compared with the empirical data.

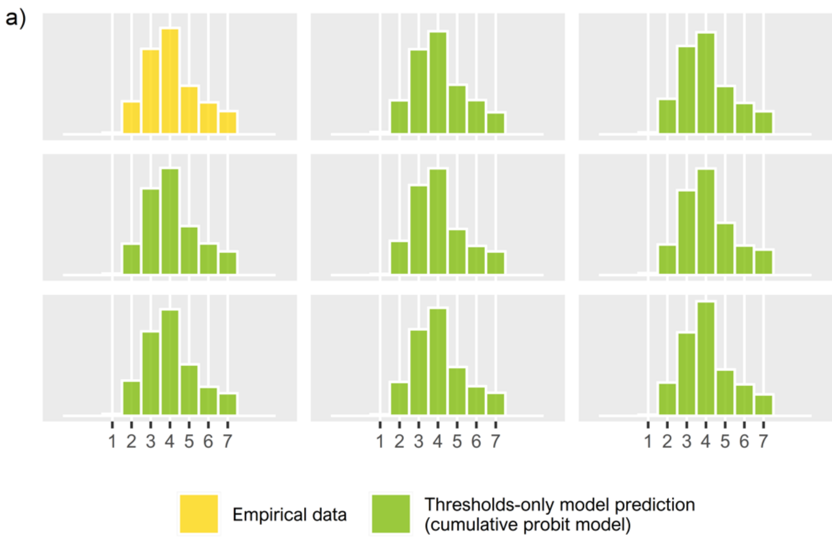


Fig. 16 – Posterior prediction for (a) the thresholds-only and (b) intercept-only model.

The posterior predictive distribution for the cumulative probit model (Fig. 16.a) accurately describes the distribution of the outcomes. Conversely, the posterior predictions for the gaussian (ordinal-as-metric) model (Fig. 16.b) are not a good fit, and they also have impossible predictive outcomes (i.e., value below the category '1' that is, 'cold' and above the category '7', that is, 'hot').

4.2.2 Fitting a categorical variable

In this section, the categorical variable gender is added to the unconditional model. Table 3 shows the results of the fitted cumulative probit and gaussian (ordinal-as-metric) model. The six thresholds for the cumulative probit model and the intercept for the Gaussian (ordinal-as-metric) model were omitted for brevity. The full table can be found in Article II (see Table 5). Moreover, the standard deviation (SD) was modelled on the log scale to constrain its value to be 0 or larger. However, there is a difference in the approach to model the unequal SD for the cumulative probit and the conventional Gaussian model. In Table 3, the *Disc.Male* parameter is not related to the standard deviation (SD) itself, but to the inverse of the SD, that is, $\sigma = 1/disc$. Consequently, the estimated SD for male is $\sigma = 1/\exp(0.14) = 0.87$ and $\sigma = \exp(0.28) = 1.32$ for the cumulative probit and gaussian (ordinal-as-metric) model, respectively.

Table 3 – Regression coefficients for the model with only a categorical variable (allowing the standard deviation to vary by group).

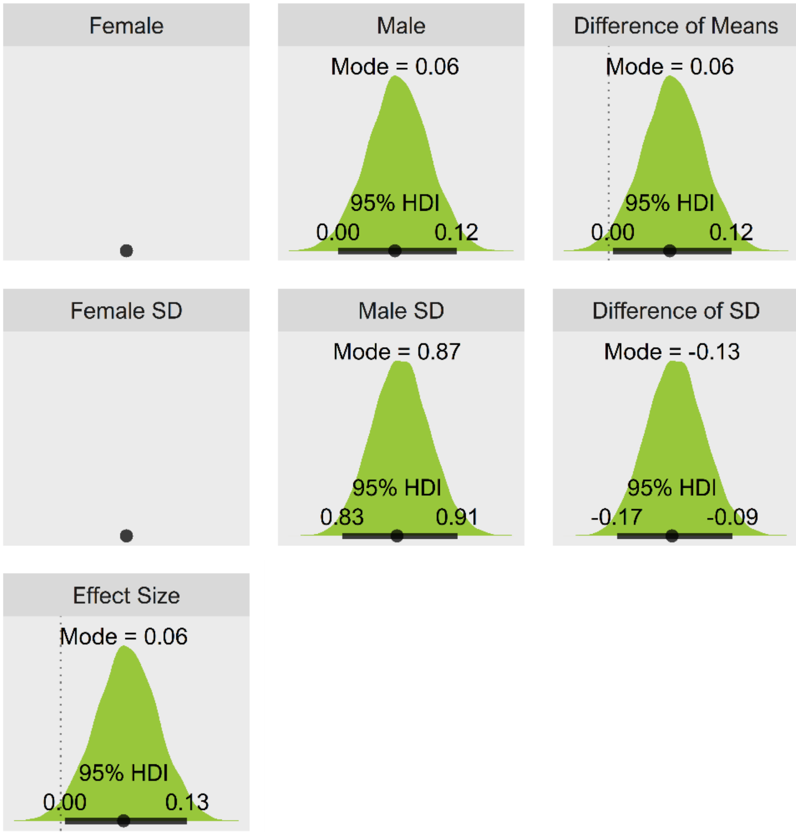
		Estimate	Est. Error	L-95 % CI*	U-95 % CI*
Cumulative probit model					
Gender	female	reference			
	male	0.06	0.03	0.00	0.12
Disc.Male		0.14**	0.02	0.09	0.18
Gaussian (ordinal-as-metric) model					
Gender	female	reference			
	male	0.06	0.04	-0.02	0.14
Sigma.Female		0.39**	0.02	0.36	0.42
Sigma.Male		0.28**	0.01	0.26	0.31

* CI stands for credible interval (based on quantiles).
** Values expressed on the logarithmic scale.

Fig. 17 shows the marginal posterior distribution of the parameters (i.e., the means and standard deviations) and the effect sizes for the cumulative probit (Fig. 17.a) and gaussian (ordinal-as-metric) (Fig. 17.b) models, respectively. The cumulative probit model does not have a distribution for female because this is the reference category, and its mean and standard deviation are fixed. In this figure, the black line and dot at the bottom of each distribution represent the highest density interval (HDI) and the mode, respectively. The HDI is a way to summarise the distribution by defining an interval that spans over the distribution so that every point inside the interval has higher credibility than any point outside it. These intervals (i.e., the black lines) are defined here to span over 95 % of the distribution; therefore, they represent the 95 % HDIs.

Focusing on effect sizes and differences in means and standard deviations, two different results can be observed from Fig. 17. For the cumulative probit model, it can be seen that zero is outside the 95 % HDI for the effect size and the difference in means and SD. However, in the gaussian (ordinal-as-metric) model, zero is included in the 95 % HDIs for the effect size and the difference in SD, while it is outside the 95 % HDI for the difference in means. As a consequence, the two models convey different conclusions. More details about the result can be founded in Article II.

a)


Female
Male
Mode = 0.06
95% HDI
0.00
0.12
Difference of Means
Mode = 0.06
95% HDI
0.00
0.12
Female SD
Male SD
Mode = 0.87
95% HDI
0.83
0.91
Difference of SD
Mode = -0.13
95% HDI
-0.17
-0.09
Effect Size
Mode = 0.06
95% HDI
0.00
0.13

b)

Fig. 17 – Posterior distributions for the model that include the variable Gender: (a) cumulative probit and (b) gaussian (ordinal-as-metric) model.

4.2.3 Fitting a linear predictor

In this section, the continuous variable air temperature was added to the previous model, that is, the model with the variable gender and unconstraint standard deviation. However, air temperature was standardised (i.e., subtracting the mean and dividing by its standard deviation) before entering the model. The results of fitting this model are presented in Table 4. The six thresholds for the cumulative probit model and the intercept for the Gaussian (ordinal-as-metric) model were omitted for brevity. The full table can be found in Article II (see Table 6). Here it can be seen that after adding the standardise air temperature as a predictor, the upper and lower 95 % CI (i.e., L-95 % CI and U-95 % CI) for the male coefficient of the gaussian (ordinal-as-metric) model does not include zero. Consequently, the two models now convey the same conclusions for gender.

Table 4 – Regression coefficients for the model with a categorical and continuous variable (allowing the standard deviation to vary by group).

		Estimate	Est. Error	L-95 % CI*	U-95 % CI*
Cumulative probit model					
Gender	female	reference			
	male	0.09	0.03	0.03	0.14
Tair.s		0.34	0.01	0.31	0.37
Disc.Male		0.12**	0.02	0.07	0.16
Gaussian (ordinal-as-metric) model					
Gender	female	reference			
	male	0.09	0.04	0.01	0.16
Tair.s		0.47	0.02	0.44	0.51
Sigma.Female		0.32**	0.02	0.28	0.35
Sigma.Male		0.22**	0.01	0.20	0.25

* CI stands for credible interval (based on quantiles).
** Values expressed on the logarithmic scale.

The marginal distribution of the standardised regression coefficient for air temperature is shown in Fig. 18. This is a standardised regression coefficient and represents a sort of effect size for air temperature. The two models give a different distribution for the coefficient, with a distinct mode and 95 % HDIs. The coefficient of the cumulative probit model is expressed on the underlying latent scale, while the gaussian (ordinal-as-metric) coefficient refers to the ordinal scale. As a consequence, the gaussian (ordinal-as-metric) coefficient for air temperature is overestimated.

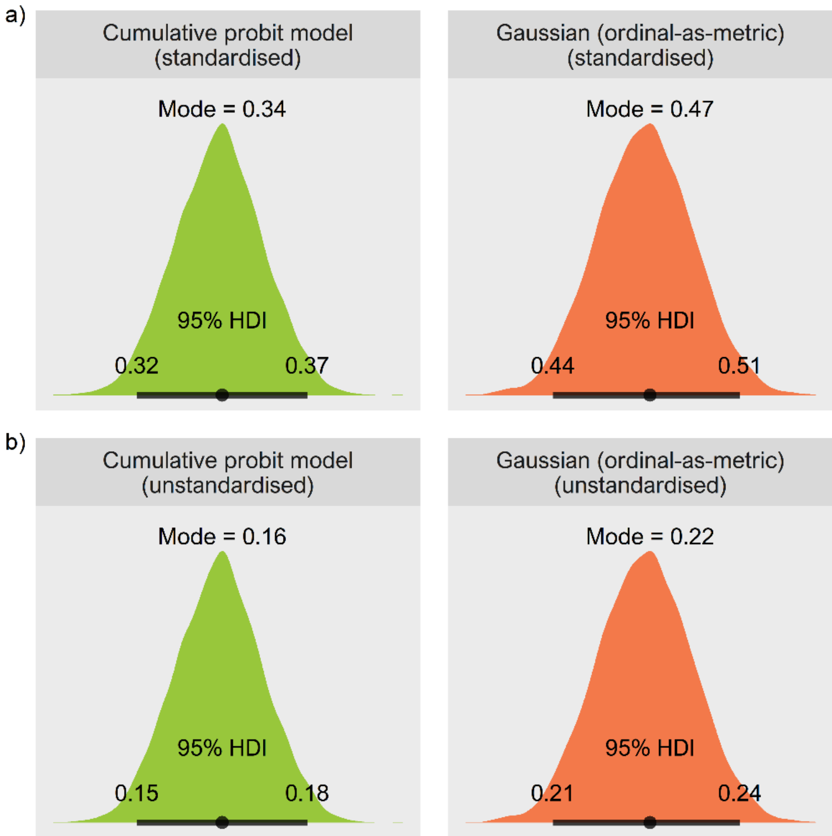


Fig. 18 – (a) Standardised and (b) 'original' regression coefficient for air temperature for the cumulative probit (green) and gaussian (ordinal-as-metric) (orange).

4.2.4 Structured thresholds

In all the previous cumulative probit models, the thresholds were defined as 'flexible' providing the standard unstructured thresholds. However, restrictions such as equidistance can be imposed on the thresholds, which restricts the distance between consecutive thresholds to be of the same size (i.e., equally spaced). This allows assessing the assumptions that the subjects used the response scale (i.e., TSV) in such a way that the distance between adjacent response categories is the same. The spacing of the equidistant threshold is plotted in Fig. 19.a. Here, the average distance between consecutive unstructured thresholds is also plotted (Fig. 19.b). It can be seen that zero is outside the 95 % HDI for the difference between the spacing for structured and unstructured thresholds (Fig. 19.c), suggesting that, in terms of 'standard decision rules', the thresholds should not be approximated as equidistant.

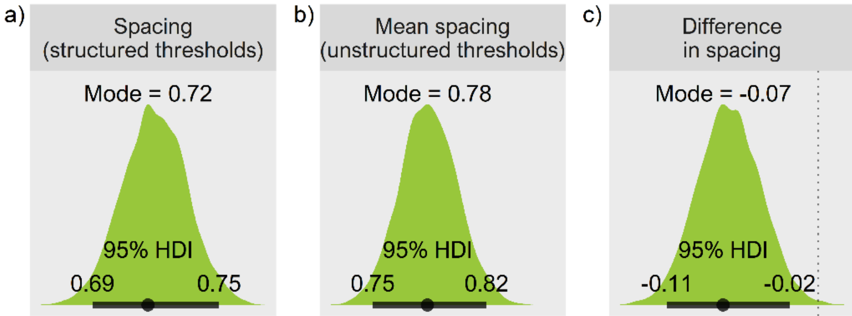


Fig. 19 – Spacing for (a) structured and (b) unstructured thresholds and (c) their difference.

Furthermore, whether the restriction on the thresholds is warranted by the data can be assessed formally by comparing the relative fit of the computed models to the data. One method to assess relative fit is approximate leave-one-out cross-validation (LOOCV) [86], where smaller values indicate better fit. Table 5 shows the estimated LOO information criterion (LOOIC) for the two models and their differences. The cumulative probit model with unstructured thresholds has a significantly better fit (smaller LOOIC value) than the structured thresholds one since the difference in LOOIC is very large (more than 12 times the corresponding standard error). In the context of model selection, a LOOIC difference higher than twice its associated standard error suggests that the model with the lower LOOIC value fits the data significantly better.

Table 5 – Values of the Leave-One-Out Information Criterion (LOOIC) and their difference for the cumulative probit model with structured and unstructured thresholds.

Model	**LOOIC**	**SE**	**LOOIC.diff***	**SE.diff****
Cumulative probit model (unstructured thresholds)	19,449.2	100.0	0.0	0.0
Cumulative probit model (structured thresholds)	20,014.0	97.2	564.81	44.39

* LOOIC.diff is the difference between the two LOOIC scores.
** SE.diff is the standard error of the LOOIC.diff.

4.3 Human-in-the-loop methods for occupant-centric building design and operation

The aim of RQ3 was to predict the thermal preference vote of human subjects exposed to a dynamic thermal environment. Two different modelling strategies were applied: the ordinal model and beta model. The results are grouped accordingly.

4.3.1 Ordinal model

Five significant predictors were identified – thermal resistance of clothing, Body Mass Index, air velocity, time of day and operative temperature – all negatively associated with $\mathrm{Logit}(\boldsymbol{\gamma}_k)$. A negative coefficient for β indicates that an increase of the associated variable x_i decreases the thermal preference vote. Stated analogously, votes for higher categories (e.g., prefer 'higher') are less likely. Here, the coefficient estimates are given in units of ordered logits (or ordered log-odds). Fig. 20 shows the predicted probabilities as functions of the operative temperature for the cluster-specific and population-averaged procedures. The probabilities calculated with the two methods are dissimilar. For example, the maximum predictive probability for 'without change' is about 91 % for the cluster-specific approach, while it is only 55 % for the population-averaged one.

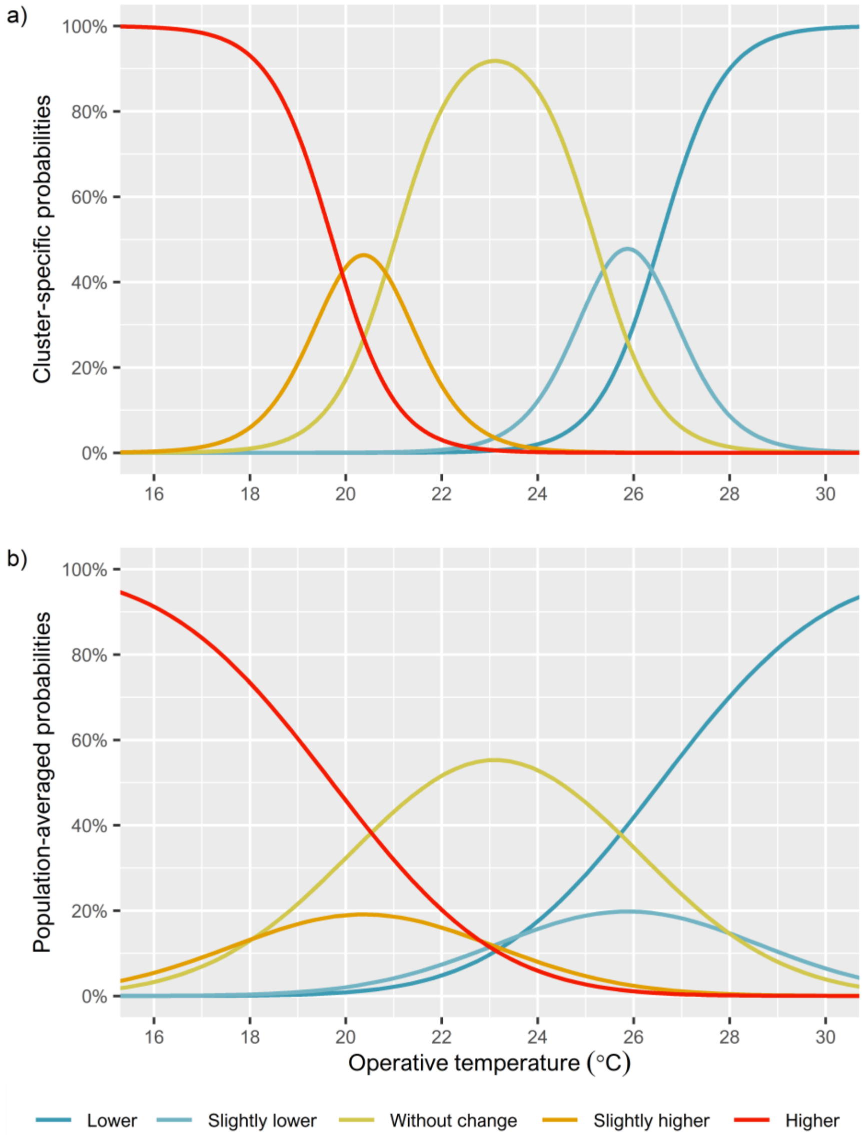


Fig. 20 – Predicted probabilities of a thermal preference vote using the (a) cluster-specific and (b) population-averaged procedures.

Fig. 21.a shows the probability mass for the ordinal model and cluster-specific procedure. These probabilities are plotted as a function of three different operative temperatures while holding the other covariates constant at their centred values and

fixing the random effects at zero. Fig. 21.b shows the population-averaged procedure's results.

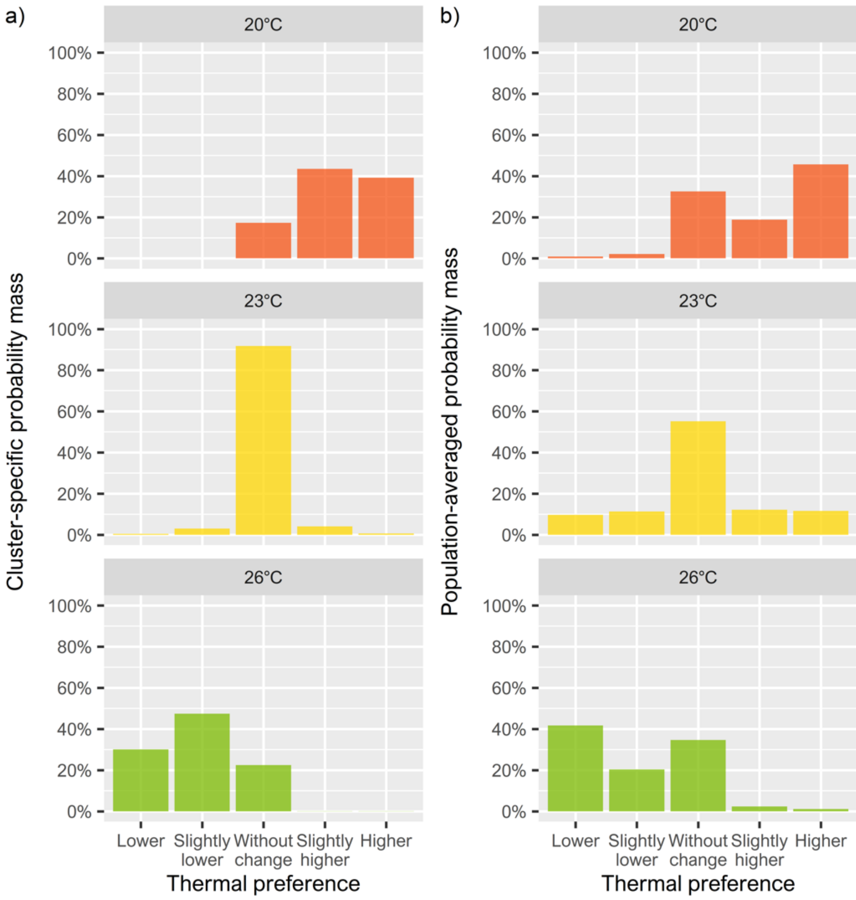


Fig. 21 – Predicted probabilities of a thermal preference vote using the (a) cluster-specific and (b) population-averaged procedures for three different operative temperatures.

4.3.2 Beta model

Four significant predictors were identified – thermal resistance of clothing, Body Mass Index, time of day and operative temperature – all negatively associated with $\mathrm{Logit}(\boldsymbol{\mu})$. Here, the coefficient estimates are given in units of ordered logits (or ordered log-odds). Fig. 22 shows the predicted responses as functions of the operative temperature using the cluster-specific and population-averaged procedures. The points are the observed thermal preference votes. While the predicted central tendency follows the general trend of the data, the predictions do not agree well with the observations, particularly close to the upper (i.e., prefer ‘higher’) and lower (i.e., prefer ‘lower’) boundaries.

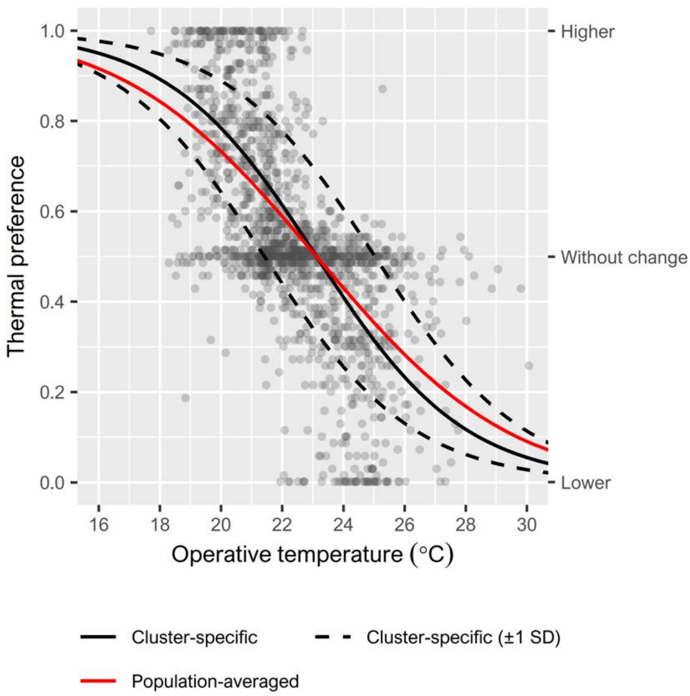


Fig. 22 – Predicted responses using the cluster-specific (black line) and population-averaged (red line) procedures.
Note. The points are the observed thermal preference votes.

Fig. 23.a shows the probability density functions (pdfs) generated from the beta model’s estimated parameters using the cluster-specific procedure. Each pdf is plotted as a function of three different operative temperatures while the other covariates are held constant at their centred values and the random effects are fixed at zero. It can be observed that the dispersion of the probability densities is relatively high. For instance, for an operative temperature of 26 °C, the probability of voting equal or lower 0.50 (i.e., from ‘lower’ to ‘without change’ on the continuous scale) is about 93 %, implying a 7 % probability of voting higher than that. Fig. 23.b shows the categorised probabilities of

the predicted thermal preference votes. Fig. 24 is analogous to Fig. 23 but shows the population-averaged procedure's results.

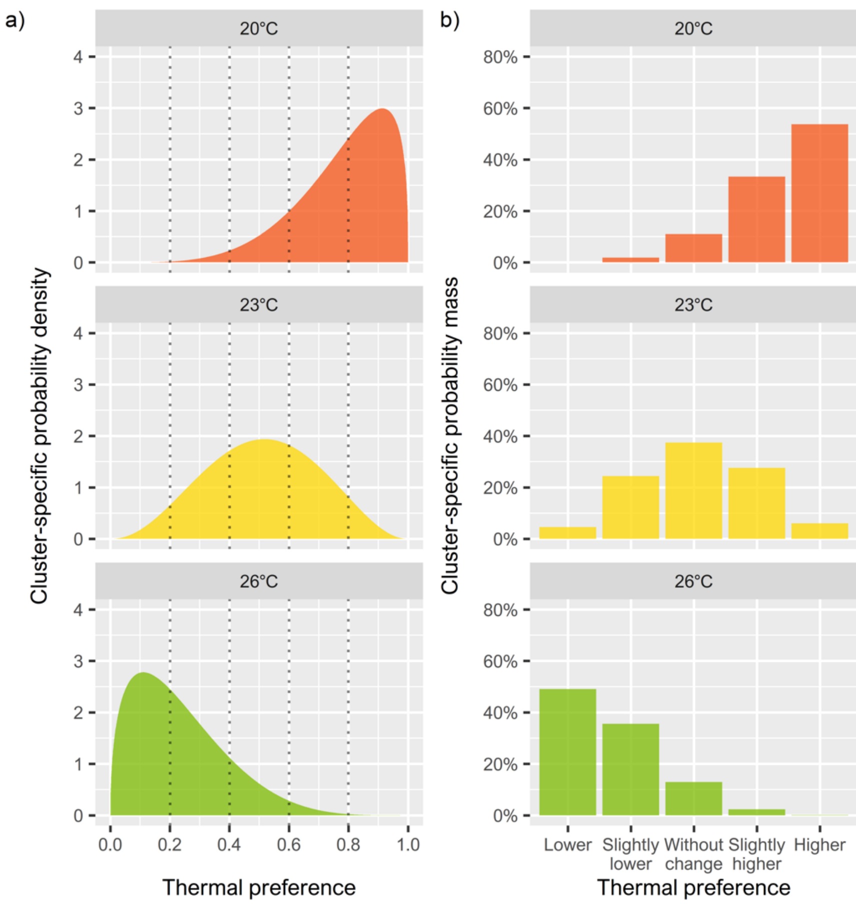


Fig. 23 – (a) Probability densities and (b) categorised probabilities of the predicted response using the cluster-specific procedure for three different operative temperatures.
Note. The dotted lines in (a) represent the thresholds used for categorisation.

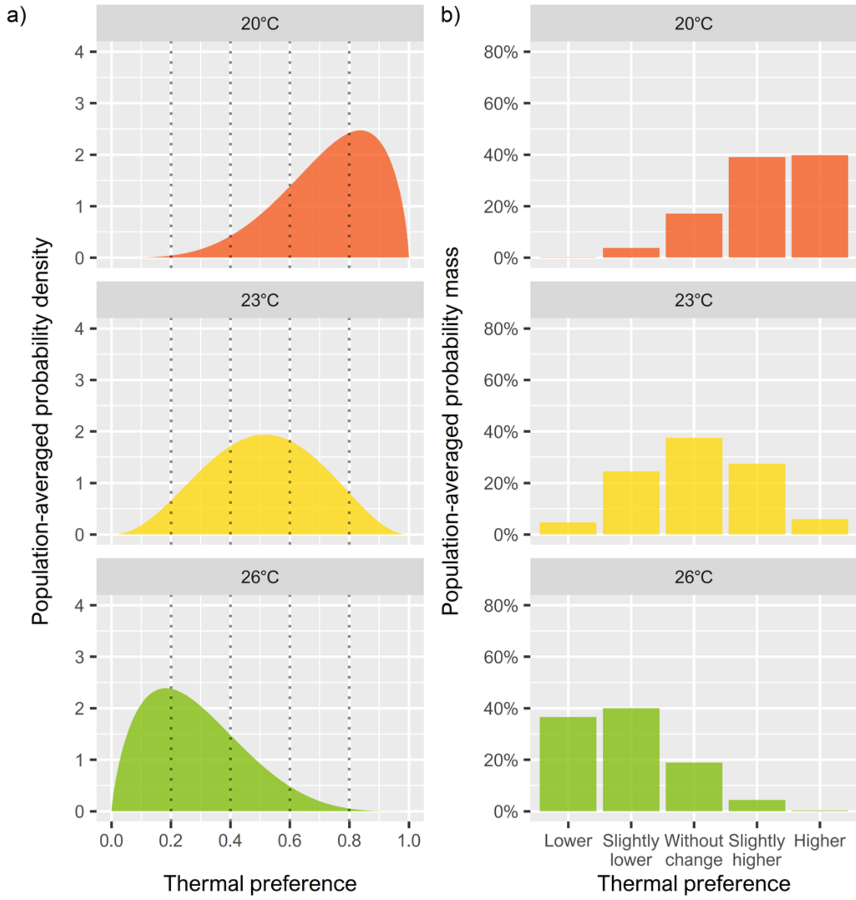


Fig. 24 – (a) Probability densities and (b) categorised probabilities of the predicted response using the population-averaged procedure for three different operative temperatures.
Note. The dotted lines in (a) represent the thresholds used for the categorisation.

4.3.3 Models' comparison

As explain in Section 4.3, the focus of the study is prediction and not inference; therefore, the specific value of the models' coefficients is not of interest. However, it is useful to compare variables selection across the models and contrast the relative importance of these variables. The automated backward elimination selected different sets of predictors for the two models. Four out of five predictors are shared by the two models, while the fifth variables differ. For the ordinal model, automated backward elimination selected air velocity, whereas for the beta model, vapour pressure was selected.

In any attempt to understand the relative importance of the parameters estimated for the models, a direct comparison between their absolute values would be meaningless because the variables are measured using different units. Furthermore, several units could be used to measure the same variable. For example, if the operative temperature had been measured in degrees Fahrenheit instead of degrees Celsius, its estimated regression coefficient would have been different. However, the importance of the variable would not have changed. The relative importance of the predictors could be obtained via standardisation (i.e., subtracting the mean from each observed variable and dividing by its standard deviation) before conducting the statistical analysis. The resulting parameters estimated by the model are on the same scale and can be directly compared. The results of this procedure are show in Table 6. Here, even though the two models have different predictors, the order of relative importance of the common predictors is the same. The variables that differ between the two models are of minor relative importance. However, this importance is purely statistical. To determine the practical importance of the variables, subject-area expertise is required. Note that *p*-values cannot be used directly to assess the importance of the predictors. A predictor can have a small *p*-value when it has a very precise estimate, low variability, or a large sample size. As a result, even effect sizes that are small in practice might have extremely low *p*-values. Understanding the practical importance of the predictors is beyond the scope of this study and is not pursued further. However, for inferential purposes, it is of the utmost importance.

Table 6 – Predictors' relative importance for both the beta and ordinal models.

Modelling strategy	**Predictor**		**Standardise coeff**	**Rank***
Ordinal model	*Clothing*		-0.464	4
	BMI		-0.567	2
	Air.vel		-0.163	5
	Time.day	morning	Reference	
		afternoon	-0.474	3
	Top		-2.917	1
Beta model	*Clothing*		-0.172	4
	BMI		-0.199	2
	Time.day	morning	Reference	
		afternoon	-0.177	3
	Vap.pre		-0.102	5
	Top		-0.793	1

*the higher the absolute value of the standardise coefficient, the higher the rank.

The AIC was used for variable selection. This metric is based on the maximised log-likelihood value with a penalty for including more parameters; it is a trade-off between goodness of fit (assessed by the likelihood function) and parsimony (the smaller the number of parameters, the lower the penalty). However, the AIC tends to over-parameterised, thus selecting models with a higher number of predictors, which could explain why the first four relatively important predictors were common to the two models, while their least relatively important predictors differed.

The AIC is generally used to compare different possible models and determine which one best fits the data. However, it cannot be used to compare models with different likelihood functions. For example, for a discrete distribution (e.g., ordinal response), the likelihood refers to the joint probability mass of the data, whereas for a continuous distribution (e.g., continuous response), the likelihood refers to the joint probability density of the data. Therefore, models based on continuous and ordinal responses cannot be compared directly. For this reason, the two models are compered graphically in terms of predicted probabilities. However, it is important to point out that this method poses a limitation: a different categorisation of the beta distribution would lead to different probabilities. The same applies for the categorisation of the thermal preference vote used to estimate the ordinal model. Nevertheless, by comparing the probabilities estimated by the two models, the following general observations can be made. On the one hand, the ordinal model is more flexible in the sense that it can handle different probability distributions (virtually any probability distribution). For example, in Fig. 21, it can handle the spike in the probabilities for the 'without change' category for an operative temperature of 23 °C. On the other hand, the beta model is more detailed since it provides a probability density function. For example, in Fig. 23.a, the predicted probability of observing a thermal preference vote between 0.45 and 0.55 for an operative temperature of 23 °C is 19.2 %.

An alternative would be to calculate the mean of the estimated probabilities for the ordinal model and compare it with the predicted mean response of the beta model. Here, the category prefer 'lower' was mapped to 1 and the category prefer 'higher' was mapped to 5. The resulting mean probabilities were then rescaled between +0.001 and +0.999 to match the predicted mean response of the beta model. Fig. 25 shows this comparison.

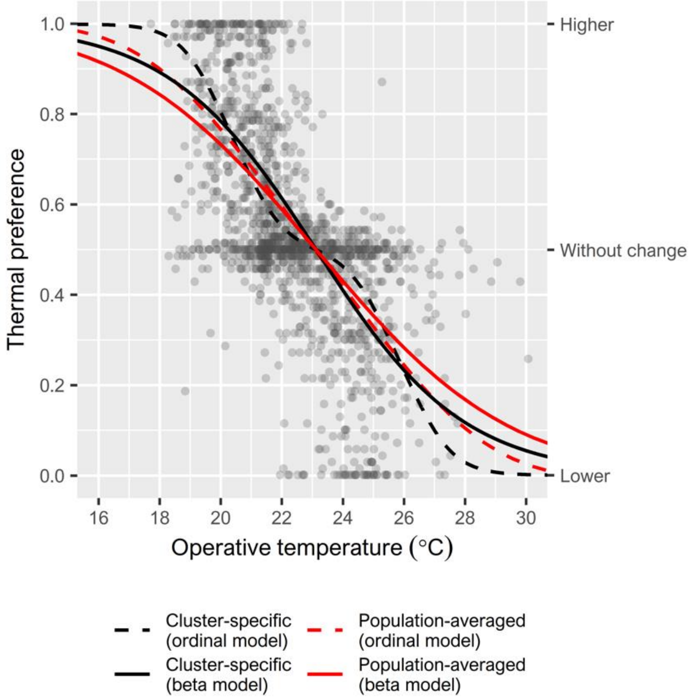


Fig. 25 – Predicted responses using the cluster-specific (black solid and dashed lines) and population-averaged (red solid and dashed lines) procedures for the beta and ordinal models, respectively.
Note. The points are the observed thermal preference votes.

The curve produced by using the cluster-specific procedure for the ordinal model has three inflexion points. This particular behaviour can be explained by looking at the predicted probabilities in Fig. 21.a. Between the operative temperatures of 22–24 °C, the predicted probabilities for 'without change' were much greater than all the others (from 80 % up to more than 90 %). Consequently, within this range, the calculated mean was greatly affected by these probabilities. The same behaviour can be observed for the population-averaged curve to a lesser extent. However, more considerable differences are visible at the tails of the curves, that is, the two extremities. Here, the beta model's mean response curve has tails that are heavier than the mean of the estimated probabilities for the ordinal model.

The predicted thermal preference votes were calculated from the two models using two different approaches: fixing the random effects at their mean of zero (cluster-specific procedure) and using a simulation approach with $N = 1 \cdot 10^4$ (population-averaged procedure). Regarding the ordinal model, from Fig. 21 the most evident difference between the cluster-specific and the population-averaged procedures are the predicted probabilities for an operative temperature of 23 °C. Here, the predictive probability for ‘without change’ is about 91 % for the cluster-specific approach, while it is only 55 % for the population-averaged one. The reason for the discrepancy lies in the fact that the variances are not close to zero. As the between-cluster variances in the random-intercepts model increase, the curves will be further apart. The advantage of having predictive probabilities as outcomes is that they are their own error measures. In Fig. 21, the predicted probability of ‘without change’ for the cluster-specific approach is 91 %; if one decided not to choose this category as the expected outcome, the probability of this being an error is, by definition, 91 %. Following the same reasoning, for the population-averaged approach, not selecting ‘without change’ as the expected outcome has a 55 % probability of being an error. As a standard practice, the ordinal model regards the category with the highest probability as the predicted outcome (i.e., thermal preference vote). However, utilising a hard threshold, such as the automatic selection of the category with the higher probability, does not fully use the information contained in the probabilities. For example, in Fig. 20.b, such a threshold would lead to ‘slightly lower’ and ‘slightly higher’ never being selected. Here the necessity of defining a utility/cost function that, for example, maximises the expected utility or minimises the expected cost. Regarding the beta model, from Fig. 23 and Fig. 24 it can be seen that, for both the cluster-specific and population-averaged procedures, the distributions of the probability densities (and analogously, the categorised probabilities) for an operative temperature equal to 23 °C are the same. The predicted mean response of the beta model intersects the thermal preference vote at 0.5, at which the median equals the mean prediction (see Fig. 25). The median (i.e., cluster-specific) curve is lower than the population-averaged curve for a predicted thermal sensation vote lower than 0.5 but is higher for a predicted thermal sensation vote higher than 0.5. Consequently, the cluster-specific probability densities (i.e., the median probabilities) become skewed faster than the population-averaged ones (i.e., the mean probabilities) at operative temperatures higher or lower than 23 °C.

Chapter 5
Discussion

This thesis investigated how to enhance user comfort in (dynamic) thermal indoor environments and how occupant feedback may help improve the design and control strategies of both new and existing buildings' indoor environments.

The first research question (RQ1), 'To what extent can the indoor thermal condition be modulated without compromising occupants' thermal comfort?', was addressed in Section 4.1. The central answer to this question was provided with a 4-months experiment carried out in the ZEB Test Cell Laboratory at NTNU. Three key results concerning thermal comfort in a dynamic environment were identified. The first one implied that the limits for drifts and ramps are not symmetric in winter conditions. The limits on temperature cycles, drifts and ramps defined in ASHRAE 55-2020 [9] are loose for cold temperature variations and conservative for warm ones. The second one concerned the discomfort mechanism for space heating and cooling processes. For warm discomfort, the operative temperature level is a significant predictor, while for cold discomfort, the relative change in operative temperature is the trigger. Finally, the distributions of participants' thermal comfort ratings during warm and cold discomfort events were remarkably similar, despite different temperature changes. This suggests that, indeed, thermal comfort is the driver of thermal behaviour. In addition, some important methodological issues concerning the semantic equivalence of different rating scales were overcome. For instance, a classic hypothesis (rule-of-thumb) is to consider an environment 'satisfactory' when the thermal sensation vote is between 'slightly cold' (–1) and 'slightly warm' (+1). In this study, this conversion is well suited for warmer variations. Still, it is utterly misleading for colder ones. Fig. 11 showed that most of the discomfort events were experienced when the environment was perceived as 'slightly cold'. In the context of multi-domain comfort, the methodology applied here could be used to analyse the relation between perception and action. It would also be possible to evaluate which contextual and personal factors affecting behaviour influence perception and vice versa.

The second research question (RQ2) highlighted the implication of the choice of the statistical method used to analyse subjective thermal comfort data. The question was posed as ‘How are the rating scales analysed for the subjective assessment of thermal environments?’. The main answers to this question are presented in Section 4.2 as an evaluation of the impact of statistical analysis. The first takeaway from this study is that statistical modelling is a highly sophisticated topic. However, some of these complexities are overlooked when applied to thermal comfort research, specifically the check that some assumptions of the methods used in analysing subjective data are not violated. In a statistical setting, but more generally in science, the veracity of the conclusions is exactly the veracity of the assumptions; that is, the conclusions are contingent upon those assumptions. A critical thinker is aware of these assumptions since they might be wrong or misinformed. The work presented in this section of the thesis sought to address this lack of critical thinking by analysing in detail, in an illustrative example, the modelling steps. The method used to assess the reliability of the models is the so-called posterior predictive checks, a commonly used technique in Bayesian analysis. In essence, after computing the posterior distribution of the parameters, many simulated data are generated and compared with the observed ones. This approach has the evident drawback of evaluating a model against the same data used to estimate its parameters. Unsurprisingly, the model predicts the data used to fit the parameters, but even this simple test fails when the model’s assumptions are severely violated. These systematic discrepancies were clearly established: the posterior predictive distributions for the cumulative probit model accurately describes the distribution of the TSV, while the ones of the gaussian (ordinal-as-metric) have impossible predictive outcomes. Furthermore, the two models convey different conclusion regarding the significance of the variables gender and the magnitude of the estimated coefficient for air temperature. In addition, it was shown that the estimated thresholds for the cumulative probit model should not be approximated as equidistant, suggesting that, in this sample, the TSV is not interval-scaled. Nonetheless, it is important to point out that we cannot claim that treating ordinal data as continuous always yields a different result or conclusion than treating them as ordinal. However, knowing in advance that a difference exists is impossible; a different result can be detected only if an ordinal analysis is also performed. Therefore, we strongly discourage the use of linear regression for analysing thermal comfort data measured on an ordinal scale. To improve the reliability of the results, we encourage researchers to use ordinal models.

The outcomes from RQ1 and RQ2 were combined to develop a model to predict the thermal preference vote of human subjects exposed to a dynamic thermal environment. This topic was the subject of the third research question (RQ3) 'How can the description of occupants' thermal preferences be used to provide more satisfying control strategies?'. Section 4.3 dealt with this question and also proposed two different procedures to facilitate the integration of the occupants and their actual needs into buildings. This section's main findings were that the two models (ordinal and beta model) used were both valid strategies for modelling thermal preference votes. On the one hand, the ordinal model is more flexible in the sense that it can handle different probability distributions (virtually any probability distribution). On the other hand, the beta model is more detailed because it provides a probability density function. However, the choice between the ordinal and the beta models should be made based on how the response variable is measured. The beta model is a suitable choice when the thermal preference votes are measured on a continuous, but bounded, scale. In contrast, the ordinal model is appropriate when a categorical scale is used. Concerning the integration of the occupants and their actual needs into buildings the two distinct procedures used were the cluster-specific and the population-averaged procedures. The population-averaged approach is suitable for the occupant-centric building design phase, where the target is the 'general' occupant characterised by features representing a larger population. On the other hand, during the building operation phase, the notion of a 'general' occupant is pointless, and the focus should be on satisfying the needs of the specific occupant or a homogenous group of people with respect to the parameters used during the model development. In this case, a cluster-specific procedure is appropriate. Operationally, this procedure can be carried out by collecting and assessing the specific occupant responses to the environment, and consequently updating the probabilities of the population-averaged procedure that is, therefore, adjusted to match the specific pattern of preferences of the specific occupant/cluster.

5.1 Limitations

The reader is referred to each individual articles for a more detailed discussion about the limitations (see Appendix A). In the following the limitations are presented in subsections, arranged by each study.

5.1.1 Regarding the experimental analysis

This study's limitations arise from the relative homogeneity of age and the unbalanced number of male and female participants. Since most of the participants were between 23 and 31 years old, the results are not completely representative of the office worker population. The gender imbalance among participants might be the main cause of non-statistically significant differences between males and females in terms of thermal discomfort (actions). To reduce the effect of the generally heterogeneous initial metabolic rate, participants spent the first half-hour before starting the session in a constant temperature environment. However, previous studies on thermal comfort in climatic chambers have shown that subjects' average thermal sensation decreases during the first two hours, even during exposure to constant temperatures [38]. On the other hand, time and organisational constraints did not allow for such an extension of this study's acclimation period. Therefore, it is possible that the potential carry-over effects influenced the participants' thermal sensation even after the 30-minute acclimation phase.

Even with some constraints (e.g., clothing adjustment), this study aimed to reproduce a typical office environment and, consequently, simulate a typical office activity pattern. Nevertheless, participants were prone to the Hawthorne effect. Typically, the Hawthorne effect is described as a change in research participants' behaviour in response to their awareness of being observed [87,88]. In this study, to avoid potential bias, participants were blinded to the environmental changes; that is, they were not informed about the change in the room temperature. However, if the participants changed their behaviour during the experiment — for example, by increasing their awareness and, therefore, sensitivity to change in the indoor environmental condition — the Hawthorne effect would have occurred.

Also, the use of the digital button could have introduced a behavioural change. There is a difference in the intention to perform an action and the action itself. It is undeniable that performing an actual action, for example, adjusting the thermostat, would have required more effort than pressing the digital button. On the other hand, the opposite is also true. A specific human-building interface affects the level of interaction that a person has with it, and therefore its usability, which could lead to a different behavioural choice. Furthermore, it would be unfeasible to provide all the real means of possible interaction with the indoor environment (e.g., for the thermal environment alone, these include open/close window, thermostat adjustment, beverage intake, personalised/local cooler/heater, and ceiling/desk fans). Therefore, even with the aforementioned limitations, the discomfort button was adopted.

5.1.2 Regarding the data analysis

Subjective assessment of thermal environments

A fundamental aspect that is usually overlooked is the assumption of independence: residuals, and thus observations, are assumed to be independent. Non-independence can arise, for example, from temporal and spatial autocorrelation. When underlying spatial or temporal processes have the potential to impact a response, the data are autocorrelated – the closer the observations are in space or time, the more highly correlated they are. These sources of non-independence can be apparent or far less so. The response of one sampling unit influencing the response of other sampling units is an example of evident non-independence. The non-independence caused by non-measured confounding influences that vary spatially or temporally is less obvious to detect. Dealing with temporal (or spatial) autocorrelation or analysing temporal (or spatial) trends is different. The former endeavours to deal with the lack of independence associated with temporal (or spatial) data, while the latter tries to model the effect of temporal (or spatial) patterns. During the data analysis stage, it was impossible to identify either spatial or temporal autocorrelation to test the assumption of independence because there was no temporal (e.g., subject ID and timestamp) or spatial (e.g., building ID) information available. Consequently, this assumption was not checked. Given that the analysis was carried out for illustrative purposes only, this issue can be overlooked. However, in a real-world analysis, the assumption of independence needs to be verified.

Furthermore, other issues, such as functional form misspecification, multicollinearity and omitted variable, were not considered during the analysis because they were outside the scope of this article. Nevertheless, when developing a model, depending on the aim of the study, these issues can play an important role and need to be considered.

Human-in-the-loop

This study's limitations arise from some simplifications introduced during the statistical modelling. For both models, the functional form was assumed to be linear for simplicity. Consequently, the models do not account for potential nonlinearities. However, nonlinearities could be considered, for example, by using smoothing splines. Another simplification derives from assuming that all the independent variables were measured exactly, that is, 'error-free'. When covariates are measured with errors, the parameter estimates do not tend to the true values, even in extensive samples. For simple linear regression, this effect is known as the attenuation bias and leads to an underestimation of the coefficient. For more complex methods, such as multilevel models, this issue deserves a proper treatise and is beyond the scope of this study.

For a beta model, the conditional variance is a function of both the mean μ_i, and the precision parameter ϕ. The parameter ϕ is known as the precision parameter because for fixed μ_i, the larger the ϕ, the smaller the variance of Y_i. Therefore, the variance is not constant but rather a function of the mean and the precision parameter, here assumed to be constant. However, the precision parameter can be modelled as a function of some predictors, for example, the operative temperature. In this study, this possibility was not explored and should examined in future studies.

To apply an ordinal model, the dependent variable must be categorical. For this reason, the dependent variable was binned into five categories according to the thresholds −0.6, −0.2, +0.2, and +0.6. However, these cut-off points were arbitrary and indirectly assumed to be the same for all participants. When a categorical scale is used to measure the dependent variable, this choice is made directly by single responders. Consequently, it is unlikely to be the same for all responders. While this study used categorisation to apply the ordinal model, we do not encourage this practice in ‘normal’ circumstances. It is more appropriate to measure the variable directly with a categorical scale. As stated earlier, cut-off points are arbitrary and generally do not have practical/scientific meaning.

Chapter 6

Conclusions

The work presented in this thesis aimed to enhance user comfort in (dynamic) thermal indoor environments, starting from a technical/methodological point of view (i.e., ‘experimental aspect’), continuing with the subsequent data analysis (i.e., ‘modelling and statistical aspect’) and ending providing occupant-centric design and control strategies for the buildings’ indoor environment (i.e., ‘application aspect’). In the next paragraphs, the main conclusions are drafted.

6.1 Concluding remarks

From a scientific perspective, the main research activities presented in this thesis have potential scientific impacts in diverse aspects. The characterisation of the human response to changing thermal environments is derived from critical literature analysis and formally includes ‘time’ in the analysis (Article I). The new knowledge developed from the experimental work encompasses both the limits of temperature drifts and ramps and the warm and cold discomfort mechanism. However, this work’s potential impact goes beyond this particular application. The methodology applied here could be extended to analyse the relation between perception and action in a multi-domain comfort context. It would also be possible to evaluate which contextual and personal factors affecting behaviour influence perception and vice versa. However, further experiments should be performed using the same experimental method to increase the reliability of the results. Moreover, conducting the investigation in real settings (i.e., in field studies) would be beneficial to avoid some limitations that generally affect experimental studies carried out in climatic chambers (e.g., the Hawthorne effect).

One of the aims of thermal comfort research is to establish the relationship between the thermal environment and the human sensation of warmth. This is usually achieved by measuring the subjective human thermal response to different thermal environments. Diverse rating scales are generally used to measure different aspects of thermal comfort, such as thermal sensation, thermal comfort, thermal preference, and thermal acceptability. In this thesis, the focus was on analysing the data once they were collected and not on the correctness of the level of measurement utilised to measure them. The statistical issues highlighted in this thesis (Article II) are not usually mentioned because the modelling steps are rarely presented, and only the final model is described. However, this is a limitation because researchers can neither assess the reliability of the model nor completely understand the limits of its applicability. Hopefully, this thesis will spur researchers to analyse these kinds of data more critically. Nevertheless, to our knowledge, the thermal comfort scales have not yet been tested for validity and reliability. While this verification is of fundamental importance, we believe this issue should be addressed with a collaborative effort among researchers within the thermal comfort community. Moreover, more emphasis should be given to the choice of the different type of rating scales employed (e.g., categorical scale, visual analogue scale, and graphic categorical scale), the number of anchors utilised, and the assumptions underlying their usage. In addition, while not of primary interest in this thesis, it emerged that there is a lack of homogeneity in the collection of common variables within the ASHRAE Global Thermal Comfort Database II. Furthermore, the Database II does not distinguish between scales, and ordinal and continuous measurements are mixed. We recommend that guidelines be developed for defining specific variables to measure. Although there is generally no 'one-size-fits-all' method (e.g., questionnaire) valid for all purposes, agreeing a 'minimum set' of variables to be consistently measured, possibly with a standardised protocol, would undoubtedly benefit the thermal comfort research community. Notably, some of the issues encountered during the analysis of the ASHRAE Global Thermal Comfort Database II have contributed to its improvement. An updated version of Database II released in June 2022 (Ref. [89]) addresses some of the issues found during this PhD (the change log with all updates is available at https://github.com/CenterForTheBuiltEnvironment/ashrae-db-II).

A comfortable indoor climate is a highly subjective matter assessed individually by each occupant. Therefore, subjective data from occupants is critical for understanding buildings' indoor environment, and may be valuable for several applications, including building design and operation. Perhaps, even help bridge the performance gap in present and future buildings. In the literature, there are numerous methods for predicting individual thermal comfort responses. Specifically, machine learning/data-driven algorithms have exploded in popularity recently for this purpose. Although these techniques appear to have the potential to improve prediction ability at the level of a single building occupant, their inherent character as 'black box' models render them fundamentally unfit to explain their outputs. In predictive modelling, direct interpretability regarding the relationship between the predictors and the outcome of interest is not required; however, transparency is desirable. One of the main contributions of this thesis (Article III) is the development of a model aimed at predicting the thermal preference vote of human subjects exposed to a dynamic thermal environment. Here, the data-generation process is viewed as a 'transparent' tool for developing good predictions. However, the modelling strategy does not aim to model the effect of temporal patterns directly but rather to account for them. Two different procedures were proposed to facilitate the integration of the occupants and their actual needs into buildings: the cluster-specific and the population-averaged procedures. The population-averaged approach is suitable for the occupant-centric building design phase, where the target is the 'general' occupant. On the other hand, during the building operation phase, the notion of a 'general' occupant is pointless, and the focus should be on satisfying the needs of the specific occupant. In this case, a cluster-specific procedure is appropriate. This procedure can be carried out by measuring the specific occupant response to the environment and consequently updating the probabilities of the population-averaged procedure. It is hoped that the knowledge generated in this doctoral research will contribute to a transformation in how we design and manage buildings. Buildings should be designed and operated to allow occupants to interact with them, engaging the occupants in maintaining, for instance, a comfortable environment rather than relying on physical metrics alone.

6.1.1 Further conclusions

Building occupants are subjected to a variety of environmental stimuli, the combination and interplay of which influence human perception, physiology, behaviour, and performance. To begin with, a review of multi-domain research was carried out with the goal of emphasising motivating origins, essential methodology, and primary findings of multi-domain investigations of human perception and behaviour in indoor environments (Article a). Subsequently, a review paper about laboratory experiments with humans in controlled environments was conducted (Article b). The aim was to identify common features of the different climatic chambers so that, in the future, it would be possible to have standardising test procedures, allowing the reproduction of the same experiments in different contexts. To conclude, a paper that aims to define a framework for designing, conducting, and reporting future multi-domain studies was presented (Article c). Hopefully, this would facilitate the integration of our understanding of multi-domain impacts on human reactions into standards and guidelines.

Understanding how people use a space and how their behaviour impacts on a building's energy performance are of fundamental importance. However, comprehending how occupant behaviour is modelled according to different purposes, available computational power, and technical solutions is critical. To this aim, a study that reviews approaches, methods and key findings related to occupant modelling in buildings was carried out (Article d). Numbers of models developed for occupancy and occupant behaviour have been included in building performance simulation (BPS) tools, especially in the last decades. However, their use, in reality, is still restricted. This may be attributable, in part, to the difficulty in comprehending their utility and the obstacles associated with their adoption into BPS. Both issues are caused by a lack of a framework for their definition and communication. To this end, a paper proposing a framework for documenting occupant models was introduced (Article e). Importantly, this approach might be viewed as a guideline to assist researchers in communicating their models in a straightforward manner. Moreover, occupant behaviour models have been developed to include people in the building control loop. Furthermore, depending on the extent of building automation, including occupant-behaviour modelling into building controls may result in improved building operation and lower energy use. Additionally, this may result in increased thermal comfort and occupant satisfaction with the indoor environment. However, occupant behaviour models are rarely included in building controls. To this end, a paper that offered a guideline for complete and harmonised occupant-behaviour model documentation was presented (Article f).

6.2 Suggested directions for future research

The research in this doctoral thesis is a first step in enhancing the understanding of user comfort in dynamic thermal indoor environments. The research methodologies introduced open the door for new investigations, and the findings generate new research questions. In the following paragraphs, some avenues for further research are described.

Controlling the indoor temperature of grid-interacting buildings within a thermal comfort range is a way to provide energy flexibility to the grid, exploiting the slow thermal inertia of a building's envelope in combination with the users' thermal comfort band. The findings presented in this thesis (Article I) have the potential to improve the performance of such controllers by providing a more accurate description of the human thermal response under dynamic conditions. For example, a model predictive control (MPC) with dynamic temperature constraints can be developed where these constraints are given by applying survival analysis. This would allow dynamic set-point modulations without jeopardising the occupant's thermal comfort. In addition, survival analysis could be used to model recurrent events (time-to-event data), such as discomfort events under cyclical variation of temperature, induced by, for instance, demand response (DR) strategies (e.g., DR-activated smart thermostats).

This thesis focuses on analysing subjective thermal comfort data once they were collected (Article II). However, how to measure them deserves a specific treatment. Psychometrics is a field of study concerned with the objective measurement of latent constructs that cannot be directly observed (e.g., intelligence). A psychometric scale (usually) comprises multiple questions or statements, each with its own rating scale, used to measure the construct of interest reliably and validly. However, thermal comfort scales use only one item (i.e., one question with an associated rating scale) to measure the construct of interest. For example, only one item is used to measure thermal sensation, thermal comfort, thermal preference and thermal acceptability. Although using single-item scales may be sufficient to measure the construct of interest, to our knowledge, thermal comfort scales have not yet been tested for validity and reliability. Also, the interplay among the different aspects of thermal comfort, such as thermal sensation, thermal comfort, thermal preference, and thermal acceptability, should be further explored and examined.

The two different procedures proposed to facilitate the integration of the occupants and their actual needs into the design and operation of buildings (Article III) should be applied in other contexts (e.g., other climatic chamber experiments or real building settings). However, the specific model and the variables should depend on the particular research aim. For instance, if the objective is to predict thermal discomfort, it is sufficient to use the variables associated with this outcome in the model. On the contrary, the association is insufficient if the aim is to prevent thermal discomfort; for this purpose, causality is required. Therefore, it is essential to understand that the modelling process, and consequently the resulting model, is only a means to an end, and the same model should not be used 'indiscriminately' for all purposes.

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Appendix A: Main publications

The following journal articles constitutes the main publications of this thesis.

(I) M. Favero, I. Sartori, S. Carlucci, Human thermal comfort under dynamic conditions: An experimental study, Building and Environment 204 (2021) 108144. doi:10.1016/j.buildenv.2021.108144.

(II) M. Favero, A. Luparelli, S. Carlucci, Analysis of subjective thermal comfort data: a statistical point of view [Manuscript submitted for publication] (2022).

(III) M. Favero, J. Kloppenborg Møller, D. Calì, S. Carlucci, Human-in-the-loop methods for occupant-centric building design and operation, Applied Energy 325 (2022) 119803. doi:10.1016/j.apenergy.2022.119803.

Paper I

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Human thermal comfort under dynamic conditions: An experimental study

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ABSTRACT

Although thermal comfort has been a research topic since the 1960s, some knowledge gaps still affect understanding of the human response to changing thermal environments. To enhance knowledge in this regard, an exploratory study is presented, which aims to understand human response to monotonic thermal variations by describing its relationship with covariates of interest. Thirty-eight participants (29 females, 9 males) worked in an office-like climate chamber and were exposed to dynamic and controlled heating and cooling ramps of the operative temperature with different speeds. Participants' perception, evaluation, preference and acceptability of the indoor thermal environment were recorded by filling in dedicated questionnaires. Additionally, participants could indicate when an uncomfortable event occurred during these temperature ramps by clicking a digital button on a dedicated app. This discomfort event was defined in behavioural terms as the decision to "take action to restore a comfort condition". Survival analysis was used to study participants' reactions to the dynamic thermal stimuli. It showed that two distinct mechanisms caused discomfort events due to overheating and undercooling: warm discomfort is driven by the absolute value of the achieved operative temperature, while the relative change in operative temperature mainly causes cold discomfort. Compared to the current recommendations regarding temperature cycles, drifts and ramps, this result shows that current standard recommendations underestimate the risk of thermal discomfort during a cooling process while overestimating it during a heating one. The new knowledge of human reaction to a dynamic thermal environment can lead to more energy-efficient and satisfactory building control strategies.

1. Introduction

Thermal comfort is a consolidated research subject, first incorporated into standardisation in 1966 [1]. After that, standardisation bodies produced standards dedicated to thermal comfort in moderate and severe thermal environments and indoor environmental quality. Nowadays, all thermal comfort standards include definitions of the requirements for indoor thermal conditions in buildings both for design and operational assessment. However, current standards only indicate the maximum variations in operative temperature for non-steady-state thermal environments. ASHRAE 55-2017 [2] and ISO 7730-2005 [3] classify temperature variations as either temperature drifts and ramps or temperature cycles. Drifts and ramps are defined as "monotonic, non-cyclic changes in operative temperature" [2], and their limits during a period are shown in Table 1. Drifts refer to passive temperature changes in an enclosed space, while ramps denote actively controlled ones. In contrast, cycles refer to "those situations where the operative temperature repeatedly rises and falls, and the period of these variations is not greater than 15 min" [2]. For these changes, ASHRAE 55 allows a maximum peak-to-peak cyclic variation in operative temperature of 1.1 K and recommends treating cyclic variations with a period greater than 15 min as drifts or ramps.

ISO 7730-2005 [3] provides less detailed indications. For temperature cycles, it sets a maximum peak-to-peak variation of 1 K, whereas, for drifts and ramps with a rate of change lower than 2.0 K/h, it prescribes steady-state methods. These standards also include step-changes, which involve changing the environment (i.e., moving to/from another space) rather than a change within the environment. Consequently, they are not described here because out of the scope of this study.

The limiting criteria in Table 1 are probably based on early laboratory studies of thermal comfort under transient exposure [4–6]. During the same period (the 1970s and 1980s), other studies were conducted on both cyclical [7,8] and monotonic temperature variations [9–13]. Hensen [14] reviewed these studies meticulously and found inconsistent

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Table 1
Limits on temperature drifts and ramps by ASHRAE 55-2017 [2].

Time period (h)	Maximum operative temperature to change allowed (K)
0.25	1.1
0.5	1.7
1	2.2
2	2.8
4	3.3

results. He offered several possible explanations for these dissimilarities, including the different voting scales and acceptability criteria and the distinct experimental conditions, among others. Despite these discrepancies, Hensen argued that the experimental results support a 2.2 K/h constraint for cyclical variations in operative temperature. As no evidence had been found to the contrary, he also concluded that this limit could also apply to temperature drifts and ramps. Since this review, only a handful of studies have been conducted on cyclical [15–17] and monotonic variations [18]. Under cyclical variations, these recent studies indicate a positive effect on occupants' thermal comfort. In contrast, for monotonic variations, different rates of temperature change result in inconsistent effects. As mentioned earlier, different acceptability criteria and voting scales could plausibly be a main source of the discrepant findings. Another factor that might be responsible for these differences involves human thermal perception and thermoregulation, described in the following sections.

1.1. Thermal perception and thermoregulation

The skin, the largest organ in the human body, is an interface that separates the body from the rest of the world. On a daily basis, its surface processes at least hundreds of physical sensations, among them environmental thermal stimuli. These stimuli are detected by the free nerve endings of the primary sensory neurons in the skin. These neurones, located in the dorsal root ganglia, convert the external stimuli into electrical signals that are then transmitted to second-order neurons (namely dorsal horn neurons), which are located in the spinal cord [19]. At this first relay centre, thermal information is further processed before being sent to the brain.

In neurophysiology, significant progress has been made in identifying primary sensory neurons' thermal response profiles [19–21]. Researchers have ascertained that the principal detectors of the thermal stimuli in the peripheral nervous system are the ion channels of the transient receptor potential (TRP) family [19]. These thermosensitive TRPs are triggered at specific threshold temperatures and function as dedicated transducers of distinct thermal modes. Among them, TRPV1 and TRPM8 are the primary sensors of hot and cold temperatures, respectively. Conversely, the understanding of spinal cord temperature encoding remained limited until recently, when Ran et al. [22] showed that the representation of heat and cold in the dorsal horn is substantially different from the operation of TRPs. They observed that heat-responding neurons are activated gradually with incremental increases in temperature, where higher temperatures activate more neurons. Therefore, higher absolute temperatures induce stronger neuron responses. Furthermore, if a steady heat stimulus persists, these neurons are not able to adapt and thus persistently respond to it. These results combined suggest that heat-responding spinal neurons encode the absolute temperature. Conversely, cold-responding neurons' reaction reaches its highest point during the cooling phase but rapidly adapts to steady cold stimuli. This behaviour allows these neurons to signal changes over a wide range of environmental temperatures. Therefore, they communicate a relative drop in absolute skin temperature rather than absolute skin temperature. As a result, from a neurophysiological point of view [22], the response to heat (i.e., an increase in temperature) in the spinal cord is encoded in absolute terms (i.e., a certain temperature level), whereas the response to cold (i.e., a decrease in temperature) is coded in relative terms (i.e., a certain temperature difference).

1.2. Thermal alliesthesia

Skin receptors (thermoreceptors), although ideal for sensing changes in the environmental temperature, do not perform well in detecting increases in core temperature, for example, during exercise. This is because the body's internal temperature would increase to an unbearably high level before the skin thermoreceptors could detect it. Not surprisingly, the body is provided with other temperature-sensitive neurons, located throughout the body core (e.g., in the liver, kidneys, and stomach) and in the brain (i.e., the preoptic hypothalamus), that play a major role in detecting changes in deep-body temperature. Nevertheless, given the body's thermal inertia, these neurons are not suitable for detecting changes in the environment. The lag time of using body core temperature-sensitive neurons would be too large to perform effective regulation. Therefore, if the body's core temperature falls within the thermoneutral zone (TNZ), peripheral inputs play the most significant role in thermoregulation. Inside the TNZ, body temperature regulation is accomplished only through the control of sensible heat loss [23] and therefore involves only autonomic thermoregulatory mechanisms. Anticipating this line of reasoning, Marks and Gonzales [24] predicted "that pleasantness and unpleasantness of thermal stimuli depend on the temperature of the skin before stimulation – which itself reflects environmental conditions – given constant internal body temperatures". Only after 40 years, Parkinson and De Dear [25] formalised this concept as "spatial alliesthesia", where the term alliesthesia, first introduced by Cabanac, is "the property of a given stimulus to arouse pleasure or displeasure according to the internal state of the subject" [26]. In spatial alliesthesia in particular, the perceptual changes are detected by cutaneous thermoreceptors, not the body core, which drive pleasure sensations. This notion becomes more relevant when considering that thermal behaviour is driven by thermal comfort [27] and is regarded as the primary influencing factor in body temperature homeostasis [28]. Also, it is essential to notice that the indoor environment's transient conditions are commonly within the TNZ, where the influence of thermal behaviour is omitted. Kingma et al. [29] analysed the relationship between the TNZ and the thermal comfort zone (TCZ). They concluded that the ambient temperature associated with the thermoneutral zone is greater than that of thermal comfort. This finding implies that thermal behaviour could be initiated even before the thermoneutral zone boundaries are reached. In terms of spatial alliesthesia, negative alliesthesia (i.e., thermal displeasure) can be viewed as thermal discomfort [25], which in turn prompts human beings to counter the thermal environment accordingly.

Following this logic, Vellei and Le Dréau [30] proposed a modified version of Fanger's predicted percentage of dissatisfied (PPD) index that considers both a static and a dynamic component. The former is based on thermal sensation derived from the predicted mean vote (PMV), while the latter includes thermal alliesthesia and thermal habituation/adaptation. Utilising the data from Zhang's experiment on cyclical temperature variations induced by demand response events [16], the authors showed the impact of these psycho-physiological phenomena on dynamic thermal perception.

1.3. Research aims

Despite the existence of previous studies on temperature cycles, drifts and ramps, their inconsistent results limit the knowledge of dynamic thermal comfort limits. Regarding the processes driving dynamic thermal perception in temperature cycles, the previously mentioned study by Vellei and Le Dréau is noteworthy. However, the dynamics of temperature cycles differ from the dynamics of temperature drifts and ramps. The latter, being monotonic changes, do not have the same stimulus repeated over time. Furthermore, this study has some potential issues related to the use of different scales to assess satisfaction. In

Zhang's experiment, the percentage of dissatisfied is calculated from actual observed data, measured using a binary acceptability scale. In contrast, Fanger's PPD index is inferred from the 7-point ASHRAE thermal sensation scale (assumed to be ≥ 2 or ≤ -2; see page 130 of [31]). Therefore, there is a problem with the semantic equivalence of these scales. In truth, this is a problem that extends to other psychometric scales (e.g., thermal comfort and thermal preference), and that the thermal comfort research community has yet to address adequately.

The present research is an exploratory study whose goal is to understand human reaction to monotonic thermal variations by describing the relationship between their response and the covariates of interest. Therefore, the emphasis of this work is to derive some insight into the relationships that exist rather than to test hypotheses that certain relationships hold. This is achieved through a laboratory experiment with "office-like subjects", simulating office settings in a ramp-induced thermal environment. In this configuration, the relationship between environmental and demographic factors (with their potential interactions) to participants' thermal discomfort event was analysed. We considered the actual thermal behaviour as the thermal comfort limit, that is, the action prompt from the discomfort event. By doing so, we avoid the issue of semantic equivalence between different psychometric scales. Nevertheless, participants' perception, evaluation, preference and acceptability of the environment were collected.

2. Methods

2.1. Participants

Participants were recruited from the university campus with a targeted age between 20 and 67. A summary of the main demographic and anthropometric characteristics of the subjects is listed in Table 2. Participation in the experiment was voluntary, and participants were informed about the possibility of withdrawing their consent at any time, without giving a reason in agreement with the principles and instructions of the European General Data Protection Regulation (GDPR). A printed information letter was distributed, and the participants signed a consent form prior to participation. The letter included information on data protection measures and general information about questionnaires and measurements. However, it did not inform the subjects about specific changes in environmental variables, such as changes in temperature. To comply with the GDPR, the experiment description was submitted to the Norwegian Centre for Research Data (NSD) and approved with reference code 525790.

2.2. Experimental set-up

The experiment was conducted in the ZEB Test Cell Laboratory on the Norwegian University of Science and Technology (NTNU) premises (Trondheim campus) between September 2019 and January 2020 (see Appendix A for a summary of the outdoor climatic conditions). Two identical climatic chambers (2.4 m × 4.2 m x 3.3 m in height, surrounded by two guard rooms kept at 22 °C) (Fig. 1), furnished like a typical single office, were used to recreate a change in the environment induced by thermal ramps. Space heating and cooling were provided from a constant air-volume system that supplied 100% fresh air from outside, distributed by a 2 m long perforated fabric tube installed at the ceiling. The temperature of the supplied air was controlled through a PID controller (implemented in LabVIEW) utilising a Class A Pt100 temperature sensor located in the extraction air duct. Chamber's walls, ceiling, and floor consist of prefabricated sandwich panels with a low thermal mass; therefore, the surface temperatures almost instantly follow the air temperature. The climatic chambers were illuminated with office pendant and task lighting, as well as natural lighting through a south-facing window with a window-to-wall ratio of 0.56. The shading configuration was composed of 13 louvres tilted at 15° mounted on the external side of the window. Further details on the facility's experimental equipment, as well as the properties of the ZEB laboratory, can be found in Goia et al. [32].

During the experiments, the indoor environment was monitored by measuring air temperatures (at 0.10, 0.60 and 1.10 m), surface temperatures (five on the two side walls, three on the floor and the ceiling, four on the window and one above the door), globe temperature (at 1.70 m), relative humidity (at 1.75 m), airspeed (at 0.10, 0.60, 1.10 and 1.70 m), CO_2 concentration (at 1.75 m), horizontal and vertical illuminance (on the work-plane and at eye levels, respectively) every minute throughout every session. In addition, a weather station installed in proximity to the southern façade of the ZEB Test Cell measured ambient air temperature, relative humidity, wind speed and direction, global solar irradiance on the horizontal plane and precipitation in 10-min intervals. The accuracy of the sensors used, both for indoor and outdoor measurements, are shown in Table 3.

2.3. Experimental conditions and procedure

The operative temperature set-point of 22.0 ± 1.0 °C was defined in accordance with the thermal comfort limit for winter according to Category A of ISO 7730-2005 [3]. Both space heating and cooling variations were tested within winter conditions. The rates of temperature changes were derived from the limit in ASHRAE 55-2017 (Table 1) [2]. Given the limit of 3 h for each experimental session (Fig. 2) and compatible with a typical office occupancy schedule, only the following thermal ramps were implemented: (i) ±4.4 K/h, (ii) ±3.4 K/h, (iii) ± 2.2 K/h and (iv) ±1.4 K/h.

The study's design was a randomised crossover trial; a longitudinal study in which participants received a randomised sequence of different exposure (i.e., thermal ramps). The schematic of the experimental session, illustrated in Fig. 2, was composed of seven and a half hours with a half-hour lunch break included (as a typical standard Norwegian workday). To increase participation, the day could be split into half days, meaning one morning session (8:00–11:30) and one afternoon session (12:00–15:30). However, participants were required to attend an even number of morning and afternoon sessions. Subjects could choose to join the experiment for two or four days and were offered compensation, upon completion of the agreed days, of 200 or 600 NOK, respectively. In addition, a lottery was set up: one lucky participant, selected from among those who successfully completed the agreed-upon days, received an Apple iPad.

After arrival, participants were asked to take a seat at the workplace assigned beforehand by the researchers. At this time, they were asked to fill out a first questionnaire consisting of questions related to demographic and anthropometric characteristics, current clothing level and satisfaction with the workplace (q1 in Fig. 2). During the first 30

Table 2
Demographic and anthropometric characteristics of participants.

Gender	Number	Age (year)	Height (cm)	Weight (kg)	BMI (kg/m^2)
		Median (IQR*)	Median (IQR*)	Median (IQR*)	Median (IQR*)
Male	9	28.0 (30.0–25.0)	174.0 (184.0–170.0)	70.0 (85.0–67.0)	24.2 (26.3–22.1)
Female	29	26.0 (31.0–22.0)	170.0 (172.0–165.0)	63.0 (70.0–53.0)	21.6 (23.4–20.7)
Total	38	26.5 (30.8–23.0)	170.5 (173.0–165.0)	65.0 (70.0–58.3)	21.8 (24.2. – 20.8)

*IQR is the interquartile range, that is, the difference between upper and lower quartiles.

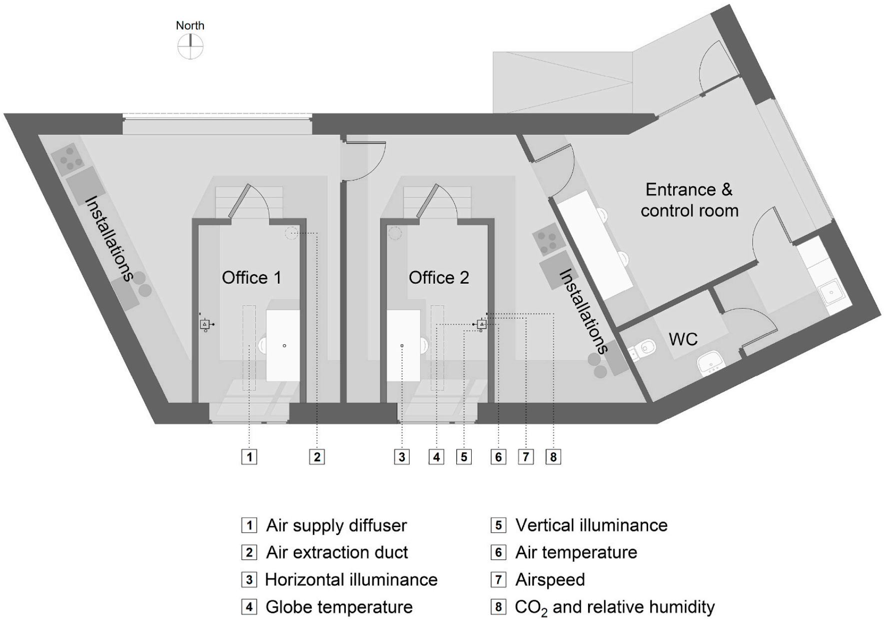

Fig. 1. Floor plan of the facility.

Table 3
Characteristics of the sensors for the measurement of indoor and outdoor conditions.

Physical variable	Type of sensor	Accuracy
Indoor		
Air temperature	Pt100	±0.3 °C
Surface temperature	T-type thermocouple	±0.5 °C
Globe temperature	Pt100	±0.3 °C
Relative humidity	Capacitive	±5%
Airspeed	Hot wire	0 ÷ 0.1 m/s = NA 0.1 ÷ 0.5 m/s = ±0.083 m/s 0.5 ÷ 1 m/s = ±(0.05 + 0.05 va*) m/s >1 m/s = ±(0.1 + 0.05 va*) m/s
CO2 concentration	Non-dispersive infrared	±70 ppm +5 $\%_{measured}$
Horizontal illuminance	Photodiode	±5%
Vertical illuminance	Photodiode	±3%
Outdoor		
Air temperature	Pt100**	±0.1 °C
Relative humidity	Capacitive**	±1.5%
Wind speed	N.32 step optoelectronic disk	0 ÷ 3 m/s = 1.5% >3 m/s = 1%
Wind direction	See above	1%
Global solar irradiance	Thermopile pyranometer	10%
Precipitation	Tipping bucket***	0 ÷ 20 mm/h = ± 0.2 mm 20 ÷ 240 mm/h = 1%

*va is mean airspeed.
**Thermohygrometer with multi-plate natural ventilation radiant screen.
***Rain gauge equipped with heater and siphon.

min, participants acclimatised to the constant set-point temperature and were free to adjust their clothing ensemble. After this period, the experimental session started. At this time, the subjects were instructed to report the final clothing level (i.e., if any change in the initial clothing level occurred during the acclimation period) and to maintain the adopted garment level throughout the experimental session. Furthermore, participants were not allowed to interact with the environment (e.g., open the window/door, regulate the thermostat). However, due to the long sessions, participants were allowed to stand up and move around the climate chamber, leave it for a short period (to visit the restroom), and consume refreshments. No specific tasks or tests were carried out during the experiment, and participants were asked to carry out their typical office activity. This contributed to the simulation of a typical office activity pattern. Nevertheless, subjects had to fill out computer-based questionnaires at different scheduled intervals (q2 in Fig. 2). By means of graphic categorical scales, these questionnaires were used to assess perception, evaluation, preference, and acceptability of the thermal, visual, acoustic and air quality of the environment. These scales, derived from the standard ISO 10551-2019 [33], are shown in Appendix B.

During the experimental session, the participants were instructed to press a digital button (available on a dedicated laptop situated on the desk, see Fig. 3) as soon as they felt uncomfortable. Here uncomfortable was defined as the decision to “take action to restore a comfort condition” (e.g., if the environment is too warm, then regulate the thermostat or open the window). It is important to point out that participants could press the button for any source of discomfort related to the indoor environment (e.g., stuffy air, noise from the ventilation system, lack of daylight) and not only for temperature-related discomfort. After pressing the digital button, a computer-based questionnaire appeared on the dedicated laptop (q3 in Fig. 2). This questionnaire was used to assess the environment (in the same manner as q2) and record the source(s) of discomfort through multiple-choice answers (shown in Appendix C). Participants were also requested to rank, from 1 to 3 (with one being the most important), the strategies (among a predefined set of listed options) that they would use to restore comfort. These strategies varied from simple actions (such as adding/removing a clothing layer and opening/closing the window) to more complex ones (such as adjusting the cooling/heating set-point temperature and plugging-in a local/personal cooler/heater).

The thermal ramp was interrupted when one of the two following conditions was met: (i) the session ended (i.e., at 11:30 and 15:30); (ii)

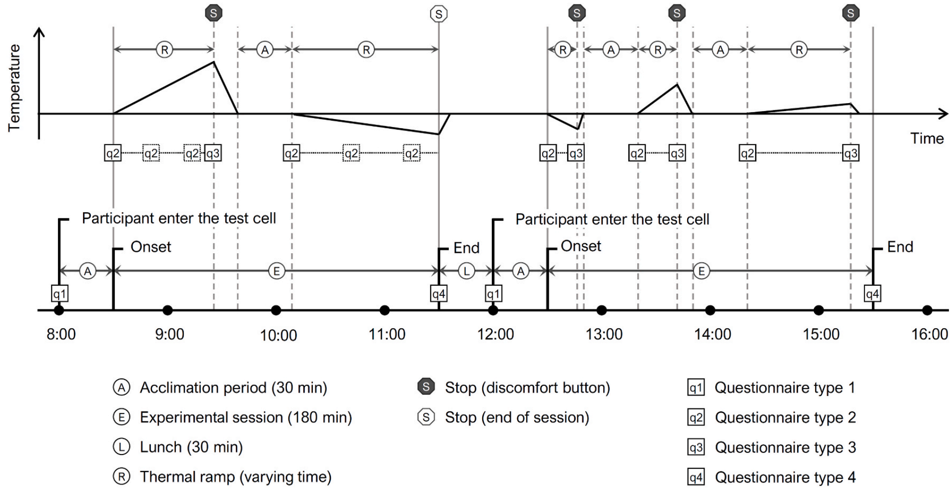

Fig. 2. Schematic of the experimental procedure (bottom) with an example of a possible scenario (top).

Fig. 3. View of the workstation in one of the two single offices.

the participant pressed the digital button. In the latter case, the thermal ramp was stopped only if the discomfort event was related to the temperature level, that is, the participant selected "temperature too high" or "temperature too low". At the end of every session, subjects were asked to fill out a questionnaire (q4 in Fig. 2) about their satisfaction with the workplace as a whole, expressed on a Likert scale.

3. Statistical analysis

Environmental, demographic and anthropometric data were studied using a survival analysis. Survival analysis comprises a family of methods that examine and model the time it takes for events to occur. However, its goal is not limited to investigating the effects on the time until the event occurs, but also to evaluate the relationship of survival time to covariates. Covariates (often referred to interchangeably as predictors or independent/explanatory variables) assess the impact of certain features on the dependent variable.

The prototype event is death – hence the name "survival analysis" and much of its terminology – but the range of applications of survival analysis is much broader. For example, the same methods are known as "failure-time analysis" in engineering and "event-history analysis" in sociology.

3.1. Survival analysis

In survival analysis, there are two crucial quantities that need to be introduced, namely the survivor function, denoted by $S(t)$, and the hazard function, denoted by $\lambda(t)$. Let T be a non-negative random variable representing the waiting time until the occurrence of an event. The survival function $S(t)$ can be written as the probability that the random variable T is larger than a specified time t, that is

$$S(t) = \Pr(T \geq t) \quad \text{Eq. (1)}$$

More generally, it is the probability that the event of interest has not occurred by duration t.

An alternative characterisation of the distribution of T is given by the hazard function, defined as

$$\lambda(t) = \lim_{dt \to 0} \frac{\Pr(t \leq T < t + dt | T \geq t)}{dt} \quad \text{Eq. (2)}$$

which gives the instantaneous rate of occurrence of the event at time t, given survival up to time t.

The two functions in Eq. (1) and Eq. (2) express, in essence, opposing concepts: while the survivor function focuses on surviving, the hazard function focuses on failing, given survival up to a certain point in time. Moreover, there is a clear relationship between these two quantities. Knowing the form of $S(t)$, the corresponding $\lambda(t)$ can be derived, and vice versa. More generally, this relationship can be expressed equivalently in either of the two formulae:

$$S(t) = \exp\left(- \int_0^t \lambda(u) du \right) \quad \text{Eq. (3)}$$

$$\lambda(t) = -\frac{d}{dt} \log S(t) \quad \text{Eq. (4)}$$

The integral in the round brackets in Eq. (3) is called the cumulative hazard (or cumulative risk) and is denoted as

$$\Lambda(t) = \int_0^t \lambda(u) du \quad \text{Eq. (5)}$$

Furthermore, censoring and its assumptions need to be mentioned as well. Censoring is a form of missing data problem in which the time-to-event is not observed. Therefore, there is only partial information about individual survival time. There are three different types of censoring, as graphically illustrated in Fig. 4:

- Left-censored: the event occurs between t_{start} and t_3, but the exact time is unknown.
- Interval-censored: the event occurs within t_1 and t_4, a specified time interval, but the exact time is unknown.
- Right-censored: the event does not occur before the end of the study, t_{end}.

There are three assumptions about censoring for survival data: independent censoring, random censoring, and non-informative censoring. These assumptions, even though they have similarities, are different and should not be used interchangeably. Among the three, independent censoring is the most relevant since it affects validity.[1] Many of the analytical techniques discussed in the next paragraph rely on this assumption for valid inference in the presence of right-censored data. For mathematical definitions of these three assumptions, the reader is referred to Kalbfleisch and Prentice [34] and Klein and Moeschberger [35], and for more intuitive definitions and examples to Kleinbaum and Klein [36].

As mentioned before, survival analysis is the name for a collection of statistical techniques. These techniques can be summarised into three categories: (i) non-parametric models, (ii) parametric models, and (iii) semi-parametric models. The main difference between the three categories is whether the outcome, namely the survival time, is assumed to follow a specific distribution. Non-parametric methods are used when no theoretical distribution adequately fits the data; therefore, they are distribution free. The Kaplan-Meier method is an example from this category. Conversely, in the parametric model, the underlying distribution of the outcome is specified. Typical examples of parametric models in a regression-type framework are linear regression, logistic regression, and Poisson regression. The outcome is assumed to follow some distribution with these models, such as the normal, binomial, or Poisson distribution. For survival analysis, several parametric distributions can be used to describe time to event data, such as exponential, Weibull and log-normal distribution, each of which is defined by a different hazard function. Semi-parametric models are a combination of the two previously mentioned categories. Even if the regression parameters (the betas) are known in these models, the outcome's distribution remains unknown. The Cox proportional hazards (PH) model belongs to this category.

In this investigation, since the outcome distribution (i.e., the survival time distribution) is unknown, non-parametric and semi-parametric models were utilised, more specifically, the Kaplan-Meier method and Cox regression. The former has been used in this study only to describe and visualise the survival curves at a preliminary stage, while the latter evaluates the relationship of survival time to covariates.

3.1.1. Kaplan-Meier method

The Kaplan-Meier (KM) estimator of a survival function at time t, $\hat{S}(t)$, is given by [37].

$$\hat{S}(t) = \prod_{i:\, t_i \leq t} \left(1 - \frac{d_i}{n_i} \right) \quad \text{Eq. (6)}$$

where d_i is the number of events at time t_i and n_i is the number at risk at time t_i. This method is based on individual survival times and assumes independence between censoring and survival, that is, the reason an observation is censored is unrelated to the cause of failure. From Eq. (6), it can be seen that Kaplan-Meier requires a minimal feature set. Kaplan-Meier only needs the time when the event (or censorship) occurred and the duration between the onset and the event. Also, as mentioned before, it is distribution-free. However, it cannot estimate the magnitude of the survival-predictor relationship of interest, nor control for multiple covariates. Therefore, it has been used only to describe and visualise the survival curves at a preliminary stage.

3.1.2. Cox proportional hazards model

The Cox proportional hazards (PH) model is the most used procedure for modelling covariates' relationship to survival or other censored outcomes. It is mainly popular because it does not require any assumptions about the shape of the hazard function (that is, the specific way that risk changes over time); however, it allows for estimating the regression coefficients.

The Cox PH model is usually written in terms of the hazard model formula

$$\lambda(t) = \lambda_0(t) e^{X\beta} \quad \text{Eq. (7)}$$

where $\lambda_0(t)$, is an unspecified non-negative function of time called the baseline hazard, while $e^{X\beta}$, is the time-independent exponential expression that involves the covariates X.

A fundamental assumption of the Cox model is proportional hazards, which implies that the hazard ratio for any two subjects i and j is constant over time.

[1] Validity is meant as lack of bias. The presence of non-independent censoring will result in a biased estimated effect.

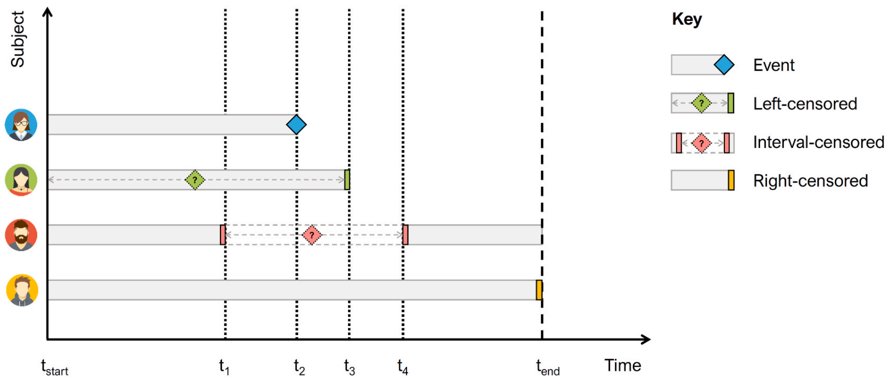

Fig. 4. Different type of censoring.

$$\frac{\lambda_0(t)e^{X_i\beta}}{\lambda_0(t)e^{X_j\beta}} = \frac{e^{X_i\beta}}{e^{X_j\beta}} \qquad \text{Eq. (8)}$$

If this assumption holds, each covariate's effect can be summarised with a single number. Since in practice this assumption is never 100% confirmed (for example, this is the case for any Cox model that include time-dependent variables), there are various strategies to deal with this. Models that rely upon this strategy are called "extended Cox models" and can be generally written as

$$\lambda(t) = \lambda_0(t)e^{X(t)\beta} \qquad \text{Eq. (9)}$$

$$\lambda(t) = \lambda_0(t)e^{X\beta(t)} \qquad \text{Eq. (10)}$$

where Eq. (9) is a time-dependent covariate, and Eq. (10) has a time-dependent coefficient. Note that the PH assumption presumes that the coefficient does not change over time: $\beta(t) = c$.

In the literature, there is another approach called the "stratified Cox procedure", in which the variable that does not meet the PH assumption is stratified. Stratification is suitable only for categorical variables and implies different baselines for each level of the variable being stratified. It can be written as

$$\lambda_g(t) = \lambda_{0g}(t)e^{X\beta} \qquad \text{Eq. (11)}$$

where g denotes the levels of the variable. Note, however, that the stratified variable is not included in the model, and it is not possible to obtain a hazard ratio value for the stratified variable adjusted for the other variables. Nevertheless, the same coefficients (the βs) are assumed for each level of the stratified variable.

The Cox model relies upon other assumptions that need to be verified, which derive from the fact that this model is a regression-type model. These assumptions state that the relationship between the covariate and the response (the logarithm of the hazard in this case) is additive and linear. The former means that the effect of changes in a covariate X_k on $\log \lambda(t)$ is independent of the values of the other covariates, while the latter states that the change in the $\log \lambda(t)$ due to a one-unit change in X_k is constant, regardless of the value of X_k. For further detail, the reader is referred to Refs. [36,38].

3.1.3. Data preparation and analysis

Data gathered during the acclimation[2] period were excluded from the data analysis. The mean radiant temperature (MRT) was calculated according to ISO 7726-1998 [39] based on the surrounding surfaces' measured temperature and the angular factor computed for a seated person in the specific climate chamber. Following the aforementioned standard, the calculated MRT was used, combined with the measured air temperature and air velocity, to calculate the operative temperature. Due to a technical problem with the air conditioning during space cooling processes, data from two female participants were excluded from the analysis. This led to a difference in the female sample size between space heating and cooling processes, from 29 to 27, respectively.

All statistical analyses were performed using R [40] with the RStudio integrated development environment (RStudio Inc., Boston, MA, USA). Survival analyses, using both the Kaplan-Meier method and Cox regression, were performed with the *survival* package [41] and the respective graphs were created with the *ggplot2* package [42] and the *survminer* package [43]. The significance level for all analyses was set at 0.05.

4. Results

The results are grouped according to (i) general results and observations, (ii) descriptive analysis from the KM method, and (iii) modelling step and results obtained from the extended Cox model.

4.1. General observations

A total of 314 thermal ramps were performed, which led to 223 thermal discomfort events. Specifically, 104 thermal discomfort events occurred during heating processes (with 155 thermal ramps), while 119 thermal discomfort events occurred during cooling processes (with 159 thermal ramps). Table 4 summarises the results for the different thermal ramps.

Fig. 5 presents a time course of the discomfort events during exposure to the different thermal ramps for both the space heating and cooling processes. In this figure, the right-censored observations are also represented (dots without the black outline). Right-censored

[2] Acclimation and acclimatisation, although etymologically indistinguishable, define two distinct processes. The former describes "adaptive changes that occur within an organism in response to experimentally induced changes in particular climatic factors" (e.g., the ambient temperature in a controlled environment). The latter denotes "adaptive changes that occur within an organism in response to changes in the natural climate" [23].

Table 4
Number of thermal discomfort events for each ramp and each process.

Ramp description	Total number of thermal ramps	Thermal ramps with a thermal discomfort event
Heating		
3.4 K/h < ramp ≤4.4 K/h	41	25
2.2 K/h < ramp ≤3.4 K/h	36	28
1.4 K/h < ramp ≤2.2 K/h	35	26
0.0 K/h < ramp ≤1.4 K/h	43	25
Cooling		
0.0 K/h > ramp ≥ −1.4 K/h	46	36
−1.4 K/h > ramp ≥ −2.2 K/h	40	34
−2.2 K/h > ramp ≥ −3.4 K/h	33	24
−3.4 K/h > ramp ≥ −4.4 K/h	40	25
Total	314	223

observations were observed when the experimental session was interrupted because the time available for the session was over – condition (i) in section 2.3. For ease of interpretation, the ASHRAE 55-2017 [2] comfort limit (dark grey X-shaped cross) and a fitted line between this limit (grey dashed line) are also plotted in Fig. 5. It can be clearly seen that the thermal discomfort events are not symmetrical. Participants were more sensitive to a cold variation than a warm one. In fact, 83% of the discomfort events for cold are within the ASHRAE comfort limit, while on the warm side, only 30% are within the comfort limit.

An overview of participants' assessment of perception, evaluation, preference, and acceptability of the thermal environment during the discomfort event is presented in Fig. 6. In this figure, participants' votes on the four previously mentioned psychometric scales are divided between heating and cooling mode. Particularly:

a) Thermal sensation: Discomfort events are not symmetric. During space heating, thermal behaviours were undertaken mostly when the environment was sensed as "warm" (+2) with ΔT up to 5 K. On the other hand, during space cooling, actions were undertaken when the environment was perceived as "slightly cool" (−1) and "cool" (−2). Here the same range of operative temperature change (−3 K) was perceived differently.
b) Thermal comfort: The distribution of discomfort events for space heating and cooling is remarkably similar. Most of the thermal behaviours were undertaken when the environment was judged to be "slightly uncomfortable" (+1) or "uncomfortable" (+2) for both space heating and cooling processes. This suggests that, indeed, thermal comfort is the driver for thermal behaviour.
c) Thermal preference: Most of the actions were undertaken with a thermal preference vote different from "without change" (0). Reasonably, a participant would initiate a thermal behaviour out of a desire for a higher or lower temperature.
d) Thermal acceptability: For both space heating and cooling processes, discomfort events follow a skewed distribution, specifically a negative skew (or left-skewed) for acceptable environments and a positive skew (or right-skewed) for unacceptable ones. Consequently, most of the actions were undertaken at the boundary between an acceptable and unacceptable environment.

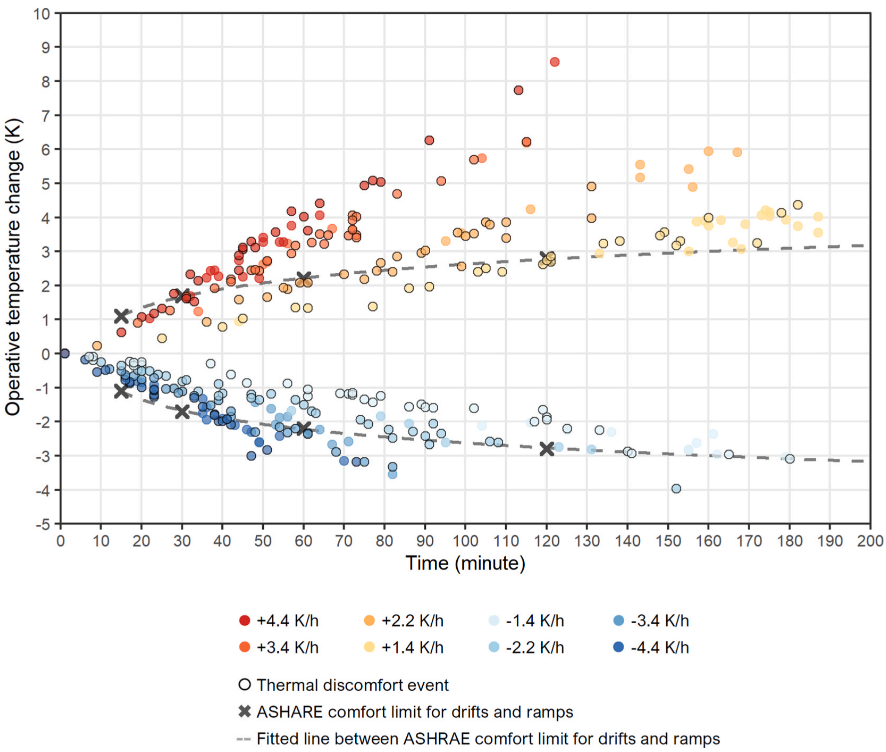

Fig. 5. Thermal ramps endpoint.

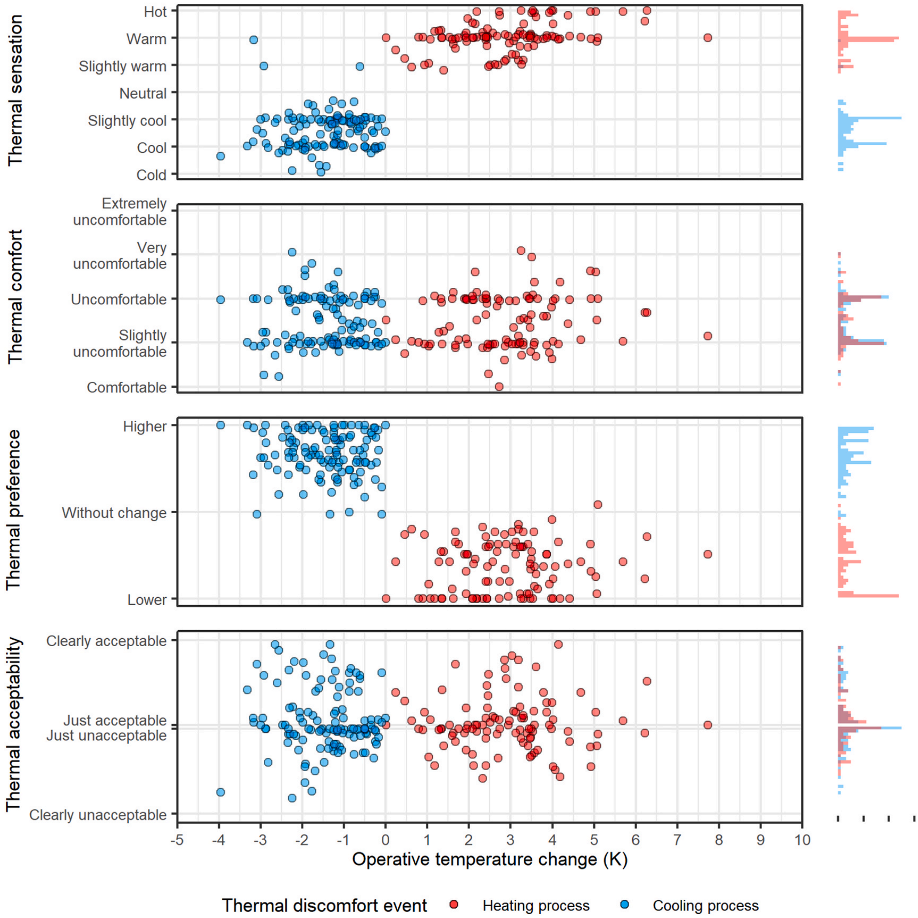

Fig. 6. Psychometric scales for thermal discomfort events. Please note that the data shown here represent the right-here right-now votes on the questionnaire at the moment of the thermal discomfort event (i.e., when the digital button was pressed).

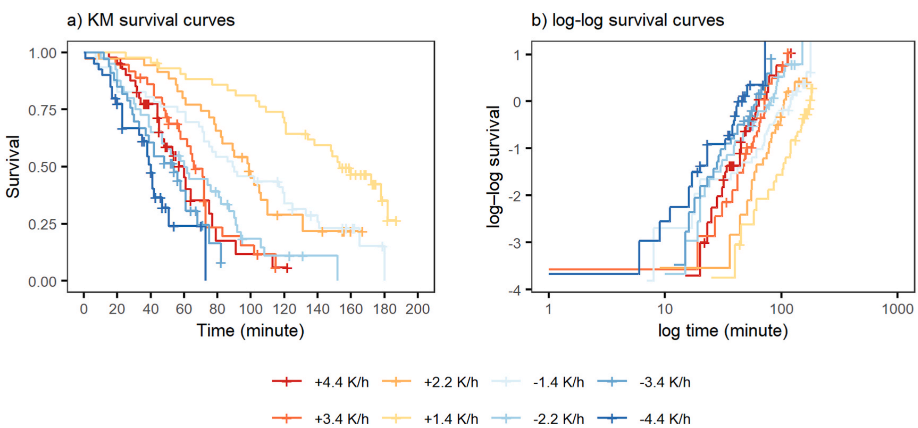

Fig. 7. KM (a) and log-log (b) survival curves for different rates of temperature change.

4.2. KM survival curves

As mentioned in section 3.1.1, the KM method has the advantage of being distribution-free, but, at the same time, it cannot estimate the magnitude of the survival predictor relationship of interest nor control for multiple covariates. Therefore, this method has been used only to describe and visualise the survival curves at a preliminary stage. Fig. 7.a shows the KM curves for the various thermal ramps, where the plus symbol represents the right censoring. In this figure, it is noticeable that the survivability for warm variations was higher than for cold ones. Also, for both space heating and cooling processes, slower variations led to longer survival than faster variations.

In Fig. 7.b, the eight thermal ramps are plotted on a log-log survival scale against time on the log scale. This plot, usually referred to as a log-log plot, is a graphical approach to evaluating the PH assumptions. If the hazards cross or are not parallel in some other way, the PH assumptions for the predictor of interest are not met. In this specific case, since the rates of temperature change for heating and cooling processes intersect, the PH assumptions for this predictor are not satisfied. On the other hand, when considering space heating and cooling separately (plot not shown), the curves for the different rates of change are roughly parallel. However, this is a necessary condition but not a sufficient condition. In fact, even if the hazards do not cross, it is still possible that the PH assumption is not met. Thus, checking for crossing hazards is not sufficient, and other approaches to evaluate the reasonableness of the PH assumption must be used.

In Fig. 8, the log-log plot has been drawn with each slope (in absolute value) plotted separately to increase readability. From this plot, it can be noticed that there is some indication of non-parallelism after 70 min for slope 3.4 K/h (Fig. 8c) and before 15 min for slope 2.2 K/h (Fig. 8b). Also, the initial distance between the curves for space heating and cooling processes is greater for a ramp slope of 1.4 K/h than a ramp slope of 4.4 K/h, indicating an effect between the temperature change and the direction of the change (i.e., increase or decrease of the temperature). Moreover, on the whole, all the curves show a divergent-convergent shape:, that is the curves initially separate but eventually join up.

In the context of monotonic temperature variations (thermal ramps), warm changes induce thermal discomfort with some delay compared to cold ones, but this delay progressively wears off. The underlying process, that is, the discomfort from thermal ramps, is delayed on the warm side, or stated analogously, the survival is prolonged temporarily. However, it is important to point out that the number of participants still at risk decreased towards the curve's end. Therefore, caution is generally required not to over-interpret the right side of this part of the plot.

4.3. Cox-regression

The descriptive analysis carried out in the previous section showed

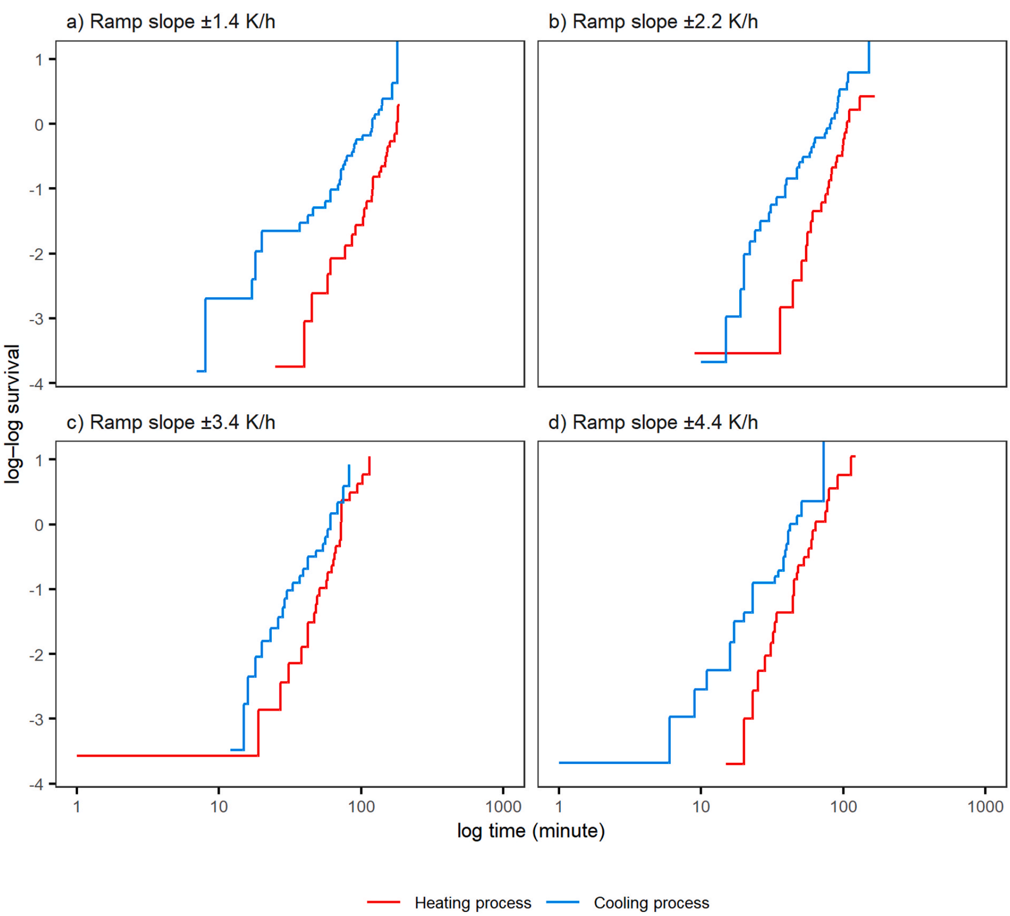

Fig. 8. Log-log survival chart for heating and cooling based on the rate of temperature changes.

Table 5
List of covariates used in the model for both space heating and cooling processes.

Variable	Code	Type	Unit
Thermal resistance of clothing	*Clothing*	Continuous, time-independent	clo
Gender	*Gender*	Categorical, time-independent	Female (reference)/Male
Age	*Age*	Continuous, time-independent	Years
Body Mass Index	*BMI*	Continuous, time-independent	kg/m^2
Time lived in Norway	*Time. Norway*	Categorical, time-independent	Less than or equal to 3 years (reference)/More than 3 years
Air velocity	*Air.vel*	Continuous, time-dependent	m/s
Time of day	*Time.day*	Categorical, time-independent	Morning (reference)/ Afternoon
Vapour pressure	*Vap.pre*	Continuous, time-dependent	N/m^2
Operative temperature change	*Top.delta*	Continuous, time-dependent	K
Initial operative temperature	*Top.start*	Continuous, time-independent	°C
Participant ID-code	*ID.subj*	Categorical, time-independent	–

that if heating and cooling are considered in the same model, the PH assumption is not met. Even though there are methods to deal with this (as mentioned in section 3.1.2), it was decided to develop separate models for the space heating and cooling processes. This choice also had the advantage of assessing the selected covariates' significant predictors separately for the two models. Table 5 lists all the covariates used in the inference of the heating and cooling models.

The rate of temperature change (i.e., ±4.4, ±3.4, ±2.2 and ± 1.4 K/h) was only considered in the descriptive analysis (Figs. 7 and 8) and not incorporated directly into the Cox-regression model. In this model, the rate of temperature change (K/h) is indirectly implied in the operative temperature change (K), a time-dependent covariate.

The variation of the operative temperature (*Top.delta*) and the initial operative temperature (*Top.start*) are the decomposition of the operative temperature. *Top.start* is defined as the operative temperature at time $t = 0$. In contrast, *Top.delta* is the difference between the operative temperature at $t > 0$ and $t = 0$. This division aims to verify whether the operative temperature level affects dynamic thermal discomfort.

The covariate *ID.subj* was used to account for correlated observations since the same subject appears in overlapping intervals. This variable was used in the analysis to create a robust variance, allowing the computation of an infinitesimal jackknife variance estimate [38].

The following modelling steps were undertaken:

1. *Purposeful selection of covariates*: After performing a first fit of the initial multivariable model, the *p* values of the individual coefficient were used to ascertain covariates that might be deleted from the model. This procedure is commonly known as backwards eliminations. The reduced model was evaluated to check if the elimination of a covariate produced a "relevant" change in the parameter estimates of the model's remaining variables. A change of about 20% was used as an indicator of the relevant change. If an important confounder was removed, it was incorporated back into the model.
2. *Define the correct functional form* (i.e., test the linearity assumption): With the previous model, the scale of the continuous variable was analysed to determine whether or not the effect of the covariates was linear in the log hazard (and therefore check if the data support this initial hypothesis). In this analysis, smoothing splines[3] were utilised for this purpose.
3. *Check for interaction terms (i.e., test the additivity assumptions)*: In this step, it was determined whether interactions between predictors needed to be added to the model. Each individual interaction was introduced separately and assessed by comparing the model with the interaction term to the main effect model. This assessment was carried out by examining any changes in the main effect's coefficients and checking the partial likelihood ratio test. All significant interactions were added jointly to the main effects model.
4. *Check the PH assumption*: In this step, the model was carefully evaluated by performing model diagnostics. Also, to avoid overfitting, the number of variables that can be included in the model should be confined. It is not trivial to make a general statement about this, but an approximate criterion is to have one covariate per ten events [44].

4.3.1. Initial models

In this section, both the initial multivariable models for heating and cooling are presented. In this step, the backwards elimination has not been yet applied.

At this point in the analysis, four main significant predictors had been detected for space heating while only two had been detected for space cooling (Table 6). Between the two models, the only common significant predictor is the operative temperature variation. As expected, its coefficient is positive for heating processes and negative for cooling processes. The cooling coefficient is greater than that for heating in absolute value, suggesting that cooling variations are more threatening to thermal comfort. It is important to remember that this coefficient represents the overall effect of the corresponding time-dependent variable, considering all times at which this variable has been measured in the study. Also, at this point, the linearity assumption between the risk and the covariate had yet to be verified.

In the following two sections, only the main results of applying the modelling steps mentioned above are illustrated.

4.3.2. Space heating process

Table 7 summarises the results of the multivariable model for heating after applying backwards elimination. Four significant predictors were identified – BMI, time lived in Norway, operative temperature variation and initial operative temperature – all positively associated with increased risk of "warm discomfort". Among them, three are continuous variables (and will be discussed later), while *Time.Norway* is categorical. This variable has been used as a proxy for inferring a long-term adaptation[4] to the Norwegian environment. In a recent study, Luo et al. [45] investigated the long-term thermal adaptation of building occupants by conducting two comparative field studies on thermal comfort in China. They observed for some years two groups of people, one that moved

[3] Splines are mathematical constructs made up of polynomial functions joined together to form a smooth curve, where the joining points are called "knots". An effective way to find a smoothing spline in survival analysis is with "penalised partial likelihood". When this quantity is maximized, it balances the goodness of fit against complexity [38].

[4] According to the glossary of terms for thermal physiology [23], adaptation is defined as "changes that reduce the physiological strain produced by stressful components of the total environment". It includes both genotypic (genetic selection) and phenotypic adaptation (changes that may occur within the lifetime of an organism, such as changes in the thermoregulatory system).

Table 6
Regression coefficients for the predictors in the initial multivariable model (before applying backwards elimination).

Predictor		Heating process				Cooling process			
		coeff	se (coeff)	z	*p*-value	coeff	se (coeff)	z	*p*-value
Clothing		0.693	0.677	1.023	.306	−1.538	1.443	−1.066	.287
Gender	female	Reference				Reference			
	male	−0.507	0.459	−1.103	.270	−0.642	0.439	−1.462	.144
Age		−0.006	0.026	−0.242	.809	0.016	0.019	0.834	.404
BMI		0.174	0.067	2.600	.009*	0.009	0.068	0.128	.898
Time.Norway	≤3 years	Reference				Reference			
	>3 years	1.142	0.325	3.511	<.001*	0.502	0.337	1.491	.136
Air.vel		3.098	4.934	0.628	.530	−4.470	6.048	−0.739	.460
Time.day	morning	Reference				Reference			
	afternoon	0.004	0.233	0.018	.986	−0.668	0.260	−2.572	.010*
Vap.pre		−0.001	0.001	−0.626	.531	0.000	0.001	−0.537	.591
Top.delta		0.784	0.110	7.146	<.001*	−0.894	0.203	−4.400	<.001*
Top.start		0.906	0.333	2.721	.007*	0.340	0.294	1.157	.247
		Likelihood ratio test = 98.35 on 10 df, $p \leq$ 2.2E-16				Likelihood ratio test = 56.92 on 10 df, p = 1.378E-08			

* indicates a significant term.

Table 7
Regression coefficients for predictors in the multivariable heating model (after applying backwards elimination).

Predictor		Heating process			
		coeff	se (coeff)	z	*p*-value
Gender	female	Reference			
	male	−0.564	0.470	−1.200	.230
BMI		0.168	0.068	2.476	.013*
Time.Norway	≤3 years	Reference			
	>3 years	1.067	0.316	3.373	<.001*
Top.delta		0.756	0.101	7.476	<.001*
Top.start		0.871	0.259	3.359	<.001*
Likelihood ratio test = 96.78 on 5 df, $p \leq$ 2.2E-16					

*indicates a significant term.

from southern China (Shanghai) to northern China (Beijing) and one that moved in the opposite direction. The authors concluded that thermal adaptation exhibits asymmetric trajectories: the southern origin groups accepted neutral and warm indoor temperatures in less than one year, while the northern origin groups took three years to adjust to colder indoor temperatures. Based on this result, it was assumed that participants who had lived in Norway for more than three years had adapted to different indoor temperatures and heating/cooling strategies. The estimated hazard ratio (HR) is $\exp(1.067) = 2.907$ for participants living in Norway for more than 3 years (95% CI [1.564, 5.403], $p <$ .001). Therefore, individuals who had lived in Norway for more than three years were, at any given time during this study, 2.907 times as likely to experience "warm discomfort" as those who had lived in Norway for less than three years. In other words, they had an increased risk of 190%.

It can be noticed that the covariate *Gender*, even though not statistically significant, still remains in the model. This because its elimination caused a relevant change in the BMI variable. Therefore, in this study, gender is a confounder for BMI. This can be explained by looking at the participants' anthropometric characteristics in Table 2. Female participants were, generally, shorter and lighter than their male counterparts.

The next step is to verify whether the linearity assumption for continuous variables in the model has been met. Initially, for each continuous variable, a smoothing spline with four degrees of freedom was fitted, and the resulting plot was checked for significant non-linearity. If non-linearity was detected, the correct functional form was derived by refitting a smoothing spline but with an "optimal" degree of freedom based on the Akaike information criterion (AIC). Otherwise, a linear relationship was assumed. It is important to mention that this flexibility comes at a price. The interpretation of the estimated coefficients resulting from splines is, in fact, meaningless. However, the linear combinations of these coefficients can be used to obtain predicted values that can be plotted and interpreted. Fig. 9 shows this analysis for BMI, operative temperature change, and initial operative temperature.

BMI, formerly called the Quetelet index, is a measure for indicating nutritional status in adults. For adults over 20 years old, the World Health Organization has divided the BMI into: (i) "Underweight" if BMI < 18.5 kg/m^2; (ii) "Normal weight" if 18.5 kg/m^2 $\leq$ BMI $\leq$ 24.9 kg/m^2; (iii) "Pre-obesity" if 25.0 kg/m^2 $\leq$ BMI $\leq$ 29.9 kg/m^2; (iv) "Obesity class I" if 30.0 kg/m^2 $\leq$ BMI $\leq$ 34.9 kg/m^2; (iv) "Obesity class II" if 35.0 kg/m^2 $\leq$ BMI $\leq$ 39.9 kg/m^2; and (vi) "Obesity class III" if BMI $\geq$ 40 kg/m^2 [46]. Fig. 9.a shows that the hazard increases from low BMI to around "normal weight" BMI levels, where it flattens out and then rises slightly in the pre-obesity category, but not significantly. This indicates that participants with lower BMI values have a lower hazard of experiencing "warm discomfort" than participants with normal and pre-obesity BMI values. However, there is no significant difference between the normal and pre-obesity category. This result is not completely in line with the literature. While it is true that the underweight population (BMI $<$ 18.5 kg/m^2) is associated with a higher comfortable temperature, the overweight population (i.e., BMI $>$ 25.0 kg/m^2) is associated with a lower comfort temperature. For instance, Indraganti et al. [47]'s field investigation in India found this difference to be 0.7 K. However, BMI does not actually measure body fat nor the proportion of muscle-to-fat. Therefore, it is possible that some of the participants were incorrectly classified in the pre-obesity category. A smoothing spline with three degrees of freedom has been selected for the functional form (the purple line in Fig. 9a).

Concerning the initial operative temperature, Fig. 9.b shows that a linear fit is within the confidence interval; therefore, a linear relationship between the log(hazard) and the initial operative temperature is assumed (purple line). Interestingly, the hazard increases with a higher value of initial operative temperature even if these values are within 22.0 ± 1.0 °C, which are the comfort limits for Category A from ISO 7730-2005 [3]. This is in agreement with Ran's neuroscience experiment [22], discussed in section 1.1. Since heat-responding spinal neurons encode absolute temperature, higher initial operative temperature values lead to higher absolute operative temperature values for the same increment in temperature.

Fig. 9.c shows that the hazard increases linearly with the increment in operative temperature until about +4 K, where it flattens out. A smoothing spline with two degrees of freedom was selected for the functional form (the purple line in Fig. 9c). Nevertheless, conceptually, it is hard to believe that the hazard of thermal discomfort associated with a monotonous rise in operative temperature levels off as higher delta temperatures are reached. A more logical fit would be a continuation of the linear relationship before the +4 K increment (the green line

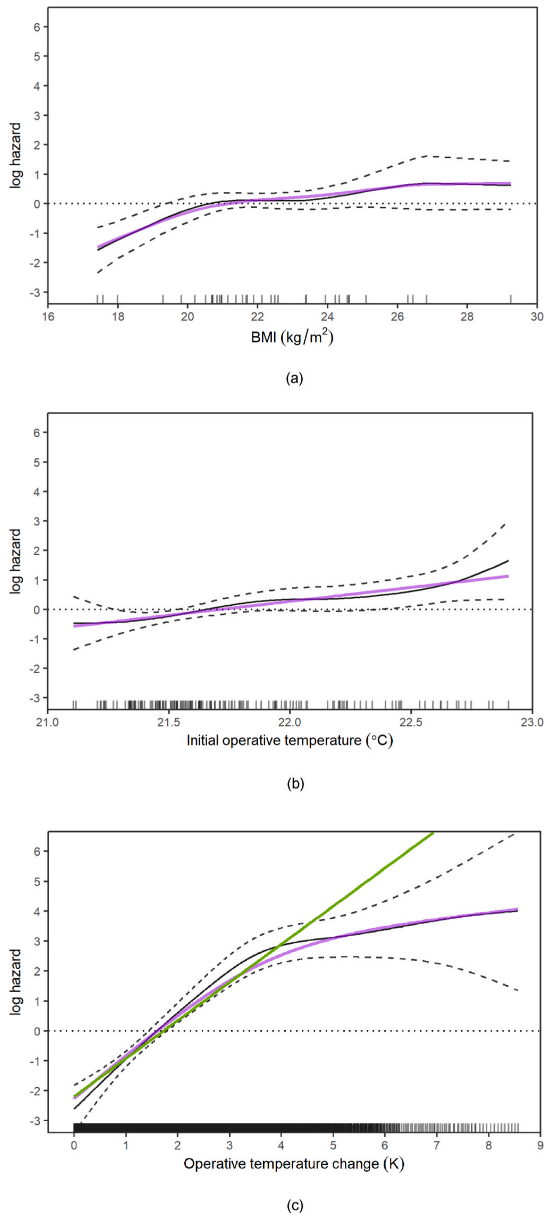

Fig. 9. Penalised spline fit of (a) BMI, (b) initial operative temperature and (c) operative temperature change for heating.

in Fig. 9c). A possible explanation for the hazard's flattening upon reaching higher delta temperatures is that different individuals have different frailty levels. More frail individuals are more likely to experience the discomfort event early. Consequently, over time, the "risk set" has an increasing proportion of less frail individuals, and the hazard flattens out. In addition, looking at Fig. 5, it can be noticed that around a +4 K increment, some participants do not experience the "warm discomfort event" before being censored.

No significant interactions have been found, and the PH assumption for the time-independent variables has been met. It is important to remember that, implicitly, time-dependent predictors do not satisfy it. For these variables, the hazard ratio is a function of time. Consequently, the coefficient of the time-dependent variable represents the overall effect of that predictor, considering all times at which this predictor has been measured in the study (for more details, the reader is referred to section 3.1.2 of this article).

4.3.3. Space cooling process

Table 8 summarises the results of the multivariable model for space cooling processes after applying backwards elimination. Three significant predictors were identified – time lived in Norway, time of day and operative temperature variation – one more compared with the initial model (see Table 6). *Time.day* and *Top.delta* are negatively associated with an increased risk of "cold discomfort", while *Time.Norway* is positively associated with the same outcome. As with the heating model, *Time.Norway* is positively associated with an increased risk of discomfort, but this time the relationship is weaker (HR = 1.854, 95% CI [1.060, 3.241], $p = .030$). The *Time.day* predictor is a categorical variable used to distinguish between the morning (8:00–11:30) and afternoon (12:00–15:30) sessions' thermal ramps. It was used to account for the circadian rhythm's influence on the risk of discomfort induced by variation in operative temperature. A circadian rhythm is a natural, internal process that regulates the sleep-wake cycle. This system also modulates other physiological functions, such as the body's core temperature, with a periodic variability over the 24 h (with maximal values in the late afternoon and minimal in the early morning). During periods of decreasing core temperatures, the average skin temperature rises to promote heat loss, and the reverse occurs during periods of rising core temperatures [48]. A circadian rhythm of heat loss from the distal limbs has been observed in humans: skin temperature and blood flow rhythms in these regions show peaks in the late evening and minima in the morning [49,50]. Consequently, an individual is in a "heat gain" mode in the morning (a rise in core temperature) and in a "heat loss" mode in the evening (a decrease in core temperature). Previous studies by Fanger et al. [51,52] found that, although the mean skin and rectal temperatures were slightly higher in the evening than in the morning, subjects did not prefer a different ambient temperature. They concluded that the same thermal comfort conditions can be used independently of the time of day or night. In this study, the hazard ratio for the time until "cold discomfort" for morning versus afternoon was 0.597 (95% CI [0.417, 0.853], $p = .005$), showing a difference between the two parts of the day. However, this result does not necessarily disagree with Fanger's previous findings. A lower risk of "cold discomfort" during the afternoon than in the morning does not inevitably imply a preferred lower temperature. It only suggests that, at any time during this study, participants during the afternoon were 0.597 times as likely to have a "cold discomfort" as during morning (that is, they experienced a reduction in risk of 40%).

It can be noticed that the covariates *Clothing* and *Gender*, even though not statistically significant, are still maintained in the model. In this

Table 8
Regression coefficients for predictors in the multivariable cooling model (after applying backwards elimination).

Predictor		Cooling process			
		coeff	se (coeff)	z	*p* value
Clothing		−1.535	1.422	−1.079	.280
Gender	female	Reference			
	male	−0.666	0.361	−1.844	.065
Time.Norway	≤3 years	Reference			
	>3 years	0.617	0.285	2.164	.030*
Time.day	morning	Reference			
	afternoon	−0.517	0.183	−2.828	.005*
Top.delta		−0.956	0.182	−5.241	<.001*
Likelihood ratio test = 54.17 on 5 df, p = 1.933E-10					

*indicates a significant term.

case, however, they remain not because they are confounders but because their presence improves the model's overall fit compared to the model without them ($\chi^2(2) = 8.438$, $p = .01471$).

The next step is to verify whether the linearity assumption for the continuous variables in the model is met. The same procedure as described previously was applied here, but only the statically significant continuous variable (i.e., operative temperature variation) is shown (Fig. 10). Here, the hazard decreases fairly linearly with the decrement in the operative temperature. Therefore, a linear relationship between the log(hazard) and the operative temperature variations was assumed (purple line).

No significant interactions were found, and the PH assumption for the time-independent variables has been met.

5. Discussion

In this study, the results obtained from the observed thermal discomfort events were precautionary for both space heating and cooling processes. The possibility of undertaking voluntary adaptation mechanisms or actions was precluded, including such simple actions as clothing adjustment. This approach agrees with the one used in the ASHARE standard 55 for temperature variation with time. The objective of ASHARE limits on temperature cycles, drifts and ramps (Table 1) is mainly to prevent occupants from experiencing discomfort due to temperature variations. Its applicability is limited to temperature fluctuations that are not under the individual occupant's direct control. Moreover, an occupant's clothing adaptation is implicitly considered only for occupant-controlled naturally conditioned spaces that meet specific criteria (see section 5.4.1 of [2]). Nevertheless, these limits seemed both loose and conservative compared with the results of this study. Cold temperature variations were perceived to be uncomfortable earlier than the standard prescribed. On the other hand, the limits for warm temperature variations were found to be excessively restrictive. This asymmetric behaviour is supported by neurophysiological findings.

As mention in section 1.1, in the spinal cord, cold-responding neurones react to temperature changes, while heat-responding ones react to the absolute temperature. Consequently, humans are more sensitive to cooling than heating, meaning that they react more quickly or more than usual to cooling than to heating. This neurophysiological interpretation can also be directly observed from this study's results, from both a descriptive and analytical perspective. The KM method gave a descriptive point of view. Fig. 7 showed that the survival probability is higher for heating processes compared with cooling ones, even for the same rate of temperature change (thermal ramp). Concerning cooling variations, it can be observed that different temperature change rates initially affected survivability similarly. The contrast between the different cooling ramps is more marked at a later time. This can also be explained using the findings of Ran's neuroscience experiment [22]. In their study, the authors observed that a larger delta temperature produced greater responses than smaller delta temperature values. Nevertheless, they noted no observable cooling rate effects on either the percentage of cold-responding neurons or their response amplitudes. Of course, faster temperature variation results in a greater delta temperature, assuming the same amount of time. However, when the amount of time is small, the temperature difference with distinct temperature change rates is smaller. Therefore, some (perhaps more sensitive) participants experienced a thermal discomfort event regardless of the rate of temperature change for cooling. In turn, this explains why, at an early phase, the survivability for a different rate of temperature change was similar. An analytical point of view was given by the Cox-regression. The model for cooling showed no statistically significant effect on the starting operative temperature. Conversely, in the heating model, the risk of experiencing a warm discomfort event increased with higher starting operative temperatures.

Furthermore, if considering elevated air movement, it is reasonable to assume that the observed thermal discomfort events for warm temperature variation could be postponed. Elevated air movement is a recognised factor that increases the acceptable range of operative temperatures [2]. In this study, the air was kept practically still to avoid local discomfort (a draft) during cooling. This resulted in air movement being an insignificant predictor.

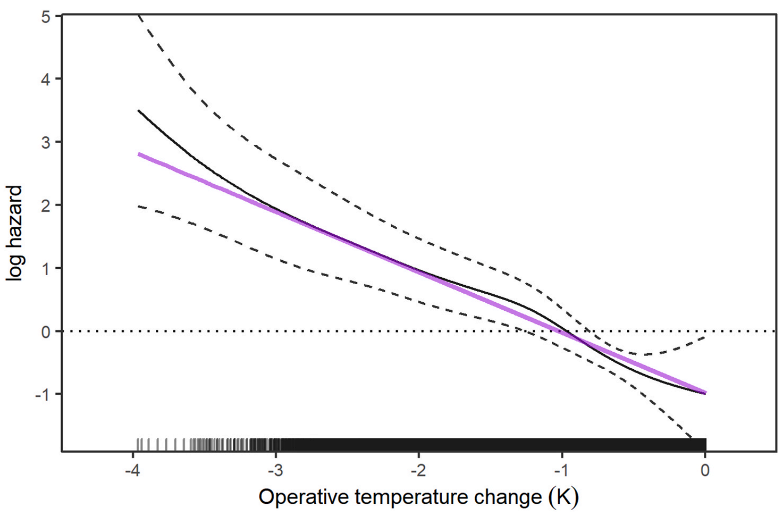

Fig. 10. Penalised spline fit of operative temperature change for cooling.

5.1. Limitations

This study's limitations arise from the relative homogeneity of age and the unbalanced number of male and female participants. Since most of the participants were between 23 and 31 years old, the results are not completely representative of the office worker population. The gender imbalance among participants might be the main cause of non-statistically significant differences between males and females in terms of thermal discomfort. To reduce the effect of the generally heterogeneous initial metabolic rate, participants spent the first half-hour before starting the session in a constant temperature environment. However, previous studies on thermal comfort in climatic chambers have shown that subjects' average thermal sensation decreases during the first 2 h, even during exposure to constant temperatures [13]. On the other hand, time and organisational constraints did not allow for such an extension of this study's acclimation period. Therefore, it is possible that the potential carry-over effects influenced the participants' thermal sensation even after the 30-min acclimation phase.

Even with some constraints (e.g., clothing adjustment), this study aimed to reproduce a typical office environment and, consequently, simulate a typical office activity pattern. Nevertheless, participants were prone to the Hawthorne effect.[5] Typically, the Hawthorne effect is described as a change in research participants' behaviour in experimental or observational studies. In this study, to avoid potential bias, participants were blinded to the environmental changes; that is, they were not informed about the change in the temperature. However, if the participants changed their behaviour during the experiment – for example, by increasing their awareness and, therefore, sensitivity to change in the indoor environmental condition – the Hawthorne effect would have occurred. Also, the use of the digital button could have introduced a behavioural change. Schweiker et al. [53], in their review of multi-domain approaches to indoor environmental perception and behaviour, pointed out that there is a difference in the intention to perform an action and the action itself. It is undeniable that performing an actual action, for example, adjusting the thermostat, would have required more effort than pressing the digital button. On the other hand, the opposite is also true. A specific human-building interface affects the level of interaction that a person has with it, and therefore its usability, which could lead to a different behavioural choice [54]. For example, even in a more familiar context, such as a residential setting, a common usability barrier for a thermostat is its complexity or the buttons' reduced size and comprehensibility [55]. Furthermore, it would be unfeasible to provide all the real means of possible interaction with the indoor environment (e.g., for the thermal environment alone, these include open/close window, thermostat adjustment, beverage intake, personalised/local cooler/heater, and ceiling/desk fans). Therefore, even with the aforementioned limitations, the discomfort button was adopted.

5.2. Conclusion and future perspectives

An experimental study has been conducted to explore the effects of ramp-induced temperature variations in an office setting. The purpose was to understand human reaction to monotonic thermal variations by describing the relationship between human response and covariates of interest. The study's design was a randomised crossover trial, a longitudinal study in which participants received a randomised sequence of different exposure (i.e., thermal ramps). Based on the analysis carried out, the following conclusions can be drawn:

- The distributions of participants' thermal comfort ratings during warm and cold discomfort events were remarkably similar, despite different temperature changes. This suggests that, indeed, thermal comfort is the driver for thermal behaviour. Thermal sensation votes were found to be asymmetric during discomfort events, while most of the thermal acceptability votes were at the boundary between an acceptable and unacceptable environment. This could indicate that thermal acceptability has a broader meaning, which, in a general sense, might be interpreted as tolerance.
- A distinct discomfort mechanism for space heating and cooling processes was observed in this experiment. For warm discomfort, the operative temperature level is a significant predictor, while for cold discomfort, the relative change in operative temperature is the trigger. This result agrees with the recent research evidence from neuroscience experiments [22].
- During heating variations, in addition to operative temperature (that is, the operative temperature variation plus the initial operative temperature), BMI and time lived in Norway significantly predicted participants' warm discomfort. For cooling processes, besides operative temperature variation, time lived in Norway and time of day were significant predictors of cold discomfort. For both space heating and cooling processes, gender and age did not significantly affect discomfort. Furthermore, no significant interaction has been identified.
- The current experimental results imply that the limits for drifts and ramps are not symmetric in winter conditions. The limits on temperature cycles, drifts and ramps defined in ASHRAE 55-2017 [2] are loose for cold temperature variations and conservative for warm ones.

In addition, this paper overcomes some important methodological issues concerning the semantic equivalence of different psychometric scales, highlighting, at the same time, the practical implications. For instance, a classic hypothesis (rule-of-thumb) is to consider an environment "satisfactory" when the thermal sensation vote is between "slightly cold" (−1) and "slightly warm" (+1). In this study, this conversion is well suited for warmer variations. Still, it is utterly misleading for colder ones. Fig. 6 shows that the majority of the discomfort events were experienced when the environment was perceived as "slightly cold".

In the context of multi-domain comfort, the methodology applied in this study could be used to analyse the relation between perception and action. It would also be possible to evaluate which contextual and personal factors affecting behaviour influence perception and vice versa.

Furthermore, the new knowledge of human reaction to a dynamic thermal environment can be used to design more energy-efficient and satisfying control strategies to enable buildings' thermal flexibility. Indeed, controlling the indoor temperature of buildings within a comfort range is a way to provide energy flexibility to the grid [56], exploiting the slow thermal inertia of a building's envelope in combination with the users' comfort band. However, the comfort band is usually assumed symmetric for space heating and cooling purposes and defined solely by absolute values of the indoor operative temperature, such as in the ASHRAE 55-2017 standard [57]. The findings presented in this paper have the potential to improve the performance of such controllers by providing a more accurate description of the human thermal response under dynamic conditions.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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[5] The Hawthorne effect got its name from a study of psychological aspects and physical and environmental influences in the workplace at the Western Electric Company's Hawthorne facility in Cicero, Illinois, during the 1920s. There, the workers increased their productivity when under observation but decreased it at the end of the study.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.buildenv.2021.108144.

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Paper II

Analysis of subjective thermal comfort data: a statistical point of view

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Abstract

Thermal comfort research aims to determine the relationship between the thermal environment and the human sense of warmth. This is usually achieved by measuring the subjective human thermal response to different thermal environments. However, it is common practice to use simple linear regression to analyse data collected using ordinal scales. This practice may lead to severe errors in inference. This study first set the methodological foundations to analyse subjective thermal comfort data from a statistical perspective. Subsequently, we show the practical consequences of fallacious assumptions by utilising a Bayesian approach and show that, at least with one dataset, a linear regression model applied to ordinal data suggests results different from those obtained using ordinal regression. Specifically, given the specified dataset, linear regression found no difference in means and effect size between genders, while the ordinal regression model led to the opposite conclusion. In addition, compared to the ordinal model, the linear regression model distorts the estimated regression coefficient for air temperature. Finally, the ordinal model shows that the distance between adjacent response categories of the ASHRAE 7-point thermal sensation scale is not equidistant. Given the abovementioned issues, we advocate utilising ordinal models instead of metric models to analyse ordinal data.

Keywords

Subjective thermal comfort data; Rating scales; Level of measurement; Ordinal regression; Bayesian analysis; Statistical thinking.

1 Introduction

One of the aims of thermal comfort research is to establish the relationship between the thermal environment and the human sensation of warmth. The sensation of warmth is quantified by rating scales, the most adopted of which is the ASHRAE 7-point thermal sensation scale, which consists of seven verbal anchors: ‘cold’, ‘cool’, ‘slightly cool’, ‘neutral’, ‘slightly warm’, ‘warm’, and ‘hot’. This is a perceptual judgement scale [1] and is utilised to measure thermal sensation. Other rating scales are also employed in thermal comfort studies: the most common ones being thermal evaluation, preference, and acceptability. ISO 10551:2019 [1], beyond those already mentioned, also introduces a 'tolerance scale', which is rarely used in the scientific literature. Each one of these scales can be presented in different formats (e.g., discontinuous *versus* continuous format) and methods (e.g., paper- *versus* computer-based). Independently of the format and method used, it is common practice to assign a numerical value to each level (i.e., the verbal anchors) of a scale. For instance, the ASHRAE 7-point thermal sensation scale generally varies from -3 ('cold') to +3 ('hot'). However, different values can be assigned, such as 1 for 'cold' and 7 for 'hot'. This interchangeability is possible because these numbers are merely placeholders without an underlying meaning. Nevertheless, it is common practice to calculate the mean of the thermal sensation votes of a group of people (e.g., [2,3]). The reasoning behind this method is that, while the variable is ordinal in nature, a vote created by averaging different responses is continuous. Furthermore, the averaged votes will result in a more normal-looking distribution and, therefore, statistical methods that assume normality (e.g., linear regression and analysis of variance) can be applied. The origin of this approach can be found in early works to measure attitudes, such as in Thurstone [4] and Likert [5]. However, there are two problems with this approach. Firstly, it is not appropriate to calculate the mean of an ordinal variable because its linearity (i.e., equally spaced divisions) is an arbitrary assumption imposed on the original scale values. This assumption was also recently questioned by Schweiker et al. [6,7]. Secondly, this approach conflates the problem of the level of measurement with that of the distribution of a variable. Averaging ordinal data may improve the degree to which the distribution of votes resembles a normal distribution, but it does not change the nature of the observations from ordinal to interval.

Concerning the analyses of subjective thermal comfort data, ISO 10551:2019 [1] gives guidance to the analysis of ordinal data. Unfortunately, it uses disputed arguments, based on McIntyre's work [8], to legitimise treating ordinal data from the ASHRAE 7-point thermal sensation scale as a continuous variable. In his paper published in 1978, McIntyre clearly stated that the 7-point warmth scale is ordinal and that, therefore, non-parametric statistics are the appropriate method. However, McIntyre also said that non-parametric statistics are generally related to hypothesis testing and are quite limiting for thermal comfort analysis. Therefore, utilising the method of graded dichotomies, he investigates whether these scales can be treated as intervals (i.e., if the psychological width of the categories can be approximated to be of equal spacing). McIntyre concluded that there is 'no reason to suppose that we are not dealing with an equal interval scale', even if nothing can be said to the extreme categories, that is 'cold' and 'hot' [8]. In addition, performing a Kolmogorov–Smirnov test[1] (K–S test), he found no significant deviation from normality and deduced that it is appropriate to use statistical methods that presuppose normality. However, checking whether an ordinal variable can be assumed to be interval for analytic purposes may work in some cases, but it does not constitute general proof. Nevertheless, this practice seemed reasonable at the time, considering that, until the 1960s, there was relatively little development of models for categorical responses (see page 1 of [9]). Furthermore, the K–S test can be applied only to continuous distributions, which is not the case analysed by McIntyre. In addition, the distribution used to compare the sample must be fully specified, that is, the location and scale parameters (i.e., mean and standard deviation) of the normal distribution must be known *a priori* and not estimated from the data. If these parameters are calculated from the data, the critical region of the K–S test is no longer valid and should be determined by simulation.

[1] The K–S test is used to test if a sample comes from a population with a specific distribution.

In the following two sections, the notion of 'level of measurement' is introduced (Section 1.1), and the issue of analysing ordinal data as metric is discussed (Section 1.2.3). Discussion regarding the different types of scales employed (e.g., categorical scale, visual analogue scale, and graphic categorical scale), the number of anchors utilised, and the assumptions underlying their usage are outside the scope of this study. The interested reader is referred to previous studies such as [6,7,10,11] for further discussions of these topics.

1.1 Level of measurement

A level of measurement is a classification that represents the nature of the information contained in the values assigned to the variables [12]. A widespread measurement classification is Stevens's typology [13], which is divided into four classes: nominal, ordinal, interval, and ratio. The nominal scale identifies or categorises the values of the variables but cannot order the categories; the ordinal scale, in which the values of the variables are ranked or ordered, is used for this purpose. For the interval scale, the intervals between the values of the variables are equally spaced, and the zero on the scale is arbitrary (i.e., the zero on the scale is a matter of convention or convenience). Conversely, the ratio scale has a true zero point, which defines the absence of the quantity being measured. As a consequence, ratios of magnitudes can be defined.

In Stevens's view, it is important to know which kind of scale one is dealing with because 'to each of these types of scales certain statistics are appropriate and others are not' [14], and a scale that retains meaning under a certain class of transformations should be limited to statistics whose meaning would not change if those transformations were applied to the data. Table 1 shows the different types of scales with their empirical operations, invariant mathematical transformations, and (permissible) measures of central tendency.

Table 1 – Types of measurement scales (from [14])

Scale	**Empirical operations**	**Permissible transformations**	**Permissible measures of central tendency**
Nominal	Determination of equality	Any one-to-one substitution	Mode
Ordinal	Determination of greater or lesser (rank-order)	Any increasing monotonic transform	Median
Interval	Determination of the equality of intervals or of differences	Multiplication by and addition of a constant	Arithmetic mean
Ratio	Determinations of the equality of ratios	Multiplication by a constant	Geometric mean Harmonic mean

Stevens went beyond his simple typology and classified not just simple operations but also statistical procedures according to the scales for which they were permissible. The idea that a particular level of measurement prescribes or proscribes statistical methods has been strongly criticised by statisticians [15-17], and alternative taxonomies have been proposed. Mosteller and Tukey's typology [18] and Chrisman's typology [19] introduced an expanded list of levels of measurement to account for various measurements that do not fit well into Stevens's framework. The difference is that they do not prescribe statistical methods nor even suggest that statistical methods should depend on the levels of measurement. Statistical analyses make assumptions about the distributions of variables and/or errors, not about measurement levels. Of course, it is necessary to verify that these assumptions comply with the data at hand. However, to conclude that there is no value in the data types would be inaccurate. The notion of scale type is important, and Stevens's nomenclature is frequently used. For example, any designed experiment must distinguish between categorical factors (usually nominal or ordinal in Stevens's terminology) and metric/continuous covariates (usually intervals or ratios) [15]. However, these scale types derive from how the data were measured rather than being fundamental characteristics of the data themselves.

1.2 Statistical methods: a brief overview

As stated previously, one of the goals of thermal comfort research is to establish a relationship between the thermal environment and the human response. In a statistical modelling framework, this is generally achieved through regression analysis. Regression analysis is *'the blanket name for a family of data analysis techniques that examine relationships between variables'* [20], which are categorised into a dependent variable ('outcome' or 'response' variable), Y, and one or more independent variables ('explanatory variables', 'predictors', 'covariates' or 'features'), X.

The most common approach utilised in thermal comfort research for the analysis of subjective thermal comfort data is linear regression. Another approach, even if far less common, is ordinal regression (e.g., [21]). The main difference between the two is that linear regression requires the dependent variable to be continuous, while ordinal regression requires it to be ordinal. Even though different regression models have different mathematical underpinnings, they share a general form that can be expressed as the function of a random component, $g(\cdot)$, which refers to the conditional probability distribution of the response variable, and a systematic component, $h(\cdot)$, which refers to the explanatory variables. The systematic component is used as the predicted tendency of Y given the predictors. Nevertheless, Y is not predicted to be exactly $h(\cdot)$, but near $h(\cdot)$. That is, the best that can be done is to predict the probability that Y will have any particular value, given x. This probability density function (PDF) is the random component $g(\cdot)$. This is a more general notation that encompasses different models (i.e., it extends more easily to other models by focusing on the conditional distribution of the response rather than the distribution of the error term [22]). The following sections briefly describe two regression-type models utilised to model subjective thermal comfort data.

1.2.1 General linear model

The most common approach utilised in thermal comfort research for the analysis of subjective thermal comfort data is the general linear model (GLM), which usually refers to the linear regression model. In this model, the continuous response variable is modelled given some predictors, generally assuming a conditional normal distribution of the response:

$$\begin{aligned} Y_i &\sim \mathrm{Normal}(\mu_i, \sigma^2) \\ \mu_i &= \eta_i \\ \eta_i &= \mathbf{x}_i^{\mathrm{T}} \boldsymbol{\beta} \end{aligned} \qquad \text{Eq. (1)}$$

where μ_i is the mean, σ is the standard deviation, and η_i is the predictor term function of some predictors $\mathbf{x}_i^{\mathrm{T}}$. The subscript i is to stress the dependency on the i^{th} observation.

1.2.2 Cumulative link model

As mentioned previously, if the response variable is assumed to be ordinal (and therefore measured as ordinal), it is proper to analyse it with ordinal models. Cumulative link models (CLMs) belong to a broad class of models known as ordinal regression models. Following the categorisation of Bürkner and Vuorre [23], in addition to the cumulative models, other two distinct model classes belong to the ordinal regression models: sequential and adjacent-category models. Each of these models has a different rationale behind it and, consequently, a different application.

The rationale behind choosing a CLM lies in the fact that this model has a latent variable representation, which is in line with the general assumption underlying the rating scales. The idea is that the dependent variable Y is the categorisation of a latent (not observable) continuous variable $\tilde{Y}$. Fig. 1 illustrates this concept. The categorical outcome, Y (Fig. 1.a and 1.b) is a categorised version of an unobservable (latent) continuous variable, $\tilde{Y}$ (Fig. 1.c and 1.d). The dotted lines in the bottom figures divide the continuous latent variable into $K+1$ bins according to the threshold parameters $\{\tau_k\}$, with $k \in \{1, \dots, K\}$. Consequently, the area under the curve in each bin represents the probability of the corresponding observed ordinal response (Fig. 1.a and 1.b). In Fig. 1, the thresholds are shown as not equidistant and equidistant (Fig. 1.c and 1.d, respectively) for illustrative purposes only. In practice, the thresholds are determined by nature; they are parameters to be estimated.

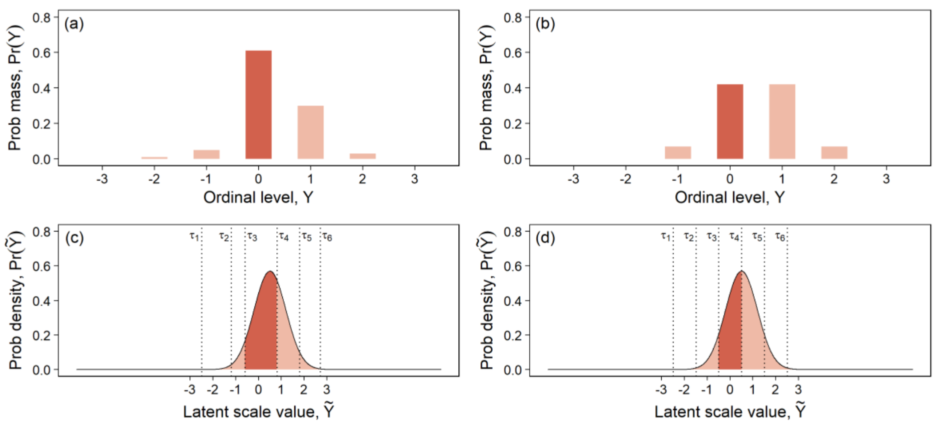


Fig. 1 – Representation of the latent variable interpretation: observed values ((a) and (b)) and underlying latent distribution ((c) and (d)).
Note. The thresholds τ_k (the dotted lines in (c) and (d)) are defined here as being not equidistant (c) and equidistant (d).

The conditional distribution of the response variable Y is assumed to follow a multinomial distribution where its probability vector is $\boldsymbol{\pi} = \{\pi_1, \dots, \pi_k\}$ with $\pi_k = \Pr(Y = k)$. The cumulative probability corresponding to π_k is $\gamma_k = \Pr(Y \leq k)$ so that $\gamma_k = \pi_1 + \dots + \pi_k$. The cumulative probabilities are then mapped to the real numbers through a link function. In this study, the probit function was chosen as the link function. The reason is that the probit link assumes the latent variable to be normally distributed[2] around the predicted central tendency (i.e., the mean of the latent scale) and is therefore comparable with linear regression. The mathematical form of the model can be written as:

[2] Technically, the distributional assumption should be made on the error term, not the response variable. However, in linear regression, to assume the error as normally distributed around zero is equivalent to assuming the response to be normally distributed around the regression line.

$$
\begin{gathered}
Y_i \sim \text{Multinomial}(n, \boldsymbol{\pi}_i) \\
\text{Probit}(\gamma_{ik}) = \tau_k - \eta_i \\
\eta_i = \mathbf{x}_i^{\mathrm{T}} \boldsymbol{\beta}
\end{gathered}
\qquad \text{Eq. (2)}
$$

where τ_k are the thresholds parameters and η_i is the linear predictor term without an intercept[3]. The subscript i is to stress the dependency on the i^{th} observation.

For more explanations and practical guidelines for using this and other methods (i.e., sequential and adjacent-category models), along with detailed mathematical derivations and discussions, the reader is referred to Bürkner and Vuorre [23].

1.2.3 Ordinal-as-metric

While it is generally recognised that ordinal data are not metric, it is commonplace to analyse them with methods that assume metric responses. This is inappropriate for the following reasons. First and foremost, the ordinal variable's categories may not be equidistant since it is unknown the psychological distance between adjacent categories and whether these distances are the same across subjects. In a survey respondent's thinking, the difference between 'neutral' and 'slightly warm', for example, may be considerably smaller than the difference between 'warm' and 'hot', as demonstrated by Schweiker et al. [6,7]. Second, the distribution of ordinal categories can be nonnormal, especially if low (e.g., 'cold') or high (e.g., 'hot') values are commonly chosen. Third, the variances of the unobserved variables underlying the observed ordinal categories can vary, for example, between periods (e.g., seasons) and groups (e.g., gender). The ordinal-as-metric method cannot account for such uneven variances.

The issue of examining ordinal data as metrics was analysed in great detail by Liddell and Kruschke [24], whose arguments are summarised hereafter. To facilitate their understanding and explanation, Fig.3 and Fig.4 in [24] have been adapted and reproduced here as Fig. 2. In this figure, the mean of the ordinal values (i.e., when the ordinal values are treated as metric) is plotted as a function of the latent mean, μ, and standard deviation (SD), σ. The four letter-labelled points represent a specific combination of μ and σ on the underlying latent scale that, if used as parameters in a cumulative probit model, would generate a particular pattern in the ordinal data. For instance, the point indicated by Ⓑ (i.e., group B) has a latent mean and standard deviation of $\mu = 2$ and $\sigma = 1$, respectively (Fig. 2.c) and an ordinal mean of 1.93 (Fig. 2.b).

[3] Omitting the intercept term allows the full set of thresholds $\tau_1, \dots, \tau_k$ to be identified.

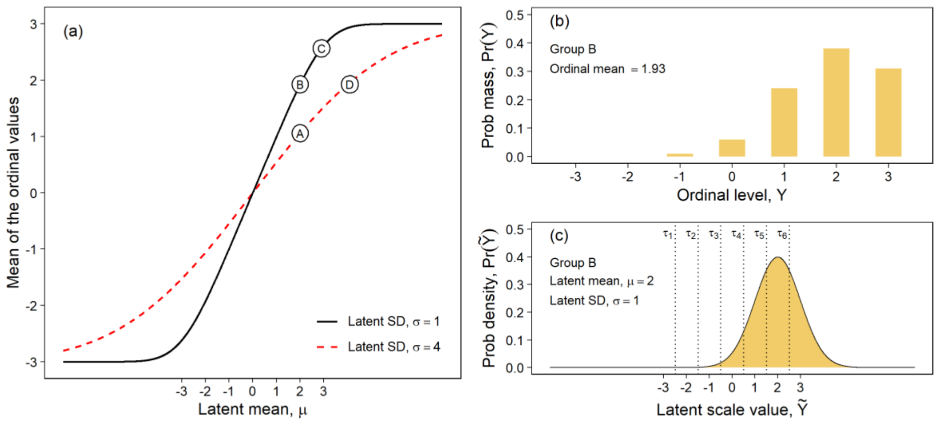


Fig. 2 – Mean of the ordinal values as a function of latent mean, μ, and SD, σ (a); ordinal level (b) and latent scale value (c) for group Ⓑ (adapted from [24]).
Note. The thresholds τ_k (the dotted lines in (c)) are defined here as being equidistant.

From Fig. 2.a, four different 'effects' can be observed:

1. Points Ⓐ and Ⓑ illustrate a false-alarm rate (Type I error): these two groups have the same latent means, but the ordinal means are estimated as very different.
2. Points Ⓑ and Ⓓ illustrate a low correct-detection rate (Type II error): for these two groups, the latent means are quite different, but the ordinal means are estimated as equal.
3. Points Ⓐ and Ⓓ illustrate a distorted effect-size estimate: here, the two groups have identical latent variances, but the difference in means on the horizontal axis (i.e., on the underlying latent scale) is larger than the corresponding difference on the vertical axis (i.e., on the ordinal-as-metric scale).
4. Points Ⓒ and Ⓓ illustrate a reversed effect-size estimate: here, the latent mean of group Ⓓ is greater than that of group Ⓒ, but the ordinal means for group Ⓒ are incorrectly estimated to be greater than those of group Ⓓ.

Liddell and Kruschke [24] posited that there are infinite combinations of underlying parameter values (μ and σ) that lead to inflated false-alarm rates, or low rates of correct detection, or distorted effect-size estimates, or inversions of differences between groups. Consequently, analysing ordinal data with metric methods (i.e., methods that assume continuous response variables), such as *t*-test, analysis of variance (ANOVA) and linear regression, could lead to the aforementioned issues. Furthermore, linear regression applied directly to ordinal values can misestimate regression coefficients, leading to incorrect inferences about differences or non-differences in slopes across conditions, as well as the existence or absence of non-linear trends. For further discussion and examples, the reader is referred to Liddell and Kruschke [24].

1.3 Objective and relevance of this study

Establishing the link between the thermal environment and the human sense of warmth is one of the goals of thermal comfort research. This is usually achieved by measuring the subjective human thermal response to different thermal environments. In this field, it is common practice to analyse subjective human thermal responses independently of how they have been measured. That is, the statistical analysis is unrelated to the modalities of the data that have been acquired. For example, Zhang and de Dear [25] state that thermal sensation vote 'although it is essentially an ordinal variable, the thermal comfort research community has usually regarded it as a continuous variable'. From this statement, the authors (i) highlight that there is a difference between ordinal and continuous variables but (ii) specify that, within the thermal comfort research community, there is the tendency to consider it as continuous. In other words, linear regression is widely used to analyse TSV measured on an ordinal scale. Liddell and Kruschke [24] showed that analysing ordinal data as if they were continuous could lead to misleading results. This is particularly relevant for thermal comfort research, since thermal comfort models are mainly based on ordinal data analysed as if they were continuous (e.g., Ref [25] citing [26-30]). This might be a concurrent factor to explain why conflicting results were found in previous research where, for example, gender was shown to be or not an influential factor in determining human responses to the thermal environment. Furthermore, these models are included in international standards, such as EN 15251:2007 [31], replaced by EN 16798-1:2019 [32], and ASHRAE 55:2020 [33], which are used in the design and operation of buildings all around the world.

This paper focuses on analysing the data once they have been collected and not on the correctness of the level of measurement utilised to measure them (see Refs [6] and [7] for further discussions of this topic). For this purpose, this study leverages the largest global thermal comfort database to date. The aim of the paper is twofold. The first aim is to overview the methods commonly used to analyse subjective thermal comfort data from a statistical perspective. The second aim is to highlight the ordinal-as-metric issue that is often not considered and to spur researchers to analyse these kinds of data more critically. It is essential to emphasise that we are not advocating that the specific approach hereafter presented as the best way to analyse these kinds of data: the approach presented is merely one of the possible ways to do so. Statistics is a field that is an art as much as it is a science. Although statistical theory is founded on exact assumptions and conditions, the real world is seldom that straightforward. Consequently, the practice of statistics involves a tremendous number of choices, and the challenge is how to make those choices.

2 Methodology

2.1 A Bayesian approach to regression

In this study, a Bayesian approach is used to analyse the data. This approach is not entirely new in thermal comfort studies (e.g., [34-36]); however, it is not an established practice either. Since statistical knowledge in this field generally tends towards 'frequentist' principles, it is essential to explain the Bayesian approach and compare it with the frequentist one. Nevertheless, the aim of this paper is neither to go into details about their differences, nor to be a full introduction to either approach. For a more complete treatment, see, for example, [37] and [38].

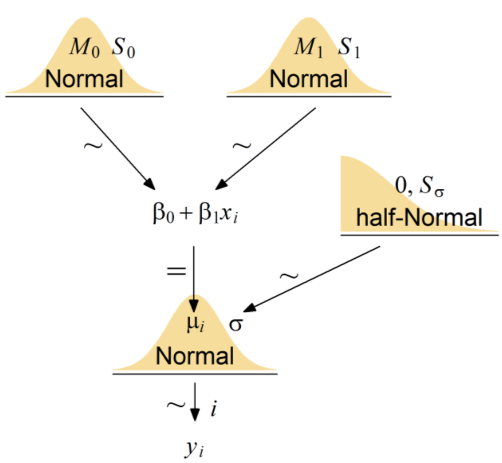
Essentially, the divide between frequentists and Bayesians is in the definition of probability. For frequentists, probabilities are associated with frequencies of events. For Bayesian, probabilities are related to their own understanding (i.e., certainty or uncertainty) of events. This difference has important implications in the analysis of data. For instance, in a frequentist view, the parameter θ is considered a fixed (i.e., constant) but unknown quantity and only the information from the sampling data is relevant for the inference. On the contrary, Bayesian statistics estimate the full (joint) posterior distribution of the parameters (i.e., the probability of the parameters given the observed set of data), which is generally calculated as:

$$\Pr(\theta \mid Y) = \frac{\Pr(Y \mid \theta)\,\Pr(\theta)}{\Pr(Y)} \qquad \text{Eq. (3)}$$

where $\Pr(Y \mid \theta)$ is the likelihood, $\Pr(\theta)$ is the prior distribution, and $\Pr(Y)$ is the marginal likelihood. Here the parameters are considered random variables and not constant, as in the frequentist approach.

In Eq. (3), the $\Pr(\theta)$ represent the prior 'belief' about the distribution of the parameters, and such a belief must be specified. Since there is no single method for choosing a prior (i.e., prior probability distribution), different priors can be introduced, leading to different posterior distributions and conclusions. This subjectivity is the main criticism of Bayesian inference. Furthermore, obtaining the posterior distribution analytically is rarely possible. Consequently, Bayesian statistics relies on Markov Chain Monte Carlo (MCMC) methods to estimate the posterior distributions of the parameters of interest. MCMC methods have a higher computational cost and fitting a model with Bayesian statistics is generally slower than the frequentist approach. However, Bayesian methods are usually more flexible and have more informative results (e.g., estimating a full posterior distribution, rather than a single point with a measure of uncertainty). Such advantages are often worth the increase in computational cost. Bayesian estimation does not have specific assumptions but relies on the model's assumptions, since those are the assumptions about the likelihood function. The fundamental assumption is that the likelihood function chosen is a reasonable representation of the data.

Generally, the assumptions behind a Bayesian model are not directly mentioned because they are stated when defining likelihood and priors. For example, Fig. 3 illustrates the formulation of a Bayesian model for simple linear regression. The corresponding mathematical formulations are added to the side for clarity.



$$y_i \sim \mathrm{Normal}(\mu_i, \sigma^2)$$

$$\mu_i = \beta_0 + \beta_1 x_i$$

$$\beta_0 \sim \mathrm{Normal}(M_0, S_0)$$

$$\beta_1 \sim \mathrm{Normal}(M_1, S_1)$$

$$\sigma \sim \text{half-Normal}(0, S_\sigma)$$

Fig. 3 – Dependency diagram for a simple linear regression model (adapted from [39]).

This figure shows the assumptions about the random component (i.e., the conditional distribution assumptions for y) and the functional form of the systematic component (i.e., the expression for μ). The distributions of the parameters β_0, β_1, and σ are the priors. Since the standard deviation cannot be less than zero, a half-normal distribution was selected as its prior (however, other distributions could have been chosen, such as exponential and uniform). For an introduction to Bayesian analysis or more advanced treatment, see [40] and [39], respectively.

2.2 Data preparation and software

As mentioned in Section 1.3, this study leverages the largest global thermal comfort database to date. This database, called ASHRAE Global Thermal Comfort Database II (downloaded from the University of California's DASH repository [41]), is an open-source database that includes approximately 107,500 sets of paired subjective comfort votes and objective instrumental measurements of the thermal environment. These observations were derived from field studies conducted worldwide between 1995 and 2016. A quality assurance check was performed on each dataset before its inclusion in the final database (see [42] for more details).

To achieve the aim of this study, the dependent variable needs to be measured on the ordinal scale. Unfortunately, the ASHRAE Global Thermal Comfort Database II does not distinguish between scales, and ordinal and continuous measurements are mixed. Additionally, even if all datasets composing the database went through a rigorous quality assurance process to harmonise their contents, it is reasonable to assume that each dataset has some unique peculiarities – different measurement protocols, questionnaires, or instruments. This aspect of the database would require that analysis of the entire database be carried out with an 'appropriate' method that considers these peculiarities (e.g., multilevel modelling) because, otherwise, the results may be unpredictably affected. For the purpose of this study, in order to reduce the uncertainty due to the unique peculiarities of different datasets, the following analysis was carried out on the data deriving from a single study.

Among the subjective thermal comfort votes available in ASHRAE Global Thermal Comfort Database II, the highest number of observations are thermal sensation votes (TSV). For this reason, TSV was selected as the dependent variable. However, the same analysis could be applied to the other rating scales if measured on the ordinal scale. For simplicity, only the two variables presented in Table 2 were utilised as covariates during the analysis. Indeed, thermal sensation depends on other variables, such as clothing, metabolic rate, air movement, radiant temperature, and relative humidity, and perhaps on several variables not yet clearly identified. Also, it is likely that not accounting for possible confounders affects the estimation of the models' coefficients. However, given that this study is an illustrative example, which aims to highlight the issue of analysing ordinal data as they were continuous, the issue of including/excluding important variables from the model can be overlooked.

Table 2 – List of covariates used in the model.

Variable	**Code**	**Type**	**Unit**
Gender	*Gender*	Categorical	female (reference) / male
Air temperature	*Tair*	Continuous	°C

The analysis was carried out on Indraganti et al.' study [43] dataset, included in the ASHRAE Global Thermal Comfort Database II. This dataset was selected because (i) it does not have missing values for thermal sensation votes, gender and air temperature; (ii) the full range of thermal sensation responses, measured on an ordinal scale, makes the dataset particularly suitable for this analysis (see Fig. 4); (iii) furthermore, the data were collected under a wide range of indoor air temperatures (min = 20.80 °C; 1st quartile = 25.80 °C; median = 26.80 °C; mean = 27.06 °C; 3rd quartile = 28.30 °C; max = 36.50 °C). The selected dataset comprised 6048 observations (~27 % female) collected during 14 months from 2787 individuals (all Indian nationals within the age group of 18-48 years). More details regarding the field survey can be found in Indraganti et al. [43].

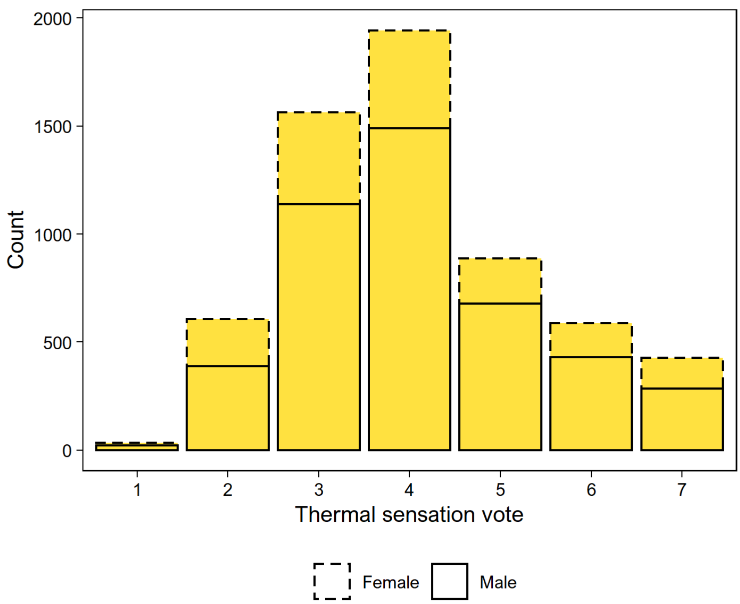


Fig. 4 – Distribution of the thermal sensation vote.

All statistical analyses were performed using R [44] with the RStudio integrated development environment [45]. Regression analyses, using both the cumulative probit and classical linear regression, were performed with the *brms* package [46], and the respective graphs were created with the *ggplot2* package [47] via the *tidybayes* package [48].

2.3 Model parametrisation

Before proceeding with the analysis, it is essential to briefly explain how *brms* parameterises the cumulative probit model because this has repercussions on its interpretation. The cumulative distribution function (CDF) of an ordinal model based on cumulative probabilities with probit link (i.e., cumulative probit model) can be stated as:

$$\Pr(Y_i \leq k \mid \{\tau_k\}, \eta_i, \sigma_i) = \Phi\left(\frac{\tau_k - \eta_i}{\sigma_i}\right)$$
$$\eta_i = \beta_0 + \sum_{1}^{l} \beta_l x_{l,i} \qquad \text{Eq. (4)}$$

$$\log(\sigma_i) = \delta_0 + \sum_{1}^{m} \delta_m x_{m,i}$$

where Φ indicates the cumulative normal distribution function, τ_k are the thresholds parameters, η_i is the linear predictor term and σ_i is the standard deviation. The subscript i is to stress the dependency on the i^{th} observation. With $K+1$ ordinal values, a model has $(K+1)+1$ parameters ($\tau_1, \ldots, \tau_k$, η_i and σ_i) and is undetermined. Therefore, two parameters need to be fixed. *Brms* parametrises the model by fixing $\beta_0 = 0$ and $\delta_0 = 0$ and freely estimating all the thresholds, $\tau_1, \ldots, \tau_k$. When there are no predictors for η_i and σ_i in the model (i.e., unconditional model), $\eta_i = \beta_0 = 0$ and $\sigma_i = \exp(\delta_0) = 1$. Therefore, instead of estimating η_i and σ_i from a normal cumulative distribution function, *brms* uses the standard normal cumulative distribution function $\Phi(z)$. As a consequence, the parameters are expressed on the latent variable scale, that is, in units of ordered probit. Furthermore, since *brms* parametrise the model as:

$$\mathrm{Probit}\big(\Pr(Y_i \leq\ k \mid \{\tau_k\}, \eta_i, \sigma_i)\big) = \frac{\tau_k - \eta_i}{\sigma_i} = \frac{\tau_k - (\mathbf{x}_i^{\mathrm{T}}\boldsymbol{\beta})}{\sigma_i} \qquad \text{Eq. (5)}$$

a positive coefficient for β indicates that an increase of 1-unit of the associated variable x_i increases the thermal sensation vote. Stated analogously, voting in higher categories is more likely. The interpretation would have been the opposite if the model was parametrised differently (i.e., with a '+' instead of a '−'). A positive coefficient for β would have indicated that an increase of 1-unit of the associated variable x_i would decrease the thermal sensation vote.

For comparison, the CDF for the ordinary linear regression model can be stated as:

$$\Pr(Y_i \leq y \mid \eta_i, \sigma_i) = \Phi\left(\frac{y - \eta_i}{\sigma_i}\right)$$

$$\eta_i = \beta_0 + \sum_{1}^{l} \beta_l x_{l,i} \qquad \text{Eq. (6)}$$

$$\log(\sigma_i) = \delta_0 + \sum_{1}^{m} \delta_m x_{m,i}$$

where Φ indicates the cumulative normal, η_i is the linear predictor term and σ_i is the standard deviation. The subscript i is to stress the dependency on the i^{th} observation. Here the β_0 and δ_0 are not fixed and therefore freely estimated by the model.

The following analysis was carried out for the cumulative probit model and compared with an ordinary linear regression, referred to as gaussian (ordinal-as-metric) model.

3 Results of the statistical analysis of subjective thermal comfort data

3.1 Unconditional model

The goal of a modelling strategy is to try to reproduce or predict an observable phenomenon via the lens of a model. Before incorporating a predictor, the unconditional model can be used to test the 'goodness' of the modelling technique. For example, if a model makes implausible predictions that are unobservable in reality,

perhaps a different technique should be adopted. The unconditional model for the cumulative probit and gaussian (ordinal-as-metric) models are the thresholds-only and intercept-only models, respectively.
The unconditional model results are shown in Table 3, while Fig. 5 shows its posterior prediction. Here the data generated from the thresholds-only and intercept-only models are compared with the empirical data.

Table 3 – Regression coefficients for the unconditional model.

	Estimate	**Est. Error**	**L-95 % CI***	**U-95 % CI***
Cumulative probit model				
Threshold 1, τ_1	-2.54	0.06	-2.66	-2.42
Threshold 2, τ_2	-1.25	0.02	-1.29	-1.21
Threshold 3, τ_3	-0.35	0.02	-0.38	-0.32
Threshold 4, τ_4	0.48	0.02	0.45	0.52
Threshold 5, τ_5	0.96	0.02	0.92	1.00
Threshold 6, τ_6	1.47	0.02	1.42	1.52
Gaussian (ordinal-as-metric) model				
Intercept	4.08	0.02	4.04	4.11
Sigma	1.37	0.01	1.35	1.39

* CI stands for credible interval (based on quantiles).

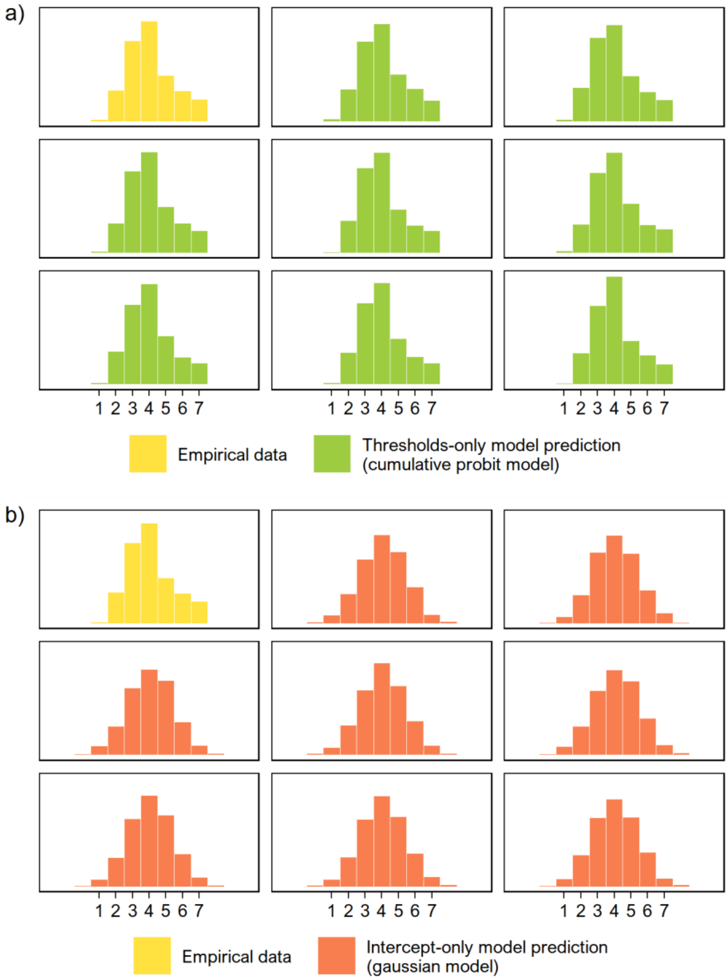


Fig. 5 – Posterior prediction for (a) the thresholds-only and (b) intercept-only model.
Note. The green and red histograms are obtained from 8 draws from the posterior predictive distribution of the thresholds-only and intercept-only models, respectively.

The posterior predictive distribution for the cumulative probit model (Fig. 5.a) visually describes the distribution of the outcomes. Conversely, the posterior predictions for the gaussian (ordinal-as-metric) model (Fig. 5.b) are not a good fit, and they also have impossible predictive outcomes (i.e., value below the category '1' that is, 'cold' and above the category '7', that is, 'hot'). Fig. 6 shows the standard normal distribution underlying the ordinal data and the position of the estimated thresholds $\{\tau_k\}$ (see Table 3). The area under the curve in each bin represents the probability of the corresponding observed ordinal response (see Fig. 4).

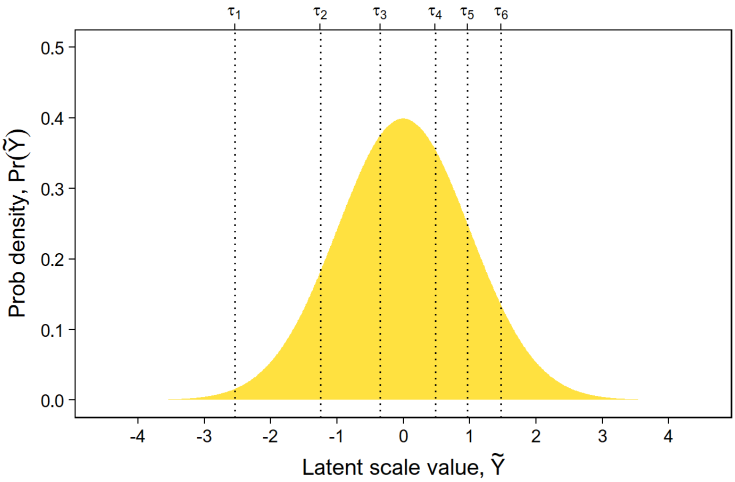


Fig. 6 – Standard normal distribution underlying the ordinal data.

A 'pseudo' CDF is plotted in Fig. 7 for illustrative purposes only [4] to inspect further and compare the two models. This direct contrast shows that the cumulative probit model better describes the data than the gaussian (ordinal-as-metric) model.

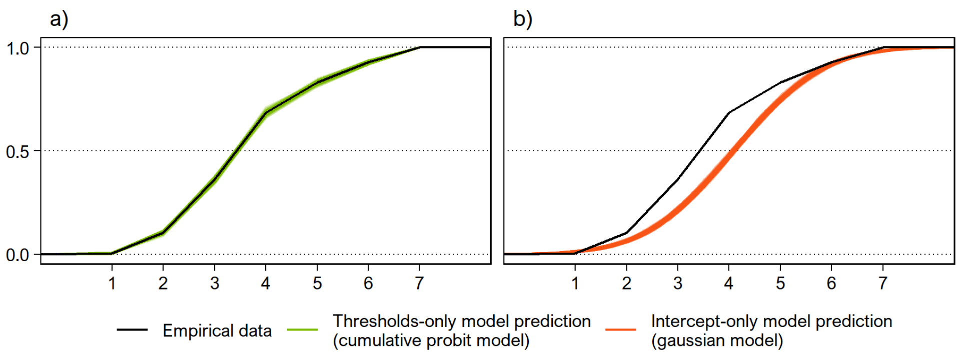


Fig. 7 – Superimposition of the CDF for the (a) cumulative probit and (b) gaussian (ordinal-as-metric) model.
Note. The green and red lines are obtained from 100 draws from the posterior predictive distribution of the thresholds-only and intercept-only models, respectively.

3.2 Fitting a categorical variable

In this section, the categorical variable *Gender* is added to the unconditional model. As described previously, *brms* parametrises the model by fixing $\eta_i = \beta_0 = 0$ and $\sigma_i = exp(\delta_0) = 1$. Therefore, the underlying Gaussian for the reference category of *Gender* (i.e., female) will be $\mathrm{Normal}(0{,}1)$. Thus, the parameter value for the

[4] Strictly speaking, a cumulative distribution function is defined as a continuous function only for continuous variables. For discrete variables, it should be a step function.

other category of *Gender* (i.e., male) is the difference in means expressed on the latent variable scale for the reference category. The results of this model are shown in Table 4.

Table 4 – Regression coefficients for the model with only a categorical variable (assuming constant standard deviation).

		Estimate	Est. Error	L-95 % CI*	U-95 % CI*
Cumulative probit model					
Threshold 1, τ_1		-2.49	0.06	-2.62	-2.37
Threshold 2, τ_2		-1.20	0.03	-1.26	-1.14
Threshold 3, τ_3		-0.30	0.03	-0.35	-0.24
Threshold 4, τ_4		0.53	0.03	0.48	0.59
Threshold 5, τ_5		1.01	0.03	0.96	1.07
Threshold 6, τ_6		1.52	0.03	1.46	1.58
Gender	female	reference			
	male	0.07	0.03	0.01	0.13
Gaussian (ordinal-as-metric) model					
Intercept		4.03	0.03	3.96	4.10
Gender	female	reference			
	male	0.06	0.04	-0.02	0.14
Sigma		1.37	0.01	1.35	1.39

* CI stands for credible interval (based on quantiles).

The model above presumes that the standard deviation of the latent variable is the same throughout the model (see Fig. 8 (top)). Unequal standard deviations can be included in the model by specifying an additional regression formula for the standard deviation component of the latent variable, $\tilde{Y}$. In the context of this example, allowing for unequal standard deviations implies inquiring whether the standard deviations for TSV differ across the two categories of *Gender*.

Table 5 – Regression coefficients for the model with only a categorical variable (allowing the standard deviation to vary by group).

		Estimate	Est. Error	L-95 % CI*	U-95 % CI*
Cumulative probit model					
Threshold 1, τ_1		-2.28	0.07	-2.41	-2.14
Threshold 2, τ_2		-1.09	0.03	-1.16	-1.02
Threshold 3, τ_3		-0.27	0.03	-0.32	-0.21
Threshold 4, τ_4		0.48	0.03	0.43	0.54
Threshold 5, τ_5		0.92	0.03	0.85	0.98
Threshold 6, τ_6		1.38	0.04	1.30	1.46
Gender	female	reference			
	male	0.06	0.03	0.00	0.12
Disc.Male		0.14**	0.02	0.09	0.18
Gaussian (ordinal-as-metric) model					
Intercept		4.04	0.04	3.96	4.11
Gender	female	reference			
	male	0.06	0.04	-0.02	0.14
Sigma.Female		0.39**	0.02	0.36	0.42
Sigma.Male		0.28**	0.01	0.26	0.31

* CI stands for credible interval (based on quantiles).
** Values expressed on the logarithmic scale.

Table 5 shows the results of the fitted cumulative probit model with group-specific η_i and σ_i values for the underlying normal distributions of the ordinal variable, Y (the results for the gaussian (ordinal-as-metric) model are added for comparison). There is a difference in the approach that *brms* uses to model unequal standard deviation for the cumulative probit and the conventional Gaussian model. The SD of both is modelled on the log scale to constrain its value to be 0 or larger. The parameter related to the latent standard deviations is called *disc* (a contraction of 'discrimination'), following the conventions in item response theory. This parameter is not related to the standard deviation itself, but to the inverse of the SD, that is, $\sigma = 1/disc$. Consequently, the estimated SD for male is $\sigma = 1/\exp(0.14) = 0.87$ and $\sigma = \exp(0.28) = 1.32$ for the cumulative probit and gaussian (ordinal-as-metric) model, respectively (values from Table 5).

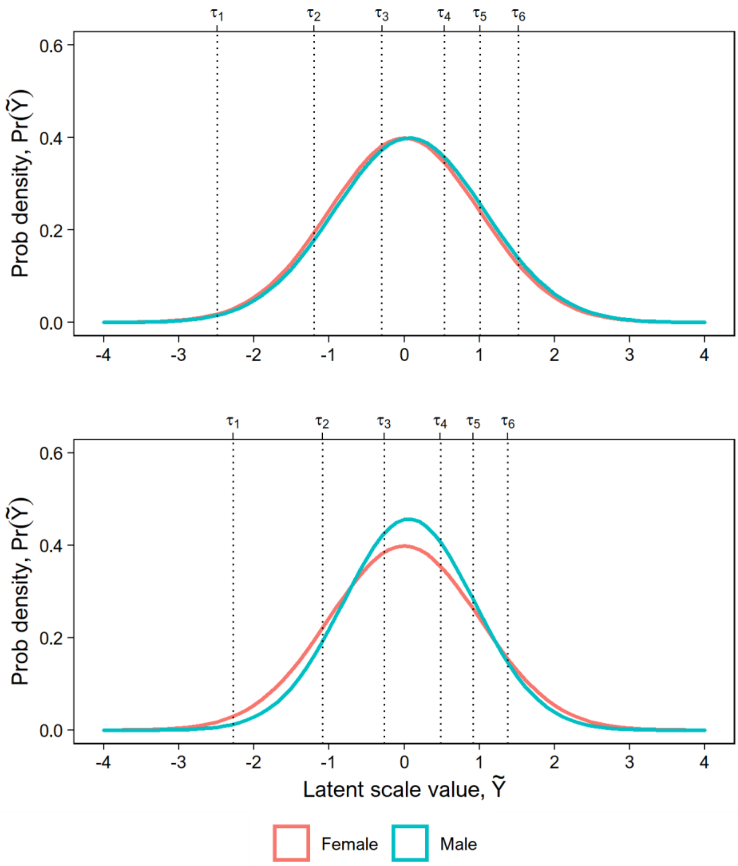


Fig. 8 – Density plot of the two underlying latent distributions for *TSV* with constant (top) and unconstraint (bottom) standard deviation for *Gender*.

Fig. 8 shows the density plot of the two underlying latent distributions for *TSV* given *Gender*, expressed in terms of the posterior means of each parameter. The underlying distribution for the reference category (i.e., female) is the standard normal, while the mean and SD for the other category (i.e., male) are estimated from the model. In Fig. 8 (bottom), the parameter value for *Male* is still the difference in means expressed on the latent variable scale for the reference group, but this time in terms of the SD of the reference group's latent variable (i.e., female). The SD for the two categories of *Gender* is not assumed to be the same, but it is allowed to vary. Also, the thresholds, $\{\tau_k\}$, are on the scale of the reference category's latent variable and are assumed to be the same for the two categories of *Gender*.

Table 5 shows that the coefficient for *Disc.Male* is positive without zero overlapping the 95 %-CI. This indicates that the SD for male is smaller than the female (i.e., $\sigma_{male} = 0.87 < \sigma_{female} = 1$) and the evidence based on the data and the applied model is sufficient in terms of 'standard decision rules'. As such, in this sample, the standard deviations for TSV differ across the two categories of *Gender*.

Fig. 9 shows the marginal posterior distribution of the parameters (i.e., the means and standard deviations) and the effect sizes for the cumulative probit (green) and gaussian (ordinal-as-metric) (orange) models, respectively. The cumulative probit model does not have a distribution for female because this is the reference category and its mean and standard deviation are fixed.

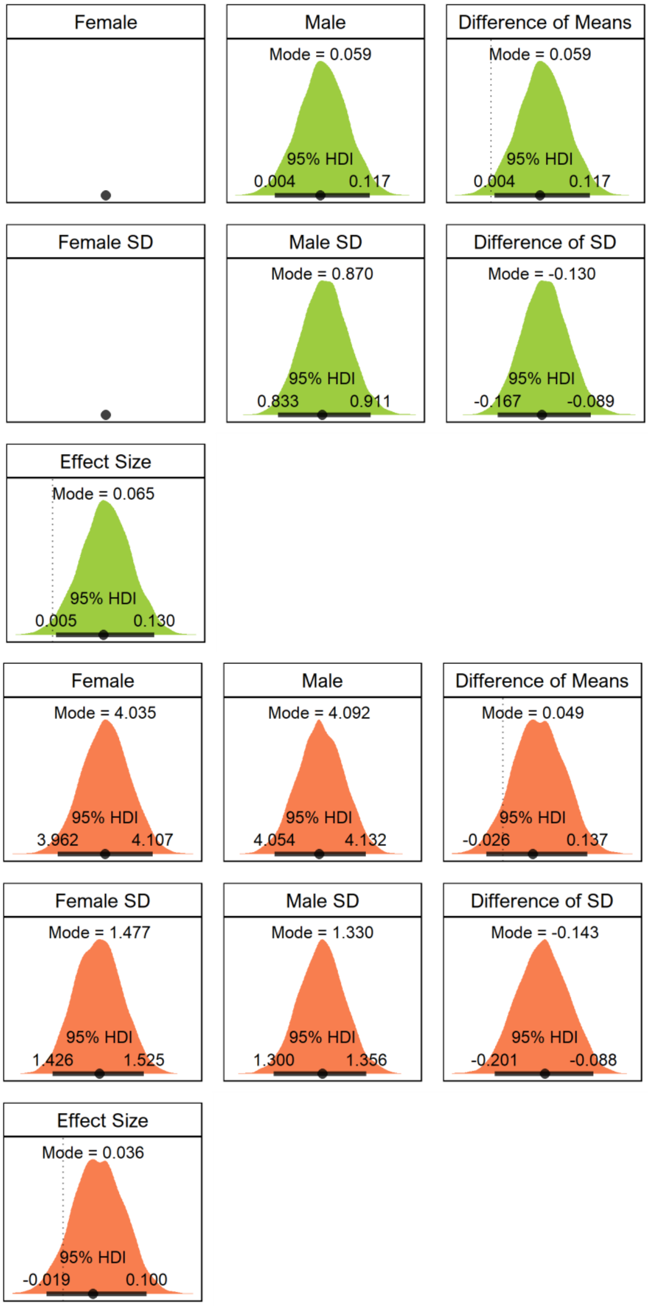


Fig. 9 – Posterior distributions for the model that include the variable *Gender*: cumulative probit (green) and gaussian (ordinal-as-metric) model (orange).

Here, the effect size is computed by dividing the difference of the means of the two groups by the pooled standard deviation given in Eq. (7):

$$\sigma_p = \sqrt{\frac{(n_1 - 1)\sigma_1^2 + (n_2 - 1)\sigma_2^2}{n_1 + n_2 - 2}} \qquad \text{Eq. (7)}$$

which is defined for two groups with unequal sample sizes (where n_1 and n_2 are the group-based sample sizes). In Fig. 9, the black line and dot at the bottom of each distribution represent the highest density interval (HDI) and the mode, respectively. The HDI is a way to summarise the distribution by defining an interval that spans over the distribution so that every point inside the interval has higher credibility than any point outside it. These intervals (i.e., the black lines) are defined here to span over 95 % of the distribution; therefore, they represent the 95 % HDIs.

Focusing on effect sizes and differences in means and standard deviations, two different results can be observed from Fig. 9. For the cumulative probit model, it can be seen that zero is outside the 95 % HDI for the effect size and the difference in means and SD. However, in the gaussian (ordinal-as-metric) model, zero is included in the 95 % HDIs for the effect size and the difference in SD while it is outside the 95 % HDI for the difference in means. As a consequence, in terms of 'standard decision rules', the two models convey different conclusions. While the cumulative probit model conveys a difference in effects size and difference in means for *Gender*, the gaussian (ordinal-as-metric) model does not.

3.3 Fitting a linear predictor

In this section, the continuous variable *Tair* was added to the previous model, that is, the model with the variable *Gender* and unconstraint standard deviation (i.e., where the standard deviation is allowed to vary by *Gender*). However, *Tair* was standardised before entering the model. Standardisation (i.e., subtracting the mean and dividing by its standard deviation) is done to improve the efficiency of MCMC sampling, that is, to reduce autocorrelation in the chains. In principle, it is unnecessary to standardise, but it would take more time for the chains to produce a reasonable, effective sample size. Furthermore, standardising does not change the parameter estimates. The results of fitting this model are presented in Table 6. Here can be seen that after adding *Tair.s* as a predictor, the upper and lower 95 % CI (i.e., L-95 % CI and U-95 % CI) for the male coefficient of the gaussian (ordinal-as-metric) model does not include zero. Consequently, the two models now convey the same conclusions regarding *Gender*; both the Gaussian (ordinal-as-metric) and cumulative probit models show a difference between males and females.

Table 6 – Regression coefficients for the model with a categorical and continuous variable (allowing the standard deviation to vary by group).

		Estimate	Est. Error	L-95 % CI*	U-95 % CI*
Cumulative probit model					
Threshold 1, τ_1		-2.39	0.07	-2.53	-2.25
Threshold 2, τ_2		-1.15	0.04	-1.23	-1.08
Threshold 3, τ_3		-0.28	0.03	-0.34	-0.23
Threshold 4, τ_4		0.53	0.03	0.47	0.59
Threshold 5, τ_5		1.01	0.03	0.94	1.08
Threshold 6, τ_6		1.52	0.04	1.44	1.60
Gender	female	reference			
	male	0.09	0.03	0.03	0.14
Tair.s		0.34	0.01	0.31	0.37
Disc.Male		0.12**	0.02	0.07	0.16
Gaussian (ordinal-as-metric) model					
Intercept		4.01	0.03	3.95	4.08
Gender	female	reference			
	male	0.09	0.04	0.01	0.16
Tair.s		0.47	0.02	0.44	0.51
Sigma.Female		0.32**	0.02	0.28	0.35
Sigma.Male		0.22**	0.01	0.20	0.25

* CI stands for credible interval (based on quantiles).
** Values expressed on the logarithmic scale.

The marginal distribution of the standardised regression coefficient for *Tair.s* is shown in Fig. 10. As explained before, this is a standardised regression coefficient and represents a sort of effect size for air temperature. The two models give a different distribution for the coefficient, with a distinct mode and 95 % HDIs. The coefficient of the cumulative probit model is expressed on the underlying latent scale, while the ordinal-gaussian (ordinal-as-metric) coefficient refers to the ordinal scale. As a consequence, the gaussian (ordinal-as-metric) coefficient for air temperature is overestimated.

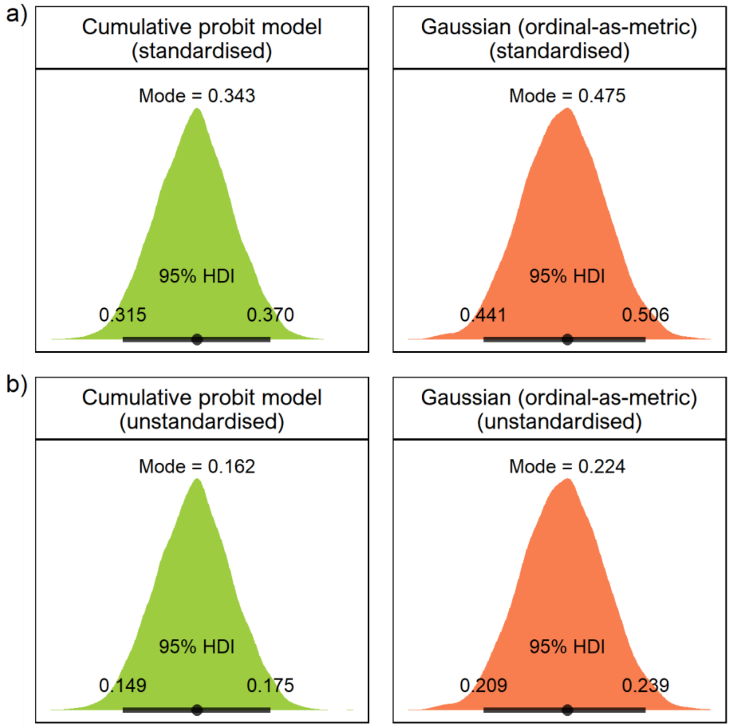


Fig. 10 – (a) Standardised and (b) 'original' regression coefficient for air temperature for the cumulative probit (green) and gaussian (ordinal-as-metric) (orange).

3.4 Structured thresholds

In all the previous cumulative probit models, the thresholds $\{\tau_k\}$ were defined as 'flexible' providing the standard unstructured thresholds. However, restrictions such as equidistance can be imposed on the thresholds, which restricts the distance between consecutive thresholds to be of the same size (i.e., equally spaced). This allows assessing the assumptions that the subjects used the response scale (i.e., TSV) in such a way that the distance between adjacent response categories is the same, that is, $\tau_k - \tau_{k-1} = \text{constant}$ for $k \in \{1, \dots, K\}$. The spacing of the equidistant threshold is plotted in Fig. 11.a. Here, the average distance between consecutive unstructured thresholds (i.e., $\frac{1}{k}\sum_1^k(\tau_k - \tau_{k-1})$) is also plotted (Fig. 11.b). It can be seen that zero is outside the 95 % HDI for the difference between the spacing for structured and unstructured thresholds (Fig. 11.c), suggesting that, in terms of 'standard decision rules', the thresholds should not be approximated as equidistant.

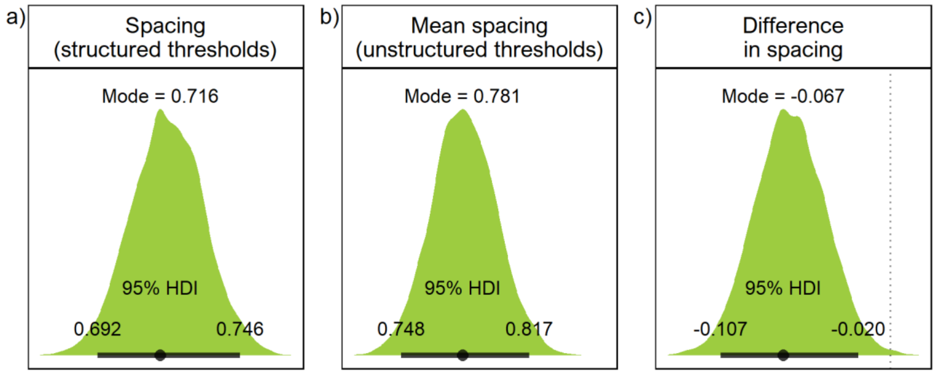


Fig. 11 – Spacing for (a) structured and (b) unstructured thresholds and (c) their difference.

Furthermore, whether the restriction on the thresholds is warranted by the data can be assessed formally by comparing the relative fit of the computed models to the data. One method to assess relative fit is approximate leave-one-out cross-validation (LOOCV) [49], where smaller values indicate better fit. Table 7 shows the estimated LOO information criterion (LOOIC) for the two models and their differences. It can be seen that the cumulative probit model with unstructured thresholds has a significantly better fit (smaller LOOIC value) than the structured thresholds one since the difference in LOOIC (i.e., LOOIC.diff) is very large (more than 12 times the corresponding standard error, SE.diff). In the context of model selection, a LOOIC difference higher than twice its associated standard error suggests that the model with the lower LOOIC value fits the data significantly better.

Table 7 – Values of the Leave-One-Out Information Criterion (LOOIC) and their difference for the cumulative probit model with structured and unstructured thresholds.

Model	**LOOIC**	**SE**	**LOOIC.diff***	**SE.diff****
Cumulative probit model (unstructured thresholds)	19,449.2	100.0	0.0	0.0
Cumulative probit model (structured thresholds)	20,014.0	97.2	564.81	44.39

* LOOIC.diff is the difference between the two LOOIC scores.
** SE.diff is the standard error of the LOOIC.diff.

4 Discussion

This study aimed to highlight the ordinal-as-metric issue during the subjective thermal comfort data analysis. Here, the method used to assess the reliability of the two models (i.e., the cumulative probit and gaussian (ordinal-as-metric) approach) is the so-called posterior predictive checks, a commonly used technique in Bayesian analysis. In essence, after computing the posterior distribution of the parameters, many simulated data are generated and compared with the observed ones. Therefore, the posterior predictive check is used to look for 'systematic discrepancies that would be meaningful to address' [39]. This approach has the evident drawback of evaluating a model against the same data used to estimate its parameters. Unsurprisingly, the model predicts the data used to fit the parameters, but even this simple test fails when the model's assumptions are severely violated. These systematic discrepancies are clearly shown in Section 3.1 when fitting the unconditional model for both the cumulative probit and gaussian (ordinal-as-metric) approach.

The influence of the statistical analysis on the conclusions has also been shown by Schweiker et al. [50]. In this study, the same thermal sensation votes were analysed with both linear and ordinal regression. The authors showed that the two statistical methods led to differences in the thermal conditions perceived as 'optimal' as well as between gender (i.e., female and male). However, compared with our study, important distinctions need to be made. To begin with, in Schweiker et al. [50], the analysis was carried out using mixed-effect models (linear and ordinal mixed-effect regression, specifically). This modelling strategy (also known as multilevel modelling) was applied to account for repeated measures (i.e., multiple observations for each subject). Moreover, the analysis was carried out within a frequentist framework. In our study, results are obtained by utilising a cumulative probit model in a Bayesian framework instead of the 'classic' frequentist approach. However, we emphasise that we are neither advocating a Bayesian approach as better than the frequentist approach nor that the cumulative probit model is the correct model to analyse ordinal data. Ordinal models in a frequentist framework provide another valid solution for analysing ordinal data (see *ordinal* package [51]). Also, other link functions besides probit are possible (e.g., logit or cloglog) and can be used. In addition, in Schweiker et al. [50], the linear mixed-effect regression model applied to ordinal data suggested a difference in means between genders. In contrast, the ordinal mixed-effect regression model led to the opposite conclusion. In our study, we obtained the opposite result: under given conditions (see Sections 3.2), the gaussian (ordinal-as-metric) approach inferred non-differences in gender, whereas the cumulative probit model showed a difference. Although these results contradict, they demonstrate the issue highlighted in this study: linear regression should not be used in place of ordinal regression to analyse ordinal data. It is essential to point out that we are not claiming that a difference between gender exists. In the literature (e.g., Refs [52] and [53]), many factors other than gender might lead to individual differences in thermal comfort — for example, age, circadian rhythm, physical disabilities, and fitness [52]. Here, the claim is about the difference in inference obtained from the same data (measured on an ordinal scale) analysed with two different methods (i.e., linear and ordinal regression). As shown in great detail by Liddell and Kruschke [24] (see also Section 1.2.3), analysing ordinal data with linear regression may, generally, lead to serious errors in inference. As such, it is not a problem concerning some specific variables (e.g., gender and air temperature in our illustrative example) but a more general issue.

One of the objectives of this work was to highlight that analysing ordinal data as they were continuous may lead to serious errors in inference (i.e., testing theoretical hypotheses). However, regression-type models can address different substantive goals and are therefore well suited to handle distinct purposes. For instance, Shmueli [54] separates a model's aim into descriptive, predictive, and causal explanations. Each of these distinct aims significantly impacts each step of the statistical modelling process and its consequences [54]. For instance, if the purpose is predictive modelling, the exact form of the data-generation process is not of interest, provided that it yields accurate predictions for the dependent variable. If the aim is inference (e.g., explanatory modelling), the estimate of the data-generation process is of interest, while making predictions of the dependent variable is not. In this study, it is not possible to draw specific conclusions regarding the accuracy of the prediction of TSVs. In this regard, Lai and Chen [55] analysed the predictive capability of linear regression compared with ordinal and multinomial regression. Using two separate datasets, the authors demonstrated that ordinal and multinomial regression predicted around half of the individual TSVs, whereas the accuracy of the linear regression model was only around 20 to 40 %. Furthermore, chi-square statistics demonstrate that the ordinal and multinomial regression model outperformed the linear regression model in predicting TSV distributions.

In Section 3.4, the assumption of equidistance between the categories of the ASHRAE 7-point thermal sensation scale was checked. Fig. 11 shows that in terms of 'standard decision rules', the estimated thresholds $\{\tau_k\}$ should not be approximated as equidistant, suggesting that, in this sample, the TSV is not interval-scaled. This result was corroborated by the formal analysis presented in Table 7. Here the cumulative probit model with flexible (i.e., unstructured) thresholds fitted the data significantly better than the one with equidistant (i.e., structured) thresholds. It has to be noted that the distances between the thresholds are affected by the form of the latent distribution, which is defined by the link function used. For instance, if the thresholds were found to be equidistant under a latent symmetric distribution (e.g., probit or logit link), under a latent skew distribution (e.g., clog-log link), they will generally not be equidistant. However, since an underlying normal distribution (i.e., probit link) was used in our example, this issue did not affect the results. The inappropriateness of the assumption of equidistance between the categories of the ASHRAE 7-point scale was also found in Schweiker et al. [6]. From a large international collaborative questionnaire study (8225 questionnaires), the authors concluded that significant differences appeared between groups of participants in relation to the distances of the anchors of the thermal sensation scale (and other scales commonly used in thermal comfort studies). Nonetheless, we cannot claim that treating ordinal data as continuous always yields a different result or conclusion than treating them as ordinal. However, knowing in advance that a difference exists is impossible; a different result can be detected only if an ordinal analysis is also performed. Therefore, it is recommended to perform an ordinal analysis directly. Furthermore, since the arguments used by McIntyre [8], which are included in ISO 10551:2019 [1], to legitimise treating ordinal data from the ASHRAE 7-point scale as a continuous variable are disputable (see Section 1 for more detail), **we strongly discourage the use of linear regression for analysing thermal comfort data measured on an ordinal scale. To improve the reliability of the results, we encourage researchers to use ordinal models.**

Moreover, ordinal models offer additional modelling possibilities that this paper has not discussed. For instance, the proportional odds assumptions can be relaxed, and the threshold parameters can depend on some regression variables. In the context of thermal comfort studies, this can be translated to having, for example, different threshold parameters for gender or season.

4.1 Limitations

A fundamental aspect that is usually overlooked is the assumption of independence: residuals, and thus observations, are assumed to be independent. Non-independence can arise, for example, from temporal and spatial autocorrelation. When underlying spatial or temporal processes have the potential to impact a response, the data are autocorrelated – the closer the observations are in space or time, the more highly correlated they are. These sources of non-independence can be apparent or far less so. The response of one sampling unit influencing the response of other sampling units is an example of evident non-independence. The non-independence caused by non-measured confounding influences that vary spatially or temporally is less obvious to detect. Dealing with temporal (or spatial) autocorrelation or analysing temporal (or spatial) trends is different. The former endeavours to deal with the lack of independence associated with temporal (or spatial) data, while the latter tries to model the effect of temporal (or spatial) patterns. During the data analysis stage, it was impossible to identify either spatial or temporal autocorrelation to test the assumption of independence because there was no temporal (e.g., subject ID and timestamp) or spatial (e.g., building ID) information available. As a consequence, this assumption was not checked. Given that the analysis was carried out for illustrative purposes only, this issue can be overlooked**. However, in a real-world analysis, the assumption of independence needs to be verified.** Furthermore, other issues, such as functional form misspecification, multicollinearity and omitted variable, were not considered during the analysis because they were outside the scope of this article. Nevertheless, when developing a model, depending on the aim of the study, these issues can play an important role and need to be considered. In addition, as stated in Section 2.2, the ASHRAE Global Thermal Comfort Database II does not distinguish between scales, and ordinal and continuous measurements are mixed. Consequently, there is a lack of homogeneity throughout the database that affects its integrity. Furthermore, there are conspicuous missing values in the ASHRAE Global Thermal Comfort Database II. This issue does not derive from the database itself but originates from the lack of explicit agreement on measuring the 'essential' variables in thermal comfort studies. If this lack of agreement continues, it could affect the future usefulness of the database because the information being added would continue to be non-homogeneous, thus limiting its usability and the new knowledge that could be extracted from it.

5 Conclusions and future perspectives

One of the aims of thermal comfort research is to establish the relationship between the thermal environment and the human sensation of warmth. Typically, this is accomplished by evaluating a subject's subjective thermal reaction to various temperature settings. Diverse rating scales are generally used to measure different aspects of thermal comfort, such as thermal sensation, thermal comfort, thermal preference, and thermal acceptability. While the problem of comparison of different scales (i.e., semantic equivalence) is an issue the thermal comfort research community is aware of, the use of reliable statistical methods to analyse the latter appears to be less discussed. In the thermal comfort domain, it is common practice to analyse subjective human thermal responses independently of how they have been measured. That is, the statistical analysis is unrelated to the modalities of the data that have been acquired. For example, even if measured on an ordinal scale, thermal sensation vote is generally treated as continuous and analysed with linear regression or other statistical tests that assume (conditional) normality. This approximation might be a concurrent factor to explain different results found in previous studies where, for example, gender was found to be or not an influential factor in explaining human responses to the thermal environment.

In this study, we first discussed why the arguments used in ISO 10551:2019 [1] to legitimise treating ordinal data from the ASHRAE 7-point thermal sensation scale as a continuous variable are disputable (see Section 1 for more detail). Secondly, to highlight the ordinal-as-metric issue during the subjective thermal comfort data analysis, the results obtained by utilising a cumulative probit and linear regression model were compared. Based on the analysis carried out on the dataset, the following conclusions can be drawn:

- Compared to the cumulative probit model, the linear regression model inferences non-differences in gender under given conditions.

- Compared to the cumulative probit model, the linear regression model distorts the estimate for the regression coefficient for the air temperature.
- The cumulative probit model shows that subjects used the ASHRAE 7-point thermal sensation in such a way that the distance between adjacent response categories is not the same; that is, they are not equidistant. Consequently, the cumulative probit model with flexible thresholds fitted the data significantly better than the one with equidistant thresholds.

As far as we know, in the field of thermal comfort research, the statistical issues highlighted in this paper are not usually mentioned because the modelling steps are rarely presented, and only the final model is described. However, this is a limitation because researchers can neither assess the reliability of the model nor completely understand the limits of its applicability. Furthermore, while not a primary output of this article, it emerged that there is a lack of homogeneity in the collection of common variables within the ASHRAE Global Thermal Comfort Database II. We recommend that guidelines be developed for defining specific variables to measure. Although there is generally no one-size-fits-all method (e.g., questionnaire) valid for all purposes, agreeing on a 'minimum set' of variables to be consistently measured, possibly with a standardised protocol, would undoubtedly benefit the thermal comfort research community.

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Paper III

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Human-in-the-loop methods for occupant-centric building design and operation

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HIGHLIGHTS

- Multilevel modelling was applied to predict subjects' thermal preference vote in a dynamic thermal environment.
- The beta and ordinal mixed-effects models are both valid alternatives for modelling subjects' thermal preference votes.
- Two procedures were used to implement subjects' feedback within the occupant-centric building design and operation paradigm.
- The population-averaged procedure is suitable for the building design phase.
- The cluster-specific procedure is appropriate for the building operation phase.

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ABSTRACT

A comfortable indoor environment should be one of the main services buildings provide. However, technical building systems are typically designed and operated according to fixed set-point temperatures determined by the 'one-size-fits-all' principle assuming universal thermal comfort requirements, which has been questioned in the last fifty years. Designing and implementing comfortable set-point modulations that consider occupant feedback would be beneficial in terms of increasing comfort, potentially reduce energy consumption and significantly support the clean energy transition. An exploratory study aimed at predicting the thermal preferences of human subjects exposed to a dynamic thermal environment is presented. Using data acquired from a laboratory experiment where subjects were exposed to precisely controlled thermal ramps in an 'office-like' climatic chamber, cluster-specific and population-averaged methods are designed to handle the group-level residual during the prediction of the thermal preference votes. The results show that both approaches are valid strategies for modelling thermal preference votes and are effective in supporting a concrete occupant-centric building design and the building's operation. Furthermore, the population-averaged approach is suitable for the occupant-centric building design phase, where the target is an 'average' occupant. The cluster-specific method is best suited to meet the needs of a specific occupant and is suitable for implementation in the operational phase of the building.

1. Introduction

A comfortable indoor environment should be one of the primary services buildings provide. Nowadays, all thermal comfort standards include recommendations concerning the indoor thermal conditions for both the design and operation phases of buildings. Currently, the most frequently cited thermal comfort standards, namely ASHRAE 55:2020 [1], ISO 7730:2005 [2] and EN 16798–1:2019 [3], which was formerly EN 15251:2007 [4], propose requirements based on Fanger model (beyond also including other approaches), which solves the heat balance equations between the human body and its surroundings, represented as a uniform environment. Fanger defined the 'Predicted Mean Vote' (PMV) as an index that predicts the mean thermal sensation vote on a standard scale for a large group of persons exposed to a given combination of metabolic activity level, clothing insulation and four thermal environmental variables characterising the indoor space: dry-bulb air temperature, mean radiant temperature, air velocity and relative

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Nomenclature

$\boldsymbol{I}$	The identity matrix
k	The category of the dependent variable
M	The total number of the simulated random effect
n	The number of events
$\boldsymbol{u}$	The vector of the random effects
$\mathbf{X}$	The design matrix of the fixed effects
$\mathbf{x}$	The vector of the fixed effects
x	Indicates a generic variable
$\mathbf{Y}$	The vector or matrix of the response variable
Y	Indicates a random value of the response variable (usually accompanied by a subscript)
$\boldsymbol{Z}$	The design matrix of the random effects
$\boldsymbol{\beta}$	The vector of parameters of the fixed effects
β	A scalar indicating a parameter of the fixed effects (usually accompanied by a subscript)
$\boldsymbol{\gamma}$	The vector of the cumulative probabilities
γ	A scalar indicating a cumalive probability (usually accompanied by a subscript)
$\boldsymbol{\eta}$	The vector of the linear predictor term
η	A scalar indicating the linear predictor term (usually accompanied by a subscript)
$\boldsymbol{\mu}$	The vector of the expected values
μ	A scalar indicating the expectd value (usually accompanied by a subscript)
$\boldsymbol{\pi}$	The vector of probabilities
π	A scalar indicating a probability (usually accompanied by a subscript)
σ^2	The variance
σ	The standard deviation
Σ	The variance–covariance matrix
τ	The latent threshold parameter
ϕ	The precision parameter

Subscripts

d	Indicates the d^{th} day
i	Indicates the i^{th} observation
k	Indicates the k^{th} category of the dependent variable
n	Indicates the dimension of a square matrix
p	Indicates the p^{th} participant
r	Indicates the r^{th} thermal ramp

humidity [5]. The PMV model is generally considered a static model because it is only suited for predicting thermal sensation under a steady state or slowly changing indoor conditions (i.e., rate of change lower than 2.0 K/h) [2]. Based on the PMV, Fanger introduced another index called the 'Predicted Percentage of Dissatisfied' (PPD) to establish a quantitative prediction of the percentage of thermally dissatisfied people. Additionally, thermal dissatisfaction can be caused by other local factors (e.g., drafts) and is known as local discomfort. For naturally conditioned spaces, ASHRAE 55:2020 [1] prescribes the use of the adaptive model, while EN 16798–1:2019 [3] suggests it only as a possible alternative to the Fanger approach. In 1973, in the first adaptive comfort paper published, Nicol and Humphreys [6] hypothesised the presence of 'control mechanisms' (feedback loops) between the occupants' thermal comfort perception and their behaviour in buildings. After this, research activity on the topic remained muted until the turn of the century, when intensification of research interest occurred, and several papers were published (e.g., [7,8]). The hypothesis of adaptive thermal comfort predicts that contextual factors and past thermal history modify occupant's thermal expectations and preferences [9]. As a result, people in warm climate zones would prefer higher indoor temperatures than people living in cold climate zones, which contrasts with the assumptions underlying comfort standards based on the PMV/PPD model [9]. Before inclusion in the standard EN 15251, the adaptive approach was also used by McCartney and Nicol [10] to develop an adaptive control algorithm (ACA) that was intended to be 'an alternative to fixed temperature setpoint controls within buildings' and 'was also tested in two air-conditioned buildings as part of the SCATs project' with promising results consisting in energy saving without compromising occupants' perceived thermal comfort [10]. In current standards, Fanger's PMV/PPD model is the prerogative of mechanically heated and/or cooled buildings, while the adaptive thermal comfort model is reserved for free-running buildings. EN 16798–1:2019 [3], citing ISO 7730:2005 [2], defines different categories of indoor environments for mechanically heated and cooled buildings, namely I, II, III and IV, with category I being the most stringent in terms of the management of interior conditions. An upper PPD bound is associated with each of the four PMV ranges (and therefore each category level), varying from 6 % to 25 % (see Table 1). A similar schema is present in ASHRAE 55:2020 [1], where the 'acceptable thermal environment for general comfort' is defined as $-0.5 < \mathrm{PMV} < +\ 0.5$, corresponding to category II in Table 1.

Table 1
Default design categories for mechanically heated and cooled buildings.

Category	PMV	PPD (%)
I	$-0.2 < \mathrm{PMV} < +0.2$	<6
II	$-0.5 < \mathrm{PMV} < +0.5$	<10
III	$-0.7 < \mathrm{PMV} < +0.7$	<15
IV	$-1.0 < \mathrm{PMV} < +1.0$	<25

The categories described in Table 1 are recommended for designing mechanically heated and cooled buildings. In practice, assuming the occupants' clothing insulation and metabolic activity levels and the relative humidity and air velocity of the environment, the PMV ranges can be represented in terms of acceptable operative temperature ranges. Maintaining a tight PMV or temperature range demands more energy than allowing a wider operative temperature range. A large increase in energy consumption could only be justified if a tightly controlled thermal environment were to be more comfortable than one under less control. Arens et al. [11] investigated this specific aspect by examining the acceptability of the temperature ranges associated with categories I, II and III of the EN 15251:2007 [4] standard via three databases on occupant satisfaction (specifically, the ASHRAE RP 884 [12], SCATs [10] and Berkeley City Center Project [13] databases). The authors found that in terms of satisfaction, building occupants do not benefit from an indoor environment that is tightly controlled (i.e., a category I environment). Furthermore, they identified only a small difference in satisfaction between categories II and III. Consequently, designing and controlling indoor environments, such as office buildings, following the strict specifications suggested, for example, for category I of EN 15251:2007 [4], is unreasonable [11]. However, the real issue can be traced back to using the PMV/PPD indexes as the theoretical basis for building control and operation in the first place. In a review paper, de Dear et al. [14] state that many rigorous field studies (e.g., [15–17]), founded by ASHRAE in the 1980 s and 90 s, have clearly found the 'one-size-fits-all' approach to achieving a universally comfortable environment 'to be a failure'. The main issue is that the PMV index represents a steady-state thermal comfort model that predicts the mean thermal sensation for a large group of people. Therefore, it fails to account for dynamic and non-uniform thermal environments as well as individual differences. In practice, the indoor environment frequently changes abruptly across buildings or between various parts within a single building. For instance, manually- operated thermostats, windows and window shades can result in considerable and non-systematic changes across the indoor environment. Automatic controllers exhibit, to a lesser degree, a similar behaviour. Moreover, activity modifies an individual's basal metabolic rate over time, and the addition or removal of clothes affects their heat balance. In other words, the steady-state assumption at the root of the Fanger comfort model is very often violated (Ref [18] citing [19]). Building temperature ranges should therefore be based on real-time empirical evidence regarding the needs of the occupants. Measures to improve occupant feedback capabilities should be included in the routine control and operation of the building as well as specified in building designs. For example, Park et al. [20] analyse occupant-centric control (OCC) research, focusing on field-implementation case studies in buildings under realistic conditions. The authors offer a methodological analysis focusing on the various strategies utilised to integrate OCC into existing building systems. Another example can be found in Jung and Jazizadeh [21]. In this review, the authors, distinguishing between simulations and field evaluations, proposed a taxonomy for human-in-the-loop HVAC operations and reviewed methods for integrating human dynamics to control HAVC.

Furthermore, implementing dynamic modulations of the set-point temperature might help time-shift and/or reduce peak space heating and cooling needs, improving the energy flexibility of buildings.

In this context, individual differences between people play an essential role. When it comes to thermal comfort, individual differences result in situations where distinct people perceive the same thermal environment in different ways (i.e., they have inter-individual differences) and/or when the same individual assesses the same environment differently at different times or in different situations (i.e., this individual presents intra-individual differences). Humphreys and Nicol [22] suggested that inter-individual differences encompass both temperature differences to be considered neutral and differences in the interpretation of the semantic scale categories. In contrast, intra-individual differences refer to personal judgments that differ from time to time. Machine learning/data-driven algorithms used for predicting individual comfort responses have exploded in popularity recently and include the classification tree (e.g., [23]), random forest (e.g., [24]), gradient boosting method (e.g., [25]), support vector machine (e.g., [26]), Gaussian process classification (e.g., [27]) and artificial neural networks (e.g., [28]). Although these techniques appear to have the potential to improve prediction ability at the level of a single building occupant, their inherent character as 'black box' models renders them fundamentally unfit to explain their outputs. In predictive modelling, direct interpretability regarding the relationship between the predictors (Xs) and the outcome of interest (Y) is not required; however, transparency is desirable.

In summary, there is a need for a reassessment of how buildings are designed and operated. Implementing comfortable set-point modulations in buildings that consider occupant feedback would be beneficial to comfort, potentially reduce energy consumption and significantly support the clean energy transition. As a consequence, HVAC design and operation should consider both the inter- and intra-individual differences among and within the occupants, respectively.

1.1. Research aim

A paradigm shift from 'set-point-based' control to 'perception-based' human-in-the-loop control of buildings is necessary to increase comfort, reduce energy consumption, and support the transition to clean energy. However, considering these aspects in the building design phase would also be beneficial.

The present research is an exploratory study aimed at predicting the thermal preference vote of human subjects exposed to a dynamic thermal environment. Therefore, the objective of this work is to develop a model for prediction (i.e., forecasting new data points), not for inference (i.e., testing theoretical hypotheses). Here, the data-generation process is viewed as a 'transparent' tool for developing good predictions. However, the modelling strategy does not aim to model the effect of temporal patterns directly but rather to account for them (i.e., account for the lack of independence associated with temporal data). The model is developed using data acquired from a laboratory experiment, where subjects were exposed to precisely-controlled thermal ramps in an 'office-like' climatic chamber.

2. Methodology

2.1. Data acquisition

The dataset used in this study comes from an experimental study conducted by Favero et al. [29] in the ZEB Test Cell Laboratory on the Norwegian University of Science and Technology (NTNU) premises (Trondheim campus) between September 2019 and January 2020. Thirty-eight participants (29 females and 9 males) were recruited from the university campus to participate in a randomised crossover trial, that is, a longitudinal study, in which they were subjected to a randomised sequence of thermal exposures (i.e., thermal ramps). Two identical climatic chambers, furnished like typical single offices, were used to recreate the changes in the environment induced by thermal ramps. Space heating and cooling were provided by a constant air-volume system that supplied 100 % fresh air from outside that was distributed by a 2 m-long perforated fabric tube installed at the ceiling. The operative temperature set-point of 22.0 ± 1.0 °C was determined using the thermal comfort limit for winter established for Category A of ISO 7730–2005 [2]. The rates of the temperature changes were: (i) $\pm$ 4.4 K/h, (ii) $\pm$ 3.4 K/h, (iii) $\pm$ 2.2 K/h and (iv) $\pm$ 1.4 K/h, as recommended by ASHRAE 55:2017 [30].

During the experiment, participants were not asked to perform any specific tasks and were allowed to carry out their typical office activities. Nevertheless, the subjects were required to fill out computer-based questionnaires at scheduled intervals. By means of graphic categorical scales (see Fig. 1), these questionnaires were used to assess perception, evaluation, preference, and acceptability of the thermal environment. Further details on the experimental set-up, as well as the experimental conditions and procedure, can be found in Favero et al. [29].

2.2. Statical modelling

Multilevel models (also commonly referred to as mixed or hierarchical models) are a regression-based approach to dealing with clustered and nested data [31]. When individuals form groups or clusters, it is reasonable to expect that two randomly selected individuals from the same group will tend to be more alike than two individuals selected from different groups. Following similar reasoning, measurements taken on the same individual on different occasions will be more highly correlated than measurements taken from different individuals. Therefore, whenever data are clustered and/or nested, the assumption of independent errors is violated.

This experimental study examines a mixture of hierarchical and crossed relationships. As shown in Fig. 2, different measurements on the thermal environment (level 1) are nested within experiment conditions (level 2), which, in turn, are cross-classified by participant and day (level 3). It is essential to mention that the multilevel structure defined here is not the property of a model but rather the property of the experimental/study design, which is then reflected in the data, which the model then encapsulates.

Within the multilevel framework, there are different modelling strategies that can be used. In this study, two different modelling strategies were applied, namely the beta mixed-effects model (a beta model including random effects) and the ordinal mixed-effects model (an

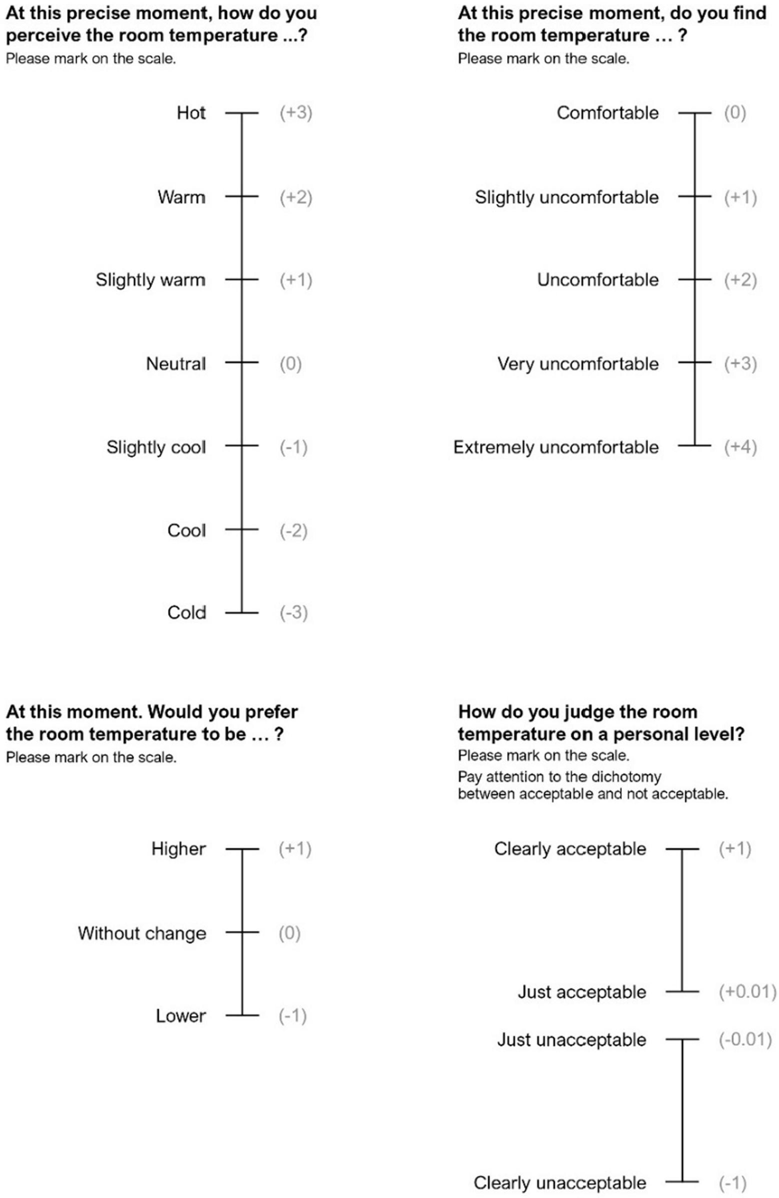

Fig. 1. Subjective scales used to assess perception, evaluation, preference, and acceptability of the thermal environment. Note. The numerical values of the scale were not shown to the participants during data collection.

ordinal model including random effects). These two approaches are described in the following sections.

2.2.1. Beta mixed-effects model

Generalised linear models[1] (GLMs) constitute a large class of models where the conditional distribution of the response variable Y_i is assumed to follow an exponential family distribution with mean μ_i. The latter is assumed to be some function of $\eta_i = \mathbf{x}_i^{\mathrm{T}}\boldsymbol{\beta}$, where $\mathbf{x}_i$ is the vector of covariates for the i^{th} observation and $\boldsymbol{\beta}$ is the respective vector of parameters to be estimated. However, one of the assumptions behind the model is the independence of the errors, which cannot be assumed whenever data are clustered and/or nested (see Section 2.2). To deal with dependent errors, GLMs can be extended to generalised linear mixed models, in which the linear predictor $\boldsymbol{\eta}$ contains random effects (i.e., $\boldsymbol{Zu}$) in addition to the fixed effects (i.e., $\boldsymbol{X\beta}$).

[1] This class of models is not to be confused with general linear model which usually refers to linear regression models – generally assuming a normal conditional distribution of the response.

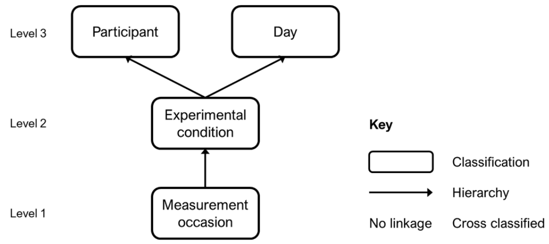

Fig. 2. Schematic of the three-level hierarchical study: repeated measures within experimental conditions cross-classified by participant and day.

In this study, the conditional distribution of the response variable $\boldsymbol{Y}$ is assumed to follow a beta distribution, where its mean $\boldsymbol{\mu}$ is linked to linear predictor $\boldsymbol{\eta}$ through a logit function:

$$\begin{aligned}&\boldsymbol{Y} \sim \mathrm{Beta}(\boldsymbol{\mu}, \phi)\\&\mathrm{Logit}(\boldsymbol{\mu}) = \boldsymbol{\eta}\\&\boldsymbol{\eta} = \boldsymbol{X\beta} + \boldsymbol{Zu}\\&\boldsymbol{u} \sim \mathrm{Normal}(\boldsymbol{0}, \boldsymbol{\Sigma})\end{aligned} \quad (1)$$

where ϕ is the precision parameter, and $\boldsymbol{X}$ (whose row i is $\mathbf{x}_i^{\mathrm{T}}$ and contains the i^{th} observation of the covariates) and $\boldsymbol{Z}$ are the design matrices for the fixed and random effects, respectively. The reader is referred to Appendix A for more details about the mathematical notation and a practical example. For the sake of clarity and brevity, the beta mixed-effects model with the logit link will hereafter be referred to as simply the beta model.

2.2.2. Ordinal mixed-effects model

Cumulative link models (CLMs) belong to the ordinal regression model class and can be performed using GLMs. A cumulative model is used when latent variable representation is desired. Here, the dependent variable Y is the categorisation of a latent (unobservable) continuous variable $\widetilde{Y}$. Therefore, there are some latent thresholds parameters τ_k, with $k \in \{1, ..., K\}$, that divide the values of $\widetilde{Y}$ into $K+1$ bins, that is, the observable ordered categories of Y. CLMs assume independence of errors and are not suited for modelling clustered and/or nested data. Their extensions for dealing with the dependent errors are the cumulative link mixed models (CLMMs).

In a CLMM, the conditional distribution of the response variable Y_i for the i^{th} observation is assumed to follow a multinomial distribution with probability vector $\boldsymbol{\pi}_i = \{\pi_{i1}, ..., \pi_{ik}\}$, where $\pi_{ik} = \Pr(Y_i = k)$. The cumulative probability corresponding to π_{ik} is $\gamma_{ik} = \Pr(Y_i \le k)$; hence, $\gamma_{ik} = \pi_{i1} + ... + \pi_{ik}$. The cumulative probabilities are then mapped to the real numbers through a link function. In this study, the logit function was chosen as that link function. The mathematical formulation of the model can be written as:

$$\begin{aligned}&\boldsymbol{Y} \sim \mathrm{Multinomial}(n, \boldsymbol{\pi})\\&\mathrm{Logit}(\boldsymbol{\gamma}_k) = \boldsymbol{1}\tau_k - \boldsymbol{\eta}\\&\boldsymbol{\eta} = \boldsymbol{X\beta} + \boldsymbol{Zu}\\&\boldsymbol{u} \sim \mathrm{Normal}(\boldsymbol{0}, \boldsymbol{\Sigma})\end{aligned} \quad (2)$$

where the τ_k are the thresholds parameters and $\boldsymbol{\eta}$ is the linear predictor term with a fixed effect component (i.e., $\boldsymbol{X\beta}$) without an intercept[2] and a random effect component (i.e., $\boldsymbol{Zu}$). The reader is referred to Appendix A for more details about the mathematical notation and a practical example. For the sake of clarity and brevity, the ordinal mixed-effects model with the logit link will hereafter be referred to as simply the ordinal model.

[2] Omitting the intercept term allows the full set of thresholds $\tau_1, ..., \tau_k$ to be identified.

2.2.3. Computing predictions using a multilevel model

Research setting aims to make predictions for certain values of x (e.g., adjusting the values of one x at a time or for combinations of x-values that reflect 'typical' persons) rather than calculating a probability for each individual in the sample. However, for a multilevel model, the treatment of the group-level residual $\boldsymbol{u}$ (i.e., group random effect) for these 'out-of-sample'[3] predictions must be considered.

In this study, two different procedures were used to handle the group-level residual during prediction. For the ordinal model, the first procedure consisted of holding the group-level residual at its mean of zero and calculating the probabilities for some specific x-values. It should be noted that the calculated predictions are not the mean response probabilities for the specific x-value because γ_{ik} is a nonlinear function of $\boldsymbol{u}$(as is $\boldsymbol{\pi}_i$). However, since $\boldsymbol{u}$ is assumed to be normally distributed with mean = median = 0, the $\mathrm{Logit}(\gamma_{ik})$ for $x = x^*$ and $\boldsymbol{u} = 0$ is equal to the median γ_{ik} for $x = x^*$ across groups. This is the case because the logit transformation does not affect the rank order of the observations. The response probabilities thus calculated have a cluster-specific interpretation.

The second procedure outlined a simulation-based approach, which consisted of the following steps:

i. Generate M values for the random effect $\boldsymbol{u}$ from the $\mathrm{Normal}(\boldsymbol{0}, \boldsymbol{\Sigma})$ distribution;
ii. For each simulated value ($m = 1, ..., M$) calculate, for the given x-value, the cumulative response probabilities for each $K+1$ ordered categories of Y;
iii. Compute the mean of the M cumulative response probabilities calculated in (ii) for each of the $K+1$ ordered categories of Y;
iv. Repeat steps (i) – (iii) for a different x-value.

The generated M values for the random effect should be a large number, here fixed at $1 \cdot 10^4$. This approach results in probabilities with a population-averaged interpretation (i.e., averaged across experimental conditions, participants and days). The same two procedures were applied to the beta model, with the difference that the prediction was not a vector (i.e., probabilities of voting in each category) but rather a single number (i.e., predicted mean).

2.3. Data pre-processing and analysis

A total of 314 thermal ramps were performed, for a total of 1522 votes. There were three missing values for thermal perception and evaluation, six for thermal preference and 14 for thermal acceptability. However, since only thermal preference was of interest in this study, only the missing values for the latter were eliminated. As a result, the final sample size was reduced to 1516 observations. Fig. 3(a) illustrates the distribution of the thermal preference votes.

As shown in Fig. 1, thermal preference ratings were measured using a graphical categorical scale. Participants could cast their vote by placing a diagonal line anywhere within the limits of the scale (i.e., within 'lower' and 'higher'). Consequently, the resulting distribution of votes is on a continuous, but bounded, scale (Fig. 3(a)). In this study, the conditional distribution of the response (i.e., $Y|\mu$) is assumed to follow a beta distribution. However, since any beta distribution's probability density function (pdf) is defined only on the interval (0,1), the dependent variable needs to be rescaled. Therefore, the thermal preference votes were scaled so that the values at the boundary of the scale, -1 (i.e., 'lower') and $+1$ (i.e., 'higher'), were mapped to $+0.001$ and $+0.999$, respectively.

As an alternative approach to the beta model, the ordinal model was

[3] The term 'out-of-sample' is used here to highlight that fixing variables at some values (e.g., their mean) may not reflect any actual person in the sample.

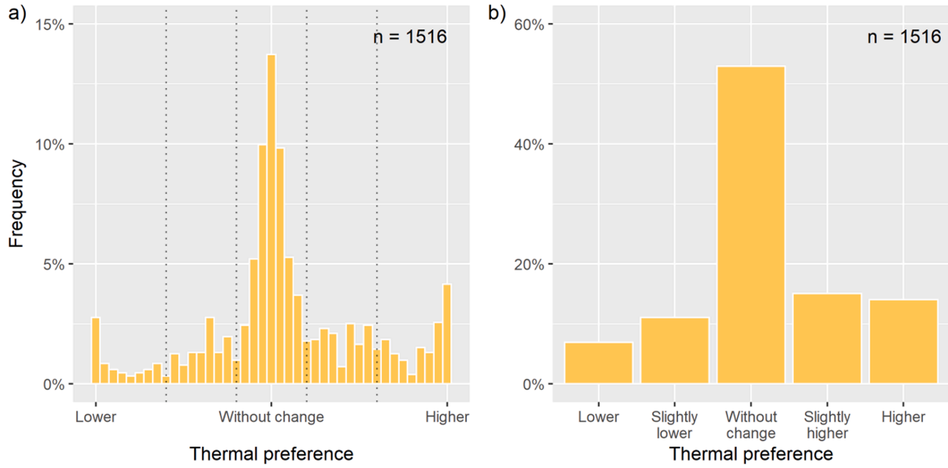

Fig. 3. Frequency distributions of (a) the thermal preference votes and (b) its categorisation. Note. The dotted lines represent the thresholds used for the categorisation, that is, -0.6, -0.2, $+0.2$, and $+0.6$.

chosen. However, the ordinal model requires the dependent variable to be categorical, which entails categorising the thermal preference votes. Therefore, the votes were binned into five categories according to the thresholds -0.6, -0.2, $+0.2$, and $+0.6$:

a) thermal preference votes < -0.6 were defined as 'lower';
b) $-0.6 \leq$ thermal preference votes < -0.2 were defined as 'slightly lower';
c) $-0.2 \leq$ thermal preference votes $\leq +0.2$ were defined as 'without change';
d) $+0.2 <$ thermal preference votes $\leq +0.6$ were defined as 'slightly higher';
e) thermal preference votes $> +0.6$ were defined as 'higher'.

The frequency distribution of the resulting bins can be observed in Fig. 3(b).

In a regression-type model, the shape of the distribution of a predictor has no direct impact on the model itself. Therefore, there is no real *a priori* need to transform or categorise a predictor based on its distribution. Of greater importance is the correlation between predictors (i.e., whether or not there is collinearity[4]). There are two types of collinearity: structural and data-based collinearity. The former is a mathematical artefact originating from composing new predictors from other predictors, such as powers (higher-order terms) or products (interaction terms) of predictors. The latter is a 'property' of the data itself, which can be the result of, for example, a poorly designed experiment. To manage the first type of collinearity, predictors lacking a meaningful zero were centred by their grand mean; it should be noted that this standardisation procedure can facilitate the interpretation of the model [32]. Data-based collinearity is more challenging and regrettably, is the most common form of the two. It is typically dealt with via the removal of one or more of the collinear predictors from the regression model. Variable selection was performed with an automated backward elimination employing the Akaike information criterion (AIC) as the selection criterion.

Table 2 presents the descriptive statistics of all the dependent variables used to infer the models. Detailed information concerning these variables can be found in Appendix B, while the instruments' accuracy can be found in Favero et al. [29].

All statistical analyses were performed using R [33] with the RStudio integrated development environment [34]. The beta model and the ordinal model were determined with the *glmmTMB* package [35] and *ordinal* package [36], respectively. Automated backward elimination was performed with the *buildmer* package [37] and all the graphs were

Table 2
Descriptive statistics of the variables used in the models.

Variable	Code	Unit	Mean*	Frequency*	Median (1st, 25th, 75th, 99th)**
Thermal resistance of clothing	*Clothing*	clo	0.86	–	0.87 (0.54, 0.78, 0.97, 1.11)
Gender	*Gender*	female	–	0.78	–
		male	–	0.22	–
Age	*Age*	years	27.11	–	25 (20, 22, 30, 49)
Body Mass Index	*BMI*	kg/m^2	22.09	–	21.67 (17.42, 20.69, 23.94, 29.24)
Time lived in Norway	*Time. Norway*	$\leq$ 3 years	–	0.53	–
		greater than 3 years	–	0.47	–
Air velocity	*Air.vel*	m/s	<0.10	–	0.00 (0.00, 0.00, 0.00, 0.06)
Time of day	*Time. day*	morning	–	0.47	–
		afternoon	–	0.53	–
Vapour pressure	*Vap.pre*	kPa	0.70	–	0.70 (0.39, 0.58, 0.82, 1.06)
Operative temperature	*Top*	°C	22.39	–	22.10 (18.79, 21.08, 23.72, 27.33)

* the mean refers to continuous variables, whereas the frequency refers to categorical variables
** where 1st, 25th, 75th and 99th represent percentiles

[4] Collinearity is semantically equivalent to multicollinearity. In a general sense, collinearity refers to 'the condition of being collinear' and is a property of a set of explanatory variables, not just pairs of them.

created with the *ggplot2* package [38]. The significance level for all analyses was set at 0.05.

3. Results

In this section, the main results of the statical analysis are presented. Table 3 list all the variables used in the two models (i.e., the beta and ordinal models).

3.1. Testing for cluster effects

In Section 2.2, the experimental study was described as a mixture of hierarchical and crossed relationships. Nevertheless, before proceeding with the analysis, it was essential to establish that the three-level cross-classified model fit the data significantly better than the simpler three-levels models and the two-level model nested within it (see Fig. 4). The single-level model (i.e., the model without random effects) was also checked. The likelihood ratio (LR) test was used to perform this initial check.

This preliminary analysis was carried out for both the beta and ordinal models, and its results are presented in Table 4. Here, the three-level cross-classified model is compared with the nested models. For both the beta and ordinal models, the three-level cross-classified model offers a better fit to the data.

3.2. Initial model

In this section, the initial full model is presented. The formulation of the linear predictor η_i is the same for the beta and ordinal models and can be written as:

$$\eta_i = \beta_1 \text{clothing\_c}_i + \beta_2(\text{gender}_i) + \beta_3 \text{age\_c}_i + \beta_4 \text{BMI\_c}_i + \beta_5(\text{time.norway}_i) + \beta_6 \text{air.vel}_i + \beta_7(\text{time.day}_i) + \beta_8 \text{vap.pre\_c}_i + \beta_9 \text{top\_c}_i + u^{(2)}_{\text{ramp\_ID}(i)} + u^{(3)}_{\text{participant\_ID}(i)} + u^{(3)}_{\text{day\_ID}(i)} \tag{3}$$

where the subscript i is used to stress dependence on the i^{th} observation. Since the three-level cross-classified model fits the data better (see Section 3.1), all three random components were added to the initial model. Only the main results of applying automated backward elimination are illustrated in the following sections.

Table 3
Covariates used in the models.

Classification (level)	Code	Variable	Type	Unit
Days (level 3)	*Day_ID*			
Participants (level 3)	*Participant_ID*			
	Gender	Gender	Categorical, time-independent	Female (reference)/ Male
	Age_c	Age (centred)	Continuous, time-independent	Years
	BMI_c	Body Mass Index (centred)	Continuous, time-independent	kg/m^2
	Time.Norway	Time lived in Norway	Categorical, time-independent	Less than or equal to 3 years (reference)/ More than 3 years
Experimental conditions (level 2)	*Ramp_ID*			
	Time.day	Time of day	Categorical, time-independent	Morning (reference)/ Afternoon
	Clothing_c	Thermal resistance of clothing	Continuous, time-independent	clo
Measurement occasions (level 1)	*Timepoint*			
	Top_c	Operative temperature (centred)	Continuous, time-dependent	°C
	Vap.pre_c	Vapour pressure (centred)	Continuous, time-dependent	kPa
	Air.vel	Air velocity	Continuous, time-dependent	m/s
	Therm.pref	Thermal preference	Continuous/ Categorical, time-dependent	–

3.3. Ordinal model

Table 5 summarises the results of the ordinal model after automated backward elimination has been applied. Here, the coefficient estimates are given in units of ordered logits (or ordered log-odds). Five significant predictors were identified – thermal resistance of clothing, Body Mass Index, air velocity, time of day and operative temperature – all negatively associated with $\text{Logit}(\gamma_k)$. The *ordinal* package [36] parametrises the model as:

$$\text{Logit}(\boldsymbol{\gamma}_k) = \mathbf{1}\tau_k - \boldsymbol{\eta} = \mathbf{1}\tau_k - \boldsymbol{X\beta} - \boldsymbol{Zu} \tag{4}$$

so a negative coefficient for β indicates that an increase of the associated variable x_i decreases the thermal preference vote. Stated analogously, votes for higher categories (e.g., prefer 'higher') are less likely. Nevertheless, the aim of this study is not inference but prediction; therefore, the specific values of the model's coefficients are not of interest. Furthermore, utilising any automated model selection procedure (e.g., automated forward selection, backward elimination or stepwise selection) should be avoided for inferential purposes. The parameter estimates are biased away from zero, the standard error and p values are too low and the confidence intervals are too narrow (page 68 of [39]), leading to misleading results. For prediction purposes, model selection can indeed provide a better bias-variance trade-off and improve the out-of-sample error [40,41].

The estimated coefficients for a multilevel model are referred to as cluster-specific effects. For instance, the coefficient of *Top_c* in Table 5 is interpreted as the effect of a one-unit change in *Top_c* on the log-odds that $\Pr(Y \leq k)$ for a given cluster (i.e., while the unobserved characteristics captured by the random effects are held constant). However, considering the effects in this manner implies that individuals are compared with the exact same value for fixed and random effects. For some variables (e.g., gender) or other specific purposes, a comparison averaging across unobserved characteristics in the population is often of interest. In such a situation, population-averaged probabilities should be derived (see Section 2.2.3).

Fig. 5 shows the predicted probabilities as functions of the operative temperature for the cluster-specific and population-averaged procedures. It can be seen that the probabilities calculated with the two methods are dissimilar. For example, the maximum predictive probability for 'without change' is about 91 % for the cluster-specific approach, while it is only 55 % for the population-averaged one. Fig. 6(a) shows the probability mass for the ordinal model and cluster-specific procedure. These probabilities are plotted as a function of three different operative temperatures while holding the other covariates constant at their centred values and fixing the random effects at zero. Fig. 6(b) shows the population-averaged procedure's results.

3.4. Beta model

Table 6 summarises the results for the beta model after automated backward elimination has been applied. Here, the estimated coefficients

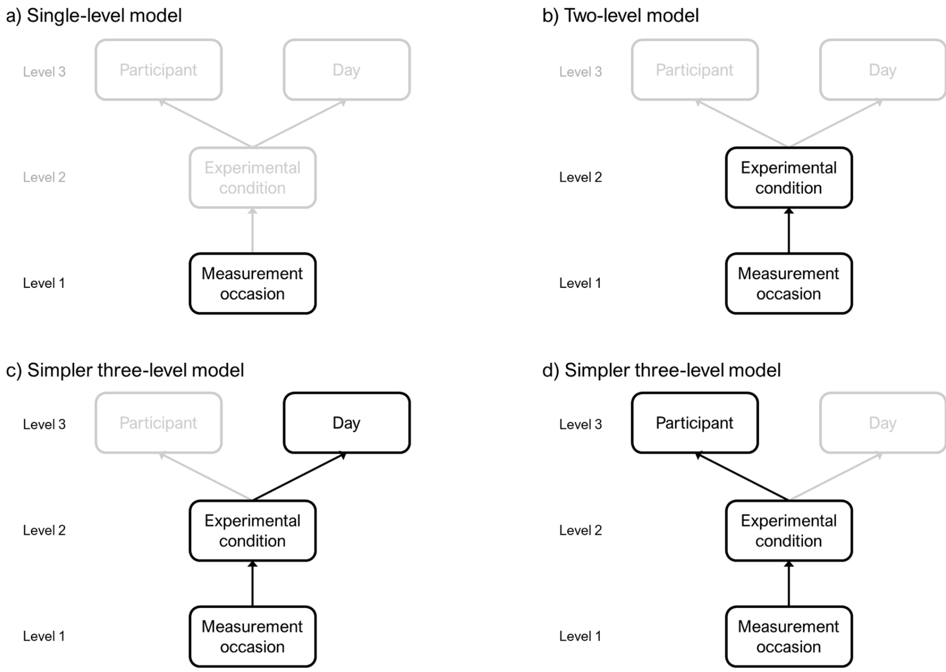

Fig. 4. Schematics of the (a) single-level model, (b) two-level model and (c and d) two simpler three-level models nested within the three-level cross-classified model.

Table 4
Preliminary check.

Modelling strategy	Model comparison	LR test statistic
Ordinal model		
	Testing for multilevel model (see Fig. 4(a))	$\chi^2(3) = 534.4, p < 0.001$
	Testing for participants and days (see Fig. 4(b))	$\chi^2(2) = 59.271, p < 0.001$
	Testing for participants (see Fig. 4(c))	$\chi^2(1) = 12.854, p < 0.001$
	Testing for days (see Fig. 4(d))	$\chi^2(1) = 55.981, p < 0.001$
Beta model		
	Testing for multilevel model (see Fig. 4(a))	$\chi^2(3) = 675.77, p < 0.001$
	Testing for participants and days (see Fig. 4(b))	$\chi^2(2) = 49.328, p < 0.001$
	Testing for participants (see Fig. 4(c))	$\chi^2(1) = 10.946, p < 0.001$
	Testing for days (see Fig. 4(d))	$\chi^2(1) = 46.525, p < 0.001$

are given in units of logits. Four significant predictors were identified – thermal resistance of clothing, Body Mass Index, time of day and operative temperature – all negatively associated with Logit(μ) (the intercept was not considered).

Fig. 7 shows the predicted responses as functions of the operative temperature using the cluster-specific and population-averaged procedures. The predicted response μ is the inverse of the link function, which in this study corresponds to the inverse of the logit:

$$\mu = \mathrm{Logit}^{-1}(\eta) = \mathrm{Logistic}(\eta) = \frac{1}{1+e^{-\eta}} = \frac{1}{1+e^{-(X\beta+Zu)}} \tag{5}$$

More details about the mathematical formulation can be found in the

Table 5
Regression coefficients for the predictors in the ordinal model (after applying automated backward elimination).

Fixed Effects		coeff	se (coeff)	z	p value
Threshold 1, τ_1		−6.325	0.383	−16.519	—
Threshold 2, τ_2		−4.245	0.345	−12.307	—
Threshold 3, τ_3		2.065	0.306	6.761	—
Threshold 4, τ_4		4.070	0.327	12.441	—
Clothing_c		−3.483	1.375	−2.532	0.011*
BMI_c		−0.218	0.093	−2.338	0.019*
Air.vel		−12.584	5.503	−2.287	0.022*
Time.day	morning	reference			
	afternoon	−0.474	0.238	−1.988	0.047*
Top_c		−1.519	0.077	−19.719	< 0.001*
Random effects		sd	var		
Ramp_ID	(Intercept)	1.585	2.512		
Day_ID	(Intercept)	1.008	1.017		
Participant_ID	(Intercept)	1.158	1.340		

Number of groups: *Ramp_ID* = 314, *Day_ID* = 68, *Participant_ID* = 38
* indicates a significant term.

Appendix A.

All the lines in Fig. 7 are plotted as a function of the operative temperature while the other covariates (i.e., the fixed effects) are held constant at their centred values. However, these lines differ in the random effects, specifically:

- The solid black line (cluster-specific procedure) has the random effect fixed at zero;
- The dashed black lines (cluster-specific procedure) have the random effect fixed at the 16th and 84th percentiles (which correspond roughly to ± 1 standard deviation above and below the mean);
- The solid red line (population-averaged procedure) has the random effect derived from simulation (see Section 2.2.3).

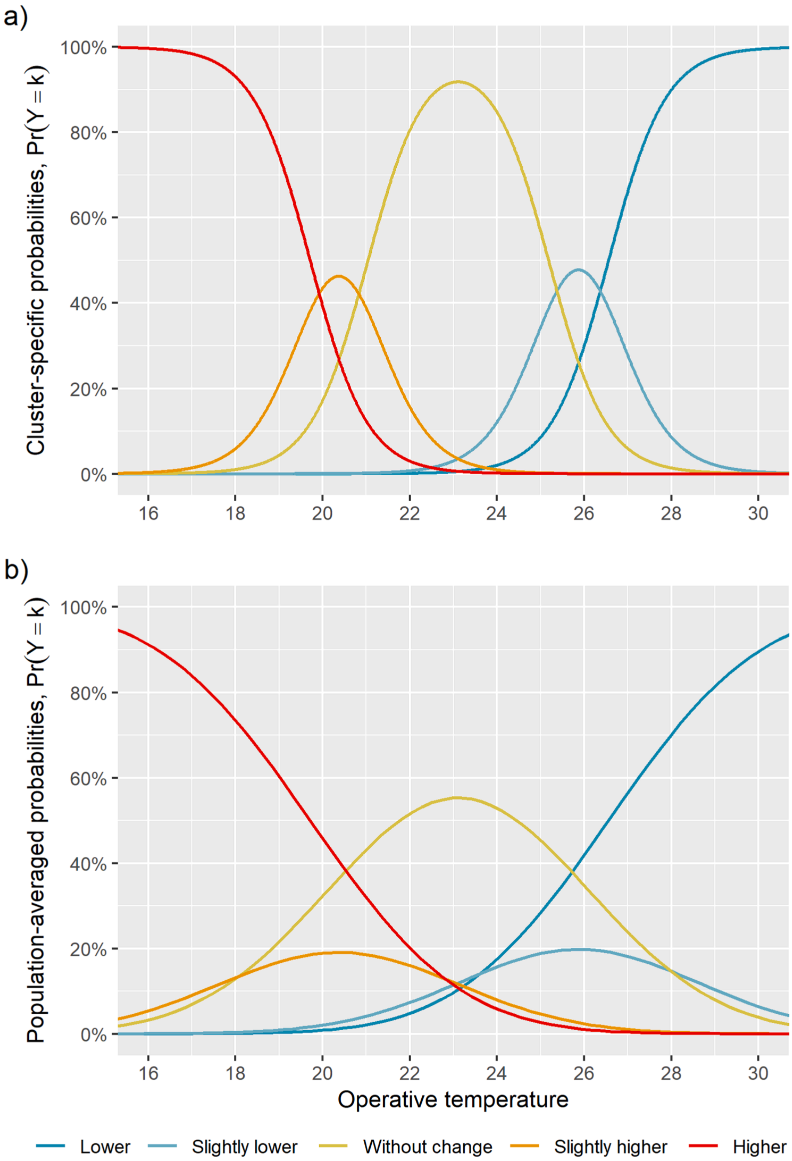

Fig. 5. Predicted probabilities of a thermal preference vote using the (a) cluster-specific and (b) population-averaged procedures.

The points in Fig. 7 are the observed thermal preference votes. While the predicted central tendency follows the general trend of the data, the predictions do not agree well with the observations, particularly close to the upper (i.e., prefer 'higher') and lower (i.e., prefer 'lower') boundaries.

Fig. 8(a) shows the pdfs generated from the beta model's estimated parameters (i.e., μ and ϕ) using the cluster-specific procedure. Each pdf is plotted as a function of three different operative temperatures while the other covariates are held constant at their centred values and the random effects are fixed at zero. It can be observed that the dispersion of the probability densities is relatively high. For instance, for an operative temperature of 26 °C, the probability of voting equal or lower 0.50 (i.e., from 'lower' to 'without change' on the continuous scale) is about 93 %, implying a 7 % probability of voting higher than that. Fig. 8(b) shows the categorised probabilities of the predicted thermal preference votes. Fig. 9 presents the pdfs generated from the beta model with the population-averaged procedure. Here, as in Fig. 8, each pdf is plotted as a function of three different operative temperatures while the other covariates are held constant at their centred values, but the random effects are the results of simulations (see Section 2.2.3).

4. Discussion

Different approaches can be found in the literature for OCC for building (e.g., [42–44]). Futhrtmore, diverse modelling strategies have been developed to predict occupant' thermal preferences, many of

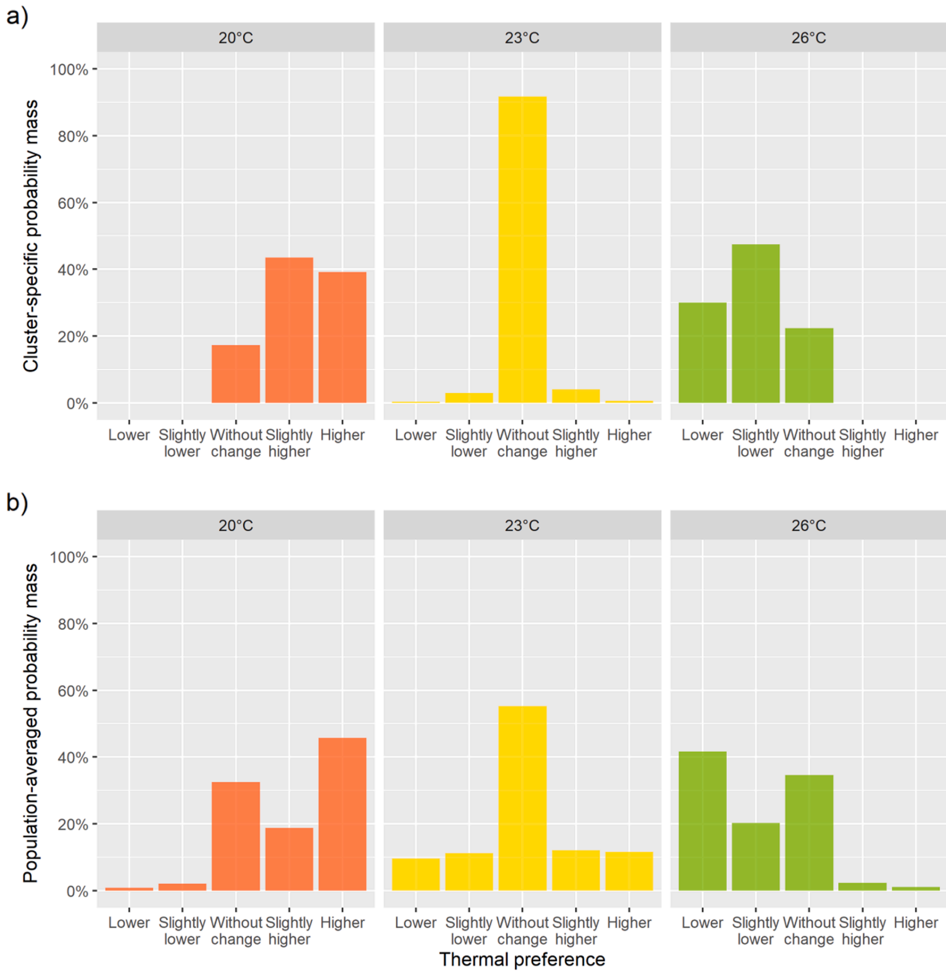

Fig. 6. Predicted probabilities of a thermal preference vote using the (a) cluster-specific and (b) population-averaged procedures for three different operative temperatures.

Table 6
Regression coefficients for the predictors in the beta model (after applying automated backward elimination).

Fixed Effects		coeff	se (coeff)	z	*p* value
(Intercept)		0.301	0.091	3.319	< 0.001*
Clothing_c		−1.291	0.456	−2.829	0.005*
BMI_c		−0.077	0.029	−2.634	0.008*
Time.day	morning	Reference			
	afternoon	−0.177	0.083	−2.136	0.033*
Vap.pre_c		−0.627	0.340	−1.845	0.065
Top_c		−0.413	0.018	−23.121	<0.001*
Random effects		sd	var		
Ramp_ID	(Intercept)	0.565	0.320		
Day_ID	(Intercept)	0.311	0.096		
Participant_ID	(Intercept)	0.343	0.177		

Number of groups: *Ramp_ID* = 314, *Day_ID* = 68, *Participant_ID* = 38
Dispersion parameter: 6.38
* indicates a significant term.

which can be found in the review of Park et al. [20], Jung and Jazizadeh [21] and Ngarambe et al. [45]. Among them a large portion are machine learning/data-driven algorithms. Even though there is sometimes overlap in goals and algorithms, statistical modelling and machine learning are based on two different concepts. The basic goal of stochastic modelling is to understand which probabilistic model could have generated the data observed. The usual procedure can be synthesised in the following steps: (i) choose a potential model from a plausible model family, (ii) fit the model to the data (i.e., estimate its parameters), and (iii) contrast the fitted model with other models. After selecting a model, this is used to conduct investigations, such as hypothesis testing and predicting new values. The estimated model becomes the lens used to interpret the data. Usually, a model that reasonably approximates the underlying stochastic process that has generated the data predicts well. On the contrary, machine learning is a data-driven application that is inspired by pattern recognition and focuses on regression, classification, and clustering techniques. The underlying stochastic process is frequently of secondary importance. Of course, stochastic models and procedures may be used to frame many machine learning approaches. However, the data are not regarded as having been created by that model. Instead, the main objective is figuring out which method or

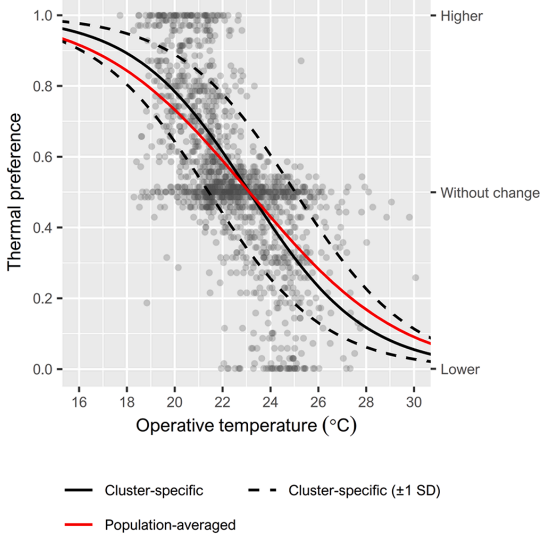

Fig. 7. Predicted responses using the cluster-specific (black line) and population-averaged (red line) procedures. Note. The points are the observed thermal preference votes.

approach performs the specific task. Although these techniques appear to have the potential to improve prediction ability at the level of a single building occupant, their inherent character as 'black box' models renders them fundamentally unfit to explain their outputs. Interpretability is one of the primary problems with machine learning and can be an issue in a specific setting. For instance, understanding why a model reached a particular conclusion is fundamental in a building design setting. In this study, the statistical modelling strategies applied are a transparent tool and, as such, can be easily used in contexts where interpretability is required. Moreover, while the data used to develop the model in this study derives from a laboratory experiment with a mechanically conditioned environment, the modelling strategies are independent of this aspect. As such, they could also be applied to a naturally conditioned space.

In the literature, examples of statistical modelling can be found in the study of Daum et al. [46]. The authors create personalised thermal comfort profiles using multinomial logistic regression, a regression technique used to analyse a dependent variable measured on a categorical scale. The main difference with ordinal regression is that the categorical data are assumed to have no intrinsic ordering. Not taking an inherent order of the dependent variable makes the model more flexible than ordinal regression. However, it is essential to mention that this flexibility comes at a price. The number of parameters to estimate will drastically increase because $k-1$ different linear predictor term (η_k) are needed for the k category of the dependent variable (only $k-1$ because one category of the dependet variable is used as reference). In our study, since the dependent variable has five categories, this would have led to having, for example, four parameters for the operative temperature to estimate instead of only one. More parameters to estimate would require a larger sample size. The other difference compared with the study of Daum et al. [46] is that the diversity between subjects is directly accounted for in the model through the random effects term. Doing so makes it possible to model and predict the thermal preference of a specific (using the cluster-specific procedure) and a 'general' occupant (using the population-averaged procedure). In addition, the beta model allows doing the same when the thermal preference votes are measured on a continuous, but bounded, scale.

In the next sections, the results previously illustrated are examined and interpreted. To begin with, the variables selected by the beta and ordinal model are contrasted and discussed. Subsequently, the beta and ordinal models are compared based on their predictive capabilities and the cluster-specific and population-averaged approaches are analysed. Finally, the limitations of the study are provided.

4.1. Variables selection

As explain in Section 1.1, the focus of the study is prediction and not inference; therefore, the specific value of the models' coefficients is not of interest. However, it is useful to compare variables selection across the models and contrast the relative importance of these variables. Table 5 and Table 6 show that automated backward elimination selected different sets of predictors for the two models. Four out of five predictors are shared by the two models (*Clothing_c*, *BMI_c*, *Time.day* and *Top_c*), while the fifth variables differ. For the ordinal model, automated backward elimination selected *Air.vel,* whereas for the beta model, *Vap.pre_c* was selected. In any attempt to understand the relative importance of the parameters estimated for the models, a direct comparison between their absolute values would be meaningless because the variables are measured using different units. Furthermore, several units could be used to measure the same variable. For example, if the operative temperature had been measured in degrees Fahrenheit instead of degrees Celsius, its estimated regression coefficient would have been different. However, the importance of the variable would not have changed. The relative importance of the predictors could be obtained via standardisation (i.e., subtracting the mean from each observed variable and dividing by its standard deviation) before conducting the statistical analysis. The resulting parameters estimated by the model are on the same scale and can be directly compared. The results of this procedure are show in Table 7. Here, even though the two models have different predictors, the order of relative importance of the common predictors is the same. The variables that differ between the two models are of minor relative importance. However, this importance is purely statistical. To determine the practical importance of the variables, subject-area expertise is required. Note that p values cannot be used directly to assess the importance of the predictors. A predictor can have a small p value when it has a very precise estimate, low variability, or a large sample size. As a result, even effect sizes that are small in practice might have extremely low p values. Understanding the practical importance of the predictors is beyond the scope of this study and is not pursued further. However, for inferential purposes, it is of the utmost importance.

As mentioned in Section 2.3, the Akaike information criterion (AIC) was used for variable selection. This metric is based on the maximised log-likelihood value with a penalty for including more parameters; it is a trade-off between goodness of fit (assessed by the likelihood function) and parsimony (the smaller the number of parameters, the lower the penalty). However, the AIC tends to over-parameterised, thus selecting models with a higher number of predictors, which could explain why the first four relatively important predictors were common to the two models, while their least relatively important predictors differed.

4.2. Models' comparison

The Akaike information criterion is generally used to compare different possible models and determine which one best fits the data. However, it cannot be used to compare models with different likelihood functions.[5] For example, for a discrete distribution (e.g., ordinal response), the likelihood refers to the joint probability mass of the data, whereas for a continuous distribution (e.g., continuous response), the likelihood refers to the joint probability density of the data. Therefore, models based on continuous and ordinal responses cannot be compared directly. For this reason, the two models are compered graphically in

[5] This is generally true for all probability-based statistics.

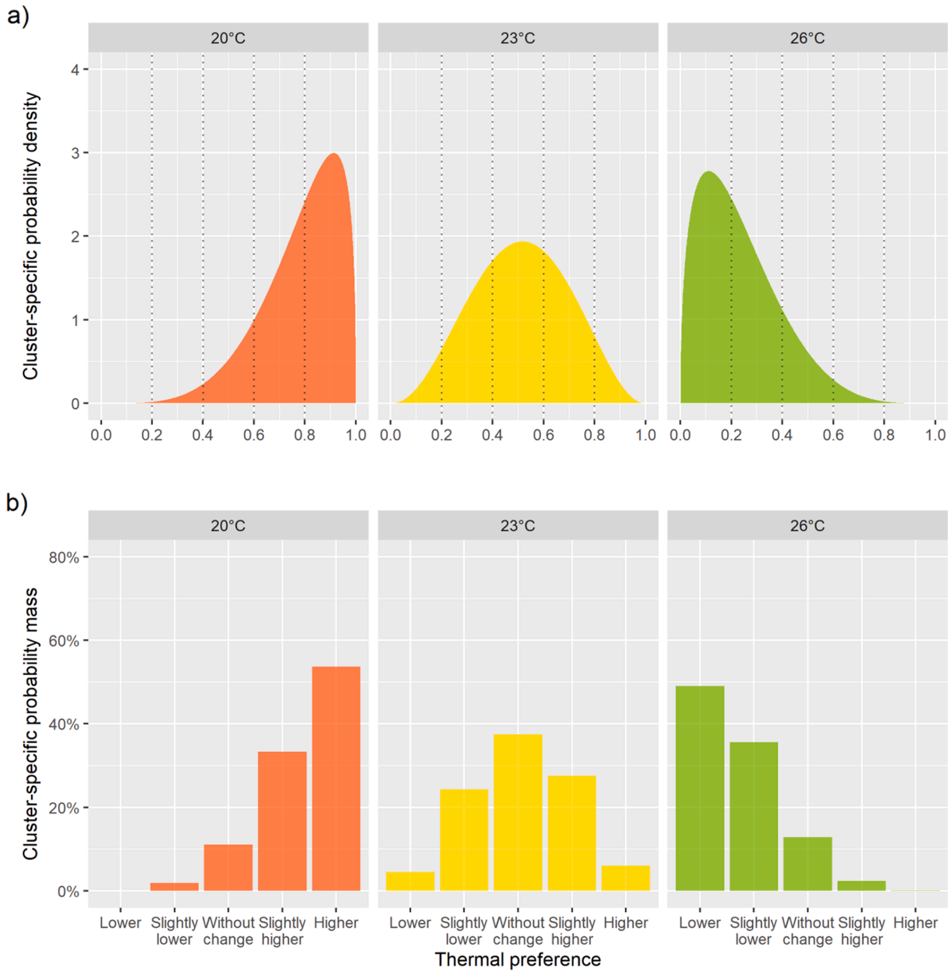

Fig. 8. (a) Probability densities and (b) categorised probabilities of the predicted response using the cluster-specific procedure for three different operative temperatures. Note. The dotted lines in (a) represent the thresholds used for categorisation.

terms of predicted probabilities (see Fig. 6, Fig. 8 and Fig. 9). However, it is important to point out that this method poses a limitation: a different categorisation of the beta distribution would lead to different probabilities. The same applies for the categorisation of the thermal preference vote used to estimate the ordinal model (see Fig. 3). Nevertheless, by comparing the probabilities estimated by the two models, the following general observations can be made. On the one hand, the ordinal model is more flexible in the sense that it can handle different probability distributions (virtually any probability distribution). For example, in Fig. 6, it can handle the spike in the probabilities for the 'without change' category for an operative temperature of 23 °C. On the other hand, the beta model is more detailed since it provides a pdf. For example, in Fig. 8(a), the predicted probability of observing a thermal preference vote between 0.45 and 0.55 for an operative temperature of 23 °C is 19.2 %. An alternative approach to comparing the two models would be to calculate the mean of the estimated probabilities for the ordinal model and contrast it with the predicted mean response of the beta model. The mean of the probabilities can be written as:

$$\text{Mean Pr} = \sum_{1}^{K} \pi_k k \tag{6}$$

where π_k is the probability of a specific category k, $k \in \{1, \ldots, K\}$. Here, the category prefer 'lower' was mapped to 1 and the category prefer 'higher' was mapped to 5. The resulting mean probabilities were then rescaled between + 0.001 and + 0.999 to match the predicted mean response of the beta model. Fig. 10 shows this comparison. For the ordinal model, the cumulative probability γ_k is the inverse of the link function, which in this study corresponds to the inverse of the logit:

$$\gamma_k = \text{Logit}^{-1}(\mathbf{1}\tau_k - \boldsymbol{\eta}) = \text{Logistic}(\mathbf{1}\tau_k - \boldsymbol{\eta}) = \frac{1}{1 + e^{-(\mathbf{1}\tau_k - \boldsymbol{\eta})}} = \frac{1}{1 + e^{-(\mathbf{1}\tau_k - X\boldsymbol{\beta} - Z\boldsymbol{u})}} \tag{7}$$

The probability of a specific category k is calculated as $\pi_k = \gamma_k - \gamma_{k-1}$. The probabilities of all the categories are then used to calculate the mean as in Eq. (6). More details about the mathematical formulation can be found in the Appendix A.

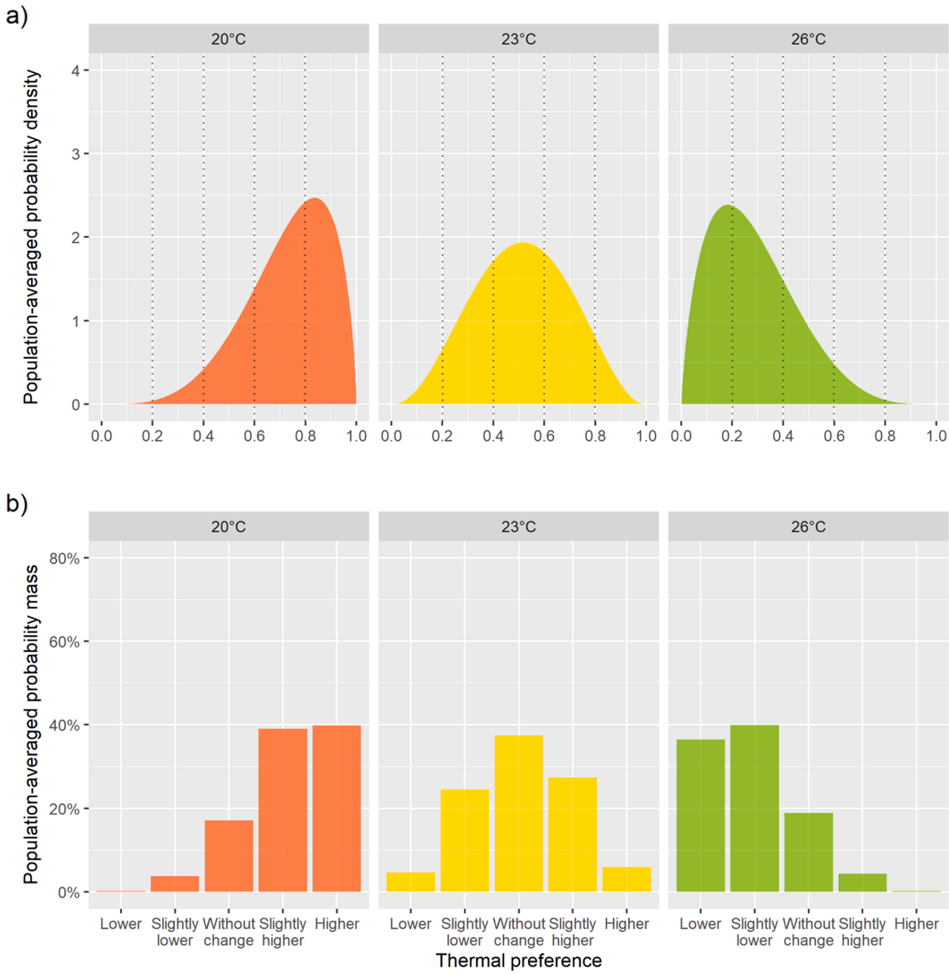

Fig. 9. (a) Probability densities and (b) categorised probabilities of the predicted response using the population-averaged procedure for three different operative temperatures. Note. The dotted lines in (a) represent the thresholds used for the categorisation.

Table 7
Predictors' relative importance for both the beta and ordinal models.

Modelling strategy	Predictor		Standardise coeff	Rank*
Ordinal model	*Clothing*		−0.464	4
	BMI		−0.567	2
	Air.vel		−0.163	5
	Time.day	morning	Reference	
		afternoon	−0.474	3
	Top		−2.917	1
Beta model	*Clothing*		−0.172	4
	BMI		−0.199	2
	Time.day	morning	Reference	
		afternoon	−0.177	3
	Vap.pre		−0.102	5
	Top		−0.793	1

* the higher the absolute value of the standardise coefficient, the higher the rank.

As in Fig. 7, all the lines in Fig. 10 are plotted as a function of the operative temperature while the other covariates (i.e., the fixed effects) are held constant at their centred values, but they differ in the random effects. Specifically:

- The solid black line (beta model, cluster-specific procedure) has the random effect fixed at zero (as in Fig. 7);
- The solid red line (beta model, population-averaged procedure) has the random effect derived from simulation (as in Fig. 7);
- The dashed black line (ordinal model, cluster-specific procedure) has the random effect fixed at zero;
- The dashed red line (ordinal model, population-averaged procedure) has the random effect derived from simulation.

It can be seen that the curve produced by using the cluster-specific procedure for the ordinal model has three inflexion points. This particular behaviour can be explained by looking at the predicted probabilities in Fig. 5(a). Between the operative temperatures of 22–24 °C, the predicted probabilities for 'without change' were much greater than all the others (from 80 % up to more than 90 %). Consequently, within this range, the calculated mean was greatly affected by these probabilities. The same behaviour can be observed for the population-averaged curve

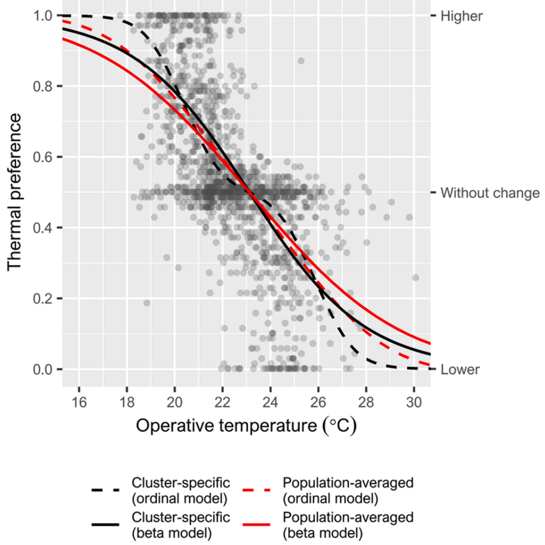

Fig. 10. Predicted responses using the cluster-specific (black solid and dashed lines) and population-averaged (red solid and dashed lines) procedures for the beta and ordinal models, respectively. Note. The points are the observed thermal preference votes.

to a lesser extent. However, more considerable differences are visible at the tails of the curves, that is, the two extremities. Here, the beta model's mean response curve has tails that are heavier than the mean of the estimated probabilities for the ordinal model. Despite these differences, both the beta and ordinal models are both valid strategies for modelling thermal preference votes. However, the choice between the two models should be made based on how the response variable is measured. The beta model is a suitable choice when the thermal preference votes are measured on a continuous, but bounded, scale. In contrast, the ordinal model is appropriate when a categorical scale is used. Unfortunately, in the thermal comfort field, it is common practice to analyse subjective human thermal responses independently of how they were measured [47].

Furthermore, both models identified the largest random-effect component at the 'experimental condition' level, indicating that differences in conditions were the primary source of variability (see Table 5 and Table 6). Therefore, the variability in how individuals react to different dynamic conditions is higher than the variability between individuals, which may indicate that there could be unmodeled information in the variance at this level (i.e., the 'experimental condition'). For instance, the different rates of temperature change could play a role both in terms of absolute magnitude (i.e., the specific value of the rate of change) and sign (i.e., heating or cooling). To this aim, modelling strategies that model the effect of temporal patterns directly should be used (e.g., time series). Furthermore, if the variability of the environmental condition were significantly reduced (i.e., a static environment created), the inter-individual differences (i.e., difference between individuals) would be dominant.

4.3. Approaches' comparison

The predicted thermal preference votes were calculated from the two models using two different approaches: fixing the random effects at their mean of zero (cluster-specific procedure) and using a simulation approach with $M = 1{\cdot}10^4$ (population-averaged procedure). Regarding the ordinal model, from Fig. 6 it can be seen that the most evident difference between the cluster-specific and the population-averaged procedures are the predicted probabilities for an operative temperature of 23 °C. Here, the predictive probability for 'without change' is about 91 % for the cluster-specific approach, while it is only 55 % for the population-averaged one. The reason for the discrepancy lies in the fact that the level 2 variance ($\hat{\sigma}^2_{\text{ramp\_ID}} = 2.512$) and the level 3 variances ($\hat{\sigma}^2_{\text{day\_ID}} = 1.017$ and $\hat{\sigma}^2_{\text{participant\_ID}} = 1.340$) are not close to zero. As the between-cluster variances $\hat{\sigma}^2_{\text{ramp\_ID}}$, $\hat{\sigma}^2_{\text{day\_ID}}$ and $\hat{\sigma}^2_{\text{participant\_ID}}$ in the random-intercepts model increase, the curves will be further apart. For an example the reader is referred to Appendix C. The advantage of having predictive probabilities as outcomes is that they are their own error measures. In Fig. 6, the predicted probability of 'without change' for the cluster-specific approach is 91 %; if one decided not to choose this category as the expected outcome, the probability of this being an error is, by definition, 91 %. Following the same reasoning, for the population-averaged approach, not selecting 'without change' as the expected outcome has a 55 % probability of being an error. As a standard practice, the ordinal model regards the category with the highest probability as the predicted outcome (i.e., thermal preference vote). However, utilising a hard threshold, such as the automatic selection of the category with the higher probability, does not fully use the information contained in the probabilities. For example, in Fig. 5(b), such a threshold would lead to 'slightly lower' and 'slightly higher' never being selected. Here the necessity of defining a utility/cost function that, for example, maximises the expected utility or minimises the expected cost. With regard to the beta model, from Fig. 8 and Fig. 9 it can be seen that, for both the cluster-specific and population-averaged procedures, the distributions of the probability densities (and analogously, the categorised probabilities) for an operative temperature equal to 23 °C are the same. The predicted mean response of the beta model intersects the thermal preference vote at 0.5, at which the prediction at $u_{\text{ramp\_ID}} = u_{\text{day\_ID}} = u_{\text{participant\_ID}} = 0$ (the median) equals the mean prediction (see Fig. 7). The median (i.e., cluster-specific) curve is lower than the population-averaged curve for a predicted thermal preference vote lower than 0.5 but is higher for a predicted thermal preference vote higher than 0.5. Consequently, the cluster-specific probability densities (i.e., the median probabilities) become skewed faster than the population-averaged ones (i.e., the mean probabilities) at operative temperatures higher or lower than 23 °C (see Fig. 8 and Fig. 9 for the operative temperatures of 20 °C and 26 °C).

4.4. Limitations

This study's limitations arise from some simplifications introduced during the statistical modelling. For both models, the functional form was assumed to be linear for simplicity (see Eq. (3)). As a consequence, the models do not account for potential nonlinearities. However, nonlinearities could be considered, for example, by using smoothing splines. Another simplification derives from assuming that all the independent variables were measured exactly, that is, 'error-free'. When covariates are measured with errors, the parameter estimates do not tend to the true values, even in extensive samples. For simple linear regression, this effect is known as the attenuation bias and leads to an underestimation of the coefficient. For more complex methods, such as multilevel models, this issue deserves a proper treatise and is beyond the scope of this study.

For a beta model, the conditional variance is $var(Y_i|\boldsymbol{U} = \boldsymbol{u}) = \mu_i(1-\mu_i)/(1+\phi)$, where μ_i is the mean and ϕ is the precision parameter. The parameter ϕ is known as the precision parameter because for fixed μ_i, the larger the ϕ, the smaller the variance of Y_i. Therefore, the variance is not constant but rather a function of the mean and the precision parameter, here assumed to be constant. However, the precision parameter can be modelled as a function of some predictors, for example, the operative temperature. In this study, this possibility was not explored and should examined in future studies.

To apply an ordinal model, the dependent variable must be categorical. For this reason, the dependent variable was binned into five categories according to the thresholds -0.6, -0.2, $+0.2$, and $+0.6$. However, these cut-off points were arbitrary and indirectly assumed to be the same for all participants. When a categorical scale is used to measure the dependent variable, this choice is made directly by single responders. Consequently, it is unlikely to be the same for all responders (see, for example, [48]). While this study used categorisation to apply the ordinal model, we do not encourage this practice in 'normal' circumstances. It is more appropriate to measure the variable directly with a categorical scale. As stated earlier, cut-off points are arbitrary and generally do not have practical/scientific meaning. Furthermore, the ordinal model has an additional assumption called 'proportional odds' (or equal slope assumptions). This assumption implies that the threshold parameters τ_k are independent of the regression variables or, equivalently, that the regression parameters are not allowed to vary with k, a specific category of Y. This restriction derives from the fact that the thresholds are theoretically linked with the response measure (and therefore assumed to be part of the measurement procedure), not to the predictor's value. However, the *ordinal* package [36], does not yet implement this feature when there is more than one random effect. Therefore, testing for partial and non-proportional odds (called 'nominal effects' in [36]) was not possible.

Moreover, multilevel models offer additional modelling possibilities that this paper has not discussed. For instance, in both the models used in this study, the slope coefficients of the predictors added to the models were assumed to be fixed across higher-level units. However, it is possible that the relationships between the responses and the predictors vary across these higher classification units (e.g., between participants). In multilevel models, it is possible to allow the effects of the predictors to vary randomly across higher classification units by adding a random slope to the model, which can be translated into checking whether, for example, the effect of the temperature differs across different occupants and to what degree of magnitude.

5. Conclusions and future perspectives

This study aimed to predict the thermal preference votes of human subjects exposed to a dynamic thermal environment. To this aim, two different statistical models were proposed, namely the beta and ordinal models. Based on the analyses carried out, the following points can be made concerning the two models:

- A three-level cross-classified model fit the data significantly better than the simpler three-levels models, the two-level model and the single-level model nested within it. Nevertheless, it is important to note that the multilevel structure described here is not a characteristic of the model. It is a feature of the experimental/study design represented by the data and encapsulated in the model. Therefore, it is essential to know how, where and when the data were collected (i.e., the metadata) to model them appropriately.
- In predictive modelling, direct interpretability regarding the model is not required; however, transparency is desirable. Multilevel models can model complex structures and at the same time, offer the advantage of having transparent outputs and modelling steps in contrast to machine learning/data-driven algorithms, which are basically 'black box' models.
- While likelihood-based statistics (e.g., Akaike information criterion, Bayesian information criterion) cannot be used to contrast the two models' performances directly, some qualitative observations can be made by comparing the probabilities estimated by the two models. On the one hand, the ordinal model is more flexible in the sense that it can handle different probability distributions (virtually any probability distribution). On the other hand, the beta model is more detailed because it provides a pdf. The two models used in this study are both valid strategies for modelling thermal preference votes. However, the choice between the ordinal and the beta models should be made based on how the response variable is measured.

Furthermore, two distinct procedures were used in this study, namely the cluster-specific and the population-averaged procedures, to predict the thermal preference votes. These two methods apply directly to the concept of occupant-centric building design and operation. The population-averaged approach is suitable for the occupant-centric building design phase, where the target is the 'general' occupant. On the other hand, during the building operation phase, the notion of a 'general' occupant is pointless, and the focus should be on satisfying the needs of the specific occupant. In this case, a cluster-specific procedure is appropriate. This procedure can be carried out by measuring the specific occupant response to the environment and consequently updating the probabilities of the population-averaged procedure. These procedures could be used to design more energy-efficient and satisfying control strategies according to occupants' feedback(e.g., Ref [49]) in an occupant-centric [20] or human-in-the-loop [21] approach.

CRediT authorship contribution statement

Matteo Favero: Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Jan Kloppenborg Møller:** Conceptualization, Formal analysis, Methodology, Validation, Writing – review & editing. **Davide Calì:** Conceptualization, Methodology, Writing – review & editing. **Salvatore Carlucci:** Conceptualization, Funding acquisition, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Mathematical background and examples

In this study-two modelling strategies are used, specifically the beta mixed-effects model with the logit link (simply referred as beta model) and the ordinal mixed-effects model with the logit link (simply referred as ordinal model). Both these models belong to a broad class of models called generalized linear mixed models.

There are four components that are common to any generalised linear mixed models:

- Random component (of the response variable): Specifies the probability distribution of the response variable, such as the normal distribution for $\boldsymbol{Y}$ (i.e., $\boldsymbol{Y} \sim \mathrm{Normal}(\boldsymbol{\mu}, \sigma^2)$) in the (classical) linear regression model. In general, there is no separate error term. Classical linear regression is a special case in which the error term can be extract from the distributional assumption (i.e., $\boldsymbol{Y} = \boldsymbol{\mu} + \boldsymbol{\varepsilon}$, where $\boldsymbol{\mu} = \boldsymbol{X\beta}$ and $\boldsymbol{\varepsilon} \sim \mathrm{Normal}(\boldsymbol{0}, \sigma^2)$);
- Link function: Specifies the link between the random and the systematic components. It denotes the relationship between the predicted response value (e.g., the mean) and the covariates;
- Systematic component: Specifies the covariates in the model, more specifically, how they are combined (usually through a linear combination);
- Random component (of the random effect): Specifies the probability distribution of the random effects, usually assuming a normal distribution with zero mean (i.e., $\boldsymbol{u} \sim \mathrm{Normal}(\boldsymbol{0}, \boldsymbol{\Sigma})$).

Below, for both beta and ordinal model, the mathematical formulation and examples are provided.

Beta model

The beta model, as specified in Eq. (1), is:

$$\begin{aligned} &\boldsymbol{Y} \sim \mathrm{Beta}(\boldsymbol{\mu}, \phi) \\ &\mathrm{Logit}(\boldsymbol{\mu}) = \boldsymbol{\eta} \\ &\boldsymbol{\eta} = \boldsymbol{X\beta} + \boldsymbol{Zu} \\ &\boldsymbol{u} \sim \mathrm{Normal}(\boldsymbol{0}, \boldsymbol{\Sigma}) \end{aligned} \tag{A1}$$

where the conditional distribution of the response variable $\boldsymbol{Y}$ is assumed to follow a beta distribution. Here, its expected value (i.e., its mean $\boldsymbol{\mu}$) is linked to linear predictor $\boldsymbol{\eta}$ through a logit function. The logit function is defined as the inverse of the cumulative distribution function (cdf) of the standard[6] logistic distribution:

$$\mathrm{Logit}^{-1}(\boldsymbol{\eta}) = \mathrm{Logistic}(\boldsymbol{\eta}) = \frac{1}{1 + e^{-\boldsymbol{\eta}}} \tag{A2}$$

Eq. (A1) is expressed in matrix notation. For a specific case it can be written as:

$$\begin{aligned} &Y_{pdri} \sim \mathrm{Beta}\left(\mu_{pdri}, \phi\right) \\ &\mathrm{Logit}\left(\mu_{pdri}\right) = \eta_{pdri} \\ &\eta_{pdri} = \mathbf{x}_{pdri}^{\mathrm{T}}\boldsymbol{\beta} + u_p + u_d + u_r \\ &u_p \sim \mathrm{Normal}\left(0, \sigma_p^2\right); \;\; \mathrm{iid} \\ &u_d \sim \mathrm{Normal}\left(0, \sigma_d^2\right); \;\; \mathrm{iid} \\ &u_r \sim \mathrm{Normal}\left(0, \sigma_r^2\right); \;\; \mathrm{iid} \end{aligned} \tag{A3}$$

where the subscript p indicates a participant, d a day, r a thermal ramp, and i is the i^{th} obsevation.

If for example, we consider:

- two participants (no. 1 and 2), where participant 1 visited the lab on days 1 and 2 while participant 2 visited the lab on days 2 and 3,
- each day has two ramps (named 1–6) and only two observation per ramp.

We obtain:

the 16×1 vector of the response variable

$$\boldsymbol{Y} = [Y_{1111}, Y_{1112}, Y_{1121}, Y_{1122}, Y_{1231}, Y_{1232}, Y_{1241}, Y_{1242}, Y_{2231}, Y_{2232}, Y_{2241}, Y_{2242}, Y_{2351}, Y_{2352}, Y_{2361}, Y_{2362},]^{\mathrm{T}}$$

the 11×1 vector of the random effects

$$\boldsymbol{u} = \left[u_{p(1)}, u_{p(2)}, u_{d(1)}, u_{d(2)}, u_{d(3)}, u_{r(1)}, u_{r(2)}, u_{r(3)}, u_{r(4)}, u_{r(5)}, u_{r(6)}\right]^{\mathrm{T}}$$

with variance–covariance matrix equal to

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_p^2 \boldsymbol{I}_2 & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{0} & \sigma_d^2 \boldsymbol{I}_3 & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{0} & \sigma_r^2 \boldsymbol{I}_6 \end{bmatrix} \text{ where } \boldsymbol{I}_n \text{ is the identity matrix of dimension } n$$

[6] The logistic distribution is defined by two parametes: a location parameter μ and a scale parameter s. When $\mu = 0$ and $s = 1$, the logistic distribution is called standard logistic distribution, that is: $\mathrm{Logistic}(x; \mu = 0, s = 1) = \frac{1}{1+e^{-(x-\mu)/s}} = \frac{1}{1+e^{-x}}$

the 16 × 11 design matrix of the random effects

$$Z = \begin{bmatrix} 1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Ordinal model

The ordinal model, as specified in Eq. (2), is:

$$\begin{aligned} & \boldsymbol{Y} \sim \text{Multinomial}(n, \boldsymbol{\pi}) \\ & \text{Logit}(\boldsymbol{\gamma}_k) = \mathbf{1}\tau_k - \boldsymbol{\eta} \\ & \boldsymbol{\eta} = \boldsymbol{X\beta} + \boldsymbol{Zu} \\ & \boldsymbol{u} \sim \text{Normal}(\mathbf{0}, \boldsymbol{\Sigma}) \end{aligned} \tag{A4}$$

where the conditional distribution of the response variable $\boldsymbol{Y}$ is assumed to follow a multinomial distribution with probability vector $\boldsymbol{\pi} = \{\pi_1, \dots, \pi_k\}$, where $\pi_k = \Pr(Y = k)$. The cumulative probability corresponding to π_k is $\gamma_k = \Pr(Y \leq k)$; hence, $\gamma_k = \pi_1 + \dots + \pi_k$. Here the cumulative probabilities are then mapped to the real numbers through a logit function. In the ordinal model, the logit is function of the linear predictor $\boldsymbol{\eta}$ and $\mathbf{1}\tau_k$, the vector of laten thresholds parameters τ_k, with $k \in \{1, \dots, K\}$. That is:

$$\boldsymbol{\gamma}_k = \text{Logit}^{-1}(\mathbf{1}\tau_k - \boldsymbol{\eta}) = \text{Logistic}(\mathbf{1}\tau_k - \boldsymbol{\eta}) = \frac{1}{1 + e^{-(\mathbf{1}\tau_k - \boldsymbol{\eta})}} \tag{A5}$$

Eq. (A4) is expressed in matrix notation. For a specific case it can be written as:

$$\begin{aligned} & \Pr\left(Y_{pdri} = k\right) = \pi_k \\ & \gamma_{pdri,k} = \Pr\left(Y_{pdri} \leq k\right) = \pi_1 + \dots + \pi_k \\ & \text{Logit}\left(\gamma_{pdri,k}\right) = \tau_k - \eta_{pdri} \\ & \eta_{pdri} = \mathbf{x}_{pdri}^{\mathrm{T}}\boldsymbol{\beta} + u_p + u_d + u_r \\ & u_p \sim \text{Normal}\left(0, \sigma_p^2\right); \text{ iid} \\ & u_d \sim \text{Normal}\left(0, \sigma_d^2\right); \text{ iid} \\ & u_r \sim \text{Normal}\left(0, \sigma_r^2\right); \text{ iid} \end{aligned} \tag{A6}$$

where the subscript p indicates a participant, d a day, r a thermal ramp, i is the i^{th} observation, and k is a category of the dependent variable.

If for example, we consider:

- two participants (no. 1 and 2), where participant 1 visited the lab on days 1 and 2 while participant 2 visited the lab on days 2 and 3,
- each day has two ramps (named 1–6) and only two observation per ramp.

We obtain, for a specific category k:

the 16 × 1 vector of the response variable

$$\boldsymbol{Y} = [Y_{1111}, Y_{1112}, Y_{1121}, Y_{1122}, Y_{1231}, Y_{1232}, Y_{1241}, Y_{1242}, Y_{2231}, Y_{2232}, Y_{2241}, Y_{2242}, Y_{2351}, Y_{2352}, Y_{2361}, Y_{2362},]^{\mathrm{T}}$$

the 11 × 1 vector of the random effects

$$\boldsymbol{u} = \left[u_{p(1)}, u_{p(2)}, u_{d(1)}, u_{d(2)}, u_{d(3)}, u_{r(1)}, u_{r(2)}, u_{r(3)}, u_{r(4)}, u_{r(5)}, u_{r(6)}\right]^{\mathrm{T}}$$

with variance–covariance matrix equal to

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_p^2 \boldsymbol{I}_2 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \sigma_d^2 \boldsymbol{I}_3 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \sigma_r^2 \boldsymbol{I}_6 \end{bmatrix} \text{ where } \boldsymbol{I}_n \text{ is the identity matrix of dimension } n$$

the 16 × 11 design matrix of the random effects

$$
\mathbf{Z} = \begin{bmatrix}
1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix}
$$

Appendix B. Frequency distributions for the independent variables

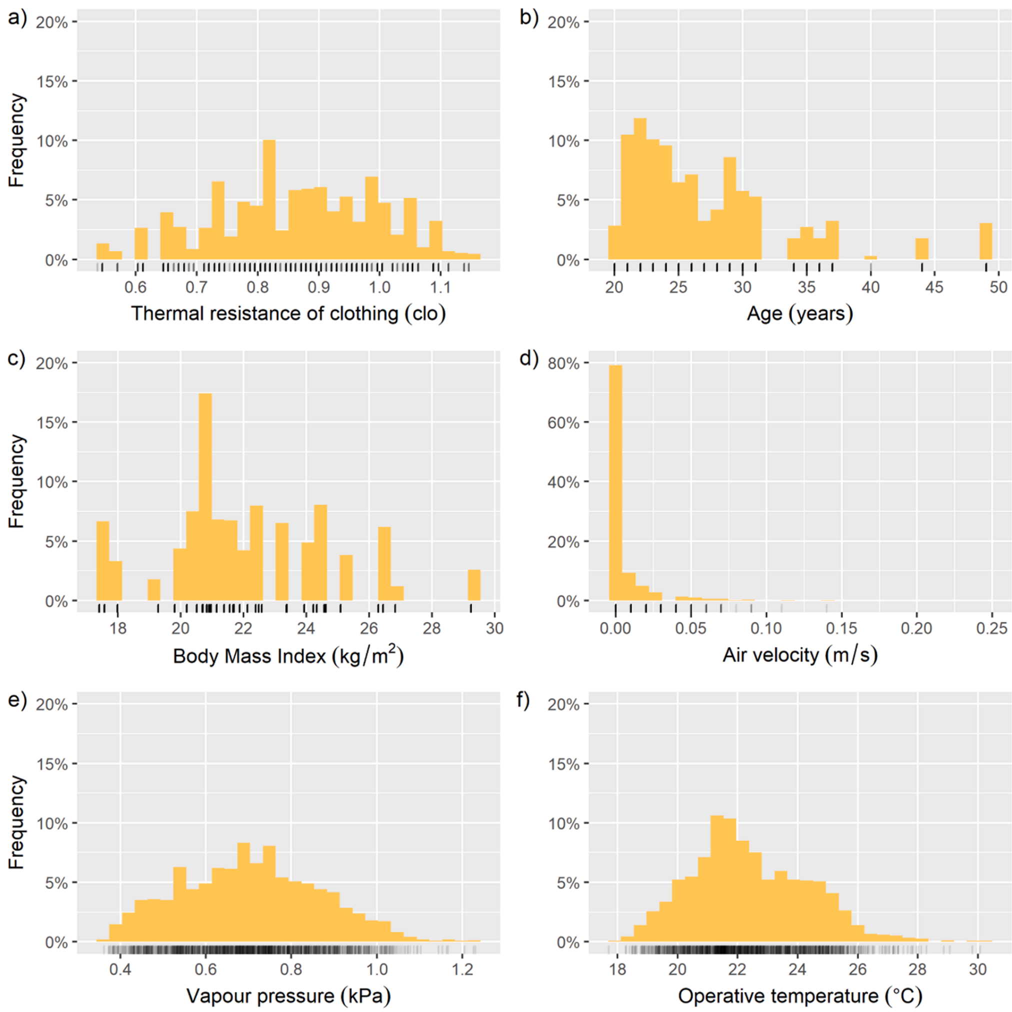

Fig. B1. Frequency distributions for the continuous variables: (a) thermal resistance of clothing, (b) age, (c) Body Mass Index, (d) air velocity, (e) vapour pressure and (f) operative temperature. Note. The vertical black marks at the bottom of each figure are the rug plots.

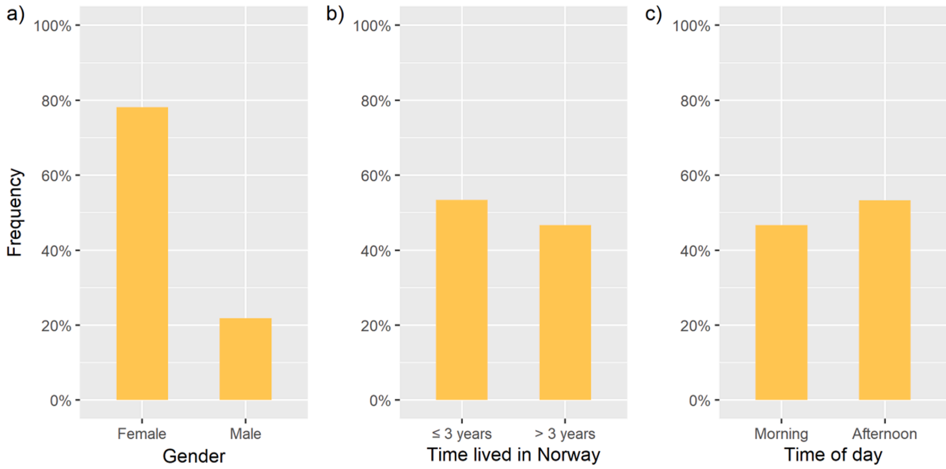

Fig. B2. Frequency distributions for the categorical variables: (a) gender, (b) time lived in Norway and (c) time of day.

Appendix C. Population-averaged and cluster-specific predictions

In Fig. 6, the differences between the predicted probabilities for the cluster-specific and the population-averaged procedures depend on the between-cluster variances. As the between-cluster variances $\hat{\sigma}^2_{\text{ramp\_ID}}$, $\hat{\sigma}^2_{\text{day\_ID}}$ and $\hat{\sigma}^2_{\text{participant\_ID}}$ in the random-intercepts model increase, the curves will be further apart. This situation can be observed in Fig. C1 for category $k \leq 3$ (i.e., from the 'lower' to 'without change' category).

The predicted cumulative response probabilities always intersect at $p = 50\%$, the point at which the prediction at $u_{\text{ramp\_ID}} = u_{\text{day\_ID}} = u_{\text{participant\_ID}} = 0$ (the median) equals the mean prediction. The median (i.e., cluster-specific) curve is lower than the population-averaged curve for predicted probabilities lower than 50 %, while the median curve is higher for probabilities greater than 50 %. As a result, for a given range of *Top* values, the cluster-specific predicted probabilities will be greater than the population-averaged ones. In this case, for the category $k = 3$ (i.e., 'without change'), for *Top* values between 20.8 °C and 25.4 °C, the cluster-specific predicted probabilities are higher than the population-averaged ones (see Fig. C2). The dashed black lines in both Fig. C1 and Fig. C2 are cluster-specific effects, where the random effects $u_{\text{ramp\_ID}}$, $u_{\text{day\_ID}}$ and $u_{\text{participant\_ID}}$ were set to their 16th and 84th percentiles (i.e., $u_{\text{ramp\_ID}} = \{-1.11, 1.19\}$, $u_{\text{day\_ID}} = \{-0.56, 0.69\}$ and $u_{\text{participant\_ID}} = \{-1.05, 0.93\}$) and then added (i.e., $\{-2.71, 2.80\}$). The 16th and 84th percentiles were chosen because they correspond roughly to $\pm$ 1 standard deviation above and below the mean and encompass about 68 % of the observed random effects for *Ramp_ID*, *Day_ID* and *Participant_ID*.

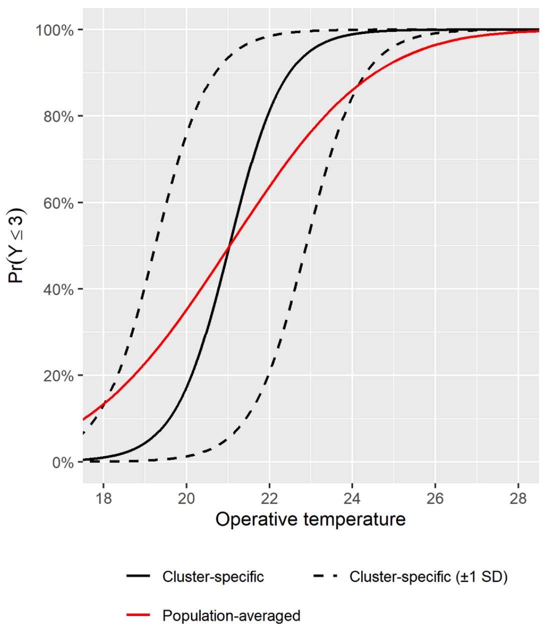

Fig. C1. Predicted cumulative response probabilities for category $k \leq 3$ (i.e., from the 'lower' to 'without change' category) using the cluster-specific (black line) and population-averaged (red solid line) procedures.

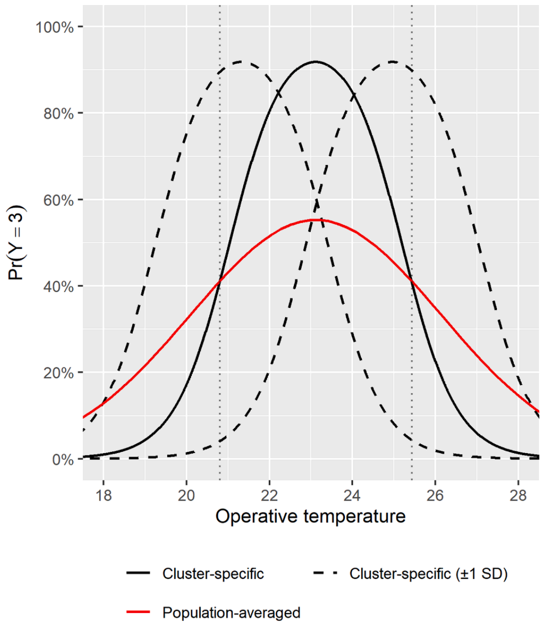

Fig. C2. Predicted response probabilities for category $k = 3$ (i.e., 'without change') using the cluster-specific (black line) and population-averaged (red line) procedures. Note. The dotted black lines represent the intersections between the cluster-specific and population-averaged probabilities.

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Appendix B: Supplementary publications

The following six journal articles constitutes the supplementary publications of this thesis.

(a) M. Schweiker, E. Ampatzi, M.S. Andargie, R.K. Andersen, E. Azar, V.M. Barthelmes, C. Berger, L. Bourikas, S. Carlucci, G. Chinazzo, L.P. Edappilly, M. Favero, S. Gauthier, A. Jamrozik, M. Kane, A. Mahdavi, C. Piselli, A.L. Pisello, A. Roetzel, A. Rysanek, K. Sharma, S. Zhang, Review of multi-domain approaches to indoor environmental perception and behaviour, Building and Environment 176 (2020). doi:10.1016/j.buildenv.2020.106804.

(b) A.L. Pisello, I. Pigliautile, M. Andargie, C. Berger, P.M. Bluyssen, S. Carlucci, G. Chinazzo, Z. Deme Belafi, B. Dong, M. Favero, A. Ghahramani, G. Havenith, A. Heydarian, D. Kastner, M. Kong, D. Licina, Y. Liu, A. Luna-Navarro, A. Mahdavi, A. Nocente, M. Schweiker, M. Touchie, M. Vellei, F. Vittori, A. Wagner, A. Wang, S. Wei, Test rooms to study human comfort in buildings: A review of controlled experiments and facilities, Renewable & sustainable energy reviews 149 (2021) 111359. doi:10.1016/j.rser.2021.111359.

(c) G. Chinazzo, R.K. Andersen, E. Azar, V.M. Barthelmes, C. Becchio, L. Belussi, C. Berger, S. Carlucci, S.P. Corgnati, S. Crosby, L. Danza, L. de Castro, M. Favero, S. Gauthier, R.T. Hellwig, Q. Jin, J. Kim, M.S. Khanie, D. Khovalyg, C. Lingua, A. Luna-Navarro, A. Mahdavi, C. Miller, I. Mino-Rodriguez, I. Pigliautile, A.L. Pisello, R.F. Rupp, A. Sadick, F. Salamone, M. Schweiker, M. Syndicus, G. Spigliantini, N.G. Vasquez, D. Vakalis, M. Vellei, S. Wei, Quality criteria for multi-domain studies in the indoor environment: critical review towards research guidelines and recommendations [Manuscript submitted for publication] (2022).

(d) S. Carlucci, M. De Simone, S.K. Firth, M.B. Kjærgaard, R. Markovic, M.S. Rahaman, M.K. Annaqeeb, S. Biandrate, A. Das, J.W. Dziedzic, G. Fajilla, M. Favero, M. Ferrando, J. Hahn, M. Han, Y. Peng, F. Salim, A. Schlüter, C. van Treeck, Modeling occupant behavior in buildings, Building and environment 174 (2020) 106768. doi:10.1016/j.buildenv.2020.106768.

(e) M. Vellei, E. Azar, K. Bandurski, C. Berger, S. Carlucci, B. Dong, M. Favero, A. Mahdavi, M. Schweiker, Documenting occupant models for building performance simulation: A state-of-the-art, Journal of building performance simulation 15 (2022) 634-655. doi:10.1080/19401493.2022.2061050.

(f) B. Dong, R. Markovic, S. Carlucci, Y. Liu, A. Wagner, A. Liguori, C. van Treeck, D. Oleynikov, E. Azar, G. Fajilla, J. Drgoňa, J. Kim, M. Vellei, M. De Simone, M. Shamsaiee, M. Bavaresco, M. Favero, M. Kjaergaard, M. Osman, M. Frahm, S.

Dabirian, D. Yan, X. Kang, A guideline to document occupant behavior models for advanced building controls, Building and Environment 219 (2022) 109195. doi:10.1016/j.buildenv.2022.109195.

Paper a

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Review of multi-domain approaches to indoor environmental perception and behaviour

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A R T I C L E   I N F O

Keywords:
Human perception
Comfort
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Personal
Multi-domain

A B S T R A C T

Building occupants are continuously exposed to multiple indoor environmental stimuli, including thermal, visual, acoustic, and air quality related factors. Moreover, personal and contextual aspects can be regarded as additional domains influencing occupants' perception and behaviour. The scientific literature in this area typically deals with these multiple stimuli in isolation. In contrast to single-domain research, multi-domain research analyses at least two different domains, for example, visual and thermal. The relatively few literature reviews that have considered multi-domain approaches to indoor-environmental perception and behaviour covered only a few dozen articles each. The present contribution addresses this paucity by reviewing 219 scientific papers on interactions and cross-domain effects that influence occupants' indoor environmental perception and behaviour. The objective of the present review is to highlight motivational backgrounds, key methodologies, and major findings of multi-domain investigations of human perception and behaviour in indoor environments. The in-depth review of these papers provides not only an overview of the state of the art, but also contributes to the identification of existing knowledge gaps in this area and the corresponding need for future research. In particular, many studies use "convenience" variables and samples, there is often a lack of theoretical foundation to studies, and there is little research linking perception to action.

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1. Introduction

1.1. Background and state-of-the-art

Inhabitants of industrialized areas spend most of their time (85–96%) inside buildings [1,2]. Meanwhile, the human sensory system receives information regarding multiple indoor environmental exposures. Building energy consumption is significantly influenced by occupant perception and behaviour; that is, occupants' evaluation of thermal, visual, acoustic, and air quality stimuli and their reactions to any resulting discomfort [3]. As such, these four principal categories of environmental stimuli are integral to building design standards [4]. Not all interactions of occupants with their built environment result from dissatisfaction, but a close link between perception and behaviour exists [5].

While environmental stimuli occur simultaneously, the majority of scientific literature considers environmental influences on human perception and occupant behaviour in isolation. Literature reviews related to single-domain perceptions cover thermal [6–8], visual [9–12], indoor air quality (IAQ) [13], or acoustic [14–16] perception, as well as single-domain influences on occupants' actions [5,17–19]. An understanding of multi-domain environmental effects is lacking. ASHRAE [4] states "*current knowledge on interactions between and among factors that most affect occupants of indoor environments is limited*". Addressing this knowledge gap, Torresin et al. [20] proposed a multi-domain research framework that identifies interactions and crossed effects between domains. Interactions are combined effects of two or more distinct domains (e.g., thermal and visual), on a third domain (e.g., overall environmental satisfaction). In contrast, crossed effects involve a main effect of one domain (e.g., thermal stimuli) on another domain (e.g., visual perception).

Literature reviews on multi-domain approaches are less numerous. Recently, Torresin et al. [20] identified 45 laboratory studies published after 1990 dealing with the effects of two or more environmental domains on perception and performance. Earlier reviews were based on smaller numbers of studies [21–23]. Frontczak et al. [23] reviewed nine studies focusing on the influence of individual domains on overall satisfaction. Candas et al. [21] discussed neurophysiological and behavioural findings on multisensory influences on thermal perception based on 25 publications. Centnerová et al. [22] reviewed eight papers with the same topic. The authors of this review could not identify earlier reviews addressing multi-domain approaches related to occupant behaviour.

In addition to the four principal indoor environmental domains,

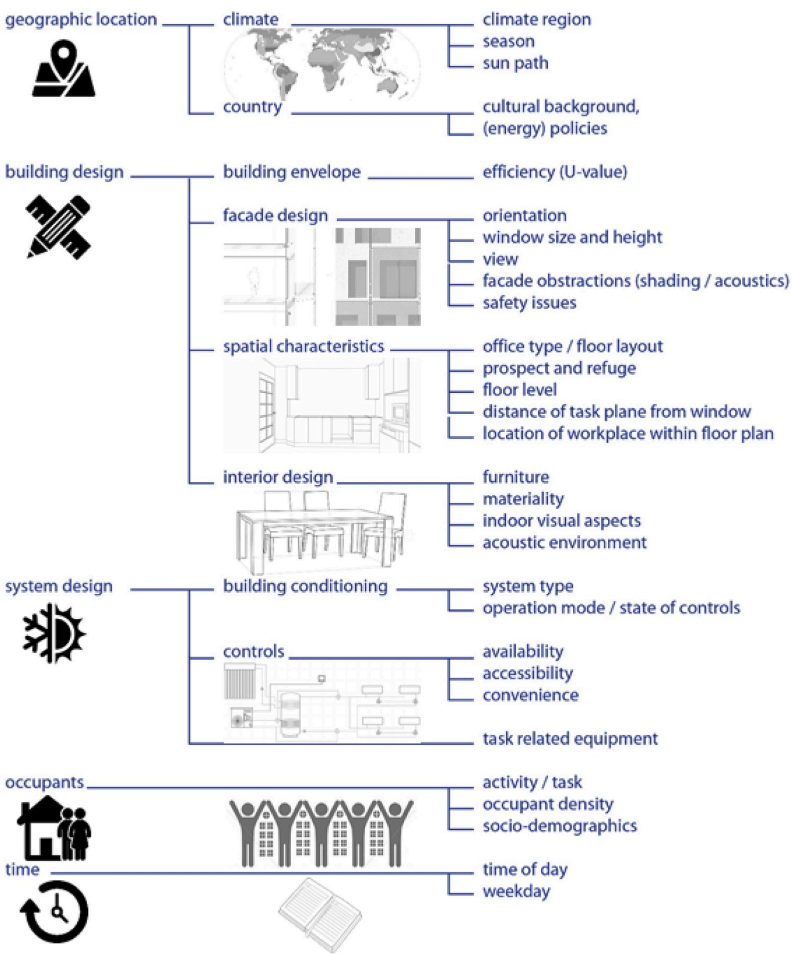

Fig. 1. Contextual variables and their categorization.

contextual and personal variables influence occupants' perception and behaviour and are summarized in Figs. 1 and 2. Schweiker et al. [5] reviewed drivers of occupant behaviour, including contextual and personal factors. However, they did not examine interactions between these factors. Frontczak et al. [23] reviewed personal and contextual influences on overall satisfaction with the indoor environment. Schweiker et al. [8] included personal (psychological) and contextual factors in their review on individual differences in thermal perception. O'Brien et al. [24] concluded that most approaches analysed aggregated average models and diversity is captured through statistical approaches, without extracting personal or contextual factors.

This brief overview reveals a lack of reviews that considered multi-domain influences on occupants' perception and behaviour. The current review aims to fill this gap as described in the following.

1.2. Objective, research questions, and scope

The primary objective is to examine multi-domain approaches with a much broader scope compared to previous reviews in order to enter into a new phase of conceptual developments in the field. This review aimed to identify motivations, key methods, findings, and gaps in the field of multi-domain approaches to human perception and behaviour in indoor environments.

The main research questions were (1) Why did researchers choose the domains and questions they considered?, (2) How did they approach multi-domain investigations?, (3) What were the key results?, and (4) What are limitations and gaps of their approaches?

The scope of this review covers studies applying a *multi-domain* approach to people's perception of the indoor environment and their resulting behavioural outcomes. The first categorization level made is between "perception" and "behaviour", as shown in Figs. 3 and 4, respectively. Studies without any physical predictors or with performance or health-related outcomes are beyond the scope.

Physical-perceptual independent variables cover measurable physical properties of the indoor and outdoor environment, e.g. indoor and outdoor air temperature for the thermal environment. All the physical properties of the thermal, visual, acoustic, and air quality environment are considered. *Physical multi-perceptual* approaches are defined as those covering variables from more than one domain of perception (e.g., thermal and visual perception). Studies dealing with multiple variables covering one domain only (e.g., solely air temperature and relative humidity, which are both from the thermal domain, on thermal perception) are not considered unless they included either contextual or personal variables. All *contextual and personal variables* shown in Figs. 1 and 2 are considered, except personal variables related to demographic factors (e.g. age, sex), or clothing if dealing with thermal perception.

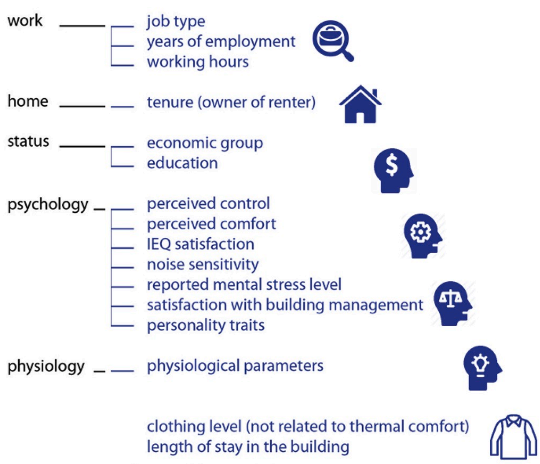

Fig. 2. Personal variables and their categorization.

Other behaviour and additional variables are included to cover studies that consider the status of one behaviour in the analysis of another behaviour. For example, window opening behaviour as dependent and the status of the heating system as independent variable.

This review covers laboratory studies, field studies, and questionnaire surveys. Studies related to perception or behaviour within the outdoor environment, virtual reality studies, or research based on simulations are out of scope. As such, this review provides a comprehensive overview of multi-domain approaches to understanding human perception and occupant behaviour indoors.

2. Methods

This review's approach is visualized in Fig. 5. The visualization is based on the "Preferred Reporting Items for Systematic Reviews and Meta-Analyses" (PRISMA) schema [25]. However, in contrast to a systematic review, first, we collected and reviewed known research, which returned 153 articles. This initial step included searches in author's individual reference databases as well as in bibliographic search engines (Table 1). Second, the more than 1000 articles citing these 153 articles or being cited by this initial collection were assessed. Together with their evaluation, we categorize our work as critical review [26].

2.1. Selection process

The units of analysis were the articles and their records. A record is defined as a dependent variable analysed within an article. As such, one article presenting analyses for two or more dependent variables (e.g. analyses of thermal and visual perception as dependent variable) has an equivalent number of records.

The exclusion criteria were: (1) out of scope; (2) other than English language; (3) full text unavailable, and (4) not peer-reviewed. In addition, (5) duplicates such as conference and journal articles presenting the same research were considered once; and (6) review papers without additional analyses such as meta-analysis were not considered.

2.2. Records' structure

The following data were extracted: dependent and independent variables; number (N) of participants, offices, and/or buildings; sex and age distributions; number of votes obtained or length of study; type of study (e.g. field or laboratory); type of building (e.g. residential or office); type of conditioning (e.g. naturally-ventilated (NV) or air-conditioned (AC)); region in which the study was conducted; data collected; statistical approach applied, and key findings.

In addition, introduction and discussion sections were scanned for the study's motivation and gaps/future research needs mentioned.

3. Comparison between perceptual and behavioural multi-domain approaches

Multi-domain approaches with perception as a dependent variable (244 records/163 articles) are three times more frequent than behavioural multi-domain studies (97 records/64 articles). Note that eight articles report results from perceptual and behavioural dependent variables (see the complete review table: https://osf.io/gnvp2/). The most frequent approach in perceptual and behavioural studies was a combination of one or more physical factors with contextual variables (Fig. 6).

In both research areas, perception and behaviour, field studies are the most frequent methods used (Fig. 7). Laboratory studies only dominate in studies that examined multi-perceptual effects without contextual or personal variables.

The sample size varies according to the type of sample analysed, i.e.

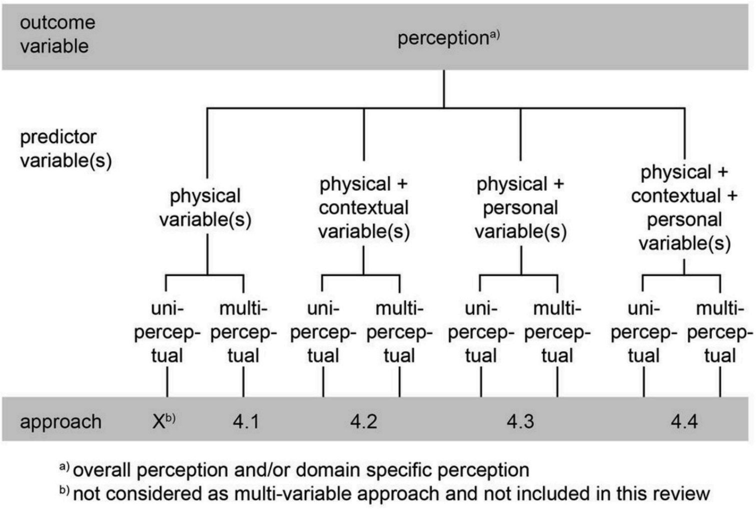

Fig. 3. Schema of multi-variable approaches with perception as the outcome variable.

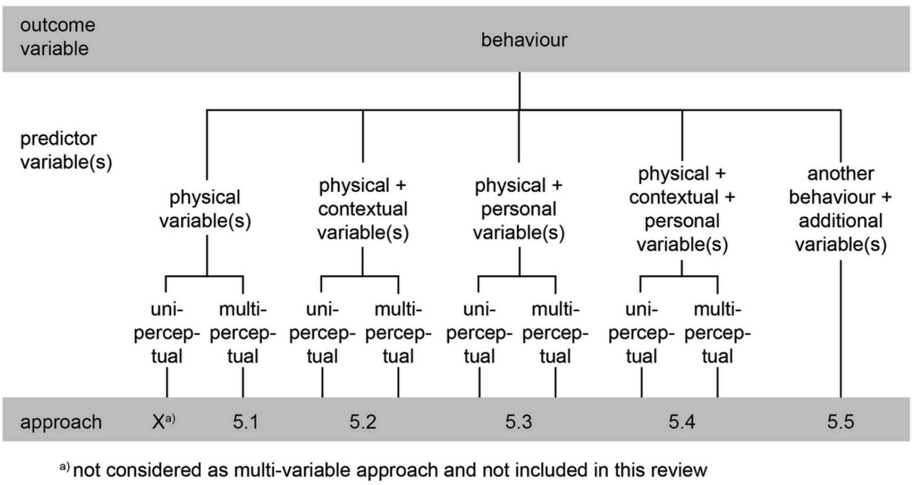

Fig. 4. Schema of multi-variable approaches with behaviour as outcome variable. Note that the approach numbers at the bottom of this figure refer to the corresponding subsection numbers within this review.

whether authors reported buildings, rooms, or participants (Table 2). The number of participants in laboratory studies ranged from 5 to 199 with nearly half of the studies with less than 30 (mean 45.6, SD 42.2, median 30). In field studies, the largest number of participants (N = 52,980 and N = 29,632) were observed in two studies combining physical and contextual variables (subsection 4.2) using existing databases of online surveys [27,28] (mean of all field studies 824.1, SD 3178, median 138). Sample sizes below 10 participants were observed in several subsections. Arguments were for example an integral research approach triangulating between four qualitative and quantitative methods [29] or in-depth insights by gathering detailed information through interviews and discussions [30]. The number of buildings varies from 1 [31] to 351 [27].

4. Perceptual studies

This section is divided into four subsections: physical; physical and contextual; physical and personal; and physical, personal, and contextual. In each subsection, we reflect on the motivational background, the methods employed for data collection and analysis, and some of the key findings. We conclude each subsection with thoughts on the current state of the art, prevailing knowledge gaps, and future research needs.

Fig. 8 summarizes the findings on crossed main effects on thermal, visual, IAQ, and acoustic perception referred to in the following.

4.1. *Physical multi-perceptual approaches*

A considerable number of studies addressed the effects of multiple environmental factors on occupant perception. While not all these

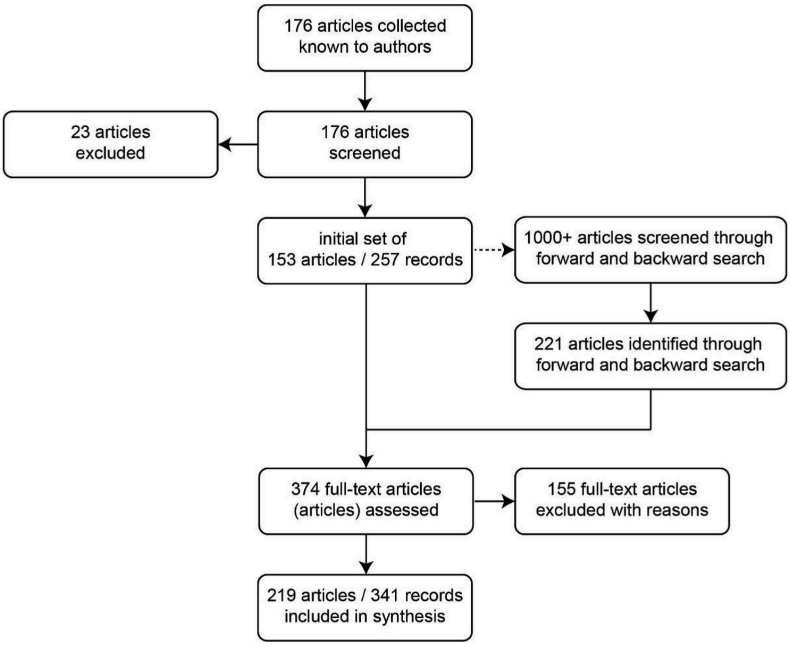

Fig. 5. Schema of the review process.

Table 1
Literature searches performed during the first phase of this review.

Database/search engine	Search terms (combinations of)
Web of Science	"thermal", "visual", "acoustic", "comfort", "satisfaction", "perception", "behaviour"
Scopus	"thermal", "visual", "acoustic", "personal", "contextual", "multi-domain", "comfort"
Science Direct	"occupant behaviour", "multi-domain", "model", "combined effects"
Google Scholar	"thermal", "visual", "acoustic", "comfort", "satisfaction", "perception", "behaviour"
Google Scholar	"indoor factors", "interaction", "combination"
Google Scholar	"Occupant", "thermal", "comfort", "satisfaction", "visual", "behaviour"
Google scholar	"occupant behaviour", "multi-domain", "model", "combined effects"
Deakin University library (linked to several databases)	"thermal comfort", "visual comfort", "acoustics"

studies specifically address the combined effects of multiple indoor environmental variables, most acknowledge at least their concurrent presence [32–109]. In the following, we focus on a number of these papers and their contributions, directly relevant to the topic of multi-domain exposures.

4.1.1. *Motivational background*

The majority of the studies cite the need for better understanding of exposure situations involving multiple indoor environmental variables. Other studies observed effects of multiple environmental variables without a specific intent to examine their interactions [53,62]. Studies considered different combinations of environmental variables, most frequently thermal and visual [34,37–39,52,67,102–104]. A few studies investigated other combinations of variables, such as visual and acoustic [45], thermal and acoustic [56,57,66], visual and IAQ [59], acoustic and IAQ [83], visual, thermal, and acoustic [48,49,62,70], as well as IAQ, thermal, and acoustic [35,41]. Researchers were mostly interested in the effect on dependent variables such as occupants' comfort, sensation, and preference [34,39,48,52,66,102–104]; and satisfaction [59,68].

4.1.2. *Approaches*

The majority of papers involved short-term laboratory studies in office settings. Only in a few studies, participants were given the opportunity to adjust certain factors of their immediate surroundings [45,59] or exercise a choice upon experiencing different settings [40].

Experimental settings typically involved different properties of the physical environments such as air temperature (thermal environment), sound type and level (acoustic environment), illumination level, glare intensity, light colour (visual environment), and airflow rates (thermal and air quality environment). Laboratory studies typically lasted a few hours or up to a day. Typically, experiments tested one or more levels of a physical variable crossed with one or more levels of another physical variable (e.g., three levels of temperature crossed with two levels of illumination, as in Kulve et al. [104]), while holding other indoor environmental variables constant.

The majority of experiments had within-subject designs, that is, all participants experienced all experimental conditions, typically counterbalanced by randomising the order of conditions. Within-subject experiments are more sensitive to the manipulation of independent variables, which is important for studies with smaller sample sizes.

The occupancy-related implications of environmental factors were queried using techniques such as surveys and questionnaires (e.g. Ref. [48]), comfort and sensation scales (e.g. Ref. [66]), and visual observations (e.g. Ref. [70]).

As expected, data analysis involved various well-established formats and techniques from descriptive and inferential statistics. The collection of statistical methods commonly referred to as ANOVA (Analysis of Variance) was frequently deployed for processing and interpretation of measurement results [40,45,52,66,68,70], as were mixed-effects models [37,39,49,67,104].

In the majority of the less frequent field studies, the setting was a university classroom and participants were students. However, field

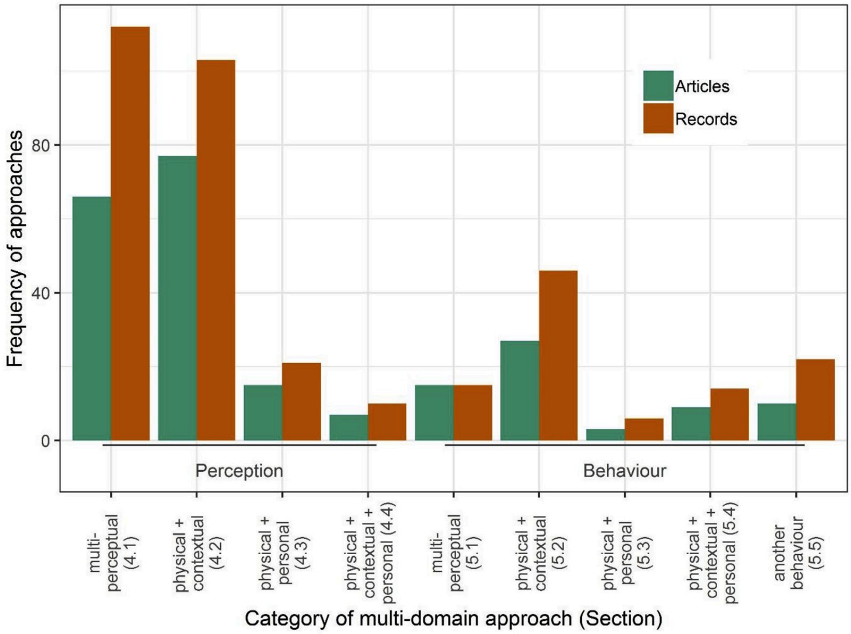

Fig. 6. Frequency of studies reviewed per approach.

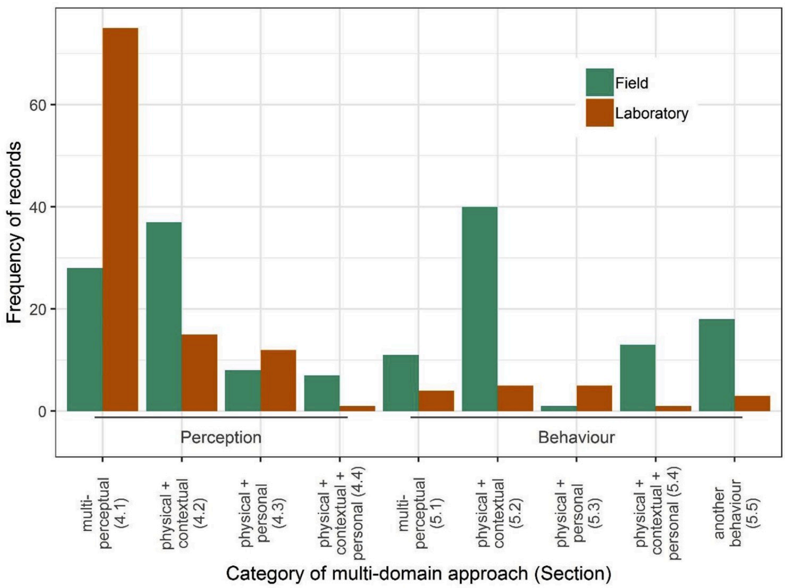

Fig. 7. Frequency of records separated by type of study.

studies were also conducted in office, hospital (e.g. Ref. [34]), and residential settings [50]. Field studies typically lasted several months.

Environmental physical conditions were monitored and participants were asked to rate their perceptions through questionnaires on comfort, sensation and satisfaction (e.g. Ref. [53,105]). Measurements of environmental conditions were associated with participants' subjective ratings, and the subjective ratings with each other, using measures such as correlation [105] or ANOVA [106]. Field studies enabled the variation of environmental conditions for large samples of subjects (e.g., 331 students in 7 varied classrooms [105]).

Table 2
Number of participants, offices, or buildings by category. N = number of records, Min = minimum, SD = standard deviation, Med = median, Max = maximum.

Section	Participants						Rooms/offices						Buildings/households					
	N	Min	Mean	SD	Med	Max	N	Min	Mean	SD	Med	Max	N	Min	Mean	SD	Med	Max
4 Perception																		
4.1 Physical multi-perceptual	109	6	99.3	186.6	35	990	0						3	1	2	1	2	3
4.2 Physical + contextual	82	7	1525.9	6674.6	168	52980	10	1	6.3	5.3	4	18	34	2	38.6	84.2	14.5	351
4.3 Physical + personal	16	20	557.9	1852.4	93	7500	8	6	56.5	51.9	46	120	6	2	4.3	3.8	2	11
4.4 Phys. + cont. + pers.	9	35	295.4	206.3	400	482	0						1	8	8		8	8
5 Behaviour																		
5.1 Physical multi-perceptual	9	5	42.2	44.8	20	128	4	1	3.5	3.1	2.5	8	4	9	17.8	6.1	19.5	23
5.2 Physical + contextual	11	17	504.9	891.3	36	2787	18	3	83.6	159.2	14	555	20	1	30.5	28.9	16.5	70
5.3 Physical + personal	4	65	65	0	65	65	2	6	63	80.6	63	120	1	2	2		2	2
5.4 Physical + cont. + pers.	6	32	1091.8	905.3	933	2787	2	4	4.5	0.7	4.5	5	4	13	35	14.7	42	43
5.5 Physical + multi-behavioural	11	8	18.5	9.3	21	40	6	3	8.5	3.6	8	14	4	1	1	0	1	1

The geographic distribution is presented in Table 3. Studies were predominantly conducted in Central Europe, North America, and Eastern Asia.

Table 3
Geographic distribution of records.

Section	Africa	Asia	Europe	North-America	Oceania	South-America
4 Perception						
4.1 Physical multi-perceptual	1	44	38	9	0	0
4.2 Physical + contextual variables	0	22	34	28	2	1
4.3 Physical + personal variables	0	3	10	6	0	0
4.4 Physical + contextual + personal variables	0	2	2	0	1	0
5 Behaviour						
5.1 Physical multi-perceptual	0	8	1	2	0	0
5.2 Physical + contextual	0	3	13	3	0	0
5.3 Physical + personal	0	0	5	1	0	0
5.4 Physical + contextual + personal	0	3	2	0	2	0
5.5 Physical + multi-behavioural	0	0	16	2	1	0

4.1.3. *Findings*

Studies described in the reviewed papers entail a host of valuable findings (Fig. 8). Tiller et al. [66] reported a slight effect of acoustic conditions on subjective ratings of thermal comfort, but no reverse effect. Nagano and Horikoshi [56] concluded that operative temperature has a slight effect on auditory comfort sensation votes and thus that the thermal environment must be taken into consideration in acoustic studies. On the other hand, they did not observe any effect of noise on reported thermal sensation. On the contrary, Pellerin et al. [107] indicated a noise effect on thermal comfort in warm conditions, but not of temperature on acoustic sensation, comfort, and preference. Yang et al. [108,109] reported that thermal comfort decreased with increased noise level, and with the noise of a fan as compared to that of babble, and that water sounds increased cold sensation and decreased thermal comfort. The authors also observed the influence of the thermal environment on acoustic comfort and sensation, but with contrasting findings, as they report a decrease of annoyance and an increase of acoustic comfort at thermoneutrality [108] as well as an increase in acoustic perception and annoyance at thermoneutrality [77,109].

Nakamura et al. [58] reported that higher colour temperature is preferred in summer and vice versa in winter. Fanger et al. [45] observed slight lighting effects on thermal comfort: people preferred a slightly lower temperature under red light than under blue light. Similar results were reported by Albers et al. [32] and by Winzen et al. [69], with electric light colour affecting thermal sensation, comfort and temperature estimation. Chinazzo et al. [39] suggested that participants' thermal sensation reports were influenced by the colour of the daylight. For instance, as compared to orange daylight exposure, a colder thermal sensation was reported in the case of blue daylight, even though the measured temperature remained the same. Daylight quantity was also reported to affect thermal perception, with increased thermal comfort under dim daylight conditions in a warm environment and under bright daylight conditions in a cold environment [103]. However, the authors indicate no effect of daylight illuminance levels on thermal sensation [103], similarly to what was reported by an earlier study with electric lighting [75]. Meanwhile, Azmoon et al. [34] observed improved thermal comfort responses because of increased light intensity.

Unexpected effects were sometimes found on variables that were not the focus of the experimental study. For example, people reported IAQ differences across temperature settings [67], or across combinations of acoustic, lighting, and temperature settings [49]. In some cases, papers noted significant effects only under restricted conditions. For example, Geng et al. [47] observed that people were less satisfied with IAQ and lighting under certain temperature settings, but not others. In some cases, papers noted statistically non-significant interactions between environmental conditions. For example, Pan et al. [83] observed that adding noise to odour mitigated the effect of odour on air-quality-related measures. However, with a sample size of N = 9, small interaction effects are unlikely detected.

Many studies observed no interactions between environmental factors tested (e.g. Ref. [37,38]), or were not designed in a way to investigate these interactions (field studies).

4.1.4. *Identified gaps and future directions*

The review of multi-physical perceptual research shows the extent of valuable knowledge generated over the past five decades. However, the

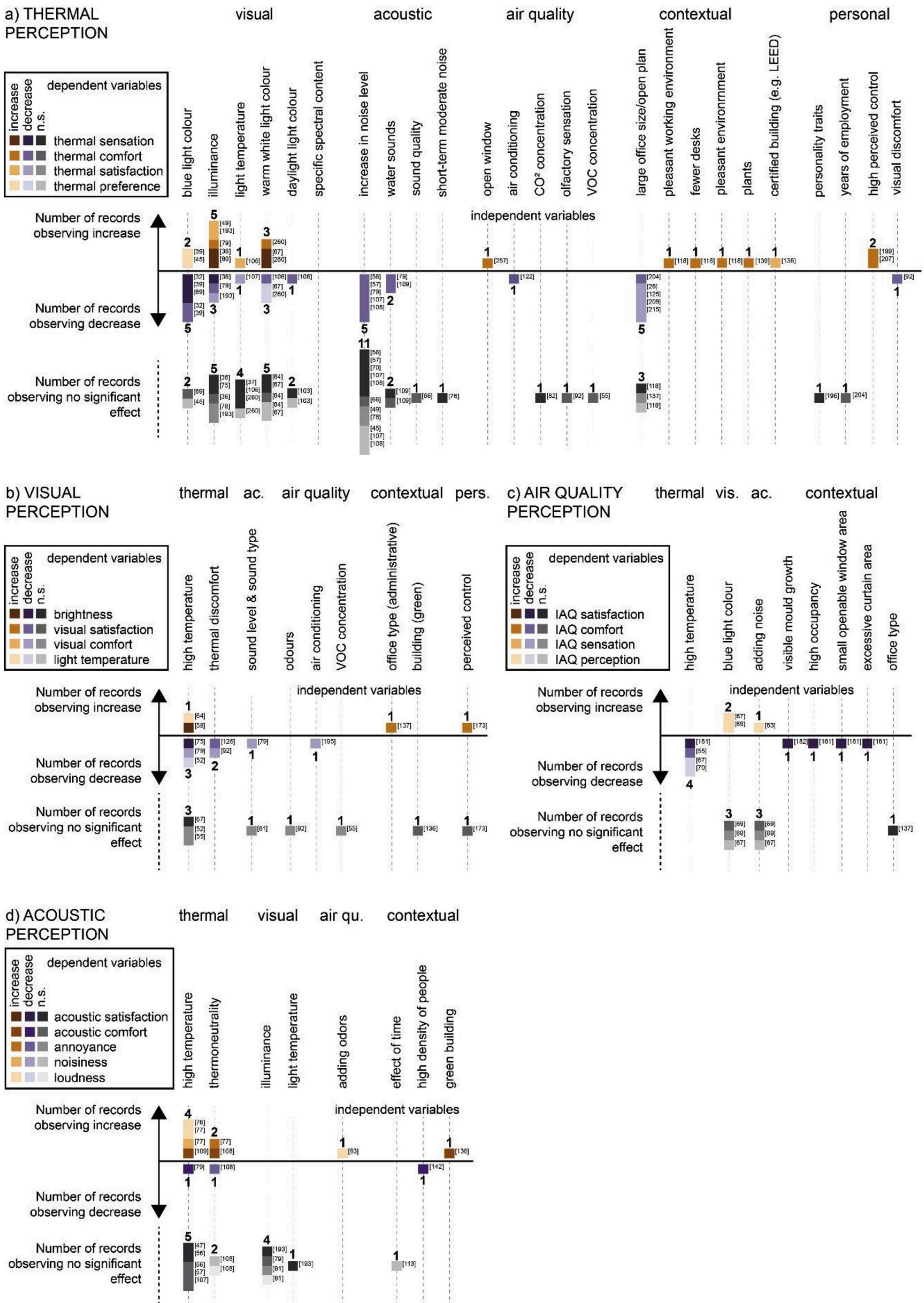

Fig. 8. Overview of crossed main effects related to thermal, visual, air quality and acoustic perception based on studies including significance tests.

yield is less extensive and less conclusive if we specifically query for frequent, clear, and consistent instances of cross-modal influence. The results are in many instances inconclusive, and in certain cases even contradictory. It is thus of paramount importance to reflect upon some of the key shortcomings and limitations of past research, which correspond more or less directly to requirements for future research efforts.

Given the difficulties of conducting research including real occupants in realistic settings (involving, amongst others practical, ethical, and economic issues), it is not surprising that most studies are short-term. Moreover, the participants, often young students, are not necessarily representative of pertinent populations, for instance, of office workers. Most studies were conducted in offices, yet other building typologies such as residential buildings are practically ignored by the literature.

Researchers frequently try to establish some measure of realism in the experimental settings, but this is rarely effectual given the difficulty in concealing the inherent artificiality of the available testing facilities. As such, the reviewed studies do not truly succeed in addressing the implications of the Hawthorne effect, even though, scholars argue about its nature and suitable methods to account for it in research [110,111].

Studies often start with some reference to previous research (frequently to authors' own previous publications), but there is very little evidence of actual carryover of past studies' findings. As such, the majority of the studies appear to practically start from scratch. Perhaps consequently, different studies do not deploy standard research designs, data collection strategies, metrics, and statistical analysis techniques, making attempts toward conducting meta-analyses factually futile.

There is arguably a paucity of collaborative, multi-institutional, international, and interdisciplinary experimental studies. Specifically, few studies seem to have truly recognized the critical importance of conceptual and methodological integration of engineering and human science methods.

One fundamental problem with most research efforts is the absence of foundational theories that would facilitate the processes of hypothesis formulation and testing. This may be of course in part due to the inherent complexity of the subject. However, the chances of obtaining scalable and generalizable results remain slim if research designs do not at least make an attempt to start from a provisional general theory of the nature of the perceptual and behavioural processes involved in multi-domain exposure situations.

4.2. Physical + contextual variables

This subsection examines studies investigating the combined effects of physical and contextual variables on environmental perception. These studies examined how context may interplay with single- or multi-sensory domain perceptions by imposing unknown or indirect influences on the physical properties of the environment or by shaping the users' perceptions and expectations in line with social or cultural experiences [27–29,42,112–192].

4.2.1. Motivational background

The drive for research varies greatly between the studies identified. Some researchers challenge the absence of an established single index for holistic comfort [124,129,167]. In other studies, the combined effects of physical and contextual variables were merely incidental rather than an intended outcome [124].

In four of the identified studies, the inclusion of contextual factors was thought to enrich environmental evaluation by factoring subjectivity into assessments typically based on only physical criteria [112,114,132,149]. Similarly, some research aimed to improve post-occupancy evaluation techniques, from how data is collected or analysed [72,168], to examine the combined influence of suspected co-contributors to satisfaction in a single-sensory domain [169].

We identified three distinct research themes focusing on specific building attributes. One addressed the concurrent influence of environmental and spatial factors present in open-plan office space configurations [42,113,137,142,170], a second examined limitations of green building design and rating systems [125,127,136,171], and a third concerned the impact of the presence of control opportunities [115,116,172,173].

4.2.2. Approaches

In contrast to the studies reviewed in section 4.1, the interest seems to be more in real settings, shown by the majority of studies applying field study approaches. Here, the influences of the contextual factors can be examined with limited cost and reduced difficulty in the experimental set-up.

Subjective evaluation through surveys is a common approach for data collection of comfort or satisfaction based on the self-reporting of participants [27,28,174]. Several studies involve measurements of indoor environmental quality metrics related to thermal, acoustic, and visual properties alongside with occupants' subjective votes [42,74,124,129,136,137,142,144,145,169,170,175–177].

The most frequent building typologies were office buildings (e.g. Ref. [115,119,126,134,140,143,147,178–180]) and educational buildings (e.g. Ref. [116,120,123,181–183]), followed by residential buildings [122,153,175], hostels and student residences [42,121], restaurants and cafés [132,142], factories [118,184], a healthcare facility [150], a shopping mall [141] and airport terminal [47].

The length of data collection differed depending on the methodology and the research focus. Longitudinal studies ranged from months to years [171,185]. Studies employing structured or semi-structured interviews may span over several seasons [141,186,187]. Short survey or interview studies last usually no more than two months [148,150,153], but can be as short as a few days [124,125,140,143,174,181,188].

Summary statistics, including mean and variance, were used by nearly all studies. In addition, several types of correlational analysis, parametric and non-parametric tests are common approaches.

Overall perception was the most frequently researched dependent variable, followed closely by thermal perception and then by visual perception, acoustics, and IAQ. Metrics for overall perception ranged from mainstream choices such as overall satisfaction, acceptability or comfort (and even 'uncomfortableness') to measures of 'psychic well-being", preference for space and affective quality of space. The metrics used for thermal, visual, acoustic, and IAQ perceptions were more conventional, with higher variance for the visual domain, including satisfaction with lighting, glare perception, eye discomfort and appearance of the environment.

4.2.3. Findings

The influence of geographic location is not conclusive. With similar climate conditions, occupant responses to warm and cold weather tend not to differ greatly across countries [28]. Similarly, Sakellaris et al. [157] found minimal differences in multiple types of perception between two locations. In contrast, thermal and IAQ perception differed between occupants of the same country, especially for those countries with a large north-south spread [98].

The interior design and furniture in office and school settings correlated strongly with comfort [133,135,143,151,157]. Perception of illuminance level strongly depended on office layout and furniture type [123,183,189]. Furthermore, since daylight levels exhibit strong spatial dependence, visual comfort at workplaces varied greatly with proximity to the window [27,151].

The perceptual aspects of visibility in classrooms [183,189], privacy in offices [27,151], and available space in offices [27] are additional factors associated with room layout and furniture selection, which correlated with visual and overall comfort levels. Few studies recommend optimal office layout or furniture selection for comfort. This is likely due to the subjective and non-quantifiable nature of these properties.

One of the most important components of the building envelope is the window [190]. Poor thermal comfort (e.g., cold or warm window) [175,191], daylight glare [191], and poor acoustic comfort [191] are reported by participants in large-windowed residential or office buildings. Additionally, the design of solar control devices and solar control techniques can affect occupant comfort, especially thermal and visual. For instance, Karlsen et al. [192] demonstrate that occupants prefer venetian blinds with adjustable slat angles to those with only on-off position. These handful of studies are among the few that made conclusions from surveys, while the majority of other studies use simulation approaches beyond the scope of this review.

Perception and comfort in green buildings vs. conventional buildings varied greatly among studies. Two studies demonstrated that occupants' overall comfort is higher for green buildings [127,144]. In contrast, Gou et al. [128] observed no significant difference in overall comfort between these building types. The contrasting results may be due to two reasons. First, overall comfort can be influenced by occupants' attitude towards the "green" identity of the building [171]. Second, the term "green" building is not universally defined, and used for buildings that are certified by different standards (e.g. LEED [144], LEED and GBL [128], BREEAM [171]). These standards differ significantly in their assessment criteria. Consequently, the building performance can vary largely.

NV and passively cooled buildings that allow occupants to control aspects of the indoor environment, resulted in positive thermal comfort perceptions outside the fixed temperature limits set in standards [120, 130,148,180]. Moreover, controllability strongly increases occupants' satisfaction with thermal indoor conditions in winter and summer [28, 120,130,148].

4.2.4. Identified gaps and future directions

The contextual variables discussed in this paper are those mentioned in the literature. Further research would be needed to evaluate whether the most researched dependent and independent variables are the most influential.

Among the building related parameters, façade design and interior design are crucial. Few studies use a surveying approach to evaluate façade design options. Thus, further field surveys are needed to associate occupant multi-domain perception with design decisions. Simulations alone cannot substantiate the claims, as they may not truly reflect the actual indoor environment. Spatial information is merely described in the text. For future studies, publishing this information in a visual format is desirable, e.g., with photos and architectural drawings such as floor plans, sections, or elevations, which can convey the spatial situation better. Examples of appropriately published spatial architectural information exist [29,125,142]. In general, further research on spatial characteristics would be desirable, because spatial characteristics and typologies also depend on building types and the number of studies considering each building type is currently small.

In most studies, the context was represented by one or a few variables. However, context is a complex system of multiple dynamically interacting variables. For example, visual perception varies with the location of a workplace within a floor plan [169], but the occupants' perception is further influenced by other spatial parameters such as orientation and fenestration of the façade [175], climate related parameters such as season, sun path/latitude [126], and indoor surface materials [114]. Our review identified no study that investigated the complexity and interplay of multiple contextual variables, which is likely due to methodological challenges with required data types and the needed quantity of data. New methodological approaches might be needed for future studies to describe and understand the complexity and interplay of contextual variables.

Most papers used statistics for data analysis, and these methodologies tend to require large sample sizes for higher validity. If context is evaluated at a high level of resolution, i.e. with in-depth analysis of the spatial geometric or architectural design characteristics, it is unlikely that large sample sizes exposed to identical characteristics can be obtained for all building types. Therefore, a broader variety of approaches and methodologies could expand the investigated contexts.

4.3. Physical + personal variables

This subsection concerns thirteen studies that combine the impact and mutual influence of measured indoor environmental conditions and personal variables on occupants' perception [52,168,193–203].

4.3.1. Motivational background

In some studies, the analysis of personal variables is tangential and brief, while in other studies, the main purpose and motivation is to understand how personal variables influence occupants' perception. The analysis of personal variables is important to understand the differences in perception observed among individuals or groups in similar environmental conditions [196]. Nevertheless, all experimental studies aimed to evaluate the possible correlation between personal variables and the different domains of environmental perception.

4.3.2. Approaches

Studies include one or more dependent variables related to thermal, visual, acoustic, IAQ, or overall perception. Other studies considered comfort perception as a dependent variable together with productivity [202], which is out of scope here.

Almost all studies were conducted in office or educational buildings or in controlled chambers that simulate a working environment. Only one study was set in a non-office commercial building, a shopping centre [193].

Field studies including physical measurements and questionnaires dominate in this subsection. To achieve higher control and a broader collection of physical variables, some studies used laboratories that reproduce commercial [193], educational [52,197], or office environments [194,196,198]. One study is based on questionnaires [168]. Yun [199], instead, applied a mixed methodology to evaluate the energy implications of personal variables, specifically of perceived control.

The applied statistical analysis methods largely vary among the studies, ranging from ANOVA and MANOVA [197,198,203] to regression [196], correlation analysis [52,168,193,194], and non-parametric analysis [195].

4.3.3. Findings

Overall, findings showed that personal variables significantly influence multi-domain comfort perception positively or negatively.

Occupants' perceived control and satisfaction with building management are among the key analysed personal variables significantly interacting with the overall perception. Robertson et al. [195] highlighted that workers' visual comfort and personal wellbeing are influenced by perceived control over lighting, especially in non-naturally ventilated buildings. Additionally, occupants' reduced perceived control over the indoor environment has a significant negative effect on their thermal comfort [199] and general perception of a building [168]. On the contrary, the availability of choice over lighting control were demonstrated to decrease occupants' perceived importance of lighting in offices [198] and their performance [197]. Focusing on the interaction of thermal, acoustic, and visual domains, Dang et al. [193] showed that, although thermal and acoustic personal satisfaction are not directly correlated with lighting parameters, they interact with personal lighting satisfaction. On the other hand, a significant effect of thermal variables and clothing level on visual perception was obtained only in artificially illuminated buildings, while in daylight the influence of other parameters, e.g. acoustics, became relevant [52]. Finally, Schweiker at al. [196] demonstrated that personality traits, i.e. neuroticism, extraversion, openness to new experiences, are moderating thermal perception. Focusing on physiological parameters, Pigliautile et al. [194] highlighted that a multi-domain approach is required to understand human comfort thoroughly.

4.3.4. Identified gaps and future directions

Generally, very few studies were identified that deal with the interaction of multi-domain perception and personal variables beyond demographics. Moreover, many of these studies concern the impact of perceived control on environmental conditions and less focus is given to other personal variables. In addition, many studies simply report the differences observed among occupants with different personal variables without attempting to understand their motivation, which limits their contribution to the factual understanding of the influence of personal variables. Another important gap is the small sample size and the lack of diversity of the samples. Although gender balance is generally fulfilled, many of the studies selected university students for their experiments. Finally, none of the reviewed papers focused on residential environments. While certain personal variables, such as perceived control and privacy, might be less significant in residential spaces compared to office buildings, other variables, such as the expectation of building performance and energy/money saving might be significant, and thus worthy of exploration.

4.4. Physical + contextual + personal variables

While some of the studies discussed in the previous subsections explored physical, contextual, and personal predictors of perceptions, none aimed to understand the interactions of these independent variables. The current subsection covers eleven research efforts that addressed this gap by simultaneously examining at least one predictor variable from each category [30,72,125,204–211].

4.4.1. Motivational background

All studies promote a multi-domain approach to perceptual evaluation. For instance, Jin et al. [211] highlight the need to study physical (i.e., objective) and non-physical (i.e., subjective) drivers of occupants' perceptions with their indoor environment. Pivac et al. [204] state the importance of physiological and social factors in the evaluation of perceptions. Indraganti et al. [209] focus on the role of occupants' demographic and personal characteristics while assessing thermal comfort. Hitchings et al. [30] highlight the need to study cultural, geographic, and seasonal adaptation effects. Other studies aimed to understand overall environmental satisfaction levels [72,125]. Overall, a unified and explicit goal of proving that physical, contextual, and personal variables combine to explain perceptions is lacking.

4.4.2. Approaches

Ten of the reviewed articles are field studies conducted in non-controlled building environments, while one [206] took place in a laboratory controlled office setting. The studied environments were office [125,204–208], residential [30,72,209,210], and retail buildings [211]. Dependent variables included domain-specific comfort metrics such as thermal comfort [30,204,209], neutral temperature [206], visual comfort [205,211], and acoustic comfort [210]. Two studies [72,125] considered domain-specific comfort metrics and overall perceived comfort levels of the respondents.

Data collection was carried out through environmental sensing devices, questionnaires, walkthroughs, inspections, interviews, and diaries. The data collection duration varies from one-time surveys (e.g. Ref. [210]) to data collected over an extended period of time (e.g., 40 days in Sadeghi et al. [205]).

The data analysis approaches include qualitative and quantitative assessments. Starting with the former, Hitchings et al. [30] used a qualitative analysis of the collected data. The other studies mostly applied statistical analysis methods to derive relationships between, on the one hand, the environmental, contextual, and personal data that were collected, and on the other, the respondents' perceptions of comfort. The statistical methods include ANOVA [125,210], X^2-tests [72], Mann-Whitney *U* test and the Kruskal-Wallis test [204], correlations [72,205,210,211], and linear regression [125,205,206,209–211].

4.4.3. Findings

While this subsection covers a broader scope of predictor categories than previous sections, the results are not more diverse. The results do not explicitly confirm that physical, contextual, and personal predictors collectively drive the reported perceptions. The findings of the articles mostly identify single or dual types of interacting perception drivers, which is in line with the observations of previous subsections.

Starting with thermal perception, Pivac et al. [204] found that environmental metrics, office type, and job type have a significant influence on the perceived thermal comfort. Indraganti and Rao [209] observed a strong correlation between the respondents' economic group and their reported comfort levels, and weaker relationship with the other considered variables such as season and tenure. Schweiker and Wagner [206], on the other hand, highlight a significant influence of perceived control on neutral temperature, while office type affected perceived control.

Related to visual perception, Jin et al. [211] found that the measured illuminance level is the dominant driver of visual comfort, while the existence of daylighting plays an essential role in subjective satisfaction. Sadeghi et al. [205] found a strong relationship between the occupants' perception of control and their acceptability of a broader range of visual conditions.

In Park et al. [210], the authors studied potential drivers of subjective responses to floor impact noise in residential buildings. They highlight a significant impact of noise sensitivity and floor slab thickness on the reported acoustic comfort levels.

The main observation by Xue et al. [72] and Freihoefer et al. [125] is a significant difference in the reported overall comfort levels between workspace types (open and closed). Xue et al. [72] found that the combined effect of thermal comfort and IAQ significantly influences visual comfort, while the abundance of daylight hours and illuminance levels showed strong positive correlations with reported visual perceptions. More interestingly, the authors confirm strong dependencies between pairs of variables such as IAQ/thermal comfort and room orientation, adaptive behaviours of shading/lighting and visual comfort, and finally, mental stress and acoustic comfort.

4.4.4. Identified gaps and future directions

The findings presented above do not provide a clear understanding of the interactions nor fundamentals of the combined effect of physical, contextual, and personal predictors of perception. The findings cannot be generalized given the small sample of studies that met the criterion used for inclusion in this subsection. Furthermore, the data analysis methods applied were mostly constrained to studying relationships between a limited number of variables (in many cases two variables), falling short of providing a comprehensive understanding of the influence of multi-variable predictors and their interactions. More diverse predictors and complex analysis tools (e.g., Principal Component Analysis and Artificial Neural Networks) can be considered in future research to draw more diverse and comprehensive conclusions on the drivers of occupant perceptions. Finally, except for Schweiker and Wagner [206], none of the studies were conducted in controlled environments, which is another potential avenue for exploring multi-domain predictors of perception.

5. Behaviour

This section summarizes studies considering the relationship between measurable conditions of indoor environmental quality and occupant behaviour.

Figs. 9 to 12 show the crossed main effects of multiple independent variables on different types of behaviour, which will be discussed in the following subsections.

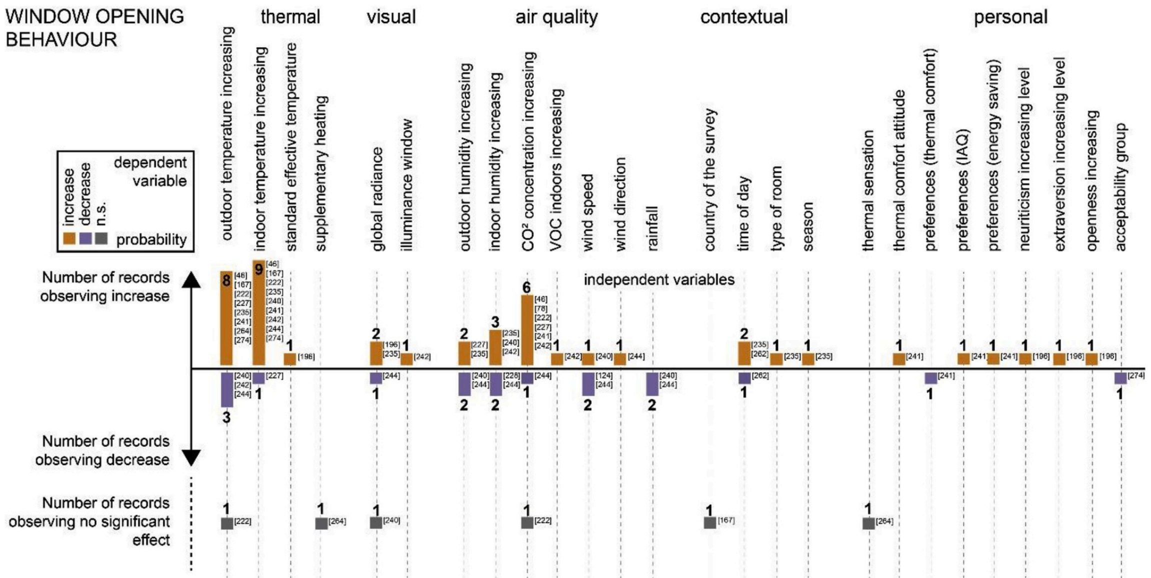

Fig. 9. Effects of physical, contextual and personal variables on window opening behaviour.

5.1. *Physical multi-perceptual approaches*

The nineteen studies analysed in this subsection attempt to relate occupant behaviour to multi-perceptual physical environmental conditions [46,212–229].

5.1.1. *Motivational background*

The motivation behind the majority of these studies was to evaluate the drivers of occupant behaviour in the context of multiple domains of occupant comfort. In general, all of the studies aimed at a better forecasting and simulation of occupant behaviour under multiple indoor environmental performance criteria. Specifically, all but a few studies were concerned with the effect of indoor and outdoor climatic conditions on occupant control of windows, blinds, and/or lighting, as well as the derivative effect of such control on perceived thermal comfort, lighting comfort, and/or building energy use.

The underlying objective was the characterization of the relationship between measurable physical parameters and occupant behaviour. Specific objectives include the evaluation of the effect of solar insolation on perceived thermal comfort, lighting comfort, and occupant controls of window blinds [215] and the development of a data-driven personalized thermal comfort model and minimum daylight requirement model to be used for model-predictive control of window blinds [213].

5.1.2. *Approaches*

All reviewed papers relied to some extent on physical monitoring of indoor environmental conditions and direct monitoring or measurement of occupant control decisions (e.g., window opening behaviour). Most studies undertook some form of occupant comfort evaluation via questionnaires, and several papers undertook monitoring of outdoor climatic conditions (e.g., outdoor air temperature and air pollution concentrations).

All but a few papers described field studies of offices or dwellings. The exceptions were laboratory studies [214,218,219]. All field studies took place in regions where there are discernible heating and cooling seasons, and no studies were undertaken in climatic regions such as the Tropics or Sub-Tropics.

The duration of behavioural studies followed one of three trends: they undertook either a short duration of measurements in a manner of days [214,219], a medium-term measurement across a single climate season [212,221,227], or a much longer-term study across several seasons up to an entire year or more [46,213,215,216,222,224–226,228,229]. Controlled laboratory studies had the shortest measurements. A notable example is Daum et al. [213], who collected over 6800 individual survey responses over a period of 3 years.

The studies' methods of data analysis included, for example, correlations between the probability of an action and environmental variables. For example, Inkarojit [215] evaluated the correlation between the probability of occupants' opening or closing windows and received solar radiation on window surfaces. Similarly, Daum et al. [213] correlated the probability of window blinds opening/closing actions and indoor air temperature. Various forms of regression methods, such as linear regression, multiple linear regression, univariate and multivariate logistic regression, were used by all studies.

5.1.3. *Findings*

Given an underlying, often implied understanding across all studies that occupant behaviour is inherently stochastic, the main format of illustrated findings were probability density functions of occupant behaviour against one or more parameters.

The findings from these papers defended widely-accepted principles of thermal and visual comfort in the built environment, as opposed to revolutionising them or putting them into question. For example, the studies which evaluated the extent to which window open/close behaviour would be driven by outdoor climatic conditions, IAQ, or other parameters, broadly concluded that indoor and outdoor air temperature, coupled with IAQ and/or solar radiation, are the primary drivers of window control by occupants [46,216,217,221,222,226,228]. Outdoor air quality was identified as a moderate parameter of influence, particularly when it is considerably poor [226]. While solar radiation should be deemed a quasi-thermal parameter with a direct effect on indoor and outdoor air temperature and indoor heat gains, IAQ is related to a different domain, so that window open/close behaviour can be understood as a multi-domain problem.

All studies that evaluated the physical drivers and indicators of window blind and lighting operation [212,213,215,225,229] observed

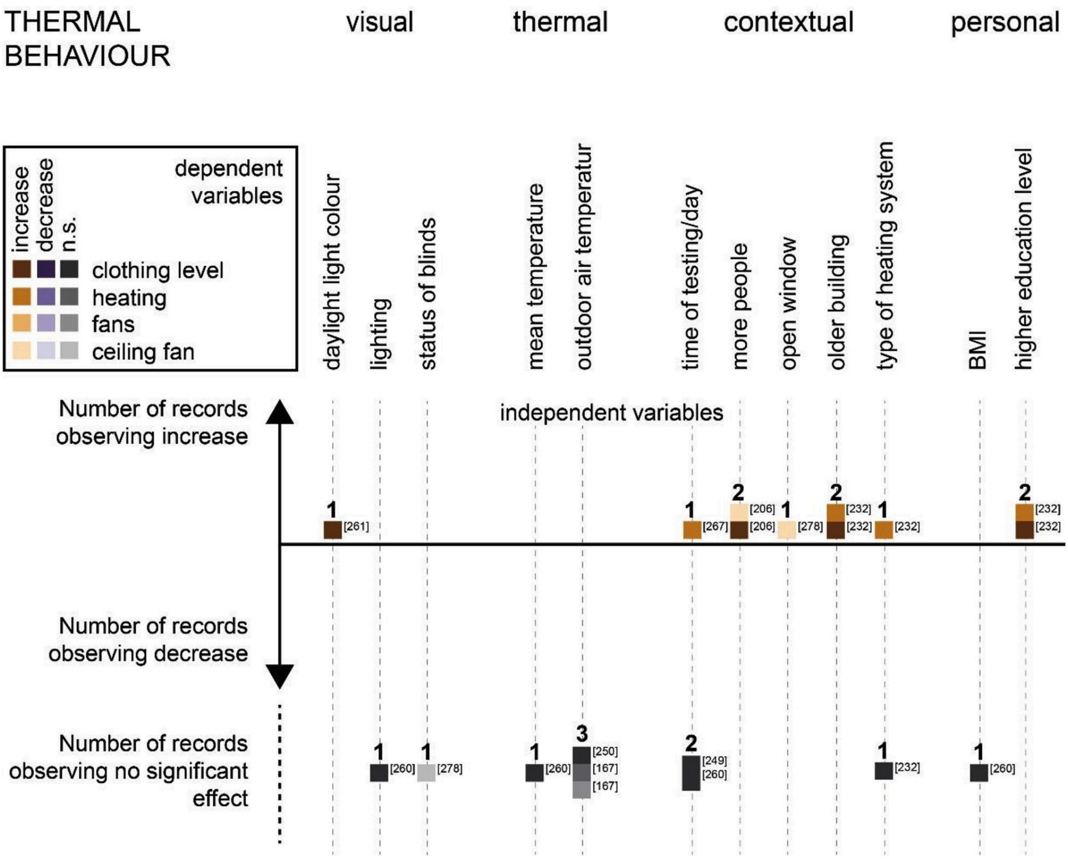

Fig. 10. Effects of physical, contextual and personal variables on different types of thermal behaviours.

the effect of multiple environmental conditions on blind and lighting controls, but still found parameters of solar insolation to be the primary driving force of control decisions. While window blinds are a form of solar and thermal control, and electric lighting is needed in the absence of daylight, it is surprising that all studies suggested that blind and lighting control are univariate problems determined by solar insolation alone.

5.1.4. *Identified gaps and future directions*

Overall, meteorological conditions were not usually measured adjacent to the buildings or sites under analysis, or at least were not reported. Differences in microclimatic conditions, from what is experienced directly outside a building envelope to what is measured from a central weather station are non-negligible. This is a potential limitation of correlations made between weather and human behaviour [226].

Of the studies examining window opening/closing behaviour, works such as Jeong et al. [216] indicate that caution must be taken when data from only one or two seasons are used. In other words, drivers of behaviour in winter may not apply in summer conditions, and studies in either season may not apply to conditions under autumn and spring. The effort to observe occupant behaviour across multiple seasons was, if not a norm across the long-term works, an identified research gap across several of the medium-term studies. As observed by Naspi et al. [222], this may be the main research gap of studies in this subsection.

Despite prior evidence that circadian lighting affects occupants' perception, only the experimental studies evaluated the effect of circadian lighting conditions on occupant behaviour. The study of circadian lighting, both natural and artificial, and its effect on human physiology and psychology warrants further attention by field studies. None of the evaluated field studies explored whether light colours, or other indicators of circadian lighting, affected occupant behaviour. In addition, noise levels were not frequently measured across studies that evaluated window open/close behaviour, even though the relationship between noise and window operation is not trivial [230].

5.2. *Physical + contextual variables*

This section provides insights into thirty-one studies aimed at predicting or explaining behaviours that include at least one type of physical and one type of contextual predictor variable.

5.2.1. *Motivational background*

Similar to the studies identified in subsection 5.1, one of the key objectives behind the majority of these papers is to account for behaviour-related uncertainty in building energy simulation and to develop models, which are hence developed to help bridge the gap between measured and predicted energy consumption [31,167,203,229,231–243]. Some of the studies stated that their contribution was based on the need to develop models for specific geographic contexts or building types (e.g., hospital wards) [244]. Linked to this objective is the investigation of cause-effect relationships between the operation of the building by occupants and different technologies installed [245].

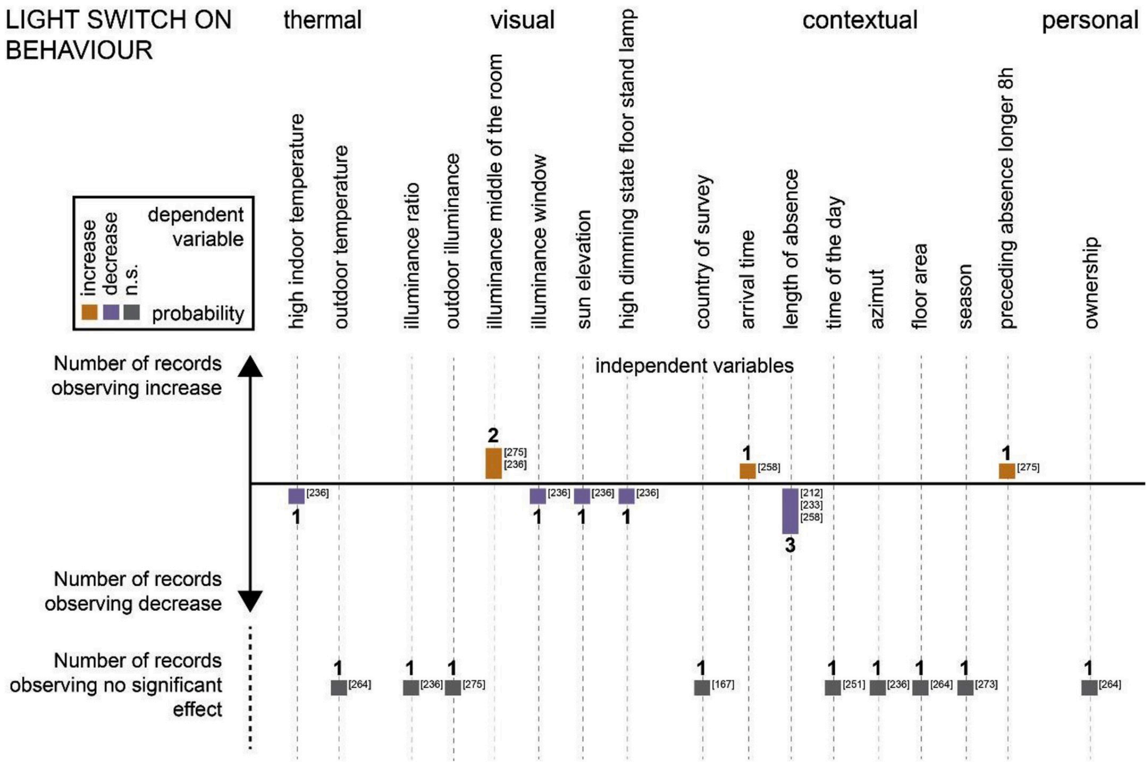

Fig. 11. Effects of physical, contextual and personal variables on light switch on behaviour.

Other studies investigated control interaction for providing enhanced input for building automation control [246] or the optimization of peak electricity loads [175]. Furthermore, researchers stated that the key objectives were to gain better insights into occupants' choices of adaptive opportunities for thermal comfort enhancement in specific climatic contexts [140,247–250], or into the effect of occupancy on perceived control and behavioural patterns [206]. Other papers modelled occupant interaction with certain controls to gain a better understanding on other environmental factors [251].

5.2.2. Approaches

The majority of papers addressed window control (N = 16), window blinds control (7), thermal adjustments (e.g. thermostat adjustment, switching on space heating and/or cooling systems)(7), lighting control (7), and adjustment of fan speed (2). Multi-domain independent variables were related to the thermal environment (36), the visual environment (17), and IAQ (13). Only one record included information on acoustic variables [248]. Amongst these independent variables, the most common for window control behaviour models were those related to indoor and outdoor temperatures [18,167,203,206,231,233,235–238,240,241,244,248,252] and IAQ [18,231,235–237,241,244,248,252]. Blinds behaviour models mostly included thermal variables [167,175,206,229,233,239,253] and visual variables [206,229,233,239,253]. The papers investigating thermal adjustments only included thermal environmental variables in combination with contextual variables [167,206,232,238,245,249,250].

The contextual factors included the time of day or arriving/leaving times [31,203,231,233,236,237,239,240,242,246], the previous control state [203], geographical location [167,238], ventilation type [140,203,238], building system and envelope characteristics (e.g., installed technologies, building envelope efficiency, window opening size) [244,245], facade orientation [175,251], dress code [249], season or cloud cover [175], socio-economics [232], and occupancy levels [206].

Most of the 26 field studies used physical measurements (24) and 11 of them also surveys. Two studies used a combination of measurements, surveys, and observations, and one field study used only observations. The duration of the data collection varied from a few days (laboratory studies such as [206]) up to several years [239].

Some of the studies combined field measurements with a questionnaire-based investigation [140,167,246], or used questionnaires [232] or interview techniques [245] independently. Most records refer to office environments (22), residential buildings (9), and hospital environments (1).

The statistical methods used were logistic regression [236,237,240,242,244], probit analysis [167,203,238], neural networks [231], Markov processes [239], data mining approaches [237], and Bayesian networks [31,241]. Other statistical analysis included Generalized Estimation Equations [246], ANOVA analysis [115], weighted and linear trend lines [140].

5.2.3. Findings

A wide range of studies found a strong dependency between the time of day and window control patterns in offices [203,236,237] and residential buildings [31,235,240,252]. Hansen et al. [232] found that window operation in Danish households was correlated with building characteristics, such as technical installations and energy efficiency of the building envelope, while it was not correlated with the building age. Shi et al. [244] found that windows with large adjustable opening sizes are more likely to be in an ajar state and the interaction frequency is much higher. Based on questionnaires, the indoor temperature at which

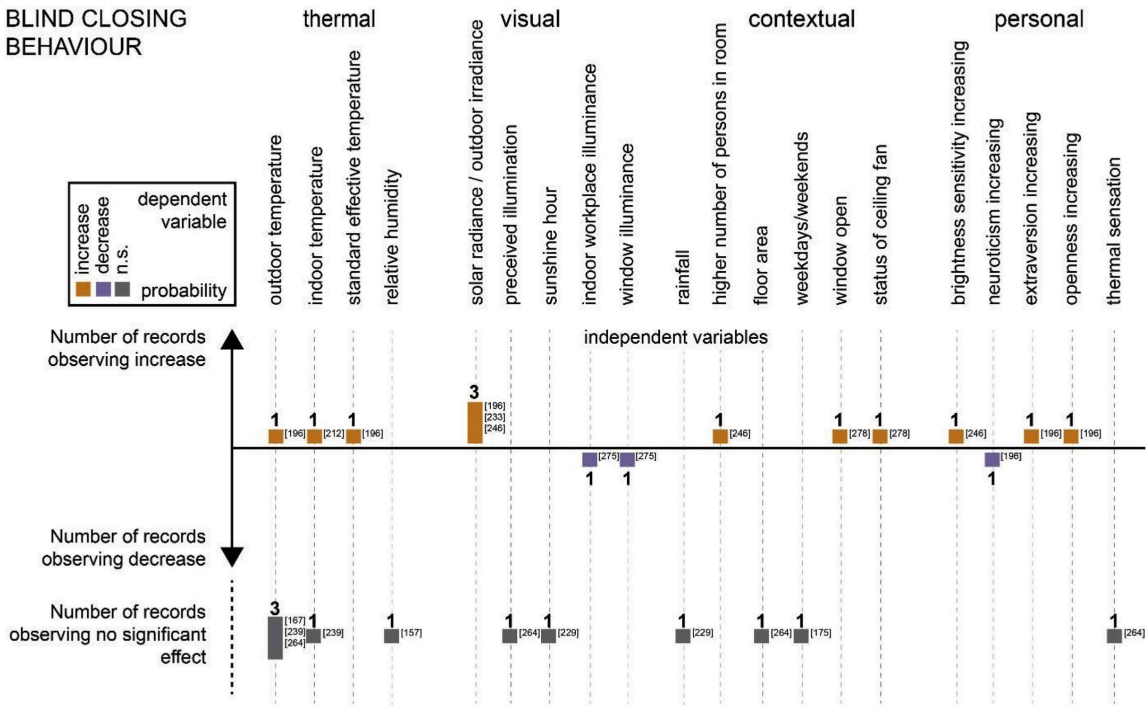

Fig. 12. Effects of physical, contextual and personal variables on blind closing behaviour.

a substantial proportion of occupants start to open windows for ventilation was observed to be similar in all climates, but window use was more common in Europe than in Pakistan [167,238]. Rainfall was also found to have a significant effect on opening a window, along with the location of the office (and its relation to safety) [254].

In line with section 5.1.3, studies including physical and contextual variables found correlations between window operation and IAQ indicators (e.g. CO_2 and VOC concentrations) [31,231,235,236,252]. Stazi et al.'s review [18] found that window opening was mostly linked to CO_2 concentration in residential buildings. According to Fabi et al. [255], all papers that measured IAQ indicators found correlations with window operation.

Several studies found a strong relationship between window blind control operation and the time of day [233,239,246], while others did not [251]. Another important contextual factor influencing window blinds operation is the facade orientation [233,246,251]. Time of day and/or arrival/leaving times play an important role also for light switch behaviour [233,242].

5.2.4. Identified gaps and future directions

Although all studies included at least one contextual variable, further work needs to create a comprehensive approach including a more extensive set of contextual and potentially personal factors.

Regarding contextual physical environmental factors, further attention should be paid to the ease and convenience of using building system interfaces, the state of other devices (or controls) and the influence of building automation routines on behavioural patterns. Furthermore, contextual factors such as interior design and furniture layout, or the relation between the indoor and outdoor environments (e.g., view to the outside) need to be further investigated. Even various social factors, such as social constraints, group interactions, the presence of multiple occupants in open space versus private offices [206], and control behaviour due to safety reasons need to be further investigated. Although some studies compared a few different geographic locations, a more comprehensive approach is needed to understand the variability of occupant behaviour in different climatic zones and/or cultural backgrounds.

Related to the research methodology, relationships between indoor variables and window transitions, based purely on survey responses (e.g. Ref. [167,238]), must be treated with caution. Since the window state affects indoor variables [235,255], conditions just prior to an event are needed to understand the relationship.

5.3. Physical + personal variables

This subsection reviewed six studies looking at physical and personal predictors, which could explain some of the differences amongst adaptive behaviours. The personal predictors include clothing habits, sociocultural expectations, personality traits, and occupancy preferences.

5.3.1. Motivational background

Most studies investigating physical and personal variables concurrently aimed to develop occupants' behaviour models to control building systems.

5.3.2. Approaches

The studies consider thermal systems [256,257], lighting systems [198,258], or thermal and lighting systems [196]. These systems were generally operating in non-stressful conditions (i.e. acceptable environmental conditions). One common dimension considered in study designs is their longitudinal aspect, with studies lasting from a day to many months.

Research exploring physical and personal variables as predictors to behaviour analysed these two predictors independently or jointly.

Indraganti et al. [256] applied descriptive and inferential analyses to explore the relationships between occupants' behaviours (14 control actions) and personal variables (dress habits). In parallel, the relationship between occupants' behaviours (air-conditioning and fan usage) and a physical variable (outdoor daily mean temperature) was explored through logistic regression. Schweiker et al. [196] applied mixed effect regression analysis to explore the effect of physical (thermal and visual) and personal (personality traits) variables on occupants' behaviours (clothing adjustments, window opening, blind closing, and ceiling fan usage). Gunay et al. [258] applied discrete-time Markov logistic regression to explore the effect of physical (ceiling illuminance) and personal (occupant's presence) variables on occupant's behaviours (light switching and window blind actions).

5.3.3. Findings

Most studies highlight that occupants respond to environmental discomfort, but fail to revert the state once discomfort disappears. Gunay et al. [258] observed that occupants closed blinds upon glare and switched on lights upon low daylight; but they then often failed to open the blinds and to switch off the lights. Occupants' locus of control is not a concern in non-stressful or acceptable good conditions [198]. Furthermore, occupants' interactions with building environmental systems may be linked to daily routine and habits [257] and differences in behavioural patterns between sub-populations based on personality traits are considerably high [196].

5.3.4. Identified gaps and future directions

Most studies highlighted a lack of the contextual dimension, including climate, seasonal effects, building types, building orientations, complexity of controls, interior layout, single/shared spaces, and organisational policies [196,198,257,258]. In addition, multi-domain physical predictors are missing except for one study including IAQ [196]. Finally, studies should consider the Hawthorne effect already discussed in section 4.1.4 and by Schweiker et al. [196]. In general, very few studies have systematically assessed the effect of personal variables other than age and gender on behaviour.

5.4. Physical + contextual + personal variables

This subsection summarizes eleven studies looking at the influence of physical environmental conditions and their interactions with contextual and personal factors on occupant behaviour [256,259–268].

5.4.1. Motivational background

As in previous subsections, modelling of occupants' behaviour for use in building performance simulations for office buildings is the main motivation common in studies across the world. Thereby, the main research focus is on window control behaviour, and its impact on the energy consumption.

5.4.2. Approaches

The majority of the publications were field studies, often based on or involving questionnaire surveys [256,257,262,264]. Almost all the studies used logistic regression to evaluate the crossed main effects of environmental and non-environmental factors on the occupants' behaviour. The analysis of the interactions between different predictors has not been established yet, but there is a growing body of literature with results that point out its importance [267,268].

The four commonly studied behaviours are interactions with windows, use of heating controls, electric lighting use, and interaction with shades.

The physical variables were the internal and outdoor air temperature, globe temperature and air velocity. Some studies collected additional measurements of carbon dioxide concentration, particulate matter [266], and solar radiation [267]. Contextual factors included building features and maintenance, the orientation of windows, floor level (security), the type of office, and socio-cultural aspects such as habits and dress code. Personal factors included perceived control.

The number of residential and office building studies was similar, but residential longitudinal studies usually had a longer duration. Office studies benefit mainly from a large number of respondents albeit often using cross-sectional surveys for shorter periods.

5.4.3. Findings

While all studies observed physical, contextual, and personal variables, window use was mainly analysed as a function of outdoor temperature [256,264], indoor temperature, and IAQ [268]. Often, the probability of an opened window is positively correlated with outdoor temperature, but Kim et al. [262] showed a bell-shaped relationship were above a certain ambient temperature this positive correlation is reversed and the number of closed windows increases again. This effect was observed in previous single-domain studies [269] and shows the importance of local context in the interpretation of the observed behaviours.

In an office building in the hot and humid climate region of India, window use was mostly defined by contextual factors such as the time of day, while the occupants did not interact with other building controls [256]. A study in China [266] concluded that the window use in the studied offices was affected by a combination of physical and contextual factors such as the number of sunshine hours. Wei et al. [265] revealed a seasonal effect and a significant influence of the location of the window (ground floor or not) and personal preference (habitual or not) on the "end-of-day" window state. Absence in subsequent days and contextual factors such as daylight saving time and façade orientation did not have a significant effect. Seasonal effects were also evident in a South Korean study [268]. In spring, window use was affected by the CO_2-concentration, whereas in summer the indoor temperature was a significant driver. In winter, indoor temperature and CO_2-concentration did not have a statistically significant effect on window use. Yun et al. [257] showed a significant relationship between comfort and perceived control over temperature in NV buildings and highlighted that a change of the windows' state is more likely with high compared to low perceived control [257].

The lighting behaviour in households was found to be influenced by the solar radiation, perceived illumination, outdoor temperature, thermal sensation and IAQ [264] showing the complexity of the interrelationships between multiple physical and personal variables.

The interaction of household occupants with the radiator thermostat set-points showed that the occupants could be classified into different behaviour categories according to the number of interactions with the heating controls [267]. The set-point changes were significantly influenced by the indoor relative humidity, outdoor ambient temperature, solar radiation, wind speed and time of day.

5.4.4. Identified gaps and future directions

The findings show the importance of contextual factors and how these non-physical factors affect occupants' perception and behaviour. They emphasize the need for systematic analysis of contextual factors and for the study of their interactions with physical and personal variables. However, there is a lack of research into the relationships and interactions amongst multi-perceptual, contextual, and personal factors and their combined influence on occupant behaviours. While there seems to be a consensus on the physical variables measured, there are still differences in the selection of contextual and personal variables and their reporting. The type of building system varied with the particularities of the location (e.g. climate, prevailing architecture and construction typologies) and seemed biased by what the sites permitted and the studies' aims. The main reason could be that these parameters are often "fixed", defined by the building and location and not directly controlled by the researchers.

Contextual factors are mainly referred to generically without systematically assessing their interactions and their impact on other predictors. Noted missing relationships include the effect of different climatic and cultural background factors on window use behaviour [257].

In relation to lighting studies, research is required to assess the effect of light on psychological factors and investigate the duration of the effects on comfort [260].

5.5. Physical + multi-behavioural approaches

The focus of the 13 studies in this subsection is on the interrelations between the indoor environmental conditions with a combination of different behavioural responses [212,225,254,258,270–278].

5.5.1. Motivational background

The aim of these studies is related again to energy savings through more realistic modelling of occupancy behaviour in simulations. The underlying objective was to characterise the relationship between physical environmental parameters and occupant behaviour including the assessment of the interactions and combined effect of multiple behaviours.

5.5.2. Approaches

Similarly to the previous subsection, the behaviours investigated were interactions with windows, heating and lighting controls including electric lights and shading.

In contrast to the previous subsection, the research in this field is focused on office buildings. Window use remains the most prominent behaviour and is studied in combination with personal adaptation behaviours (e.g. physiological responses [278], clothing adjustments, and interactions with the heating and cooling systems [274]). Responses to changes in visual conditions are discussed in light of interactions with shades and electric lighting [212].

The physical variables commonly considered were the indoor and outdoor air temperature, relative humidity, wind speed, illuminance, and the level of CO_2-concentration as an indicator of IAQ. The non-physical variables differed again with the building characteristics and the researchers' objectives and included season, period of day, type of room and current state of controls. However, the analysis of the significance and impact of different variables followed mostly again a cross-main effects approach.

Data collection occurred through surveys with concurrent field measurements, except for one study in a controlled office-like environment [278].

5.5.3. Findings

Despite the influence of indoor and outdoor physical variables, confirming observations of previous subsections, occupancy state (arrival/departure) was the most often studied other behaviour. Langevin et al. [274] found a significant influence of indoor/outdoor temperature and arrival time on clothing, fan, heater, and window use behaviours. While the occupancy state interacted with window opening [236], the previous or next absence for more than 8 h did not have a significant effect on the opening behaviour during departure or the closing behaviour upon arrival [275]. In contrast, the closing behaviour during departure and the opening behaviour upon arrival were influenced by the absence duration. Fabi's review of the physical predictors that influence light switching behaviour identified the key drivers to be absence duration and daylight [273]. Season, light sensor control, and time spent with the light off were not significant predictors. Similarly, lighting use is a function of the daylight availability and the duration of absence before switching the lights on or after switching the lights off [212]. In the intermediate period, the only significant variable is the worktop daylight illuminance level. The same study concluded that the majority of shade adjustments take place during the first arrival or last departure of the day.

Schweiker et al.'s analysis of the interactions between behaviours indicates a significant impact of fan operation and clothing level on window behaviour but no significant effect of sun shading [278]. In addition, the window state significantly affects fan and sun shading use. Sanati et al. [271] found no significant relationship between sunlight availability, window occlusion, and electric light usage in a single university building.

5.5.4. Identified gaps and future directions

The low number of studies in this subsection showed that the influence amongst the studied behaviours themselves is seldom thoroughly assessed. Fabi et al. [236] suggested that there is a need to investigate the correlation of behaviour responses to multiple, instantaneous factors.

6. Discussion and conclusion

Overall, this review reveals the diversity of approaches and findings of multi-domain analysis. This section compares and discusses the findings and identified gaps from individual subsections above.

6.1. Motivational background

In perceptual studies, the main motivation is a better understanding of the phenomena involved. In behavioural studies, the aim is mostly model development for predictive purposes. This does not mean that perceptual studies do not involve any aspects of prediction, but, the authors stated the focus is on understanding, rather than modelling.

6.2. Approaches

A variety of methodological approaches for research design and assessment are presented in the literature. Whereas laboratory studies are the most frequent type of perceptual multi-physical studies (subsection 4.1), field studies dominate in all other categories. New approaches using virtual environment (e.g. Ref. [272]) published promising results, but still lack sufficient evidence that they permit the reproduction of effects observed in reality.

Geographical contexts are mainly from developed countries (https://www.un.org/en/development/desa/policy/wesp/wesp_current/2014wesp_country_classification.pdf), which likely represents the availability of research funding, rather than the contextual diversity or the population size in a particular context. Therefore, the findings presented are not necessarily representative of buildings, lifestyles, climate zones or cultural regions in developing countries.

Context is more likely considered in studies of human behaviour than perception. This may be due to the advantages of laboratory studies to control multi-physical influences on perception without contextual considerations. For example, the experimental design by Kulve et al. [104] enabled researchers to avoid natural correlations among environmental variables and to causally test the effect of variables on outcomes of interest. In addition, it allowed testing if cross-modal effects occurred at a specific level of one variable (e.g., only in comfortable thermal conditions) or were independent of the level of the other variable (i.e. the same cross-modal effect occurred at all the levels of the other variable).

Few studies considered personal variables beyond demographics despite their inclusion by means of questionnaires being an easy extension in laboratory studies. Participants in laboratory studies are not otherwise distracted from their work or leisure activities as would be the case in field studies. Still, the application of findings relating to personal factors in the building design process with generally unknown user profiles is less clear, but potentially beneficial for specific buildings (e.g. retirement homes) or individualized operation strategies.

Contextual influences and occupant behaviour are more difficult to study in an artificial setting of a laboratory environment. The low frequency of interactions (i.e., 1 to 4 actions per day) would require very long and expensive study periods uncommon in laboratory settings. Still, more attempts would be beneficial to reveal true causalities, because field studies also have drawbacks. The lack of experimental control over environmental conditions means that the conditions cannot be causally related to human outcomes, and that environmental conditions are likely to naturally co-occur in predictable ways (e.g., a position near a window in the summer is likely warmer and brighter than one on the interior of a room).

The question of causality is also relevant to several papers addressing contextual factors, such as green vs. conventional buildings or NV vs. AC buildings in field studies with a limited number of buildings. These studies assign observed differences in perception or behavioural patterns to the type of building, while neglecting the multitude of other potential influences (e.g., non-documented contextual or personal differences). Without addressing, discussing, or eliminating potential confounding variables, assigned causalities could be mistaken. For potential meta-analyses and other comparisons, well-documented contextual elements of the environment under investigation are crucial. Unfortunately, contextual elements and spatial characteristics such as relative position to control devices are often poorly documented – if at all – in the text. Therefore, we recommend using the categories presented in Fig. 1 together with aspects mentioned in previously published ontologies [279] to describe the contextual aspects.

The assessment of the dependent variables varies largely. While there are meaningful differences in behavioural studies, the perceptual studies vary in the dimension assessed (e.g., thermal sensation, preference, or acceptability), and the type of scale (e.g., categorical, continuous). There is a tendency to ignore previous approaches and develop one's own instruments, without benchmarking them against existing ones (see also subsection 4.1.4). As discussed earlier [20], this variety impedes comparing results across studies, and understanding whether differences between outcomes of two studies are a result of the instrument or differences in (unreported) contextual or personal aspects.

In addition to the diversity in data collection approaches, the analysis approaches taken are at different levels. Studies, most often in laboratories, exist, which apply multi-domain approaches from study design to analysis. At the same time, the number of field studies reporting the collection of multi-perceptual data is increasing. However, their potential is poorly utilized, because the multi-perceptual nature of the data is not considered during analysis. The reasons for such omission can be manifold. First, limits in word counts in combination with the complexity of describing multi-physical data and their analysis might lessen the potential to report multi-domain analysis approaches first, but cannot be an argument for missing subsequent publications. Second, multi-domain interaction or cross-over statistical analyses might have been conducted, but not reported due to non-significant results; a common issue leading to scientific bias as reported earlier [5]. Third, a lack of statistical skills might have impeded the integration of interaction terms in statistical analysis.

To overcome these shortcomings, all researchers, reviewers, and editors are encouraged to demand extensive descriptions and analysis methods for multi-domain studies until there is a substantial body of evidence that certain aspects are not relevant for a specific perception or behaviour.

Further research shortcomings in all categories are small sample sizes, low diversity in participants, representativeness of samples, and environment. In contrast to previous reviews' discussions [20], which emphasize the general need for larger sample sizes, we argue that the actual number of cases is not the main problem. Examples exist throughout scientific literature in a variety of disciplines, which show the benefits of studies with small sample sizes that still increase the existing knowledge (see Flyvbjerg [280] for an extended discussion). Small sample sizes are to be criticized when lacking a clear strategy for sample selection and being based on so-called convenience samples, i.e. those at hand of the researcher. In contrast, Flyvbjerg [280] discusses information-oriented sampling strategies including the selection of critical cases or maximum variation cases, which enable the extraction of new knowledge even with small sample sizes. At the same time, he emphasizes that small sample sizes are very suitable for falsification of theories – sometimes a single case is sufficient – but less for generalizing.

6.3. Findings

Overall, results are often inconclusive and in part contradictory (see Figs. 8–12). Few observations are repeatedly shown: significant effects of visual properties on thermal perception exist, though they are partially contradictory and a comparable number of studies found no significant interactions. A general statement seems impossible due to findings, that warm light colours are perceived as satisfactory in cold environments and vice-versa. Thermal properties have been shown to influence acoustic perception, while the number of non-significant findings is again of the same magnitude. Related to occupant behaviour, most evidence was observed for the interaction of thermal and IAQ related variables on window opening behaviour. Such a finding is not surprising given that windows enable occupants to control IAQ and thermal conditions except for reasons of outdoor conditions such as high air pollution. Contradictory results are apparent in all categories of multi-domain studies. While such observation can be attributed to the low number of studies in subsections 4.4 and 5.4 and 5.5, it is more surprising for subsections 4.1, 4.2, 5.1, and 5.2, which are based on a much larger number of items.

Despite the large variety of independent variables assessed, there is a need to clarify whether those variables are the most influential ones to explain variances observed in perception or behaviour, or solely the most accessible ones. This necessity is linked to the next gap in the reviewed literature: a missing theoretical foundation. One could assume that many, if not all studies, are based on underlying theories of human physiology and perception. However, very few articles mention theories when describing their study design or discussing their findings. Not all studies need to be designed to falsify an existing theory; case studies, especially very detailed ones looking at individual cases, are also very suitable to develop new theories inductively. Nevertheless, a theoretical foundation is meaningful to link and explain potentially diverse findings and to justify the selection or exclusion of specific physical, contextual, or personal variables. Theories relevant for multi-domain approaches may originate from disciplines like psychology, sociology, but also from neurology or physiology. One of the few research items mentioning theoretical foundations is Candas et al. [21], who mention neurophysiological aspects related to multisensory integration in their introduction. However, they do not relate their review findings to such approaches. The literature on multisensory integration [281–283] outlines first explanations to what extent interactions can be additive, antagonistic, or synergetic. For example, Talsma et al. [283] propose a framework that shows the interaction between multi-physical perception and attention.

There are few studies linking perception and action. In behavioural studies, physical quantities are assessed which relate to perceptual domains. For example, the assessed indoor air temperature can be related to thermal perception. As such, the perception of such physical indoor environmental qualities is an assumed prerequisite for the action. Given the low observed correlations between observed physical variables and behavioural actions (R^2 are frequently below 0.2), it might be necessary to include additional variables or to consider different approaches to understand occupant behaviour. Thereby, several aspects are to be considered. First, perceptual studies show a large variance between and within individuals in the perception of the same physical stimuli. Second, theories in the field of psychology together with empirical findings suggest a difference between the intention to perform an action and the action itself [284–286]. Not surprisingly, previous research has revealed a multitude of factors influencing occupant behaviour [5], which potentially affect the relationship between intention and action (e.g., the level of perceived control, the distance to means of control, or other work tasks that require full attention). Therefore, we recommend looking further at the relationship between perception and action and evaluating whether those contextual and personal factors affecting behaviour effect perception and vice versa.

6.4. Future directions

Based on the results and discussion presented in this review, we propose the following points to be considered by authors and reviewers of future multi-domain approaches.

The first point is easily applicable and points to a limitation of this review: keywords for multi-domain studies. Commonly, an *a priori* defined set of search terms is used for a systematic review. However, an initial review of keywords used by a selection of relevant multi-domain articles revealed that the keywords for the individual domains investigated are used, but that there is no specific keyword to clarify the multi-domain approach. Therefore, a systematic search through a set of keywords would have required searching for all possible combinations of individual domain keywords. Given the number of authors involved and their diverse backgrounds from different domains, we decided to start with the collection of articles known to us in combination with a backward and forward search of cited or citing articles. This strategy might have failed to find all relevant research items. However, articles, which have not been cited or do not cite any of the 200+ articles considered for this review might be of minor relevance and likely not adding much to our general conclusions. Still, we suggest future studies to use a unique keyword such as “multi-domain” or “combined effects” in order to facilitate future review efforts.

Second, researchers should clarify whether their research is intended to explore new influences, i.e. supporting the development of new theories or the extension of existing ones, or test an existing theory. In addition, researchers should clearly state the limitations of their studies, especially when dealing with small samples, discuss the applicability and comparability of results in the context of existing knowledge, and be careful with false causalities arising from unobserved confounding factors. Thereby, generalization is relevant to find common patterns. However, addressing individual differences and revealing factors leading to such differences, even for single cases, is of high importance in order to consider outliers as valuable points of information. The latter assertion is valid either because these points are true outliers and explanations are available (see e.g. O’Brien et al. [287] for a qualitative approach to explain outliers). Or, because they point to methodological issues (e.g., the question asked is prone to misinterpretation under specific circumstances).

Third, advanced statistical analysis methods for capturing interactions and their complexity are recommended. Aside from the application of multiple regression including interaction terms, hierarchical modelling or structural equation modelling, which permit understanding of interdependent relationships, are appropriate methods for this task. Additionally, analysis methods derived from machine learning approaches may be useful to detect underlying patterns in large and rich datasets. When reporting statistical results, significant levels together with effect sizes are crucial information for later meta-analysis.

Fourth, missing agreement on classification of contextual and personal variables leads to the same terms being used for different aspects. Therefore, general classifications (e.g., “green buildings”) should be avoided in favour of explicit descriptions (e.g., LEED Platinum certified buildings).

Fifth, interactions are complex by nature. Given the large variety of potential interactions between physical, contextual and personal variables, collective approaches, which build upon the knowledge generated, are necessary. We thus encourage researchers to join or establish collaborative activities such as those developed within international research groups like the IEA EBC Annex 79 “Occupant-Centric Building Design and Operation” (http://annex79.iea-ebc.org/), which is the basis for this review. Moreover, a common framework is necessary, which facilitates meta-analysis efforts in the future and allows aligning one’s own research with previous research. As a start, our review table is available as a dynamic open-access document permitting others to add their research related to multi-domain approaches (https://osf.io/gnvp2/). We hope that this document will serve as a growing knowledge base to increase collectively our knowledge related to multi-domain influences on perception and behaviour.

Sixth is the balance between the benefit and the risk of increasing the complexity of perceptual or behavioural models partly addressed in behavioural studies by means of statistical measures such as Akaikes Information Criterion [288]. Future studies need to investigate under which circumstances additional factors are meaningful, given issues such as over-fitting and error propagation. This question is best answered based on a solid theoretical foundation together with a clear description of the potential application of the results.

Combining all these conclusions necessitates designing studies within a framework of occupant perception and behaviour that accounts for the complexity of the physiological-perception-cognition-decision-action-automation-building system. First examples for such frameworks have been proposed [289,290] and attempts to challenge them by means of field or laboratory studies are highly recommended. In addition, the development of guidelines on this topic is an expected future development of this work.

Declaration of competing interest

There are no known conflicts of interest.

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Paper b

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Test rooms to study human comfort in buildings: A review of controlled experiments and facilities

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ABSTRACT

Occupants' comfort perception affects building energy consumptions. To improve the understanding of human comfort, which is crucial to reduce energy demand, laboratory experiments with humans in controlled environments (test rooms) are fundamental, but their potential also depends on the characteristic of each research facility. Nowadays, there is no common understanding for definitions, concepts, and procedures related to human comfort studies performed in test rooms. Identifying common features would allow standardising test procedures, reproducing the same experiments in different contexts, and sharing knowledge and test possibilities. This review identifies 187 existing test rooms worldwide: 396 papers were systematically selected, thoroughly reviewed, and analysed in terms of performed experiments and related test room details. The review highlights a rising interest in the topic during the last years, since 46% of related papers has been published between 2016 and 2020. A growing interest in non-thermal sensory domains (such as visual and air quality) and multi-domain studies about occupant's whole comfort emerged from the results. These research trends have entailed a change in the way test rooms are designed, equipped and controlled, progressively becoming more realistic inhabitable environments. Nevertheless, some lacks in comfort investigation are highlighted: some continents (like Africa and South America) and climate zones are found to be underrepresented, while involved subjects are mainly

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students performing office tasks. This review aspires to guide scientists and professionals toward the improved design or the audit of test room experimental facilities, especially in countries and climate zones where human comfort indoors is under-studied.

List of abbreviations

IEQ	Indoor Environmental Quality
WWR	Window-to-wall ratio (expressed in %)
HVAC	Heating, Ventilating and Air Conditioning
ACH	Air Change per Hour
VOCs	Volatile Organic Compounds
SPL	Sound Pressure Level (expressed in dB)
SBS	Sick Building Syndrome
EEG	Electroencephalogram
EDA	Electrodermal activity
ECG	Electrocardiogram
EOG	Electrooculography

1. Introduction

People in developed countries spend 85–90% of their time indoors [1]. Notwithstanding undeniable improvements in the quality of building interiors in the past decades, a range of health risks and discomfort issues associated with exposure to the indoor environment persists. Researchers have demonstrated the strong connection between the indoor environmental quality (IEQ) of a building and occupants' comfort, health, and productivity [2,3]. Moreover, buildings' energy consumption is largely affected by occupants' behaviour [4], triggered by their perception of the surrounding environment [5]. Therefore, decoding human comfort is a crucial issue in building science for enhancing building design and operation from a sustainable perspective and through a human-centric approach [6].

The scientific community approaches human indoor comfort by coupling measurements of the physical environment (e.g., air temperature, sound pressure level, air pollutant concentrations, illuminance) and occupants' feedback collected via surveys, behavioural and/or physiological monitoring. Applied experimental protocols can be broadly categorized into (i) in-field monitoring and (ii) laboratory experiments.

In-field experiments allow researchers to observe subjects in a real environment such as workplaces [7,8], residential [9] or educational [10] buildings, or even semi-open transitional urban spaces [11]. This approach provides essential outcomes, especially for assessing the impact of real-space configurations on occupants' perception [12], the effects of building characteristics on occupants' wellbeing [13], or the impact of occupants' behaviour on buildings' energy consumption [14, 15]. However, it does not allow to directly control the environmental parameters of the investigated spaces. Indeed, it is not feasible to isolate the contribution of a single environmental factor or a specific combination of multiple environmental stimuli on subjective responses, for example, overall comfort perception or productivity [16] in in-field research, while this is fundamental to establish a cause-effect relationship related to the comprehension of human comfort and the related occupancy behaviour [17]. These issues can be solved through experiments in controlled environments where desired physical boundaries can be determined and replicated, so different subjects can be exposed to the same stimuli and the influence of subjective factors elucidated [18]. Moreover, laboratory experiments generally allow researchers to perform a more detailed investigation of human subjects and collect physiological signals less commonly monitored in-field.

Many research institutions have built their own environmentally controlled experimental facilities to perform human comfort-related experiments worldwide and throughout the years. Each facility is designed to achieve specific research goals, thus presenting different dimensions, internal layouts, envelope characteristics, energy systems, and monitoring setup. Different equipment types are also included depending on the final aim of an experimental campaign targeting a specific comfort domain. Examples include thermal manikins, commonly simulating human thermal comfort [19] or inhalation exposure [20], or different apparatus for studying the human reaction to specific environmental input such as glare discomfort [21,22]. The test room design influences the experimental design and the accuracy of related modelling. The construction and technological details of the test room decide on the extent and scope of the different stimuli that can be provided as well as the different spatial layouts that can be generated. Being an essential determinant of experimental methodology, a careful design process of these facilities is of primary importance.

Due to the rising interest in better understanding human comfort, many reviews shed light on different perspectives of the topic. Several reviews summarise visual-related studies, reporting both lab and field investigations, as well as simulation studies [24–27]. Others focus on thermal comfort and different modelling approaches [28], main experimental procedures [29,30], or its energy-related implications [31]. Nevertheless, none addresses the diversity of laboratory facilities, which is a key component in the design of human-centred comfort experiments.

The identification of standard tools for advancing knowledge in the field would be helpful for the scientific community. An accepted glossary for identifying such facilities is still missing. Many papers refer to these facilities as test rooms or chambers or test-cells or simply laboratories. Here, "test room" was chosen as the most representative definition, highlighting the differences between facilities designed for human comfort studies and laboratory equipment devoted to material testing. Moreover, we define a "test room" as an enclosed space, environmentally controlled and properly instrumented, in which human-centric comfort studies can be performed through actual occupants' presence and monitoring.

This review aims at describing existing test rooms worldwide and at summarizing experimental studies on human comfort performed in such facilities to outline trends in the field, common components, and define new research perspectives. Precise selection criteria of the papers have been identified and used for the critical review (Section 2), and common technical features and trends in construction have been taken into account (Section 3), while Section 4 focuses on the specific experiments conducted in these facilities to deepen human comfort theory. Each experiment was categorized based on the type of domain(s) of human perception involved (thermal, visual, olfactory, and aural). In this context, a distinction was made between single-domain studies, which describe experiments focusing on thermal, visual, indoor air quality or acoustical stimuli only, and multi-domain studies [18,32], which simultaneously address two or more domains; for instance, the analysis of thermal and acoustic stimuli on overall comfort perception, or the analysis of thermal perception as influenced by lighting or air quality conditions. The key findings and conclusions, including suggestions for future research agenda, are summarised and critically discussed in Sections 5 and 6, respectively.

2. Materials and methods

A systematic bibliographic search was planned and conducted to establish a database as comprehensive as possible, looking at existing test rooms for human comfort experiments according to available scientific literature and not to miss any test rooms that the authors are aware of. The final database is thus the result of two main steps: an automatic search and a supplementary hand search (Fig. 1).

The automatic search was systematically conducted through Scopus and Web of Science scientific databases to identify papers concerning human comfort investigation in test rooms, as available up to June 2020. The search was limited to journal papers written in English after 1985 to keep the search consistent between the two scientific databases due to the temporal limitation of Web of Science. To cover the scientific literature on the theme published before 1985, a further search was conducted in Google Scholar. Different typologies of documents such as books, book chapters, reviews, or conference proceedings were thus excluded from the search to improve consistency and avoid repetitions of the same study that may have been presented in different document types. Five queries were designed within these boundaries, corresponding to each aspect of indoor human comfort. The queries were structured in three parts, progressively focusing on the purpose of the review:

(i) on the laboratory facility where human comfort experiments took place,
(ii) on the main aim of the studies, i.e., human comfort, and
(iii) on the specific comfort domain of interest (e.g., thermal, visual, acoustic, air-quality related).

Each part of the query was detailed after a discussion among the authors that are experts in human comfort studies and come from different countries and cultural backgrounds. These cultural differences provide a comprehensive definition of the facilities object of the review. The first two parts of the query were used for all the five queries and consisted of the following keywords: (testroom OR test-room OR chamber OR laborator* OR "test cell") AND comfort. The term "human" was not included for not missing any contributions that may fit the scope but did not explicitly mention humans' involvement. The publications not dealing with human comfort were excluded through the double-screening procedure, as specified in the following. In addition to these keywords, the five queries were distinguished by including the following specific keywords:

1. Thermal
2. Visual OR Lighting
3. Acoustic
4. Air quality OR Pollution
5. Energy

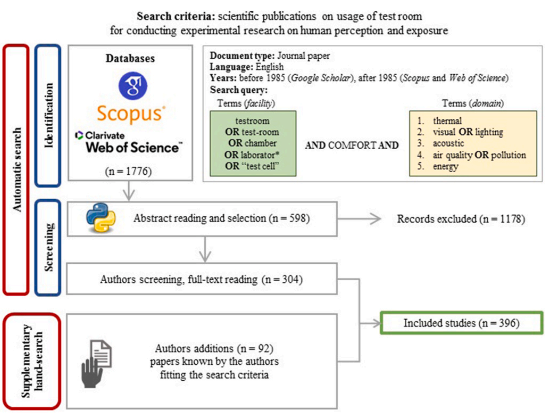

Fig. 1. Papers selection workflow.

Each specific query focused on a single comfort aspect addressed from the perspective of the provided physical stimulus, as associated with thermal, visual, aural and olfactory human perception. In contrast, the fifth query focused on the theme of energy that is commonly associated with human comfort studies aimed at improving indoor environmental quality while reducing building energy consumption.

The automatic bibliographic search resulted in 1776 papers. A cleaning procedure of the database was performed by focusing only on experiments both carried out in a controlled environment and addressing human perception and exposure. This procedure accounts for two main steps. The first screening was conducted through a specifically developed script in Python language for automatic abstract screening by excluding papers presenting specific words referred to out-of-scope disciplines such as medicine or veterinary medicine. After this first screening, 598 papers were still included in the review process. and went through the second screening phase: the papers were carefully read and selected according to the primary purpose of the review. Only papers describing experiments performed in the controlled environments (test rooms) whose internal dimensions and conditions were suitable for human experiments were considered for this review.

The hand search was carried out for reducing the automatic search biases and limiting the number of existing test rooms not covered by this review. Additional papers were included according to the previous knowledge of the authors and the selection criteria that is the usage of a controlled environment for conducting experimental research on human perception and exposure. More than half of the additional papers (49 out of the 92) concern the visual comfort domain, meaning that common keywords coming from the other domains were not suitable to catch all the visual comfort studies. The final number of analysed papers was 396.

Table 1 summarises the number of analysed papers per topic and year of publication, considering four time periods: (i) up to 2000, (ii) 2001–2010, (iii) 2011–2015, and (iv) 2016–2020. Defined time periods highlight the considerable increase in published papers on controlled test room experiments on human comfort. Indeed, the increase ratio observed during the first decade of the 21st century (1.9) is comparable to the one observed for the first (1.5) and second (1.7) part of the following decade.

The table depicts a predominant interest of the scientific community in thermal comfort investigations (conducted either in isolation or in combination with other factors) followed by energy-related studies (total of 85 papers) and visual comfort assessments. Air quality studies are less common, especially as a single stimulus for the participants involved in test room experiments. Indeed, the total amount of reviewed papers related to air quality assessment is 84. Only 18 of them were found to focus on air quality only as a single stimulus, disabling the olfactory from the thermal perception and all the other spheres of comfort. More detailed presentation of the aims and procedures of the air-quality-only studies is provided in Subsection 4.4.

Fig. 2 shows trends of publication for each specific domain of comfort, without distinguishing between single and multi-domains experiments, with respect to studies published before 2000. Thermal comfort-related experiments present the slowest increasing ratio from the reference scenario. Air quality-related experiments show the greatest increase in the number of published papers, with a slight decrease in the last five years. A similar trend can be observed for energy-related studies. Visual comfort-related studies are gaining more attention with currently seven times more papers compared to available publications before 2000. Aural comfort is the least investigated domain in controlled environments. Reviewed papers including a focus on acoustic comfort are 32 in total, half of which published in the last five years.

3. The test rooms around the world

From the 396 papers selected according to the systematic review process, 187 different test rooms located in 126 research institutes around the world have been identified based on the descriptions

Table 1
Number of journals papers published throughout years (up to June 2020) and concerning each analysed topic.

Domain(s)		Time periods				
		≤2000	2001–10	2011–15	2016–20[b]	Total
1 domain	Thermal	26	39	50	89	204
	Air quality	3	3	4	8	18
	Acoustic	0	2	2	7	11
	Visual	5	10	23	32	70
2 domains	Thermal + Air quality	0	10	22	19	51
	Thermal + Acoustic	0	3	0	3	6
	Thermal + Visual	1	0	1	17	19
	Air quality + Acoustic	0	1	0	1	2
	Air quality + Visual	0	0	0	0	0
	Acoustic + Visual	0	0	1	1	2
3 domains	Thermal + Air quality + Acoustic	1	0	1	1	3
	Thermal + Air quality + Visual	0	1	1	0	2
	Thermal + Acoustic + Visual	1	0	0	1	2
	Air quality + Acoustic + Visual	0	0	0	0	0
4 domains	Thermal + Air quality + Acoustic + Visual	0	0	1	5	6
Total		37	69	106	181	396
	energy related[a]	5	15	29	36	85

[a] The energy-related topic is transversal to the others.
[b] The count for 2020 considers only those documents indexed until June 2020.

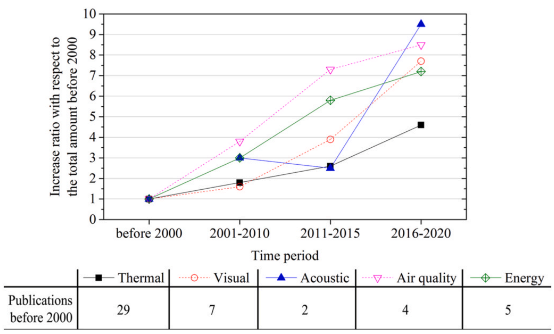

Fig. 2. Publication increase ratio with respect to the number of published papers before 2000 for each query.

provided in the papers.

Fig. 3 summarises the test rooms distribution across continents (a,b) and different climate conditions (c), referring to the Köppen-Geiger climate classification [33]. Nowadays, the great majority of test rooms are located in Europe and Asia (82%), and in a temperate climate, without dry seasons, characterized by hot (Cfa) and warm (Cfb) summer. 29 out of the 44 test rooms located in the Cfa climate zone are in Asia (South and coastal area of Japan and South-Eastern China mainly), while 54 out of the 57 test rooms located in Cfb zones are in Europe (North-Western countries mostly). Fig. 3b presents how the worldwide distribution of these facilities varied across time (all the test rooms were dated per the oldest related paper available in the review dataset). European countries have the oldest tradition in human-related experiments conducted in controlled test room settings: 50% of the facilities already existing before 2000 were located in Europe. The number of facilities in Asia has grown over the last 20 years from 18 to 41% of the total number worldwide in 2020, overcoming the number of facilities located in North America (13%).

The following subsections are intended to provide helpful information for researchers evaluating whether to create or buy a test room for human comfort studies. These illustrate the range of test room characteristics that enable the researcher to perform different experiments and investigate specific aspects of human comfort. An overview of construction and technical details is provided in section 3.1 and 3.2, in accordance with the available information from the reviewed papers. Then, sections 3.3 and 3.4 provide insights into the economic investment required to set up these kinds of facilities, either if these are customized or commercially available. Since none of the reviewed papers provides information on test room costs and related economic investment, data provided in sections 3.3 and 3.4 come from an additional search: an online survey was submitted to authors of the identified significant and recent literature, seeking details on key aspects of the needed economic investment (including design, construction, operation and maintenance costs). Finally, commercial test room producers (eight institutions from the U.S. and five institutions from Europe) were directly contacted to provide dedicated insights for the readers, reported in section 3.4.

3.1. Construction details

The construction details were specifically examined to determine how passive elements of the test room, including windows, shades, layout, size, and position within or external to an existing building, may allow or hinder different types of investigations. Unfortunately, comprehensive descriptions of the test rooms construction details are not always available. It was not possible to assess whether the test rooms are located inside a building or are entirely independent buildings for 10% of the 187 test rooms identified. According to the available information, only 7% of the facilities are independent buildings, external to any other building [34–47]. Five of these independent test rooms are located on a platform that allows the whole structure to rotate [34–37, 41]. The great majority are situated inside the related research institute. Among these, it is possible to distinguish between facilities completely detached from the surrounding structure (43%) and test rooms that are specifically equipped rooms within the hosting building (32%).

Some test rooms include more than one room. These rooms could be adjacent, but with independent entrances, or connected through an intermediate door. The latter configuration allows researchers to continuously monitor participants' reactions when exposed to different controlled environmental conditions [48]. Eight of the external facilities have just one room, but the possibility to work with movable internal partitions is mentioned for four of them [38,41,43,44]. The other six outdoor test rooms present two rooms, and four out of the six have movable partitions for changing the interior space layout [34,35,40,45]. For the inside test rooms, single room configurations are most common (79%), some of which can be modified through movable interior partitions (19%). More information about the number of rooms embedded in the test rooms and their dimensions are summarised in Table 2.

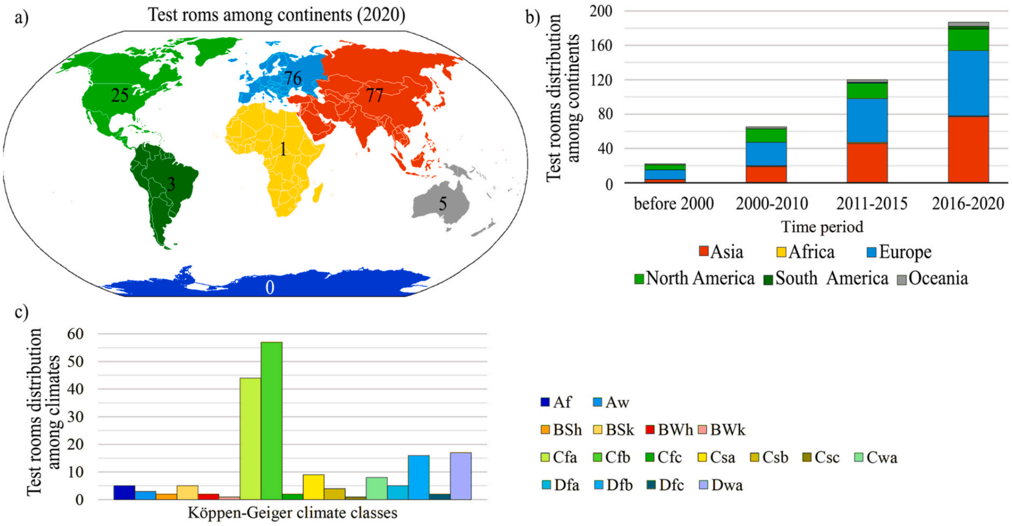

Fig. 3. (a) Number of test room facilities located in the seven continents; (b) amount of test rooms located in each continent for each defined time period; (c) frequency distribution of test rooms with respect to Köppen-Geiger climate classes [33].

Table 2
Test rooms composition and dimensions with respect to their position (inside or outside another building).

Test rooms position		Number of rooms				Dimensions [m^3]				Total
		1	2	>2	N/A	<9	9–20	>20	N/A	
Inside	Detached[a]	53	8	1	4	5	16	36	9	66
	Integrated[a]	37	8	2	2	0	4	43	2	49
	N/A	32	2	0	6	1	5	20	14	40
Outside		8	6	0	0	0	4	10	0	14
N/A		7	1	0	10	0	1	4	13	18
Total		137	25	3	22	6	30	113	38	187

[a] With respect to the building structure of the related research centre.

It was not possible to define whether the described test rooms present any type of openings for 41% of the recognized facilities, 25% of the test rooms located inside have no openings, 18% have windows facing the outside, 16% have windows to interior spaces, and just 2% have both windows to the outdoors and the indoors (Fig. 4). Among the 14 experimental facilities built outside, only one does not have windows [46]. At the same time, five include an adjustable envelope to vary the window-to-wall ratio (WWR) [35,37,41,43,45], five have a WWR lower than 0.5 [38,39,42,44,47], and three have a WWR in between 0.6 and 0.8 [34,36,40]. Concerning the shading system, it is clearly stated that there are external blinds in three test rooms [34,36,47], four present internal shading systems [38,40,42,44], while just one has both [39].

Half of the test rooms have no specific internal layout, meaning that there is no intention to simulate a real space but only to expose subjects to controlled environmental stimuli. Equipment for performing physical exercises are included in 10% of these test rooms [49–64]. All the others have no specific furniture, even if 49% are larger than 20 m^3. Finally, 12% of the analysed test rooms are presented in different papers with different internal layouts, 32% are equipped as offices, 3% as classrooms [65–69], and less than 1% present other configurations [70–73].

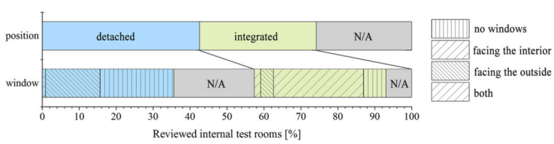

Fig. 4. Overview of the most common combination of characteristics for inside test rooms, in terms of its position with respect to the main structure and the windows availability.

The above presented physical characteristics of the reviewed test rooms can be associated with their capability of performing different types of experiments, focusing on different domains of human comfort. The external test rooms are more commonly devoted to visual-related experiments. Indeed, six out of the 14 exterior test rooms are associated with visual-only experiments, while only one was used for testing human comfort conditions due only to thermal boundaries. When more than one domain is explored, four test rooms hosted experiments providing combinations of thermal and visual stimuli; the air quality influence was additionally explored in one test room while all the four domains of comfort were explored in only two of the 14 external test rooms.

With respect to performed experiments, it is more complicated to deduce the most common combination of construction details for the test rooms located inside other facilities due to a lack of information on all the analysed features. Only 82 out of 155 reviewed test rooms are described in terms of both (i) their position in the hosting facility (detached or integrated) and (ii) windows availability facing the inside or the outside. Accounting for these two aspects, detached test rooms generally have no window (56%) and are more commonly adopted for investigating human comfort under thermal stimuli only (46%). Those test rooms that are integrated into the main structure, as specially equipped rooms, commonly have windows facing the outside (68%) and are mainly used for experiments on visual domain only (54%).

3.2. Technical details

Similar to the presentation of construction details, the technical capabilities of the test rooms directly inform what types of experiments can be conducted. Specifically, this subsection outlines which parameters are controllable and to what degree. As a first step, an analysis of the most common parameters that could be controlled by the test room systems was conducted. For this purpose, the relevant information was extracted from the corresponding papers for each test room and categorized as presented in Table 3.

This categorization is more granular than the multi-physics domains introduced in Section 2 (thermal, visual, air quality and acoustic comfort) to better characterize the specific system types used to influence each domain parameter. Indeed, in some cases, multiple controlled parameters will impact a single domain such as air temperature, mean radiant temperature and incoming solar radiation, all impacting thermal comfort. Additionally, the controlled parameters were subdivided into centralized and personalized systems (generally located at a desktop or at a participant/manikin). In the process of this categorization, 91 test rooms were selected for further analysis because related publications provided relevant and sufficient information. Fig. 5 summarises the number of test rooms which can control each of the listed parameters. In some cases, one test room is counted multiple times in this plot, once for each parameter its system controls.

The most common centrally controlled parameter is air temperature, followed by humidity and air quality control. All these three parameters can potentially be controlled by HVAC (Heating, Ventilation and Air Conditioning) systems with a humidifier and/or dehumidifier equipment, heating and/or cooling coils, and air filtering. The common practice of controlling thermal conditions in actual buildings, together with the predominant focus on thermal comfort studies (highlighted in Section 2), is likely why these controlled parameters are found to be so common. Fig. 6 summarises the ranges for each of these three controlled parameters for all of the test rooms where ranges were reported. As shown, nearly all the test rooms can control air temperature between 15 and 30 °C, and relative humidity between 30 and 70%, but air-speed control was more variable. Almost all test rooms were able to control these parameters at least in the ranges covered by indoor comfort standards such as ISO 7730 [74] and, in many cases, well beyond this range, particularly with respect to the seven low-temperature chambers.

Only a few papers included details of the other parameter ranges. Control of air change rates in the test rooms, which is accomplished through multi- or variable speed fans, ranged from 0 to 36 air changes per hour (ACH) but generally allowed for control within the minimums required by the EN 12931 (0.5–3.6 ACH for residential buildings) [75]

Table 3
Categorization of technological systems and related controlled parameters.

Technological control system for comfort	Controlled parameters
Ventilation and space conditioning	Air temperature Air velocity Air humidity Air quality (gas concentration, air changes per hour)
Heating/cooling surfaces	Envelope superficial temperature Radiator or other element temperature (e.g., clothes, furniture)
Light sources	Illuminance Solar radiation (artificial, e.g., solar simulator) Solar radiation (natural, e.g., actively controlled blinds and shades, electrochromic glass)
Acoustic systems	Background noise level (sound intensity, sound pressure level) Sound typology (soundscape)

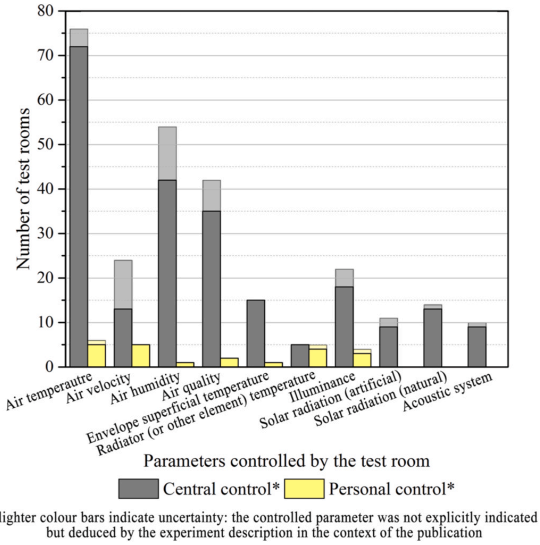

Fig. 5. Frequency distribution of reviewed test rooms which can control the listed parameters.

and by EN 16798 part 3 for offices (1–8 ACH) [76]. Only five test rooms reported the temperature range at which their radiant wall systems (either electric or hydronic panels) could be controlled (generally between 10 and 40 °C). For rooms with reported artificial lighting, the range 100–800 lx covered and exceeded the requirements (e.g., EN 12464) [77]. A few publications also reported the ability to vary the correlated colour temperature of the artificial light (2000 K to 10,000 K). There was insufficient information about artificial solar radiation and acoustic systems to report ranges here.

Only 11 of the reviewed test rooms included parameters that could be controlled at a personal level. Furthermore, most of these personalized systems were only temporary for specific experiments and not a fixed part of the test room. Typical setups would be ventilation tubes aimed at a desktop, heated/cooled clothing and chairs, electrical heated mats or computer equipment (mouse, keyboard), and electrical radiators.

The parameters controlled by the test rooms were also examined based on the estimated date of construction of the test room to identify trends or most prevalent innovative technologies, as shown in Fig. 7. It is also unknown if or when test rooms have been upgraded, nor do we have insight about the upgrades made. Thus, the results in Fig. 7 represent the latest built stage of the test rooms according to the publications and may differ from their technologies at the given date of construction. The graph suggests a trend towards incorporating the control of acoustic sources, artificial and natural solar radiation, illumination, and radiant heat sources, including radiators and radiant wall panels.

Furthermore, the analysis revealed that personalized control systems are becoming popular in newer test rooms constructed after 2000. Finally, in the latest test rooms built between 2011 and 2020, there also seems to be a trend for controlled multi-domain installations with six test rooms since 2013, controlling at least three domains.

3.3. Economic investment

The economics of test rooms is rarely reported. Therefore, a survey to assess key elements related to this topic was designed. All co-authors of this manuscript and authors of identified literature were invited to complete it. In total, 18 responses related to separate test rooms were

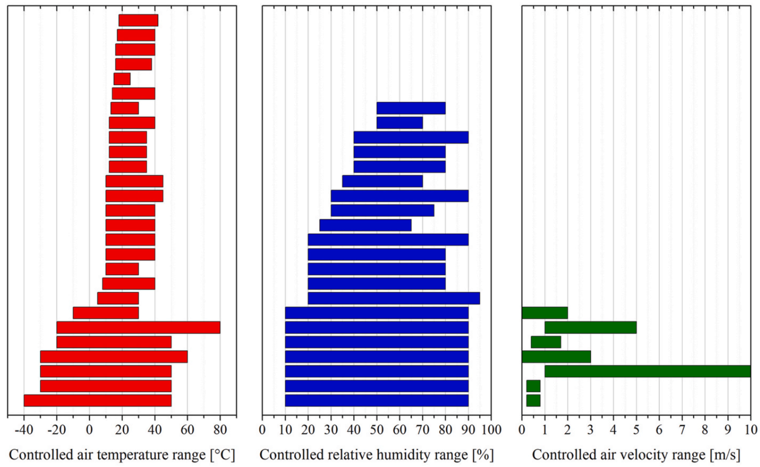

Fig. 6. Ranges of controlled air temperature, relative humidity and air velocity in the reviewed test rooms.

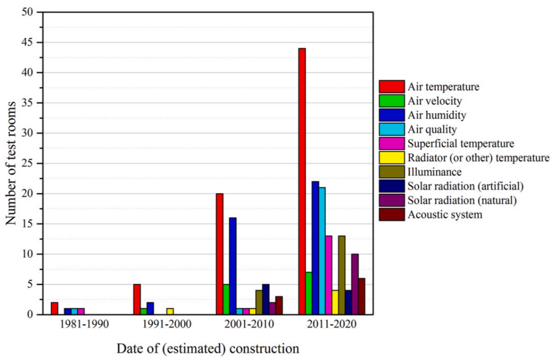

Fig. 7. Time distribution of implemented technologies for controlling specific parameters (see the legend) identifying trends in test room construction.

obtained, of which 14 have been completed, and four are still under construction. Except for one completed in 1990, all others have been built within the last ten years. The majority of the test rooms is either a test room constructed within an existing building (N = 8) or a building itself (6). Three test rooms are newly built test rooms within a new building, and one test room is an existing room refurbished and upgraded to serve as a test room. The vast majority is located in Europe (13), followed by Asia (3) and North America (2).

Local currencies have been converted to EURO based on currency rates from September 4th’ 2020. The total budget ranges from EUR 45,500 to EUR 943,000 (mean = EUR 347,000 ± 299,000, median = EUR 240,000). For eight test rooms, information was provided in more detail. On average, shell construction costs (especially for those test rooms built as stand-alone test rooms within new buildings) are highest (mean = EUR 175,000), followed by costs for design, contracting, and commission (EUR 91,000), heating and cooling system (EUR 31,000 and 34,000), and in-built sensors and the Building Management System (EUR 33,000 and 19,000). This large variety can be explained partly by the variety in the type of construction, controlled and monitored variables and the ranges within which these variables can be controlled. In addition, it can be expected that prices vary locally and between countries. Seven out of 18 test rooms were fully funded by governmental sources, either from basic funding (N = 3) or project funding (4). In addition to public and project funding, five test rooms were partially funded by the industry (min 5%, mean 24%, max 70%).

In addition to initial construction and installation costs, running costs (e.g., electricity, gas, water) and/or maintenance costs were assessed. Running costs were reported solely for three test rooms, but differed largely (EUR 2500 to 17,500 per year). Interestingly, the source of funding for running costs was provided for 14 test rooms, of which nine responded that the university pays for running costs, three state project funding, and the other shared funding either between the university and the lab (10/90%) or the university and project funding (20/80%). The large discrepancy in response numbers between actual costs and funding source may signify that researchers are not aware of the running costs. Maintenance costs were provided for eight test rooms and range between EUR 930 to EUR 10,000 per year (EUR 5100 ± 3500). Funding sources for maintenance costs vary more than running costs for 12 out of 14 facilities, for which such information was provided. In three cases each, maintenance is paid fully from the laboratories’ basic funding or project funding. In two cases, the university covers all maintenance costs. In the other cases, maintenance costs were shared between the university, basic funding of laboratory and project funding with varying degrees. Only in one case, 25% of maintenance costs are provided by industrial partners.

3.4. Commercial test rooms

Commercial test rooms are available on the market to provide researchers who want to use an already existing and tested product with an off-the-shelf option. These test rooms tend to use a similar structure and envelope materials as prefabricated foam-insulation panels with stainless steel, galvanized or coated aluminium (usually white) interior surfaces for fast and easy installation. This is for protecting the test room surface from being damaged or corroded by moisture and chemicals. The stainless-steel chamber can also help minimize the adsorption of VOCs by the surfaces, which is critical to some indoor air quality studies. However, for human-centred thermal studies, the reflective properties of the interior surfaces also determine the radiative heat exchange in the space, thus additional materials or painting are needed to simulate a ‘real-life’ condition. The test room usually has at least one hinged door made of the same material and optional windows of different sizes. Important differences between offerings tend to be in the type of airflow achieved in the test room. Cheaper and smaller systems tend to have the heat exchangers inside the room and achieve spatial stability by producing turbulent flows. More laminar flows are achieved with wall-to-wall or floor-to-ceiling air flows across the whole wall/floor, which requires a plenum space inside the test room, thereby increasing the external size. Most of the rooms come with predesigned and pre-packaged conditioning systems that can provide space heating and cooling, ventilation, humidification, and dehumidification to the room. Air temperature, relative humidity, and ventilation rate are under control and monitored. Some test rooms are even equipped with pressure, CO_2, and O_2 sensors.

The operating condition of commercial test rooms depends on their application that can be testing equipment, storing experimental materials, and also human-centric tests. Here, since we only focus on the test rooms for the human-centric test, the surveyed test rooms only include those capable of providing conditions indicated by the green box in Fig. 8.

These commercial test rooms can be as small as 1.5 m^2 and as large as up to 10 m^2 with a height in between 2.4 and 2.6 m. The price of the test rooms (N = 13 units personally contacted by the authors) ranges from EUR 54,600 to 210,000. The average quote from U.S. companies is around EUR 128,100 with a standard deviation of EUR 44,000, while the average quotation from Europe is around EUR 99,800 with a standard deviation of EUR 27,400. On average, the test rooms from the U.S. (8) are a little more expensive than in Europe (5). The explanation may include regional reasons such as shipping and labour, material and sensors cost, and size difference. One should note that the size and quotes obtained in this study are based on the smallest test room with the basic features of temperature, relative humidity, and ventilation control with at least one occupant. The quotes were obtained in August 2020, and for the commercial test rooms made in the U.S., the quote was converted to EUR based on the exchange rate on September 4th, 2020 [1 USD = 0.84 EUR].

4. Test room experiments on human-environmental comfort

This section focuses on the experiments conducted in the test room above presented in terms of their structure and main functionalities. Each subsection presents an overview of the main aims and procedures of test room experiments answering the question, what is the scientific

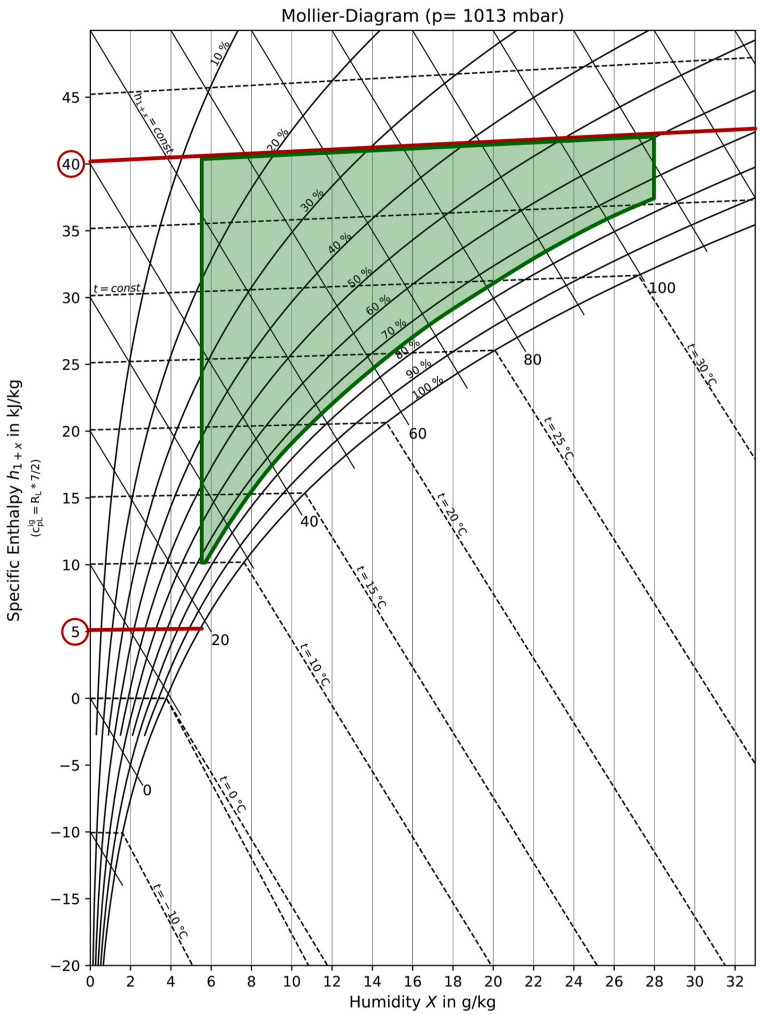

Fig. 8. Required operating conditions of the surveyed commercial test rooms.

community looking for through test room experiments? Scopes of the experiments are broadly clustered in the presented subsections with respect to (i) the comfort domain of interest (sections 4.1-4.5), (ii) the subjects' involvement (possibility to interact with the test room during an experiment, section 4.6), and (iii) the investigation of the energy related aspects (section 4.7), which are all relevant aspects for human comfort studies. Concerning the applied procedures, the main distinction is adopted between stationary and dynamic conditions.

4.1. Thermal-only experiments

This subsection reviews 204 papers on test room studies that explored the effects of thermal conditions on participants. The scope of the reviewed thermal experiments can be broadly classified into three categories: (i) fundamental research aiming at providing a better understanding of human thermal comfort; (ii) technology-oriented experiments, whose purpose is to test the thermal comfort performances of specific types of heating and/or cooling systems or newly developed clothing; (iii) predictive studies with the purpose of data collection to test and train novel predictive models. Fundamental studies are more common than technology-oriented and predictive studies, respectively 57%, 36% and 7%, and their distribution over the last four decades is shown in Fig. 9a. Fundamental studies include research focusing on a variety of different aspects influencing human thermal comfort such as thermal adaptation [78–82], thermal acclimatization [83–86], increased air velocity [87–90], relative humidity [60,91–94], gender [95–98], age [52,99–102], transient thermal conditions [93,103–107], perceived control [108], and the influence of emotional states [109, 110]. About 30% of the thermal experiments are dedicated to the study of non-uniform thermal conditions. Non-uniformities and thermal asymmetries are not seen only as a cause of discomfort; indeed, many recent studies aim to understand how comfort can be enhanced with local thermal stimuli [111–120].

The technology-oriented experiments mainly look at the thermal comfort performances of specific types of equipment, such as innovative heating and/or cooling systems (thermo-electric air cooling systems [38, 121], stratum, mixing and displacement ventilation [122–124], underfloor air distribution systems [122,125], radiant cooling/heating panels, floors and ceilings [126–129], ceiling fans [130], etc.). In particular, the last 20 years have seen a progressive increase in the number of experiments dedicated to local heating and/or cooling systems (personal cooling with phase change materials [112,113], heated/cooled chairs [114–116], seats heated with encapsulated carbonized fabric [120], feet heaters [117,118], etc.). About 40% of the technology-oriented experiments aim to test new clothing (uniforms for heat strain or cold thermal stress attenuation in the construction industry [50,51,131,132], sports clothing [53,133–135], protective clothing systems [136,137], cooled/heated garments [138,139], etc.). The distribution of the technology-oriented experiments based on the type of system studied (heating or cooling, local heating and/or cooling, clothing) over the four different climate groups is shown in Fig. 8b. As expected, in tropical climates there is a prevalence of experiments studying cooling systems, while in continental climates, the focus is on new clothing systems.

The predictive studies provide experimental data to either develop, test and train novel data-driven predictive models. Many of them aim to predict either thermal comfort or thermal stress (e.g., heat strain indexes [140,141]). Instead, others are attempting to build models for predicting metabolic rate and clothing insulation levels [64,142].

A majority (46%) of the reviewed thermal experiments deal with both warm and cold thermal conditions, 39% of them only focus on warm conditions and the remaining 15% on cold conditions. They mainly consider sedentary activity levels (77%), only a few of them focus on high metabolic rate activities (21%) and a minority on sleeping (2%). Furthermore, most of them consider stationary thermal environments, while the experiments dealing with dynamic conditions mainly study step-change transients [93,103–107]. In the last 20 years, female and male participants have been equally represented in the thermal experiments; nevertheless, elderly and children continue to be underrepresented groups (in only 3% of the experiments). Concerning the sample size, a majority of the experiments (57%) employ between 10 and 50 participants, 31% of them recruit less than 10 participants, and only 12% more than 50 participants. In most of the experiments (about 70%), participants are passive recipients of thermal stimuli without any

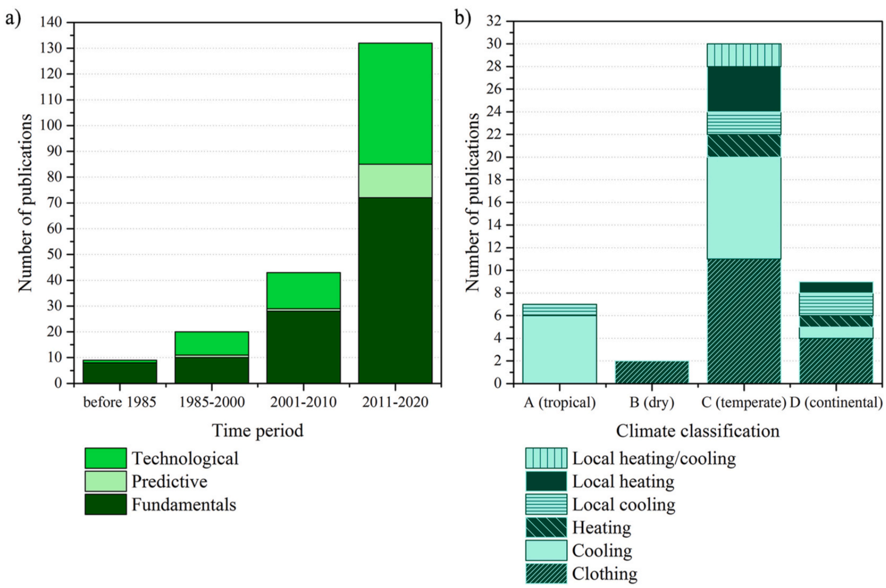

Fig. 9. (a) Thermal studies aim distribution over time periods; (b) thermal technology-oriented studies, studied system over climate classification.

possibility of adaptation/control.

The ASHRAE 7-point thermal sensation scale is the most used metric of thermal perception, followed by thermal comfort, thermal acceptability, thermal preferences, and cognitive performances. Air temperature is the most frequently monitored environmental variable (in 90% of the experiments), followed by relative humidity (75%), air velocity (63%), globe temperature (36%), and wall surface temperatures (9%). Air turbulence intensity, luminance, and solar irradiation (artificially provided) are more rarely monitored. Oxygen and carbon dioxide measurements are mainly used to estimate the metabolic rate, less often as a proxy of air quality. Skin temperature is the most common personal measurement (60% of the experiments), followed by heart rate/heart rate variability (27%), rectal/body core temperature (18%), body weight for sweat rate determination (7%), skin wetness (6%), ear/oral temperature (5%), skin surface blood flow (4%), blood pressure (3%), and skin heat flux (2%). Some very recently emerging topics are the use of immersive virtual reality [143–145] and the monitoring of brain electrical activity patterns [109,146].

4.2. Acoustic-only experiments

This subsection looks at 11 test room studies exploring the effects of acoustic conditions on participants by investigating different human responses and developing or evaluating new metrics for soundscapes description (Fig. 10). The test room experiments' aims include investigating maximum heavy-weight impact sound levels for perceived comfort [147], effects of sound pressure levels (SPL) and sound types on children's task performance [148], factors that contribute to sound complexity [149], effects of speech noise and speech transmission index (STI) in offices on cognitive performance [150,151], suitable masking sound frequency distribution for offices [152], effects of low-frequency noise in offices [153], effects of various noise sources on occupants in multi-family buildings [154], useful acoustic parameters that effectively describe to perceived sensations of urban sounds [155,156], and effects of introducing natural sounds to urban noise [157].

Many of the studies followed the general procedure of exposing participants to stimuli (recordings of sounds at various SPLs, frequencies, or decay rates) while performing cognitive tests and/or completed subjective assessments of the acoustic environments.

Test room setups and specific data collection procedures varied considerably among the studies. For instance, the provided stimuli length ranged from 10 s to 45 min, and the time that participants were given to respond to objective and subjective assessments ranged from 5 s to as long as the participants wanted to take. Most of the studies used loudspeakers to play the studied sounds, except Hermida and Pavón [156] and Hong et al. [157], who used headphones, and Jeon et al. [147], who used both loudspeakers and headphones. Only three studies [150–152] had test room setups that mimicked the type of real-world environment that they were investigating. Concerning the overall environmental control, three studies [150,152,153] mentioned that other indoor environmental conditions (such as temperature and lighting level) were kept constant in the test rooms. In contrast, others did not give any description of non-acoustic environmental conditions in the test rooms that could potentially affect the study outcomes.

For acoustic experiments involving human participants, it is common practice to screen participants' hearing abilities before conducting listening tests to avoid bias in the perception analysis. However, only four studies [147,149,153,157] screened their participants' hearing abilities using audiometers and other devices, and three studies [148,152,155] used subjective assessments to determine hearing abilities. Other studies either did not do similar screening or did not specify how they determined participants' hearing abilities. In addition, only three studies included evaluation of the effects of demographics, for example, age [147,148,150] and gender, and personal factors, such as personality traits [150], on participants' responses. Finally, just one study [153] monitored the physiological responses of participants (including the electrical activity of the brain, eye activity, heart rate, and heart rate variability) to low-frequency sound exposure using electroencephalography (EEG), electrocardiogram (ECG), electromyography (EMG), and electrooculography (EOG) signals.

Regarding sample size, six out of the 11 reviewed studies involved between 10 and 50 participants, with a minimum of 23 [152], while all the others involved more than 50 participants up to a maximum of 290 [148].

4.3. Visual – lighting-only experiments

The following overview focuses on visual-related experiments aiming at studying subjective evaluations of the visual environment performed in controlled environments. Studies conducted with the use of a scale model (e.g. Refs. [158–160]), with a small apparatus (e.g. Refs. [161–163]), in a booth (e.g. Ref. [164]) or in virtual reality (e.g. Refs. [165,166]) were excluded from the analysis as they were not performed in real-scale controlled environments. Investigations on electric lighting evaluations primarily aiming at testing lamp brightness and colour rendition based on lamp characteristics (e.g. Refs. [167–170]) were also not included. The resulting sample analysed consisted of 70 papers.

As introduced in Section 2, visual-related studies in controlled experiments have increased over the last decade, with more than 77% of

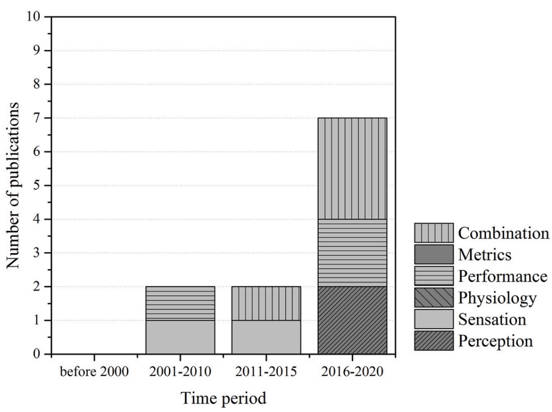

Fig. 10. Distribution of acoustic studies' aim over time.

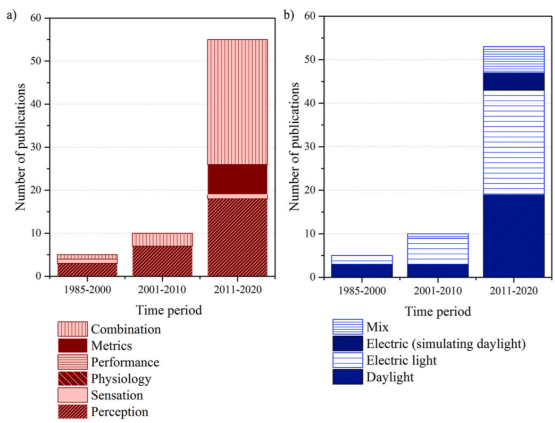

Fig. 11. (a) Distribution of visual studies' aim over time; (b) investigated light source distribution over time periods.

the considered studies conducted between 2010 and 2020 (Fig. 11). The type of light source investigated has been relatively constant throughout the years, with an equal number of studies focusing on electric light and daylight (Fig. 11b). The majority of studies focused on glare (more than 50%), either to evaluate subjective perceptions due to variations of lighting conditions or other factors' influences (such as time of the day or openings and blinds features) [21,22,37,39,42,66,171–182], develop, evaluate or validate metrics, thresholds or indexes [35,68,183–193], investigate glare influence on performance and physiology [187, 194–196] or study a combination of such objectives (Fig. 11a). Other studies investigated visual perceptions of the visual environment, surface finishing preference, physiological responses, performance, sleepiness, vitality, arousal, tension, mood, self-control and cognitive-biological processes (light-reactive hormones of melatonin and cortisol) mainly related to the light quantity and correlated colour temperature (CCT), but also in relation to light uniformity, wall luminance, light source type, flicker rate, view and chromatic glazing [164, 197–216]. The majority of the studies did not allow for personal control of the environment, testing pre-defined conditions, and were conducted with 10–50 participants. Only in a few studies participants were requested or simply allowed to vary their visual environment through the operation of blinds and electric lights, either to evaluate glare conditions or to assess how occupants perceived their visual environments associated with diverse luminous ambiences created by daylight in apartment buildings [73,189,191].

Most of the investigations were conducted in re-configured office spaces located in existing buildings, transformed into experimental test rooms in which it was possible to control or at least measure visual parameters. The traditional configuration was a side-lit single office, generally bigger than 20 m^3. Still, some investigations used a corner office [193], a mock-up of an open-plan office with multiple workplaces [209], a re-configured classroom [66], a full-scale mock-up conference room [208], or divided an existing office room with internal vertical partitions, resulting in smaller experimental spaces [217,218]. Some glare experiments used full-size apparatuses consisting of a semi hexagonal lighting chamber equipped with a chin rest [22,172,173,176] or of a semi-spherical screen with two halogen lamps mounted on a 1-m radius round boom [21,185]. Only fewer studies were conducted in a stand-alone test room, either located indoor [197,198,200–204, 210–213,219] or outdoor [35,42,179,188,192,194,220,221]. Some of the outdoor facilities were rotating structures [35,179,192,195,220], allowing daylight conditions to be tested with a reduced impact of the daylight variations due to the season and time of the day. Very few test spaces were designed to have a side-by-side configuration with two identical spaces, one for participants and the other for measurements [35,171,183,187,189,190,194,220]. This particular setting, aiming at decreasing interventions in lab experiments, is particularly suitable for visual-related investigations as photometric data are relatively affected by the presence of people, contrary to the other indoor factors that have to be measured close to participants. The presence of a window to the outdoors was linked to the type of experiment investigated. Almost all experimental spaces provided with a window investigated daylight, except for those studies that performed the experiments at night [222] or in which windows were shaded with a black-out fabric or blocked [164,180,199,207,217]. The studies investigating a mix of daylight and electric light were provided with shading devices [189,190,205,220, 223]. On the other hand, not all the studies on daylight were provided with a real window to the outdoor (intended as an opening with a view), but used artificial windows [37,177,181,192,204] or anidolic systems on the southern façade [224]. Non-visual factors were measured, controlled, or balanced across experimental conditions in almost all stand-alone test room experiments, and only in fewer re-configured offices [199,205,217,218,223,225]. The factors considered were primarily air temperature and humidity, but also noise [217,218] and air quality [37,197,198].

4.4. Air quality-only experiments

This subsection describes the controlled air quality-only experiments in test rooms summarised in 18 papers according to the reviewed database. Additional four papers that fall under two-domain experiments are included in the analysis since thermal and air quality aspects are hard to disentangle as the thermal analysis is ancillary to the air quality assessment [72,226–228]. Among the representative selections of 22 air quality studies in test rooms, researchers have focused on the three main topics: (i) understanding perceived air quality, productivity and health under a range of environmental parameters [71,72, 229–235]; (ii) human inhalation exposure and spatio-temporal variation of air pollution in a space [20,228,236–241]; and (iii) airflow distribution in occupied spaces and ventilation effectiveness [226,227, 242–244] (Fig. 12). These topics were pursued through a combination of questionnaire surveys, environmental measurements (near a study participant, in bulk air or ventilation ducts), and physiological measures. Discrepancies in facilities among the selected studies include test room layouts (office space, classroom, aircraft cabin, hospital room), test room volumes (small below 10 m^3, medium 10–50 m^3, or larger than 50 m^3), surface materials (stainless steel, polytetrafluoroethylene, aluminium, glass or their combination), type of air pollutant generation (continuous or episodic), ventilation type (mechanical or mix-mode ventilation), ventilation strategy (mixing, displacement, underfloor or personalized ventilation), degree of air mixing (ventilation only or additional use of mechanical fans), operating procedure (dynamic or stationary conditions), and participant type (real occupancy or use of breathing thermal manikins).

In the reviewed air quality papers, all test rooms were located inside of the building and had control over the ventilation rate, air temperature and relative humidity. While nearly all studies reported air temperature and relative humidity values and associated uncertainties, only 12 out of 22 studies reported air change rate values (mean = 3.89 h^{-1}), out of which only three described the method of estimation [237–239]. These studies used the tracer gas decay method by means of low adsorption tracer gases such as CO_2. The majority of the selected studies were performed in test rooms larger than 20 m^3 (mean floor area = 30 ± 27 m^2), which is important for mimicking various indoor layouts occupied with people and for studying air contaminant distribution in the space. Twelve studies focused on mimicking office environments, whereas other studies focused on aircraft (2), classroom (1), hospital (1) and other unspecified environments (6). Studies involving perceived air quality, Sick Building Syndrome (SBS) symptoms and productivity under variable levels of gas-phase pollutants [71,72, 229–235] had a significantly higher number of study participants (76 ± 9.3) compared to studies focusing on human inhalation exposure and spatio-temporal variation of indoor air pollutants (8.2 ± 13.6) [20,

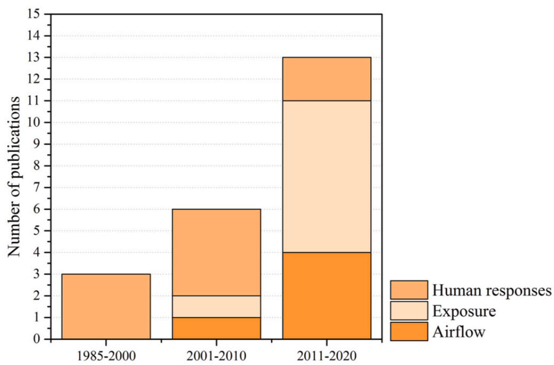

Fig. 12. Distribution of air quality studies' main topic over time.

228,236–241] and airflow distribution in occupied spaces and ventilation effectiveness (2.3 ± 2.1) [226,227,242–244]. The majority of studies focused on measurements of CO_2 (9), followed by VOCs (7), particulate matter (4), and other inorganic gasses such as NO_2, N_2O, O_3, and CO. Measurements of these air pollutants were performed with scientific instruments, which were not an integral part of the test rooms. None of those studies reported the adoption of the optimal inner coating of the test room surfaces, which is essential to determine how these coatings influence heterogeneous reactions with volatile organic compounds and other gaseous pollutants. Among the selected papers, only a fraction (2) reported issues that could arise due to pollutant uptake or emissions in the test rooms. Furthermore, in all studies, there was a lack of integration between advanced online and offline instrumentation and analytical techniques within the test rooms.

4.5. Multi-domain and whole comfort experiments

The goals of a multi-domain experiment can be categorized into (i) evaluate the effect of specific building technologies or control strategies on occupant multi-domain comfort [119,245–250]; (ii) understand cross-modal and interaction between different domains [46,72,251–268]; (iii) model the physiological [97,100,228,269,270] or behavioural [271–273] response of occupant to combined multi-domain stimuli and to understand the effect of IEQ on stress [274,275]; (iv) identifying new multi-domain metrics such as air enthalpy [251], air distribution index [276] and bio-signals such as skin temperature [277] for the whole comfort. In some cases, the energy consequences of such multi-domain interactions are also captured, as for the studies investigating novel personalized thermostats [272,278,279] or novel visual comfort systems [39,45] to improve energy efficiency and comfort. Among the studies focusing on the effect of specific building technologies or control strategies on occupant multi-domain comfort, the development of novel personal comfort systems in buildings [113,116,245,246,248,280–286] and vehicles [118] has received particular attention.

The interest in studying occupant response to multi-domain stimuli has increasingly grown since 2000, especially after 2010. Multi-domain experiments constitute 23% of the overall 396 occupant comfort experiments in test rooms, as given by the review database. Most of these studies investigated the relationship between two physical domains, while studies focusing on three or more physical domains were just 4% of the whole database. In terms of investigated combinations of domains, thermal and air quality represent the most studied one, followed by thermal with visual and thermal with acoustic (Fig. 13).

The majority of the studies were conducted under stationary conditions, while only a third of the studies exposed occupants to changing environmental or dynamic conditions. Dynamic conditions were achieved either by step changes in indoor conditions [246,248,251,257,274,287–289] or, especially concerning thermal-related studies, by fast and long changes [79,265,275,290], meaning that a rate of change greater than 2 K per hour is provided for more than 1 h of exposure. Only a few studies investigated multi-domain effects under high-speed conditions [91,250,291] or slow and long dynamical changes [263,271,292].

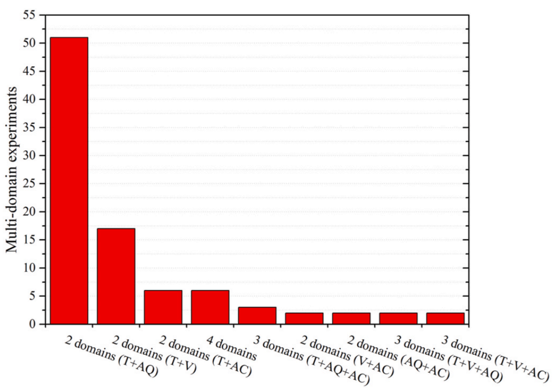

Fig. 13. Multi-domain experiments by combination of each domain.

In addition to highly accurate monitoring of environmental parameters, most studies capture occupants' responses as a combination of subjective and physiological parameters. Nearly half of the studies (53%) relied only on subjective occupants' responses. Table 4 shows the subjective metrics and physiological parameters monitored in the experiments. In terms of subjective measurements, based on survey or behavioural observations, environmental sensations are the most employed, followed by environmental preference and acceptability. In terms of physiological parameters, skin temperature and heart rate are the most monitored ones, also due to the thermal domain being investigated at least in 94% of the overall multi-domain experiments. Lastly, the use of EEG, ECG, and EDA has just recently started to be adopted, mostly after 2015, to understand multi-physical occupants' responses in test rooms, especially when investigating interactions between different comfort domains.

Table 4
Different approaches for capturing occupants' responses in multi-domain experiments in test rooms.

Occupant response		References
Subjective (survey based or from behavioural observations)	Environmental sensation	[44,46,47,60,67,78,79,85,86,89–91,99–101,118,120,122,124–126,245,250,253,256,257,264,267–269,273,275–277,290–297]
	Environmental comfort	[44,47,60,72,85,89,91,99,100,118,120,122,125,245,252,253,267–269,291,294,296–299]
	Environmental preference	[44,47,79,86,99,102,122,248,252,253,257,267,268,291,295,297]
	Acceptability	[47,85,86,91,122,124,248,249,253,275,294,295,297]
	Environmental satisfaction	[46,78,252]
	Emotion response	[46,264,289]
	Alertness	[50]
	Stress level	[274]
	Work performance	[90,268,273,275,289,294,295]
	Clothing level	[125,249,261,269,277]
Physiological parameters (sensing device based)	Skin temperature	[44,46,79,86,99–102,117,120,125,253,258,259,292,300]
	Skin moisture	[301]
	Core temperature	[86,102,258,259]
	Electrodermal activity (EDA)	[44,46]
	Electrocardiogram (ECG)	[47,100,294]
	Electrooculography (EOG)	[297]
	Electroencephalogram (EEG)	[47,274,289,294,297]
	Acceleration	[46,302]
	Heart rate	[44,46,266,289,292,303]
	Nasal dimension by acoustic rhinometry	[301]
	Photoplethysmography	[302]
	Metabolic rate	[277]
	Frequency of blinking	[303]
	Mucociliary transport	[303]
	Saliva and tear mucus film samples	[295]

4.6. Participants interacting with the environment

This section focuses on those experiments whose protocol allowed participants to freely interact with the test room components and systems. The interactions taken into account for this further classification include adjusting settings of the test room conditioning system, dimming/switching lights, opening/closing windows and shading systems, adjusting personal comfort devices. According to the reviewed scientific publications, this section is based on 21 papers (see Table 5). Nine of those 21 have been published in 2018–2020, and ten originate from European universities or institutes.

Two papers describe a test room facility developed and constructed to test all environmental factors (lighting, acoustics, air, and thermal quality) [43,304], including interactions with the environment through design and systems, making it possible to provide both input data to and output data from the occupants. Most of the publications were concerned with thermal quality in relation to thermal comfort, sensations and/or preferences [102,124,305–307], in combination with (personal) control [36,111,281–283,308,309], together with air quality [232] or visual quality [45,310]. The latter was studied in three reported studies [73,189,191], of which one was concerned with daylight, glare, shading and control [73]. Only one study included all the IEQ aspects [311].

The participants involved in the different studies mostly comprise of students and healthy young adults. Only one study was concerned with children (primary school children with an average age of 10 years) [311]. One study included a comparison between young (average23 years) and older males (average 67 years) [102], and one study looked at the impact of ethnicity [309]. In most publications, the responses or interactions of a participant with an object or variable/parameter in the environment are reported. The studied controlling devices varied from (local) heating or ventilation devices [283], light dimmers [310] or blind/solar shading control device [73], wearable conditioning devices [111], and furniture [281]. Table 5 summarises the 21 papers concerning those experiments where the building occupant is able to interact with the test room in the form of personal judgments or specific actuator-to-reaction.

4.7. Energy-related human comfort experiments

Out of 396 reviewed papers, 85 considered energy-related issues while carrying out thermal-, visual-, indoor air quality-, and acoustic-related experiments. Of these, 28 papers had a multi-domain focus with 22 papers considering both thermal and air quality-related experiments, five papers presenting thermal- and visual-related experiments [97,232,281,312–314], and only one paper discussing the effect of personal control on thermal, visual, and air quality perceived by building occupants [310]. Among the single comfort domain studies, thermal investigations are by far the most widely carried out (50), followed by visual investigation (5). Olfactory and aural comfort were studied together with energy considerations in just one article each [156,232].

The first document of the database was published in 1978. For the following 30 years, much slower growth was observed in the number of publications on energy-related human comfort experiments. After 2008, the scientific interest in this topic has progressively increased because of the increasing research interest in human-centric building design [315], personalized control strategies [316], and perceptual and behavioural environmental studies [32] (Fig. 14).

The majority of experiments have been conducted in test rooms located inside buildings with controlled environmental conditions, and only three experiments were run considering the actual outdoor weather [46,97,312]. Furthermore, 45 experimental procedures employed dynamic conditions and 32 studies used steady-state conditions. Dynamic studies are generally more recent (the average publication year is 2013), while steady-state conditions are more common in older studies (the average publication year is 2011); this can be explained by the recent

Table 5
List of reviewed studies concerning human comfort experiments in test rooms where the participants could directly interact with the facility.

Year pub.	Investigated domain	Studied parameters/object	Interaction between the participant and the test room	Reference
1991	Thermal	Adjust ambient temperature	Adjustment of test room temperature	[307]
1995	Thermal	Two age groups	Adjustment of test room temperature	[102]
2000	Thermal	Adjusting air movement (supplied via ceiling)	Adjustment of the Personal Comfort System (PCS)	[308]
2007	Thermal	3 task air-conditioning systems	Adjustment of the Personal Comfort System (PCS)	[306]
2009	Thermal	Control of 2 fans at chair (under seat, behind backrest)	Adjustment of the Personal Comfort System (PCS)	[282]
2009	Visual	Dimming of light; airflow from ceiling-based nozzle	Adjustment of the Personal Comfort System (PCS)	[310]
2012	Thermal	4 fans at corners chair to enhance displacement vent	Adjustment of the Personal Comfort System (PCS)	[124]
2012	Thermal & Air quality	Air movement (air terminal device), air pollution, temperature and RH	Adjustment of the Personal Comfort System (PCS)	[232]
2012	Visual	Artificial lighting and blinds control, daylight	Adjustments of shading system	[73]
2014	Thermal	Ceiling fan	Adjustment of shading system, ceiling fan, operable windows	[36]
2014	Visual	Daylight	Adjustment of shading system	[189]
2015	Thermal	Heated/cooled chair	Adjustment of the Personal Comfort System (PCS)	[281]
2018	Thermal	Control of personalized heating system	Adjustment of the Personal Comfort System (PCS)	[283]
2018	Visual & Thermal & Air quality & Acoustics	Facades, controls, interior, etc.	Adjustment of shading system, façade properties, thermal settings	[43]
2018	Visual & Thermal & Air quality & Acoustics	Walls, lighting, sound, thermal, air, interior, etc.	Control of HVAC and lighting system	[304]
2019	Thermal & Visual	Windows, blinds and ceiling lights	Adjustment of desk light, ceiling light, solar shading, operable windows	[45]
2019	Visual & Thermal & Air quality & Acoustics	IEQ in their own classroom	IEQ problems in classrooms and solutions for those problems	[311]
2020	Visual	Daylight, glare, shading	Adjustment of shading system	[191]
2020	Thermal	Thermal sensation, thermal preference	Adjustment of the Personal Comfort System (PCS)	[305]
2020	Thermal	Wearable wrist devices for warming or cooling	Adjustment of the Personal Comfort System (PCS)	[111]
2020	Thermal	Self-selected air temperature, thermal sensation, comfort and preferences; skin temperature	Adjustment of the personal comfort system	[309]

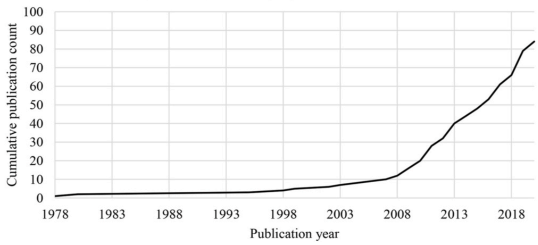

Fig. 14. Cumulative number of publications describing energy-related issues in human comfort experiments in test rooms.

availability of easier and user-friendly control interfaces and power modulation for electric motors and pumps.

Regarding the technical systems used during the experiments, only considering the documents where this information was expressed, most of the investigations used air-conditioning systems and only a few tested hypotheses under radiant systems (9 papers), controlled mechanical ventilation (8), artificial lighting (10), and sound equipment (1) [156]. Additionally, 38 papers reported experiments, which adopted personal environmental control systems, which are effective means of testing energy-saving control strategies and are well received by the occupants.

5. Summary of key findings

This review analysed a wide range of test rooms for the experimental investigation of human comfort indoors and provided an overview of scientific experiments that are conducted in such facilities and that were published in scientific papers. All reported information was deducted from reviewed papers. According to such an approach, it has to be mentioned that experimental facilities may exist which have not (yet) published any results in peer-reviewed journal articles. The reason may be because (i) it is too new to present results, or (ii) the facility is dedicated to industrial or other research not meant for public sharing of results. This limitation may affect some of our conclusions. Nevertheless, while accepting this limitation, we believe that the number of facilities not included in our review is small due to the two search strategies applied and that the knowledge generated in those facilities not publishing their work, for one reason or the other, is in any case not directly available for the scientific community and less suitable to enhance human comfort theories.

A general observation pertains to the growing number of such facilities. The total number of 187, specifically referred to in the present contribution, is about eight times higher than the number of comparable facilities before 2000. However, the geographic distribution of these facilities does not reflect the variance of climatic regions around the world: 82% are located in moderate climatic regions. Notwithstanding, the increasing number of test rooms may reflect the growing realization of the influence of indoor environments on human health, comfort, and productivity. This trend is reflected in the increasing number of publications reporting research conducted in these facilities. In this review, a total number of 396 publications were considered.

Looking at the publications from a topical standpoint reveals the scientific community's primary interest in human thermal comfort (204 papers), followed by energy-related studies (85), visual comfort (70), air quality (18), and acoustic comfort (11). Roughly a quarter of the reviewed publications explored indoor-environmental exposure situations involving more than one domain. Only a small number of publications (21) investigated circumstances in which participants could assume an active role and had the opportunity to interact with relevant features of the indoor environment.

Our findings suggest that about 92% of the test rooms were built inside of a building. This is interesting: while the performance characterization of building components has mainly been tested in outdoor testing facilities [317], the investigation of indoor comfort has been conducted either in actual occupied buildings or in dedicated test rooms located indoors with potential better controlled experimental procedures and microclimate conditions. However, based on the reviewed publications alone, it is not possible to draw up a more detailed picture of the test rooms' design and construction. For instance, in 47% of the reviewed publications, it was not possible to ascertain whether the test room envelope entailed any type of openings. Lack of such details makes it difficult to independently replicate and subsequently validate the results coming from experiments in test rooms. Our review also addresses another critical point: there is a lack of information regarding investment, operation, and maintenance costs associated with the facilities. A dedicated survey designed and distributed on our side received responses only from 18 facility owners or operators, pointing to the need for further efforts in the transferability of know-how with the test rooms.

Certain observations apply to studies that focused exclusively on thermal comfort: studies on fundamental issues dominate in this area (57%) versus technology-oriented (36%) and predictive studies (7%). An increasing number of experiments in the last 20 years focus on local heating/cooling systems. A large share of technology-oriented studies (40%) focuses on developing new, insulating, and thermally active clothing. This may indicate a shift in the industry from the traditional room-air-conditioning design perspective to a more personalized thermal comfort approach. The majority of the reviewed studies were conducted in office-like environments with small samples (10–50 people) engaging in sedentary activities. Few papers focused on the elderly or children (3%), and in 70% of the studies, participants were passive recipients only. Some studies introduced new, recently emerging methods such as immersive virtual reality and monitoring of brain activity patterns.

Studies related to acoustic comfort mostly followed a general procedure where participants were exposed, on a short-term basis, to stimuli while performing cognitive tasks or completed subjective tests. Interestingly, only four studies (less than 40%) screened the hearing abilities of the participants. This may have introduced bias in their results.

Studies on lighting and visual comfort significantly increased in the last decade, addressing both daylight and electric light: their bulk is concerned with glare problems in the workplace, primarily deal with glare perception and entail the development and evaluation of related metrics, thresholds or indexes. The investigations also pertain to various human responses related to light quantity and CCT. Most of these latter investigations focused on the non-image-forming effects of light. Only a few studies allowed participants to change the visual conditions by interacting with blinds and electric lights.

IAQ-related studies mostly addressed three topics, namely the perceived air quality's impact on productivity and health, the spatio-temporal variation of air pollution and inhalation exposure, and the airflow distribution and ventilation effectiveness. Some reviewed publications did not report the experimental conditions (e.g., ventilation rates) in detail. In contrast, none of the studies reported surface materials, which is essential concerning how they influence heterogeneous reactions with volatile organic compounds and other gaseous pollutants. The majority of the studies were conducted in sufficiently large test rooms, hence allowing for the consideration of realistic room layouts and air contaminant distribution patterns.

About investigations of multi-domain exposure situations, thermal and indoor air quality represent the most frequently studied combination, followed by thermal-visual and thermal-acoustic combinations. Only one-third of the studies exposed participants to dynamic environmental conditions. 53% of the studies relied solely on subjective responses. In the last few years, a new trend can be seen in the related scientific literature, whereby diagnostic methods from neurophysiology (such as EEG, ECG and EDA) have been applied to explore multi-domain exposure situations.

6. Research gaps and future trends in test room experiments for human comfort

Despite a growing interest in multi-domain studies, we still do not have an agreed-upon conceptual framework and a systematic methodology for a mature and holistic science of human-centric indoor environments. Common design guidelines and a shared terminology for innovative test rooms and experimental procedures would allow establishing a shared understanding of the driving phenomena and the inclusion of the non-physical (psychological and contextual factors) dimensions. This can be further supported by the deployment of low-invasive physiological sensing techniques. A better understanding of the visual, IAQ and acoustic factors and their mutual influence on human comfort and occupants' perception requires further investigation. Future trends in test room experiments (and thus facility design) must account for a multi-domain and multi-disciplinary approach.

On a geographical and demographic basis, despite the increased interest in human comfort and the large availability of test room setups, these facilities are limited to specific climatic regions, while concerning tested subjects' composition, these are mainly students and faculty members. These sociological and geographical weak points may cause a non-negligible bias in the interpretations of experimental results and knowledge generation. We see the need for dedicated studies in those climatic and demographic contexts where experimental data are still not available to increase diversity and cross-validation.

In terms of test room design: test rooms mostly emulate office spaces with a limited number of occupants. Therefore, another research gap to close is the analysis of other settings and contexts, such as realistic open-plan offices and different building typologies (educational, residential, hospitals, etc.). This factor may affect the quality of the collected data and limit the research findings to office-only investigations (difficult to replicate and extend).

Concerning experiments, increased attention is being paid to occupants, also driven by the recent trends toward human-centric building design and operation. This is also reflected in the fast growth of multi-domain studies in the last decade, where the focus is the whole comfort perception analysis. Additionally, even technology-oriented studies are focused on human applications. About 40% of the technology-oriented studies aimed at developing and testing wearable systems for improved personal comfort, such as smart clothing and sensing techniques. This observation shows the necessity for a more systematic collaborative research framework whereby the environmental comfort is not handled exclusively by building physicists or engineers and architects. The topic requires a significant and proactive interaction with researchers in human factors, human-machine interaction, big data analytics, and social science, as we see more studies are focusing on psycho-physiological factors alongside IEQ and human-centric approaches.

From the operation perspective, the economic analysis showed the necessity for a better common understanding of the economic model behind test room design and construction. This may be helpful to foster local and global collaboration and connection to industry, taking advantage of the unique resources that each location provides. For this purpose, a higher transparency of existing business/economic models is recommended. Private-public partnerships may also be established with shared economic models allowing both researchers and industry partners to use these facilities to conduct controlled experimental studies, e.g., for technology development. Such models can also help sustain and expand the test rooms' role in underlining the importance of whole comfort experiments. Toward this end, funding agencies/industry partners should be informed and engaged in providing funding support to maintain/sustain and expand existing testbeds dedicated to a better understanding of human comfort in buildings.

In this context, standardization in the design and experimental validation procedures is still missing, with the consequent limitations in error and uncertainty analysis, quality control and replicability potential. Therefore, the creation of a unified framework for keeping track of the functionality of the test room facilities is expected to establish a common ground for collaboration and cross-validation and would help to identify cultural and geographical differences and biases.

This cannot be done without a joint effort in terms of open-source research in and for society, where the resources of test room facilities and collected data are freely available for fostering the impact of these multi-domain and multi-disciplinary investigations. In this scenario, future efforts by the authors and their institutions would support research via a systematic data sharing process and a publicly available and continuously updated test room portfolio. Finally, a first Round-Robin test in test room facilities worldwide is expected to emerge as a follow up to this review.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Paper c

Quality criteria for multi-domain studies in the indoor environment: critical review towards research guidelines and recommendations

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Abstract

The perception, physiology, behavior, and performance of building occupants are influenced by multi-domain exposures: the simultaneous presence of multiple environmental stimuli, i.e., visual, thermal, acoustic, and air quality. Despite being extensive, the literature on multi-domain exposures presents heterogeneous methodological approaches and inconsistent study reporting, which hinders direct comparison between studies and meta-analyses. Therefore, in addition to carrying out more multi-domain studies, such investigations need to be designed, conducted, and documented in a systematic and transparent way. With the goal to facilitate and support future multi-domain studies and their meta-analyses, this work provides (1) a range of criteria for multi-domain study design and reporting (i.e., defined as quality criteria), and (2) a critical review of the multi-domain literature based on the described criteria, which can serve as guidelines and recommendations for future studies on the topic. The identified quality criteria encompass study set-up, study deployment and analysis, and study outcome, stressing the importance of adopting a consistent terminology and result reporting style. The developed critical review highlights several shortcomings in the design, deployment, and documentation of multi-domain studies, emphasizing the need for quality improvements of future multi-domain research. The ultimate goal of this work is to consolidate our knowledge on multi-domain exposures for its integration into regulatory resources and guidelines, which are currently dominated by single-domain knowledge.

Keywords: IEQ; Human Comfort; Combined effects; Cross-modal effects; Transparent reporting; Research quality assurance

1 Introduction

In industrialized areas, people spend about 90% of their time indoors [1], where they are simultaneously exposed to multiple indoor environmental stimuli, i.e., thermal, visual, acoustic, and air quality variables. It is well known that indoor environmental stimuli affect how people perceive the indoor environment [2], their behaviors [3], health [4], [5], and work-related matters such as real and self-estimated performance [6]–[8], job absenteeism [9], and job satisfaction [10]–[12]. Consequently, indoor environmental stimuli have indirect implications on energy consumption linked to changes in human behavior (e.g., openings/closing windows when mechanical systems are operating) [13]–[15] and on companies' financial revenues, due to the aforementioned work-related issues [16] and health effects [17]. Therefore, it is paramount to understand occupants' responses to indoor environmental stimuli to design and operate comfortable, healthy, and productive spaces.

Over the past years, many efforts have been devoted to studying human responses to indoor environmental stimuli. Investigations were predominantly carried out for each stimulus, considering visual, thermal, acoustic, and air quality separately. These studies resulted in comfort models and metrics (e.g., Fanger's predicted mean vote model [18], daylight glare probability model [19]), which are included in technical standards and design guidelines (e.g., [20], [21]), and provide comfort requirements for temperature, light, noise and air quality separately. Consequently, buildings and current technologies devoted to controlling the indoor environment are designed on the supposedly independent effects of indoor environmental stimuli [22], [23].

From a cognitive perspective, this approach implies that human perception is a modular function, composed of independent sensory modalities processing sensory stimuli independently of each other as separate *modules*. For example, the underlying assumption of this mono-sensory approach is that light does not influence thermal perception, and temperature does not affect how the visual environment is perceived. However, it has been shown that human perceptual experience is not modular but is shaped by the combination and integration of a multitude of stimuli experienced simultaneously [24]–[27]. The integration of different sensory modalities is called multisensory integration and results in more robust estimates of occupants' perception [28]–[30]. Examples of multisensory integration relevant to the indoor environment can be found in Calvert et al. [29] and Bertelson & Gelder [31], while anthropological and architectural approaches in Hall [32] and Rapoport [33].

As sensory perception is inherently multimodal, so is people's perception of the indoor environment. While synesthesia (e.g., music excites the perception of color [34]) seems to be a widely known example of the underlying topic, it understates and occasionally misrepresents the nature and importance of integration and binding problems in human perception. Not always human senses are equally involved (think of a visual acuity test such as Snellen Chart), and oftentimes a specific quality of an indoor environment stands out and annoys or satisfies people predominantly. Yet, the overall impression and the effects of an indoor environment remain interwoven and holistic, which is why a multimodal and integrative approach to the investigation of indoor environments appears more valid and representative. Multisensory integration might be one of the factors explaining discrepancies observed between predicted and reported occupant satisfaction [35]–[37], as people are often not satisfied with their indoor environment although threshold values indicated by standards are met. A recent analysis of an extensive survey database shows that only two-thirds of building occupants are satisfied with their environment and multiple environmental stimuli contribute to dissatisfaction, including sound privacy, temperature, and noise level [38].

Although the explanation of how our brains integrate various sensory information is yet to be solved by neuroscience and related fields, it is a good starting point for researchers in the Indoor Environmental Quality (IEQ) domain to expand research in a multimodal manner. Research in this field is necessary considering that "current knowledge on interactions between and among factors that most affect occupants of indoor environments is limited" [39, p. 2]. Since each IEQ stimulus includes several variables, such as (relative) humidity and (air, mean radiant or operative) temperature for the thermal environment, considering all the potential interactions in a single study is unfeasible, even more, if several human responses are considered.

For this reason, existing studies focus on the interaction of a few stimuli with selected human responses. To gain a comprehensive understanding of the effect of all the stimuli that can be found in the built environment on all human responses, it is, therefore, necessary to conduct reviews and meta-analyses to combine the results from several studies. This *collective approach* builds upon the knowledge generated as suggested in Schweiker et al. [40].

In recent years, some studies have analyzed the existing literature to understand human responses to multiple indoor environmental stimuli. Torresin et al. [41] reviewed 45 laboratory studies that examined the effects of two or more environmental stimuli on human perception and performance. Wu et al. [42] expanded their review to include field studies and identified multi-domain effects (thermal, acoustic, and illumination) on human perception. Schweiker et al. [40] recognized the link between human perception and behavior and conducted a comprehensive review of multi-domain influences on occupant perception and behavior based on field and laboratory studies. By identifying motivations, theoretical foundations, key methods, findings, and gaps in the field of multi-domain approaches, the authors conclude that "*results were often inconclusive and in part contradictory*" and emphasize the need to establish a common framework to analyze diverse results, design future studies, and develop standards and guidelines. The incomplete knowledge of multi-domain effects and the inconsistencies across results have been also highlighted in other studies [43], [44]. According to Rupp et al. [45], this outcome is the result of a lack of interdisciplinary research between different disciplines within building science (i.e., visual, thermal, acoustic, and air quality), and between research fields such as psychology, physiology, engineering, and architecture. In addition, the direct comparison of the results of studies can be misleading as the great majority of them differ in terms of objectives, magnitude of considered stimuli, experimental design and setting, studied population, analysis conducted and reporting of the results. Without a common way of designing, conducting, and reporting multi-domain studies, comparisons are difficult to conduct. This is not the first field to recognize and call for the development of more rigorous study designs, transparent reporting, and quality assurance checklists (e.g., [46]).

To address this need, the present work identifies criteria covering the key research aspects that should be considered when designing, conducting, and reporting multi-domain studies and critically reviews the published studies on the basis of these criteria. It is necessary to highlight that this work does not review existing multi-domain investigations for conducting a meta-analysis of their results. In other words, this study does not focus on the questions: "is factor *x* affecting the perception of factor *y*?" or "are interactions between factors *x* and y affecting human response *z*?", but rather on the methodological aspects and characteristics of the reported information for addressing these questions. The described criteria are defined as "quality criteria" as their presence and accurate description in the literature can determine the degree of excellence of a study, which in turn allows its replicability and comparability. The quality criteria can thus be considered as research guidelines and recommendations that aim to establish a solid foundation for future multi-domain studies as a unified approach to facilitate meta-analyses on this topic, helping to untangle the complex effects of multi-domain stimuli on different human responses.

First, the methods applied in this paper are described. Then, the quality criteria are outlined in terms of (1) study set-up (dependent and independent variables, hypothesis, setting features, exposure features, experimental design quality), (2) study deployment and analysis (data collection and processing, participants, data analysis), and (3) study outcome (reporting results, study discussion and conclusion) (see details in

Figure 2). Next, the critical review of the multi-domain literature is performed based on the quality criteria. Finally, the key findings of the critical review are summarized, and future directions are highlighted.

2 Methods

Three steps were followed to define the quality criteria and carry out the critical review of existing multi-domain studies: (i) selection of multi-domain studies, (ii) categorization of the studies based on the type of multi-domain effect (i.e., cross-modal or combined) and study type (i.e., laboratory or field study), (iii) definition of the quality criteria.

2.1 Multi-domain studies selection

The selection of research studies analyzed in this work is based on three recent literature reviews reporting studies on the effect of multiple indoor environmental stimuli on different human responses: Schweiker et al. [40], Torresin et al. [41], and Wu et al. [42]. Furthermore, the list of papers analyzed in the reviews was expanded to include additional studies based on forward reference searching and authors' knowledge. The list of considered papers is reported in Appendix A.

Not all studies reported in the three reviews were included in the analysis. Three main selection criteria were applied to meet the aim of the research, described as follows: (i) the study had to involve the response of people (i.e., no simulations, no physical measurements only); (ii) the study had to focus on perception, behavior, and/or performance (i.e., not on physiology only); and (iii) the study had to have as independent variables the physical measurements of two or more of the four IEQ stimuli (i.e., visual, thermal, indoor air quality, and acoustic). Papers in languages other than in English, with an unavailable full text, or not peer-reviewed are also excluded. The excluded papers are reported in Appendix B.

2.2 Multi-domain studies' categorization

The existing literature is reviewed and analyzed by distinguishing the papers according to two study features: type of effect investigated and study type.

Two types of effects are considered in this research (see Figure 1), described as follows:

- *Cross-modal* effect is when one stimulus influences a non-related response, which is usually triggered by another stimulus (e.g., when light influences thermal responses).
- *Combined effect* is when multiple stimuli, in combination, affect a response not directly related to a specific indoor stimulus (i.e., individual perception such as overall comfort perception and physical status, behavior, physiology, and performance). The stimulus can be environmental or belong to other domains (e.g., personal, and contextual).

A cross-modal effect can be further categorized into (i) Cross-modal *main* effect; and (ii) Cross-modal *interaction* effect. The difference between the two types of cross-modal effects depends on the levels of the considered stimuli (e.g., dim, and bright are two levels for the visual stimulus, and hot and cold are two levels for the thermal stimulus). Cross-modal main effects occur when the response to stimulus A is influenced by the presence of stimulus B, independently of the levels that they have. Cross-modal interaction effects occur when the effect of different levels of stimulus B on the response to stimulus A differs according to stimulus

A's level. See Figure 1 for a graphical representation of the cross-modal effects. The sub-categorization into main and interaction effects is reported to provide a complete description of multi-domain effects, but it is not used to analyze the reviewed literature in Section 4. However, the authors believe that a comprehensive description of the type of effects could benefit the reporting and interpretation of future multi-domain studies. Figure 1 schematizes cross-modal and combined effects (multi-domain studies), distinguishing them from the same-modality effects (single-domain studies), which are not considered in this research.

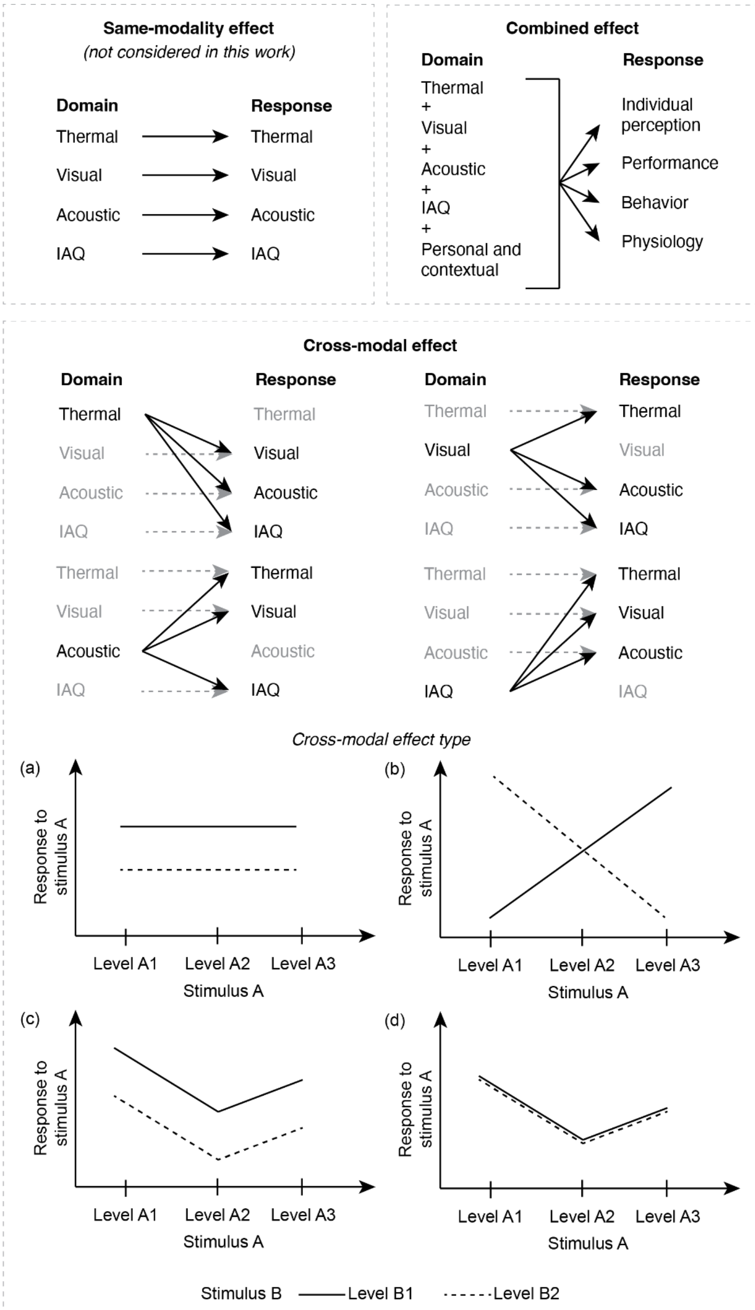

Figure 1: Top: Schematic description of the type of effect: cross-modal, combined and same-modality effects. The light gray dashed lines in the cross-modality effect refer to the influence of one domain (e.g., temperature) on the same-modality response (e.g., thermal comfort) when another domain is considered in the investigation (e.g., illuminance). In a multi-domain study, such effect does not have to be included (e.g., a study could look solely at visual influences on thermal perception without observing the effects of thermal properties (or their interactions with the visual properties) but only controlling for them). Bottom: Graphic representation of the types of cross-modal effects between two stimuli. a) Cross-modal main effect of stimulus B and no effect of stimulus A; b) cross-modal main effect of stimulus B and the main effect of stimulus A; c)

cross-modal interaction effect of stimuli A and B; d) the main effect of stimulus A, no effect of stimulus B. Adapted and expanded from Coolican [47].

The study types considered in the analysis are: (i) lab study (including test room, climate chamber, and airplane simulator) [48], and (ii) field study [49]. The living lab (i.e., a conventional space equipped with measurement tools in which occupants conduct their normal lives or work [50] is a study type not used in the considered papers and hence it is not used to categorize the papers in the following analysis.
Table 1 summarizes the distribution of the considered studies according to the effect type and study type. Lab studies outnumbered field studies, while cross-modal and combined effects were equally investigated across studies. Most of the cross-modal effects were investigated in lab studies, while an equal number of combined effects were tested in both lab and field studies. Sometimes, cross-modal and combined effect types were investigated in the same study, in the great majority of the cases in lab studies.

Table 1: Distribution of the considered studies according to the effect type and study type.

		Effect type			Total
		Cross-modal	Combined	Combined and cross-modal	
Study type	Lab	36%	17%	23%	76%
	Field	4%	19%	1%	24%
Total		40%	36%	24%	100%

2.3 Research quality criteria

The research quality criteria (Figure 2) were used to critically analyze the published studies and can serve as research guidelines and recommendations for future studies. These criteria are categorized into three groups, defined as (1) study set-up, (2) study deployment and analysis, and (3) study outcome (Figure 2). The collection of quality criteria was determined first on the basis of the authors' experience with multi-domain studies, previous review efforts, and intensive online meetings within and beyond IEA EBC Annex-79 meetings[1]. Such basis was constantly reviewed during the analysis of the studies considered for this work and augmented upon necessity. The selected criteria focused on methodological and reporting features. The introductory sections with the related analysis of previous literature and reference to validated theoretical models and theoretical assumptions are not considered in the analysis as multi-domain studies have been reported to rarely carryover previous studies' findings and to lack foundational theories to formulate and test research hypothesis [40].
Some of the considered research quality criteria are common to all experimental investigations, while others are specific to multi-domain studies. However, to guide future researchers on what to consider while designing, deploying, and reporting multi-domain investigations, all quality criteria are described in the same depth in the next section followed by their application in a critical review of published literature.

[1] "Occupant-centric building design and operation" (http://annex79.iea-ebc.org/)

Figure 2: Research quality criteria considered in the critical review of existing multi-domain studies and that can serve as guidelines and recommendations for future multi-domain research.

3 Description of research quality criteria for multi-domain studies

The quality criteria shown in Figure 2 are described in the following.

3.1 Study set-up

3.1.1 Dependent variables

A clear description of the investigated dependent variable(s) is of primary importance since they express the human responses to variations of the independent variables (i.e., the investigated stimuli).

The dependent variables in multi-domain studies refer to the different human responses that can be captured in experimental or observational settings. Figure 3 illustrates the type of human responses that can be collected and the associated methods of assessment in both field and laboratory investigations, and in relation to the type of effect considered (combined or cross-modal). Responses can be described according to the nature of the data collection approach, i.e., subjective or objective. Subjective data from occupants is collected by interviews or survey methods querying self-reported perceptions or opinions. Objective responses include physiological signals, test grades and other quantitative observations (e.g., number of interactions between occupants and building components).

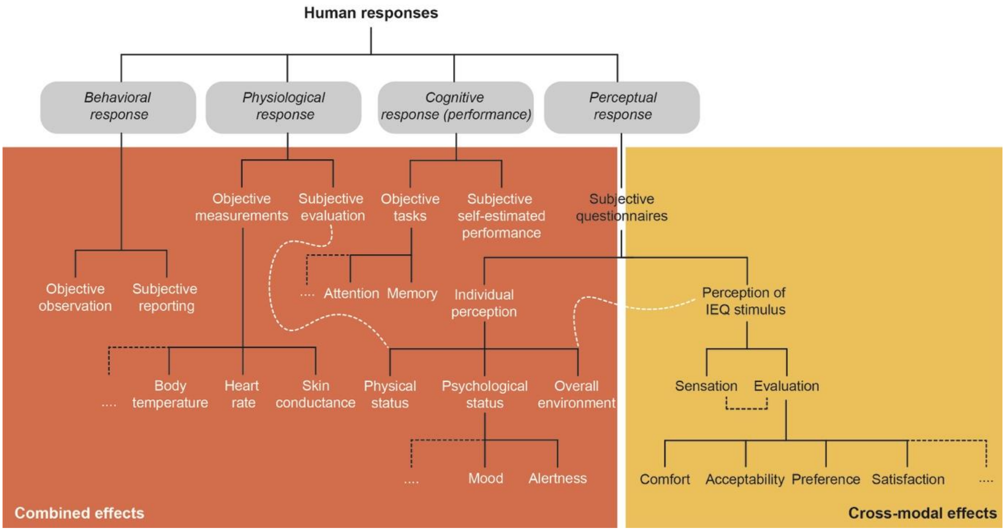

Figure 3: Schematic representation of the type of human responses that can be collected in studies investigating cross-modal or combined effects.

In addition to a clear description of the human response type under consideration, studies should clearly report how these responses were gathered by specifying the method(s) of assessment and the adopted tools used (e.g., questionnaire for perception responses, test type for performance responses, sensing technology for behavioral and physiological responses). Such tools must be described in detail to allow reproducibility and a comprehensive understanding of the followed methodology. In addition to the details of the assessment method, the time and frequency of assessment must also be reported. Special attention must be given to the description of the questionnaires and the related responses when subjective evaluations are sought. Questionnaire responses, if not in an open-ended format, refer to scales that can be categorical (CS), visual analogue (VAS), categorical scale combined with VAS (graphic CS), semantic differential, or dichotomous. To get comparable data and results, agreement on specific aspects of the subjective assessment scales is of primary importance. These can be summarized in (i) adopted terminology in the questions and responses, (ii) type of scale used, and (iii) (only in case of CS) number of provided response categories. From this point of view, it is essential to report the original text of the adopted questionnaire, preferably in both the original language and English.

3.1.2 Independent variables

Multi-domain studies are characterized by the presence of more than one environmental stimulus, presented in combination. Such environmental stimuli are the independent variables of the study. Reporting the type of combination of the environmental stimuli is taken for granted as it represents the essence of each multi-domain investigation. However, the detailed description of the independent variables needs further attention. Correctly describing independent variables in multi-domain investigations is crucial for conducting replication studies and facilitating meta-analysis and comparison across studies. The way of reporting independent variables depends on the study approach, either experimental or observational. In experimental investigations, usually carried out in a climate chamber or an environmentally controlled space, the experimenter manipulates the independent variables to measure their effect on the dependent variable. In contrast, in observational studies conducted in field setups, the experimenter cannot usually control the independent variables, which are measured to observe correlations between independent and dependent variables.

In multi-domain papers reporting experimental studies, researchers should always clearly indicate the independent environmental variables in terms of type (e.g., air temperature), the number of levels (e.g., 3), and design values (e.g., 22 °C, 25 °C, and 28 °C). In experimental cross-modal studies, both same-modality and cross-modal independent variables must be clearly described. For example, in a study investigating the effect of Correlated Color Temperature (CCT) of light on thermal perception, the cross-modal independent variable CCT must be reported together with the air temperature, representing the same-modality variable.

In multi-domain papers reporting observational studies, as the independent variables are usually not controlled but measured, researchers must clearly report the measured variables' descriptive statistics, i.e., measures of central tendency and variability. This information is critical for evaluating the external validity of the study's findings, and whether the findings are generalizable to the study's source population of people and buildings. If the researchers cut the independent variables' continuous values into bins for analysis (e.g., [51]), then each bin must be described in terms of value counts and mean or median. Such description is necessary as the choice of bin number and position is arbitrary and generally do not have practical/scientific meaning and could influence the results. Analyzing solely with the described bin method may lead to some loss of information. Therefore, it must be complementary to other descriptions of the independent variables.

It is recommended to opt for continuous and numerical design values (rather than categorical ones such as "blue" and "red" when colors are assessed) that enable replication studies and facilitate meta-analysis. When several levels of the same independent variable are considered, it is a good practice to assign different labels to the different levels, facilitating the comprehension of both the experimental design and the results. Another good practice is the consideration of possible covariates (e.g., summarized for thermal comfort by Wang et al. [52] or Schweiker et al. [53]) that are not environmental, for example, gender, age, and body mass index. Refer to 3.1.4 and 3.2.2 for further discussion on the topic.

3.1.3 Research hypothesis

Stating and describing the research hypotheses of a study leads to a better comprehension of the work, even if it consists of an exploratory study searching for discoveries, trends, correlations, or relationships between the measurements in which outcomes would generate new ideas or hypotheses (that need to be confirmed in follow-up studies). When conducting a causal research based on a pre-existing theory and aimed to determine what occurs to one measurement on average when another measurement is changed, it is possible to state causal hypotheses. The causal hypothesis should be stated in all cases where the scientific literature reasonably sounds or where the current state of knowledge on the topic makes it possible. This makes it easier to determine the research scope and establish a correlation between the initial assumptions and the results.

Research hypotheses should be described in terms of “directions.” A hypothesis with direction expresses a direct or inverse relationship between dependent and independent variables: if the independent variables increase (or decrease), the dependent variable increases (or decreases). An example is the Hue-Heat Hypothesis, posing that warm-appearing colors, such as red or yellow, make people feel warmer, while the opposite effect is obtained with cold-appearing colors [54], [55]. A hypothesis “without direction” expresses a general relationship between dependent and independent variables regarding the influence one may have on the other (e.g., thermal conditions influence acoustic sensation and perception [56]).

3.1.4 Setting feature

Experimental setting features play a fundamental role in the combination and interaction of the variables investigated in multi-domain studies. The following paragraphs summarize the importance of collecting and reporting information regarding: the environmental conditions not varied as independent variables, the building and space type, the space layout, equipment, ventilation, and lighting, the control opportunity, and the experimental location.

Along with a detailed description of the environmental stimuli investigated as independent variables, it is necessary to include a comprehensive description of all the environmental features, considering as well those that were not included as independent variables. Such a comprehensive description of the indoor environment might help to understand potential differences across studies and detect confounding factors.

The type of building or space (i.e., office, educational, residential, or others) determines several aspects of the experimental setting, e.g., indoor space layout, furniture, occupants’ activity, or interaction with other people. Specifying the building or space type in a field study but also the “emulated” space in an experimental lab setting is crucial.

Besides indicating building and space typology, a description of the space layout, equipment, ventilation, and lighting gives a comprehensive and immediate overview of the space. Layout description should include dimensions and photos for furniture type and disposition, for instance, the distance between the seats and relevant building elements (e.g., windows). Describing relevant equipment (such as HVAC, artificial lighting etc.) and building elements (windows, shadings etc.) is also important, as these influence indoor environmental conditions and occupants’ interaction with available interfaces [57]. Lighting type and related details should be described, that is, electric, natural, or a combination of the previous, and possibly specifying if electric lighting was designed to obtain extreme conditions (e.g., a poorly lit environment). Related to lighting, fenestration systems should be detailed with reference to shadings (internal or external) or, if present, advanced technologies (e.g., smart windows, low-emissivity coatings etc.).

Another relevant feature involves the interactions that occupants can have with building interfaces (i.e., occupant control). Occupant control can influence not only human interactions but also the satisfaction and behavior of users in different domains [58], [59]. Thus, reporting exhaustive information on control opportunities within the indoor space is highly recommended.

Despite not being directly related to the experimental indoor space, knowing the location brings insights into the climatic conditions and indicates participants' cultural approach, including their habits, perception, and reporting attitudes.

3.1.5 Exposure feature

This section covers the conditions to which subjects are exposed (i.e., exposure features). Such information is essential when analyzing the results and ease the replicability of the experiments. The first aspect to consider when defining and describing the exposure features is whether the experimenter measures human responses to different exposures within-subjects (i.e., all participants are exposed to all conditions), between-subjects (i.e., each participant is exposed to some of the conditions), or a mix of the two (i.e., participants are exposed to all conditions of one experimental variable and to some of the conditions of another experimental variable). An important aspect to provide clearly in this latter case is the number and combination of tested experimental conditions (e.g., mixed design with one between-subjects condition and two within-subjects conditions).

Each study must then define and report the characteristics of exposure, which we can divide into (i) the "exposure type" (i.e., steady-state, dynamic, or combined), (ii) the length of exposure for each experimental condition (e.g., exposure to warm temperature for 30 minutes and to each light condition for 10 minutes), (iii) the number (and demographic information) of participants per experimental condition, and (iv) the timing of the exposure (during the day and the year). For example, seasonal variations are important to be recorded given their impact on several human responses [60]. In addition, publications suggest the potential variations of human responses during the day [61]–[63], highlighting the importance of recording and reporting the exact time of the day during which the experiment is conducted. In the case of within-subjects design, it is also necessary to report the number of experimental conditions experienced in a day by the same participant and their potential distribution over several days. It is also good practice to report the total length of the experiment for each participant, especially in the presence of within-subjects design when each participant is exposed to a series of experimental conditions.

The adaptation time (or acclimation time, i.e., is the time given to the participants to adapt to the experimental conditions) is another exposure feature that should be considered and reported in all studies. The consideration of the adaptation time is more relevant in studies involving the thermal domain since the human body requires longer time to reach a steady-state thermal response in a new thermal condition and/or at a different activity level [64] and strongly depends on the temperature difference between experimental and pre-experimental conditions.

3.1.6 Experimental design quality

Recently, a replication crisis has been in the spotlight of the scientific community [65], [66]. This crisis is mainly attributed to selective reporting bias (i.e., reporting only significant results and omitting non-significant results) and poor experimental design quality (e.g., lack of a random assignment of subjects). A quality experimental design should follow several principles commonly reported in statistics books (e.g., [47], [67], [68]): (i) randomly assigned or counterbalanced experimental conditions; (ii) blinded (single- or double-blind) experimental procedure; (iii) controlled confounding variables (experimentally or statistically); (iv) reported study null condition; and (v) repeated one or more experimental conditions.

Besides the recommendations above for specific experimental design elements, a pre-design step for countering the replication crisis trend of underreporting results that did not reach significance is pre-registration. In pre-registration, before beginning to run an experiment or study, the authors outline their hypotheses, methods, and analyses in a public registry (e.g., https://aspredicted.org/). If this step had been taken, the reporting of randomization, blinding, controls, and hypotheses in the analyzed multi-domain studies would have also been accomplished. None of the reviewed studies were pre-registered, as far as could be determined. The lack of pre-registration is a common feature of all the experiments conducted in the Building Science field and not only for multi-domain experiments. A noteworthy exception in this field is the study by Schweiker et al. [69], which had been registered on osf.io.

3.2 Study deployment and analysis

3.2.1 Data collection and processing

A comprehensive reporting of the data collected and the way such data is processed before the statistical analysis is essential as it facilitates comparison, meta-analysis, and the reproduction of an experiment.
In multi-domain studies, it is important to measure and report all the environmental stimuli – not only the investigated independent variables but additional factors that are hypothesized to be relevant. For example, in a study on the cross-modal effect of light on thermal perception, the air quality, and acoustic conditions should be reported as well (at the best of the researcher's knowledge). Without measuring the possible confounders, the analysis necessarily excludes them, and therefore the results of the analysis are less valid. Besides the type of environmental stimuli collected, it is important to report how the measurements were performed and the data processed before the statistical analysis. More specifically, the measurements' location, frequency, processing (e.g., "is data averaged over a specific period of time? How is missing data treated?"), and differences from the design conditions should always be reported or discussed. Regarding the measurement location, it is important to highlight that measurements, whenever possible, should be taken in proximity to the occupant, based on the recommendations of the domain-specific guidelines, to correctly evaluate the effect of one environmental stimulus on another domain perception or behavior since those are the actual environmental conditions that affect the occupant.

3.2.2 Participants

Like all studies involving human subjects, multi-domain studies should include a concise but exhaustive description of participants' characteristics to (i) demonstrate the representativeness of the research findings (sample size and confidence interval), (ii) provide insights on the generalizability of the findings as well as possible limitations of the study (external and internal validity), and (iii) test the impact of these confounding factors on the hypothesis testing and provide confidence of the results. Sufficiently detailed information, as far as possible by obeying privacy issues (e.g. following the General Data protection regulation, GDPR [70]) on the distribution of participants (e.g., total number, number of males/females/not disclosed gender), the personal characteristics of the subjects (e.g., culture/origin, age/height/weight, health status, and verification of physical conditions before the experiment), as well as information related to their experimental involvement (e.g., direct observation, described task, participation payment, detail on the ethical approval and consent), is required for reviewing research findings and aid future replication studies.

3.2.3 Statistical analysis

Statistical methods are fundamental instruments in experimental studies to support the interpretation of the results and develop accurate, reliable, and representative experimental designs. To this end, statistical tools are used for characterizing the recorded observations, testing for differences among data series, quantifying the effect size, developing, and validating models, and identifying the sample size required to detect an effect in an experiment given the desired significance level, effect size, and statistical power. The adoption of a specific statistical method should always be justified. Also, the studies should communicate clearly the hypotheses tested and the assumptions set together with the adopted statistical tests and significance levels. Although publication space is scarce, and journals often urge authors to draft their manuscripts as concise as possible, detailed reporting of statistical analyses is mandatory if authors wish to present their results in a replicable fashion and to make their findings amenable to meta-analytical efforts [71]. To rely on the results of statistical methods, to promote transparency and reproducibility of experiments, and to ensure robustness to systematic errors, it is essential that studies clearly state the sample size, identified through an a priori power analysis or justified by any other method (e.g., resource constraints, accuracy, heuristics) to provide evidence of representativity. Effect sizes are important as a measure of how meaningful the difference between different variables or groups is to demonstrate the actual real-life significance of the experimental outcomes. It not only indicates the strength of the statistical results, but also puts a study into perspective by facilitating the comparison across different studies and helping to determine sample sizes for future studies.

Beyond the basic descriptive findings such as measures of central tendency, error, and dispersion as well as data distribution characteristics, a detailed summary of the statistical results also includes the reporting of non-significant results, degrees of freedom (related to sample size), missing data, and potential exclusions of data points as well as imputation methods, if applied. Lastly, any changes and adaptations applied to the statistical models and tests need to be stated [72].

In case the full report of these figures is not possible in a paper's results section or may appear redundant to the reviewers (indeed, some statistics can be reverse-engineered and checked for plausibility from reported results with tools such as G*Power or statcheck, see [73], [74]), authors are encouraged to seek online supplemental publication possibilities which are provided by a growing number of journals. Lastly, although the full extent of how strong various research fields are plagued by publication bias remains unknown, selective publication of only significant findings bears the threat of misrepresenting findings and puts the burden of detailed checks and evaluations on the researchers conducting the research synthesis [75], [76]. Finally, it is recommended that the statistical method is decided before the experimental design, guided by the aim of the study. In this way, the experiment is designed to get the data needed to support the data analysis and aim of the study.

3.3 Study outcome

3.3.1 Reporting results

This section does not focus on the specific results obtained in the considered papers (e.g., "is temperature affecting visual sensation?") but on the content that should be reported in the result section of each study and the way such content should be presented. In general, for reasons of transparency, comparability, and general advancements in a particular research area, the results must contain sufficient information regarding each individual outcome to facilitate replication or metanalysis efforts. This is especially true for the case of multi-domain studies due to a large number of potentially dependent and independent variables, which cannot be addressed through a single study. Given the need to report on each permutation of possible interactions between variables, the number of reported outcomes increases exponentially when compared to single variable studies. As space is usually limited, documenting data alongside the paper – including a detailed description of the number of data points excluded and argument (statistical, thematic) for exclusion can be done in a separate document, such as data descriptors, e.g. [77], [78].

While the section about results in general reports problem-specific findings intended to answer a specific research hypothesis, the following basic information needs to be provided[2]: (1) descriptive statistics for each individual variable collected (depending on data type, e.g. measures of central tendency and variability alongside with sample size); and (2) results from inferential statistics, disregarding whether they are statistically significant or not (see reporting bias in science and the potential of misrepresentation of scientific results [79]). From this perspective, it is of utmost importance to report all main and interaction effects, the exact level of significance (i.e., $p = .04$ and not $p < .05$) [80], and the effect size, whenever it is possible to determine it. The results should be in line with the type of the statistical test and its purpose described in the paper (most likely in the Methods section). The observed effects, but not stated as primary or secondary research hypotheses, need to be flagged as "*explorative*".

Specifically for multi-domain studies, a classification of the expected and observed effect is recommended, that is, whether it is a cross-modal effect, or a combined effect. In addition, further classification of the results should be reported according to the effect type. For cross-modal effects, it is necessary to indicate the "direction" (i.e., positive, negative or no effect) of the effect instead of merely reporting the presence of an interaction. The direction should be described according to the level(s) of the same-modality independent variable. For example, if temperature influences visual perception, the study should clarify if the effect of a specific visual level (e.g., dim illuminance) is positive or negative according to a specific thermal level (e.g., cold temperature).

Figure 4 schematizes the possible cross-modal effects between two stimuli and the resulting directions. As illustrated, the presence of a stimulus B can result in a negative effect (i.e., strengthen a negative or weaken a positive response of stimulus A alone as in Figure 4a and Figure 4b), positive effect (i.e., weaken a negative or strengthen a positive response of stimulus A alone as in Figure 4d and Figure 4e) or no effect (i.e., response to stimulus A is not affected by the presence of stimulus B as in Figure 4c) on the response to stimulus A.

[2] For some readers, some of these points may appear as common knowledge. However, our review showed that there are still a substantial number of papers published without including even basic information such as measures of dispersion like standard deviations.

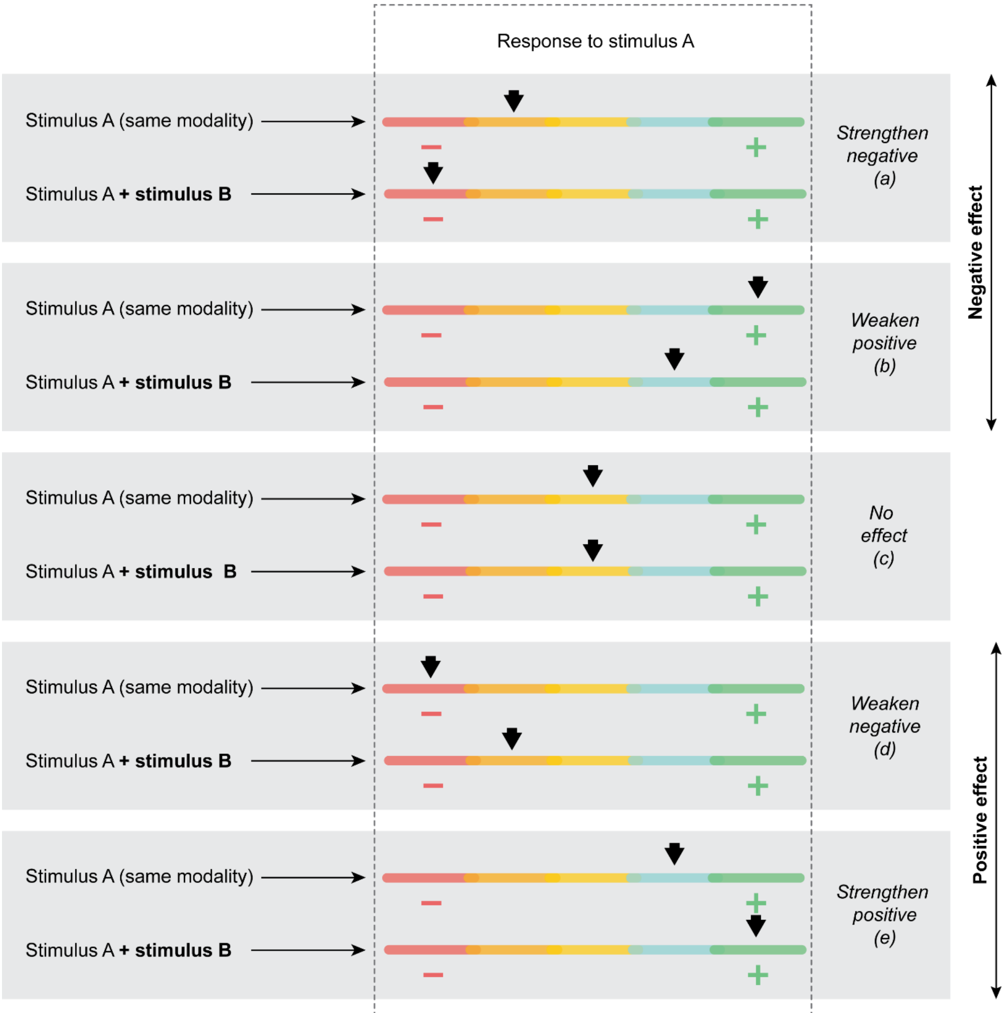

Figure 4: Schematic example of cross-modal effects of stimulus B on the response to stimulus A and the resulting effect directions.

Table 2 illustrates a possible scheme for summarizing the results of a cross-modal effect between two stimuli, with three levels each. The number of columns and rows can be adapted to the number of levels tested for each stimulus. The following descriptions of the results are suggested as examples:

- Significant *negative* effect: the presence of stimulus B at level x (e.g., illuminance, dimmer condition*)* *strengthen the negative* or *weaken the positive or neutral* response of stimulus A (e.g., thermal comfort) at y level (or all levels) of stimulus A (e.g., colder and warmer). In Table 2, this effect is shown in the first column of stimulus B.
- Significant *positive* effect: the presence of stimulus B at level x (e.g., illuminance, brighter condition) *weaken the negative* or *strengthen the positive* response of stimulus A (e.g., thermal comfort) at y level (or all levels) of stimulus A (e.g., colder and warmer). Table 2, this effect is shown in the last column of stimulus B.

Contrary to the example described, note that the effects can be different according to the level of stimulus A (e.g., be positive at low level and negative at high level). Results could also be represented graphically as in Figure 1.

Concerning combined effects, when not described as a combined index, they can be further specified into additive, synergistic, or antagonistic, with reference to the *medical analogies* described in the ASHRAE Guideline 10-2016 [39, p. 7]. Figure 5 describes the possible combined effect types, according to the following definitions reported in the standard:

• Additive: when each of the stimuli affects the human response and their combined presence results in the sum of their separate effects (no effect of interactions);

• Synergistic: when the combined presence of two or more stimuli results in a greater effect than the sum of their separate effects (enhancement effect of interactions);

• Antagonistic: when the effect of the combined presence of two or more stimuli is less than the sum of their separate effects (diminishing effect of interactions).

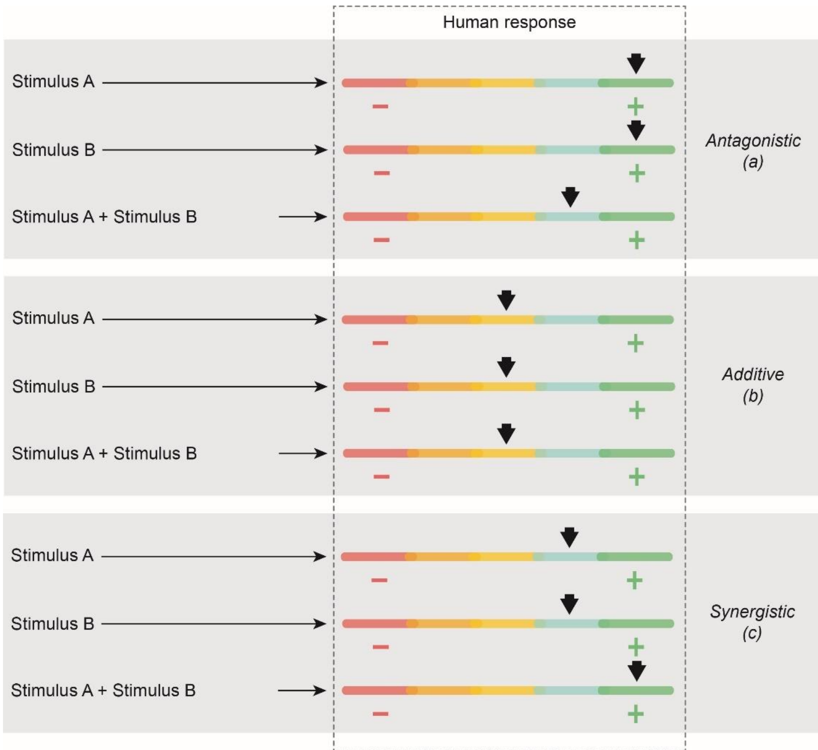

Figure 5: Schematic example of combined effects of stimuli A and B on human response and the resulting effect description.

Also, in the case of combined effects, results could be described as illustrated in Table 3 according to the levels of the considered stimuli.

Table 2: Template for results reporting for cross-modal effects of stimulus A + stimulus B on the response to stimulus A.

		Original effect of stimulus A on the response to stimulus A (same-modality)	**Effect of Stimulus A + Stimulus B on the response to stimulus A**		
			Stimulus B levels (e.g., visual – illuminance)		
			Lower level (e.g., dimmer)	Comfort level	Higher level (e.g., brighter)
Stimulus A levels (e.g., thermal – air temperature)	Lower level (e.g., colder)	discomfort	*e.g., negative*		*e.g., positive*
	Comfort level	comfort	*e.g., negative*		*e.g., positive*
	Higher level (e.g., warmer)	discomfort	*e.g., negative*		*e.g., positive*

Table 3: Template for results reporting for combined effects of stimulus A and B on human responses.

		Effect of Stimulus A + Stimulus B on human response "x"		
		Stimulus B level		
		Lower level	Comfort level	Higher level
Stimulus A level	Lower level	e.g., additive		
	Comfort level			
	Higher level			

3.3.2 Study discussion and conclusion

As for all research papers, it is obvious that multi-domain studies should present the discussion and conclusion sections. They should naturally follow and comment on the results of the study (hence being data-informed and not speculative), with reference to the results of previous studies on the topic. These sections should also include future studies, study limitations, mechanism explanations, and practical implications. With the declaration of future studies and the identification of the limitations, authors provide food for thought for the scientific communities pointing out the direction of the research highlighting the way to create a shared opinion. The tentative explanation of the mechanisms related to the results can be used as the basis for future research. Finally, the identification of practical implications of the research creates a direct link between the experiment and the impact on human life and society.

4 Critical review of existing multi-domain research

The following sections review existing multi-domain research based on the quality criteria defined in Section 3, presenting a transversal analysis of the percentage of studies reporting the aspects whenever a specific quality criterion is not present in all studies.

4.1 Review of study set-up

4.1.1 Dependent variables: human responses

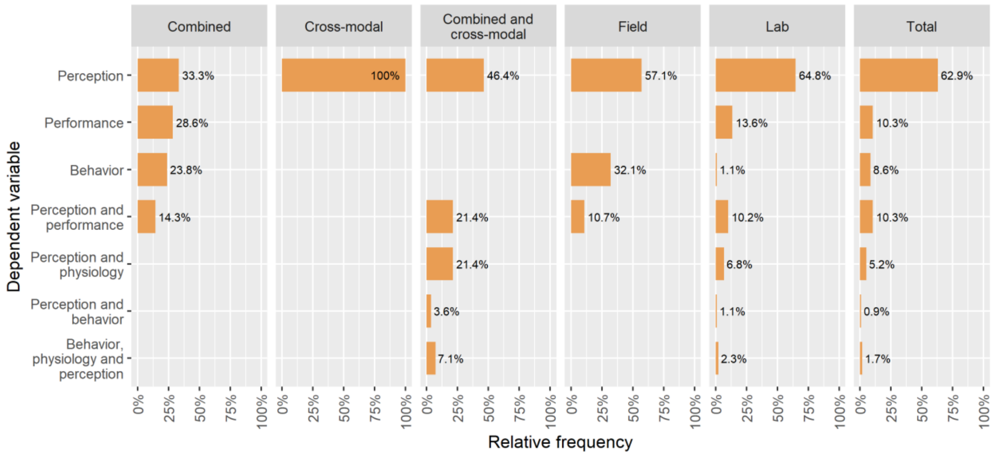

Figure 6: Distribution of human response types in multi-domain studies according to the type of effect (combined, cross-modal) and the study type (field or lab).

Figure 6 summarizes the distribution of human response types investigated in the considered multi-domain studies and shows that most of the studies investigated perceptual responses. In most of the studies, perceptual responses were the only human responses considered, and only in a few studies were human responses considered in combination with performance (e.g., [81]–[85]), physiology (e.g., [86]–[88]), or behavior [89]–[91]. Behavior and performance alone were investigated in fewer studies compared to perception. The limited number of studies reporting physiological responses may be due to the papers considered in this research, although it included studies with physiological responses in combination with other human responses only. Physiological responses were collected in lab studies only. This outcome may suggest that sensing techniques for collecting physiological signals are still too invasive or too expensive to be used in field studies. Similarly, performance studies were only conducted in lab environments. Behavioral responses were primarily collected in field studies, unless they were investigated with other human responses in lab studies [90]–[94]. Additionally, behavioral investigations in field studies were based on the collection of data on windows and blinds operations [95]–[102], thermostat setpoints [81] and ventilation speed settings [94]. Perception responses were equally collected in both lab and field studies.

When observing the distribution of data collection approaches (objective and subjective) adopted for gathering human responses, performance, behavior, and physiological responses were primarily collected via objective approaches. Performance was objectively assessed through dedicated performance tests while exploring different cognitive dimensions (e.g., proofreading, arithmetic, problem solving, creative thinking, etc.), which were generally quantified through the number of correct answers provided [103]–[106], the associated response times [84], [107], or both [108]. The subjective assessment of the performance was conducted through questionnaires [81]–[83], [109]. Methods for the objective evaluation of human behavior were based on the experimenter's observations of subjects' clothing adaptation throughout the test (e.g., number of clothing items put on/off) [92], sensors to assess windows and blinds state [102], or equipment settings (e.g., selected fan speed level) [94]. Information on windows state was also commonly collected through physical measurements by means of sensors, especially in long-term field studies [95], [97], [101], [102]. The objective approach for physiological aspects relied upon the use of wearable sensing technologies. The most investigated signals were heart rate, skin temperature, and blood pressure, while other signals such as core temperature, electroencephalography (EEG), electrooculography (EOG), blink measurement, eye movement, respiration rate and skin conductance (also through the use of an algorithm for the detection of artifacts [110]) were rarely included in multi-domain studies [55], [108]. The subjective approach to collecting physiological observations focused on direct questions about subjects' perception of health symptoms (e.g., eye irritation, throat irritation, and skin dryness) via questionnaires [87], [88], [111].

When studying human perception through subjective assessment, the top five assessment categories were perception, comfort, satisfaction, acceptability, and preference. They were primarily assessed through categorical scales. Perception, satisfaction, and preference were most often expressed through a 7-points scale, while comfort was mainly investigated on a 5-points scale, and acceptance on a 3-points, 4-points, or dichotomous scale (acceptable, not acceptable). Some trends can be identified, most likely as a result of questionnaires referencing standards pertaining to human perception research [21], [112], [113]. It must be noted that sometimes, despite evaluating the same assessment category (e.g., thermal sensation) and indicating the same number of response categories, the labels used can vary [114]. Similarly, visual analogue scales can have varying ranges (e.g., 0 to 100 or 0 to 60) [111], [115]. These differences may increase the difficulty of comparing results across studies.

4.1.2 Independent variables: combined environmental stimuli

Figure 7 reports the distribution of independent variable combinations in the considered papers. In general, thermal and visual stimuli were the most investigated combination of independent variables, mainly studied in cross-modal investigations. Thermal and IAQ, and thermal and acoustic, were the second and third most common combinations in cross-modal studies, highlighting the dominant interest in thermal studies. In contrast, combined effect papers tended to focus more on all four environmental stimuli and their effect on overall perception and performance. Behavior and physiological responses were primarily studied in response to thermal and visual, and thermal and IAQ combinations. The least studied combinations were visual and IAQ, and acoustic and IAQ, both in cross-modal and combined investigations.

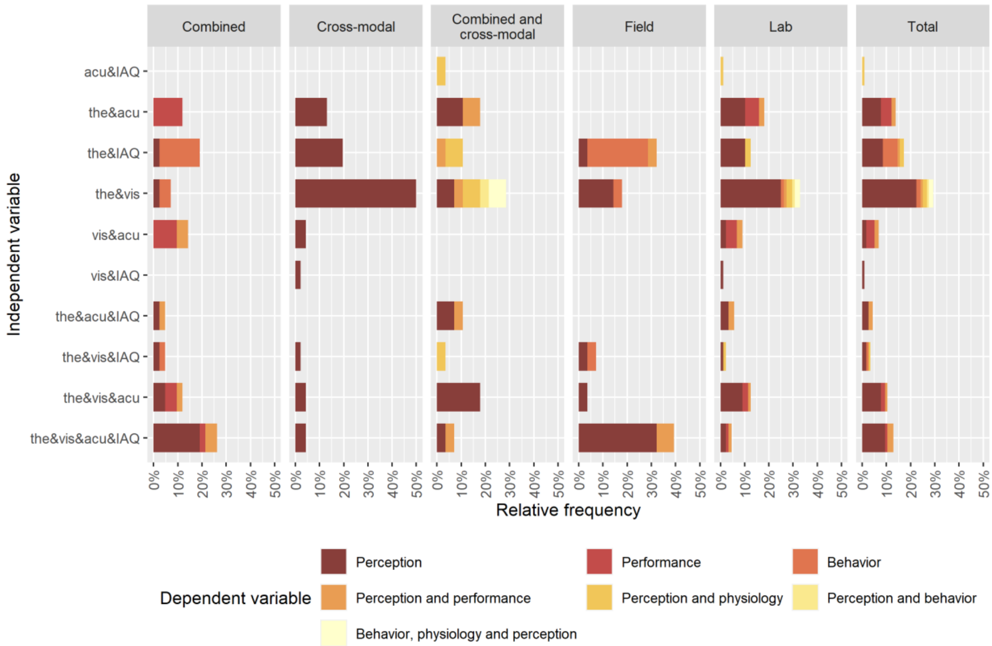

Figure 7: Distribution of independent and dependent variables, according to the type of effect (combined, cross-modal), study type (lab, field) in the reviewed papers. Acu = Acoustics; IAQ = Indoor Air Quality; The = Thermal; Vis = Visual.

All the reviewed studies reporting experimental investigations about cross-modal effects indicated the type of cross-modal independent variables. Only a few studies did not report the number of levels (*3%*) or the design values (*6%*). In contrast, the same-modality independent variable was sometimes not described in terms of type (*12%*) and design value (1*8%*). Figure 8 summarizes the design values of the independent variables (facet headings) used in experimental cross-modal investigations. The sensory domains on which their effect was tested are indicated on the x-axis. For example, the first box on the top-left of the graph illustrates the values of indoor air temperature tested to assess their influence on acoustic, IAQ and visual responses. The "thermal" response is not indicated as it is a same-modality response. Each dot represents a tested condition, while the box-plots illustrate the overall ranges of values for each independent variable (i.e., mean and interquartile range). It can be observed that the thermal independent variables (air temperature, relative humidity, air velocity and Fanger's Predicted Mean Vote - PMV) were the most considered independent variables, investigated to assess their influence on all the non-thermal domains. This outcome can be expected given the strong interest in thermal studies previously highlighted. For all independent variables, extreme values were commonly used in experimental investigations. The choice of extreme stimuli can be justified because if a cross-modal effect is not observed for extreme stimuli, it is unlikely that it will occur in normal conditions (if it assumed that the relationship between the dependent and independent variable is linear). Interestingly, when the same independent variable was tested on different sensory domains (e.g., air temperature effect on acoustic, IAQ and visual perception), the distribution and median of its values were consistent across domains.

Figure 8 highlights the least and more explored combinations or range of independent variables tested in cross-modal investigations, an information that can be used to guide future multi-domain studies. Ventilation rate was not represented, as only one value (30 l/s influence on thermal and acoustic responses) was present in the considered studies.

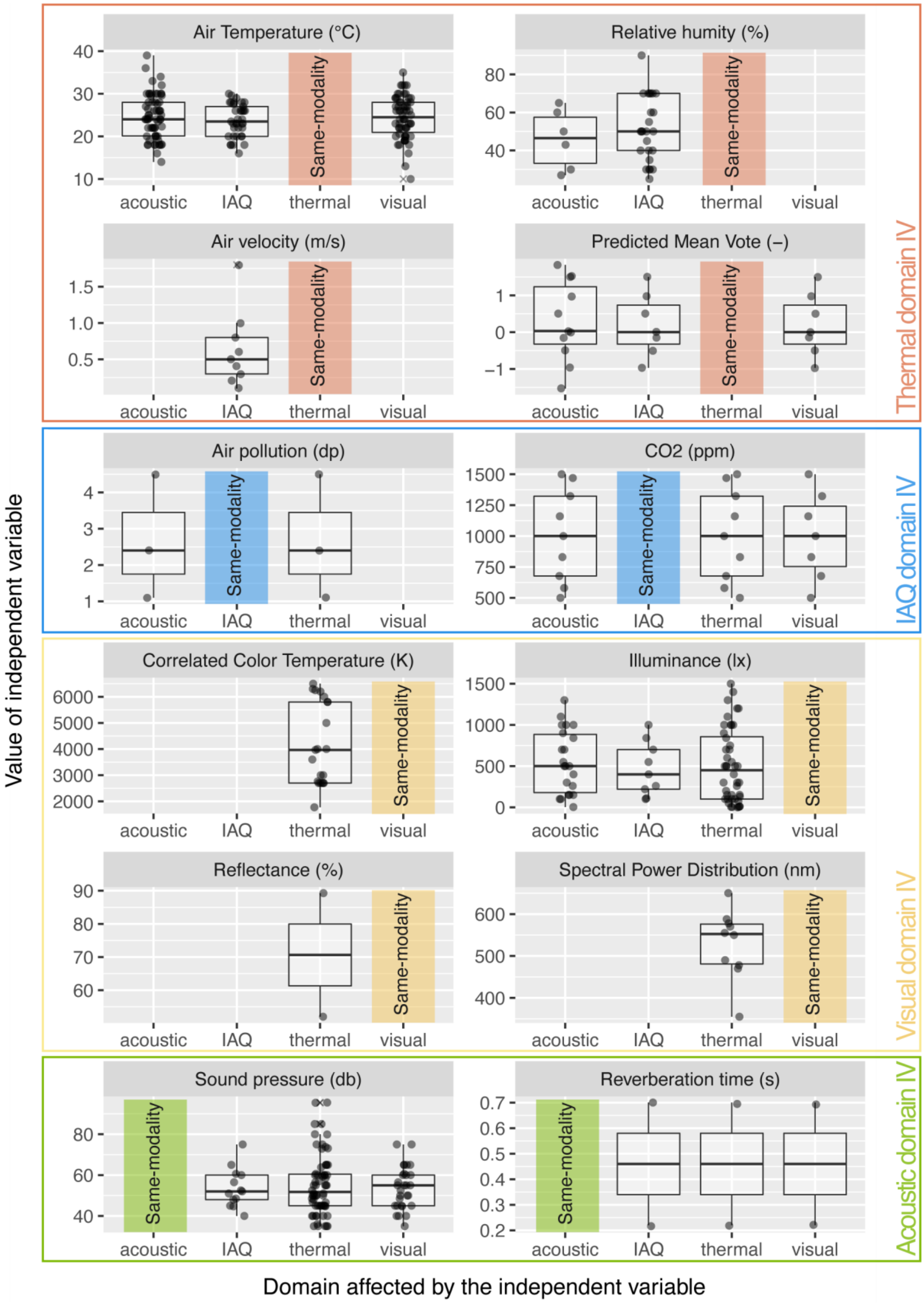

Figure 8: Number of cross-modal studies depending on the domain and reported value of the Independent variable (IV). Each dot represents the value of the independent variable investigated in the literature. Dots are randomly jittered to discern more values and their left or right position with respect to the vertical line in each boxplot has no additional meaning.

The great majority of the reviewed studies reporting experimental investigations about combined effects clearly indicated the type of independent environmental variables. Design values were specified in most of the studies as well (*98%* of studies reporting thermal stimuli, *88%* visual, *95%* IAQ and acoustic). Level values were less frequently reported for each environmental variable: *71%* for thermal and *76%* for visual, IAQ, and acoustic. Figure 9 shows the combination of the independent environmental variables reported in experimental studies investigating combined effects. It can be observed that air temperature and illuminance were the most studied variables. Figure 9 also indicates the dependent variables, confirming the overwhelming focus on overall comfort and performance as discussed before and highlighted in Figure 7. The range of considered values broadly varied between variables and the investigated human response. Figure 9, similarly as Figure 8 for cross-modal effects, highlights the least and most explored environmental stimuli combinations tested in combined effects research, a piece of information that could be used for future multi-domain studies.

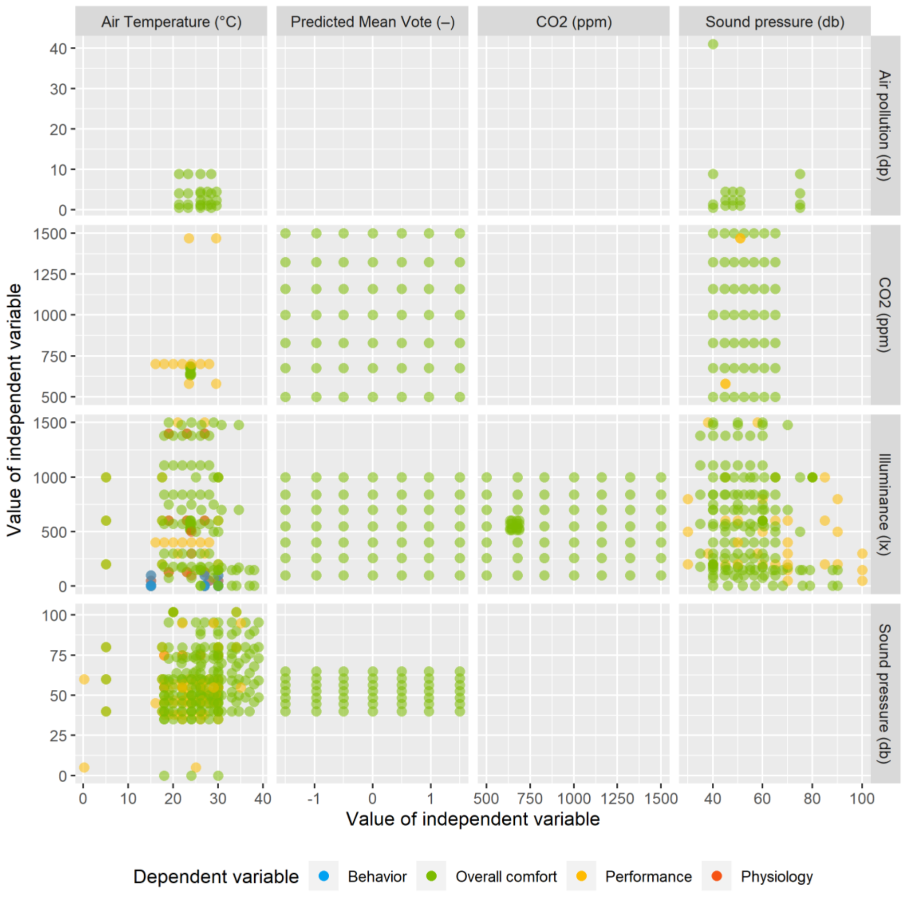

Figure 9: Combination of independent variable values employed in experimental investigations studying combined effects, considering the dependent variables (indicated with colors). Ventilation rate, air velocity, relative humidity, CCT, and VOC (Volatile Organic Compounds) are not represented as only a few data points

were present in the considered studies. Some outliers of the represented independent variables were excluded as well (i.e., 3000, 4000 lx). Each dot represents an investigated independent variable.

Finally, in most of the reviewed multi-domain investigations, the independent variable values were continuous, only rarely categorical (e.g., natural versus electrical light, wall colors, good vs. bad light comfort conditions).

4.1.3 Research hypothesis

Only *53%* of the considered articles reported the research hypothesis, divided into those where the hypothesis was "with direction" or "without direction" (Figure 10). Studies carried out in laboratories had the highest percentage of hypothesis statements (*59%*) with almost the same percentage for "with direction" (*28%*) and "without direction" (*30%*). In addition, most articles with a hypothesis statement belonged to "cross-modal" experiments, mainly carried out in laboratories. In research on the combined effect, only *26%* of the papers stated the hypothesis. Among them, the study by Lin [116] can be considered as a best practice of the category "with direction" because the author clearly stated the hypothesis of the work: "higher noise intensity and either too low or too high illumination intensity will reduce visual performance". The papers on the combined effect not reporting the hypothesis might be due to the lack of research and data on the topic [84], [107], [108], [117]–[119].

More than *60%* of field studies did not state the hypothesis. This may be due to the number of uncontrolled variables that make it difficult to formulate a clear hypothesis. In this case, the research was based on generic assumptions that needed to be verified in the current conditions.

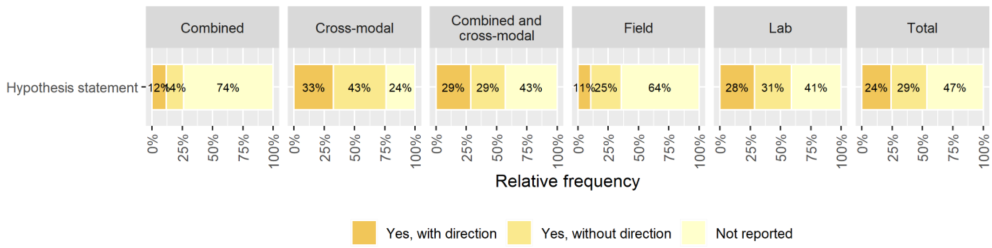

Figure 10: Relative frequencies of hypothesis statements in the considered studies.

4.1.4 Setting feature

The considered setting features and their presence in the literature are summarized in Figure 11 and discussed in the following.

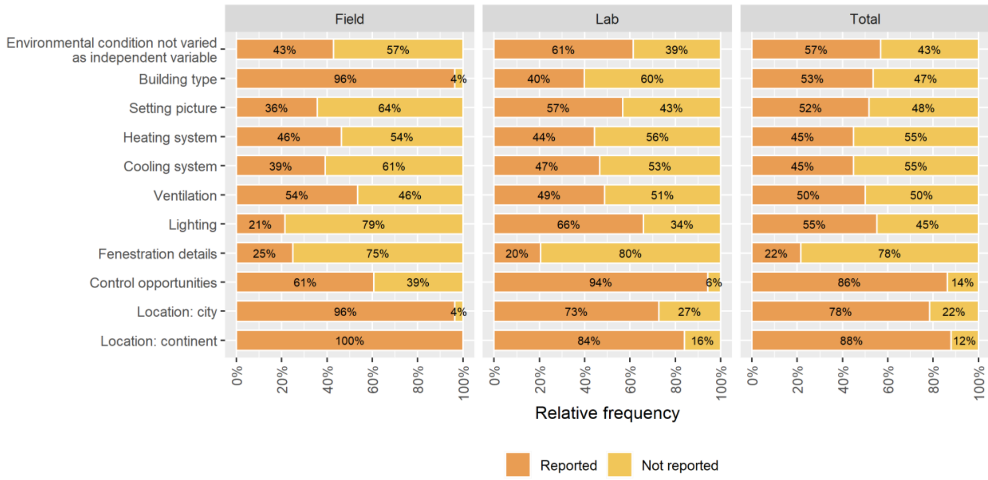

Figure 11: Relative frequencies of the experimental setting features in the considered studies.

Despite the fundamental importance of a comprehensive description of all the environmental conditions (besides the ones varied as independent variables), most of the considered studies did not report them. Only about *20%* reported a comprehensive overview (e.g., [54], [55], [120]) (i.e., with all environmental stimuli described), while an additional *37%* included a partial description. The description was often present in lab studies, especially when it was comprehensive (Figure 11). Many studies described only the features that were relevant in the investigated domains, neglecting the potential cross-modal influence of other domain-related features.

The building or space type was not reported in *47%* of all the studies. In laboratory studies, the "emulated" space type was not reported in *60%* of cases. From the studies that did report the building or space type, it can be observed that multi-domain studies were mainly carried out in offices (*34%*), followed by educational (*10%*) and residential buildings (*5%*).

In the investigated studies, *48%* omitted space pictures and *35%* reported it without participants (ethical issues may play a role in this case). A good reference for description can be found in several studies [83], [121]–[124]. Best practices of pictures can be found in [94], [105], [125]. *55%* of studies did not report any information about the heating and cooling systems, and only *50%* provided information on ventilation type. Examples of these systems descriptions can be found in Tiller et al. [84] and Yang and Moon [126]. Description of ventilation type can be found in Skwarczynski et al. [127]. Lighting information was provided in *55%* of studies, with a large prevalence using electric lighting (*37%*). The reduced number of studies on daylight could be explained by the challenging experimental conditions that such an environmental variable entails. Winzen et al. [131] and Chinazzo et al. [55] described the lighting system. Among the investigated studies, information about the fenestration system was only accounted for in *22%* of papers. Reference descriptions can be found in Haldi and Robinson [124] and Garretón et al. [132].

Among the studies considered in this work, *86%* provided information on control opportunities, especially in laboratory experiments. Discrepancies between laboratory and field studies can also be recognized in terms of occupants' level of control over the environment since lab experiments were largely characterized by the lack of control by occupants (*92%*). The same situation can be found in only *11%* of field experiments.

Reporting exhaustive information on occupants' possible interactions with all available interfaces was not common since studies usually provided insights solely about actions that affected the investigated variables. Most of the studies (*88%)* provided details on the experiment location (e.g., reporting the city and country), offering the possibility of interpreting results with a more accurate consideration of local climatic conditions as well as sociological attitudes of the population [54], [114], [133]. Europe and Asia hosted most of the studies (*38%* and *35%*, respectively), followed by North America (*11%)*, South America and Oceania (about *1%*).

4.1.5 Exposure feature

In the analyzed studies, the most frequent design was within-subjects (*40%* of studies), particularly common in lab studies, followed by between-subjects (*18%*) and mixed designs (*15%*). However, many papers did not clearly report on their study design (*27%*), especially in field studies, which might be due to the fact that field studies normally work with between-subjects-design as they measure existing environmental conditions without modifying them. A within-subject design in a field study would be called an intervention study. It is challenging to summarize the number and combination of tested experimental conditions in a concise manner as they vary highly across studies. For example, Huebner et al. [92] reported several conditions tested within-subjects, with all subjects experiencing dynamic temperature variations, and two conditions experienced between subjects (two CCTs). Laurentin et al. [134] tested six conditions within-subjects (two temperatures and three light types).

What is important to notice was the lack of reporting of exposure characteristics in many studies. While some missing information can be justified by the study type (e.g., the length of exposure for each experimental condition was rarely reported in field studies due to the lack of clear exposures), others should be reported in all studies to increase replicability and better understand study results. It was the case of the total length of the experiment per participant, not reported in *82%* of field studies and *15%* of lab studies, which greatly influences the outcome of the experiment given the potential fatigue of longer experimental sessions, especially in laboratory settings. It is surprising to see that the timing of the experiment during both the day and the year was not reported in many field studies (*40%* and *25%,* respectively), and even less in lab studies in which the time of the day was not reported in about *55%* of the studies and the time of the year in *61%* of them.

The last analyzed aspect of the exposure feature is the adaptation time. More than half of the studies reported the adaptation time, especially in lab settings (Figure 12). There was a tendency in most of the laboratory studies to use 30 minutes as an adaptation time; however, the time ranged from 5 to 55 minutes among the experiments, indicating a lack of consensus regarding this parameter.

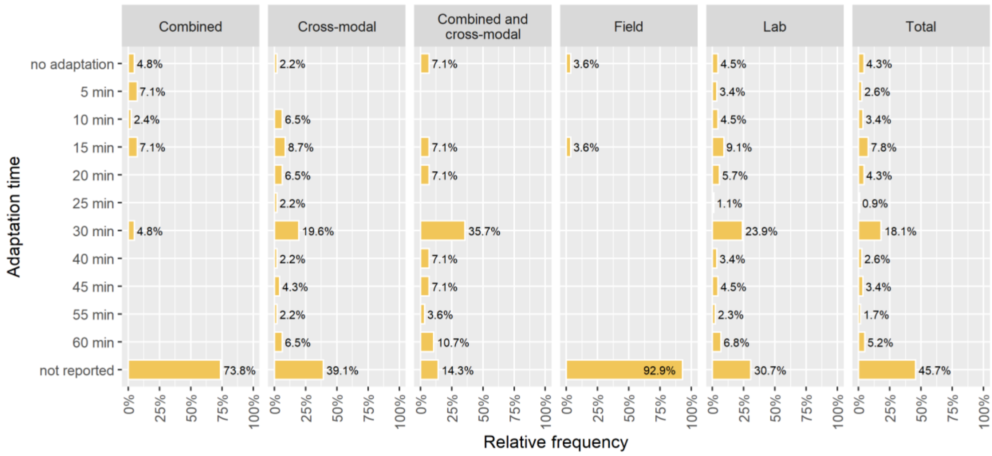

Figure 12: Adaptation time in minutes reported in the studies (y-axis) in laboratory experiments.

4.1.6 Experimental design quality

As shown in Figure 13, there were substantive gaps in reporting across all the elements of good experimental design analyzed here. Half of the reviewed papers did not report how the participants were assigned to the experimental conditions, especially in field studies where *82%* did not indicate this information. The risk of bias due to participants' expectations during the experimental sessions was reduced through single-blind and double-blind procedures in *34%* and *2%*, respectively. The rest, mostly field studies, did not mention blinding. In IEQ studies, a procedure can be considered blind when the experimental conditions are not directly explained to participants (i.e., another goal is introduced instead of presenting the study as "the effect of x conditions on y human response"). It must be highlighted that it is very challenging to make some conditions blinded (e.g., temperature or light conditions), especially in repeated measures. Hence, a truly blind procedure might be hard to achieve in IEQ studies, especially with extreme environmental conditions.

To reach the internal validity of the results, the experimental design must account for confounding variables. The most common variables controlled during data collection involved thermal stimuli (clothing insulation, relative humidity, and air velocity), followed by illuminance. Such variables can be controlled during the experiments or in the subsequent statistical analysis. The number of studies that did not report this information is high, especially in field studies. This is a surprising result considering the more numerous confounding factors present in real buildings than those found while performing controlled experiments. A null condition was reported in *28%* of the studies, all of them developed in a laboratory setting. Depending on the type of stimuli investigated, different null conditions were used, such as comfortable indoor temperature or daylight transmitted through uncolored filters [55]. In a repeated stimulus design, the consistency of the responses to the same stimuli can be tested, which is a good practice to verify the reliability of the results [47], [67]. Yet, this approach did not seem to be common in the considered studies.

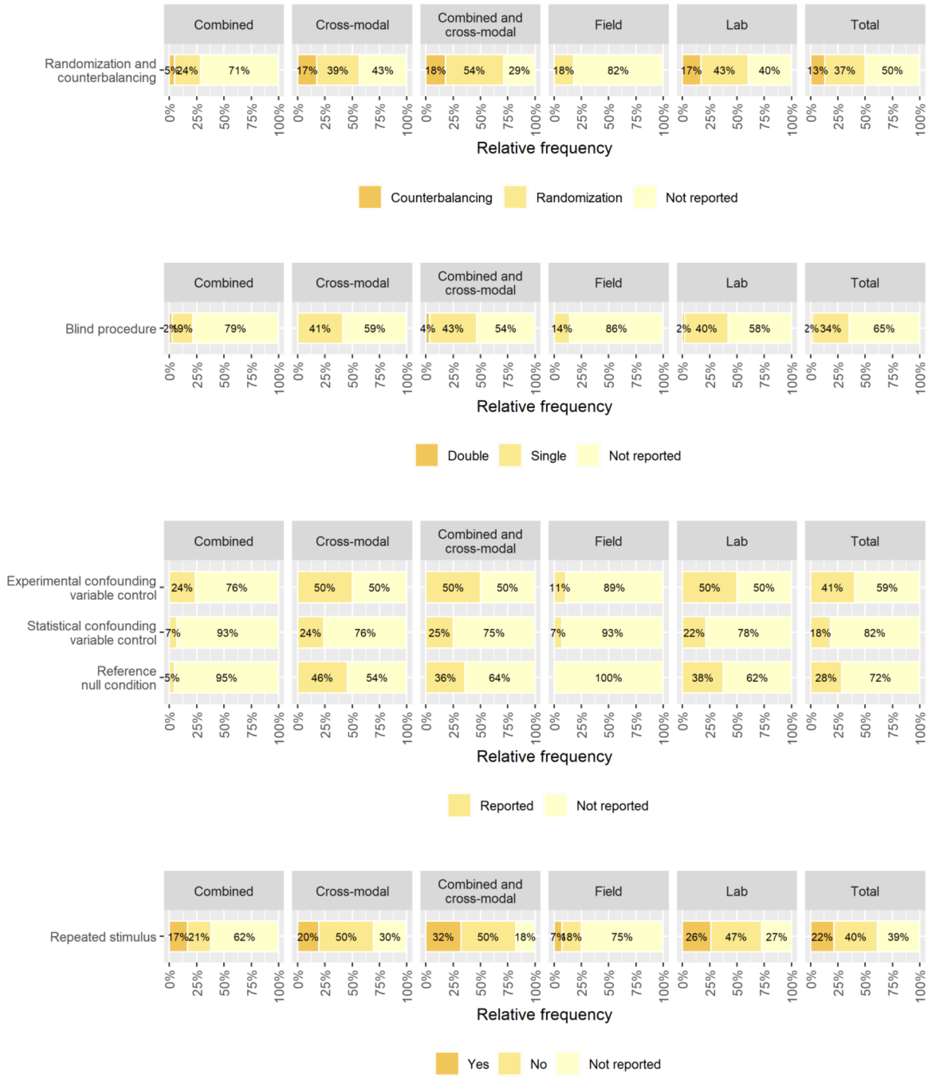

Figure 13: Relative frequencies of information about the experimental design quality reported in the considered studies by effect type and study type.

4.2 Review of study deployment and analysis

4.2.1 Data collection and processing

Table 4 shows the frequency of the studies reporting the measured environmental parameters. The thermal parameters (i.e., temperature and relative humidity) were the most frequently measured and reported for both field and lab studies. The predominance of thermal measurements is linked to the numerous experiments concerning thermal aspects. However, it must be noted that such measurement was also present in other studies (approximately in *71%* of all the reviewed studies). This outcome is potentially due to the great influence that thermal conditions play on occupants' experience of space and the relative ease of measuring thermal parameters due to the availability of low-cost sensors [135]. The visual domain was the second most frequently measured aspect, with *47%* of studies reporting illuminance values.

	Effect type			Study type		Total
Environmental measurements	**Combined**	**Cross-modal**	**Combined and cross-modal**	**Field**	**Lab**	
Air temperature	26	33	21	22	58	80
Air velocity/speed	9	16	10	12	23	35
Global radiation	0	1	0	1	0	1
Globe temperature	5	4	3	4	8	12
Humidity	1	3	0	0	4	4
Local outdoor temperature	0	1	0	1	0	1
Mean radiant temperature	3	1	0	4	0	4
Operative temperature	0	0	4	0	4	4
Outdoor relative humidity	4	0	0	4	0	4
Relative humidity	18	22	17	18	39	57
Surface temperature	0	0	3	0	3	3
Wet bulb temperature	0	0	3	0	3	3
Clearness index	0	1	0	1	0	1
Correlated colour temperature	0	4	0	0	4	4
Illuminance level	21	17	17	13	42	55
Illumination intensity	1	0	0	0	1	1
Luminance	1	0	0	0	1	1
CO2 concentration	13	2	7	15	7	22
Particulate matter	4	0	0	4	0	4
Ventilation rate	0	3	1	1	3	4
Sound/noise level	12	3	3	3	15	18

Table 4: Number of reviewed studies reporting to measure the environmental parameters.

Overall, general information for reproducibility was scarcely reported in the considered papers, as shown in Figure 14. For instance, most studies did not report the frequency with which measurements were taken (*78%* of studies), the processing method used after data collection (*59%*), or the comparison between measured and design conditions (*83%*). These results include both field and lab studies. This lack of information on environmental measurements is a severe limitation of existing multi-domain studies. The location of the measurements was the only information that was reported more often, presented in *66%* of the studies. Environmental measurements at the proximity of each participant were more common in lab studies than in field experiments, where sensors were usually deployed to measure the average room condition.

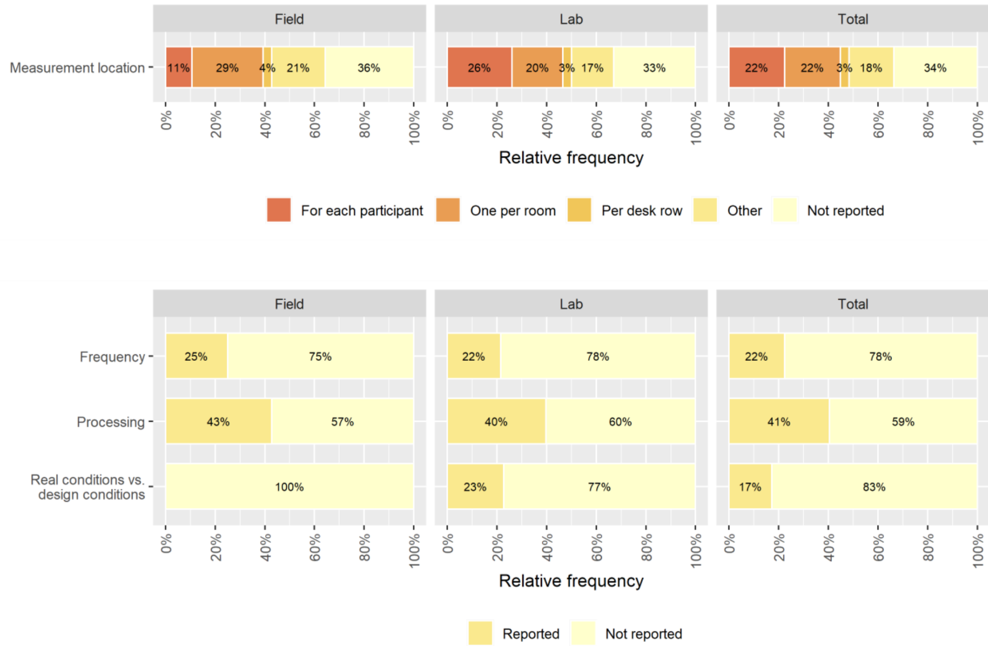

Figure 14: Relative frequency of reviewed studies reporting information on environmental stimuli measurements. The label “other” includes, e.g., per desk row, and in the corner desk.

4.2.2 Participants

Figure 15 highlights the percentage of studies reporting the participant characteristics. Overall, field studies had a higher number of participants (mean = 141) compared to laboratory studies (mean = 35). Distribution by sex was reported in most laboratory studies (*91%*) and approximately half of the field studies (*46%*). As shown in Figure 15, age is reported more than most other single characteristics *(73%).* The origin of the participants was reported in only *18%* of the analyzed papers. The verification of physical conditions before the experiment (e.g., sleep, vision, food/alcohol/caffeine intake) was reported in more than half of the laboratory papers *(55%),* but rarely in field studies (*11%*). Indications about the subjects’ health status, height, weight, and origin were reported in one-third or fewer of the papers. Finally, participants’ involvement in experiments was more frequently reported in laboratory studies than in field studies across all measures. Of the measures, the description of tasks/activities was the most commonly reported (*77%*). In the described tasks/activities, the predominant activities were office activity (*29%*) and class activity (*7%*), while in laboratory studies, the most reported activities were reading (*17%*), sitting (*15%*), and conducting performance tests (*13%)*. Participants’ payment for taking part in the project is reported in *44%* of the papers. None of the field studies foresaw a payment to the participants, while *47%* of the laboratory studies remunerated the participants. Surprisingly, information on the ethical approval and whether a tailored information sheet was distributed to the participants was reported only in *21%* of the analyzed studies (*7%* and *25%* in field and laboratory studies, respectively).

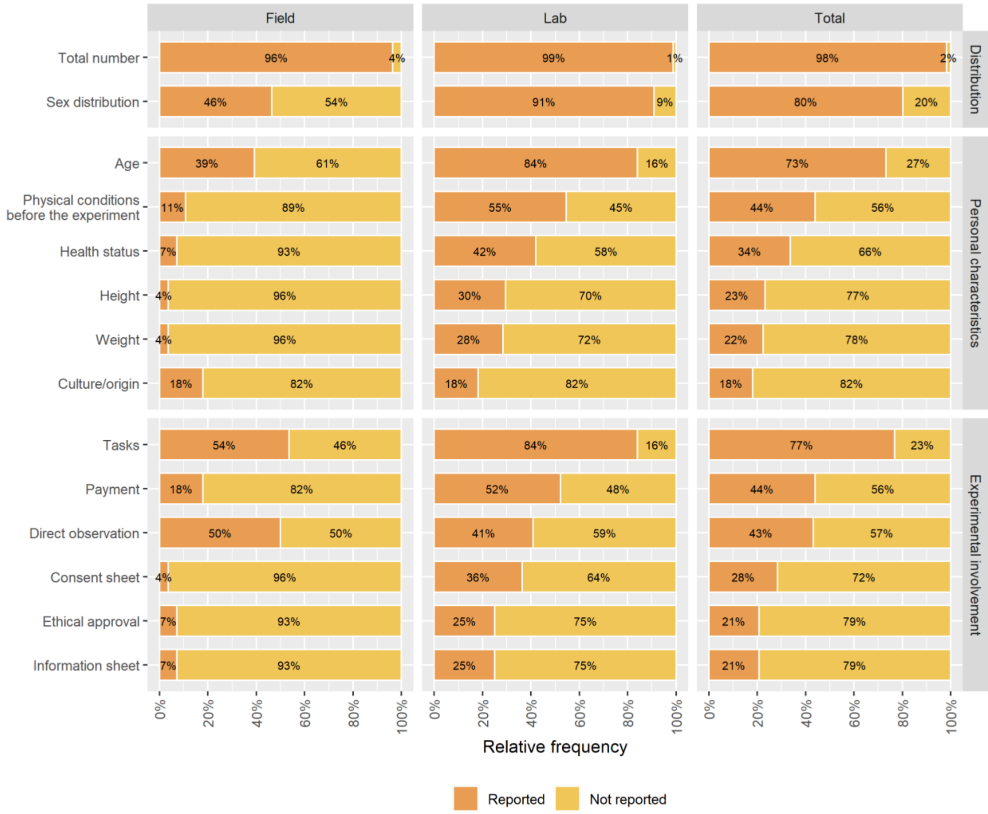

Figure 15: Relative frequencies of information about participants reported in the considered studies.

While most studies provided detailed information on the number of participants, most of the described participant-related aspects seem to be underreported or not clearly stated in the papers. This leads to the risk that readers will make assumptions about certain aspects (e.g., assume that all participants were nationals from the country where the study was conducted). In future studies, researchers should report participants' characteristics in detail to clearly define to whom the study's findings apply. As best practice references, the studies that, according to our review, reported most of the relevant aspects related to participants' characteristics and their involvement were Kim and Tokura [93], Chinazzo et al. [128], Golasi et al. [136], and Wang et al. [137].

4.2.3 Statistical analysis

Among the considered publications, 44 statistical methods were used to analyze the combined and cross-modal effects. Figure 16 shows the main statistical methods used in the reviewed studies and the percentage of the studies adopting different methods. The most used statistical methods were the analysis of variance (ANOVA), linear regression, and *t*-test. The least used methods were categorized in the "other" group, which includes, for example, Mann-Whitney-U test [138], change-point regression [97], and permutation test [105].

The methods were also analyzed and categorized based on their “appropriate” use. For example, the *t*-test was deemed as “not appropriate” if multiple *t*-tests were applied directly as the primary test and not as a follow-up test of a “higher-order” test such as ANOVA. In addition, the absence of a statistical analysis was categorized as “not appropriate”.

In Figure 16, it can be seen that mixed-effect models (also commonly referred to as multilevel or hierarchical models), although used, are not applied often. However, these models are valuable tools developed to address the violation of the independence assumption (required by traditional statistical analyzes such as ANOVA and ordinary least-squares regression). This assumption is violated whenever the observations are nested and/or clustered. For example, nested and/or clustered observations can arise from temporal and spatial autocorrelation. In the context of multi-domain studies, an application of these methods can be found in [55], [128]–[130], [139]. In this figure, it can also be observed that only 5.9% of the statistical methods used (14 out of 236) perform preliminary tests to assess the collected data (e.g., Shapiro-Wilk to check the data distribution).

Adopting a specific statistical method was justified in only *40%* of the papers. This result shows that the authors either assumed the readers could infer the statistical reasoning or considered it not an important aspect of the manuscript.

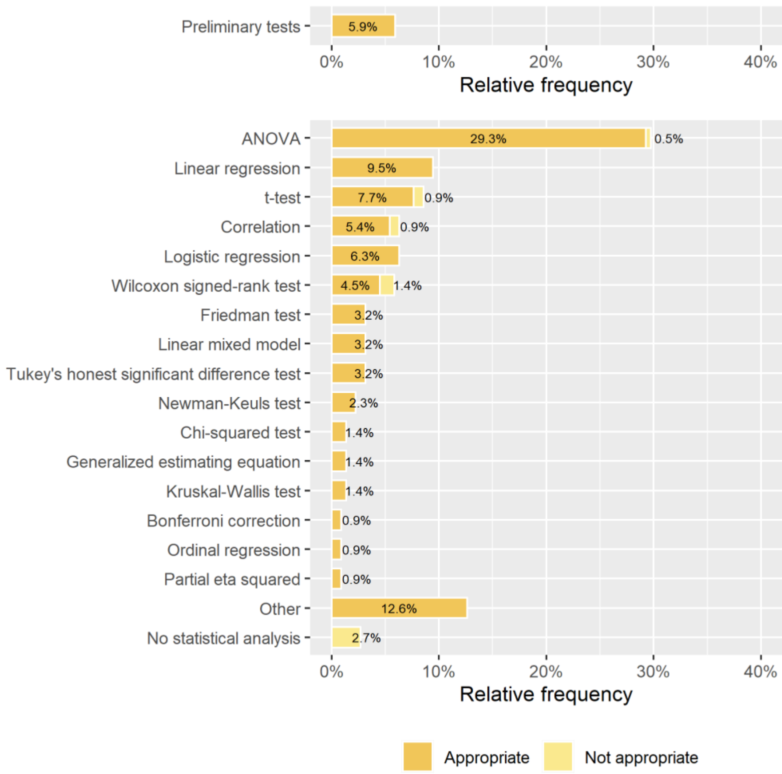

Figure 16: The percentage of different statistical methods used (thereinto, ANOVA includes repeated measures ANOVA, one-way ANOVA, two-way ANOVA, three-way ANOVA, factorial ANOVA, mixed model ANOVA, Welch’s ANOVA, ANCOVA, MANOVA, MANCOVA; generalized estimating equations includes a

model assuming a binomial distribution with logistic link, a model assuming a normal distribution with identity link function; correlation includes partial correlation analysis, Pearson's correlation coefficient, Spearman's rank correlation coefficient).

Only *4%* of the studies reported a power analysis, both in field and lab studies. This aspect attracts a quite interesting outcome because, in most of the cases, either the experimental design was not entirely reported in the publication, or the minimum number of observations of an experiment was simply stated but not justified.

Despite its importance, only *22%* of the studies explicitly reported the effect size, both in field and lab studies. It means that most of the studies referred only to statistical significance testing to evaluate their results.

While the domain outcomes of the reviewed studies are of paramount importance and contribute to the development of the field knowledge, unfortunately, the description of the statistical methodology was often approximate or missing. In most cases, statistical methods were applied without a dedicated description of data acquisition, analysis, curation, storage, and usage. In some cases, even validity and representativity of outcomes cannot be inferred due to missing information on data accuracy, completeness, consistency, relevance, and uniformity.

4.3 Review of study outcome

4.3.1 Reporting results

To our knowledge, the definitions of the results and results reporting style are described for the first time in this study. Therefore, it is difficult to analyze the presence of such information in the considered papers. Most of the time, we observed that results were reported in an incomplete way (e.g., only statistically significant results were described, or not all the effects of all the considered stimuli were reported). In addition, the direction of the effect in cross-modal studies and the type of combined effect were rarely stated. Finally, a graphical representation of the cross-modal and combined effects was reported in only a few studies (e.g., [130], [140], [141]).

4.3.2 Study discussion and conclusion

Figure 17 shows the relative frequency of data-informed conclusions and frequency of reporting future studies, study limitations, mechanism explanations, and practical implications.

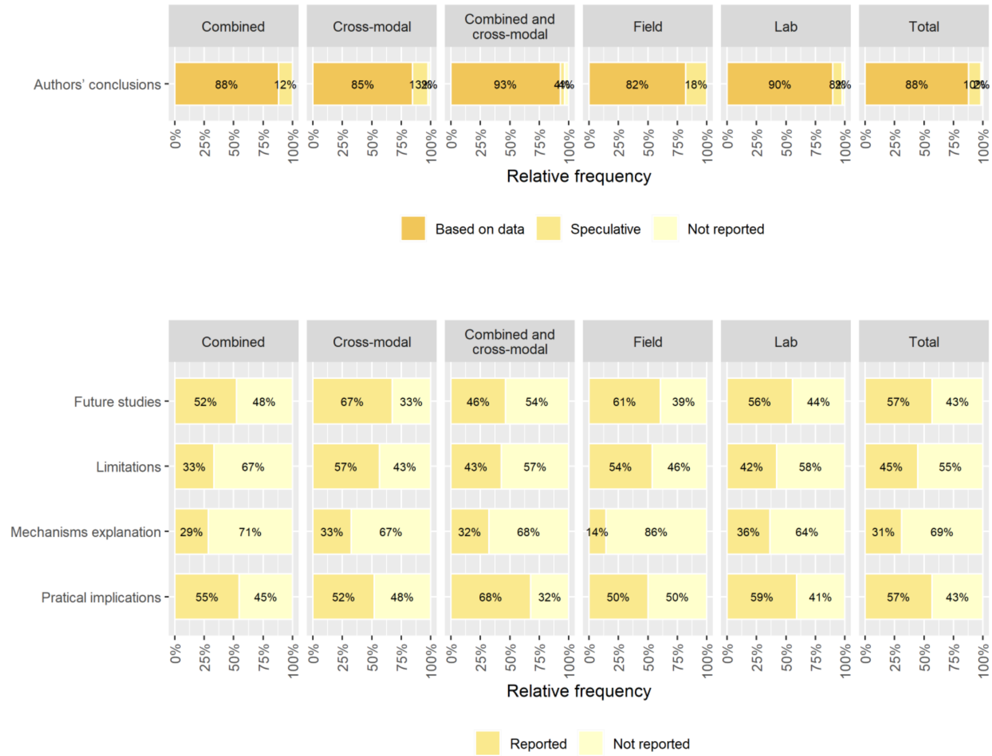

Figure 17: Relative frequencies of information about conclusions and discussions reported in the considered studies, according to the effect type and study type.

Most of the articles (88%) presented conclusions based on data, while the remainder seems to be speculative. Such distribution was similar across effect types, but not across laboratory versus field studies: the percentage of conclusions based on data is higher in research carried out in laboratory than in-field, 90% against 82%, respectively. This difference can be related to the opportunity to control some potential confounding factors in laboratory that are not always detectable in a real case.

Roughly half of the studies did not identify future studies, limitations or practical implications, although there were some differences within the sub-types. For instance, limitations were related to the study type, with some of them only relevant for field studies (e.g., limited control) and others for lab studies (e.g., limited exposure time). Also, in studies carried out in the field, the percentage of papers with mechanisms explanation was lower than those in a laboratory, 64% and 86%, respectively. The results of these studies can be influenced by variables that cannot be controlled, making it difficult to reach an unambiguous result [142]. However, in many cases, authors were able to provide a description of the mechanism [97], [121], even with a step forward from the initial hypothesis [143]. In research carried out in laboratory, the use of a wide range of sensors and the control of variables allowed some authors to explain the results while also considering a physiological point of view [90], [93], [127], [144], [145]. In other studies, authors deepened the effect of specific stimuli on the perception of comfort [146] or on performance [116].

In the articles presenting future studies several authors propose further research in the form of new configurations of existing independent variables or expanding their ranges and identifying new parameters of the same independent variables or new environmental factors. These future developments are more visible in cross-modal analysis where the interaction among the independent variables are often partials. Other future studies include the investigation of different size, age, and origins of the participant group, of new building typologies or settings, different exposure time and experimental length, and of new computational models.

Practical implications were not reported in 43% of the analyzed papers. Examples of good descriptions of practical implications can be found in several papers [85], [116], [147].

5 Conclusions and recommendations

5.1 Key observations

The premise of this paper, as well as that of most of the work it assesses, is that people's experience of and response to indoor environmental conditions involve multiple domains. Nonetheless, the bulk of regulatory resources for building professionals is single-domain. This may be attributed to the complexity of multi-domain exposures and the mechanisms by which they influence buildings' occupants and implies a need for increased multi-domain research. Moreover, while additional studies are necessary, they are not sufficient for progress in this area. To achieve a deeper understanding of the nature of multi-domain exposure implications for occupants' health, comfort, and productivity, the related research must also satisfy several qualitative requirements. Such research must be designed, conducted, and documented in a systematic and transparent manner, such that the results are reproducible and suitable for meta-analyses. This paper's assessment of the past research efforts in this area identified several shortcomings, notwithstanding the studies' general relevance, importance, and in some cases, pioneering significance. Therefore, as the following summary of the observed key challenges implies, necessary quality improvements of future multi-domain research need to address both the studies' design, deployment, and reporting. The key observations are divided into those related to each aspect of the critical review and those associated with a transversal analysis of the results.

Key observations of the critical review:

- Dependent variables: existing studies mainly focused on the investigation of subjective perceptual responses, most commonly through numeric scales (including 3-point, 5-point, and 7-point scales) to capture test participants' responses regarding perception, comfort, satisfaction, and preference. At times, a different number of points and different labels were used, even though the same assessment category was involved. This, as well as the inconsistent use of dimensions in analogue scales, disables the comparison of results from different studies and poses a problem for conducting large-scale meta-analyses. Performance, behavior, and physiology are still untapped research venues that could lead to new breakthroughs in multi-domain studies.

- Independent variables: thorough documentation of the prevailing values of the independent variables is a basic requirement for doing multi-domain studies. Most reviewed research generally provided such documentation, even though the types and design values in some same-modality independent variables were not reported. Future comparative studies and meta-analyses could benefit from a more consistent choice of the design values for independent variables. It is recommended to always adopt numerical design values which will enable future replication studies and meta-analyses. Moreover, documentation of non-environmental independent variables (e.g., relevant information on participants and outdoor conditions) could strengthen the interpretation scope of the studies' findings.

- Research hypothesis: the comprehension and utility of results from experimental research, would be arguably higher when research hypotheses are explicitly stated, including their "direction." Surprisingly, about *40%* of the laboratory studies and *60%* of field studies did not state the research hypotheses. Whenever the hypothesis was stated, only a fraction indicated the direction – a very small one in field studies.
- Setting features: the description of the settings is a key aspect, yet not sufficiently reported in most reviewed studies. Such information includes building location, type, space layout, HVAC, building elements (e.g., windows and shades), control interfaces, and lighting systems. Consequently, confounding factors and potential cross-modal effects of other features could be overlooked.
- Exposure features: in many instances, characteristics of the exposure situation (e.g., type, timing, and length of exposure) were not reported in many studies. This represents a problem when trying to replicate a study or include its findings in an overarching meta-analysis of multiple investigations. The analysis of previous studies also shows a lack of consistency regarding the adaptation time, which might influence the results of the experiments.
- Experimental design quality: the consideration of experimental design criteria/principles is of critical importance to assure high standards of scientific quality. The reviewed studies were analyzed regarding randomization, counterbalance, experimental procedure (single or double blind, at least when explaining the goal of the study), experimental and statistical confounding variables, reporting of null condition, and repetition of certain experimental conditions. The reviewed studies did not consistently report these aspects. For instance, *82%* of the reviewed field studies did not include information on how participants were assigned to specific experimental conditions.
- Data collection and processing: the measurement and data processing of environmental conditions (not only explicitly targeted independent variables, but other elements of the experiments' boundary conditions) in the course of multi-domain studies is of high importance, especially in view of reproducibility criteria. A sufficient level of reporting on environmental measurements and their analysis was provided only in a small number of multi-domain studies. This implies the need for streamlined assessment and reporting procedures for both environmental conditions and human responses.
- Participants: studies involving human participants should provide detailed information on their distribution, relevant personal characteristics, and their role/involvement in the experiments. The assessment of the reviewed studies regarding this criterion yields a rather unsatisfactory picture. Aside from their number (almost always reported), essential information regarding participants was either underreported or not clearly stated. This circumstance undermines the credibility of the studies concerning, among other things, their representativeness and generalizability. In addition, information

about the ethical approval and the related documentation (consent and information sheet) is lacking in almost 80% of the publications, raising concerns about the ethics of the performed studies.

- Statistical analysis: a considerable number (N = 44) of different statistical methods were employed in the reviewed studies (mostly ANOVA). Among the formal tests of the distribution of the data, it is striking that the Shapiro-Wilk test, although recommended among the possible formal tests (e.g., Kolmogorov-Smirnov, Lilliefors and Anderson-Darling) [148], is only used in 5.9% of the cases, while the tests where the normality distribution should be verified are much more (more than 55% if we consider the sum of the papers where ANOVA, t-test and linear regression are used). Future studies should adopt a statistical approach that first checks the distribution of the sample and then applies tests where the normal distribution is an underlying assumption that corresponds to the main hypothesis. About 60% of the studies did not include any justification for the choice of the applied statistical method. A low fraction of the studies conducted a power analysis (*4%*) and reported effect sizes (22%). This hampers the reproducibility of experiments, feasibility of meta-analyses, and review of collective insights.
- Reporting results: the reporting of the results in published studies is inconsistent and sometimes incomplete (e.g., not all the results are reported, graphical representations are missing). The use of the same terminology to describe the type of effect investigated (i.e., cross-modal or combined) and their results is paramount to conduct future meta-analyses on multi-domain studies. For cross-modal effects, the direction of the effect (i.e., positive, negative or no effect) must be reported for each of the levels of the considered stimuli. For combined effects, the results can be described following the terminology described in the ASHRAE Guideline 10-2016 [39]. In future studies, researchers are invited to describe the results comprehensively and adopt the suggested reporting style for both cross-modal and combined effects (including terminology and the suggested tabular representation). In addition, considering that understanding cross-modal and combined effects solely based on the outcome of statistical analysis (e.g., model coefficients) may be a complex task for those without a solid background in statistics, we advise the complimentary usage of as simple as possible graphical representations of the cross-modal and combined effects (as depicted in Figure 1).
- Study discussion and conclusions: despite always presenting the conclusions (mostly based on the data), a large part of the considered papers does not include future studies (43%), limitations (55%), explanation of the mechanisms behind the results (69%), and practical implications (43%). The lack of such information reduces the possibility to advance the knowledge on the topic and understanding its relevance for people and society.

Transversal key observations:

- Multi-domain studies have been reported to rarely carryover previous studies' findings and to lack foundational theories to formulate and test research hypothesis [40]. Therefore, introductory sections were not reviewed in this study. Future multi-domain investigations should build upon previous findings to generate theoretical assumptions or start from theory-based motivations based on human perceptual and behavioral processes to formulate their research hypotheses.
- Field studies were less likely to report features (e.g., site, location, equipment etc.), hypotheses, assumptions, and variables. Laboratory and field experiments have intrinsic differences, but this is not a

justification for leaving out the information required for valid, generalizable, replicable, and reproducible studies.

- The low fraction of the studies that conducted a power analysis, followed a good experimental design, described sufficient population characteristics, and effect sizes, suggests a possible replication crisis identified elsewhere [65], [66]. The adjacent field of psychology serves as a reservoir of a decade's worth of scientific discussion and proposed methodological improvements (e.g., pre-registration prior to the start of the study, transparent data processing practices, and reporting effects sizes) [149] that should serve as example in future studies. It has been suggested that the social-structural factors that contribute to the replication crisis are not limited to psychology [150] and may apply to other fields [151].

It can be concluded that multi-domain studies were often not thoroughly documented and reported in a systematic and detailed manner or did not adhere to paramount research quality criteria. These issues may be rooted in the lack of robust schemes for conceptualizing and reporting both cross-modal and combined effects. This study aimed to establish sound guidelines and recommendations for designing, deploying and reporting multi-domain studies for addressing this challenge and foster more structured and coherent future multi-domain studies. Standardizing methods and reporting formats for multi-domain studies will enhance the rigor in reviewing these studies and enable future meta-analyses.

5.2 Future multi-domain studies

Although the provided recommendations were developed for investigations about (indoor) environmental stimuli, their application can be extended to studies investigating personal (e.g., sex, age, culture) and contextual aspects (e.g., time of the day, season, building typology, control opportunities). These aspects can be considered as additional domains influencing human responses in multi-domain studies [40].

The publications and context covered by this work outline momentum towards characterizing the multi-dimensional impact of the built environment on occupants. This foundation and the lessons learned provide the context for future work. Research in this area going forward could focus on filling the gaps of information about indoor environmental stimuli and human responses through innovative technologies and methods. For example, the use of continuous, field-based biosensing methods, like those being developed in mobile health research, can enable the detection of a broader range of human physiological responses [152]. The human response can be captured in a more scalable way using innovative interfaces that are integrated specifically into mobile devices and wearables [153]. There are, moreover, relatively new statistical techniques for testing causal claims relevant to multi-domain studies from a properly designed field study setup. For an overview of some of the recent developments in techniques, see [154]. Many of the proposed quality criteria are complementary to the rigorous study design required for a causal framework. The quality criteria summarized in Figure 2 and their description in section 3 can therefore serve as guidance for study design and reporting in future multi-domain studies.

During the reviewing process, we uncovered a wide range of possible interdisciplinary research opportunities through collaboration with the research communities of machine learning, building controls, wellness, public health, and real estate communities, as well as between research fields such as psychology, physiology, engineering, and architecture. The methodological best quality criteria uncovered during the review process can be further enhanced by these interdisciplinary collaborations to create hybrid approaches that accelerate the transfer of IEQ research results into actionable outputs, such as the amendment of building design and operation standards and guidelines. Future work may also consider the increasingly dynamic nature in which buildings are used, especially in office spaces where a larger diversity of activities can occur due to the enhanced workplace flexibility.

Declarations of competing interest

There are no known conflicts of interest.

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Appendix A

Ref.	List of considered papers
[111]	A chamber-experiment investigation of the interaction between perceptions of noise and odor in humans
[155]	A comparative study of discomfort caused by indoor air pollution, thermal load and noise
[51]	A field study investigation on the influence of light level on subjective thermal perception in different seasons
[156]	A multiple linear regression approach to correlate the Indoor Environmental Factors to the global comfort in a Zero-Energy building
[157]	A multivariate-logistic model for acceptance of indoor environmental quality (IEQ) in offices
[133]	A new index combining thermal, acoustic, and visual comfort of moderate environments in temperate climates
[158]	A study on the effects of thermal, luminous, and acoustic environments on indoor environmental comfort in offices
[159]	A weighting procedure to analyse the Indoor Environmental Quality of a Zero-Energy Building
[88]	Air movement and perceived air quality
[81]	An applied framework to evaluate the impact of indoor office environmental factors on occupants’ comfort and working conditions
[160]	An evaluation model for indoor environmental quality (IEQ) acceptance in residential buildings
[161]	Can colour and noise influence man’s thermal comfort?
[94]	Colour as a psychological agent to manipulate perceived indoor thermal environment for effective energy usage
[107]	Combined effects of acoustic and visual distraction on cognitive performance and well-being
[56]	Combined effects of acoustic, thermal, and illumination conditions on the comfort of discrete senses and overall indoor environment
[55]	Combined effects of daylight transmitted through coloured glazing and indoor temperature on thermal responses and overall comfort
[108]	Combined effects of noise and air temperature on human neurophysiological responses in a simulated indoor environment
[84]	Combined Effects of noise and temperature on human comfort and performance
[162]	Combined effects of short-term noise exposure and hygrothermal conditions on indoor environmental perceptions
[163]	Combined effects of sound and illuminance on indoor environmental perception
[164]	Combined effects of temperature and noise on human discomfort

[165]	Correlations between thermal satisfaction and non-thermal conditions of indoor environmental quality: Bayesian inference of a field study of offices
[147]	Cross-modal effects of illuminance and room temperature on indoor environmental perception
[166]	Cross-modal effects of noise and thermal conditions on indoor environmental perception and speech recognition
[140]	Cross-modal effects of thermal and visual conditions on outdoor thermal and visual comfort perception
[128]	Daylight affects human thermal perception
[167]	Decision support for improving occupant environmental satisfaction in office buildings: The relationship between sub-set of IEQ satisfaction and overall environmental satisfaction
[168]	Determining the Indoor Environment Quality for an Educational Building
[169]	Developing an indoor environment quality tool for assessment of mechanically ventilated office buildings in the UK – A preliminary study
[170]	Development of a multivariate regression model for overall satisfaction in public buildings based on field studies
[171]	Development of equi-comfort charts constituted with temperature and noise at 150 and 3 lx
[118]	Effect of colored illumination upon perceived temperature
[130]	Effect of Indoor Temperature and Glazing with Saturated Color on Visual Perception of Daylight
[116]	Effect of noise intensity and illumination intensity on visual performance
[134]	Effect of thermal conditions and light source type on visual comfort appraisal
[145]	Effects of different light intensities during the forenoon on the afternoon thermal sensation in mild cold
[172]	Effects of indoor temperature and background noise on floor impact noise perception
[173]	Effects of noise and heat stress on primary and subsidiary task performance
[144]	Effects of noise type, noise intensity, and illumination intensity on reading performance
[119]	Effects of noise, heat and indoor lighting on cognitive performance and self-reported affect
[132]	Effects of perceived indoor temperature on daylight glare perception
[126]	Effects of recorded water sounds on intrusive traffic noise perception under three indoor temperatures
[174]	Effects of steady-state noise and temperature conditions on environmental perception and acceptability
[175]	Effects of thermal discomfort in an office on perceived air quality, SBS symptoms, physiological responses, and human performance
[110]	Evaluation of the Visual Stimuli on Personal Thermal Comfort Perception in Real and Virtual Environments Using Machine Learning Approaches
[137]	Experimental investigation about thermal effect of colour on thermal sensation and comfort
[99]	Experimental study on occupants' interaction with windows and lights in Mediterranean offices during the non-heating season
[176]	Facilitatory effects of environmental sounds on hue-heat phenomena
[120]	First SenseLab studies with primary school children: exposure to different environmental configurations in the experience room
[54]	How correlated colour temperature manipulates human thermal perception and comfort
[177]	Impact of individual IEQ factors on passengers ' overall satisfaction in Chinese airport terminals
[127]	Impact of individually controlled facially applied air movement on perceived air quality at high humidity
[142]	Impact of indoor air temperature and humidity in an office on perceived air quality, SBS symptoms and performance

[178]	Impact of Temperature and Humidity on Perception of Indoor Air Quality During Immediate and Longer Whole-Body Exposures
[179]	Impact of temperature and humidity on the perception of indoor air quality
[180]	In search of evidence for the hue-heat hypothesis in the aircraft cabin
[181]	Incandescent affect: turning on the hot emotional system with bright light
[182]	Influence of air temperature on preference for color temperature of general lighting in the room
[93]	Influence of different light intensities during the daytime on evening dressing behavior in the cold
[129]	Influence of indoor temperature and daylight illuminance on visual perception
[90]	Influence of Light Intensities on Dressing Behavior in Elderly People
[136]	Influence of lighting colour temperature on indoor thermal perception: A strategy to save energy from the HVAC installations
[91]	Influence of Two Different Light Intensities from 16:00 to 20:30 Hours on Evening Dressing Behavior in the Cold
[183]	Influence of visual factors on noise annoyance evaluation caused by road traffic noise in indoor environment
[146]	Interactions and comprehensive effect of indoor environmental quality factors on occupant satisfaction
[184]	Interactions and range effects in experiments on pairs of stresses: mild heat and low frequency noise
[139]	Interactions between the perception of light and temperature
[138]	Interrelations of Comfort Parameters in a Simulated Aircraft Cabin
[185]	Investigating the effect of CO2 concentration on reported thermal comfort
[186]	Investigation of the relationships between thermal, acoustic, illuminous environments and human perceptions
[187]	Investigation of the subjective evaluation of indoor illumination level on perceived air quality
[86]	Irrelevant speech and indoor lighting: effects on cognitive performance and self-reported affect
[188]	Light intensity and thermal responses
[189]	Linear, non-linear and alternative algorithms in the correlation of IEQ factors with global comfort: a case study
[100]	Modeling occupant behavior of the manual control of windows in residential buildings
[96]	Monitoring and modelling of manually-controlled venetian blinds in private offices: A pilot study
[190]	New comfort index during combined conditions of moderate low ambient temperature and traffic noise
[115]	New index of combined effect of temperature and noise on human comfort: summer experiments on hot ambient temperature and traffic noise
[191]	Nonlinear relationships between individual IEQ factors and overall workspace satisfaction
[97]	Occupant behavior regarding the manual control of windows in residential buildings
[192]	Occupant response to different correlated colour temperatures of white LED lighting
[101]	Occupants' interactions with windows in 8 residential apartments in Beijing and Nanjing, China
[106]	Office noise and illumination effects on reading comprehension
[193]	On the interaction between lighting and thermal comfort: an integrated approach to IEQ
[124]	On the unification of thermal perception and adaptive actions
[194]	Perceived air quality and the thermal environment
[98]	Probability of occupant operation of windows during transition seasons in office buildings
[195]	Quantification of the synthesized evaluation of the combined environment

[92]	Saving energy with light? Experimental studies assessing the impact of colour temperature on thermal comfort
[87]	Sensory and physiological effects on humans of combined exposures to air temperatures and volatile organic compounds
[196]	Simultaneous effects of irrelevant speech, temperature and ventilation rate on performance and satisfaction in open-plan offices
[83]	Student learning performance and indoor environmental quality (IEQ) in air-conditioned university teaching rooms
[197]	Study on human responses under different CO2 concentration and illuminance in underground refuge chamber
[198]	The combined effects of many different indoor environmental factors on acceptability and office work performance
[199]	The combined effects of noise and illumination on the performance efficiency of visual search and neuromotor task components
[200]	The combined effects of temperature, background noise and lighting on the non-physical task performance of university students
[201]	The effect of correlated colour temperature of lighting on thermal sensation and thermal comfort in a simulated indoor workplace
[85]	The effects of moderate heat stress and open-plan office noise distraction on SBS symptoms and on the performance of office work
[122]	The effects of temperature, light, and sound on perceived work environment
[105]	The impact of a view from a window on thermal comfort, emotion, and cognitive performance
[117]	The impact of human perception of simultaneous exposure to thermal load, low frequency ventilation noise and indoor air pollution
[125]	The impact of thermal environment on occupant IEQ perception and productivity
[202]	The influence of coloured light in the aircraft cabin on passenger thermal comfort
[82]	The influence of exposure to multiple indoor environmental parameters on human perception
[89]	The influence of heat, air jet cooling and noise on performance in classrooms
[103]	The interaction of noise and mild heat on cognitive performance and serial reaction time
[203]	The Relationship between Thermal Comfort and Light Intensity with Sleep Quality and Eye Tiredness in Shift Work Nurses
[95]	Understanding window behaviour in a mixed-mode buildings and the impact on energy performance
[204]	Upper limits of air humidity for preventing warm respiratory discomfort
[205]	Ventilation requirements in buildings—I. Control of occupancy odor and tobacco smoke odor
[206]	Visual effects of wood on thermal perception of interior environments
[207]	Warmth, glare and a background of quiet speech: A comparison of their effects on performance
[114]	What's So Hot About Red?
[208]	What's so hot about sound?-influence of HVAC sounds on thermal comfort
[102]	Window opening behavior of occupants in residential buildings in Beijing

Appendix B

The described exclusion criteria lead to the exclusion of studies involving contextual, personal or other behavior (all sections besides 4.1 and 5.1 in Schweiker et al. [40]). In particular, the following studies were excluded from the analysis:

- Studies focusing on the effect of personal control [209];

- Studies focusing on physiological responses only[3] (e.g., [210]);
- Studies in which the independent variables are not physical measurements - such as those in which overall comfort/index or performance are evaluated on the basis of subjective evaluations of the indoor environmental stimuli (e.g., [211], [211]–[218]);
- Studies reporting results of experts' questionnaires [219];
- Studies where interactions are analyzed just looking at the correlation between human responses [220];
- Studies investigating the effect of the combined presence of multiple indoor stimuli on the measurements of another factor [123];
- Studies focusing neither on cross-modal nor on combined effects [133];
- Preliminary studies in which the quantitative results described are not the goal of the study [189];
- Proof-of-concept studies [221]
- Experiments in Virtual Reality [222], [223].

[3] Physiological responses are analyzed in papers where this type of response is reported together with other perceptual, behavioral, and cognitive responses.

Paper d

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Modeling occupant behavior in buildings

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A R T I C L E I N F O

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A B S T R A C T

In the last four decades several methods have been used to model occupants' presence and actions (OPA) in buildings according to different purposes, available computational power, and technical solutions. This study reviews approaches, methods and key findings related to OPA modeling in buildings. An extensive database of related research documents is systematically constructed, and, using bibliometric analysis techniques, the scientific production and landscape are described. The initial literature screening identified more than 750 studies, out of which 278 publications were selected. They provide an overarching view of the development of OPA modeling methods. The research field has evolved from longitudinal collaborative efforts since the late 1970s and, so far, covers diverse building typologies mostly concentrated in a few climate zones. The modeling approaches in the selected literature are grouped into three categories (rule-based models, stochastic OPA modeling, and data-driven methods) for modeling occupancy-related target functions and a set of occupants' actions (window, solar shading, electric lighting, thermostat adjustment, clothing adjustment and appliance use). The explanatory modeling is conventionally based on the model-based paradigm where occupant behavior is assumed to be stochastic, while the data-driven paradigm has found wide applications for the predictive modeling of OPA, applicable to control systems. The lack of established standard evaluation protocols was identified as a scientifically important yet rarely addressed research question. In addition, machine learning and deep learning are emerging in recent years as promising methods to address OPA modeling in real-world applications.

1. Introduction

In the last four decades several methods have been used to model occupants' presence and actions (OPA) in buildings to meet different research objectives given available computational power and technical solutions. Often the purpose has been to understand how people use a space and how their behavior impacts on a building's energy performance. Indeed, occupant behavior is also one of the main sources of

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uncertainty in building's energy modeling [1]. In particular, the over-simplification of the OPA description can introduce a large discrepancy between the simulated and actual energy consumption of a building [2, 3]. These and other issues have driven the exploitation of various approaches to explain and predict OPA in order to accurately model OPA in building energy simulation tools and to improve building management systems to decrease building's energy consumption. In order to address these issues, the attention of the building research community on OPA modeling has increased in recent years [4]. One initiative approved by the International Energy Agency (IEA) in 2013 is the Energy in Buildings and Communities (EBC) Annex 66 [5] that aimed to study the importance of occupant behavior in buildings and its modeling techniques and to formalize simulation approaches regarding occupant behavior. Following this, in 2017 IEA approved the EBC Annex 79 "Occupant-centric building design and operation", which aims to explore open issues on the implementation and application of occupant modeling into practice [6]. In the context of IEA-EBC Annex 79, this review aims at providing a thorough and carefully-designed overview of the methods and techniques used for modeling OPA in buildings in order to create the current state-of-the-art and identify the latest trends in this research sector. Given these ambitious objectives, a systematic approach is used to review the scientific literature to reduce the risk of missing important contributions in the field, and bibliometric analysis tools are adopted to extract patterns and information from the identified database of documents. In the scope of this work, the existing OPA studies are grouped into three paradigms: rule-based models, stochastic OPA models, and data-driven methods. The first paradigm includes, but is not restricted to, the time-dependent users' profiles as defined, for example, in the ASHRAE standard 90.1 [7]. The second paradigm considers the occupant behavior to be stochastic since behavior varies between occupants and may evolve over time [8] and is the result of complex relationships between contextual factors, adaptive triggers, and non-adaptive triggers [9]. The third paradigm refers to data-driven methods where a black-box model is derived from relating input and output data [10] so that, the modeling is conducted without an explicit aim to understand the OPA [11] and/or only with the limited inclusion of the domain engineering knowledge [12]. Resultantly, the data-driven OPA modeling, for the scope of this study, can be defined as "an approach to modeling that focuses on using the computational intelligence and particularly machine learning (ML) methods in building models that would complement or replace the "knowledge-driven" models describing physical behavior" [12]. The present study aims at describing the features of methods used for OPA modeling in buildings rather than reporting their mathematical formulation that can be found in statistical and ML handbooks. A summary of a few modelling techniques is available in Ref. [13].

1.1. Related work

Numerous reviews about OPA modeling have tried to categorize and formalize the different approaches to OPA modeling [9]. However, they are usually limited in the covered time span, in the building typology investigated or in the OPA under study. For example, Gunay et al. [14] have reviewed the modeling approaches developed for the simulation engine EnergyPlus regarding occupant presence, window and shading operations, lighting, and clothing adjustment developed since 2014. Yang et al. [15], focusing on institutional buildings, have studied the available estimation, detection and modeling methods to assess presence and movement of occupants. Gilani and O'Brien [16] have reviewed the estimation and detection methods to study OPA in office buildings. Chen et al. [17] have studied presence estimation and detection methods developed between 2005 and 2017. Zhang et al. [4] have reviewed the modeling methods for OPA regarding residential and commercial buildings. Balvedi et al. [18] focused on residential buildings in the temporal coverage from 2006 to 2017. Dong et al. [19] did an extensive literature review including all typologies of buildings, but without considering any modeling method regarding occupants' movement and activity or their clothing adjustment. Li et al. [20] covered a large period, till 2018, and all typologies of buildings, however, clothing adjustment was not considered. Finally, Salimi and Hammad [21] covered all OPA aspects, considering a time coverage from 2008 till 2018 and focusing on office buildings. Table 1 compares the main features of analyzed literature reviews and identifies the main gaps that the present study aims to fill.

1.2. Motivation and objectives

The overview of the state-of-the-art presented in Table 1 reveals a lack of review studies that cover thoroughly the different aspects of OPA modeling and the different building typologies, as well as the latest developments in this field. Therefore, standing as an addition to the work done in the IEA-EBC Annex 66 and embracing the new propositions of the IEA-EBC Annex 79, the main purpose of this study is (1) building an updated biographical database of the studies that have developed models on OPA, (2) based on analysis of this database, providing an overview of the scientific production and the current scientific landscape on OPA modeling, (3) identifying the key methods adopted in OPA modeling by considering different OPAs and by comparing documents that propose rule-base methods, data-driven methods, and a stochastic description of OPA, and (4) drawing a future outlook in OPA modeling.

2. Methodology

The purpose of this work is enabling a comprehensive analysis of the existing literature in the field of occupant behavioral modeling in building performance analysis. The presented systematic literature review is conducted following the PRISMA methodology, and the research question and the related literature search are built according to the guidelines proposed by Denyer and Tranfield [22]. Although the PRISMA methodology is a useful guideline for a critical development of systematic reviews, it is not an instrument that can automatically guarantee their quality [23]; thus, a large pool of experts from the IEA-EBC Annex 79 community has been involved in the planning, development and execution of this study. As such, the authors are aware of the possibility of relevant articles that might be missing in the review but are confident that the identified bibliographic database represents the main tendencies and approaches adopted into the field so far.

The PRISMA methodology considers four main phases: (1) identification, (2) screening, (3) eligibility, and (4) inclusion of studies. The summary of the PRISMA methodology is presented with a flow chart that shows the number of bibliographic records initially identified by the search query and subsequently included in this study (Fig. 1).

2.1. Identification of studies

The first step consists in constructing the research question. In this work, the CIMO-logic [24] is adopted, where CIMO stands for Context, Intervention, Mechanism and Output, and the research question is: "How do we model (M) the occupant presence and actions (I) to simulate the performance (O) of buildings (C)?" (Table 2).

Next, a comprehensive list of keywords is populated for each of the CIMO terms, and a research query is construct using the Boolean operators AND, OR and NOT and exploiting the list of keywords (1) to include all the keywords that have the same root but different declinations (e.g., for considering both British and American spelling), (2) to consider precise technical wording, (3) to exclude some divergent terms. Afterwards, exclusion criteria are applied to limit the search to usable documents in order to limit the search only to journal articles, conference papers, reviews, books, book chapters and articles in press written in English. Old articles and conferences proceeding not available anymore were also excluded. Finally, the search query is executed in the Scopus, Web of Science and EI Compendex databases. However, due to

Table 1
Comparison of literature reviews on Occupant Presence and Actions since 2015.

Authors	Year	Temporal coverage	Typology of buildings	Occupant presence and actions							
				Presence	Movement activity	Window operation	Shading operation	Lighting operation	Thermostat adjustment	Appliance use	Clothing adjustment
Gunay, O'Brien, Beausoleil-Morrison	2015	Up to 2014	All	•		•	•	•			•
Yang, Santamouris, Lee	2016	Up to 2016	Institutional	•	•						
Gilani, O'Brien	2016	Up to 2015	Office	•		•	•	•	•	•	•
Chen, Jiang, Xie	2018	2005–2017	All	•							
Zhang, Bai, Mills, Pezzey	2018	Up to 2016	Residential and Commercial	•	•	•		•	•	•	•
Balvedi, Ghisi, Lamberts	2018	2006–2017	Residential	•	•	•	•	•	•	•	
Dong, Yan, Li, Jin, Feng, Fontenot	2018	Up to 2017	All	•		•	•	•	•		
Li, Yu, Haghighat, Zhang	2019	Up to 2018	All	•	•	•	•	•	•	•	
Salimi, Hammad	2019	2008–2018 +adding	Office	•	•	•	•	•	•	•	•

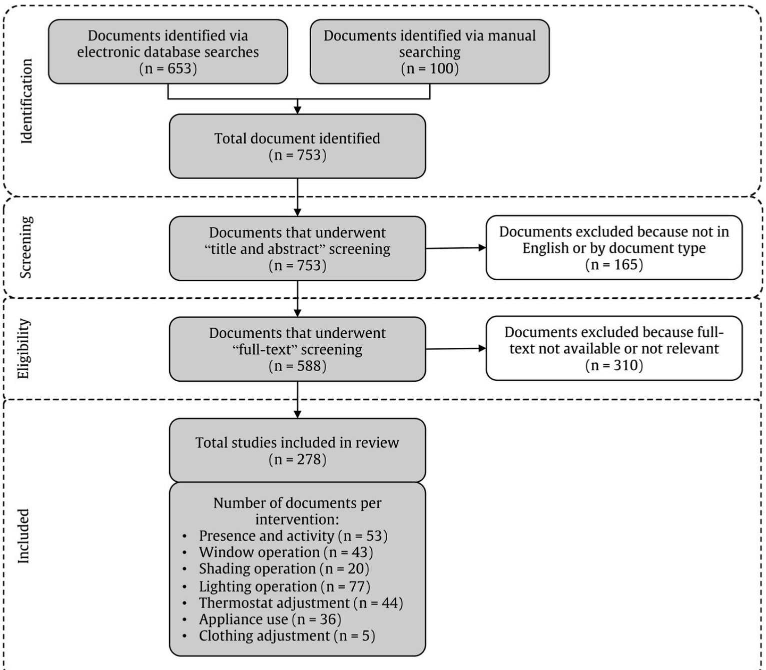

Fig. 1. *Literature screening process following the PRISMA framework (Moher et al., 2009).*

compatibility issues with the bibliometric tools, the file exported by EI Compendex could not be used. Furthermore, the files exported by Scopus and Web of Science could not be merged and, given the wider coverage, the Scopus file was eventually used for the literature search.

During the screening phase, the titles and abstracts of the identified documents were read, and several publications were excluded because not relevant. Afterwards, only studies with full-text were considered eligible for further analysis. Then, quality and consistency assessments were conducted by reading all the full-texts of the eligible documents. Those documents (i) not matching the research question, (ii) not relevant, (iii) without sufficient data, and (iv) presenting overlaps were also removed from the final database. Also, a few studies were removed due to overlap (e.g., the same set of data or models presented in both journal articles and conference papers). Finally, the bibliographic database was consolidated, and the bibliometric analysis were executed in Bibliometrix [25] to identify relationships between topics, patterns in the

Table 2
The CIMO-logic for studying modeling of Occupant Presence and Actions in buildings.

Context (*Where? In which context the intervention is embedded?*)	Intervention (*What? Which is the main topic?*)	Mechanism (*How? Which is the medium?*)	Outcome (*To get what? What is the wanted information?*)
Buildings (all building types)	Occupant presence and actions: • Presence and activity • Window operation • Shading operation • Lighting operation • Thermostat adjustment • Appliance use • Clothing adjustment	Modeling techniques: • Rule-based models • Stochastic OPA modeling • Data-driven methods	Outputs: • Energy performance • Indoor comfort

metadata of publications and thematic evolution.

2.2. Bibliometric analysis

The bibliometric analysis provides information on the relevance of the identified bibliographic records and uses science mapping to extract knowledge at the nexus among conceptual, intellectual and social structures.

2.2.1. Collaboration network

A collaboration network involves the analysis of authors' productivity, affiliations, and countries (of their affiliated organizations) and is represented on a map. It specifically deals with the scientific production disaggregated by country and the collaboration between authors with affiliations in each country. When a document is written by two authors whose affiliations belong to different countries, it is considered a collaboration.

2.2.2. Co-word analysis

A co-word analysis is a quantitative method for mapping the structure of a science field [26]. This technique analyzes the pattern of co-occurrence of pairs of words, which is the simultaneous occurrence of two words in a piece of text. The co-word analysis is performed by adopting clustering algorithms that identify the main themes characterizing the work under study. Outcomes of the co-word analysis are typically displayed with a co-occurrence network. The dimension of the node representing a keyword is proportional to its frequency of appearance in the analyzed bibliographic database, while the thickness of the connecting lines is proportional to the equivalent index value. The equivalent index e_{ij} is defined as $e_{ij} = c_{ij}^2/(c_i\ c_j)$, where c_{ij} represents the number of the documents in which both the keywords co-occur, c_i and c_j are the numbers of the documents in which each keyword appears.

3. Analysis of bibliographic metadata

In recent years, the interest on OPA modeling and the related scientific production have increased (Fig. 2) [5,27]. It should be noted that the literature search in this article was conducted in August 2019, therefore, the count for 2019 does not account for the documents published in the second half of the year.

The median of the publication year is 2015 and the average is 2013, in other words, a large share of the collected documents has mainly been published in the last four to six years. Specifically, there is a strong rise in published documents on OPA since 2010. By consequence, this review may be considered as an assessment of the current practice in OPA modeling in buildings. Looking at the temporal evolution of the published documents by source, the journals that have published more documents regarding OPA modeling in the latest years are *Building and Environment* and *Energy and Buildings*, followed by the *Journal of Building Performance Simulation* (Fig. 3).

Regarding the document production by country, the United States of America is the most productive country with 74 published documents from 1979 onwards. In addition, its collaborations are the most numerous (with 20 co-authored documents) and the most spread around the world (11 collaborations involve multiple countries) (Fig. 4). Europe, as a whole, is very productive with eight out of 16 countries having more than 10 publications (UK, Italy, Switzerland, Germany, Denmark, France, Belgium and Netherlands). European collaborations

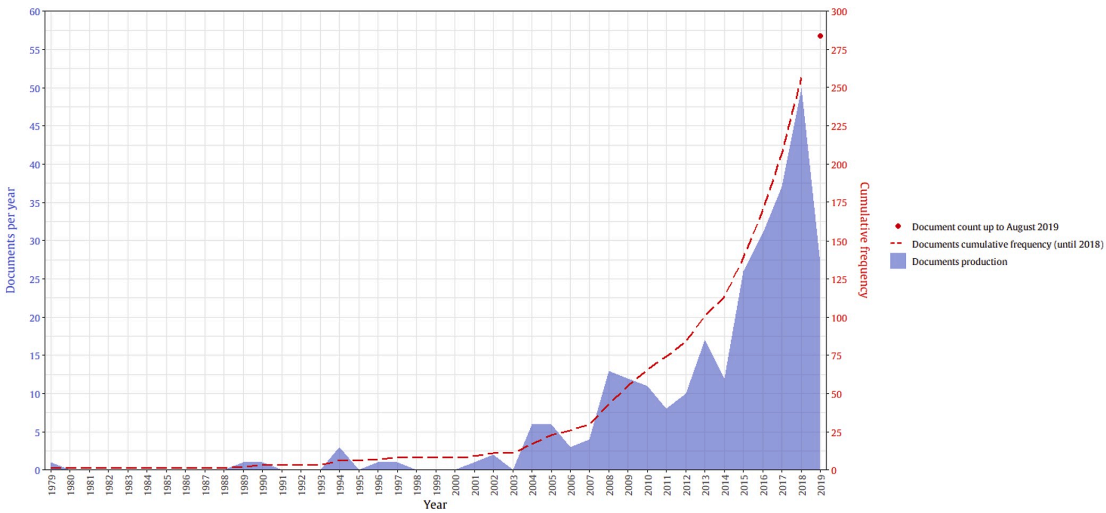

Fig. 2. *Annual scientific production of documents presenting Occupant Presence and Actions models. The count for 2019 considers only those documents indexed until August 2019.*

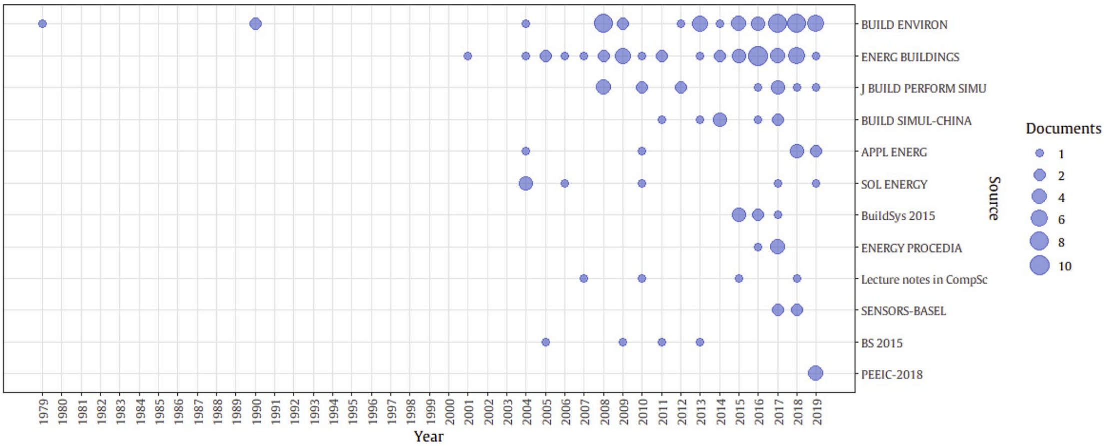

Fig. 3. Chronological development of publication by sources.

are mostly internal, but there are also connections with countries from all continents.

4. Analysis of the documents on OPA modeling

The bibliographic collection is composed of 278 documents from 146 sources published from 1979 to nowadays. On average, each document is cited 46.1 times. The documents were written by 809 authors who appeared 1003 times as co-authors within this document collection with an average of 3.54 co-authors per document. These figures show a consolidated and spread international collaboration on this topic.

After the screening phase and having read all the full-texts, contextual data was extracted from the 278 documents and used to characterize the overall production of OPA models. Few documents propose more than one model and address more occupant actions; therefore, the number of models analyzed is up to 310. Fig. 5 displays aggregated figures on the number and percentage over the total number of collected models.

For the OPA model development, measurements are the most frequent data source. They represent a reliable manner to gather data and control uncertainty, but privacy issues may be encountered during the execution of measurement campaigns [28,29], typically when data collection happens in large buildings with general visitors for people-count purpose. From the analysis of the building use, offices are the most studied building type followed by residential units. In particular, the number of documents related to offices is around 60% higher than for residential buildings. This imbalance may be due to a more predictable occupant behavior in offices, an easier experimental setting, and a more direct transferability of models and results. In addition, the experiments on occupant behavior in offices can be less affected by privacy concerns when compared to the residential buildings. Naturally ventilated buildings are the most commonly researched building type and control strategy. This could be a result of the wider availability of collected data and the high variability of people interacting with a building and its devices, resulting more interesting from a model developmental perspective. However, several documents do not report explicit contextual information on the above three aspects and, hence, these descriptive statistics must be read as indicative figures.

All documents are also categorized on the base of the modeling approach used to develop the OPA models. It emerged that, in the last years, thanks to extended measurement campaigns and a higher wealth of available data, data-driven models are attracting increased interest for their capability to manage large data sources without missing the aleatory nature of OPA in buildings [30], followed by stochastic OPA modeling techniques, and rule-based methods. Next, the documents were grouped according to the Köppen-Geiger's climate classification system [31]. A high proportion of models are developed in temperate and continental climates identified respectively by the letters C and D

Fig. 4. The collaboration network map shows country collaborations and production.

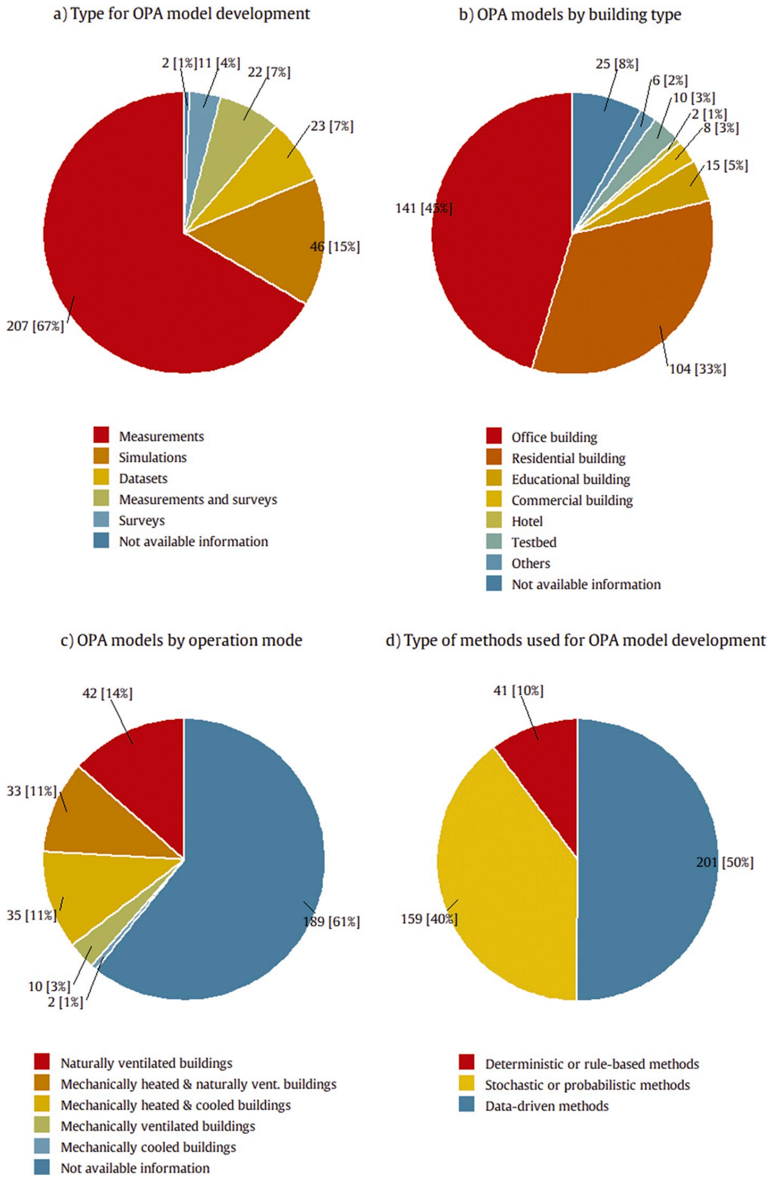

Fig. 5. Graphical description of the Occupant Presence and Actions models collected in the bibliographic database (number of OPA models; percentage).

with 50% and 21% out of the total number of models respectively. Follow tropical climates (A) with 5% and arid climates (B) with 2%. In about 22% of the models, the climate condition was not mentioned.

The first five climatic zones by the number of developed OPA models represent almost the whole Europe, the USA and most populated portion of China (Fig. 6), which are also the most productive countries per number of publications.

4.1. Scientific landscape

Two main analyses are performed to describe the scientific landscape drawn by the bibliographic database: the three-field plot and the co-occurrence network map. These analyses help to understand the research trends and the connections among the themes rising from the state of the art.

The three-field plot displayed in Fig. 7, shows the number of connections (size of the boxes) and strength of the connection (size of the connection lines) between most frequent words in abstracts (left field), Authors' Keywords (middle field) and scientific journals (right field).

The most frequent words in the abstracts point out the main and general terms of the research questions (like 'energy', 'building control'). In the middle field of the author's keywords, the main concepts on which the domain is built (like 'occupant behavior', 'thermal comfort', 'windows opening', 'lighting control', 'machine learning' and 'office

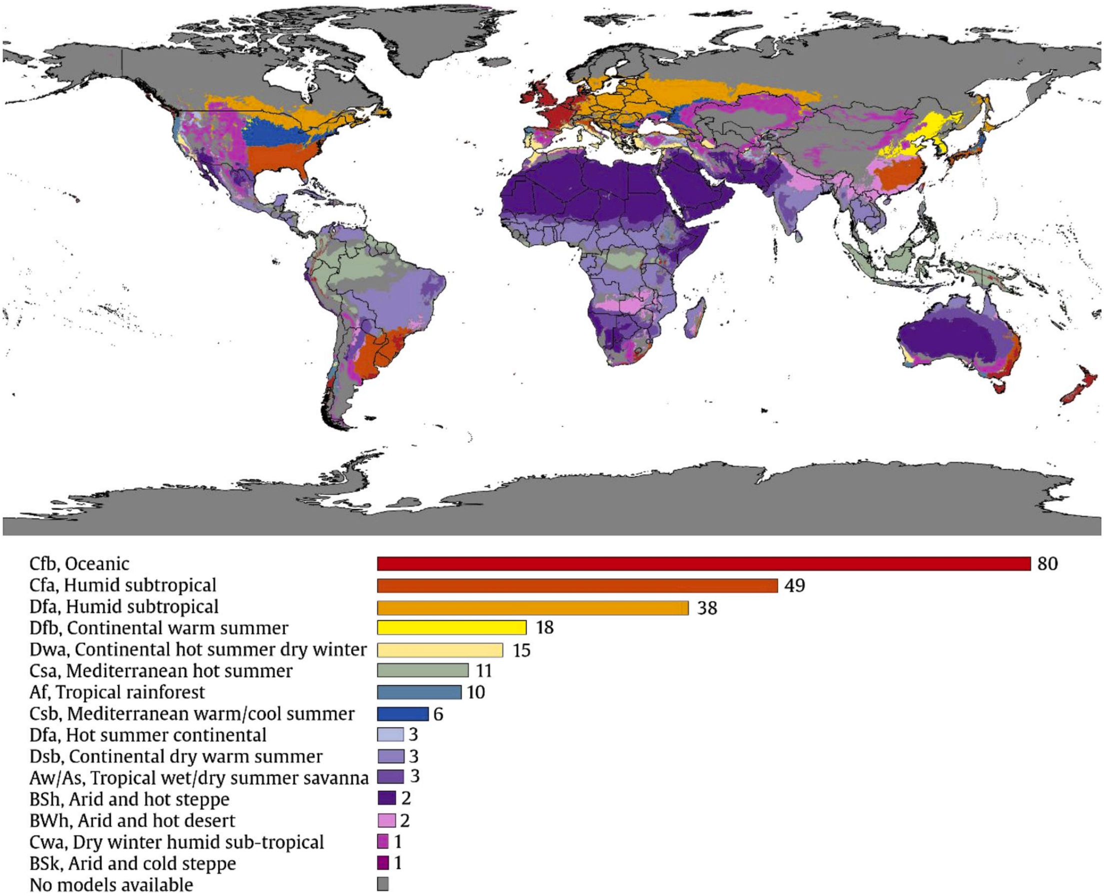

Fig. 6. Number of available OPA models by Köppen-Geiger's climate zones in the bibliographic database.

building') is presented. Finally, the main keywords as available in the journals are shown. For example, 'occupant behavior' is a very general term that is present in all the most representative journals, but 'thermal comfort' is mostly present in *Building and Environment* and *Energy and Buildings*, 'lighting control' is mostly related to *Solar Energy* and *Energy and Buildings*, and 'machine learning' is more present in *Applied Energy* and *Building and Environment*. This analysis provides insights to researchers new to the field to aid identifying the most suitable journals for publishing their studies.

The co-occurrence network in Fig. 8 shows the different clusters of Authors' Keywords, which are identified by the Walktrap clustering algorithm assuming 50 nodes and normalizing the relationships by the association strength [25].

The largest cluster (in green) collects the most traditional keywords (e.g., 'occupant behavior', 'office building', 'energy efficiency', 'thermal comfort') and some satellite terms typical of stochastic modeling. The second cluster (in red) pivots on 'neural network' and includes several data-driven topics like 'machine learning', 'data mining', 'prediction' and other term referring to widely used application like 'building management systems' and 'smart buildings'. The third cluster (in brown) is somewhat distant from the other terms and is very concentrated. It deals primarily with 'occupant presence' and includes terms like 'presence detection', 'number estimation', 'building occupancy' and 'cross-space modeling'. The orange cluster pivots on 'building automation' for 'building energy efficiency' together with 'occupancy detection' and 'activity recognition'. The blue cluster vertex on 'demand side management' and includes the terms 'demand response' and 'occupancy'. The purple cluster focusses on 'intelligent lighting control', with terms like 'daylight harvesting' and 'smart lighting'. The keyword 'daylighting' is isolated but connected with 'lighting control' while 'visual comfort' and 'indoor positioning' are isolated and not connected.

5. Explanatory and predictive power for occupant presence and actions modeling

In contrast to other scientific disciplines, the research on OPA requires models with both explanatory and predictive power, which represents a particular challenge. Motivated by the latter need for dual modeling objective, this section provides a comparison of the existing modeling formalisms for both causal explanation and predictive modeling.

OPA models were developed (1) to optimize the building design, (2) to represent the occupants in building performance simulation (BPS), and (3) to predict the human behavior for the inclusion in building control systems. The first two goals may be achieved by explaining the relationship between OPA and a set of objective measurements. For instance, by knowing the fixed working hours it may be understood the reason why an occupant was present at the workspace. Alternatively, the

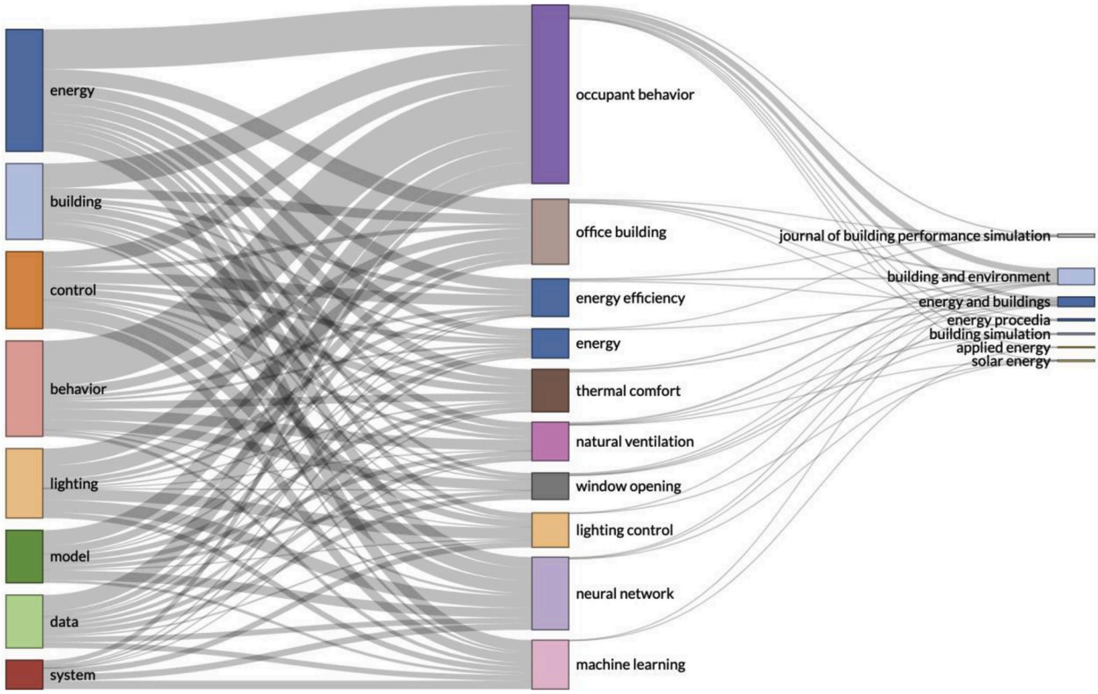

Fig. 7. *Evolution of the most frequent words in the abstracts (left field) to the keywords (middle field) and to the journal sources (right field) for the papers in the bibliometric database.*

causal explanation of the intervention on sunshades may be visual discomfort that can be correlated with the solar radiation on the window surface. Here an important property of the chosen methods is to possess high exploratory power.

Regarding the third goal, OPA models for the application in building control require predictive power, in order to forecast the events or states on the future time-steps with satisfactory accuracy. In this place, models that possess high explanatory power are often assumed to inherently possess predictive power [32]. However, the research on statistical modeling pointed out that the distinctive models are required for prediction and causal explanation [32,33]. The need for non-identical methods for representing the impact of occupants in BPS and for predictive modeling has already been pointed out by Mahdavi and Tahmasebi [34], hence, this distinction has sometimes been overlooked by the modeling studies.

The causal explanation can be addressed using statistical and linear models [32]. The research on explaining occupant behavior has a longer tradition when compared to the predictive OPA in buildings modeling. Therefore, the set of statistical and linear models in use widely overlaps with the established general modeling formalisms that were reviewed by D'Oca et al. [35]. In addition to the methods proposed by the latter study (namely Bernoulli models, generalized linear models, and survival models), the generalized class of probabilistic graphical models, which also includes discrete Markov models, showed to be powerful tools for the research on human-building interaction. For instance, logistic regression and linear models have been applied to investigate the relationship between the thermal conditions and the resulting occupants' actions [36,37]. Furthermore, the results of the past exploratory studies on the human-building interactions led to a better hypothesis formulation regarding the drivers of occupant behavior as well as defining the baseline predictive OPA models.

The prediction of OPA has been commonly addressed using ML-based methods. The literature screening has pointed out that the occupants' presence, activity recognition, and movement detection have been widely researched in the context of predictive modeling. For that purpose, the well-established modeling formalisms relied on probabilistic modeling, probabilistic graphical models, and conventional ML such as Support Vector Machine (SVM) and k-nearest neighbors (k-NN) algorithm. In the case of occupants' action prediction, different NN architectures have been investigated to model adaptive actions such as the use of lighting, solar shadings, windows, appliances, and clothing adjustment. The alternative widely explored methods include the conventional ML methods, such as k-NN, SVMs for classification and regression, as well as the variations of decision trees and ensembles of decision trees. The application of probabilistic methods and probabilistic graphical models led to promising modeling results for the application in the built environment. Hence, these classes of methods have not been comprehensively explored in the scope of existing OPA research. Moreover, stochastic models were also explored for their predictive capabilities for OPA. As a result, the logistic regression has been established as a baseline predictive model for window opening behavior, while in the scope of the recent study, the logistic regression showed promising results for learning the thermostat setpoints [38].

A first significant difference between the stochastic methods for the causality explanation and for the predictive modeling lies in the required data split. In the case of stochastic modeling, a set of data points is used to establish the hypothesis, while a set of distinct data points is eventually used to test the goodness of the hypothesis. Commonly, these two data sets were collected on the same occupant or on the same building, and the amount of available data is constrained by the design in terms of extent of the monitoring campaign [11]. Since these hypotheses widely address the relationship between the unique building design and the behavior, there are no strong requirements of the sample size.

Fig. 8. Co-occurrence network of Author Keywords from papers in the bibliographic database.

An additional significant difference between the stochastic and ML modeling is the interpretability of models. Here, we refer to interpretability as the description of the internal rules of a system in a way that is understandable to humans [39]. Commonly, the ML models are developed to maximize the prediction accuracy and the results are often not interpretable using domain knowledge. This lack of interpretability has been seen as a major drawback for considering the ML approaches in the building design phase. However, as already pointed out by existing research, the most accurate explanations are not easily interpretable to people; and conversely, the most interpretable descriptions often do not provide predictive power [39]. Therefore, human interpretability is not a crucial property of the OPA models for inclusion in building control systems. Rather, the strict evaluation protocols in terms of models' effectiveness and the critical analysis of the predictive powers may be seen as the necessary components for the consideration of the ML methods in building control.

6. Modeling occupant presence

Human occupancy information is crucial for any modern building management system. The retrieved information can be utilized to understand both space utilization and building energy optimization, which enables informed decision making. Occupant presence is commonly declined in three sub-domains: occupancy detection, estimation and prediction; activity prediction and room occupation; and people movement between zones.

In this section, 53 documents published between 2004 and 2019 were analyzed. According to the developed bibliographic database, the annual scientific production in occupant presence modeling research reaches its peak (11 documents) during the period 2016–2018. The documents with most impact (in terms of a total number of citations) were published in Energy and Buildings. Next, there are documents published in journals with diverse scopes that do not belong to the core sources identified by Bradford's law, like *Energy Conversion and Management* and *Geodesy and Cartography*. These results point out that occupant presence modeling is a topic not exclusively related to energy and indoor environmental research in buildings.

The data-driven models represent 56% of the total, followed by stochastic OPA modeling techniques (30%) and the rule-based models (14%). In particular, 27% of the data-driven models use NN techniques, 13% SVMs, and 11% Hidden Markov model (HMM). Regarding the stochastic OPA modeling techniques, 42% make use of Markov chain models, 17% of linear time series models, while 13% of the Monte Carlo method.

Fig. 9 shows the percentage of documents using a typology of methods on the overall documents published in that year considered in this review. In the last years, data-driven models are emerging compared to the other two typologies. A cause for that could be the increase of data wealth due to the digitalization of the building lifecycle, large sensors installation campaigns, and availability of smart meters.

6.1. Occupancy detection, estimation, and prediction

Occupancy detection usually refers to the binary inference of occupant presence and absence in different zones of an indoor or outdoor space while occupancy estimation usually refers to the occupancy count. Occupancy prediction is to forecast the in a future time window. Occupancy detection, estimation, and prediction are challenging tasks due to many reasons. For instance, there is a wide variety of sites of interest (such as individual and open plan workplaces, shopping malls, cinemas, etc.), which differ in size and operation mode. Hence, the appropriate contextual information must be considered for effective deployment of any system for occupancy detection, estimation, and prediction. Recent technological developments and the proliferation of pervasive technologies have opened up many opportunities to detect, estimate, and predict indoor occupancy leveraging various sensors and smart devices [40].

Many sensor-based technologies are available to detect and estimate occupancy in different types of sites [41]. A comprehensive review that compares the capabilities of different sensor types and their fusion for occupancy detection and estimation is presented in Ref. [17]. However, these technologies require extensive installation of hardware and continuous maintenance. Moreover, their accuracy can be influenced by specific physical orientation (i.e. seating, standing, walking styles) of occupants since the sensors are usually placed under the desk or overhead. To reduce the cost of extensive sensor installation, a probabilistic method for room-level occupancy counting is presented in Ref. [42]. This model utilizes common sensors available at different rooms for disaggregating accurate building-level occupancy counts to room-level occupancy counts. Another probabilistic fusion technique to estimate indoor occupancy from 3D camera counts is presented in Ref. [43]. Data from smart electricity meters is also used to detect the occupant presence [44,45]. The basic idea is to conduct cluster analysis on continuous variables, like power load, carbon dioxide (CO_2) concentration, and estimate occupant presence. Another research highlights the use of different sensing systems including radio frequency, infrared, ultrasound, video cameras, and wireless local area network in recent literature [15]. However, these technologies are susceptible to surrounding electromagnetic conditions, inconsistent connections and may raise privacy concerns [15].

From the analysis of the developed bibliographic database, many state-of-the-art ML tools have been deployed to develop smart building applications which include occupancy detection, estimation, and prediction. Several classification models including Linear Discriminant Analysis, Classification and Regression Trees, and Random Forest models are evaluated for occupancy detection utilizing data from light, temperature, humidity and CO_2 measurements. The data coming from various smart sensors are utilized to provide real-time as well as future

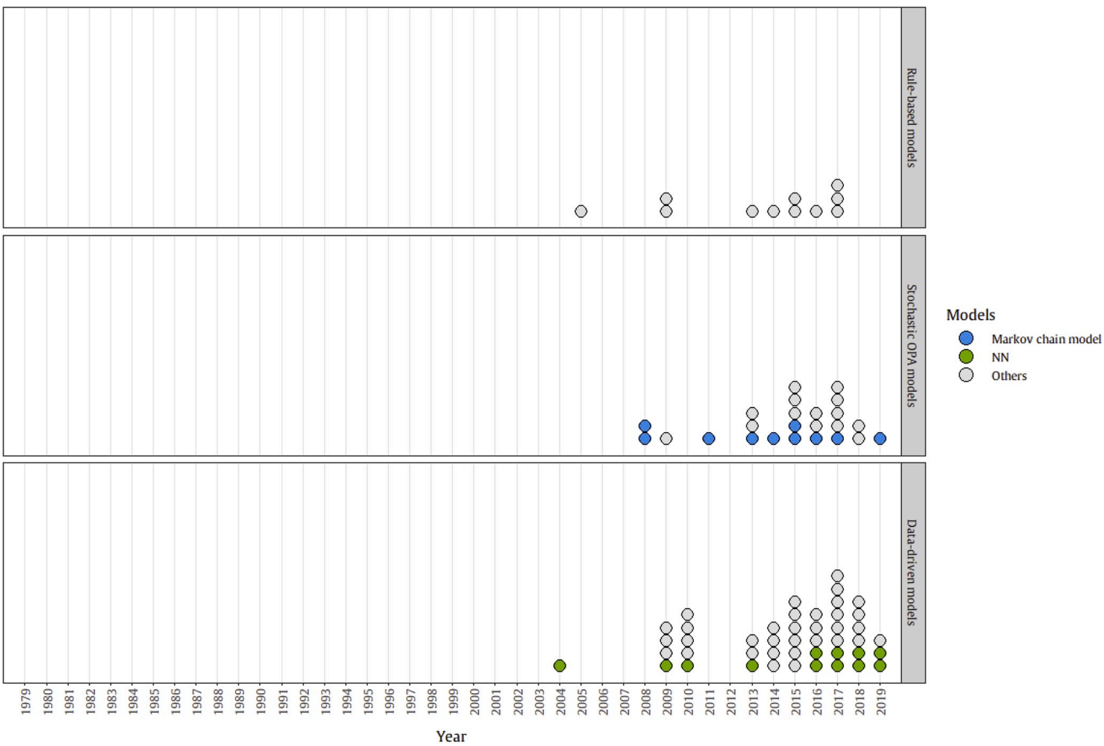

Fig. 9. *Yearly percentage of presence models with respect to the total number of published models belonging to the bibliographic database in each year.*

predictions of occupancy status. However, it shall be mentioned that, since sensor data varies in dimensions and frequencies from one domain to another, a model trained for one domain cannot be applied effectively in another domain. To address this challenge, a semi-supervised domain adaptation method for CO_2-based human occupancy counter is presented in Ref. [46].

Finally, several evaluation metrics are used to validate the occupancy detection and estimation models including prediction accuracy, precision, recall, f-1 score, mean average error (MAE), mean average percentage error (MAPE), and root mean squared error (RMSE). However, it would not be fair to quantify the widespread use of a model and evaluation metric as the performance of a model generally depends on the specific application, size and quality of the data. For example, the deep learning-based models require a large dataset for better performance while compromising the interpretability. If the purpose is casualty analysis, it is possible that the statistical and ML models are a better choice over deep learning (DL).

The models discussed above are mainly developed and deployed using data from a specific site. Given the variety application scenarios, one of the key challenges is to transfer such models build for one site to another site as it may require extensive parameter tuning. In the future, efficient transfer learning methods could be adapted to mitigate this gap and more research effort needs to be given towards the adaptation of explainable machine learning and DL techniques. This will allow the research community and beyond to better understand the outcomes of the deployed models.

6.2. Occupant activity recognition

To adjust and operate control systems based on indoor occupant behavior, it becomes crucial for a building management system to recognize the indoor occupants' presence and its associated activities. The ability to identify or forecast a particular activity can minimize the exhaustion of unnecessary energy resources. Indeed, the difference in occupant activity might have a significant effect on the building's energy performance. Conservative behavior by occupants has been shown to save up to 30% of the building's energy consumption, while careless or reckless behavior can increase that amount by one-third [47]. Proper modeling of occupant activities is necessary to estimate building energy consumption and adjust the building's energy demands to optimize it [48]. Other notable uses of activity recognition and prediction include their use in health monitoring, to provide automated assistance and detect uncommon situations [49].

Activity recognition constitutes the monitoring of OPA along with the change of state in their environment. It is based on two main types of approaches, vision-based activity recognition and physical measurement-based or maybe environmental sensor-based. The former uses surveillance-based systems such as cameras [50], 3D-stereo vision systems [42], infra-red or depth registration [51], while the latter uses wearable or deployed sensors or RFID tags [52]. The typical solution for the detection of the occupant's activity involves a fusion of different environment monitoring techniques [53–56]. Most of the developed models are built on a foundation on quantity data but there are few examples that used quality-based data as the main development source [57]. Earlier works regarding the prediction of the occupant activities made use of probabilistic models and Bayesian belief networks [58]. Recent research efforts have also focused on Markov-chain models and HMM to estimate and forecast occupant activity levels [59,60]. Usually, most of the developed models are validated by ground truth data, obtained from visual observation via video recordings or notebook reporting [61]. Another development in the field of activity recognition and prediction is the use of DL methods for human activity recognition, where models are making use of Convolutional Neural Networks (CNN) [62–64] SVM [65,66], and Recurrent Neural Networks [67,68].

The main gaps for activity recognition are having a wider range of activities, since most of the research efforts to date have targeted a selected number of pre-defined activities [58,62–67]. In addition, the interdependence between activities has to be recognized as well [69]. Future efforts can be outlined to incorporate the personalization perspective for accurate activity recognition, along with adaptation with evolving activities, and context aware recognition [70].

6.3. People movement between zones

People's movement between zones is intended as the transition of occupants from one room to another inside a building. Occupants with their movement change also the sensible and latent loads between zones and so influence the temperature and humidity in rooms. This topic is fundamental for detailed building models, in which the spaces are described at room-level and, on average, occupancy probability assigned to all the rooms are too simplistic.

The bibliometric analysis suggests that the topic of detection and modeling of indoor movement of occupants is gaining momentum as it is strictly related to the topic of smart buildings. The indoor tracking of occupants is not a new field of research [71]. However, only in the last years, some descriptive and predictive models are emerging aiming specifically the better description of occupants for buildings energy modeling [72]. The description of the localization of occupants in real-time is fundamental for a large variety of smart buildings services; specifically, energy management and indoor environmental control [73]. For example, the proper load calculation due to occupants and their spatial distribution could avoid over-heating/cooling or under-heating/cooling of areas which is of a major importance especially for large public spaces [72,74]. Furthermore, these models could help to track and learn inhabitant's daily routine unobtrusively with the aim to optimize energy usage without affecting occupants' comfort [75]. Moreover, although satellite-based radio navigation systems are the common method that provides accurate track and modeling of movements outside buildings [76] and their use for positioning inside buildings is theoretically possible [77], it is difficult with traditional Global Positioning System (GPS) receivers to locate occupants in buildings [71]. Firstly, because the signal must be unobstructed, indeed conservative models suggest that the attenuation in buildings can reach levels of 2.9 dB per meter of structure [76]. Secondly, because this typology of systems requires the user to carry a tag.

Generalizing, the overall research process can be summarized into two consecutive tasks: people movement detection, identification, and localization, and people movement modeling for forecasting and simulation.

The literature relates mainly to the first task, in which arrays of binary sensors [78], environmental sensors [79], cameras [80], pressure sensors [81], inertial and vibration sensors [82,83], radio-frequency identification sensors [84], Bluetooth [75,85] and Wireless Local Area Network (WLAN) [86–88] are used to detect occupants and track their movements [89]. Generally, environmental sensors are the cheapest solution, but they provide less information about human movement, unless densely spread in the indoor space. Cameras or infrared sensors provide good accuracy, but they are usually expensive sensors with high maintenance costs and privacy issues. Pressure sensors, inertial and vibration sensors are usually employed under the floor, making the maintenance and the installation to be planned. Finally, the sensors like relying on Bluetooth or WLAN provide very detailed results, however, often they need that the occupant carries constantly a device.

The second task is usually performed with machine-learning algorithms that are able to learn representation from the data and use them to forecast, simulate and model the occupants' presence in rooms and their movements [74,75,90,91]. Some studies solve the simulation and forecasting via stochastic models, due to the lack of surveys and statistical information with proper detail [72,92].

To summarize, the topic of modeling people's presence, movement between zones and activity is relatively new, and ML methods are emerging as a promising approach to forecast, simulate, and model the occupants' presence in rooms and their movements inside buildings.

7. Modeling occupant actions

People interact with a building and its devices in various manners to meet individual needs. Occupant actions have a role in modulating energy fluxes exchanged by a space and the outdoors and, hence, have an important impact on the actual energy use in buildings and perceived occupants' comfort. In this study, considered occupant actions are windows operation, solar shading operation, electric lighting operation, thermostat adjustment, appliance use, and clothing adjustment.

7.1. Window operation

Window operation is an important control mechanism that, enabling physical connection with the outdoors, provides occupants with the ability to control the local indoor environment (i.e. regulate the indoor air quality and room air temperature). Moreover, since the '70s, building regulations are progressively increasing the energy conservation requirements of the building envelope with a reduction of infiltrations and conductive heat losses. Thus, the share of the ventilation losses on a building's overall energy balance is enlarging. In this context, window operations become even more important, and there is a high demand for window operation models that create realistic patterns for use in building energy simulations and for the predictive modeling for building control systems.

In this section, 43 documents published since 1990 were analyzed. According to the analysis of the developed bibliographic database, the control mechanisms, even though clearly influenced by physical conditions, tend to be governed by a stochastic rather than a deterministic relationship [93]. Stochastic models estimate an outcome by assuming a probabilistic relationship with one or more predictor variables. For modeling window opening behavior, the most common approach used so far are logit models and logistic regressions. These models can be used to predict the probability of a window's state (i.e. open or closed) [36, 94–104] or the probability that a certain action will occur (i.e. window opening or closing action) [105–108]. The former has been typically implemented with a Bernoulli process while the latter with a Markov process. A Bernoulli process [37] is a sequence of independent binary random variables where the current state has no impact on the future state; by definition, it ignores the actual dynamic processes leading occupants to perform actions. This limitation can be overcome using a Markov process [37,94,103,109–111], since it is a random process where future states are dependent only on a current state together with the probabilities of the state changing. However, to integrate these simulation approaches in a conventional BPS tool, since the time advances in fixed time steps, they have to be discrete (discrete-time random process). Therefore, the temporal resolution of predictions is limited (e.g., short duration openings could be ignored if they last less than the given time step). Furthermore, the time in which the active state (e.g., window closed) will be reversed is not predicted. To pose a solution, Haldi and Robinson [112] developed a hybrid approach: state transitions were predicted as Markov processes, while a continuous-time approach was employed through a survival analysis to estimate the time to reversal of the state.

Several studies implement NN and also DL has been used so far [113]. NNs are capable of learning the relationship between input signals and capturing key information through the training process based on historical records. Furthermore, they also possess a number of other strengths such as fault tolerance, robustness, and noise immunity [114, 115]. However, the architecture choice and hyperparameters optimization in the current NNs are still developed on an ad hoc basis. This implies that NNs applications are usually case dependent [116]. They have to be designed and validated each time for every different applications.

From the analysis of the bibliographic database, it was observed that other ML techniques adopted to analyze window-opening behavior are based on a Gaussian distribution model (e.g. Ref. [95]), a Bayesian network (e.g. Ref. [117]), a cluster analysis and mining association rules (e.g. Ref. [118]).

Researchers have adopted different indices to evaluate the performance of their models, such as the true positive rate (TPR), true negative rate (TNR), the accuracy of the model (ACC), the mean absolute error (MAE), the mean signed deviation (MSD), and area under the curve (AUC). Consequently, there is a lack of horizontal comparison among these models. The motivation behind this difference is due to the fact that a convergence towards a systematic set of statistics for the prediction of the performance of behavioral models is missing. In this regard, Mahdavi and Tahmasebi [34] suggest two categories of indicators: indicators addressing aggregate aspects of models' predictions, and indicators addressing the interval-by-interval congruence between predictions and measurements.

Following the Köppen climate classification scheme, the majority of the analyzed window opening models were developed in temperate climate zones Cfb (43%), Cfa (23%), Csa (2%), while the remaining in continental climate Dwa (16%) and Dfb (16%). Furthermore, most published studies referring to occupant window behavior have been carried out in European countries [37,94,102,105–107,109–113,117, 119–133]. Since window operation enables physical connection with the outdoor environment, it can be directly influenced by different conditions such as the atmospheric environment but also contextual factors such as routine/habits [134] and individual preferences [135]. It is therefore evident that in-depth research of window behavior in other climates and contexts is necessary.

While statistical models are a quite consolidate approach to model window operation (Fig. 10), data-driven models still requires further exploration, although DL has been recently used to investigate window operation [113].

7.2. Solar shading operation

Solar shading devices coupled with electric lighting are fundamental instruments to provide indoor thermal and visual comfort. The use of solar shading controls the internal daylight and influences the resulting solar heat gains. On one hand, solar shading can allow solar radiation to enter and passively heat the indoor environment, and on the other hand, it influences the operation of electric lighting that contributes to indoor sensible heat gains. Furthermore, solar shading is also used to provide privacy by blocking the view into a room from the outside.

In this section, 20 documents published since 1979 were analyzed. Solar shading operation is mainly modeled by predicting a shading state (or its change) as a binary variable (i.e. open or closed) [122,123,132, 136–142] or by estimating a shading device multi state [143–147]. Moreover, there are some specific models that predict the Venetian blind slat angle [148,149] and some others that couple the slat angle with the blind multi state [150,151].

The occupant-controlled shading devices has become of great interest in building performance simulation for different reasons.

A fundamental role in OPA models is played by the choice of the predictor variables. From the bibliometric analysis, it emerges that the most used predictors in shading control models are indoor and/or outdoor air temperatures [122,123,132,140,151], work plane daylight level [137,139,142,143], indoor illuminance [138,146,150], external radiation [146,150], and rainfall [122]. Since most of the models use external conditions as predictors, the climate in which the data for model construction are gathered is of great interest. In the analyzed bibliographic database, almost all models for shading operation come from temperate [123,137,139,140,146] and Continental [122,132,136, 138,141–143,147–151] climates, except for Kurian et al. [145] that worked in the tropics. Next, except from Andersen et al. [140] that predict shading movements in residential building, all other models are built for offices [122,123,132,136–139,141–143,147,149–151].

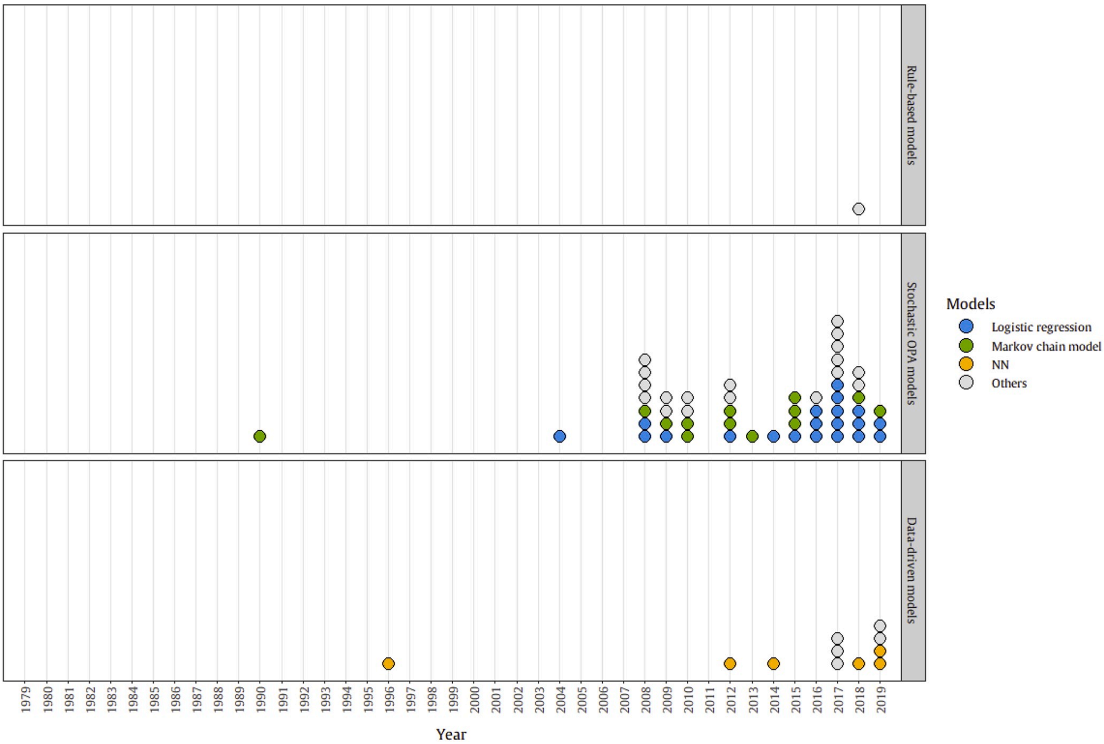

Fig. 10. *Timeline of window operation models.*

From the performed analysis came that the first shading control model was developed by Hunt in 1979 who used a stochastic method (Fig. 11). Since 2000, even data-driven methods have been used as accurate tools to predict the occupant-driven use of solar shading, with fuzzy logic and regularized logistic regression as the most used methods. NNs have been used for controlling the slat angle of Venetian blinds to optimize the energy consumption for lighting, and space heating and cooling [143,148,149], and also reinforced learning has been adopted to develop a controller to adjust both electric lighting and blind position [150].

In summary, models reflecting the operation of solar shading on tropical and arid climates are missing. Furthermore, more investigations should address residential and other types of buildings, providing a wider support for building energy modeling.

7.3. Lighting operation

In this section, 77 documents published between 1994 and 2019 and focused on electric lighting operation were analyzed. The analysis of the collected bibliographic records shows that, in the last 20 years, smart lighting control systems have been proposed to simultaneously satisfy personalized lighting levels and harvest natural daylight reducing energy consumption [152–154]. The first lighting controls were created such as on/off switch control or dimming by using sensors' outputs. Also, user-centric models based on occupants' location and their activities were used to define optimal lighting intensity level as a balance between user satisfaction and energy cost [155–157]. Lighting models that use sensor input (mostly occupancy and illuminance level) were primarily applied in office buildings. These models aimed to optimize the lighting conditions with respect to the work satisfaction and productivity [158,159]. NN technique was adopted in dwellings to implement programming schedules of lighting control in Ref. [160].

With regard to the climatic conditions, the majority of the analyzed investigations were developed in temperate climate zones Cfa (18%), Cfb (16%), Csa (12%), and some studies fall into the continental climate Dfb (12%). The main percentage of investigations (55%) was conducted in office buildings, followed by houses (17%) and laboratories (9%). The less analyzed building types are dormitories, hotels, and commercial buildings. Analyzing the type of data adopted for the models' development, it appears that the most common sources come from measurements (42%) and simulations (26%). Some documents adopt both measurements and simulations (18%). Surveys are rarely adopted alone, but they are typically coupled with measurements (9%) or with both measurements and simulations (4%). Regarding the models' categories, the highest percentage of identified documents belongs to the category of discriminative ML models (66%) followed by stochastic OPA modeling techniques and deterministic models that present similar applications. Some studies implement more than one model that falls into the same or into different typologies.

The most frequent category is the data-driven models [121,144,148,149,152,155–158,160–194]], followed by the stochastic OPA modeling methods [153,159,161,184–190,195–212] and, then, the rule-based methods [139,157,160,206,213–223].

NNs allow forecasting multiple continuous variables based on design parameters because they are able to predict unique light use schedules for each design variant [172]. Furthermore, nonlinear transformation from input variables to output variables enables the designer to make predictions or classifications with regard to lighting controls [161,193]. However, their main drawbacks are that it takes too much time for the training phase [161] and needs to be trained again if the layout of any lamp is changed [163,165,166]. Regression models can help in predicting the lighting consumption of buildings [210] by providing an

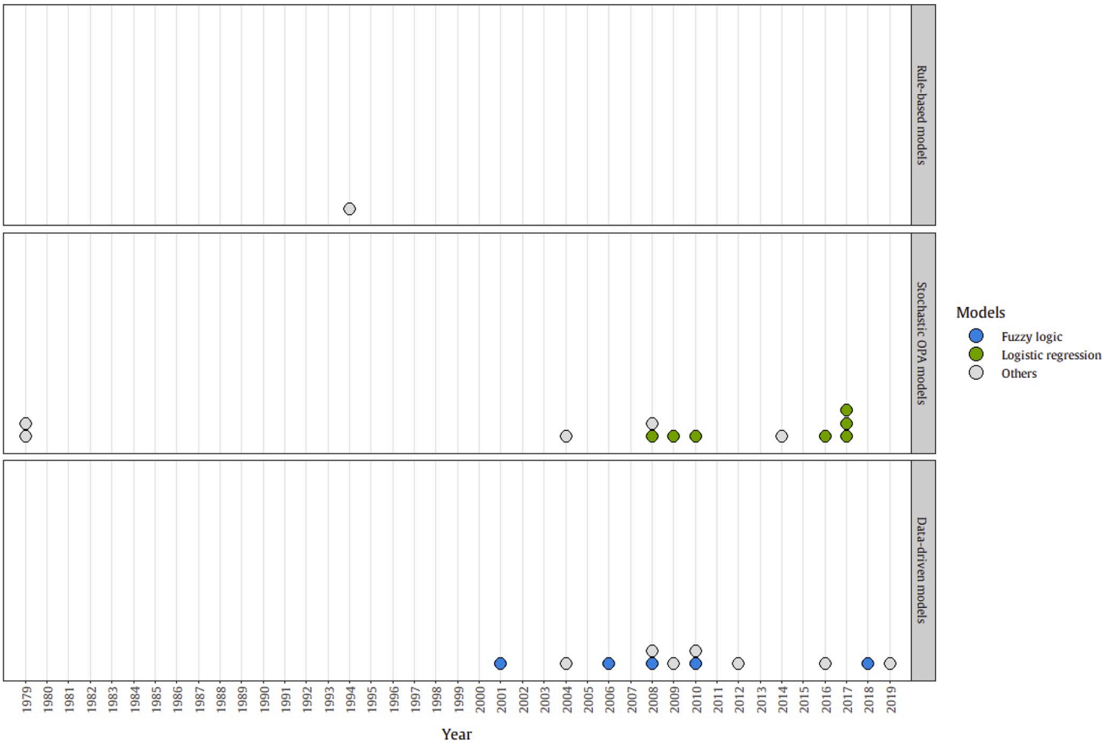

Fig. 11. *Timeline of solar shading operation models.*

accurate estimation of the energy consumption compared to the results obtainable with extrapolation methods that use data from office lighting systems [191]. Furthermore, regression models were used to predict a state (i.e. on/off) (e.g. Ref. [212]), to estimate the probability of light switch actions (e.g. Ref. [207]), and the interactions with window shades (e.g. Ref. [206]). Rule-based models are a simpler manner to set a lighting control strategy and, in the case of large datasets, they provide acceptable results when compared with stochastic OPA models [206].

The historical overview shows an increasing development of models since 2004 (Fig. 12). Rule-based models like schedules and profiles were implemented for this intervention [215,216]. Logit model [224] was the first technique used to describe stochastically OPA behavior in European countries and Pakistan [195], but its application was time limited. Successively, there was the implementation of Markov chain model [159,205]. Since 2005, NNs [225] have become the most used data-driven method due to their abilities to learn from input data and the breakthroughs made in computing power at the beginning of the 20th century. Other methods for lighting modeling, for example, SVMs and decision tree, have emerged since 2010, but are relatively less used than NNs. As a prediction method, linear regression is easy to use, and the historical use rate is similar to SVMs and decision trees.

Researchers validated their models by means of different evaluation metrics: error or accuracy [149,155,164,166,170,177,179,180,186,201–204]; comparison between the performances of the proposed system and the existing system in terms of energy saving or illumination level [139,153,173,174,181,191,192,194,199,206,221]; MSE [155–157,161,163,168,193,208]; RMSE [121,152,166,183,184,208,210,211]; statistical parameters such as standard deviation, kurtosis, and skewness [165,167,197,209].

The analysis of the existing literature showed that the research about electric lighting modeling was mainly conducted in locations characterized by temperate climatic conditions. Nevertheless, the user's interaction with electric lighting is influenced by the daylight availability that depends on local sky conditions and latitude. This limitation can negatively affect model's generalization and suggests future studies in diverse geographical contexts.

Also, offices were the most investigated indoor environments due to the easiness to apply sensors and collect measured data. Thus, research should be dedicated to residential, educational, and commercial buildings.

Discriminative ML models were widely developed and tested, stochastic and deterministic models require more investigation in order to verify their efficacy. Generally, accurate analyses about user's habits, preferences, and perceptions of indoor conditions are missing and so investigations could be improved by administrating targeted surveys during the monitoring phase.

7.4. Thermostat adjustment

Thermostat adjustment behavior is a key component of building performance modeling as it directly influences the amount of energy used for space Heating, Ventilation, and Air-Conditioning (HVAC) systems. Thermostats are used as control devices to determine when space heating, cooling, or ventilation should be applied to a building thermal zone. Thermostats typically include sensors that measure the air temperature or humidity of the building thermal zone and will request space heating, cooling, or ventilation if the indoor climate is above or below a set-point value. The occupants within buildings interact with a thermostat by adjusting the set-points for temperatures and humidity and by setting schedules for when the HVAC systems should be active and inactive. Thus, the occupant behavior (setting the set-points and the schedules) is one factor determining when an HVAC system switches on

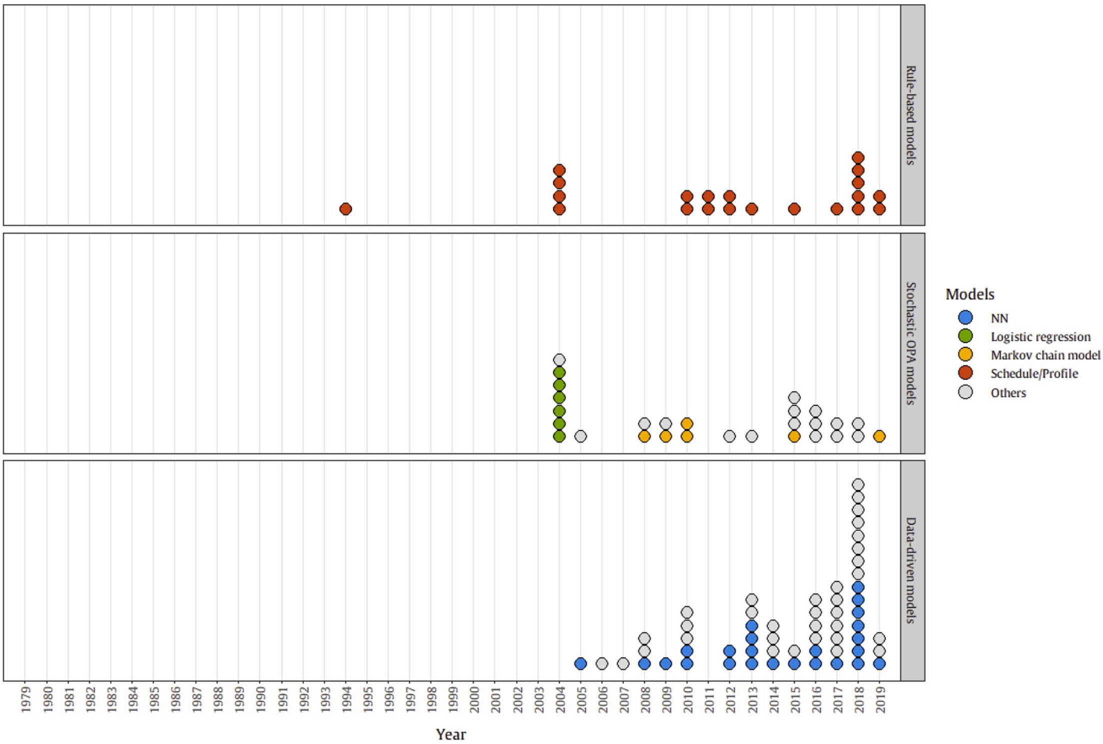

Fig. 12. *Timeline of models for operate electric lighting.*

and off; other factors include the many thermal processes which influence the indoor climate such as the thermal properties of the building envelope, the internal heat gains and the capacity of the HVAC.

The choice of thermostat set-points and operation schedules by the building simulation modeler will have a significant impact on the predictions of energy use and occupants' thermal comfort. This is a key factor of the performance gap as international and national building performance standards and calculations often assume constant, simplistic occupant behavior for the thermostat control. In reality, many occupants will continually adjust the thermostat set-points and schedules depending on when they are at home or at work, the external weather conditions and for occasions such as holidays. The difference between these assumptions and the actual occupant behavior may lead to significant uncertainty in the predictions of building energy use [226].

In this section, 44 documents published after 1989 are analyzed. The occupant behavior modeling methods have been identified in the developed bibliographic database (Fig. 13). The most used methods include General/generalized linear model (33%) [227,228], Markov chain models (23%) [229,230] and logit analysis (20%) [121,132]. The studies are based on a wide range of buildings such as residential buildings (54%), offices (26%), commercial buildings, educational buildings (7%), and commercial buildings (6%). Measurement campaigns are used to collect training and calibration data for model development, including internal temperatures (set-point and indoor air temperature), occupancy/presence, heating/cooling/ventilation energy demand, and outdoor weather. For residential applications, it can be difficult to directly measure thermostat set-points and schedules (as this requires a direct interface with the control equipment) and often indirect measurements are used as a proxy such as estimating thermostat settings using the zone air temperature [132,231,232]. This further adds to the uncertainty of the model predictions. In the numerous studies in this field, there is no agreement on the choice or amount of measurement variables that are required to construct the occupant behavior models or the choice of evaluation metrics which should be employed to validate the models.

In connection to the previously described thermostat set point adjustments, the occupants' interactions with the HVAC systems have also been explored in residential [227,233–235] as well as in office and commercial contexts [236,237]. As a result, the use of the HVAC in residential buildings has been conducted using approaches such as Markov transfer probabilities [227] and descriptive statistics [233–235]. In the case of commercial buildings, the application of logistic regression and rule-based agent models have been identified as a suitable modeling approach [236]. This study pointed out that both logistic regression-based models and the agent-based framework could identify approximately 50% of the fan use or heater use events correctly, while the proportion of the false positive rate remained around 20%. In another study of office and commercial buildings, NN was evaluated for performance among four different machine-learning algorithms [237], which actively learned occupants' interactions with thermostats under dynamic, time and space varied contexts. For a period of five months, the interaction model was conducted to an HVAC system in the case study building. The results reported 4%–25% energy consumption reduction as compared to static temperature set points at the low values of the preferred temperature range.

Significant further work is required in this area. The field of OPA thermostat set-point modeling is underdeveloped in relation to other OPA areas because of the challenges in collecting thermostat data (in residential settings) and in modeling the complex interrelated effects of occupant thermal comfort, building thermal response and dynamic external conditions. A clear data collection methodology and

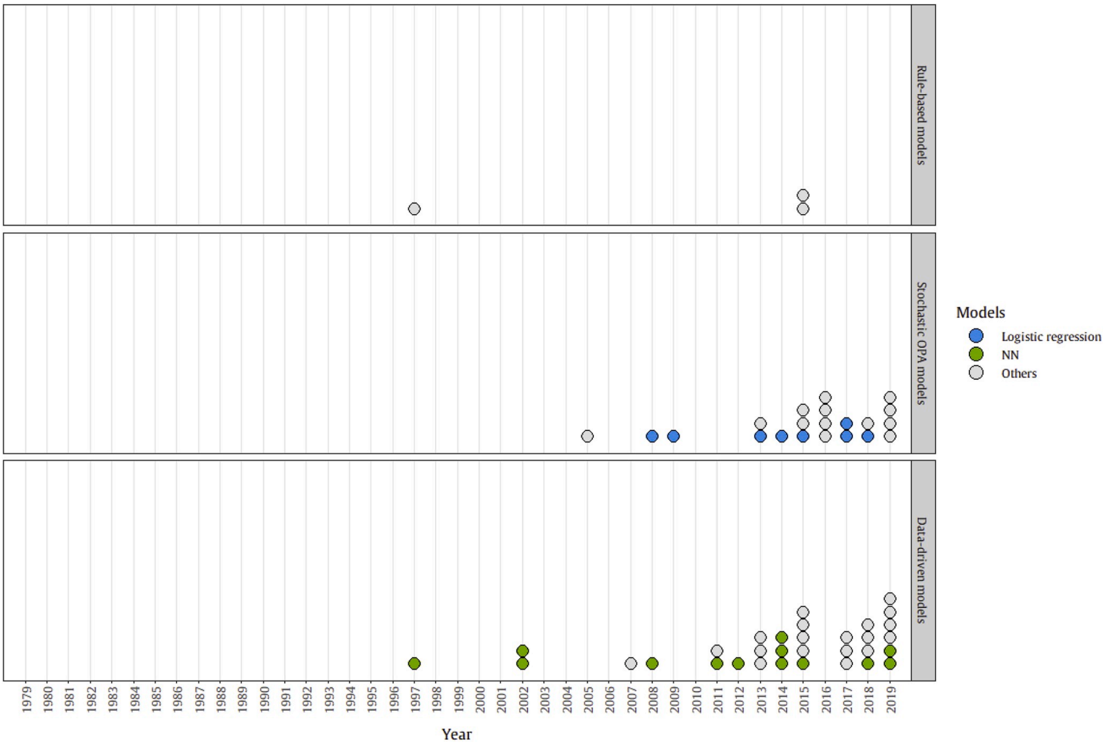

Fig. 13. *Timeline of models for thermostat adjustment.*

standardized model testing framework needs to be developed, with clear reporting criteria and evaluation metrics. To maximize the potential of existing and future datasets, a common data collection vocabulary or ontology should be created which would enable data reuse and ultimately meta-analysis of multiple datasets across different building types, sample sizes and country of origin.

7.5. Appliance use

Appliance are electrical devices that support people's daily life, ranging from small machines (like laptop computers, air purifiers, coffeemakers and microwaves) to large ones (like fridges, clothes washers and dryers). Especially in the residential sector, appliances become one type of key electricity consumers. The energy demand for household appliances is growing as rising living standards worldwide [238]. Human behavior has an impact on appliance operation and spurs the associated energy consumption within buildings. Better understanding such activities offers potentials to operate appliances and their energy supplies (including the power grid and renewable energy) in an efficient way. Measuring and modeling appliance usages triggered by occupants, if properly visualized and communicated to together with suggestions, can promote energy-saving awareness [239]. Yu et al. [240] proposed a data mining-based method for estimating the saving potentials related to standby energy use considering the occupant behavior. Meanwhile, energy/load management based on appliance operation minimizes the variation of power supply [241], shifts appliance operation from the peak electricity demand [242] and makes appliance adapt to changes in electricity price [243].

In this section, 36 documents published since 1994 were analyzed. They describe models for identifying and modeling appliance states that were based on measurements, simulation, and surveys. Overall, the majority of the data used is measured data from field studies and home applications (69%). The studies were undertaken mostly in temperate climates (Cfa 39%, Cfb 33%, Csb 6%) with some models in continental (Dfb 11%) and arid climates (Bsh 6%, Bwh 6%). Sensing infrastructure for the data collection differed for the individual studies. It included four distinct groups of sensing devices: energy-related measurement (power, voltage, and current meters); communications technology (barcode and Bluetooth); environmental sensing (temperature, carbon monoxide, and acoustic sensors); and activity-related sensing (triaxial accelerometer and gyroscope, motion, door, and ultrasonic positioning sensors). Among them, power meters installed at the main power inlet of households were widely used by the studies as predictors.

Appliances are operated in on/off or multi states. Identifying their states was mainly described stochastically or predicted with data-driven methods. The former approaches use Bayesian networks [244,245] and hierarchical clustering models [246]. The latter use two different machine-learning-based algorithms: HMMs [239,247–249] and NNs [250–252]. To model occupants' indoor behavior and activities in interaction with appliances, diverse algorithms were employed in the studies, such as pedestrian dead reckoning [253], Bayesian network mode and linear regression [254], k-means and Gaussian mixture [69], random forest [255], and SVMs [256]. According to power usage of appliances, Gaussian mixture [257], k-means [258], optimization based on defined objective function [243] were used to infer load distribution and scheduling for systems. Similarly, power data showed potentials to extract building occupancy using data-driven approaches, such as decision trees [259] and NNs [260]. Two studies used both power data and occupant surveys [261,262]. Based on such data, the former study aimed to identify occupant behavioral predictors using a linear method, and the latter employed a Gaussian mixture method to model load patterns of the appliance in offices. For appliance controls in households, NNs [263] and stochastic sliding mode control [241] were utilized. As shown in Fig. 14, most of the studies were based on recognition of appliance states and associated occupant activities using data-driven models.

Evaluation metrics applied to verify the above behavior modeling for appliance uses included precision, recall, F-score, RMS, RMSE, NRMSE, MAE, distance and positioning accuracy, and variances of positioning errors.

Most of the studies focused on one type of data (i.e. total electricity consumption of individual buildings or households) or one case study with several specified appliances. In actual buildings, diverse appliances are used by occupants which are affected by the purposes of the buildings (for example, residential and commercial buildings), and occupants' requirements. Meanwhile, occupant behavior interacting with appliances differs from device to device and person to person. In future research, one of the key research questions could be how to generalize methodologies for different appliance applications.

7.6. Clothing adjustment

Clothing has been considered as a critical interface between humans and their surrounding environmental settings [264–267] and is an influential input parameter in a few thermal comfort models. According to current knowledge, age, gender, and relative humidity have no significant effect on the clothing insulation levels chosen by people [267]. However, Humphreys [267] stated that the outdoor daily mean temperature to be the most crucial parameter affecting clothing insulation levels. Studies before this one had studied clothing insulation using conventional linear regression approaches. Deng and Chen [264] argued that the association between clothing and potential factors that affects clothing behavior might not be linear, hence, they developed clothing prediction models using ordinal logistic regression and NN using data collected in offices. The training accuracies of the NN model for three kinds of actions (lowering the set point or reducing the clothing level, no response, and raising the set point or adding clothing) were 89.4%, 87.3%, and 91.2%, respectively, and its overall training accuracy in predicting all three kinds of behaviors was 87.5%, resulting in an accurate tool for predicting occupants' behavior in the offices.

The main predictors used for the clothing adaptation in the existing literature include indoor air and operative temperature, relative humidity, CO_2, air velocity, outdoor air temperature, skin temperature, human activities and time of the day [268].

The common evaluation metrics used in the existing literature are R^2, RMSE, MAE, MAPE for the regression models, and accuracy, F1-score, precision, and recall for the classification models.

Most of the existing methods in clothing insulation estimation assume the values to be fixed by using in-situ clothing estimation methods, thermal models, or depending on the outdoor air and indoor operative temperatures [265–267,269,270]. Also, some data-driven methods (e.g., NNs, SVMs, and regression models) have been used to establish thermal comfort inside a built environment [264–267,269–271]. These data-driven models reflect the occupants' responses and interactions

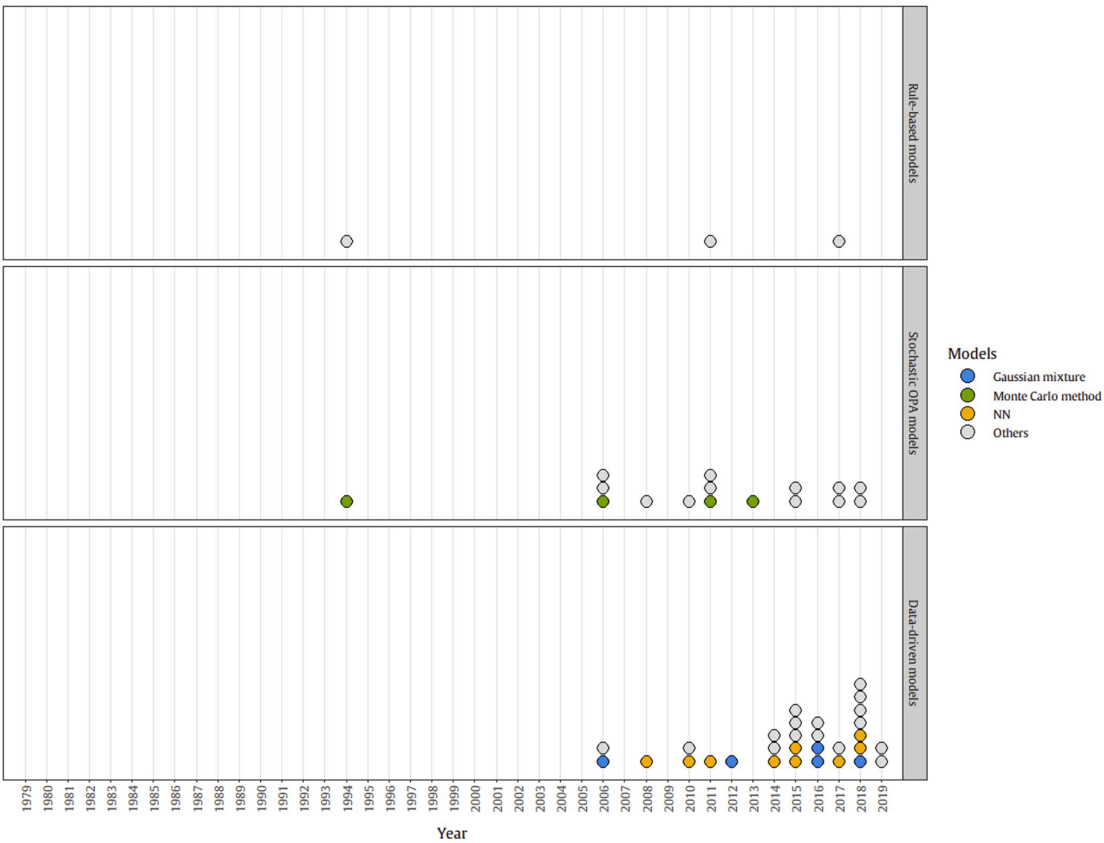

Fig. 14. *Timeline of models for appliance operation.*

with the building utilities and management facilities. Recently, the focus has shifted toward applying ML and DL models for predicting indoor clothing levels [264,267].

From the literature, it is affirmative that the clothing adaptation to any given situation is associated to three influencing factors: occupant behavioral adjustment, physiological factors, and psychological factors [265–267]. Therefore, for future research directions, the interrelationships and correlations between different influencing factors can be studied meticulously in those building types not already analyzed and under different individual conditions, like different metabolic activity levels.

7.7. Combined occupant actions

Researchers have also developed models that combine more than one user's actions with the aim of analyzing the multiple aspects of comfort and energy consumption in buildings. Lighting operation is one of the most co-modeled aspects due to its impact on both visual comfort, thermal comfort, and electricity demand. For example, schedules/profiles, stochastic OPA modeling techniques, and data-driven models were implemented by combining lighting operation with shading control [139,141,144,148–151,154,192,272]. Regression models were also exploited for modeling different combined actions: light switching with window operation [121], window and solar shading operation [123], and light switching with both window and solar shading operations [122]. With the aim of analyzing visual discomfort, data-driven techniques were used in Refs. [176,177] to model lighting switch in combination with blinds operation and change of the space heating set-point temperature. Furthermore, light switching and window operation combined with space heating and cooling operation were also modeled by means of schedule/profile and stochastic OPA models [185,215]. Moreover, data-driven models [210] and stochastic OPA models [196] were implemented to predict the energy consumption of buildings by considering both lighting and appliances use. More recently, Haldi et al. [122] investigated the combined operation of windows, solar shading, and light switching and developed logit models for residential buildings and offices. These models included random effects for all predictors that account the inter-individual variability in behavior among different occupants. This attempt allows overcoming the issue of modeling an occupants' average behavior and explicitly considering diversity and variability in occupant behavior.

Modeling combined actions seems a more effective approach providing a wider view of human actions and their impact in terms of energy consumption and occupants' comfort. The available literature still demonstrates gaps in this development and intersectional studies should be encouraged.

8. Future outlook in OPA modeling

Among the studies grouped under the data-driven models, there is a subset of studies recently published [54,62–64,67,113,252,264,267, 273–275], which use DL techniques. DL is adopted for obtaining rich information about occupant behavior and is proven to be competent in extrapolating discriminatory features from raw sensor data accumulated from building management systems [273–276]. Traditional ML approaches perform tasks without exploiting the correlations between diverse input sensor data. For example, CNN tries to overcome this issue by implementing convolution across n-dimensional temporal sequence to apprehend the dependencies in the input sensor data. However, the size of the kernel is an important parameter that can restrict the range of captured dependencies in the input sensor data for the CNN model [276]. Other advances in embracing dDL methods are:

1) ML classifiers rely heavily upon heuristic handcrafted features (i.e. the manual selection of features) and require expertise in domain knowledge. The manual selection of features could lead to inductive bias, because the algorithm uses inputs that it has not yet encountered to predict the target outputs. Typically, such bias is supplied by hand through the dexterity and insights of domain experts. Advancements in DL make it possible for automated feature extraction and selection, thus overcoming the inductive bias [273–276].
2) Shallow features can be recognized well with ML but a difficulty in identifying context-aware activities of occupant behavior (e.g., cooking a meal) or extracting other dimensions of occupant behavior [20,277–279].
3) In traditional approaches, extensive training data and labeled annotations are mandatory for supervised learning, but in real-world applications, most of the data remain unlabeled (unsupervised). Due to this, typical models are unadaptable to a diverse range of context-aware occupant actions and model configurations [20,45, 275–279].
4) Another significant difference between DL and ML methods is the problem-solving capability and critical analysis approach. DL tends to solve the issue end-to-end, whereas ML needs the problem statement to be broken into stages/parts and explained separately and combined at the final phase.

In summary, unlike ML approaches, DL classifiers are trained through feature learning rather than distinct task-specific algorithms [276]. However, DL is applicable when the task indented has a large dataset to work with; for smaller datasets, ML algorithms performs well with high accuracy. In general, when there is a lack and inadequacy of domain knowledge for feature introspection, DL outperforms most of the existing ML techniques [20,275–278].

9. Conclusions

In this study, the PRISMA methodology is exploited to conduct a systematic literature review on the topic of Occupant Presence and Actions (OPA) modeling in buildings. The identified documents were collected in a bibliographic database and analyzed. The analysis was supported by a data-driven bibliometric tool to provide an extended investigation of the methods and findings on the topic and to draw insights into the current state and future prospects of OPA modeling. This work, in the context of IEA EBC Annex 79, aimed to systematically cover all aspects of OPA modeling in different typologies of buildings.

The bibliometric analysis showed that the most productive geographic regions are North America, Europe, and China and that the intensity of the collaborations is large and well established between research groups in such regions. The documents analyzed in the database mainly involved measurement data in office buildings located in temperate and continental climates. Therefore, there is a need to develop new research studies outside these consolidated domains to provide a wider coverage of the knowledge domain, specially, in those climate contexts where models are missing, and it is expected a substantial increase of population and the construction rate (e.g., Africa, Indo-China region, Latin America). Regarding the methods, data-driven models are emerging as the most used modeling methods in recent years, which may be due to the large wealth of data coming from sensors installation. In particular, there is a recent interest in adopting deep learning techniques to model some OPA aspects for both explaining and predicting purposes. Most of the studies on occupant presence and activity detection aim at understanding occupant behavior, while the majority of studies on occupant actions are aiming at predicting occupants' interaction with given building devices for adaptive controls' development. It is highly appreciated the development of combined occupant behavioral models that provide a wider and closer-to-reality description of occupant use of the building and its systems. This is a domain where newer research is needed to increase accuracy of behavioral modeling.

In general, to maximize the potential of existing and future datasets, a common data collection vocabulary or ontology should be created which would enable data reuse and ultimately meta-analysis of multiple datasets across different building types, sample sizes and country of origin.

This review has to be intended as a work to be regularly updated and expanded with the rise in number and detail of the OPA modeling methods to provide information on developments and new tendencies in the field. To facilitate this task, this article provides a dynamic open-access review table as a supplementary material (https://osf.io/gnvp2/?view_only=00b08233881f471795d1d8dee79e9828), which can be expanded by other researchers to include future studies in order to represent an updated overview on the scientific production on occupant presence and action modeling.

Limitations of the current work are the possible and involuntary omission of OPA modeling documents not spotted by the literature search and not at the knowledge of the authors. However, the PRISMA methodology is designed to keep such oversights to a minimum.

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Paper e

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A guideline to document occupant behavior models for advanced building controls

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ABSTRACT

The availability of computational power, and a wealth of data from sensors have boosted the development of model-based predictive control for smart and effective control of advanced buildings in the last decade. More recently occupant-behavior models have been developed for including people in the building control loops. However, while important objectives of scientific research are reproducibility and replicability of results, not all information is available from published documents. Therefore, the aim of this paper is to propose a guideline for a thorough and standardized occupant-behavior model documentation. For that purpose, the literature screening for the existing occupant behavior models in building control was conducted, and the occupant behavior modeling processes were studied to extract practices and gaps for each of the following phases: problem statement, data collection, and preprocessing, model development, model evaluation, and model implementation. The literature screening pointed out that the current state-of-the-art on model documentation shows little unification, which poses a particular burden for the model application and replication in field studies. In addition to the standardized model documentation, this work presented a model-evaluation schema that enabled benchmarking of different models in field settings as well as the recommendations on how OB models are integrated with the building system.

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1. Introduction

Building energy consumption has been proven to be a systematic procedure comprehensively influenced by not only engineering technologies but also cultural concepts, occupant behavior, social equity, etc. Occupant behavior (OB), discussed in this paper, refers to occupancy presence and the number of people in the spaces of a building, and human building interactions, such as window and blind operations, turning on/off lighting, as well as thermostat adjustment and use of electric appliances. As, occupants are one of the major factors that influence energy consumption [[1], p. 79], depending on the level of building automation, the inclusion of the occupant-behavior modeling in building controls could lead to optimized building operation and reduced energy consumption [2,3]. Furthermore, the inclusion of human-building interaction [4] or OB in the control loop [5] could lead to a higher thermal comfort level and a general increase in occupants' satisfaction with the indoor environment.

However, OB models are rarely included in building controls, despite the vast scientific evidence that considering OB in building energy management could lead to optimized building performance [6]. Prior research studies show that the reason for the limited field applications of OB models could be the lack of OB model standardization and clear documentation [7,8], which results in models' limited replicability. The development of OB model standardization can enable easy integration and compatibility with existing or new building automation system (BAS). For instance, the inputs and outputs of OB models can be mapped with sensors and objects in BAS to enable occupant-centric building controls. Additionally, this standardization will ensure that the functionalities and requirements of an OB model are in alignment with building control requirement.

1.1. Existing reviews

The state-of-the-art, as well as an overview of related reviews that focus on OB modeling, are presented by Refs. [9–12], while the human dimension of energy consumption is reviewed by Ref. [13]. As concluded in the work by Carlucci et al. the predictive OB models are emerging, and this trend is evolving in parallel with the rise in the number of data-driven OB models. In this place, such predictive nature of data-driven OB models makes them promise for the application in advanced building controls such as model-based and model predictive controls. For the detailed revision of OB in the context of building control the reader is referred to Refs. [7,14–16]. Furthermore [17], reviewed occupant-centric control strategies, while the OB modeling was not in the particular focus of the latter work.

Complementary to the reviews of general OB modeling, the OB in the context of building simulation and in the context of building control has also been the focus of several recent studies [18–22].

1.2. Contribution of this paper

This work aims to fill the gaps required for the inclusion of OBs into building control, by proposing a guideline for model documentation and evaluation based on a comprehensive review of the scientific evidence and current state of technology. Since the building control and OB modeling were researched separately during the past years, the literature evidence did not provide a clear set of OB models that are developed and implemented in building control. For instance, OB models were commonly developed with a mentioned practical application for HVAC control, general building automation of smart buildings. However, the existing literature evidence does not provide clear recommendations, on which OB models can be used in building control and how to document these models for their real-world deployment. In order to bridge the gap between the two communities, we relied on our best domain expert knowledge and considered the OB models that are applicable to the building control.

From the control side, we put the spotlight on the OB models for the application in rule-based and more advanced control such as model based predictive controls. Further adaptive control paradigms that could include, but are not restricted to reinforcement learning, are not considered in the scope of this work. In this place, comprehensive and unified model documentation is required for model standardization and wide applicability. This model documentation also includes the guideline for suitable model performance evaluation, which is of crucial importance for the realistic presentation of the model's capabilities. In summary, this study aims to: (1) standardize OB model documentation to promote transparency through clear communication among researchers, reproducibility of experiments, (2) help researchers to select and adopt suitable models to fit their research needs, and (3) help researchers to understand the prerequisite, performance, application of the models they intend to use. In order to fulfill these goals, this work focus on the following research questions:

(1) How are occupant models for real-time/predictive controls currently documented in the scientific literature?
(2) How should occupant models be documented and implemented?
(3) What are the evaluation metrics for different occupant behavior models?
(4) What are the software platforms for future researchers to evaluate/validate their models?

2. Methodology

2.1. Guideline development

This section documents the development of the proposed guideline. As Fig. 1 shows, four major parts are included in this guideline: 1) Model description and applications which describes information representation, model inputs and output, and domain of applicability; 2) Model development detailed out data preparation, modeling formalism, and gaps in current model development documentation; 3) Model evaluation provides guidelines of selecting performance metrics which include absolute metrics, domain metrics, and indirect performance metrics; 4) Finally, in model implementation, we discussed the computational environment, computational time, experiment setup, and integration into MPC.

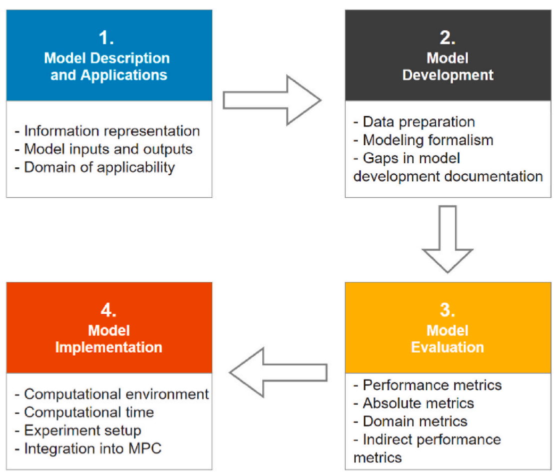

Fig. 1. Overview of the guideline development.

2.2. Review approaches and structure of the article

Based on an in-depth literature review process, this article aims to provide a guideline for a thorough and standardized occupant-behavior model documentation. The review focuses on six different categories of OBs, including Appliance Use, Lighting Operation, Occupancy Estimation and Prediction, Shading Operation, Thermostat Adjustment, and Window Operation. The literature search was conducted in Google Scholar with "Building" plus the aforementioned categories as keywords. Following the pre-defined categories, all the related literature was selected. Among those literature, OB models were reviewed from different perspectives, such as model description and applications (Section 3), model development (Section 4), model evaluation (Section 5), and model implementation (Section 6). We discussed our findings and future challenges in Section 7, and Section 8 concludes this paper.

3. Model description and applications

In order to answer the first research question, we have conducted a review on how current OB models are presented. The description of an occupant model typically includes three parts: information representation, model inputs, and model outputs. We will discuss those elements in the following sections. In addition, the domain of applicability is reviewed as well.

3.1. Information representation

Several ontologies and schemas, such as Industry Foundation Class (IFC), Green Building XML (gbXML), BPD Ontology, Brick, ASHRAE 201,. Have been developed to organize knowledge and structure data by describing both static (e.g. building geometry) and dynamic building data (e.g. time series temperature data) about building technical system, equipment, sensors, and corresponding relationships [23]. Each ontology or schema has its own focus area. For example, gbXML has been used to represent mostly energy performance simulation models with detailed material properties and geometries. BPD Ontology and Brick focus more on building operation data, which is typically measured by physical sensors and has a relationship with its location and measurement type. All ontologies or schemas aim to describe data and their relationship with building's devices. However, it is concluded that there is a lack of detailed documentation on existing data sets and models mostly due to the lack of guidelines as described in the discussion section. In addition, there is no metadata schema or ontology that can represent the full spectrum of occupant behavior models. For example, the occupant presence potentially could be represented by IFC as the "Timeseries" and attached to the "IfcOccupant" Class. However, the description of other occupant behaviors is very limited. Another necessary part of the occupant behavior modeling is a systematic description of input variables and parameters, prediction horizon or time interval. According to the review done by Na [8], eight out of 24 selected data tools can represent indoor and outdoor environmental data; however, none of the existing tools can store occupant behavior model parameters, unfortunately.

Furthermore, the terminology is an essential part of information representation. Na [8] concludes that only three data tools have defined terminology for occupant behavior-related data, which are ADI [24], Brick [25], and Project Haystack [26]. Within those three different metadata schemas, they have different naming for the same building component. The current lack of standardization in the names of sensors in commercial buildings creates challenges not only for occupant behavior modeling but also for building data integration and interoperability in general. There is a need to adapt different naming from the schemas and ontologies to have a unified naming guideline when documenting occupant behavior models.

3.2. Model inputs and outputs

The current section details the inputs (independent variables) and outputs (dependent variables) used in the OB models reviewed in the current work. The information is presented for the six main categories of behaviors considered in the models: (1) Appliance use, (2) Lighting operation, (3) Occupancy estimation and prediction, (4) Thermostat adjustment, (5) Shading operation, and (6) Window operation.

Fig. 2 presents a count of the inputs and outputs used when modeling appliance use (left side of the figure) and lighting operation (right side of the figure). Starting with the former, the most commonly studied outputs are predicting the multi-state of appliances, or their energy consumption levels. The most frequent inputs used to predict the mentioned output are mostly the plug-load energy (i.e., historical data used to predict future use), followed by the space's occupancy status (i.e., using occupancy presence/absence information to predict appliance usage). As for lighting operation (Fig. 2, right), the most frequent outputs are the state (either binary or multi-state) and the operation time. Illuminance levels, occupancy status, and power consumption of other systems (e.g., plug-loads) are the main inputs used to model lighting operation.

Fig. 3 summarizes the inputs and outputs used in occupancy estimation and prediction (left side) and thermostat adjustment (right side). Starting with occupancy models, the two most dominant outputs are the presence status (binary) and the number of occupants. Unlike the previous target behaviors, a wide variety of inputs is used to predict occupancy, including historical occupancy patterns, motion detection, power usage, and indoor environmental measures (e.g., illuminance, temperature, relative humidity, CO2, and VOC levels). As for thermostat adjustment (Fig. 3, right), the temperature setpoint setting is the most frequent target variable. Other outputs include indoor temperature, the probability of adjusting thermostat settings, and energy consumption. Here again, various parameters are used as predictors for these models, such as indoor/outdoor temperatures and humidity, solar radiation, CO2 levels, hour of the day, and electricity load and price.

Fig. 4 presents the count of inputs and outputs used in models of shading operation (left side) and window operation (right side). For shading operation, the listed outputs are all well represented in the reviewed models. They include the shading state (binary or multi-state), the probability of having blinds up or down, and the portion of blinds up or down. The predictors of the stated outputs are primarily environmental in this case, namely indoor/outdoor temperature, illuminance, and solar radiation. Moving to the right side of Fig. 4, the most considered output of window operation is the probability of window state, followed by the probability of taking action (e.g., opening/closing a window) and the portion of a window open, respectively. Here again, the inputs to such models are mostly environmental, namely indoor/outdoor temperature and humidity, wind speed and direction, solar radiation, rainfall, and concentrations of CO2 and particulate matter.

3.3. Domain of applicability

This section details how the spatio-temporal domain is documented in the OB models reviewed in the current work. The temporal dimension is represented by time granularity, prediction horizon, and control horizon. While the spatial dimension is represented by the space (e.g., room, floor, building level) the OB model is addressing.

The time granularity is the time-step or shortest time window operation from which the information regarding the occupant's behavior is used for prediction (e.g., presence model in 15-min resolution). Fig. 5 shows the distribution of the availability of this information in the reviewed papers according to each target behavior. Models of lighting operation are the least documented in terms of time granularity. For the other target behaviors, about 30% of the papers do not report the used time discretization information. Sometimes, the time-step is not explicitly documented because the authors imply that the time granularity of the model is the same as that of the sensed data. The

Appliance Use Inputs↓ Outputs→	Multi-State	Binary-State	Energy Consumption	Prob. of On/Off	Presence	Schedule
Visual Data	1	0	1	1	2	0
Acoustic data	2	0	0	0	0	0
Plug Load	16	0	11	0	1	1
Price	1	0	0	0	0	0
Wireless Signal	1	0	1	0	2	0
Tin	1	0	0	0	0	0
Tout	1	0	1	0	0	0
Door Operation	1	0	0	0	0	0
Presence	2	0	7	0	1	2
RH(in)	0	0	1	0	2	0
CO2	1	0	0	0	2	0
Wind Speed	0	0	1	0	0	0

Lighting Operation Inputs↓ Outputs→	Binary	Multi-State	Portion of Light On	Visual Comfort	Probab. of Switching	Power Consumption	Operation Time
Tin	0	0	0	0	0	1	0
Tout	1	0	0	1	0	1	0
RH(in)	0	0	0	0	0	1	0
RH(out)	0	0	0	1	0	1	0
Wind Speed	1	0	0	1	0	0	0
Illuminance	11	21	1	1	1	3	6
Solar Radiation	1	1	1	1	0	1	1
Occupancy	5	5	1	2	0	1	11
Power	2	4	2	1	1	2	10
Color	0	1	0	0	0	0	0
Visual Comfort	0	2	1	0	1	1	0

Fig. 2. Count of inputs and outputs used in models of appliance use (left) and lighting operation (right) behaviors.

Occupancy Estimation and Prediction Inputs↓ Outputs→	Presence (Binary)	Occupant Number	Percent Occupied	Position
Occupant Entry/Leave	0	2	0	0
Occupant Number	0	3	0	0
Presence	6	2	1	0
Motion	3	5	0	0
Illuminance(in)	3	3	0	0
Tin	4	2	0	0
RH(in)	4	2	0	0
LED Reading (Volt)	0	1	0	0
CO2 concentration	5	7	0	0
VOC	2	0	0	0
Power Usage	6	1	0	0
echo intensity	1	0	0	0
Acoustic Level	1	3	0	0
Telephone State	1	0	0	0
Keyboard/Mouse State	0	1	0	0
Chair State	0	1	0	0
AC State	1	0	0	0
Door State	1	1	0	0
Light State	0	1	0	0
Window State	1	0	0	0
Signal Strength	0	0	0	2
Number of Device on	0	1	0	0
MAC address	0	3	0	0
Device Location	0	1	0	0

Thermostat Adjustment Inputs↓ Outputs→	Multi-State	Binary-State	Energy Consumption	Cycle Idle Time	Prob. of Adjustment	COP	Tin	Tsetpoint	Portion of Adjustment	Tsupply
Tin	1	1	5	0	5	1	4	12	2	0
Tout	1	1	3	0	4	1	5	10	3	1
Presence	0	1	2	0	0	0	2	6	0	1
RH(in)	0	1	0	0	2	0	1	6	0	0
RH(out)	0	1	0	0	1	1	1	4	0	0
Solar Radiation	0	1	2	0	1	0	2	3	0	1
Wind Speed	0	0	1	0	1	0	0	1	0	0
CO2	1	0	1	0	2	0	1	3	0	0
Tsetpoint	0	0	1	0	0	0	0	0	0	0
WinOpen	0	0	1	0	1	0	0	1	0	0
ShadeOpen	0	0	0	0	1	0	0	0	0	0
Hour	0	0	0	0	0	0	0	3	0	0
Electricity Load	0	0	1	0	0	0	0	4	0	0
Electricity Price	0	0	0	0	0	0	0	3	0	0
Air Movement	0	0	0	0	0	0	0	1	0	0
Occupant thermal	0	0	0	0	0	0	1	1	0	1
Clothing thermal	0	0	0	0	0	0	0	1	0	0

Fig. 3. Count of inputs and outputs used in models of occupancy (left) and thermostat adjustment (right) behaviors.

documented time granularities cover a broad range from less than 1 min to hours (Fig. 6). This depends on several factors, including the granularity of the sensed data available, the temporal range in which the change of behavior in question occurs, and the envisaged predictive horizon. A time resolution between 10 and 19 min is the most frequently adopted.

The predictive horizon is the time horizon over which the OB is modeled. The predictive horizon is much less documented than the time granularity (Fig. 7) and covers a wide range of values, from less than 1–24 h (Fig. 8). This is to be expected since it is strongly dependent on the controlled variable. For example, the predictive horizon for building predictive HVAC control is related to the type of heating and cooling system and can be relatively long for radiant floor heating systems compared to air-based ones, the response time of which is very fast.

The control horizon is the time horizon over which the control variable is modeled. The control horizon is commonly equal to or longer

Shading Operation Inputs↓ Outputs→	Shading (Binary-State)	Shading (Multi-State)	Prob. of Blind Up/down	Portion of Blind Up/down
Tin	4	4	4	3
RH(in)	1	2	4	2
Illuminance(in)	3	6	3	2
VOC(in)	0	0	2	1
CO2	0	0	1	0
Air Velocity(in)	1	0	1	2
Heating/Cooling	1	0	0	1
Lighting Load	1	0	0	1
Tout	3	5	5	3
RH(out)	0	3	2	0
Illuminance(out)	1	0	0	1
Solar radiation	3	5	4	4
Solar	0	2	1	0
Wind Speed(out)	0	1	2	0
Heating/Cooling	1	0	0	1
Lighting Load	1	0	0	1

Window Operation Inputs↓ Outputs→	Multi-State	Prob. of window state	Prob. Pf Action	Time of Opening	Portion of window open
Tin	2	20	15	1	10
Tout	2	20	15	0	10
RH(in)	1	10	9	1	3
RH(out)	1	13	8	0	4
Air Velocity	0	0	0	0	1
Wind Speed	1	12	8	0	5
Wind Direction	1	9	2	0	3
Illuminance (in)	0	0	0	0	0
Illuminance (out)	1	2	1	1	1
Solar Radiation (out)	1	5	6	0	3
Sunshine Hour/ Date/ Time	0	4	1	0	2
Rainfall	0	6	2	0	1
CO2	0	12	8	0	5
PM2.5/PM10 (out)	0	6	2	0	2
VOC	0	0	1	0	1
Image	0	1	0	0	0
Position sun protection	0	1	0	0	0
Occupancy	1	2	1	0	1
Person charactersitic	1	1	1	0	1
Room charactersitic	1	1	1	0	1
Time of day	1	1	1	0	1

Fig. 4. Count of inputs and outputs used in models of shading operation (left) and window operation (right) behaviors.

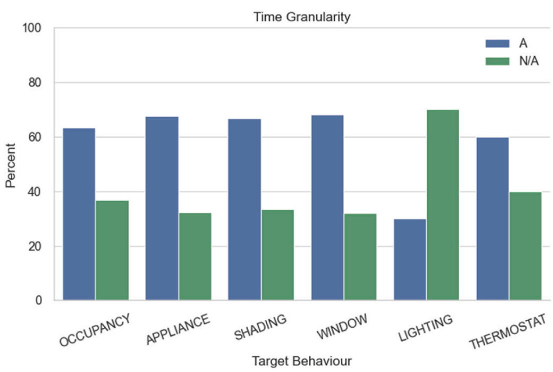

Fig. 5. Availability of the time granularity according to the target behavior.

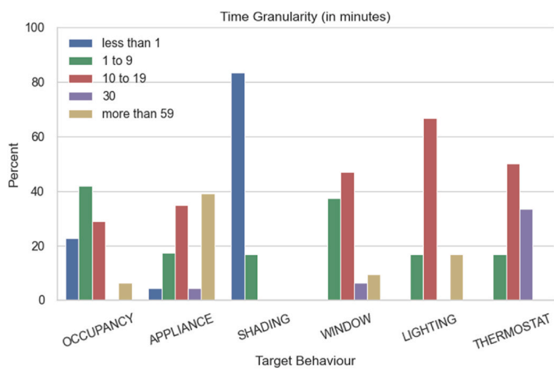

Fig. 6. Distribution of the time granularity in minutes according to the target behavior. (If a model was developed with more than one time-step; only the smallest was considered in the figure).

than the predictive horizon. The control horizon is explicitly documented in only 5% of the reviewed papers. The lack of this information can be explained by the fact that the great majority of the reviewed papers propose OB models as an input for model predictive control (MPC) but do not actually apply it in predictive control. However, the practical implementation of these OB models in the field is currently lacking.

Regarding the space granularity, i.e. the space (room, floor, building level) the OB model is addressing, a majority of occupancy, shading, and lighting models have been developed only at room level (Fig. 9). Instead, appliance use, window operation, and thermostat adjustment models have been mostly addressing the building level that, for the residential case, corresponds to an entire house. Only a minority of OB models have been addressing a lab-based installation, such as a test cubicle.

4. Model development

To develop an occupant model, one needs to prepare raw data into a format that can be used for modeling data (4.1) and identify a modeling method or algorithm that is applicable and practical for a particular

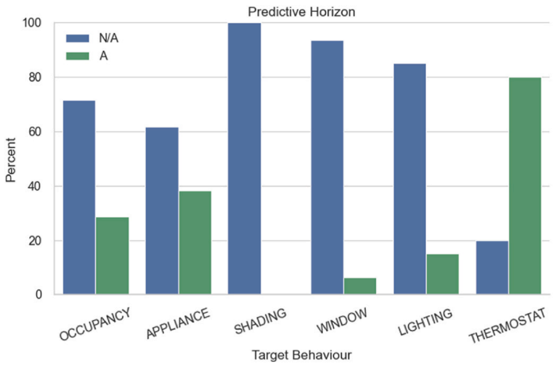

Fig. 7. Availability of the predictive horizon according to the target behavior.

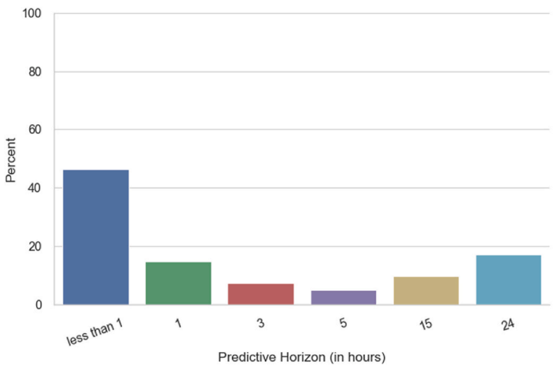

Fig. 8. Distribution of the predictive horizon in hours according to the target behavior. (If a model was developed with more than 1 predictive horizon; only the smallest value was considered in the figure).

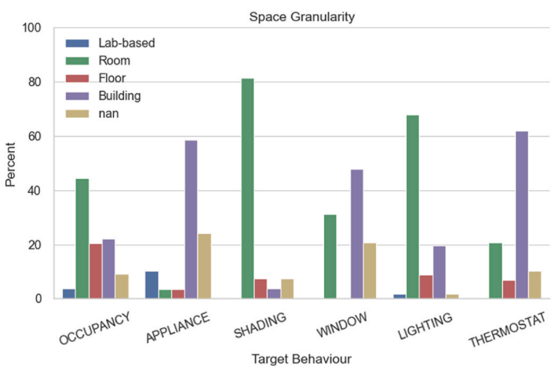

Fig. 9. Distribution of the space granularity for occupancy models.

problem (4.2). In this section, we will review diverse approaches and techniques employed in occupant models and discuss gaps in current research and development in this field (4.3).

4.1. Data preparation

Data used in occupant modeling is often collected in different structures, granularities, and volumes as described in section 2. Hence, it is important to prepare or preprocess the raw data into a format that is suitable for intended analysis and modeling [27]. Preprocessing can include, but is not limited to, the following steps:

1. Cleaning and imputing the missing and corrupt data, outliers by discarding or replacing them with inferenced values (e.g., moving average, mean, or median) to be easily parsed by machine;
2. Reducing data dimensions using row-wise for data sample reduction or column-wise for data variable reduction and random sampling methods;
3. Data scaling using min-max normalization [28], distribution-based standardization [29], or structure-based techniques [30] to scale the data into a consistent range;
4. Feature creation to construct new variables of existing features for data analysis;
5. Data partitioning using supervised (e.g., decision tree [31]) and unsupervised techniques (e.g., k-means [32], Gaussian Mixture Models [33]) to divide the dataset into the test and training subsets to evaluate the trained model based on the test set;
6. Merging data from different sources with various time intervals within time-series data.

Preparing data is often the most time-consuming portion of data-driven modeling. Yet, only a few studies in the reviewed literature describe the data preprocessing methods used for occupant models. The examples are as follows. Jin et al. [34] used the confusion matrix to evaluate the quality of PIR sensor data and remove inaccurate occupancy states. Q-test was used to identify outliers [10]. To handle the missing values, Yu et al. [29] used the moving average method to fill in missing entries. Also, they calculated the SHapley Additive exPlanation (SHAP) values of each feature to reduce the HVAC operation data dimensions. Ashouri et al. [28] employed min-max normalization to standardize energy consumption data. K-means clustering was used to recognize distinct air handling unit operation patterns and group the BAS data accordingly [29]. In another study, hierarchical clustering was conducted to extract the occupancy patterns in the building and create new features for occupancy models [35]. Given that methods and assumptions used in the preprocessing stage can affect data analysis and prediction outcome, there needs to be a concerted effort to document detailed preprocessing steps in future studies.

4.2. Modeling formalism

In this section, the models' category distribution is presented for each target behavior. The modeling categories were defined based on the state of the research: deterministic rule-based models, statistical/stochastic, and data-driven [36]. Rule-based models are the deductive models that use an a priori set of rules for describing occupant behaviors in building models, including deterministic models and schedules. The statistical/stochastic is stochastically modeled the OB to represent the various behaviors among the population [9], potential change over time [18], and complexity [10]. These models are commonly represented by statistical models such as a-priori probability density functions [37]. The third modeling formalism is the data-driven modeling, where the focus was put on computational intelligence or machine learning without an explicit aim to explain the relationship between the input variables and the OB [38]. It includes the ML models and ABM.

The reviewed OB models for building control are screened for the used modeling formalism, and the results are presented in Fig. 10.

The data-driven methods are the most used. The second most implemented category is represented by statistical models that have been applied especially to model windows operation (80%). Rule-based models' category has been applied mainly for shading and has not been tested for appliance use and window operation behavior. Some documents did not provide information about the implemented models. It

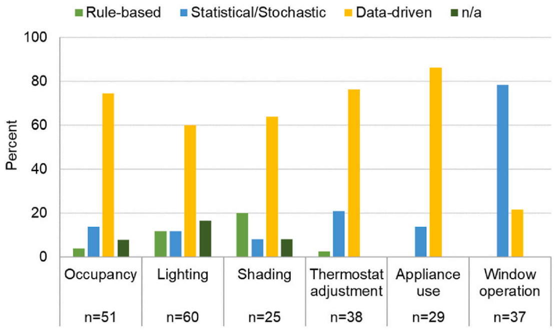

Fig. 10. Distribution of the model categories according to the target behavior.

happened for occupancy, lighting, and shading behavior in a percentage of 8%, 17%, and 8%, respectively.

Fig. 11 deepens the most adopted models in the target behavior, considering those with a percentage higher than 10%. Regarding the rule-based category, most of the reviewed studies do not provide detailed information on the models used, merely defining their belonging category. Schedules have been implemented in around 40% of the cases related to lighting usage.

About the statistical models, the Markov chain appeared the most adopted for occupancy and thermostat adjustment; Markov chain Monte Carlo models have been often implemented for modeling lighting use. Regression models have been mainly found in the case of window and shading operations with a percentage of around 74% and 100%, respectively. Often, information on the adopted model was not provided, as in the case of appliance usage (67%).

Regarding the data-driven models, neural networks (NN) have been the most common. Control logic and fuzzy logic were utilized with the same percentage of neural networks (around 20%) for shading operation. Similarly, also in the case of appliance use, clustering and long short term memory (LSTM) were implemented with the same percentage of neural networks.

Fig. 12 provides the distribution of models' categories in six building types. Rule-based modeling has been mainly applied in commercial buildings for occupancy, lighting, and shading operation. Furthermore, they have been implemented in residential buildings for occupancy, in educational buildings for lighting, and in institutional edifices to model shading operation. The statistical approach has been principally used in residential buildings and prevailed in the case of thermostat, appliance use, and window operation; the application in commercial buildings was diffuse in case of occupancy, shading, and window behavior. In the case of lighting, the implementation of statistical models was equally distributed in residential and commercial buildings. Moreover, statistical models are diffuse to predict occupancy and window operation in

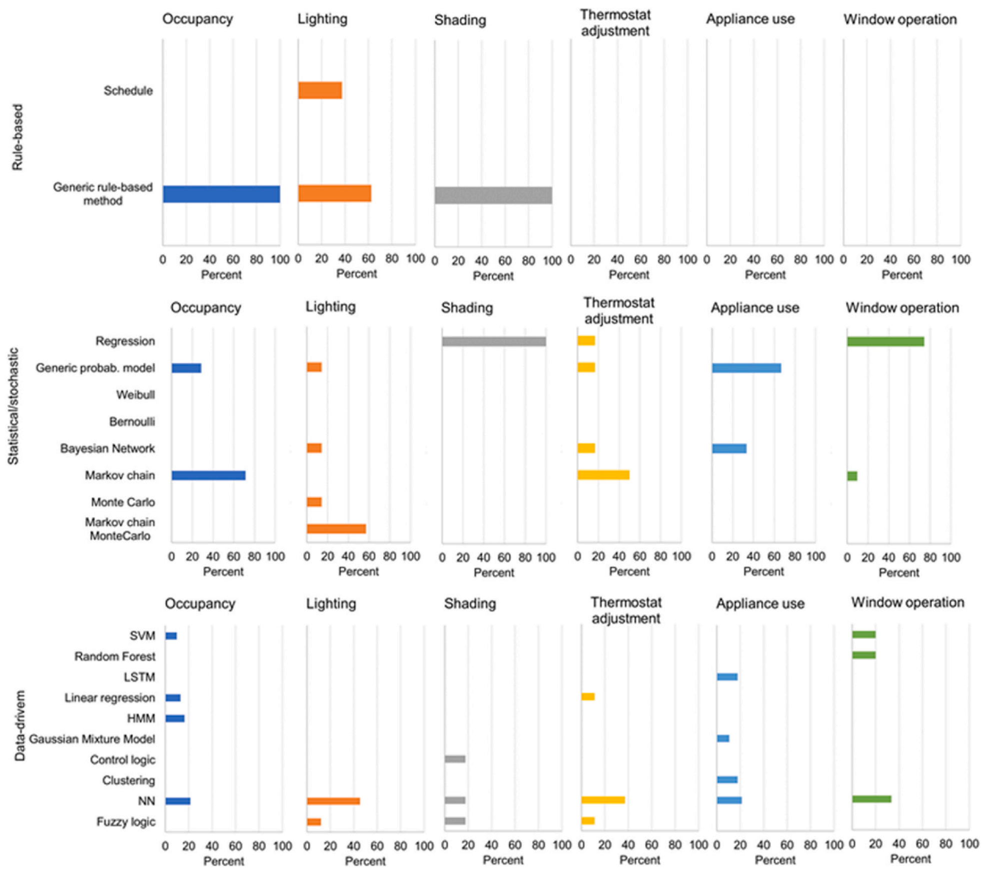

Fig. 11. Most adopted models according to the target behavior and the model categories (rule-based, statistical/stochastic, and data-driven).

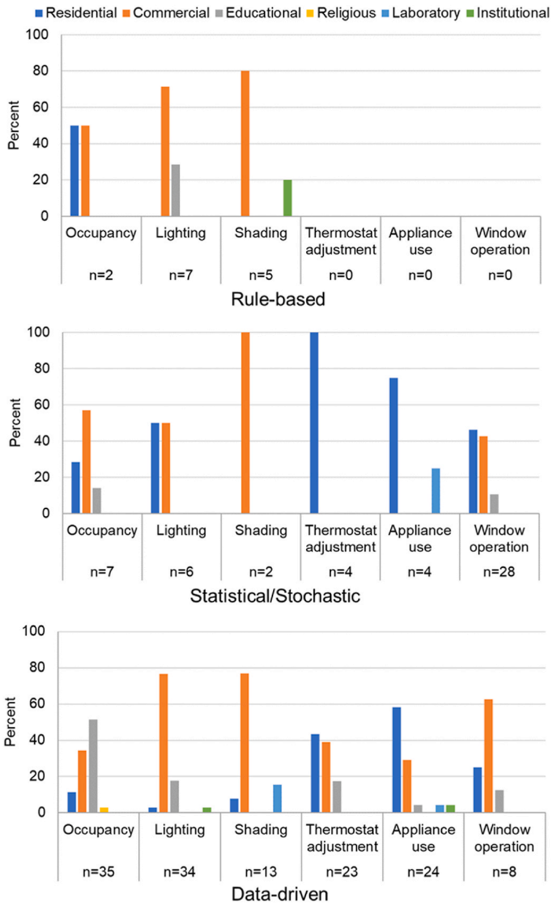

Fig. 12. Model categories (rule-based, statistical/stochastic, and data-driven) according to the target behavior and building typology.

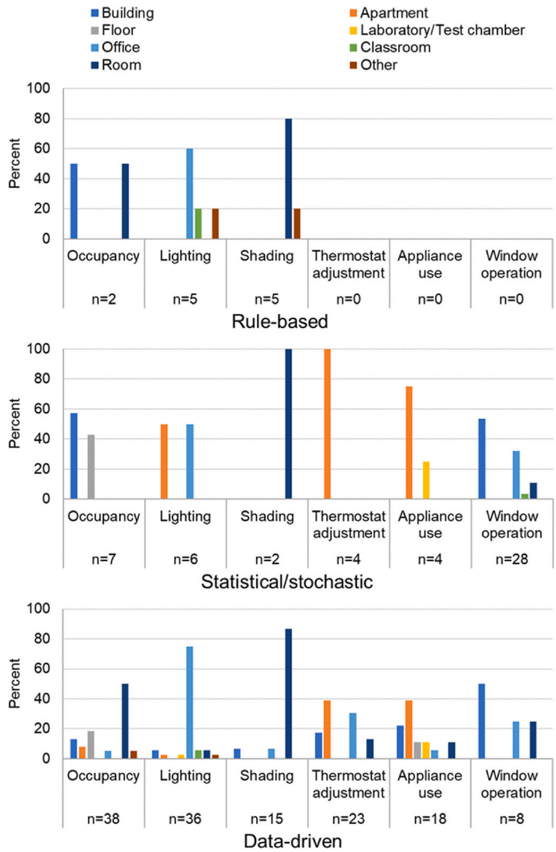

Fig. 13. Spatial granularity in model categories (rule-based, statistical/stochastic, and data-driven) according to the target behavior.

educational edifices, whereas appliances use in laboratories.

The data-driven category found notable implementations in commercial buildings for lighting, shading, and window operation in both residential and commercial buildings for thermostat adjustment and appliance use. Educational buildings prevail for occupancy modeling, and laboratory edifices for shading operation. Other buildings typologies, such as religious and institutional buildings, have been rarely investigated for occupancy, lighting, and appliance use.

Fig. 13 presents the model categories distribution considering the space granularity. In general, shading and occupancy behavior have been investigated at room level and lighting in offices.

On the other hand, thermostat adjustment and appliance use have been modeled in apartments as they are principally studied in residential buildings.

Occupancy is also frequently detected in buildings, whereas lighting operation has been modeled considering more varied space typologies: controlled environments, such as laboratories and test chambers, classrooms, and offices.

Fig. 14 presents the model categories distribution considering the time granularity. Generally, rule-based models were developed collecting occupancy data with a time step minor than 10 min, whereas the temporal time step was prolonged and longer than 60 min in case of shading behavior. In statistical models, occupancy, thermostat, and window were commonly detected with a time step minor than 20 min. Lighting operation behavior was mainly modeled by data collected with a temporal step minor than 10 min. In the data-driven category, the time step used for appliances usage detection was generally equal to 45 min. For the other behaviors, brief time steps, less than 20 min, were also utilized.

4.3. Gaps in model development documentation

Scientific research should be 'reproducible and replicable'. Reproducibility 'means obtaining consistent results using the same input data, code, computational steps, and conditions' while replicability 'means obtaining consistent results across studies aimed at answering the same scientific questions using different data (https://www.nap.edu/catalog/25303/reproducibility-and-replicability-in-science). Reproducibility is challenging to attain because it involves sharing the data, which may be nowadays limited by, for instance, personal data protection needs and privacy issues. Replicability could be easily achievable compared with reproducibility. However, it demands documenting the steps undertaken in the development of the model in a transparent and detailed way. Therefore, the critical aspect is to detail the entire process – the complete workflow – rather than a specific part of it (e.g., the results).

With these premises, the model development should start with the explicit formulation of its problem; that is the modeling purpose. This implies that if a model is developed for control purposes, it should be

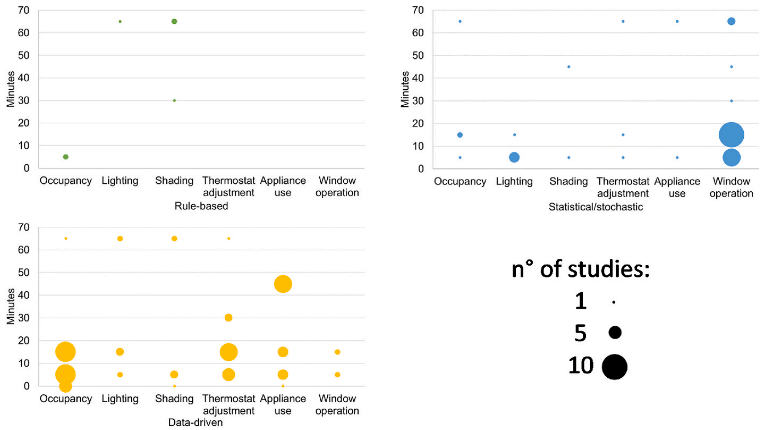

Fig. 14. Time granularity in model categories (rule-based, statistical/stochastic, and data-driven) according to the target behavior.

ready to be directly implemented in control logic. Consequently, this aspect should be already addressed in the model development. For example, for application in model based control or MPC, the control horizon depends on the kind of heating and cooling system used: it can be rather long for radiant floor heating systems compared to air-based systems. Subsequently, the modeling formalism that provides the OB sequence during the whole predictive horizon should be chosen and described. Reasons for the selection of a particular method should be given from both a practical and theoretical point of view. It should also explain how the predictors included in the model were chosen. This includes stating whether feature selection was used to reduce the data dimension and which approach was used. Also, it is important that the variables included in the model are commonly monitored in buildings. For instance, if RH is included in the model as a predictor but is not measured in the building, the model is not applicable in practice.

From the reviewed literature, only 35% of the papers state that the aim was building/zone/HVAC control application, and only 19% offer a formal integration of the model into a control logic. Therefore, the majority of the available occupant models are not designed with control purposes in mind, which directly impacts the modeling formalism used. This kind of model aimed to represent what the behaviors were based on the data collected and not what the behavior will be. In models for control purposes, time becomes a critical factor that a model should directly account for. This translates to recognizing and considering the model's input variables as a function of time.

Another issue regards the integration of real-time data into the model to be updated when new information is collected. This would also require measures of the dependent variable, that is, the behavior that the model aims to predict. The ability to self-update and adapt to real-time data strongly affects the modeling strategy's choice.

Furthermore, most of the behaviors are modeled independently from each other. However, in reality, this is rarely the case. For instance, the shading operation can affect both lighting operation and thermostat adjustment behavior. Moreover, the necessary condition for most of the occupant behavior is occupancy estimation and prediction. This implies being able to measure it or predict it. In the latter case, this will result in ulterior uncertainty in predicting behavior. For example, if window operation behavior is the dependent variable to predict, its prediction will be affected by the model error plus the prediction error for the occupancy status.

5. Model evaluation

Mode evaluation is a logic and necessary next step after model development. This section focuses on the model evaluation and documenting the model's performance. It consists of the reviewed literature evidence on the OB model evaluation and a proposed guideline for the standardized documentation of model performance. For that purpose, the performance metrics are structured into absolute, domain-specific, and indirect metrics, and their purpose is briefly elaborated. Finally, the sensitivity analysis is introduced, as an additional tool to quantify the model performance and document the uncertainties.

5.1. Performance metrics

The model evaluation [39] is structured into absolute evaluation, domain metrics, and indirect metrics as showing in Fig. 15. The absolute metrics relate to the performance indicators used for general statistical or data-driven modeling. Here, we quantify how often an OB model provides a correct prediction, or we use the absolute metrics to evaluate the performance in case of data imbalance. The domain metrics are defined using the OB and buildings physics knowledge. For instance, in the case of window operation modeling, we are not only interested in what percentage of window states is modeled correctly, but also how often a window operation occurs or what the median duration of sequences with open windows is. Lastly, the indirect metrics quantify the impact of the modeled OB on the data modeling objectives of building control: does the use of the window operation model lead to improved thermal comfort, or how does it affect the HVAC system, such as the resulting impact on energy consumption or thermal comfort.

5.1.1. Absolute metrics

The absolute metrics is based on the definition proposed by Ref. [40], namely "the metrics that are based on the absolute error calculation". The main goal is to assess the goodness of the model for fulfilling a particular task, to compare alternative approaches, and to quantify if the design updates made on an OB model led to the model's improvement. The initial step in the selection of the evaluation metrics is the assessment of the nature of the modeling objective; for example, whether the target variable is categorical or continuous.

Since the absolute metrics may result in bias in the interpretation of the results [41], these should be selected based on the nature of the modeled data and target function formulation. In this regard, the target function formulations considered for the OB modeling are continuous, categorical and the special case of binary categorical variables. The resulting absolute evaluation metrics should be defined based on the target function formulation and the particular challenge in each OB model.

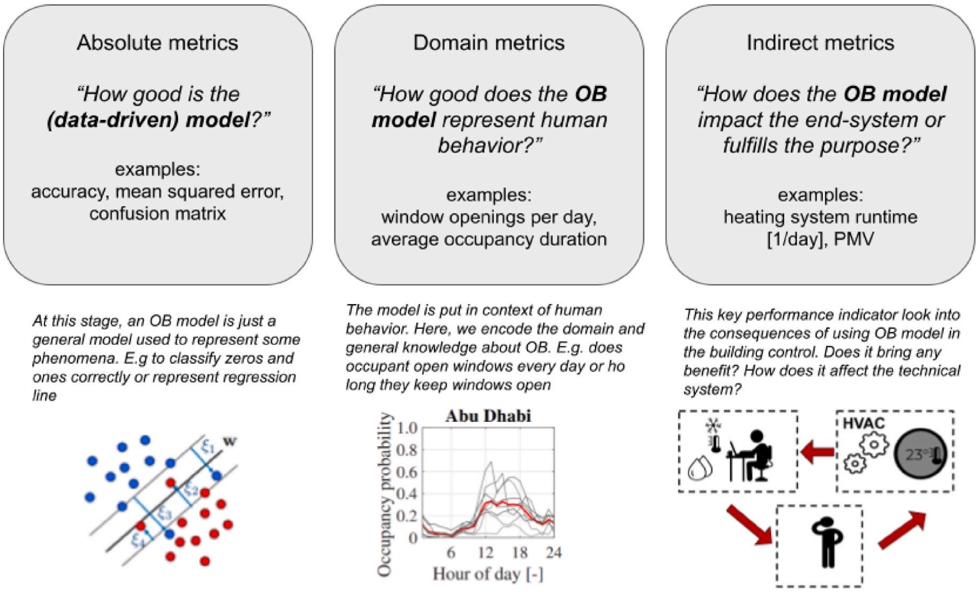

Fig. 15. Model evaluation metrics for OB in building control.

The literature screening showed that there is a significant portion of the modeling studies in which the validation and testing performance was not performed. Furthermore, the conducted literature review pointed out the lack of standardized model evaluation metrics. However, similarly to the generic data-driven or statistical modeling, the performance is commonly reported using mean average error (MAE), mean squared error (MSE). Additionally, the precision, recall, and F1 scores were used by some of the existing studies that focused on classification tasks.

Based on the empirical evidence on the target variable formulation and the nature of OB data, the minimal requirements on the set of absolute metrics for each OB are summarized in Table 1. In summary, most of the OB modeling should be treated as classification problems. The multi-class categorical target functions include the shading operation, while the window operation, occupancy estimation and prediction, lighting operation, and appliance use should be modeled as the binary classification. At the same time, the occupancy count can be modeled as a regression problem.

We use modeling window status as an example. The fundamental issue to be addressed is the imbalanced prior probabilities of the window states. Therefore, the model evaluation should include the MAE, confusion matrix, and F1 scores. Similar to the window states, the occupancy estimation and prediction, appliance use, and lighting operation are also commonly formulated as binary classification problems, and the model's performance can be quantified using the same metrics. To this end, the model goodness quantified using confusion matrix and F1 score could also be reported using precision and recall. The models that represent shading operation can be evaluated using MAE, confusion matrix, and Fβ score. The reader is referred to Li et al. [42] for further elaboration on the choice of the evaluation metrics.

In the case of the thermostat setpoint modeling, there are very limited studies on model validation. However, we argue that the setpoint modeling should be treated as a continuous problem since the setpoint changes could be treated as rare events. By treating the thermostat set point modeling as a regression problem, the relative value of the thermostat set point is to be modeled, while the setpoint changes would be addressed in an implicit fashion.

5.1.2. Domain metrics

The domain metrics are defined as a fit-for-purpose metric that evaluates the competence of the model in representing a certain OB considering the stochasticity of results. The intention of developing these metrics is to provide comparable means for assessing how well do OB models represent particular forms of human behavior. Moreover, considering the main purpose of building as a comfortable and productive space for people [43,44], these metrics standardize building performance from the perspective of its occupants. In the existing work, Tahmasebi and Mahdavi [45] presented domain metrics for comparing

Table 1
Recommended target formulation and minimal set of evaluation metrics for each modeled OB.

	Data type			Absolute metrics								
	Continuous	Categorical	Binary	ACC	Balanced accuracy	Confusion matrix	F1	Fβ	MAE	MSE	RMSE	*N*-RMSE
Window Operation		X	X	X		X	X		X			
Thermostat Adjustment	X								X	X	X	X
Occupancy Estimation and Prediction	X	X	X	X		X	X		X	X	X	
Shading Operation		X		X		X		X	X			
Lighting Operation		X	X	X		X	X		X			
Appliance Use		X	X	X	X	X	X		X			

the performance of OB models in building simulation. However, the related literature in the context of building control is sparse and there is a need for developing consistent domain metrics [46–48].

The domain metrics are categorized based on types into aggregated and interval-by-interval groups as summarized in Table 2. The aggregated domain metrics stand out as proper evaluation criteria when the tested OB model is used for long-term purposes such as (estimating total energy saving, benchmarking building performance, etc.). On the other hand, the interval-by-interval metrics are preferable for evaluating OB models in short-term applications such as (building control, MPC, demand response studies, etc.). Table 1 summarizes the metrics defined for each distinct behavior, and it highlights the research gap in developing novel interval-to-interval metrics for thermostat domains. To fill this gap, we argue that some of the developed metrics could be transferred between different domains with minor adjustments. For example, the occupancy state matching error is the percentage of false state predictions which indicate the mismatch between actual and predicted occupancy; this metric could be adjusted for evaluating appliance use models. Chong et al. [46] used the coverage width-based criterion that comprehensively evaluates the quality of prediction interval to evaluate the performance of occupancy estimation and prediction models which can easily be adjusted to evaluate the performance of OB thermostat adjustment models.

Table 2
Domain metrics for each OB type.

	Purpose	Domain	Metric	Refs
Aggregated	Long-term purposes (estimate energy saving, model building performance, etc.)	Lighting Operation	Typical lighting operation profile Frequency of switching-on actions	[48]
		Window Operation	Overall fraction of open state [%] Mean number of actions per day averaged over the observation time Open state durations' median and interquartile range [hour] Closed state durations' median and interquartile range [hour].	[47]
		Occupancy Estimation and Prediction	Occupancy State Matching (SM) error Occupancy Duration (OD) error [h] Number of Transitions (NT) error	[49]
		Appliance Use	Appliance's daily turn on times Appliance's average use duration Accumulated on-state duration	[50]
		Thermostat Adjustment	N. A	
Interval-by-interval	Short-term purposes (demand response, MPC, etc.)	Lighting Operation	The stepwise energy use	[48]
		Window Operation	N. A	
		Occupancy Estimation and Prediction	First Arrival time (FA) error [h] Last Departure time (LD) error [h]	[49]
			Prediction interval (PI) Coverage width-based criterion (CWC)	[46]
		Appliance Use	N. A	
		Thermostat Adjustment	Prediction interval (PI)[a] Coverage width-based criterion (CWC)[a]	[49]

[a] Metrics are suitable to be shifted from different domain.

5.1.3. Indirect performance metrics

Indirect performance metrics evaluate to which extent the OB model contributes to fulfilling the control goal, such as energy consumption reduction or improving thermal comfort. For example, the integration of occupancy estimation and prediction into temperature control can minimize the heating demand. In that case, the used energy could be defined as the control metric together with absolute and direct metrics in the comprehensive model evaluation. One of the examples of jointly used domain and indirect evaluation metrics is presented by Peng et al. [51] the occupancy model was evaluated using both domain metrics (probability and duration of room occupancy) and indirect metrics (total consumed energy consumption).

A summary of literature about control metrics applied for the different OB models can be obtained from Appendix I. The literature screening pointed out that there is only limited evidence of the documented indirect control metrics for OB models, which could be a result of the rare availability of control use cases. When included, control metrics are frequently used to compare the performance of control including OB modeling versus one without it. The control metrics can be absolute or relative, for example, the energy consumption or saving in kWh (absolute) or the energy reduction in percent (relative).

In the literature, where control metrics are available, the main focus of most control algorithms is to minimize energy consumption while maintaining comfort constraints. Naylor et al. [17] reviewed occupant-centric building control strategies in regard to their energy reduction and obtained between 20 and 50% reduction in most cases. Despite the energy reduction, the comfort should usually remain in a certain range, e.g. an indoor temperature between 20 and 23 °C. The most dominant comfort control metric obtained from literature is thermal comfort, as most cases of including OB (occupancy, thermostat, windows, shading) into control are related to HVAC systems [52,53]. Shading operation is not only relevant for thermal but also visual comfort metrics. Indeed, previous work has combined parameters from both domains in an algorithm to control window blinds [54]. Lightning is only related to visual comfort, mainly by guaranteeing appropriate illuminance levels at workstations. By doing so, visual comfort and energy efficiency metrics may be combined - even during non-office hours, using algorithms able to minimize illuminance targets for unoccupied workstations [55]. For thermal comfort, most authors use the control metrics indoor air temperature, the predicted percentage of dissatisfied (PPD), or the predicted mean vote (PMV); for visual comfort, illuminance, or false-off frequency are typically used.

6. Model implementation

This section aims to provide a guideline on the best practices for implementing OB models in a software environment. This part assumes that the creator has completed the model development phase for the OB models so that these models are in the form of a stand-alone application. In this context, we refer to a stand-alone application as "a set of a USER's information processing requirements" [56]. In that context, this section provides recommendations regarding the model's computational environment, runtime analysis and scalability analysis for the real-time capabilities, and the experimental hardware settings.

Primarily, we focus on the OB models' implementation as the outcome of the academic or general research activities. The aim of this section is to propose the documentation that enables model's reproducibility in building control systems that may have different software architectures [57].

6.1. Computational environment

The documentation on the computational environment in the sense of OB models in building control should include requirements for specific operating systems (OS), programming languages, and library or other software dependencies. Beyond this information, the used versions should also be reported. The details required are relevant both for the model's reproducibility in form of the application and due to the copyright requirements of each dependency in case of the (potentially commercial) field deployment. Furthermore, the operating system and programming language should be documented in the context of the runtime evaluation that is a crucial component of the OB model documentation and that is a programming language and OS-specific.

When selecting a suitable computational environment for model development, the evidence regarding the widely adopted environments could be beneficial, and this information is summarized in Table 3. Among others, R and Matlab/Simulink are the most commonly utilized programming language and software packages that can be employed for almost every type of OB. Oppositely, in terms of programming languages C/C++ and VBA and for software packages IBM SPSS and Weka are less used for developing already existing OB models. In practice, one can observe a large variability for different platforms and the computational efficiency of OB algorithms [57]. Nevertheless, information related to the utilized operating system is sparsely documented in existing studies.

6.2. Computation time

Commonly, the OB models are developed with the aim to be included in the end-systems such as building control that typically operates in real-time. Since the computation resources within building control and related end-systems are limited, an estimate of the required resources is required to assure the real-time operation. In this place, we refer to the computation resources of the OB models, which are defined as standalone modules that can be coupled with an end-system in various distributed manners. We focus on the runtime of the developed final models where the executed steps include the data-preprocessing and computing the value of the OB target variable. In the case of the machine learning-based models, this would correspond to a model test, while the model training and validation are considered to be previously completed. The hosting of these models is taking place within the building control, using a cloud-edge solution or on a remote cloud. In case of any of the listed computation settings, the following information should be provided:

- In which computation environment is the runtime analysis conducted?
- What is OB model inference runtime?
- Inference memory requirements?
- Optional: total required training runtime
- How does the OB model scale in space and time with the number of modeled OB instances?

The runtimes should be expressed either in core hours or the clock time, given the standard setting. The runtime should be documented together with the used hardware model. Since the majority of the OB models were created in the scope of academic research efforts, there is limited literature evidence on the runtime documentation. Among the others, the reader is referred to Refs. [57–59], and [60] for some best practices.

Additionally, the model's scalability is of particular importance and should be documented. Namely, OB models can be applied to a large number of occupants within a building and therefore the model's scalability in space and time (footnote: for further information regarding the space and time complexity, the reader is referred to Ref. [61] should be documented and expressed using "big O" notation with respect either to the number of occupants, rooms or buildings (further information about the "big O″ notation is summarized by Ref. [62]. Additionally, in case an O model is intended to be used for varied temporal resolution and predictive horizon, the time complexity should also be documented with respect to these two parameters.

6.3. Experiment setup

With the computational environment guidelines discussed above, this section focuses on presenting the experiment setup by summarizing the findings from the literature review. Sensor choices and implementation location will be discussed in the following subsections. The discussions are based on six main categories of occupant behavior models, as followed throughout this paper. The sensor choices subsection offers information of sensors that have been deployed among different studies, implementation locations subsection presents different locations of deployed sensors in different research experiments. This section aims to provide guidelines for future occupant behavior researchers to deploy sensors and set up experiments.

6.3.1. Sensor choices

From the reviewed literature, in total 85% of the studies have explicitly provided information about sensors that have been deployed. Table 4 summarizes the commonly used types of sensors and the aggregated frequency that they have been picked in the literature. The color scales in the table represent how often the specific sensors were adopted. It can be observed that, for "Appliance Use" studies, current/power sensors and smart meters are very commonly used; for "Light Operation" studies, lighting sensors and PIR sensors are primarily adopted; for "Occupancy Estimation and Prediction" studies, PIR sensor and CO2 sensor are commonly used; for "Shading Operation" studies, lighting sensors and indoor temperature sensors are commonly used; for "Thermostat Adjustment", indoor temperature sensors, sound sensors, and airspeed sensors are primarily used; for "Window Operation" studies, indoor temperature sensors and window state sensors are commonly used. Apart from the aforementioned most commonly used sensors, other sensors are also summarized in the table.

Table 3
The most common computational environments for each OB model.

Domain	Programming languages					Software packages/tools					
	R	Python	C/C++	Java	VBA	IBM SPSS	Modelica/Dymola	Matlab/Simulink	Weka	LabVIEW	RapidMiner
Window Operation	X	X				X	X	X			X
Thermostat Adjustment	X		X					X			
Occupancy Estimation and Prediction	X	X		X			X	X		X	
Shading Operation	X							X			
Lighting Operation	X			X	X			X			
Appliance Use								X	X	X	X

Table 4
Sensor Choices of the Reviewed Studies.

Sensor Type	Appliance Use	Lighting Operation	Occupancy Estimation and Prediction	Shading Operation	Thermostat Adjustment	Window Operation
AC State	2	0	1	0	1	0
Air Pressure	0	0	1	0	5	2
Air Speed	0	1	2	0	10	8
Airflow Rate	0	1	3	0	5	0
Bluetooth Beacon	1	0	1	0	0	0
Camera	4	3	11	0	2	2
Chair	0	0	1	0	0	0
CO	0	0	1	0	1	1
CO2	1	0	18	0	7	16
Current/Power	10	2	5	1	5	0
Door State	1	0	4	0	0	1
GPS Location	0	0	1	0	0	0
Keyboard&Mouse	0	0	1	0	0	0
LED	0	1	1	0	0	0
Light	2	36	8	11	1	5
Light Switch	0	5	1	0	0	0
Motion (Unspecified)	2	6	4	1	1	0
PIR	3	11	19	2	1	6
RF	0	1	1	0	0	0
RH	1	1	12	1	9	18
Smart Meter	9	2	5	0	1	0
Smart Plug	4	0	0	0	0	0
Solar Irradiance	0	3	2	5	10	7
Sound (Acoustic)	0	0	6	0	0	0
Sound (Echo-Based)	1	0	2	0	0	0
Sound recording device	1	0	0	0	0	0
Telephone(State)	0	0	1	0	0	0
Temperature (Indoor)	0	3	13	6	16	33
VOC	0	0	2	0	0	1
WiFi Connection/Probe	1	3	5	0	0	0
Window State	0	2	0	0	2	32

6.3.2. Implementation location

Table 5 summarized the common locations of sensors deployed from the literature. The locations are categorized into two levels: Space Level and Building Level. Under each level of locations, detailed locations and related sensor types are provided. Based on the review work, this table provides a guideline for future researchers to refer to when deploying sensors in an experimental set up.

6.4. Integration into MPC

OB models can be used in MPC for setpoint/reference scheduling or for including measurable and predictable disturbances and for shaping the constraints. An illustrative example for the consideration of OB in MPC is presented in Fig. 16. In terms of disturbances, the OB should be considered as a cause of thermal gains from people, thermal losses from appliances or ventilation gain, and losses during window operations. This includes information about the number of occupants, time of use, and possibly information about used equipment. As measuring a direct heat dissipation is difficult, the forecasted behavior has to be used to infer the information about internal heat gains. Additionally, the OB could be considered by the constraints, such as by setting different upper and lower indoor air temperature bounds during occupancy hours. In case a specific setpoint instead of bounds is desired, the setpoint can also be explicitly defined in the cost function.

As reviewed in subsection 4.2.3, the indirect metrics evaluate the control outputs comfort and energy consumption. For the integration of OB models into MPC, we focus on the most relevant and most common use case in literature, HVAC control. The relevance results from the significant energy savings potential. Additionally, most OB models could be meaningfully coupled with HVAC control (such as Appliance Use, Lighting Operation, Occupancy Estimation and Prediction, Shading Operation, Thermostat Adjustment, Window Operation models). Most relevantly, the thermostat adjustment and attendance profiles shape the occupants' demand for thermal satisfaction by HVAC. Knowledge about absences and reduced thermal demands can significantly reduce the energy demand. The other OB models, shading and windows operation, have an impact on the thermal energy balance.

There are several requirements that need to be documented with OB

Table 5
The locations of sensors deployed from the reviewed studies.

Level of Locations	Locations	Sensor Type
Space Level	Ceiling	● CO2 Sensor
		● CO Sensor
		● Light Sensor
	Chair	● Chair Sensor
	Desk	● Keyboard & Mouse
		● Telephone (State)
	Door Frame	● Door State Sensor
	Wall	● Air Pressure Sensor
		● Air Speed Sensor
		● Bluetooth Beacon
		● GPS Location
		● LED Sensor
		● Light Switch
		● Motion (Unspecified)
		● Smart Plug
		● Sound Sensor (Acoustic)
		● Sound Sensor (Echo-Based)
		● Sound Recording Device
		● PIR Sensor
		● RF Sensor
		● RH Sensor
		● Temperature Sensor (Indoor)
		● VOC Sensor
		● WiFi Connection/Probe
	Window Frame	● Window State Sensor
Building Level	Electrical Panel	● Current/Power Sensor
		● Smart Meter
	HVAC Equipment	● AC State Sensor
		● Airflow Rate Sensor
	Main Entrance	● Camera
	Rooftop	● Solar Irradiance Sensor

model to ensure the use in advanced optimal control methods such as MPC. Firstly, the models must provide a forecast of the occupancy behavior over the length of the prediction horizon of the optimization problem, which is typically between 1 and 24 h. The quality of the presence and OB forecasts also depends on the type of measurement sensors used to gather the occupancy data [63]. Most accurate predictions are obtained from occupancy dedicated-sensor data such as PIR and cameras. However, as pointed out in Ref. [64], other sensors such as CO_2 [65] or plug power can also provide sufficiently accurate data for control-oriented occupancy models.

7. Discussion and future challenges

Based on the previous review, to define a standard guideline to document occupant behavior for building controls poses the following challenges:

7.1. Model description and formal representation

The current model description varies among different schemas and formalization methods in terms of naming schema, description structures, and presentation of OB models. In addition, neither the OB model nor the building control model lacks a standard representation for model inputs, outputs, and model description. Hence, it creates a gap between OB and building control models. This results in a customized working process for every OB-driven building control study in the literature. In addition, such a process is not consistent and creates a very different performance (e.g. energy savings) even using the same type of OB model. As a matter of fact, the various inputs for the same OB model reflect this inconsistency. Prior researchers were using different sensors and instruments to develop different mathematical models to model and simulate the same behavior over decades. There is a need to standardize the model description and representation based on one formal language. Recently, a review paper [8] on data tools for building information and performance also concludes that ontologies or schemas represent the need to be developed. An effort to extend the current Brick schema to represent the OB model is ongoing.

7.2. Model development

Currently, the model development is not fully described in the scientific articles. Information is missing on preprocessing procedures and model selection limiting the reproducibility and even replicability of the results of the studies. To overcome these challenges in model development documentation, the authors should clearly state the model purpose, and the practical and theoretical arguments supporting the choice of a given modeling technique. Also, to foster transparency and clarity, they should explicitly document the adopted cleaning and imputing procedures for the missing and corrupt data, the outliers treatment chosen, the data dimensional reduction process implemented, the data scaling method used, the techniques used for feature creation, the approach adopted for partitioning the original dataset for the definition of the test and training subsets, and the anonymization techniques used, if any. Furthermore, an important challenge is to develop newer multi-domain models, which can consider the multi-exposure of occupants to indoor environmental conditions and a multitude of controlling opportunities for a better and tailored adjustment of the building devices.

7.3. Model evaluation

The standardized and comprehensive model evaluation is crucial for OB model deployment in real-world scenarios of building control products. Therefore, a standardized evaluation schema is proposed for each distinct form of OB. With the ambition to provide a comprehensive evaluation, this work proposes joint use of three sets of evaluation metrics, namely absolute metrics, domain metrics, and indirect metrics. The absolute metrics were derived based on the vast literature evidence on the evaluation of general data-driven methods and their existing applications for OB modeling. Furthermore, we argue that the OB model evaluation has to include specific domain metrics. These are based on domain expertise in OB modeling and are supported by the existing literature evidence.

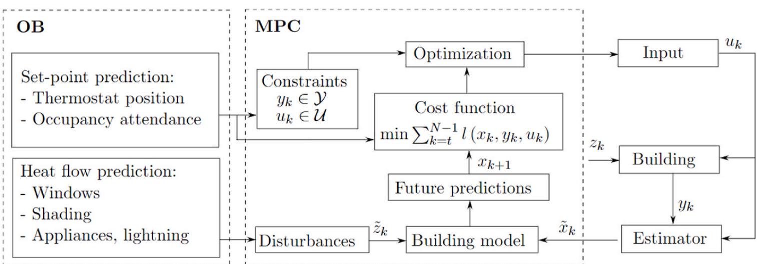

Fig. 16. An overview of the MPC structure with the proposed inclusions of the OB.

As human behavior is highly diverse and sensitive to unpredictable events, sensitivity analysis could be used as a supportive tool to assess the uncertainties related to the used OB model. Sensitivity analysis (SA) is a statistical technique that assesses the effects that changes in input or design variables have on the model output variables [16,66]. There are two approaches to SA that could be applied when a model can be also used for building control purposes. The simpler is the local sensitivity analysis, where the impact of an input variable's variation on a model response is estimated while keeping the values of the other input factors constant. The global sensitivity analysis, on the opposite, tests simultaneously all the input variables and enables assessing the impact of both individual input variables and their interactions on the model output. However, the existing applications of the sensitivity analysis for OB in building control are sparse, further adoption would provide useful insights on testing control algorithm robustness against noise or uncertainty in input variables and parameters.

7.4. Benefits of the inclusion of OB models in building control

Finally, the indirect metrics quantify how well the model contributes to fulfilling the higher goal of building control, such as maintaining comfort or optimizing energy consumption. Up to date, the impact of the OB model on the end-system has been limitedly explored. Namely, most of the existing OB models were not tested in field studies, and therefore, the relationship between whole system performance and the OB model is rarely analyzed. In order to come one step closer to filling this gap, this work proposed a set of indirect metrics for evaluating the impact of OB models for inclusion in HVAC control. The future challenge includes assessing the suitability of proposed metrics in field studies. Furthermore, the indirect metrics for alternative systems, such as shadings should be explored.

7.5. Model implementation

The documented model implementation should include the information about the used computational environment in which the OB model is tested, the experimental setting, and the recommendations for the intended application in the building control. Here, a particular challenge is that the buildings are commonly a one-time product. As there is limited literature evidence on documenting the model implementation, future research should focus on how to standardize information related to implementation in different buildings or HVAC systems.

Furthermore, the future model documentation should include the estimated OB model inference time. As highlighted in Ref. [67], state-of-the-art OB models are too computationally expensive to be included in real-time control applications, such as MPC. In order to obtain stable and reliable results, the computation of the next control signal should be indeed completed before the start of the actual period of observation. Based on the previous literature review, the time related to a single forward pass of the proposed data-driven models, i.e. inference time, is however rarely documented.

7.6. Model integration into advanced building control

One of the challenges of leveraging occupancy estimation and prediction models is their integration into advanced building control algorithms, e.g. MPC. These controllers are typically based on HVAC and building envelope thermal dynamics models and consider future system dynamics and future control inputs or constraints. Special care needs to be given to properly couple the occupancy estimation and prediction models into these dynamic equations. The OB models can serve as additional control variables (setpoint, constraint, or disturbances) for the building dynamics equations. These dynamic equations are usually represented by a set of first-order differential equations. As a common practice in the control engineering field, these equations can be reformulated into a state space model and into discrete time [68,69].

8. Conclusion

In this paper, we evaluated current documentation of OB models for advanced building controls from four different perspectives: model description and formal representation, model development and evaluation, inclusion of OB model into building controls, and modeling implementation. During the literature review, we found that the building control and OB modeling were mostly researched distinctly. Most of the OB models were developed as stand-alone models. In that context, there is only a spoonful of publications that proposed a formal integration of the OB models into building control (e.g. Refs. [70,71]). Based on a comprehensive review and analysis on current documentation of OB model for advanced building controls, it can be concluded that: 1) There is no standard representation of various OB models; 2) no unified guidelines of OB model development; 3) a standardized evaluation schema is proposed for each distinct form of OB models; 4) a set of indirect metrics for evaluating the impact of OB models for the inclusion in HVAC control is defined; and 5) a systematic documentation of indented model implementation is proposed; and 6) OB models can be integrated into MPC for HVAC as predicted setpoints, constraints, or disturbances.

Given the current review and discussions, this paper also provides following future research opportunities: a) A formal representation of OB models based on the same schema and semantics. While there is an on-going effort in the Brick schema [25], such presentation can be further enriched with more common data sets [72]; b) open sourcing a library with OB model documentation that follows this guideline, c) deployment of existing OB models in building control studies.

Limitation of the study: 1) In this paper, the "occupant" is referred to as office workers in general. The review does not cover other occupant types such as elderly, who has different interactions in response to thermal stimuli; 2) The review study found very limited or no papers considering how to integrate sensor drifting into controls. Although it is an important issue for the control implementation, the paper focuses mainly on documenting occupant behavior. Future studies could further explore this topic; and 3) The guideline paper does not cover occupant behavior of personalized cooling and heating systems. This could be included in the future studies.

CRediT authorship contribution statement

Bing Dong: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Romana Markovic:** Conceptualization, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Salvatore Carlucci:** Writing – review & editing, Writing – original draft, Resources, Methodology, Investigation, Conceptualization. **Yapan Liu:** Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing, Conceptualization. **Andreas Wagner:** Writing – original draft, Resources, Methodology, Investigation, Conceptualization. **Antonio Liguori:** Conceptualization, Investigation, Methodology, Writing – original draft. **Christoph van Treeck:** Writing – original draft, Resources, Investigation, Conceptualization. **Dmitry Oleynikov:** Conceptualization, Investigation, Methodology, Writing – original draft. **Elie Azar:** Writing – original draft, Visualization, Methodology, Investigation, Conceptualization. **Gianmarco Fajilla:** Conceptualization, Investigation, Methodology, Writing – original draft. **Ján Drgoňa:** Writing – original draft, Visualization, Methodology, Investigation, Conceptualization. **Joyce Kim:** Conceptualization, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Marika Vellei:** Writing – original draft, Visualization, Methodology, Investigation, Conceptualization. **Marilena De Simone:** Visualization, Writing – original draft, Writing – review & editing, Conceptualization, Investigation, Methodology. **Masood Shamsaiee:** Writing – original draft, Methodology,

Investigation, Conceptualization. **Mateus Bavaresco:** Conceptualization, Investigation, Methodology, Writing – original draft. **Matteo Favero:** Writing – original draft, Methodology, Investigation, Conceptualization. **Mikkel Kjaergaard:** Conceptualization, Investigation, Methodology, Writing – original draft. **Mohamed Osman:** Writing – original draft, Methodology, Investigation, Conceptualization. **Moritz Frahm:** Conceptualization, Investigation, Methodology, Visualization, Writing – original draft. **Sanam Dabirian:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Conceptualization. **Da Yan:** Conceptualization, Investigation, Methodology, Writing – original draft. **Xuyuan Kang:** Writing – original draft, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Appendix I. Summary of the indirect metrics for each OB modeling objective

Model	Comfort-related metrics	Energy-related metrics
Occupancy Estimation and Prediction	Thermal comfort and indoor air quality: hours of setpoints not met	energy consumption/saving, start/stop time, in most cases related to HVAC
Thermostat Adjustment	Thermal comfort: indoor temperature, PMV, PPD	energy consumption/saving, monetary savings, related to HVAC, duration of unnecessary heating [h], peak load change (energy shifting for DR), energy use during peak, setpoint reduction, HVAC coefficient of performance
Window Operation	–	energy consumption/saving, related to HVAC
Shading Operation	Thermal comfort: air temperature, PPD, overheated hours; Visual comfort: illuminance	energy consumption/saving, related to HVAC and lighting, optimal dimming
Lighting Operation	Visual comfort: illuminance, false off frequency, discomfort probability	energy consumption/saving, optimal dimming (% of lighting power used needed on daylight availability), peak power, illuminance reduction in unoccupied workstations
Appliance Use	–	energy consumption/saving, related to HVAC and the appliances

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