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A multi-country panel study of behaviour, perceptions and expectations during different stages of the COVID-19 pandemic

Gloria Amaris [a,e], Julián Arellana [b], Matthew Beck [c], Roger Behrens [d], Chiara Calastri [e], Stephane Hess [e,a], Fangqing Song [e], Hazvinei Tsitsi Tamuka Moyo [d], Mark Zuidgeest [d,*]

[a] Department of Psychology, Norwegian University of Science and Technology, NO-7491 Trondheim, Norway
[b] College of Engineering, Universidad del Norte, Barranquilla, Colombia
[c] Institute of Transport and Logistics Studies (ITLS), The University of Sydney Business School, University of Sydney, Sydney, NSW, Australia
[d] Centre for Transport Studies, University of Cape Town, Rondebosch, South Africa
[e] Choice Modelling Centre & Institute for Transport Studies (ITS), University of Leeds, Leeds, United Kingdom

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ABSTRACT

It is widely accepted that the COVID-19 pandemic has dramatically changed travel patterns since 2020, largely due to restrictions on people's movement and work-fromhome practices. A large number of studies have been conducted to understand such changes from a trip maker's perspective, using different types of mobility data collected across the world. This study uses survey panel data on travel behaviour and activity participation collected between May 2020 and November 2020 in the United Kingdom, Australia, Colombia and South Africa using a consistent survey approach. We identify a role for three key underlying latent constructs, namely 1) concerns about COVID-19, 2) approval of government interventions and 3) scepticism towards COVID-19 measures. Using a hybrid choice model, we study the role of these constructs in explaining stated travel choices in two hypothetical post-pandemic scenarios. The model results show significantly different perceptions towards COVID-19 concerns and government handling of the COVID-19 pandemic (including restrictions) across countries. The model estimates show a clear influence for the latent constructs in explaining stated behaviour in the hypothetical post-pandemic scenarios across the four countries, where this is also impacted by lockdown stringency levels as well as socio-demographics.

1. Introduction

It is widely accepted that the COVID-19 pandemic has dramatically disrupted travel patterns worldwide. Initially, this was largely due to restrictions on people's movement, including school, work and business closures, and consequent work-from-home (WFH) and distance learning (DL) practices. As societies worldwide strive to establish a 'new normal', many have argued that travel will not entirely revert to pre-pandemic patterns (van Wee and Witlox 2021) and that the "recovery period" presents potential opportunities to establish a more sustainable way of travelling, in line with many countries' decarbonization objectives (Rothengatter et al. 2021). A wealth of studies has been conducted to understand how travel has changed since March 2020 from the traveller's perspective, collecting different types of mobility data in separate parts of the world. Some studies adopted a longitudinal perspective in a given country, allowing the observation of changes over the different phases of the pandemic (e.g., Molloy et al., 2021 for Switzerland, Beck and Hensher, 2021a for Australia, or de Haas et al., 2020 for The Netherlands) while others have compared different countries at one point in time (e.g. Barbieri et al., 2021).

Longitudinal studies, with repeated observations of the same individual over time, make it possible to observe changes in behaviour and patterns across individuals and/or groups. They allow analysts to more surely establish causal relationships between variables by studying how behaviour changes following changes in independent variables, such as lockdown stringency levels. This has the potential to produce more robust behavioural models that can be applied to, for example, future mobility scenarios. In this study, we use survey panel data on changes in

* Corresponding author.
E-mail addresses: gloria.amaris12@gmail.com (G. Amaris), jarellana@uninorte.edu.co (J. Arellana), matthew.beck@sydney.edu.au (M. Beck), roger.behrens@uct.ac.za (R. Behrens), c.calastri@leeds.ac.uk (C. Calastri), s.hess@leeds.ac.uk (S. Hess), f.song1@leeds.ac.uk (F. Song), tmkhaz001@myuct.ac.za (H. Tsitsi Tamuka Moyo), mark.zuidgeest@uct.ac.za (M. Zuidgeest).

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activity participation, including WFH, DL and travel, across time and within and across countries. The research team collected extensive data about travel behaviour in four countries on four continents (the United Kingdom, Australia, Colombia and South Africa), using identical surveys with only minor adaptations to conform to the different cultural settings. In this paper, we look at the impact of perceptions towards COVID-19 on anticipated choices for three different travel modes in hypothetical future (post-pandemic) scenarios. The data collection period covers the first six months of the pandemic (May 2020 to November 2020), when the experience with COVID-19 and associated measures to combat the pandemic varied widely around the globe. This is instructive for three reasons. First, studies that examine mobility patterns over time over geographies as widespread as this study are rare. Second, it gives an understanding of how different policy measures around the globe interact with attitudes, preferences and behaviours. Third, it facilitates insights into how the 'new normal' behaviours may arise as a result of the different trajectories of the pandemic within each country. Based on information collected over multiple waves, we apply a hybrid choice model to analyse how perceptions (towards fear of the virus, appropriateness of measures imposed by governments and acceptability of face masks/tracking) change over time and to establish a causal link between perceptions and anticipated travel behaviour in the four countries.

The paper starts with an overview of COVID-19 contagion patterns, impacts and responses across the four countries, before presenting the set-up of the longitudinal survey and data in Section 3. In Section 4 we present the latent attitudinal constructs, which are inputs to the hybrid choice model, which is discussed in Section 5. In Section 6 the results of the modelling are presented and discussed. Conclusions are presented in Section 7.

2. Context and literature

2.1. COVID-19 contagion patterns, impacts and responses

Global and local trends in COVID-19 cases, deaths and lockdown measures have heavily affected travel behaviour patterns and opinions about travel and activity participation (Van Wee and Witlox, 2021). In this section, we draw from available secondary big datasets (Google and Apple) to compare the relative contagion trajectories, lockdown responses, and associated impacts on travel behaviour patterns in the United Kingdom, Australia, Colombia, and South Africa.

Fig. 1(a, b) plots the normalised daily recorded infections and fatalities in the four countries between 22 January 2020 and 10 March 2022, which includes our data collection period. These contagion data illustrate the wave pattern of infections and fatalities, as well as the relatively higher transmissibility (particularly in Australia and the United Kingdom) and the lower mortality of the *Omicron* wave, which started in November 2021. Insights into possible underreporting of COVID-19-related deaths can be gained from 'excess death' data, as shown in Fig. 1(c). This is calculated as the difference in the number of deaths and the predicted deaths based on historical mortality patterns, divided by the predicted number of deaths. A positive percentage thus shows a higher-than-expected number of deaths. The similarity of each country's normalised COVID-19-related death and excess death wave patterns, illustrated in Fig. 1(b, c), suggests that significantly more COVID-19-related deaths may have occurred than were reported, with the exception of Australia. During the period of data collection (the dashed rectangles in the figure), none of the four countries had initiated their vaccination programmes.

After the World Health Organization (WHO) declared COVID-19 a pandemic in March 2020, lockdown restrictions were implemented by governments across the globe, including in the four countries we studied. Lockdown restrictions typically implied a combination of 1) closures of key activity locations (particularly education and work locations); 2) reductions of public transport service and vehicle capacities; 3) stay-at-home requirements; 4) movement restrictions (domestic and international); and 5) limits on the size of public gatherings. Fig. 1 (d) plots a fluctuating 'lockdown stringency index', which is the mean score of nine metrics[1] rescaled to a value between 0 and 100 (100 being strictest) as published by The Oxford Coronavirus Government Response Tracker project (Hale et al., 2022).

The figure illustrates that while the four countries introduced restrictions in the first three weeks of March 2020, the adjustment of lockdown levels over time varied significantly across them. Although the initial intent of governments was to adjust stringency levels to match risk, the trajectories of the 'stringency index' values relative to fatalities suggest that, in some countries such as the United Kingdom, restrictions were adjusted to match both risk and public acceptability.

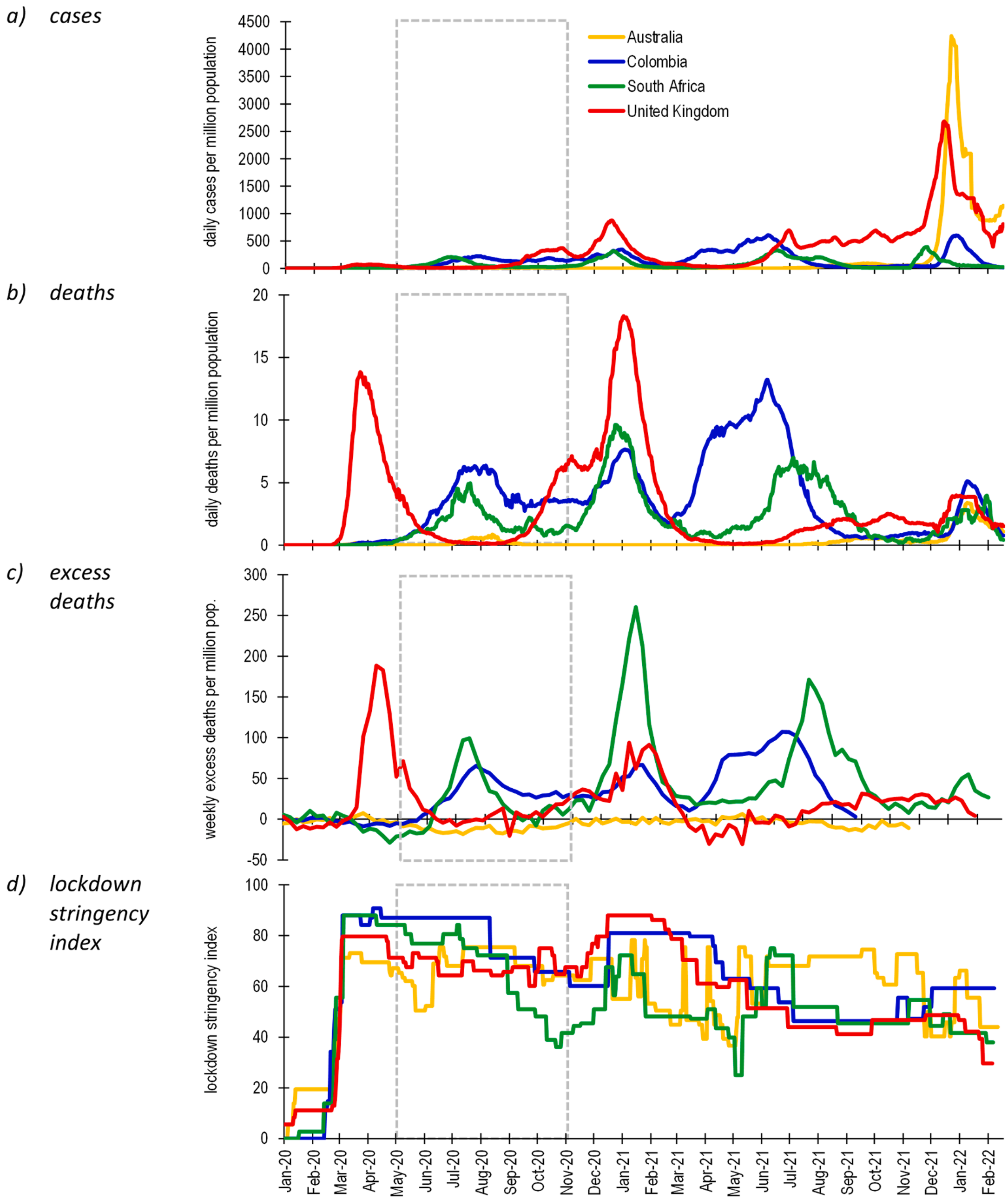
Google has assembled comparative big data on the impacts of lockdown restrictions on trip-making from the location tracking functionality of smartphones (and other mobile devices), with trip purposes imputed from land-use geographical information overlays. Apple Inc. has similarly assembled big data from mode-specific wayfinding requests. A shortcoming of both these datasets is that they contain no information on the individuals from which the data is collected. By definition, however, they are limited to a subset of the population that uses smartphones (or similar devices), and as a result, in countries with lower mean household incomes (Colombia and South Africa), data are particularly skewed towards wealthier socio-economic groups. Longer term trend analysis could also be skewed by population technology adoption curves (i.e., in contexts with low baseline smartphone penetration, observed increases in trips to activity places might reflect an increase in technology adoption rather than an increase in baseline trip-making). In the case of the Google data, Google cautions that there may be regional differences that render comparisons misleading.

In the absence of better comparative country data, the countries involved in this study are nonetheless compared. This comparison serves simply to provide crude insight into the contexts within which the different country surveys were conducted. So, notwithstanding the above limitations, percentage changes in trip-making for different purposes before and after lockdown restrictions were imposed are illustrated in Fig. 2(a–c). The before-lockdown baseline (i.e., the zero value on the vertical axis) was set to the median value for each day of the week, calculated from daily measurements over a five-week period between 3 January 2020 and 6 February 2020.

Fig. 2(a) suggests that, in the short term, the reduction in trips to workplaces varied in scale across countries. Colombia, South Africa, and the United Kingdom saw a reduction of around 75%, whereas in Australia the maximum reduction was lower at around 50%, as travel for essential work was permitted should WFH not be possible. Colombia returned to pre-lockdown levels within 16 months, whereas Australia and the United Kingdom remained below the baseline even after 24 months.

Changes in frequency for two categories of shopping trips are shown in Fig. 2(b, c). The figure reveals that shopping trips for essential items returned to baseline frequencies much sooner than trips for non-essential items. Fig. 2(b) plots trips to obtain food and medication. Short-term reductions in essential shopping trips ranged between 20% (Australia) and 60% (Colombia), with a return to or surpassing baseline levels occurring within two to nine months. After 24 months, Colombia and South Africa exceeded the baseline trip frequencies by around 45%. Fig. 2(c) plots trips to purchase non-essential items and to participate in other discretionary recreational activities. The figure furthermore reveals short-term reductions in non-essential shopping (and recreation) trips ranging between 45% (Australia) and 80% (Colombia), with a return to baseline levels occurring later than essential shopping trips.

[1] The nine metrics related to school closures; workplace closures; cancellation of public events; restrictions on public gatherings; closures of public transport; stay-at-home requirements; public information campaigns; restrictions on internal movements; and international travel controls.



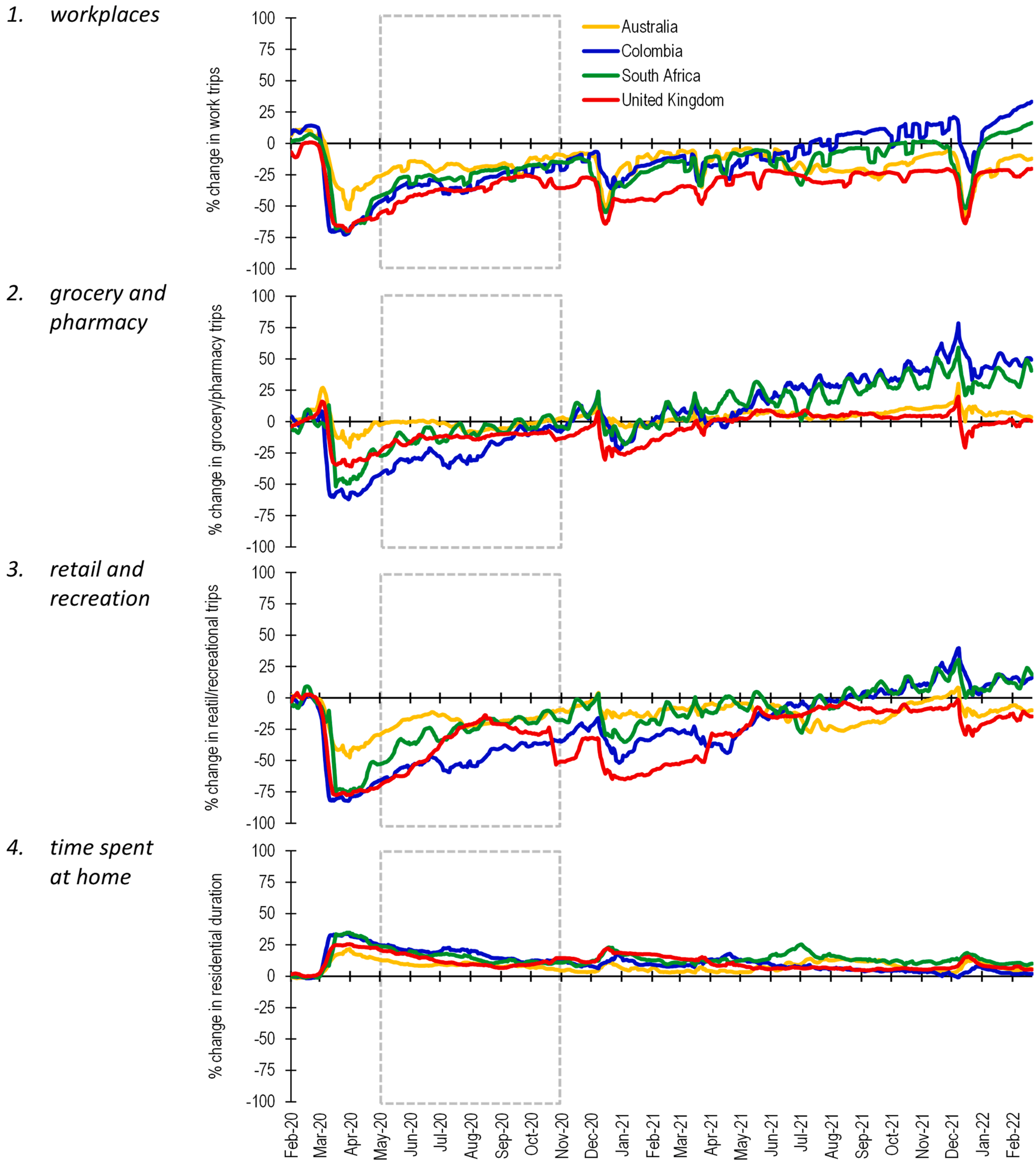
Data sources: Our World in Data (https://ourworldindata.org/coronavirus); Centre for Systems Science and Engineering (https://www.arcgis.com/apps/dashboards/bda7594740fd40299423467b48e9ecf6); The Economist (https://github.com/TheEconomist/covid-19-excess-deaths-tracker)

Fig. 1. Normalised COVID-19 contagion and lockdown stringency, by country (grey dashed box shows data collection period).

Fig. 2(d) presents the corollary of parts (a–c). It illustrates that as trips to out-of-home activities were foregone (and to some extent substituted for remote work, education, social, entertainment, etc. activities), the amount of time people spent at home increased. All countries continued to show higher-than-baseline time spent at home even 24 months from when lockdown restrictions were first introduced.

Insight into changes in trip-making by different travel modes is illustrated in Fig. 3(a–c). Fig. 3(a, b) draws from the Apple wayfinding request data, which serve as a proxy for changes in trip-making by car and foot. Fig. 3(a) suggests that public transport service restrictions led to a relative increase in trip-making by car. At the end of our study period, driving and walking were back to or surpassed base levels in all four countries, yet public transport levels stayed lower. After 21 months, all four countries had recorded car trip wayfinding requests greater than pre-pandemic levels. Fig. 3(b) similarly suggests that public transport disruptions led to an increase in pedestrian trips. In particular, Colombia and the United Kingdom recorded significant increases in walking trip wayfinding requests compared to pre-pandemic levels. The result for Colombia is in line with Guzman et al. (2021), who reported substantial increases in walking and cycling trips in the household proximity to reach shopping, sports, cultural, recreational, and health opportunities in Bogotá.

Fig. 3 draws from the Google location tracking data, which serve as a proxy for changes in trip-making by public transport. These smartphone-based data may be further skewed in countries where the origins of public transport trips are often not formal public transport interchanges, ranks, stations, or stops (i.e., Colombia and South Africa). In these contexts, the loss of passengers experienced by formal and informal

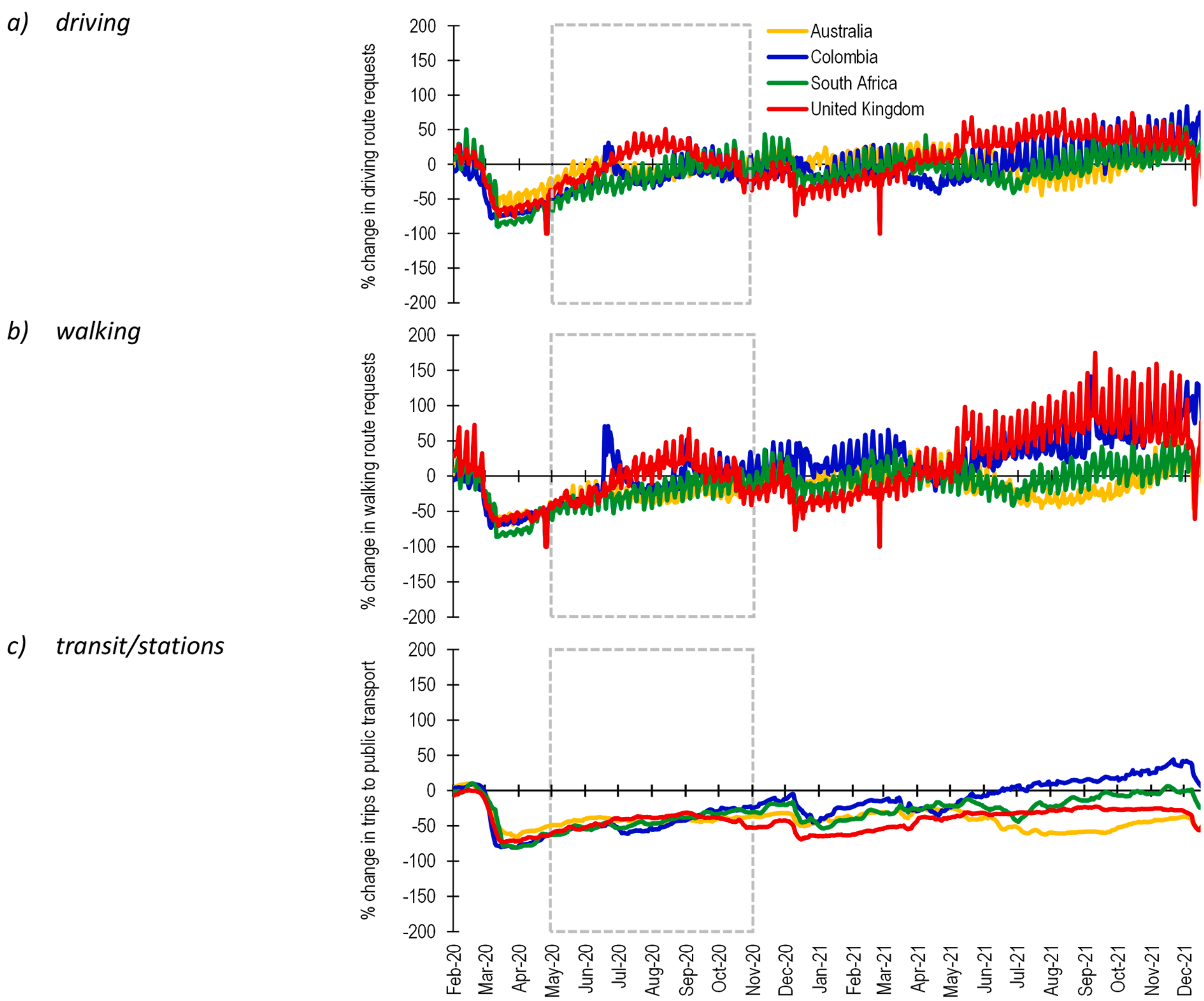


Data source: [Google COVID-19 Community Mobility Reports (https://www.google.com/covid19/mobility/)](https://www.google.com/covid19/mobility/)

Notes:

1. 'Grocery and pharmacy' trips are to destinations like grocery markets, farmers markets, specialty food shops, drug stores, and pharmacies.
2. 'Retail and recreation' trips are to destinations like restaurants, café, shopping centres, theme parks, museums, libraries, and movie theatres.
3. The dashed line indicates the period of data collection across the four countries.

Fig. 2. Change in trips to workplaces and shopping activities, and time spent at home, by country.



Data source: Google COVID-19 Community Mobility Reports (https://www.google.com/covid19/mobility/); Apple Mobility Trends Reports (https://covid19.apple.com/mobility)

Notes:
1. 'Transit stations' trips are to destinations like public transport service hubs such as the subway, bus, and train stations.
2. The dashed line indicates the period of data collection across the four countries.

Fig. 3. Change in trips by travel mode, by country.

operators may be dissimilar. The figure suggests, nonetheless, that there have been significant losses in public transport ridership. After 24 months, Colombia and South Africa had recovered to pre-pandemic levels, but Australia and the United Kingdom remained below. This pattern is consistent with the findings of Brondum et al. (2021), who showed, using the same dataset, that low-income and lower-middle-income band countries returned to baseline public transport trip-making earlier than higher-income band countries (in December 2020).

The above secondary data analysis reveals both similarities and differences in the contagion trajectories, lockdown responses, and trip-making impacts of the four study countries. This raises the question as to whether these similarities and differences have impacted the perceptions and choices of trip-makers in the four countries in different ways. The next section describes the existing literature in this field before discussing the research method employed in this study.

2.2. Literature on changes in travel behaviour due to COVID-19

There has been widespread speculation that mandatory remote activity participation and trip substitution during lockdown restrictions may have altered attitudes and intentions and may lead to enduring changes in travel behaviour patterns (e.g., Van Wee and Witlox 2021). Since late 2020, much has been written about the impacts of lockdown regulations on travel behaviour. A bibliometric analysis by Kutela et al. (2021) found 488 papers dealing with the impact of COVID-19 on transport systems, while Benita (2021) found 194 papers focused specifically on impacts on passenger travel behaviour. A non-exhaustive search of this literature revealed a dozen studies focusing in whole or in part on attitudinal changes in travel behaviour.

Common objectives across these studies included measuring changes in attitudes to working from home (Balbontin et al. 2021; Jain et al. 2022); perceptions of risk in trip making (Agyeiwaah et al. 2021; Barbieri et al. 2020, 2021; Beck and Hensher 2021b; Luo and Lam 2020); and mode choice determinants (Aaditya and Rahul 2021; De Haas et al. 2020; Scorrano and Danielis 2021). Other studies have looked at mode change behaviour (de Vos, 2020), or broader topics, such as Dong et al. (2022) studying the impact of changed human behaviour during the pandemic on traffic crashes.

The geographical contexts researched by these studies span Australia (Beck and Hensher 2021; Jain et al. 2022), China (Agyeiwaah et al.

2021; Li et al. 2020; Luo and Lam 2020; Wu and Lau 2022), India (Aaditya and Rahul 2021), Italy (Scorrano and Danielis 2021), Spain (Sánchez-Cañizares et al. 2021), and The Netherlands (De Haas et al. 2020). Balbontin et al. (2021) and Barbieri et al. (2020, 2021) undertook multi-country comparisons, while Bian et al (2021) compared behaviour on the East and West Coast of the United States (New York and Seattle).

Several of the studies identified applied Ajzen's (1991) 'theory of planned behaviour' to explore changes in attitudes, norms and behavioural controls (Jain et al. 2022; Li et al. 2020; Sánchez-Cañizares et al. 2021). Other theoretical frameworks included Lazarus's (1991) 'cognitive appraisal theory' (Agyeiwaah et al., 2021) and Rogers's (1975) 'protection motivation theory' (Wu and Lau 2022). While some studies were able to utilise existing panel surveys (De Haas et al. 2020) or survey large probability samples (Jain et al. 2022), convenience non-probability sampling was common (Agyeiwaah et al. 2021; Li et al. 2020). Analysis of data beyond descriptive statistical analysis took the form of Structural Equations Modelling (SEM) (Agyeiwaah et al. 2021; Jain et al., 2022; Luo and Lam 2020; Sánchez-Cañizares et al. 2021) and choice modelling, involving hybrid choice modelling, in both Aaditya and Rahul (2021), who looked at the psychological impacts of the pandemic on mode choice behaviour to show that awareness regarding the COVID-19 pandemic noticeably affected travel behaviour in private transport, and Scorrano and Danielis (2021), who look at mode choice determinants and attitudes before and after the pandemic and find that, for the Italian city of Trieste, attitudes towards physical exercise and risk aversion towards COVID-19 affected the propensity to cycling positively.

3. Materials

3.1. Data

The online questionnaire was first developed and tested in the United Kingdom (UK), leveraging earlier surveys conducted in Australia. The survey was then translated (to Spanish for Colombia) and contextualised for the other three countries, Australia (AU), Colombia (CO) and South Africa (SA). Local researchers in each country carried out the translation and contextualization. Minor content adjustments reflecting differences in terminology around COVID-19, shopping and travelling were also made. Ethical approval was obtained in each study country.

The sign-up questionnaire coincided with the first survey wave in all four countries. Two (CO and AU) or three (UK and SA) follow-up waves followed. The sign-up questionnaire primarily gathered information about personal and household characteristics as well as the participants' activities and travel behaviour before the outbreak of the pandemic. The later survey waves mainly focused on participants' activities and travel behaviour during the pandemic (i.e., the week before they filled out the questionnaire) and their expectations about the post-pandemic future. The following waves had the same content and structure, revolving around four themes, which are described next.

3.1.1. Activities and travel

Respondents were asked questions about activities and travel behaviour undertaken during the week before filling out each survey. The questions covered in-store and online grocery shopping (frequency, mode use, availability of groceries, satisfaction); recreational activities and travel behaviour (location, in person, online, frequency and duration, park visits); family activities and travel behaviour (childcare, home education, DL); air travel (frequency, purpose, class of travel); as well as study/work activities and travel behaviour (employment status, WFH/DL, productivity, satisfaction).

3.1.2. Perceptions towards COVID-19

Respondents were given twelve perception questions related to themes such as wearing face masks in public; contact tracing; (timing of) government interventions; future of travel; risks associated with COVID-19; social interactions; data security; in-store shopping; social distancing; public transport; as well as changing lockdown levels. These questions used a 5-point Likert scale answers (from *strongly disagree* to *strongly agree*).

3.1.3. Expectations about a post-pandemic future

Respondents were asked about when they expect to travel long-distance again (public transport or air) in view of the risks of catching/ spreading the COVID-19 virus. Two stated preference scenarios were presented to capture respondents' anticipated use of public transport, taxi and shared ride services. In particular:

- The first scenario asked respondents to *"imagine a period in 6 weeks when: there is no limit on outdoor activities; use of public transport is discouraged; pubs, restaurants, theatres, workplace, schools reopen; but everyone MUST practice social distancing"*.
- The second scenario asked respondents to *"imagine a situation where everything goes back to normal"*.

In both scenarios, respondents are asked whether they would reduce the use of each of the three modes of transport (public transport, taxi and shared ride services), increase it, or keep it the same as now. These questions were presented in each wave of the survey, thus capturing expectations as the pandemic evolved.

3.1.4. General wellbeing

The final section of the survey included questions related to respondents' general wellbeing at the time of the survey in terms of feeling physically fit and emotionally strong. Next, they were asked about their purchase behaviour (in terms of WFH equipment and internet facilities), home location and availability of recreational spaces. Finally, questions were asked about their opinion, as well as appreciation, and response to national regulations to combat COVID-19.

3.2. Sampling and sample size

The survey was administered online on the platform *Qualtrics* using convenience sampling in the United Kingdom, Australia and South Africa. In Colombia, the survey was administered in *QuestionPro*. Respondents could use a computer, tablet computer, or mobile phone to complete the surveys. Table 1 below presents the sample sizes and survey dates for each country, whilst Table 2 presents the basic demographics of the sample. The online convenience sampling produced an overrepresentation of highly educated respondents in each country.[2] Consequently, our sample is not representative of the overall population. Nevertheless, the main objective of this study was to shed light on the behavioural process linking the evolution of perceptions and expectations with actual travel behaviour, without the ambition of being able to generalise our results. Moreover, much of the work and study from home

Table 1
Sample sizes and survey dates, by country.

	Sign-up	Wave 1	Wave 2	Wave 3
Australia (AU)	286 (June 20)	286 (June 20)	226 (Aug 20)	–
Colombia (CO)	479 (May 20)	271 (June 20)	157 (Nov 20)	–
South Africa (ZA)	232 (June 20)	162 (Sept 20)	120 (Oct 20)	84 (Nov 20)
United Kingdom (UK)	398 (May 2020)	328 (May 2020)	288 (June 2020)	228 (Aug 2020)

[2] Education levels were not collected in Australia due to sampling constraints.

Table 2
Demographics of the sample, percentage share of the sample by country.

Variable	Level	All four countries	CO	SA	UK	AU
Gender [-]	Female	51%	37%	45%	73%	36%
	Male	49%	63%	55%	27%	64%
Age [y]	Up to 29	19%	62%	15%	17%	0%
	Between 30 and 49	61%	32%	73%	64%	60%
	Over 50	20%	6%	13%	19%	40%
Education [-]	PhD	19%	8%	13%	27%	.
	Master	36%	36%	40%	33%	.
	Bachelor	36%	52%	33%	33%	.
	Other	9%	4%	14%	7%	.

literature has shown that it is those employed in white-collar occupations (who in turn are more likely to be highly educated) who have experienced most of the changes in travel activity and commuting, and for whom the change is likely to be structural given the nature of their work (Beck and Hensher 2022).

Retention rates across waves are relatively low in both Colombia and South Africa. Even though online presence is generally not a problem in these countries, the affordability of mobile data may have played a role in the high churn (dropout) rates observed.

4. Establishing latent attitudinal constructs

Fig. 4 summarizes the responses of people who *agreed* or *somewhat agreed* with the twelve perception questions, combining data across all waves. More respondents in the United Kingdom (95%) believed that the risk associated with COVID-19 will persist for a longer time. In addition, a larger proportion of South African (62%) and Australian (68%) respondents agreed with the statement that the government implemented appropriate measures to combat the COVID-19 pandemic. In the UK (8%), far fewer respondents felt that the government moved lockdown levels up or down at the right time, while South Africans agreed far more with this statement (70%), but far less (31%) with the statement that it was too early to ease restrictions. Colombians (86%) avoid social contacts with other people more than the respondents in other countries, while they (89%) also feel that more tracing is needed. Interestingly, we observe that attitudes in Australia are generally among the most favourable towards the actions taken to reduce the spread of COVID-19 (in particular agreeing that the measures applied by governments are appropriate), yet they show relatively lower (69%) levels of agreement that the risk of COVID-19 will persist for a long time.

A principal component analysis (PCA) was performed on observed responses to the 12 perception questions I_i^k (with $i = 1,\dots,12$), as captured in each of the waves k (cf. Section 3.1.2). The PCA was performed on the pooled data as well as specific to each country. However, both approaches produced similar findings. The sampling adequacy of the data for a PCA was confirmed through a Kaiser-Meyer-Olkin (KMO) test,[3] which had a value of 0.959. In addition, a Bartlett's Test of Sphericity confirmed with high confidence that there is substantial correlation in the data.

Using the pooled data, the PCA reduced the initial dimensionality of the twelve questions to three principal components, when we used a stopping rule of 90% of total variance to identify nontrivial components. Even though four factors explain just over 90%, we decided to stick to the three principal components, which together explain 88.15% of the total variance, as the fourth one was borderline with an eigenvalue of 1.094 (we can only retain factors with eigenvalues greater than 1 as per Kaiser's criterion). The factor loadings for the variables in each factor are depicted in Table 3 below – for ease of reading, subscripts for waves and countries are not shown here, but each person in each country contributed an observation for each question in every wave. The three principal components along with their associated indicators (as per Fig. 4) are depicted in Table 4, and these formed the groupings for the latent variables in Section 5.

5. Model specification

The key tool of analysis is a hybrid choice model (HCM), see e.g. Walker and Ben-Akiva (2002), sometimes also referred to as Integrated Choice and Latent Variable (ICLV) model. This model at the same explains the responses to the perception questions and the choices made in the hypothetical future scenarios. The link between these two components is made through latent variables that represent the underlying unobserved constructs.

We now describe the different components of the model in turn, starting with the structural model for the latent variables, before turning to the measurement model for the perception questions, and finally the choice model for the stated behaviour in the scenarios.

5.1. Structural equation for latent variables

Based on the PCA from Section 4, our model uses three LVs, $\alpha_{l,n,k}$, with $l = \{1, 2, 3\}$, where the subscript n relates to respondents and k relates to the wave. Each of the three latent variables includes a deterministic and a random part. The random part is person-specific, but constant across waves, thus creating correlation across waves for the same person. The deterministic part includes 1) a country-specific wave effect, 2) a generic lockdown stringency effect and 3) country-specific socio-demographic effects.

The structural equation for latent variable l for respondent n in wave k is given by:

$$\alpha_{l,n,k} = \sum_c (C_n == c)\left(\theta^c_{l,k} + \rho_l s_n^{c,k} + \sum_p \left(\gamma^{c}_{l,p}{}' z_{p,n}\right)\right) + \eta_{l,n} \tag{1}$$

This equation includes a summation over countries (UK = 1, CO = 2, AU = 3, SA = 4), but for each individual, the bracket ($C_n == c$) is only true for one specific country, where C_n is the country for respondent n. We first have $\theta^c_{l,k}$, which is an effect capturing the differences in latent variable l across countries c and waves k, where this is normalised to zero for the UK in wave 1 ($\theta^1_{l,1} = 0, \forall l$). Next, $s_n^{c,k}$ is the (continuous) lockdown stringency level in country c as experienced by person n, at the time of wave k as per Fig. 1d, thus allowing for the specific phase of the pandemic to have an impact on people's latent attitudes. Its estimated impact on the latent variable is given by ρ_l – a generic parameter across countries was used as the stringency level for Colombia did not change during the period of data collection, making country-specific parameters unidentifiable. Finally, $z_{p,n}$ is a vector of P respondent characteristics for respondent n, whilst $\gamma^c_{l,p}$ is a vector of estimated parameters capturing the impact of $z_{p,n}$ on the latent variable $\alpha_{l,n,k}$. These socio-demographics are categorical, where we use dummy coding, and include age (with *persons 29 years or younger* as base), education level (those with a *bachelor degree or less* as base) and gender (*males* serve as base). Finally, $\eta_{l,n}$ is a random disturbance which follows a standard Normal distribution across individuals, i.e. $\eta_{l,n} \sim$ N(0,1).

5.2. Measurement model for perception questions

The three latent variables $\alpha_{l,n,k}$ are used to explain the responses to the twelve perception questions which used a five-point Likert scale (*strongly disagree* to *strongly agree*). Given the ordinal nature of these questions, we used an Ordered Logit (OL) model to explain the values, where the likelihood of the observed value for question i for respondent n in wave k ($L_{I_{i,n,k}}$) is given by:

[3] KMO values between 0.8 and 1.0 indicate the sampling is adequate.

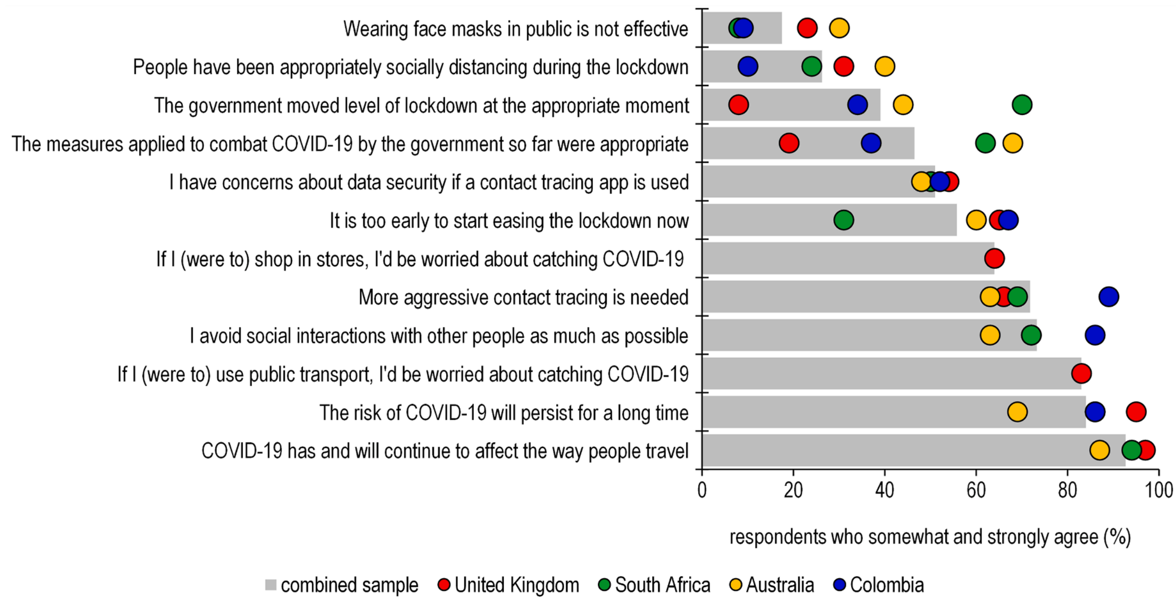


Fig. 4. Combined response ratings for the twelve questions capturing perceptions.

Table 3
Correlation coefficients for variables loaded on the three factors.

Perception question	Factor 1 (79.574 %)*	Factor 2 (5.087 %)	Factor 3 (3.489 %)
I_1	0.992		
I_2	0.872		
I_3	0.719		
I_4		0.873	
I_5		0.816	
I_6	0.748		
I_7			0.721
I_8			0.827
I_9			0.701
I_{10}	0.874		
I_{11}	1.003		
I_{12}	0.686		

* Percentage of variance for each component. Extraction Method: Principal Component Analysis, Rotation method: Oblimin with Kaiser Normalization.

$$L_{I_{i,n,k}}(\tau_i,\mu_i,\alpha_{i^*,n,k}) = \sum_{v=1}^{4}(I_{i,n,k}==v)\left[\frac{e^{\tau_{i,v}-\mu_{i,i^*}\alpha_{i^*,n,k}}}{1+e^{\tau_{i,v}-\mu_{i,i^*}\alpha_{i^*,n,k}}}-\frac{e^{\tau_{i,v-1}-\mu_{i,i^*}\alpha_{i^*,n,k}}}{1+e^{\tau_{i,v-1}-\mu_{i,i^*}\alpha_{i^*,n,k}}}\right] \tag{2}$$

The measurement model for each of the twelve perception questions uses only one latent variable, where the notation i^* is used to refer to the latent variable used for question i, where, as shown in Table 4, we have that $i^* = 1 if i \in (1,2,3,6,10,11,12)$; $i^* = 2 if i \in (4,5)$; $i^* = 3 if i \in (7,8,9)$. In Eq. (2), μ_{i,i^*} is a parameter that captures the impact on the response to the perception question i by the associated latent variable (represented by the index i^*). $\tau_{i,s}$ is a vector of 6 threshold parameters for perception question i and response scale s with the normalisation that $\tau_{i,0} = -\infty$ and $\tau_{i,5} = +\infty, \forall i$. The term $(I_{i,n,k} == v)$ takes a value of one if and only if respondent n chooses answer v for the perception question I_i for respondent n in wave k.

Respondents answer the twelve questions across K waves, where $K_n = 3$ for respondents in the UK and SA, i.e., $C_n \in (1,4)$, and $K_n = 2$ for respondents in the CO and AU, i.e., $C_n \in (2,3)$. The likelihood of the responses to all perception questions by respondent n (L_{I_n}) is then given by:

Table 4
Latent Variable modelling structure and associated statements.

LV	*Factor name*	I_i	*Perception question*
LV1	*"Concern about the COVID-19 pandemic"*	I_1	*If I (were to) shop in stores' I'd be worried about catching COVID-19.*
		I_2	*If I (were to) use public transport, I'd be worried about catching COVID-19.*
		I_3	*The risk of COVID-19 will persist in the UK for a long time.*
		I_6	*More aggressive contact tracing is needed.*
		I_{10}	*I avoid social interactions with other people as much as possible.*
		I_{11}	*It is too early to start easing the lockdown now.*
		I_{12}	*COVID-19 has and will continue to affect the way people travel.*
LV2	*"Support for government measures"*	I_4	*The government moved from the containment to the delay phase of its COVID-19 response at the appropriate moment.*
		I_5	*The measures applied to combat COVID-19 by the government so far were appropriate.*
LV3	*"Scepticism about measures taken"*	I_7	*I have concerns about data security if a contact tracing app is used.*
		I_8	*Wearing face masks in public is not effective.*
		I_9	*People have been appropriately socially distancing during the lockdown.*

$$L_{I_n}(\tau,\mu,\alpha_{\cdot,n,\cdot}) = \prod_{k=1}^{K_n}\prod_{i=1}^{12} L_{I_{i,n,k}}(\tau_i,\mu_i,\alpha_{i^*,n,k}) \tag{3}$$

5.3. Choice model for stated preference scenarios

The final component of our structure is a choice model that explains the answers to the two post-pandemic scenarios ($t = 1,2$) about anticipated use of different modes ($m = 1$ for public transport, $m = 2$ for metered taxi and $m = 3$ for shared ride services, such as Uber and Bolt).

The answer to these scenarios have three possible levels (*less*, *same*, *more*). Multinomial Logit (MNL)[4] models are used for this measurement component, with the latent variables as explanators in the utilities of "more" and "less", along with constants and some co-variates, and with "same" as the base.

The utility $V_{j_{n,k,m,t}}$ for the ordinal alternative j ($j = 1$ for less; $j = 2$ for same; $j = 3$ for more) for person n in wave k for mode m in scenario t (where $t = 1$ for limitations continuing post-pandemic; $t = 2$ for back to normal) is given by:

$$V_{less_{n,k,m,t}} = \delta_{less_{m,t}} + \sum_{l=1}^{3} \zeta_{less_{l,m}} \alpha_{l,n,k} + \sum_{p=1}^{P} \beta_{less_{p,m,t}} z_{p,n} + \varepsilon_{less_{n,k,m,t}}$$

$$V_{same_{n,k,m,t}} = 0 \tag{4}$$

$$V_{more_{n,k,m,t}} = \delta_{more_{m,t}} + \sum_{l=1}^{3} \zeta_{more_{l,m}} \alpha_{l,n,k} + \sum_{p=1}^{P} \beta_{more_{p,m,t}} z_{p,n} + \varepsilon_{more_{n,k,m,t}}$$

where:

- $\delta_{j,m,t}$ is a mode – scenario specific constant
- $\zeta_{j_{l,m,t}}$ is a vector of parameters capturing the impact of the latent variables $\alpha_{l,n,}$ with separate effects by mode, but generic across the two future scenarios
- $\beta_{j_{p,m,t}}$ is a vector of parameters capturing the impact of person-specific variables, with separate effects by mode and across the two future scenarios
- $\varepsilon_{j_{n,k,m,t}}$ is a type I extreme value error, distributed across individuals, alternatives, waves and scenarios

We then get that the likelihood of the observed sequence of stated choices (L_{SC_n}) for the two anticipated mode-futures scenarios for person n across waves, conditional on the estimated parameters and latent variables is given by a product of MNL choice probabilities:

$$L_{SC_n}\left(\delta_{j_{m,t}}, \zeta_{j_{l,m}}, \alpha_{\cdot n}, \beta_{j_{p,m,t}}\right) = \prod_{k=1}^{K_n} \prod_{t=1}^{2} \prod_{m=1}^{3} \frac{e^{V_{j^*_{n,k,m,t}}}}{\sum_{j=1}^{3} e^{V_{j_{n,k,m,t}}}} \tag{5}$$

where $j^*_{n,k,m,t}$ is the ordinal alternative ($j = 1$ for less; $j = 2$ for same; $j = 3$ for more) chosen by respondent n in wave k for mode m in futures scenario t.

5.4. Overall model structure

The combined log-likelihood (LL) for the hybrid model is now given by integrating over the distribution of the random part of the LVs:

$$LL(\theta, \rho, \gamma, \tau, \mu, \delta, \zeta, \beta) = \sum_{n=1}^{N} \log \int_{\eta_{\cdot,n}} L_{I_n}\left(\tau, \mu, \alpha_{\cdot,n,\cdot}\right) \cdot L_{SC_n}\left(\delta_{j_{m,t}}, \zeta_{j_{l,m}}, \alpha_{\cdot n}, \beta_{j_{p,m,t}}\right) \phi\left(\eta_{\cdot,n}\right) d\eta_{\cdot,n} \tag{6}$$

where $\phi(\eta_{\cdot,n})$ is the standard Normal density function. Both the measurement model $L_{I_n}(\tau, \mu, \alpha_{\cdot,n,\cdot})$ and the choice model component $L_{SC_n}\left(\delta_{j_{m,t}}, \zeta_{j_{l,m}}, \alpha_{\cdot n}, \beta_{j_{p,m,t}}\right)$ depend on the vector of latent variables, and the log-likelihood function of the model thus uses integration over the random component of the latent variables. This log-likelihood does not have a closed-form solution due to the presence of the vector of three random disturbances η_n and therefore needed to be approximated using numerical simulation, where, given the large sample size and computational demands, we restricted ourselves to using 100 Halton draws, after initial tests showed stable performance. The models were estimated using *Apollo*[5] (Hess and Palma, 2019).

An overview of the model structure is given in Fig. 5.

6. Empirical results

A detailed specification search was carried out to arrive at the final specification of the MNL and hybrid choice models. The MNL model explains the answers to the post-lockdown scenarios, while the HCM model in addition incorporates latent variables and explains the answers to perception questions.

The modelling results are presented in Tables 5 to 8 below. Given the focus on behavioural findings, we generally accept lower than usual levels of confidence in our statistical tests.

6.1. Measurement model results

To understand the impact of the LVs on the responses to the perception questions we need to look at the parameters $\mu_{i,l,n}$ in Table 5. These results show the impact of the latent variables in the Ordered Logit measurement models for the attitudinal questions. Specifically, these are models that explain 1) the stated concern for contracting COVID-19, 2) support for COVID-19 related government interventions and 3) scepticism towards additional COVID-19 measures.

The latent variable Concern (LV1) is positively associated with all the perception questions in that factor (i.e., perceptions 1, 2, 3, 6, 10, 11 and 12). This allows us to interpret increases in this latent variable as relating to increased concern about COVID-19. Similarly, the latent variable Support for government (LV2) is positively associated with the perception questions in that factor (4 and 5), and most so for perception question 4. This allows us to interpret increases in this latent variable as relating to increased support for government handling of COVID-19. Finally, the latent variable Scepticism (LV3) is positively associated with perception questions 8 and 9, with the latter one being the strongest. This latent variable is not significantly associated to perception question 7 on contact tracing. This allows us to interpret increases in this latent variable as relating to increased scepticism about COVID-19 mitigation measures.

The threshold parameters ($\tau_{i,v}$) at the bottom part of the table reflect the distribution of responses to the perception questions, and are of course monotonically increasing, as required.

6.2. Structural equation for latent variables

The estimates for the parameters used in the structural equations for the latent variables are presented in Table 6 (for country-specific effects) and Table 7 (for respondent-specific effects).

Table 6 presents the country-specific wave effect ($\theta^c_{l,k}$) and stringency effect (ρ_l) on the three latent variables ($\alpha_{l,n,k}$). The country-specific wave

[4] For comparison, MNL models were also estimated as standalone structures without the overall hybrid model, and thus without the latent variables.

[5] https://www.apollochoicemodelling.com/.

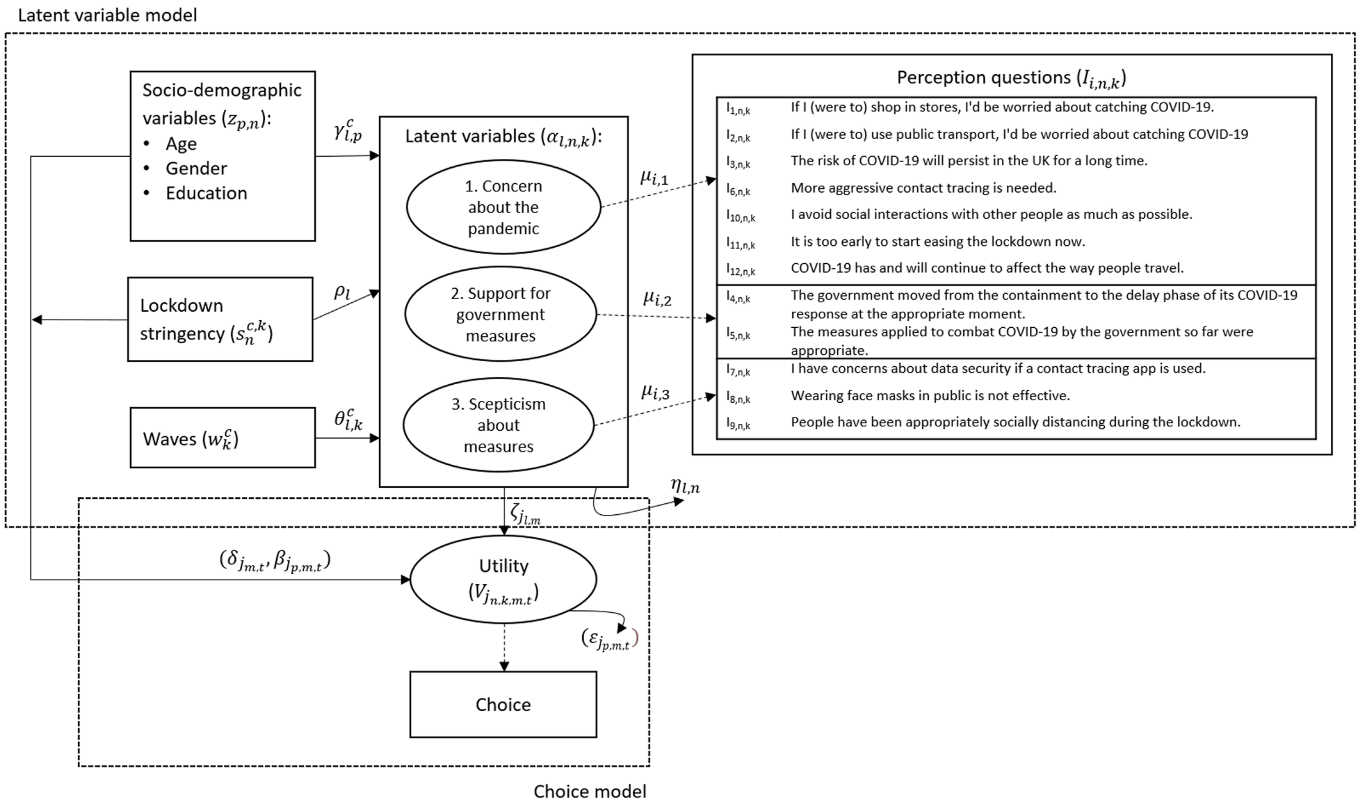


Fig. 5. Hybrid modelling framework.

effect (with UK wave 1 as the base) shows how the latent perceptions evolve over time and how this differs across countries. Regarding LV1 and LV2, we note a monotonic trend as we progress through the waves in all countries except for Australia, showing that most people are getting less concerned (LV1) but more supportive of government measures (LV2). Compared to the first wave administered in the UK, Colombians seem more concerned about COVID-19, whereas people from Australia and South Africa showed lower concerns in their first waves. As to LV3, Colombians were less sceptical about the effectiveness of measures (LV3) compared to the UK sample, Australians and South Africans in each wave. The wave effects of LV3 vary across countries. People in the UK showed an increase in scepticism about the effectiveness of measures in wave 2 compared to wave 1, before it decreased again. The results show an increasing value of LV3 in Colombia and South Africa but a decreasing scepticism in Australia compared to the first wave.

The impact of the stringency levels (ρ_l) show that across the countries, respondents become more sceptical about the effectiveness of the COVID-19 measures taken (LV3) as the lockdown restrictions increase.

Table 7 looks at the impact ($\gamma^c_{l,p}$) of the country- specific socio-demographic variables ($z^c_{p,n}$) age, gender and education level on the three latent variables ($\alpha_{l,n,k}$). Here, the effects are far less pronounced, suggesting that attitudes cannot necessarily be linked to observed respondent characteristics. Age had no effect on the LVs and was removed from the model, whereas gender only plays a role in the UK, Colombia and South Africa, where women in the UK and Colombia are more concerned about COVID-19 than their male counterparts. Women in the UK are also less supportive of government policy (LV2) than men, whilst in Colombia, women are more supportive of government policy (LV2). In South Africa, women tend to be less sceptical towards COVID-19 measures (LV3). Education level explains some of the LVs, yet with only moderately high confidence across the three latent variables. For example, highly educated people in the UK (PhD) seem to be less approving of government measures around COVID-19 (LV2) compared to someone with a bachelor's degree or less. In contrast, people with a master's or PhD degree in South Africa are more supportive of the government's measures than people with a lower education level. Meanwhile, more highly educated South Africans also tend to be more sceptical about COVID-19 measures.

6.3. *Choice model results*

We finally look at the estimates of the choice model component of the hybrid model alongside those of the MNL model, with estimates shown in Table 8.

The mode-futures scenario specific constants ($\delta_{j_{m,t}}$) in Table 8 suggest an inherent preference for reduced use of public transport and ride-sharing when post-pandemic lockdown measures remain in place (as in scenario 1), which is in line with findings reported in Balbontin et al. (2022); Van Wee and Witlox (2021); and Aaditya and Rahul (2021).

In the MNL model, we see a consistent reduced likelihood of increased use for *all* presented modes in the continued lockdown scenario 1 as well as in the back to normal scenario 2, i.e., there is a tendency to drive/ride less overall, which is also confirmed through the positive parameter for riding less and in the case of public transport and ridesharing in scenario 1 and for taxi in scenario 2.

In the HCM model, the picture is of course more complex due to the presence of the latent variables. The parameter $\zeta_{j_{l,m}}$ capture the impact of the latent variables ($\alpha_{l,n,k}$) on the respondents' preferences for modes m across the two post-pandemic scenarios. We find strong impacts of both LV1 and LV3 on all three modes. A stronger concern about COVID-19 (LV1) will increase the probability of reduced travel by public transport in future scenarios. Those people who are more sceptical about the COVID-19 measures (LV3) tend to indicate a higher likelihood to decrease the use of all three modes even if lockdown measures still hold, and a lower likelihood to increase. Those people who have confidence in their governments' COVID-19 regulations (LV2) tend to indicate likely increase in the use of all modes.

When looking at the impact of age ($\beta_{\text{age}_{m,t}}$) on preferences in the

Table 5
Results of measurement models.

Model	HCM	Parameters	Estimate	Robust T-ratio
LL(start)	**−38123.75**			
LL(final)	**−34734.03**			
Influence of latent variables on responses to perception questions ($\mu_{i,l}$)	*LV1*	$\mu_{1,1}$	1.1626	10.70
		$\mu_{2,1}$	1.1131	9.35
		$\mu_{3,1}$	0.8081	8.35
		$\mu_{6,1}$	0.7090	9.4
		$\mu_{10,1}$	0.8803	11.15
		$\mu_{11,1}$	0.7700	9.10
		$\mu_{12,1}$	0.5866	7.12
	LV2	$\mu_{4,2}$	1.3456	14.43
		$\mu_{5,2}$	1.2914	13.12
	LV3	$\mu_{7,3}$	−0.0019	−0.03
		$\mu_{8,3}$	0.5011	5.69
		$\mu_{9,3}$	0.5038	8.36
Threshold parameters for measurement model response to perception questions ($\tau_{i,s}$)	I_1	$\tau_{1,1}$	−4.5447	−4.67
		$\tau_{1,2}$	−2.9043	−2.98
		$\tau_{1,3}$	−2.0442	−2.09
		$\tau_{1,4}$	0.6557	0.67
	I_2	$\tau_{2,1}$	−5.1937	−5.49
		$\tau_{2,2}$	−3.8106	−4.07
		$\tau_{2,3}$	−3.1124	−3.32
		$\tau_{2,4}$	−1.0291	−1.10
	I_3	$\tau_{3,1}$	−5.4071	−7.44
		$\tau_{3,2}$	−4.3241	−6.14
		$\tau_{3,3}$	−3.0539	−4.34
		$\tau_{3,4}$	−0.6222	−0.89
	I_4	$\tau_{4,1}$	0.6704	0.54
		$\tau_{4,2}$	2.5370	2.05
		$\tau_{4,3}$	4.0435	3.25
		$\tau_{4,4}$	6.1816	4.90
	I_5	$\tau_{5,1}$	0.3465	0.30
		$\tau_{5,2}$	2.1994	1.89
		$\tau_{5,3}$	3.2136	2.76
		$\tau_{5,4}$	5.9201	5.08
	I_6	$\tau_{6,1}$	−4.7342	−7.45
		$\tau_{6,2}$	−3.7259	−5.96
		$\tau_{6,3}$	−2.1002	−3.41
		$\tau_{6,4}$	−0.7139	−1.17
	I_7	$\tau_{7,1}$	−2.1610	−10.29
		$\tau_{7,2}$	−0.9195	−4.70
		$\tau_{7,3}$	−0.0765	−0.40
		$\tau_{7,4}$	1.2395	6.37
	I_8	$\tau_{8,1}$	0.5925	0.80
		$\tau_{8,2}$	1.9584	2.58
		$\tau_{8,3}$	2.9304	3.82
		$\tau_{8,4}$	4.4666	5.75
	I_9	$\tau_{9,1}$	−0.1617	−0.23
		$\tau_{9,2}$	1.7649	2.52
		$\tau_{9,3}$	2.4296	3.46
		$\tau_{9,4}$	4.8625	6.80
	I_{10}	$\tau_{10,1}$	−4.6070	−6.05
		$\tau_{10,2}$	−2.9736	−3.95
		$\tau_{10,3}$	−2.0465	−2.74
		$\tau_{10,4}$	−0.1623	−0.22
	I_{11}	$\tau_{11,1}$	−3.8042	−5.69
		$\tau_{11,2}$	−2.2632	−3.40
		$\tau_{11,3}$	−1.2474	−1.88
		$\tau_{11,4}$	0.4029	0.61
	I_{12}	$\tau_{12,1}$	−5.8082	−9.87
		$\tau_{12,2}$	−4.3839	−8.44
		$\tau_{12,3}$	−3.4270	−6.78
		$\tau_{12,4}$	−0.8305	−1.65

various $m \times t$ scenarios in the HCM model, it is shown that there is hardly any effect of age on preferences in these scenarios. Only, and particularly in the MNL only model, those aged 50 or more seem to indicate a lower tendency to travel more by ride hailing by older people if restriction policies are still in place.

The bottom part of Table 8 looks at the parameter $\beta_{\text{stringency}_{m,t}}$ which

Table 6
Structural equation model (country-specific wave effect and stringency effect on perceptions).

Model	HCM	Parameters	Estimate	Robust T-ratio
LL(start)	**−38123.75**			
LL(final)	**−34734.03**			
Country-specific wave effects on perceptions ($\theta^{c}_{l,k}$)	*LV1*	$\theta^{UK}_{1,1}$ (base)	0.0000	NA
		$\theta^{UK}_{1,2}$	−0.3720	−4.29
		$\theta^{UK}_{1,3}$	−0.6759	−6.65
		$\theta^{CO}_{1,1}$	0.7581	2.02
		$\theta^{CO}_{1,2}$	0.0694	0.17
		$\theta^{AU}_{1,1}$	−1.4673	−4.96
		$\theta^{AU}_{1,2}$	−0.8413	−2.74
		$\theta^{SA}_{1,1}$	0.1534	0.45
		$\theta^{SA}_{1,2}$	−0.9394	−2.67
		$\theta^{SA}_{1,3}$	−1.1328	−2.23
	LV2	$\theta^{UK}_{2,1}$ (base)	0.0000	NA
		$\theta^{UK}_{2,2}$	0.2561	2.76
		$\theta^{UK}_{2,3}$	0.2645	2.29
		$\theta^{CO}_{2,1}$	0.3353	0.8
		$\theta^{CO}_{2,2}$	0.5165	1.39
		$\theta^{AU}_{2,1}$	2.3951	8.95
		$\theta^{AU}_{2,2}$	1.8928	6.87
		$\theta^{SA}_{2,1}$	1.6266	5.19
		$\theta^{SA}_{2,2}$	1.8105	5.79
		$\theta^{SA}_{2,3}$	2.3592	4.56
	LV3	$\theta^{UK}_{3,1}$ (base)	0.0000	NA
		$\theta^{UK}_{3,2}$	0.3796	2.55
		$\theta^{UK}_{3,3}$	−0.3013	−1.26
		$\theta^{CO}_{3,1}$	−2.4691	−5.23
		$\theta^{CO}_{3,2}$	−2.1881	−4.46
		$\theta^{AU}_{3,1}$	1.0049	3.031
		$\theta^{AU}_{3,2}$	0.1637	0.45
		$\theta^{SA}_{3,1}$	−0.7099	−1.77
		$\theta^{SA}_{3,2}$	−0.2611	−0.52
		$\theta^{SA}_{3,3}$	−0.0265	−0.03
Impact of lockdown stringency on perceptions (ρ_l)		ρ_1	−1.1266	−1.03
		ρ_2	1.5145	1.22
		ρ_3	4.4355	2.32

shows the impact of the lockdown stringency at the time of the survey on respondents' post-pandemic preferences for any of the three modes in the two scenarios. Focusing on the results of the HCM, the estimates for scenario 1 show that, for respondents answering the questions at a time of stricter lockdowns (i.e. a higher stringency index), there is a reduced likelihood of indicating decreased travel and an increased likelihood of indicating increased willingness to travel in future. This makes behavioural sense, as respondents who were experiencing stricter lockdowns are more likely to want to travel more after restrictions are eased.

7. Discussion and conclusions

The COVID-19 pandemic has had tremendous impacts on activity participation and travel. In the interest of understanding how COVID-19 contagion patterns, impacts and responses differ across countries, this study used survey panel data from four countries on four continents to capture the impact of lockdown characteristics, perceptions towards the COVID-19 pandemic as well as personal characteristics on travel behaviour and activity participation in two post-pandemic scenarios. It represents one of the few papers in the literature that covers such diverse geography, and pandemic experiences and explores how preferences change over the divergent trajectories in these societies.

Using a principal component analysis, three different latent variables

Table 7
Structural equation model (socio-demographic effects on perceptions).

Model	HCM			
LL(start)	**−38123.75**			
LL(final)	**−34734.03**	**Parameters**	**Estimate**	**Robust T-ratio**
Impact of gender on perceptions in LVs ($\gamma^c_{l,p}$)	*LV1*	$\gamma^{UK}_{1,male}$ (base)	0.0000	NA
		$\gamma^{UK}_{1,female}$	0.3206	1.37
		$\gamma^{CO}_{1,male}$ (base)	0.0000	NA
		$\gamma^{CO}_{1,female}$	0.2899	1.36
		$\gamma^{AU}_{1,male}$ (base)	0.0000	NA
		$\gamma^{AU}_{1,female}$	0.1249	0.84
		$\gamma^{SA}_{1,male}$ (base)	0.0000	NA
		$\gamma^{SA}_{1,female}$	0.2810	1.27
	LV2	$\gamma^{UK}_{2,male}$ (base)	0.0000	NA
		$\gamma^{UK}_{2,female}$	−0.2794	−1.49
		$\gamma^{CO}_{2,male}$ (base)	0.0000	NA
		$\gamma^{CO}_{2,female}$	0.4404	1.86
		$\gamma^{AU}_{2,male}$ (base)	0.0000	NA
		$\gamma^{AU}_{2,female}$	−0.1230	−1.27
		$\gamma^{SA}_{2,male}$ (base)	0.0000	NA
		$\gamma^{SA}_{2,female}$	0.2185	1.13
	LV3	$\gamma^{UK}_{3,male}$ (base)	0.0000	NA
		$\gamma^{UK}_{3,female}$	0.0906	0.46
		$\gamma^{CO}_{3,male}$ (base)	0.0000	NA
		$\gamma^{CO}_{3,female}$	0.0279	0.12
		$\gamma^{AU}_{3,male}$ (base)	0.0000	NA
		$\gamma^{AU}_{3,female}$	−0.0655	−0.60
		$\gamma^{SA}_{3,male}$ (base)	0.0000	NA
		$\gamma^{SA}_{3,female}$	−0.3670	−1.99
Impact of education on perceptions in LVs ($\gamma^c_{l,p}$)	*LV1*	$\gamma^{UK}_{1,bachelor}$ (base)	0.0000	NA
		$\gamma^{UK}_{1,master}$	−0.0185	−0.07
		$\gamma^{UK}_{1,PhD}$	0.0402	0.1
		$\gamma^{CO}_{1,bachelor}$ (base)	0.0000	NA
		$\gamma^{CO}_{1,master}$	0.4349	1.91
		$\gamma^{CO}_{1,PhD}$	0.3110	1.03
		$\gamma^{SA}_{1,bachelor}$ (base)	0.0000	NA
		$\gamma^{SA}_{1,master}$	−0.2779	−1.03
		$\gamma^{SA}_{1,PhD}$	0.2459	0.72
	LV2	$\gamma^{UK}_{2,bachelor}$ (base)	0.0000	NA
		$\gamma^{UK}_{2,master}$	−0.1210	−0.5
		$\gamma^{UK}_{2,PhD}$	−0.3598	−1.6
		$\gamma^{CO}_{2,bachelor}$ (base)	0.0000	NA
		$\gamma^{CO}_{2,master}$	0.2612	1.14
		$\gamma^{CO}_{2,PhD}$	0.2859	0.70
		$\gamma^{SA}_{2,bachelor}$ (base)	0.0000	NA
		$\gamma^{SA}_{2,master}$	0.4813	1.85
		$\gamma^{SA}_{2,PhD}$	0.4990	1.56
	LV3	$\gamma^{UK}_{3,bachelor}$ (base)	0.0000	NA
		$\gamma^{UK}_{3,master}$	−0.2173	−1.08
		$\gamma^{UK}_{3,PhD}$	−0.1265	−0.52
		$\gamma^{CO}_{3,bachelor}$ (base)	0.0000	NA
		$\gamma^{CO}_{3,master}$	0.1006	0.42
		$\gamma^{CO}_{3,PhD}$	0.0137	0.04
		$\gamma^{SA}_{3,bachelor}$ (base)	0.0000	NA
		$\gamma^{SA}_{3,master}$	0.4036	1.28
		$\gamma^{SA}_{3,PhD}$	0.3473	0.93

relating to 1) concerns around COVID-19, 2) government interventions, and 3) scepticism towards COVID-19 measures could be defined. We then developed a hybrid choice model that captures the evolution of these latent attitudes over time and measured their role in explaining anticipated travel behaviour in post-pandemic scenarios.

We observe differences in the latent perceptions across countries, as well as changes over time (across the survey waves), where these changes do not follow the same trend across countries. Similarly, there are socio-demographic effects explaining differences in perceptions as well as differences in the anticipated changes in travel behaviour, where these again differ across countries. The role of underlying perceptions in influencing the anticipated changes in travel behaviour makes strong behavioural sense, notably with those people who are more concerned about COVID-19 being less likely to indicate a return to their pre-pandemic travel patterns. Finally, we studied the role of the stringency index, i.e. how the severity of the restrictions in place at the time of the survey impacted responses. We note that more severe restrictions increase scepticism about the measures implemented. There is also a strong effect of current restrictions on planned travel – respondents answering the stated preference scenarios while under stricter restrictions are more likely to plan increased travel post-pandemic, suggesting a strong rebound effect. This also explains some of the behaviour observed in the results where people became more sceptic, resulting in increased use of all modes despite the increased risk associated with COVID-19. There is potential heterogeneity in different age groups, with the most effects being represented by people in the 50 and above age group, who are more likely to continue travelling less in all scenarios. This makes sense as this is the age group that was considered more vulnerable in the early stages of COVID-19.

An important question is what can be learnt from our results going forward. It seems clear that attitudes relating to concern about the pandemic as well as support and scepticism about government measures are influenced by the state of the pandemic as well as respondent and country-specific differences. Given that these attitudes play a role in how people might travel after a *return to normality*, as well as how they might react to government interventions, this calls for a careful post-pandemic evaluation of the impact of restrictions and the communication surrounding them. Government interventions as measured by the stringency index have a counter-productive impact on scepticism, suggesting that careful and time-limited use of restrictions is important. There is also a clear indication of a rebound effect, meaning that if restrictions are very severe, then behaviour might return very quickly to pre-pandemic levels, meaning that a rapid relaxation could have counter-productive public health effects, as seen for example in the easing of restrictions in the United Kingdom in summer 2020. These are important findings for policymakers as they underscore the impact of direct intervention rather than a more passive approach towards restricting the movement of people; also, the clear communication of the rationale behind the interventions is important to create buy-in among the public. To contextualise this somewhat, in the early stages of the pandemic, Australia was for example remarkably successful in combatting the spread of COVID-19. In early 2020 the national borders were closed to non-citizens in a first move to limit the introduction of the virus. In late March, with just eight deaths from COVID-19, the entire country was in lockdown. While relatively draconian compared to the other countries in the study, the significant impact of lockdown levels on travel preferences as demonstrated in the paper means that the early

Table 8
Choice model results.

Model			**MNL only**		**HCM**	
LL(start)			**−7855.078**		**−38123.75**	
LL(final)			**−6788.692**		**−34734.03**	
		Parameters	**Estimate**	**Robust T-ratio**	**Estimate**	**Robust T-ratio**
Baseline preferences in $m \times t$ scenarios ($\delta_{j_{m,t}}$)	*Post-pandemic scenario 1*	$\delta_{less_{pt,s1}}$	2.1018	1.97	4.0583	2.27
		$\delta_{more_{pt,s1}}$	−2.573	−1.68	1.0437	0.49
		$\delta_{less_{taxi,s1}}$	−0.2213	−0.27	2.2978	1.09
		$\delta_{more_{taxi,s1}}$	−4.189	−2.45	−0.5021	−0.17
		$\delta_{less_{ride,s1}}$	1.814	1.39	3.0907	1.29
		$\delta_{more_{ride,s1}}$	−5.322	−2.32	1.2739	0.55
	Post-pandemic scenario 2	$\delta_{less_{pt,s2}}$	0.1478	0.13	1.9449	1.44
		$\delta_{more_{pt,s2}}$	−7.773	−3.66	−1.6263	−0.80
		$\delta_{less_{taxi,s2}}$	1.9995	2.16	0.8917	0.48
		$\delta_{more_{taxi,s2}}$	−0.9166	−0.69	−4.5492	−1.65
		$\delta_{less_{ride,s2}}$	−0.4589	−0.62	0.5590	0.24
		$\delta_{more_{ride,s2}}$	−5.1520	−3.30	−3.5385	−1.44
Influence of LV on preference on mode m ($\zeta_{j_{l,m}}$)	*PT*	$\zeta_{less_{1,pt}}$			1.0308	8.28
		$\zeta_{less_{2,pt}}$			−0.0273	−0.22
		$\zeta_{less_{3,pt}}$			0.7325	4.38
		$\zeta_{more_{1,pt}}$			−0.0382	−0.23
		$\zeta_{more_{2,pt}}$			0.1468	1.1
		$\zeta_{more_{3,pt}}$			−0.7281	−4.10
	Taxi	$\zeta_{less_{1,taxi}}$			1.2980	8.54
		$\zeta_{less_{2,taxi}}$			0.1379	0.83
		$\zeta_{less_{3,taxi}}$			1.0906	4.65
		$\zeta_{more_{1,taxi}}$			−0.0457	−0.20
		$\zeta_{more_{2,taxi}}$			0.2652	1.51
		$\zeta_{more_{3,taxi}}$			−1.1440	−4.13
	Ride sharing	$\zeta_{less_{1,ride}}$			1.4119	8.88
		$\zeta_{less_{2,ride}}$			0.2052	1.19
		$\zeta_{less_{3,ride}}$			1.1721	4.48
		$\zeta_{more_{1,ride}}$			−0.1548	−0.63
		$\zeta_{more_{2,ride}}$			0.3179	1.85
		$\zeta_{more_{3,ride}}$			−1.1772	−4.56
Impact of age on preference in m × t scenario ($\beta_{j_{p,m,t}}$)	*Post-pandemic scenario 1 - PT*	$\beta_{less_{<29,pt,s1}}$	0.2710	0.30	0.0348	0.03
		$\beta_{less_{30<age<49,pt,s1}}$	0.5818	0.66	0.0636	0.05
		$\beta_{less_{>50,pt,s1}}$	0.4163	0.47	−0.0093	−0.00
		$\beta_{more_{<29,pt,s1}}$	−0.392	−0.36	−0.2684	−0.26
		$\beta_{more_{30<age<49,pt,s1}}$	−0.834	−0.77	−0.3115	−0.31
		$\beta_{more_{>50,pt,s1}}$	−1.098	−0.98	−0.6951	−0.69
	Post-pandemic scenario 2 -PT	$\beta_{less_{<29,pt,s2}}$	0.1350	0.19	−0.2677	−0.37
		$\beta_{less_{30<age<49,pt,s2}}$	−0.008	−0.01	−0.6687	−0.92
		$\beta_{less_{>50,pt,s2}}$	−0.046	−0.06	−0.6322	−0.86
		$\beta_{more_{<29,pt,s2}}$	0.5661	0.42	0.7028	0.61
		$\beta_{more_{30<age<49,pt,s2}}$	−0.006	−0.00	0.6964	0.61
		$\beta_{more_{>50,pt,s2}}$	−0.021	−0.01	0.6193	0.53
	Post-pandemic scenario 1 -Taxi	$\beta_{less_{<29,taxi,s1}}$	−0.9375	−0.78	−1.1953	−0.91
		$\beta_{less_{30<age<49,taxi,s1}}$	−0.7573	−0.64	−1.4365	−1.08
		$\beta_{less_{>50,taxi,s1}}$	−0.9276	−0.78	−1.4535	−1.10
		$\beta_{more_{<29,taxi,s1}}$	−1.0752	−0.62	−0.5821	−0.43
		$\beta_{more_{30<age<49,taxi,s1}}$	−1.1781	−0.68	−0.0494	−0.036
		$\beta_{more_{>50,taxi,s1}}$	−1.9957	−1.12	−1.3496	−0.96
	Post-pandemic scenario 2 -Taxi	$\beta_{less_{<29,taxi,s2}}$	−0.3934	−0.38	−0.9517	−0.81
		$\beta_{less_{30<age<49,taxi,s2}}$	−0.4660	−0.45	−1.3980	−1.18
		$\beta_{less_{>50,taxi,s2}}$	−0.8145	−0.79	−1.7050	−1.43
		$\beta_{more_{<29,taxi,s2}}$	−0.5045	−0.31	−0.6430	−0.49
		$\beta_{more_{30<age<49,taxi,s2}}$	−0.844	−0.52	−0.0585	−0.04
		$\beta_{more_{>50,taxi,s2}}$	−1.7990	−1.09	−1.4484	−1.08
	Post-pandemic scenario 1 -Ride	$\beta_{less_{<29,ride,s1}}$	−0.2761	−0.36	−0.5054	−0.440
		$\beta_{less_{30<age<49,ride,s1}}$	−0.151	−0.20	−0.8349	−0.73
		$\beta_{less_{>50,ride,s1}}$	−0.6005	−0.80	−1.3006	−1.12
		$\beta_{more_{<29,ride,s1}}$	−0.7148	−0.85	−1.1204	−1.22
		$\beta_{more_{30<age<49,ride,s1}}$	−1.4192	−1.71	−1.0531	−1.21

(*continued on next page*)

Table 8 (*continued*)

Model			MNL only		HCM	
		$\beta_{more_{>50,ride,s1}}$	−2.3394	−2.57	−2.3453	−2.51
	Post-pandemic scenario 2 -Ride	$\beta_{less_{<29,ride,s2}}$	−0.0158	−0.02	−0.6546	−0.58
		$\beta_{less_{30<age<49,ride,s2}}$	−0.3096	−0.52	−1.3365	−1.17
		$\beta_{less_{>50,ride,s2}}$	−0.4112	−0.67	−1.2918	−1.12
		$\beta_{more_{<29,ride,s2}}$	1.2955	1.11	1.1504	1.03
		$\beta_{more_{30<age<49,ride,s2}}$	0.4983	0.43	1.2389	1.14
		$\beta_{more_{>50,ride,s2}}$	−0.1764	−0.14	0.0788	0.06
Impact of lockdown stringency on preference in $m \times t$ scenario ($\beta_{j_{p,m,t}}$)	*Scenario 1 -PT*	$\beta_{less_{stringency,pt,s1}}$	−2.9938	−3.23	−6.5965	−4.13
		$\beta_{more_{stringency,pt,s1}}$	2.9551	2.09	−0.6888	−0.35
	Scenario 2 -PT	$\beta_{less_{stringency,pt,s2}}$	0.3256	0.48	−3.5796	−2.73
		$\beta_{more_{stringency,pt,s2}}$	4.3079	3.56	1.9381	1.61
	Scenario 1 -Taxi	$\beta_{less_{stringency,taxi,s1}}$	−1.5975	−1.70	−4.8613	−2.42
		$\beta_{more_{stringency,taxi,s1}}$	7.0385	4.25	1.7100	0.74
	Scenario 2 -Taxi	$\beta_{less_{stringency,taxi,s2}}$	−0.2377	−0.29	−3.5584	−1.94
		$\beta_{more_{stringency,taxi,s2}}$	9.7310	6.46	7.0069	3.93
	Scenario 1 -Ride	$\beta_{less_{stringency,ride,s1}}$	−2.5590	−2.85	−6.9424	−3.46
		$\beta_{more_{stringency,ride,s1}}$	1.2781	0.86	0.3068	0.14
	Scenario 2 -Ride	$\beta_{less_{stringency,ride,s2}}$	0.2747	0.42	−3.7464	−2.35
		$\beta_{more_{stringency,ride,s2}}$	4.5730	3.43	4.0310	2.70

move in Australia was decisive in being able to arrest the COVID-19 curve in the early stages of the pandemic. Even so, in all jurisdictions including Australia, the preference to resume travelling more via all modes once pandemic restrictions were lifted not only further underscores the importance of those restrictions in suppressing the travel of people and thus the spread of the virus but also serves to reinforce the need for policymakers to carefully consider how and when those restrictions on movement would be eased to avoid exponential contagion (Beck and Hensher 2021).

Even though the study is somewhat constrained by the fact that data collection was conducted early in the COVID-19 pandemic over a relatively short period of 6 months; a period in which stringency levels did not vary as much as they for example did later on in 2021, we can draw some lessons for policymakers regarding the way they respond to new COVID-19 variants or future pandemic scenarios. Swift and uniform action in the early stages of the pandemic which is supported by the population is important in reducing the extant desire of people to travel and connect. It is important to communicate the necessity and the effectiveness of such restrictions on movement, as those sceptical about government action will continue to travel and thus increase the risk of widespread contagion. Equally, the removal of government-imposed restrictions will lead to a strong desire to want to return to all modes of travel, which will also mean that policymakers will need to consider carefully when and how to ease restrictions such that the desire to increase movement does not bring with it an uncontrollable increase in cases.

From an equity perspective, we see that during lockdown scenarios, the preference to use public transport and, in particular, ride-share modes are impacted detrimentally. These are critical modes of transportation for lower-income individuals, who may not have the means to use other private modes of transport or work from home. In this case, policymakers must consider service provision from the public good perspective (of public transport in particular) in the face of the observed fall in patronage, understanding that while fewer people may be using these modes, they still serve an important social objective which might also be of particular importance for essential workers. Finally, we see that the pandemic has suppressed the travel intentions among older segments of the population; a logical result given the increased risk posed to them by COVID-19. Given that the pandemic has created social constraints and crowd avoidance concerns among this older population, policymakers will also need to consider alternative approaches to ensuring that these members of society are included in transport and mobility systems during pandemics and can thus obtain still important benefits of social inclusion.

Of course, an interesting avenue for future work will be to study how actual (as opposed to anticipated) travel behaviour changed after the pandemic, and whether that relates in any way to the severity of restrictions in that country.

CRediT authorship contribution statement

Gloria Amaris: Conceptualization, Methodology, Formal analysis, Writing – original draft. **Julián Arellana:** Conceptualization, Data curation. **Matthew Beck:** Conceptualization, Data curation, Writing – review & editing. **Roger Behrens:** Conceptualization, Visualization, Writing – review & editing. **Chiara Calastri:** Conceptualization, Methodology, Data curation, Writing – review & editing. **Stephane Hess:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Fangqing Song:** Conceptualization, Data curation, Project administration, Writing – review & editing. **Hazvinei Tsitsi Tamuka Moyo:** Conceptualization, Data curation, Writing – review & editing. **Mark Zuidgeest:** Methodology, Conceptualization, Data curation, Project administration, Writing – original draft, 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.

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