Doctoral theses at NTNU, 2023:426

Sofie Bang

Applications of AI in Construction

From ambition to practice

Doctoral thesis

NTNU
Norwegian University of Science and Technology
Thesis for the Degree of Philosophiae Doctor
Faculty of Engineering
Department of Mechanical and Industrial Engineering

NTNU
Norwegian University of Science and Technology

Sofie Bang

Applications of AI in Construction

From ambition to practice

Thesis for the Degree of Philosophiae Doctor

Trondheim, November 2023

Norwegian University of Science and Technology
Faculty of Engineering
Department of Mechanical and Industrial Engineering

NTNU

Norwegian University of
Science and Technology

NTNU
Norwegian University of Science and Technology

Thesis for the Degree of Philosophiae Doctor

Faculty of Engineering
Department of Mechanical and Industrial Engineering

ISBN 978-82-326-7552-4 (printed ver.)
ISBN 978-82-326-7551-7 (electronic ver.)
ISSN 1503-8181 (printed ver.)
ISSN 2703-8084 (online ver.)

Doctoral theses at NTNU, 2023:426

Printed by NTNU Grafisk senter

Applications of AI in Construction

From ambition to practice

Sofie Bang

Preface

This thesis is prepared in partial fulfilment of the requirements for the degree of Philosophiae Doctor (PhD) at the Department of Mechanical and Industrial Engineering and Faculty of Engineering at the Norwegian University of Science and Technology (NTNU).

The research was funded by the founding members of Construction City Cluster, AF Gruppen, Betonmast, and OBOS. Construction City promises to be 'the future of construction' and I genuinely believe that the work conducted in this thesis can be a piece of that puzzle.

My first meeting with the construction industry was through my first university Summer Internship in 2017. From the beginning, I heard a lot of talk about all the problems the industry is facing in terms of productivity and sustainability. It soon became apparent that, more than anything, this was a testament to the amount of unfulfilled potential the industry represents. I have never been a 'Status Quo' type of person, and rather than asking 'why' we might want to try a given approach, I always found myself asking 'why not' – in hindsight, I am beyond grateful that this was my response when given the opportunity to pursue my PhD.

My PhD journey (like most) has been filled with highs and lows. I have felt defeat and exhaustion, but also pride, hope, mastery and joy. Never for a minute have I been left on my own, and there are not enough words to thank all of those who have made this PhD possible.

Acknowledgements

To properly thank everyone who has been involved in my PhD journey, I would have to write another document the size of this thesis.

First, I want to thank my main supervisor, Professor Nils Olsson, and my co-supervisor Professor Bjørn Andersen. Thank you for your invaluable guidance and support, and for staying constructive and positive through the journey that the PhD represents. Thank you for supporting and questioning my choices, for your kindness and patience, and words of encouragement when they were needed the most.

I would like to thank my co-authors, Professor Antoine Rauzy, Alessia Bellini, and Professor Ole Jonny Klakegg, for all valuable discussions and contributions. I would also like to acknowledge and thank Magnus Aarvold, William Hartvig, Preben Aase, and Markus Egeland, who wrote the master theses on which Paper III and Paper V are based.

Furthermore, I would like to thank my colleagues in Construction City, for giving me this opportunity, for providing me with an arena to present my research, and for an invaluable network of industry professionals.

Colleagues and friends in the office, thank you for all academic and non-academic discussions, and (sometimes, unreasonably long) coffee breaks: Alessia Bellini, Bertha Ngereja, Bejtush Ademi, Nora Johanne Klungseth, and Jan Alexander Langlo; an extra thank you to Siss Kristin Frivik, for providing not only good conversations and good laughs but also a spare room in your home when working from Trondheim.

Thank you to 'my' research group at the University of Salford, and my fellow PhD students. Thank you to Professor Zeeshan Aziz for organising my exchange and to Dr. Paul Coates and Professor Jason Underwood for helping me stay in touch with the research environment well after my departure.

Lastly, and in no way least, I want to thank my family and friends, for providing all the love, support, and patience one could ever need. I am grateful to my parents, who taught me the importance of hard work, and to never turn down a challenge. Thank you to my brothers, Henning, Sander, and Torben, who, despite calling my PhD work cringe, have provided some amazingly non-academic breaks and even admitted that maybe a PhD can be cool. You are my role models. My friends have promised to make my defence 'memorable' – for this, I want to thank them in advance. Finally, to my dream teammate and partner, Rhys, for not only being an impeccable Guest Contributor, but for providing the best distractions, and all the love and patience I could ask for.

Abstract

The topic of Artificial Intelligence (AI) in construction has sparked a lot of interest in recent years, with the emergence of new techniques, algorithms, and tools that have enhanced the way machines learn, reason, and interact with the real world. As a result, AI has moved from a largely theoretical field to a practical one, with a wide range of applications across industries.

Despite an increasing interest in AI in the construction industry, a gap remains between the potential the technology holds and its actual implementation at scale; there appears to be more hype than practical application.

Previous research has extensively explored the technical development of AI systems for specific areas of application, but more research is needed on the application of these systems in the construction context. More research on system design is necessary, and roadmaps and methodologies on how this can be done in practice are needed. This thesis explores the thematic intersection between the topics of project management, sustainability, and AI – an intersection that, until now, has remained relatively unexplored. Bridging the research gap is believed to help unlock the potential that AI holds for the construction industry.

The thesis addresses the following Research Questions (RQs):

- RQ1: What is the current state of the field, and what are the main challenges the field is facing?
- RQ2: What are the main dimensions of AI development and deployment in a construction context?
- RQ3: How can industry actors move from ambition to practice – starting today?

The work presented in this thesis is an extended summary of the research activities carried out throughout the PhD project period. The thesis is built on six studies and the resulting papers.

Paper I found that the biggest knowledge gap in the field is related to the practical implementation of AI technologies, and the implications related to the scalability and robustness of these technologies. Paper II proposed a set of effective AI-powered measures for waste reduction on construction sites and outlined relevant practical implications. The study defined a possible approach for developing a holistic implementation framework. Paper III illustrated how meaningful AI-based analyses can be conducted for low-resolution construction data. In Paper IV, the main barriers related to effective data management in the construction context were identified. Paper V explored how AI systems can be implemented as an integral part of existing processes, rather than an add-on. In Paper VI, AI proficiency and maturity among AI system developers, users, and implementers were assessed, and a system level implementation framework proposed.

Current state and main challenges

The construction industry is widely considered less digitalised compared to other industries. Still, progress is demonstrated for construction by both researchers and industry actors.

On the system level, a wide range of tools have been developed and successfully applied. However, few report on the use of AI beyond pilots and Proof of Concepts (PoCs); most research is focused on the potential use or technical development of AI models. On the project level, in-house or commercially available tools have been applied to one or more activities and processes. Findings indicate that this is generally done in isolation, meaning that next to no changes are made to how the project is planned or executed. This, in turn, means that the AI system simply becomes an add-on. On the organisational level, many actors are talking about digitalisation and utilisation of AI. Yet, similarly to on the project level, required infrastructure is rarely established outside the group or department responsible for the development.

Challenges found across the system, project, and organisation levels are uneven application of resources to problems; lack of data and metadata; lack of anchoring in strategy; application work becoming too resource intensive; gaps between the academic field and the industry; limited transferability; lack of contextualisation; and fragmentation.

Main dimensions of implementation and integration

Findings and discussions uncovered seven main dimensions of implementation and integration of AI systems and tools in the construction context. The dimensions are strongly interrelated and interdependent. The dimensions

are identified as data management; characteristics of the AI model; deployment; monitoring and maintenance; the human factor; organisational structures, roles, and responsibilities; and ethical considerations.

Proposed frameworks

The proposed system level framework is built to facilitate streamlined integration with existing processes and activities. The framework consists of seven steps: (S1) identifying the problem, (S2) assessment of feasibility, (S3) data collection, (S4) data pre-processing, (S5) model development, (S6) integration, and (S7) maintenance and monitoring. Fifteen sub-steps are defined, to guide the development and implementation process.

The framework for the project level is based on the NS 3467:2023 *Stages and deliverables in the life cycle of construction works* (Standard Norge, 2023) and outlines relevant areas of application, stakeholder management activities, and elements of infrastructure for each of the defined project phases.

On the organisation level, establishing data warehouses is identified as the most effective way to facilitate sustainable development and deployment of AI – both on the system and project level. Data fetched from the data warehouse can be used for analytics, data mining, reports, and system development.

The main contributions of the thesis can be summarised as follows:

- Bridging a gap between the fields of project management, AI, and sustainability.
- Empirical validation and detailed descriptions of practical implications as a supplement to conceptual theory.
- Providing a comprehensive and practically oriented overview of the current state of the field and identify the eight perceived main challenges to hinder effective and efficient application.
- Identifying the main dimensions of AI system development and implementation.
- Proposing standardised frameworks for the system, project, and organisation level. The frameworks are expected to contribute to increasing transparency, collaboration between stakeholders and to ultimately increase the sustainability of the process of development and implementation.

For academics, the thesis provides a well-defined starting point with many opportunities for future research. The thesis provides empirical validation of findings in a field that has previously been lacking empirical data and research on implementation and performance beyond small-scale testing and PoCs.

Practitioners can gain a deeper understanding of the potential and limitations within their own practices to take the first of many steps towards effective application of AI.

Abbreviations

AI	Artificial Intelligence
ANN	Artificial Neural Network
BIM	Building Information Modelling
DF	Data Frame
DL	Deep Learning
DPD	Data Protection Directive
EA	Evolutionary Algorithm
ECTS	European Credit Transfer System
EDA	Exploratory Data Analysis
EU	European Union
GA	Genetic Algorithm
GDPR	General Data Protection Regulation
IoT	Internet of Things
KBS	Knowledge-Based System
KBT	Knowledge-Based Technique
ML	Machine Learning
NLG	Natural Language Generation
NLP	Natural Language Processing
NSD	Norwegian Centre for Research Data (Norsk Senter for Forskningsdata)
NTNU	Norwegian University of Science and Technology
PMI	Project Management Institute
PoC	Proof-of-Concept
QA	Quality Assurance
RBS	Rule-Based System
RFC	Random Forest Classifier
RIBA	Royal Institute of British Architects
SDG	Sustainable Development Goals

Declaration of Authorship

ID	Paper	Declaration of authorship
Paper I	Bang, S. and Olsson, N. (2022) «Artificial Intelligence in Construction Projects: A Systematic Scoping Review» Published in Journal of Engineering, Project, and Production Management, 12(3), 224-238. DOI: 10.32738/JEPPM-2022-0021	The PhD candidate is first author. The candidate collected and analysed all data and wrote more than 90% of the paper.
Paper II	Bang, S. and Andersen, B. (2022) «Utilising Artificial Intelligence in Construction Site Waste Reduction» Published in Journal of Engineering, Project, and Production Management, 12(3), 239-249. DOI: 10.32738/JEPPM-2022-0022	The PhD candidate is first author. The candidate collected all data through 32 interviews, a project visit, participation in chosen seminars, an analysis of 161 construction projects, and a questionnaire. The candidate performed data analyses and wrote more than 90% of the paper. The PhD candidate wrote more than 90% of the paper.
Paper III	Bang, S., Aarvold, M. O., Hartvig, W. J., Olsson, N. O. E. and Rauzy, A. (2022) «Application of Machine Learning to Limited Datasets: Prediction of Project Success» Published in Journal of Information Technology in Construction, 27, 732-755. DOI: 10.36680/j.itcon.2022.036	The PhD candidate is first author. The paper is based on the works of the second and third authors, conducted through their master thesis in the spring of 2020. The PhD candidate wrote more than 85% of the paper.
Paper IV	Bellini, A. and Bang, S. (2022) «Barriers and Prospects for Data Management as an Enabler of Circular Economy in the Built Environment: An Exploratory Study» Presented on SBEfin 2022 – Emerging Concepts for Sustainable Built Environments 23-25 November 2022 Helsinki	The PhD candidate is second author. The PhD candidate participated in and conducted all 18 interviews, coding, analysis, and wrote 40% of the paper.

Paper V	Bang, S., Aase, P., Egeland, M., and Klakegg, O. J. (2023) «Construction Project Quality Assurance with AI-powered 3D Laser Scanning and BIM: A Standardised Framework» Revision submitted to Construction Innovation	The PhD candidate is first author. The paper is based on the works of the second and third authors, conducted through their master thesis in the spring of 2022. The PhD candidate wrote more than 85% of the paper.
Paper VI	Bang, S. (2023) «Sustainable Implementation of AI in Construction: Challenges and Opportunities for Data Management» Submitted to Buildings	The PhD candidate is the only author. The candidate collected all data through 36 interviews, a document study, a site visit, and 14 system demos. The PhD candidate wrote 100% of the paper.

Table of Contents

List of Figures

List of Tables

1 Introduction

This chapter presents the background, context, and purpose of the research; an outline of the research process; the resulting papers; and the structure of the thesis.

1.1 Background

Recent years have witnessed a significant shift in the field of Artificial Intelligence (AI), with the emergence of new techniques, algorithms, and tools that have enhanced the way machines learn, reason, and interact with the real world (Boje et al., 2020; Darko et al., 2020). Rapid advances have led to breakthroughs in speech recognition, computer vision, Natural Language Processing (NLP), Natural Language Generation (NLG), and cognitive computing. As a result, AI has moved from a largely theoretical field (Pylyshyn, 1980; Russell, 1997; Russel and Norvig, 2010) to a practical one, with a wide range of applications across industries, including healthcare (Amann et al., 2020; Qadri et al., 2020), finance (Mhlanga, 2020; Goodell et al., 2021), transportation (Ai et al., 2020; Singh et al., 2021), education (Chen et al., 2020; Zhang and Aslan, 2021) manufacturing (Kamble et al., 2020; Çinar et al., 2020), and construction (Xiao et al., 2018; Pan and Zhang, 2021).

Data science is a field where no single component is new, but combinations of components are new. The same holds true for AI. Due to a change in the underlying economics that enable technological advances, data storage has become cheaper, and processing power has increased exponentially in the last decade (Kuniavsky, 2010). At the same time, the cost of older technology decreases drastically as new technology develops without losing its ability to process information. This development is illustrated in Figure 1-1. More recently, rapid developments in and expansion of theoretical foundations and empirical knowledge have contributed to the advancement of the field (Burgess, 2018; Zuhang et al., 2020). Theoretical breakthroughs in one domain have helped to inform subsequent breakthroughs in other domains. Advances have facilitated the generation, availability, and accessibility of new data that were previously unattainable (Burgess, 2018; Duan et al., 2019), supported by the concepts of Big Data and the Internet of Things (IoT) (Yaqoob et al., 2016; Allam and Dhunny, 2019). This is especially significant for the construction context, as data access is identified as a key resource for driving the transformation of construction management methodology (Xu et al., 2022).

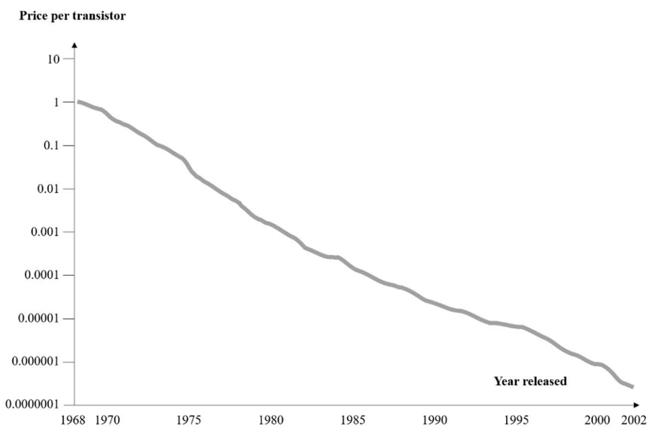


Figure 1-1. Per transistor cost of CPUs, 1968-2002 (Kuniavsky, 2010).

The concept of AI is broad, but it can be defined as a system or structure with 'the ability to perform tasks in complex environments without constant guidance by a user' (University of Helsinki, 2018). AI is a highly interdisciplinary field comprising elements from computer science, logic, mathematics, psychology, and neuroscience (Tørresen, 2013; Tidemann, 2023). In the construction context, AI systems can be grouped into four categories: Machine Learning (ML) techniques, Knowledge-Based Techniques (KBTs), Evolutionary Algorithms (EAs), and hybrid systems (Akinade, 2017).

In recent years, AI has played an increasingly important role in the construction industry among academics and practitioners (Xiao et al., 2018; Darko et al., 2020). Areas of application include estimation and cost control (Juszczyk, 2017); logistics, planning, and scheduling (de Soto et al., 2017; Cheng and Hoang, 2018); and project performance and success estimation (Mirahadi and Zayed, 2016; Jaber et al., 2019). AI has demonstrated the ability to increase sustainability in the construction industry by improving resource efficiency and optimising the use of materials and resources (Camacho et al., 2018; Bilal et al., 2019); facilitating resource-effective off-site construction (Wang et al., 2020); optimisation of building and construction design (Hsu et al., 2020); and improving on-site safety (Poh et al., 2018).

Despite an increasing interest in AI in the construction industry, the adoption of the technology is still in early stages (Momade et al., 2021), and the industry is widely considered among the least digitised industries in the world (Abioye et al., 2021).

The construction industry has a significant impact on both the environment and society. Today, the industry accounts for nearly 40% of worldwide energy consumption and energy-related gas emissions (Global Alliance for Buildings and Construction, 2017), and the need for more environmentally sustainable solutions is growing rapidly. Furthermore, construction activities contribute substantially to the social economy (Pan and Zhang, 2021). Despite its economic importance, the industry is traditionally considered less productive (Todsen, 2018; Abioye et al., 2021), leading to a waste of human, material, and financial resources (Pan and Zhang, 2021). Construction projects struggle to maintain productivity and, consequently, struggle to deliver on time, cost, and quality (Goralski and Tan, 2020; Abioye et al., 2021; Pan and Zhang, 2021).

Project management is the main tool for implementing the goals of an organisation and a project, and good project management is therefore vital for project success (Pinto and Prescott, 1988). Achieving project success in the construction context requires specialised skills and expertise due to the dynamic environments the projects operate within, increasing complexity and uncertainty (Pan and Zhang, 2021).

A significant potential to increase productivity and sustainability in projects lies in the utilisation of AI (Becqué et al., 2016; Mejlænder-Larsen, 2019; Goralski and Tan, 2020; Nishant et al., 2020; Feroz et al., 2021; Pan and Zhang, 2021). To fully utilise the potential that AI systems hold, and to do so sustainably, organisations need a strategic approach beyond simply applying a tool (Goralski and Tan, 2020). This means that careful planning and collaboration will be necessary. Establishing and maintaining public trust in AI technologies will depend on inclusive, transparent, and agile governance (Abioye et al., 2021). The infrastructure surrounding AI tools is generally perceived as an 'add-on' (Hagendorff, 2020). AI on its own is not a strategy, and an AI system should be integrated with existing organisation and project infrastructure. AI can contribute to increasing sustainability; however, it is crucial that the development and implementation of AI-based systems and tools are also sustainable (Hagendorff, 2020; Vinuesa et al., 2020). There is an important distinction between AI for sustainability, and AI being sustainable.

This thesis is important because it contributes to bridging a research gap in the thematic intersection of AI, project management, and sustainability in the construction context. Further exploration of this intersection is believed to enable actors to move effectively from ambition to practice.

This thesis addresses a research gap that can unlock the potential that AI holds for the construction industry, and ultimately increase social, environmental, and economic sustainability (Nishant et al., 2020; Pan and Zhang, 2021). Research focusing on the practical application of AI is scarce, and research in this area could lead to valuable contributions on both organisation and project levels – and for society in its entirety, due to significant savings for society through improved project performance.

Although the topic of AI in construction has received significant attention, the majority of existing literature is concerned with the technical development of AI systems for specific areas of application (Ilter and Dikbas, 2009; Martínez and Fernández-Rodríguez, 2015; Juszczyk, 2017; Basaif and Alashwal, 2018), and more systematic and systemic research is needed on the application of these tools in the construction management context (Darko et al., 2020; Nishant et al., 2020; Xu et al., 2022). Previous research has indicated the potential for AI systems throughout the entire project lifecycle (Pan and Zhang, 2021). More research on system design is needed (Xu et al., 2022), and roadmaps and methodologies should be developed to determine how this can be done in practice (Darko et al., 2020). Holistic frameworks facilitating collaboration between stakeholders must be established to fully benefit from AI and minimise its associated risks (Goralski and Tan, 2020), and more research is needed.

The research findings of this thesis should be of interest to both researchers and practitioners who are contemplating a shift from traditional project management methods to methods supported by AI-based tools, so that they can not only achieve increased sustainability, but also to do so in a sustainable way.

1.2 Purpose and research questions

The research conducted in this thesis aims to facilitate the utilisation of AI in construction projects, by obtaining insights into the practical implications of implementation and integration. The purpose of the thesis is to help move the use of AI in the construction industry from ambition and theory into practice. Thus, the overarching objective is to bridge the gap between the theoretical potential of the development and deployment of AI systems in construction, and the practical implementation.

To achieve this, the research objectives (ROs) of this dissertation are as follows:

- RO1: Map previous and current uses of AI in construction projects, and map the main challenges related to effective use.
- RO2: Assess key dimensions of the development and deployment of AI systems in construction.
- RO3: Provide a framework for industry actors to move from ambition to practice, on a system, project, and organisation level.

To provide a holistic overview of the opportunities and challenges that lie within the increased use of AI-based tools, the thesis maps and assesses previous and ongoing initiatives in research and industry, both nationally and internationally. Furthermore, by examining the lessons learned in previous industry initiatives, as well as the conceptual state-of-the-art, the thesis provides an understanding of practical implications.

The thesis addresses the following research questions (RQs):

- RQ1: What is the current state of the field, and what are the main challenges the field is facing?
- RQ2: What are the distinct stages and components involved in the development and deployment of AI systems in the construction context?
- RQ3: How can identified challenges and dimensions be translated into actionable strategies on the system, project, and organization level?

1.3 Research scope

The objective of this thesis was to explore the intersection between the domains of AI, project management, and sustainability in the construction context. The scope is illustrated in Figure 1-2.

In essence, the thesis wants to explore how effective use of AI from a project management perspective can be done sustainably, to improve sustainability in construction projects. Importantly, the emphasis on project management functions did not exclude other aspects of construction projects in their entirety; rather, the thesis has intended to adopt a project management perspective on construction project delivery and outcomes. To limit the scope, strictly technical aspects traditionally related to construction engineering functions were omitted; however, due to the inherent mutual interdependence of construction functions it is essential to provide contextualised insights. The topic is explored on the system level; on the project level, for the entire project, through all phases; and on the organisation level. To study the practical application of AI, theoretical findings are applied to relevant use cases.

The thesis touches upon three very broad topics, so it became necessary to limit the scope of the studies and the whole thesis by defining a set of criteria for limitations and exclusions. It was decided to focus on the intersections between the three defined topics; more specifically it was decided to focus on the intersection between technology, process, and people (for the AI dimension) and the three pillars of environmental, economic, and social sustainability (for the sustainability dimension). As one touches upon one dimension, one does usually touch upon one or several other dimensions, and to exclude the other topics entirely was not considered necessary or desirable – but the three domains were chosen as the main focal points for the study.

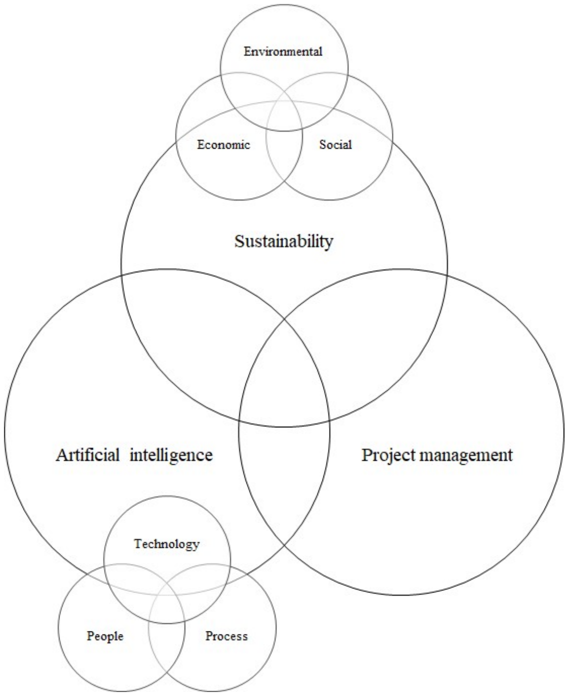


Figure 1-2. Theoretical framework for the thesis.

Investigating each dimension in the context of the other two is expected to provide an enhanced understanding of the thematic intersection between the three for both academics and practitioners.

Each selected area of application was chosen based on an assessment of the following four dimensions:

- Availability of literature
- Previous research
- Ongoing initiatives in the industry
- Available experts in the field

The thesis is expected to reach a diverse audience due to the multi-disciplinary relevance of the work carried out. For instance, the methodological elements developed, and the findings of the studies, may be relevant to individuals working with computer-aided tools, whether from an architecture or an engineering perspective, but also to people working in the research and development of specific technologies.

The limitations of the individual studies are elaborated upon in respective papers. Another limitation of this thesis is the access to relevant data and relevant informants; the novelty of the topic reduced the number of relevant case projects and experts in the specific intersection. The delimitations of this thesis include all studies being built on data and insights from experts working in the Norwegian construction industry, mainly, and Norwegian companies. However, the methodology developed for each study, and the whole thesis, is generalisable for other countries and industries.

1.4 Process and papers

The work presented in this thesis is an extended summary of the research activity carried out.

The research questions have been modified since the beginning of the process, as the continuous literature review and the findings of the individual studies have emerged, providing a better understanding of the topic. The overarching aim and objectives remained the same over the course of the process.

The thesis is built on six studies and the resulting papers, submitted to scientific journals and conferences. As such, the aim of this thesis is to provide a comprehensive summary of the research conducted in each of the studies, as well as the work and conducted research that binds the six individual studies together. This thesis connects and elaborates on the contribution of each of the studies in answering the overall aim and purpose. The studies illustrate the potential and limitations of AI systems and tools to ultimately enhance construction activities effectively and sustainably.

All six papers were submitted to internationally recognised journals or conferences with refereeing schemes. Figure 1-3 illustrates how the individual papers inform the defined research questions.

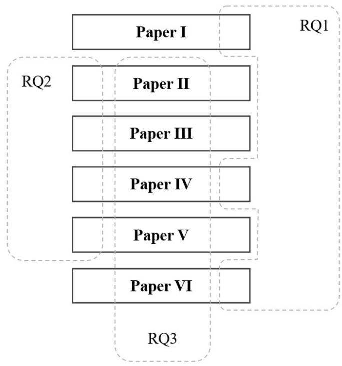


Figure 1-3. Connections between papers and research questions.

1.5 Structure of the thesis

The structure of the thesis is described in Table 1-1.

Chapter 1 provides the introduction to the thesis and the research, describing the background and context of the research. Chapter 2 presents a literature review of relevant research areas resulting from the initial and continuous literature review. Chapter 3 describes the research methods and design according to the research onion framework and reflects on research quality and limitations. In Chapter 4, the research findings of each of the individual studies are presented and discussed. Chapter 5 connects the findings from each of the individual studies and the theoretical foundation. Chapter 6 provides the final conclusions and reflections, answers the research questions as defined, contributions to theory and practice, and potentials for future research.

The finalised papers are attached in the Appendix.

Table 1-1. Overview of thesis structure.

Chapter	Description
Chapter 1: Introduction	• Background • Purpose and research questions • Research scope • Process and papers • Structure of the thesis
Chapter 2: Theoretical framework	• Literature review and presentation of state-of-the-art • Research gap
Chapter 3: Research design	• Description of research design according to the research onion taxonomy • Assessment of design
Chapter 4: Findings from individual papers	• Presentation and discussion of findings from individual studies • Structured according to individual papers

Chapter 5: Discussion	• Presentation and discussion of thesis main findings • Structured according to emerging themes
Chapter 6: Conclusion	• Answers to research questions • Main contributions • Limitations and opportunities for future research • Personal reflections
References	• List of cited literature
Appendices	• Papers I through VI

2 Theoretical framework

This chapter will present the theoretical framework resulting from an initial and continuous literature review of the main thesis topics. Considerations related to the theory and practice of the main topics are presented. The main topics are, as described in the introduction: project management, AI, and sustainability.

Research is lacking in the intersection between the three, but each of the three fields are thoroughly explored. Figure 2-1 describes the basis of the theoretical framework. Some main characteristics from the field of project management that are of importance for the research conducted in this thesis are presented. Concepts related to change management on the organisational level and construction management on the project level are explored. The concept of AI and a categorisation framework for different types of AI in the construction context are introduced, categorising AI-based techniques and systems as ML, Knowledge-Based Systems (KBSs), evolutionary systems, or hybrid systems. The chapter further discusses some key considerations and practical implications of utilising AI according to the technology, process, and people perspectives. Some implications of economic, environmental, and social sustainability in projects and for the use of AI are discussed.

In the final section of the chapter, a research gap is identified based on the findings from the literature review.

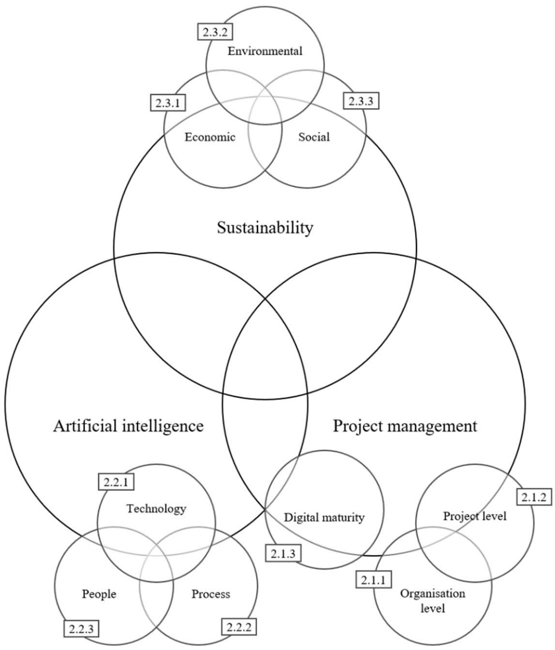


Figure 2-1. Basis for the theoretical framework.

2.1 Project management

The Project Management Institute (PMI) defines a project as 'a temporary endeavour undertaken to create a unique product, service, or result' (PMI, 2021). For the purpose of this thesis, 'project management' will refer to the management of projects both on the organisational level, and on the construction project level.

Every project is undertaken for a specific purpose, and the ultimate goal of every project is value creation (Johansen et al., 2019). The primary objective in project management is to deliver a product or service that meets or exceeds a set of predefined requirements and expectations within time, cost, and quality constraints. The three dimensions of time, cost, and quality are traditionally used to measure and indicate project success, and these are commonly referred to as 'the iron triangle' (Rezvani and Khosravi, 2018).

Projects are normally divided into phases. PMI (2021) outlines five phases of a project: definition (initiation), design (planning), development (execution), deployment (monitoring and controlling), and departure (closing). The five phases are illustrated in Figure 2-2. More specific frameworks are developed, tailored to certain national industries. Among these are The Royal Institute of British Architects (RIBA) Plan of Work in the UK construction industry, and the NS 3467:2023 Stages and deliverables in the life cycle of construction works in the Norwegian construction industry (Standard Norge, 2023).

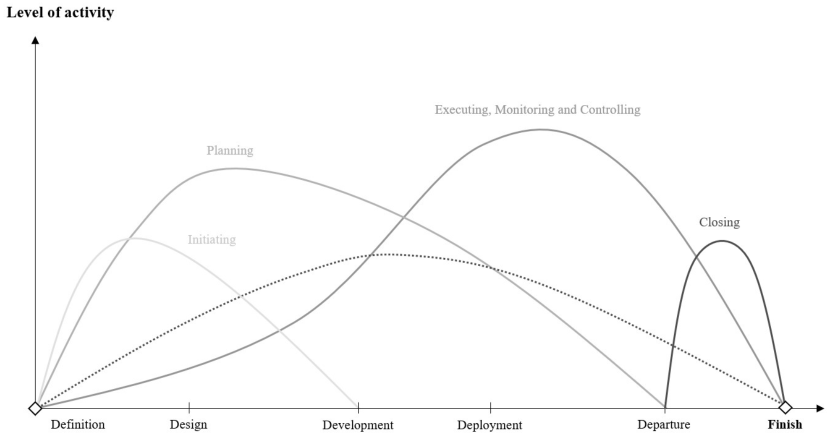


Figure 2-2. Five phases of a project (PMI, 2021).

The field of project management has evolved significantly over the years, with new methodologies, tools, and technologies emerging. The approach to project management can strongly depend on the characteristics of the project in question (Hussein, 2016).

2.1.1 Organisation level

For effective digital transformation, innovation on the organisation level is equally important as technological innovation (Xiahou et al., 2022).

Project management is a key component in change management. Change management refers to the tools, processes, and techniques used to manage and facilitate change within an organisation (Cameron and Green, 2015). Technologies, requirements, and industries are changing rapidly, meaning that organisations must be able to utilise these new technologies (Burgess, 2018). In a 'change team', team members should be gathered from representative parts of the organisation (Cameron and Green, 2015).

The Lewin Model of Change (Lewin, 1951) is widely used in the change management context, and involves three stages: unfreeze, move (or change), and refreeze (Cameron and Green, 2015), and is intended to facilitate an iterative change process (Burnes, 2019). The first stage, unfreezing, involves preparing for the desired change; the second stage implements the desired change; lastly, the refreezing stage solidifies the desired change as new behaviours are reinforced and integrated. Figure 2-3 shows the iterative Lewin Model of Change.

Hao et al. (2008) propose a modified model specifically for the construction context: (1) identify changes, (2) evaluate and propose changes, (3) approve changes, (4) implement changes, (5) analyse changes.

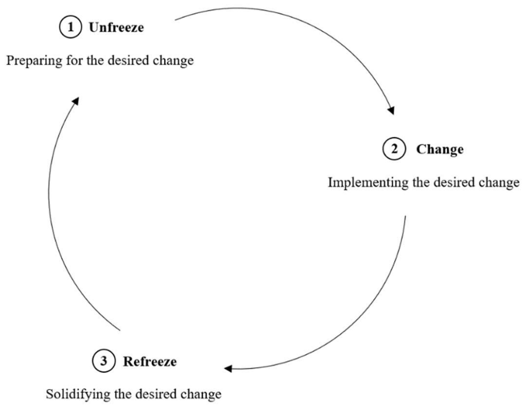


Figure 2-3. Lewin model of change (Lewin, 1951).

2.1.2 Project level

Construction management is a subfield of project management, which focuses on the planning and execution of construction projects. The construction industry is one of the largest sectors, nationally and internationally, and has a significant impact on environment and economy (Abioye, 2021). Construction projects are susceptible to change due to their complexity, duration, magnitude, number of stakeholders, and reliance on external factors. Changes in design, scope, materials, and regulations are common, and can have a significant impact on cost, schedule, and quality (Hao et al., 2008; Pan and Zhang, 2021).

Specific frameworks are developed from the PMI framework and tailored to certain national industries. For instance, the RIBA Plan of Work in the UK construction industry, or the NS 3467:2023 *Stages and deliverables in the life cycle of construction works* in the Norwegian construction industry. Figure 2-4 shows the relationship between the three frameworks.

Neste Steg (2015)	**1. Strategic definition**	**2. Program and concept development**	**3. Development of selected concept**	**4. Detailed design**	**5. Production and delivery**	**6. Handover and commissioning**	**7. Use and management**	**8. Termination**
	Identifying needs, goals, ambitions, and business constraints.	Defining requirements, needs, and constraints for the project. Clarifying overarching principles and concepts. Assessing alternatives and feasibility.	Clarification of consequences. Concretizing the project in relation to requirements, needs, and constraints for implementation.	Necessary detailing and concretization of the project to ensure that requirements and needs are addressed in the production basis.	Executing the project according to the production basis.	Ensuring that the project has been completed according to the order and preparing for use.	Ensuring that the project meets the business's strategic definition and ensuring necessary adaptations and development throughout the building's lifespan.	Ensuring that the building is terminated (sale, business termination, or demolition) in the most sustainable way possible.
RIBA Plan of Work (2013)	**0. Strategic definition**	**1. Preparation and Briefing**	**2. Concept design**	**3. Spatial Coordination & 4. Technical design**	**5. Manufacturing and Construction**	**6. Handover**	**7. Use**	
PMI	**Feasibility study**	**Development of concepts**	**Pre-engineering**	**Detailed engineering**	**Construction**	**Completion**	**Operation**	

Figure 2-4. Project phase frameworks.

According to the NS 3467:2023 2023 *Stages and deliverables in the life cycle of construction works*, phase one (P1) Strategic definition includes identifying needs, goals, ambitions, and business constraints (Standard Norge, 2023). The phase consists of prioritisation of markets, projects, and implementation capabilities, as well as market assessments and evaluations. Deliverables from this phase are market assessments and evaluations to identify potential opportunities and challenges. Phase two (P2) Program and concept development includes the development of initial project plans and frameworks and the establishment of project requirements and objectives. At the conclusion of this phase, preliminary management documents describing the project objectives and requirements are developed. In phase three (P3) Development of selected concept, project plans and frameworks are refined and verified, and the development of detailed construction plans and specifications is initiated. Deliverables are preliminary construction plans, specifications, and design documents. Phase four (P4) Detailed design includes necessary detailing and concretisation of the project, clarification of project requirements and construction methods. It also includes the mobilisation of construction teams and resources. At the end of the phase, the work is summarised in construction and production documents. Phase five (P5) Production and delivery may be the most compound phase of the framework, comprising a wide range of activities, including: management of construction, production, and delivery teams; control of physical construction and installation; delivery of project outcomes according to defined objectives and frameworks; and systematic completion and closeout of the project. Deliverables include the physical construction and installation outcomes, along with documentation and performance measures. The main goal of phase six (P6) Handover and commissioning is to ensure that the project has been completed according to the order. This involves the implementation of necessary corrective actions for defects or deficiencies, and the finalisation of contracts and agreements. The phase concludes with final process evaluations and settlements. Phase seven (P7) Use and management involves optimisation of project operations and maintenance, alongside testing and evaluation of project performance according to contracts. The main deliverable from this phase is completion of warranty responsibilities. In the final phase, (P8) Termination, the main objective is to ensure that the building is terminated in the most sustainable way. This can include the disposal of property or assets and the conclusion of contractual obligations. At the end of the phase, complete documentation for the disposal or transfer of assets is compiled.

Recent developments show a trend towards larger and more complex construction projects (Whyte et al., 2016; Fischer et al., 2017). This is likely to increase the need for building and defining more effective, efficient, and sustainable processes and frameworks, increasing interaction between project actors across the value chain and enabling productive and constructive exchange of information. Previous research indicates the potential for AI systems throughout the entire project lifecycle (Pan and Zhang, 2021).

The construction industry is under pressure to reduce project delivery time and costs, while maintaining quality in an environment that is becoming increasingly complex. For a long time, the industry has been considered less digitally mature compared to other industries, such as manufacturing, finance, and healthcare; however, the maturity level is now seen to indicate the progression towards an increased capability to evaluate and implement digital technologies (Wernicke et al., 2021).

2.1.3 Digital maturity

Adeptly managing digitalisation in projects is becoming increasingly important in order to improve efficiency and sustainability, ensure project success, and stay competitive (Aliu et al., 2023).

The Adoption Innovation Curve is a model used to represent the rate at which new technologies are adopted by a given population over time (Rogers, 1995). The Adoption Innovation Curve places adopters into one of five categories: (1) innovators, (2) early adopters, (3) early majority, (4) late majority, and (5) laggards. The Adoption Innovation Curve is illustrated in Figure 2-5. Rogers (1995) notes that those who adopt early, groups (1) through (3) can be characterised as more 'venturesome' and are less risk averse. Late adopters are risk averse, possibly due to being less able to financially withstand a failure (Rogers, 1995).

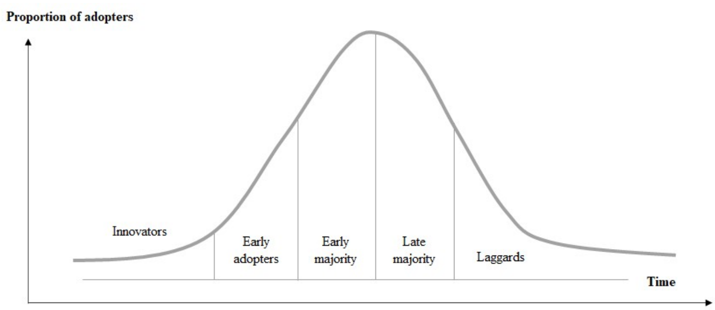


Figure 2-5. Adoption Innovation Curve (Rogers, 1995).

Actors in the construction industry are often thought to be 'late majority' and 'laggards' in the adoption of digital tools (Ayinla and Aadamu, 2018). Bosch-Sijtsema et al. (2021) assessed 11 digital technologies portrayed in future trend reports and hype curves for the construction industry, and this assessment found that the construction industry is currently behind the traditional Gartner Hype Cycle of emerging technologies, when compared with other industries. The Gartner Hype Cycle (Fenn, 1995) is a graphical representation of maturity, adoption, and application of emerging technologies in any given environment or industry. The Hype Cycle is illustrated in Figure 2-6.

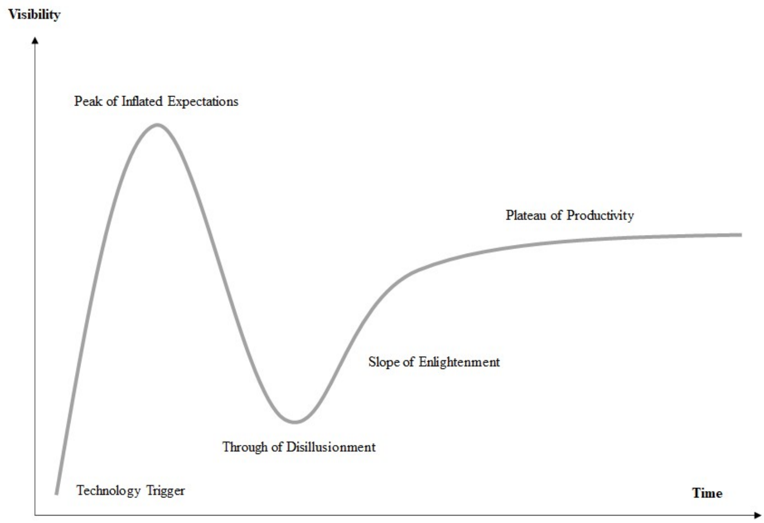


Figure 2-6. The Gartner Hype Cycle (Fenn, 1995).

Bosch-Sijtsema et al. (2021) note that the construction industry is currently behind the traditional Gartner Hype Curves, and they define four 'zones' for digital technologies in the construction industry: confusion, excitement, experimentation, and integration. In the 2022 Gartner Hype Cycle, accelerated automation of AI was identified as one of three main emerging themes (Gartner, 2023).

The adoption of digital technologies, and specifically AI-powered tools, is believed to hold the potential to enhance the construction industry, and how the industry approaches challenges related to sustainability, health and safety, risk assessment, planning and scheduling, strategy, project performance, cost control, and calculations for operations and lifecycles (Hossain and Nadeem, 2019). However, assessments of the construction industry status suggest that the industry has yet to achieve the desired level of maturity.

2.2 Artificial intelligence

The concept of AI is broad; a wide range of definitions exist and have evolved over time.

The term AI was originally coined by Stanford Professor John McCarthy in 1955, as '*the science and engineering of making intelligent machines*' (Stanford University, 2020). McCarthy (2007) elaborated on this definition, describing AI as '*the science and engineering of making intelligent machines, especially intelligent computer programs*' noting that '*it is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable*'. Winston (1992) defines AI as '*the study of the computations that make it possible to perceive, reason, and act*'. Similarly, Russell and Norvig (2010) present four categories of AI definitions. The four categories base the definition of AI on the ability of a system to think humanly, think rationally, act humanly, or act rationally, noting that '*historically, all four approaches to AI have been followed*'. Recent definitions also emphasise the ability of machines themselves to learn, rather than just mimicking human behaviour (Stanford University, 2020). The University of Helsinki published the course Elements of AI in 2018 in an effort to make AI more accessible and comprehensible for the general public, defining AI as a system or a structure that has '*the ability to perform tasks in complex environments without constant guidance by a user*' (University of Helsinki, 2018).

One single definition of AI is currently lacking. The field of AI is constantly evolving, and different industries and environments refer to different sets of definitions. As the boundaries of AI technologies continues to expand, so does the diversity of its applications.

The field is highly interdisciplinary and is comprised of elements from a wide range of fields, including computer science, logic, mathematics, psychology, and neuroscience (Tørresen, 2013; Tidemann, 2023).

As mentioned in the introduction, the technology-process-people framework was used as the basis for the AI dimension. The framework is widely used for analysing and improving organisation and project performance, especially in the context of technology-driven initiatives (Gu and London, 2010; Forbes and Ahmed, 2020). The three perspectives of the framework and the intersections between them are illustrated in Figure 2-7.

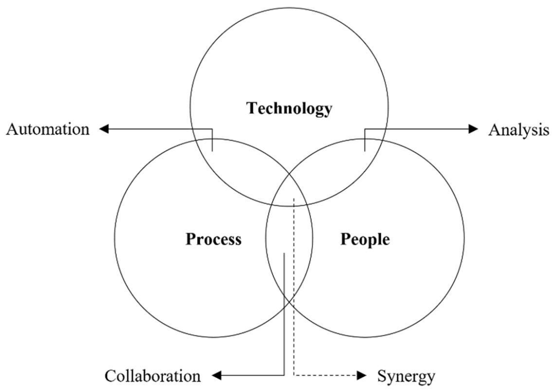


Figure 2-7. The three perspectives of the technology-process-people framework.

2.2.1 Technology

The technology perspective is related to the tools, systems, and technical infrastructure used within a project or organisation. Technology should be designed with the user in mind (Barlett-Bragg, 2017), and to enable streamlined integration with existing processes.

AI technology is believed to facilitate an increase in productivity throughout the entire construction project lifecycle, ultimately improving the sustainability of environmental, economic, and social factors (Blanco et al., 2018; Oprach et al., 2019; Wang et al., 2020). The use of AI has increased in the field of construction engineering and management in recent years (Xiao et al., 2018), mainly due to the potential it holds for the industry.

AI is a part of a bigger digital shift reaching construction sites, more commonly referred to as Construction 4.0. Technologies contained within the framework of Construction 4.0 include a wide range of areas of application and groups (Forcael et al., 2020; Perrier et al., 2020; Sawhney et al., 2020), such as cloud-based systems, Building Information Modelling (BIM), sensors, robotics and automation, smart equipment, IoT, Big Data and analytics, blockchain, additive manufacturing, etcetera.

IoT refers to the interconnection of physical objects through embedded sensors and network connectivity, allowing for real-time data collection, analysis, and control (Al-Fuqaha et al., 2015). IoT is expected to contribute to bridge diverse technologies to ultimately enable new applications. Big Data refers to the vast amounts of both structured and unstructured data that are generated by various sources (Chen et al., 2014). Compared to traditional datasets, Big Data is typically mainly constituted by masses of unstructured data. It is believed that Big Data will have large social and economic impacts and contribute to cross fusion of science (Chen et al., 2014).

AI already has, and has had, multiple areas of application in the construction industry, including estimation and cost control (Cheng et al., 2009; Cheng et al., 2015; Shin, 2015; Juszczyk, 2017; Elmousalami, 2019; Yaqubi and Salhotra, 2019; Juszczyk et al., 2019; Juszczyk and Lesniak, 2019; Bilal and Oyedele, 2020; Cheng et al., 2020; Juszczyk, 2020); logistics, planning, and scheduling (Golparvar-Fard et al., 2015; Podolski, 2016; Xing et al., 2016; de Soto et al., 2017; Camacho et al., 2018; Cheng and Hoang, 2018; Dawood et al., 2019; Hu and Castro-Lacouture, 2019); strategy (Mousavi et al., 2015; Kog and Yaman, 2016; Sharafi et al., 2018; Taherdoost and

Brard, 2019; Fallahpour et al., 2020); health and safety (Ayhan and Tokdemir, 2018; Goh et al., 2018; Poh et al., 2018; Han et al., 2020; Nnaji and Karakhan, 2020; Xu et al., 2020); project performance and success estimation (Gudauskas et al., 2015; Hajdasz, 2015; Mirahadi and Zayed, 2016; Hanna et al., 2018; Jaber et al., 2019; Vickranth et al., 2019; Nguyen et al., 2020); design optimisation (Liu et al., 2015; Rodriguez-Trejo et al., 2017); and risk and safety monitoring and management (Pruvost and Scherer, 2017; Samantra et al., 2017; Zou et al., 2017; Goh et al., 2018; Poh et al., 2018; Basaif et al., 2020; Han et al., 2020; Xu et al., 2020), among others.

In the construction context, AI systems can be grouped into four categories (Akinade, 2017): ML, KBTs, EAs, and hybrid systems.

Machine learning

ML algorithms can learn from data (Tidemann, 2023). ML is a term that is used for a range of techniques, deducing rules from the datasets the system is trained on. The techniques are based on statistical models, and the aim of the systems is to find patterns in large amounts of data, so that the machine can learn (Tidemann and Elster, 2022). ML techniques are commonly divided in three subcategories: supervised learning, unsupervised learning, and reinforcement learning (Russell and Norvig, 2010).

Supervised learning teaches the system, the machine, to understand that a certain input can predict a certain output (Russell and Norvig, 2010). It is the most common form of ML (Tidemann, 2023). In supervised learning, labelled datasets are used to train algorithms; the input data is labelled with corresponding outputs or target variables (Russell and Norvig, 2010). The goal is to predict the output for new, unseen data, after learning to identify patterns and relationships between input and output variables. Tidemann and Elster (2022) use the example of distinguishing dogs from birds. Dogs have four legs, while birds have just two. In addition, birds have wings, and dogs do not. When presented with a picture of a four-legged animal, the model identifies this as a dog. If the animal in the picture has only one pair of legs and a pair of wings, it is likely to be a bird. This is an example of a classification challenge (Tidemann and Elster, 2022). If the aim of the model is to estimate the size of the animal, it would be a regression challenge.

In unsupervised learning, there are no defined labels or outputs. The task is for the algorithm itself to identify patterns or structures in the input data (Tidemann and Elster, 2022). Clustering is the detection of potentially useful clusters of input examples and is the most common unsupervised learning task (Russell and Norvig, 2010). From this, the algorithm learns to identify anomalies or outliers. This ability makes the unsupervised approach good for anomaly detection or dimensionality reduction. Data visualisation can be considered as a form of unsupervised learning.

Reinforcement learning is commonly used in cases where a system is required to operate in an environment that provides feedback about good or bad choices, with some delay (University of Helsinki, 2018). The model interacts with the environment and receives feedback in the form of rewards or penalties. The form these might take depends on the environment. Russell and Norvig (2010) use the example of a system playing chess. A win is rewarded with two points, indicating that the system made good choices. It is up to the system itself to determine the actions that ultimately led to this reinforcement (Tidemann and Elster, 2022). The strength of reinforcement learning lies within scenarios where there are many ways to reach a desired goal.

In practice, the three types might not be as easy to distinguish (Russell and Norvig, 2010); an example of this is semi-supervised learning (University of Helsinki, 2018), that is partly supervised and partly unsupervised.

Artificial Neural Networks (ANNs) are a type of algorithm that can be used for ML. ANNs mimic the human brain, and are a collection of units, or neurons, that receive and transmit signals (University of Helsinki, 2018). The properties of the neural network are determined by the characteristics and topology of these neurons (Russell and Norvig, 2010). Deep Learning (DL) is a subset of ML based on ANNs with multiple layers (Tidemann, 2023). With every layer, the computational capabilities of the system increase. The increased capabilities allow the network to learn more complex structures with realistic amounts of data (University of Helsinki, 2018). DL can be supervised, unsupervised, or reinforced.

The main limitation of ML techniques is the lack of technical justification for results and decisions (Akinade, 2017), as ML algorithms can act like ‘black boxes’ (Abioye et al., 2021).

Figure 2-8 summarises the relationship between the concepts of AI, ML and DL.

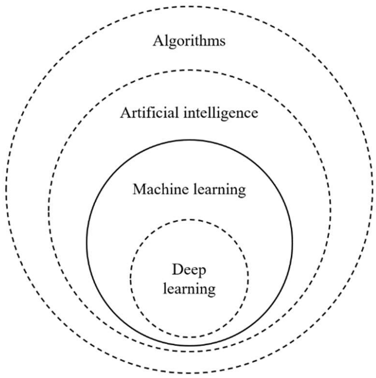


Figure 2-8. The relationship between AI, ML, and DL.

In the construction industry, ANNs, support vector machines, and fuzzy logic seem to be the most widely used ML techniques (Irani and Kamal, 2014; Akinade, 2017).

In the construction context, ML algorithms have been used for profit margin estimation (Bilal and Oyedele, 2020), construction site accident classification (Cheng et al., 2020), building life cycle assessments (Hong et al., 2020), clash relevance prediction (Hu and Castro-Lacouture, 2019), automated progress monitoring (Golparvar-Fard et al., 2015), on-demand site monitoring (Rahimian et al., 2020), automated classification of documents (Caldas et al., 2002; Fang et al., 2020; Hassan and Le, 2020), estimation of construction cost (Cheng and Hoang, 2014), and delay risk reduction (Gondia et al., 2020), among others.

Knowledge-based systems

KBSs mimic the problem-solving expertise of humans to identify solutions to complex problems in very specific domains (Sowa, 2000). Frequently utilised KBS approaches include expert systems, Rule-Based Systems (RBSs), case-based reasoning, and semantic networks (Akinade, 2017).

Expert systems mainly exhibit pre-programmed behaviour (Tidemann, 2023). Expert systems thrive in standardised and predictable environments, such as chess. Rule-based approaches are built on logical RBSs, with an added ‘fudge factor’ to accommodate uncertainty (Russell and Norvig, 2010). Case-based reasoning involves solving new problems by applying solutions to previously encountered problems; this logic is based on the idea that similar problems will have similar solutions.

The strength of KBS lies within the strong explanation abilities they hold (Akinade, 2017; Abioye et al., 2021). Still, they lack the ability to learn and discover knowledge over time.

Evolutionary algorithms

EAs are based on the concept of biological evolution (Russell and Norvig, 2010), and are a form of optimisation algorithm inspired by the process of natural selection. EA techniques optimise factors and possible scenarios to find the most suitable outcome, by generating new solutions over multiple ‘generations’ (Dasgupta and Michalewicz, 1997). EA can cover broad territory, from Genetic Algorithms (GAs) to ant colony optimisation, particle swarm optimisation, and artificial bee colonies (Akinade, 2017).

In the construction context, EA are commonly used for optimisation problems, such as scheduling, resource allocation, and layout design.

Compared to the other groups of techniques, these algorithms require relatively little domain-specific information, and are easy to implement (Akinade, 2017); however, the heuristics are difficult to generalise.

Hybrid systems

Hybrid systems combine two or more AI approaches to maximise the strengths and overcome the weaknesses of individual approaches (Russell and Norvig, 2010). Hybrid systems can be categorised according to architecture as stand-alone, transformational, hierarchical, or integrated (Akinade, 2017). Hybrid systems could be complex to design and implement but allow the construction of synergetic solutions to specific problems.

There appears to be an increase in the application of hybrid models in construction in recent years (Xiao et al., 2018; Momade et al., 2021). This could suggest increased use of more compound systems as the technology and the industry develop, as hybrid systems can solve more complex tasks than any single system (Akinade, 2017).

2.2.2 Process

In the context of AI, the process perspective is related to the way AI systems are implemented and integrated into existing procedures, protocols, and workflows established within an organisation or project. Organisation or project infrastructure must facilitate the effective use of AI to be sustainable long-term (Burgess, 2018; Vinuesa et al., 2020; Xu et al., 2022). There is no doubt that AI in recent years has created massive hype, demonstrated impressive potential, and generated an even more impressive interest in the topic. In practice, there is a wide range of practical implications associated with the implementation of AI-based tools from the process perspective (Wooldridge and Jennings, 1995; Burgess, 2018; Dwivedi et al., 2021).

Some key challenges in the sustainable process perspective are related to data management and governance, and cyber security (Agrafiotis et al., 2018; Al-Ruithe et al., 2018; Burgess, 2018; Ghosh et al., 2018; Abraham et al., 2019; Vinuesa et al., 2020).

In the construction management context, data collection and sharing are among the central process-oriented challenges associated with the increased use of AI (Burgess, 2018; Xu et al., 2022); data is identified as one of the key resources for driving the transformation of construction management methodology (Xu et al., 2022).

Data governance refers to the roles, policies, and frameworks that are put in place to manage the collection, storage, and utilisation of data (Ladley, 2020). In the context of AI, governance refers to the roles, policies, and frameworks that are put in place to manage the development, deployment, and continued use of AI systems. The aim is for AI systems to be utilised ethically, responsibly, and sustainably. AI needs to be supported by the necessary regulatory insight and oversight for AI-based technologies to enable effective and sustainable development and deployment (Burgess, 2018; Vinuesa et al., 2020).

Data governance includes exercising authority and control over the management of data to increase its value and minimise associated costs and risks (Abraham et al., 2019). Al-Ruithe et al. (2018) argue that more disruptive technologies will require more extensive data governance strategies and programs. Abraham et al. (2019) define six dimensions of data governance: governance mechanisms, organisational scope, data scope, domain scope, antecedents, and consequences of data governance.

Al-Ruithe et al. (2018) classify the challenges associated with the implementation of cloud data governance as mainly technological, legal, and business related. Technological challenges include security, privacy and data protection, availability, performance, data classification (caused by the lack of classification frameworks for data based on sensitivity), and data migration (between systems). Legal challenges are related to compliance with regulations, and statutory, regulatory, and legal requirements between industries and jurisdictions. Organisational challenges are related to the characteristics of an organisation, such as top management support, organisation size, and digital maturity (Al-Ruithe et al., 2018; Abraham et al., 2019).

Cyber security measures should be related to all three categories. As technology is rapidly advancing, the threat landscape of cyber-attacks is changing (Agrafiotis et al., 2018). Cyber security aims to protect both devices and services of unauthorised access from within the devices and externally; and to protect the services, hardware resources, information, and data – both in transition and storage (Ghosh et al., 2018). By extension, cyber security can refer both to the security of a system itself and the people involved in the development or deployment of a system. Li (2018) notes that, on one hand, AI technologies and tools can be used to improve cyber security, by constructing smart models for implementing malware classification and intrusion detection. On the other hand, AI systems are likely to face cyber threats themselves. In a field that is ever-changing, new threats emerge just as quickly; cyber security is a field that requires ongoing attention and investment.

A range of technologies exists to improve security, including cryptographic systems, firewalls, intrusion detection systems, anti-malware software and scanners, and secure socket layers (Ghosh et al., 2018). Successful cyber security relies not only on technology and technical tools, but on well-defined risk management strategies, with well-trained and well-informed personnel, policies, and procedures.

2.2.3 People

The perspective of people is related to the human resources of the organisation, their skills, knowledge, attitudes, and behaviours. Recruiting, training, and building talent and competence are key.

In the context of AI, the people perspective is associated with challenges related to collaboration, lack of trust and transparency, and ethical considerations (Dignum, 2017; Burgess, 2018; Dignum, 2018; Politou et al., 2018; Sjåstad, 2019; Abioye et al., 2021; Xu et al., 2022).

More collaboration is needed for the continued progress of AI in construction management (Xu et al., 2022). There is a talent shortage in the contextual intersection between AI and construction (Abioye et al., 2021), and interdisciplinary collaboration between construction experts and AI experts is considered necessary to continue to drive the field forward. Collaboration is needed to generate solutions that can effectively meet the demands of the construction industry. Involvement is essential to establish a sense of ownership.

Explainability of AI systems is another challenge (Abioye et al., 2021). Many AI systems, and especially ML models, are largely black-box systems. This means that the input and output of the system is observable to a user, but the process within the system is not transparent. This can lead to a lack of trust in the system (Sjåstad, 2019; Abioye et al., 2021), and ultimately, aversion. Aversion refers to the negative attitudes or perceptions that individuals or groups hold. Sjåstad (2019) defines the topic of 'algorithm aversion' as the tendency to prefer a human decision despite knowing that data-driven algorithms hold a higher degree of accuracy. Sjåstad (2019) presents four possible psychological explanations: (1) exaggerated trust in human experts, (2) different weighting of machine-made errors versus human errors, (3) social needs and (4) the fear of lost individuality. When measuring the perceived success of a system, the perception seems to be that the machine performance is compared to zero mistakes – rather than the human number of mistakes (Sjåstad, 2019).

Understanding the sources and nature of aversion against AI is important for developing strategies to address the underlying concerns and build long-term trust in the technology. Among the factors that can improve trust in AI systems are transparency, verifiability, and robustness of a solution (Belle, 2023). These factors are closely related to ethical challenges that are encountered.

As the capabilities for autonomous and AI-based decision-making evolve, an important issue to consider is the ethical impact caused by these systems. Dignum (2018) notes that ethical considerations and implications of AI systems have several levels: Ethics *by* design (the integration of ethical reasoning capabilities when the system is built); ethics *in* design (regulatory and engineering methods that support the analysis and evaluation of ethical implications as AI systems replace traditional social structures); and ethics *for* design (the standards that ensure the integrity of developers and users in research, design, construct, employment and management of AI systems).

Some key considerations related to ethics in design are privacy, bias, accountability, and transparency (Dignum, 2017; Burgess, 2018; Dignum, 2018; Politou et al., 2018).

In 2015, the European Union (EU) voted to implement the General Data Protection Regulation (GDPR) to replace the Data Protection Directive (DPD) from 1995. The aim was to give the people of the EU better control over their own personal data. The main data protection principles in the GDPR are revised but are based on the principles set out in DPD: fairness, lawfulness, and transparency (Article 5(1)(a)); purpose limitation (Article 5(1)(b)); data minimisation (Article 5(1)(c)); accuracy (Article 5(1)(d)); storage limitation (Article 5(1)(e)); accountability (Article 5(2)); integrity and confidentiality (Article 5(1)(f)) (Politou et al., 2018).

Informed consent can be said to have been given based on an understanding of the facts, implications, and consequences of the consent (Politou et al., 2018). Privacy by design principles include concepts such as data minimisation, purpose limitation, control, and transparency (Politou et al., 2018). Data minimisation is the practice of collecting and processing only the minimum amount of data necessary for a specific purpose. Purpose limitation is a principle that requires personal data to be collected and processed only for specific purposes, and it requires that the data is not used for any purpose that is incompatible with the purpose for which it was originally collected (Politou et al., 2018).

As AI is becoming more widely used for decision-making in many industries, the concept of algorithmic bias becomes increasingly important. Bias in the context of AI refers to the potential for algorithms to produce unfair or discriminatory results. This can occur when the data used to train the system is biased, or certain characteristics of the algorithm promote bias. The main reason for algorithmic bias is human bias in the data the algorithm is built upon (University of Helsinki, 2018). Bias can manifest in a variety of ways, including inaccurate or discriminatory predictions, underrepresentation, or overrepresentation (Belle, 2023).

Accountability can refer to the responsibility of individuals and organisations for the decisions and actions of the AI systems they develop and deploy. Accountability can be guaranteed, at least to some extent, through ensuring explainable, ethical, and transparent processes and systems. Dignum (2018) argues that responsibility should be considered one of the fundamental stances underlying AI research and autonomy. Transparency means openness regarding data collection and processing practices; in the context of GDPR, this includes the types of personal data that are collected, the purposes for which the data is processed, and any third parties with whom the data might be shared.

Loukides et al. (2018) define five framing guidelines to help maintain an ethical approach when building data products: consent, clarity, consistency (for trust), control (and transparency), and consequences (and harm). The guidelines should not only dictate the work of the designer but the entire organisation (Loukides et al., 2018). For the development and deployment of AI systems to be sustainable long-term and short-term, each consideration needs to be addressed.

2.3 Sustainability

The goal is not only for a process to produce a sustainable outcome – but also for the process to be sustainable.

Sustainability is defined along three dimensions: environmental sustainability, economic sustainability, and social sustainability; the three pillars are illustrated in Figure 2-9. Sustainable development refers to a development meeting the needs of the present generations, without compromising the ability of future generations to meet theirs (Tjernshaugen, 2022). Goralski and Tan (2020) argue that the academic community has an important role in preparing future management to address the opportunities and challenges AI represents.

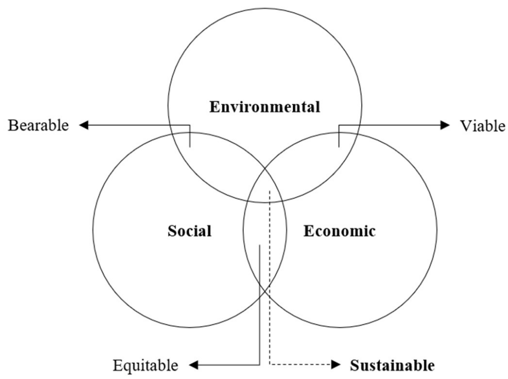


Figure 2-9. The three pillars of sustainability.

2.3.1 Economic sustainability

The economic pillar, in short, emphasises the importance of profitability for a company or organisation to maintain its sustainability. Economic sustainability is concerned with the stability of economic systems and the creation of systems that promote sustainable development and inclusive growth. The economic pillar is not to be seen as advocating profitability at any cost, but rather as a practical approach that serves as a counterbalance to potentially unrealistic measures represented in the context of the two remaining pillars. For the construction industry, maintaining economic sustainability could mean an increase in margins, making choices that ensure a long-term return on investments, and measuring short-term effects against long-term effects upon investment (Akadiri et al., 2012). The construction industry represents a significant contributor to national and international economies and is therefore able to affect the long-term viability and stability of economic systems; ultimately, it can help create economic and social systems that promote sustainable development and inclusive growth.

The construction industry is a significant contributor to the overall economy (Akadiri et al., 2012; Pan and Zhang, 2021). In the construction context, economic sustainability can relate to improved project delivery and increased profitability and productivity (Halliday, 2007; Shen et al., 2010). Despite the perceived attention to environmental sustainability, previous research shows that economic factors are more considered than social and environmental factors in construction project feasibility studies (Shen et al., 2010). Holistic frameworks should incorporate all three pillars of sustainability in equal measure.

AI can contribute to producing economically sustainable outcomes, through estimation and cost control, and increasing productivity in logistics, planning, and scheduling. For the development and deployment of AI to be sustainable, more work is needed. High initial costs are identified as one of the key areas affecting the adoption of AI in construction (Abioye et al., 2021). However, not all AI applications require large additional costs (Golvarparvar-Fard et al., 2015). This indicates a need for frameworks facilitating a more economically viable approach to the use of AI to enable the scaling of systems.

2.3.2 Environmental sustainability

The environmental pillar is currently receiving the most attention in the construction context (Shen et al., 2010; Lima et al., 2021). A growing number of companies and organisations are working to maintain a so-called 'green profile' and to ultimately reduce their carbon footprints. Thus, environmental sustainability is concerned with the long-term viability and health of natural systems, as well as the development and implementation of policies and practices that promote sustainable resource use and conservation.

The United Nations (UN) Department of Economic and Social Affairs has defined Sustainable Development Goals (SDGs) (United Nations Department of Economic and Social Affairs, 2023) aimed at ending poverty, reducing inequality, spurring economic growth, and halting climate change by 2030. During this work towards the SDGs, numerous agreements have been formed, including the Paris Agreement, aiming to provide a framework to avoid dangerous climate change, and to equip nations worldwide with the ability to deal with the impacts of climate change (United Nations Department of Economic and Social Affairs, 2023). Nationally, The Norwegian Ministry of Climate and Environment has defined 23 environmental goals, six of which relate to emission reduction and climate neutrality. Despite the ongoing green shift, reports indicate that the transition must happen faster if Norway is to achieve its climate goals.

In 2021, 48.9 million tons of CO2 equivalents were emitted from Norwegian territory, and the construction sector is a significant contributor to both direct and indirect emissions (SSB, 2022). The construction industry purchasing power has a major impact on emissions from industry, transport, energy production, and waste. Transport to and from the construction site is identified as one of the key sources of direct emissions in the sector, with estimates suggesting that greenhouse gas emissions from the construction site can be reduced by almost 99% (Energi Norge, Norsk Fjernvarme, Bellona and Enova SF, 2017).

The construction industry plays a critical role in shaping the built environment and driving economic growth, nationally and internationally. The complexity of each project creates challenges for effective communication and coordination, and ultimately for creating sustainable and safe construction projects (Pan and Zhang, 2021). The industry has a significant impact on the environment and society; today, construction is accountable for nearly 40% of worldwide energy consumption and energy-related gas emissions (Global Alliance for Buildings and Construction, 2017) and the need for more sustainable solutions is growing swiftly.

For the construction industry, maintaining environmental sustainability could mean contributing to waste reduction, reduced consumption of natural resources, reduced emissions, and definition of requirements and certifications that support SDGs nationally and internationally. AI has been shown to hold potential within these areas and can help expand traditional environmental governance (Nishant et al., 2020).

2.3.3 Social sustainability

The pillar of social sustainability can refer to the people inside and outside an organisation (Akadiri et al., 2012). Internally, for the project organisation, sustainability can mean a safe workplace with a good working environment that systematically works to prevent and avert health and safety issues among employees (Halliday, 2007; Shen et al., 2010; Akadiri et al., 2012). A good working environment on the construction site can contribute to ensuring the health of employees and promoting a better quality of life. Externally, social sustainability can mean maintaining support from stakeholders outside the organisation, such as clients, other partners, or society in general. Social sustainability is thus concerned with the resilience of social systems, as well as the development of policies and practices that promote social well-being and human flourishing.

In the construction context, maintaining social sustainability, in summary, could mean protecting the health and safety of workers, risk management, choosing projects that long-term will create value for society as a whole, and conducting projects in a manner that does not harm or limit the proximate community in any way, short-term or long-term (Halliday, 2007; Shen et al., 2010; Akadiri et al., 2012).

AI systems and tools can contribute to the proactive support of health and safety measures on-site, and risk management. For AI to be sustainable from the social perspective, AI ethics should focus on both technical details and social aspects (Dignum, 2017; Dignum, 2018; Hagendorff, 2020). This could mean creating connections between abstract ethical principles and the practical application of AI. Systematically increasing explainability and transparency in AI systems can contribute to increased trust in the tools and the potential they represent (Abioye et al., 2021).

2.3.4 Recent developments

More and more companies are putting the SDGs on their agendas, and an increased focus on sustainability can bring benefits in the form of increased competitiveness. An investigation conducted by Grønn Byggallianse and Høgskolen i Østfold (2019) deals with the perceived added value of green buildings among owners, tenants, and investors in construction projects. In the survey, over 80% of respondents considered the increased focus on sustainability to add value to projects. The following indicators of perceived value were used: increased turnover; increased rental income; increased interest from potential tenants; reduced operating costs; reduced risk of meeting future regulatory and user requirements; reduced risk of technical quality; and improved reputation.

Actors that best adapt to the climate challenge are expected to do best in competition in the coming decades. By participating in the transition to a low-emission society, companies can create a competitive advantage.

Digital technology is widely accepted as a valuable tool to increase sustainability in construction and has been proven to contribute to timely delivery, improved information flows, improved efficiency of operations, and improved return on investments (Kineber et al., 2023a). Similarly, a significant potential is seen in the utilisation of AI-based tools and techniques (Goralski and Tan, 2020; Nishant et al., 2020; Feroz et al., 2021; Pan and Zhang, 2021). However, the construction industry has yet to see the same shift as other industries.

As the use of AI systems is becoming more prominent in the construction industry, there is a need for more research on how AI can be developed and deployed sustainably.

2.4 Summary and research gap

This chapter has explored the existing theoretical foundation of the main topics of this thesis: project management, AI, and sustainability. All three topics have an extensive body of knowledge on their specifics.

Extensive research has been conducted in the domain of making construction processes and projects more effective, productive, and sustainable, and concepts related to adoption and innovation are thoroughly explored (Fenn, 1995; Rogers, 1995; Ayinla and Adamu, 2018; Bosch-Sijtsema et al., 2021; Wernicke et al., 2021). A range of frameworks and methodologies exist and have evolved over the years (Lewin, 1951; Hao et al., 2008; Cameron and Green, 2015; Burnes, 2019). Despite this, specifics related to the implementation and integration of AI solutions, particularly in the context of sustainability, are currently lacking. To map and understand the extent of the challenges that are encountered in developing and deploying AI, and what they mean for the dimensions of people, process, and technology, more research is needed.

Extensive research has also been conducted in the domain of computer science, developing algorithms and tools to solve specific problems in the construction industry, including estimation and cost control; logistics, planning, and scheduling; strategy; health and safety; project performance and success estimation; and risk, among others. Although the topic of AI in construction has received significant attention, the majority of the existing literature is concerned with the technical development of AI systems for specific areas of application (Ilter and Dikbas, 2009; Martínez and Fernández-Rodríguez, 2015; Juszczyk, 2017; Basaif and Alashwal, 2018), and more research is needed on the application of these tools in the construction management context (Darko et al., 2020; Xu et al., 2022). More research on system design is needed (Xu et al., 2022), and roadmaps and methodologies should be developed on how this can be done in practice (Darko et al., 2020; Wang et al., 2020).

Research has also provided detailed insights into the necessary elements of infrastructure required to support such technologies and solutions (Agrafiotis et al., 2018; Dignum, 2018; Ghosh et al., 2018; Loukides et al., 2018; Politou et al., 2018; Abraham et al., 2019; Belle, 2023), but frameworks encompassing these factors appear to be lacking. Research seems to have focused mainly on pilots, tests, Proofs-of-Concepts (PoCs) or conceptualisations, and less on robustness, scalability, and standardisation frameworks; this research is currently lacking. Studies demonstrate great results when applying developed algorithms to specific use cases, projects, or pilots. However, the evidence of successful large-scale implementation seems to be lacking. Since studies show successful implementation on a small scale, it seems reasonable to assume that a challenge lies within the infrastructure for successful integration and scaling. To explore the implications of scaling and standardising in this context, more research is needed.

Digital tools and solutions, including AI, are shown to hold the potential to increase sustainability in the process output (Goralski and Tan, 2020; Nishant et al., 2020; Feroz et al., 2021; Pan and Zhang, 2021; Kineber et al., 2023a). However, more research is needed into how the implementation and integration process itself can become more sustainable, and how all three dimensions can be maintained moving forward. High initial costs are identified as one of the key areas affecting the adoption of AI in construction (Abioye et al., 2021); this suggests a need for frameworks that allows for a more financially viable development and implementation.

In conclusion, a gap exists in the research on the contextual intersection between construction, AI, practical implementation, and implications thereof. In addition, a substantial amount of the existing research is first and foremost grounded in conceptual theory rather than practical implications and empirical validations; the thematic intersection between the three topics, project management, AI, and sustainability, remains relatively unexplored.

This thesis aims to fill this gap in the literature, choosing a holistic approach to the complex task of building systems and solutions resulting in sustainable deliveries and deliverables. Bridging the gap between the fields could provide valuable contributions in all three fields and improve a greater understanding of each field in the context of the others. The aim is to provide a framework for the actors who want to get started, who want to start now, and who, ultimately, want to move from ambition to practice.

3 Research design

This chapter will present the research design of the thesis within the framework of the research onion taxonomy (Saunders et al., 2019). Each of the six layers of the research onion is assessed, discussing in detail how the perspectives of each layer contributed to the final research design, and how they impacted the research and the thesis. The characteristics of the quantitative and qualitative data analyses are presented, followed by an assessment of the research design including reliability, validity, generalisability, and ethical considerations.

Figure 3-1 illustrates an overview of the research process over the course of the PhD project and the main deliverables leading forward to the completion of the thesis.

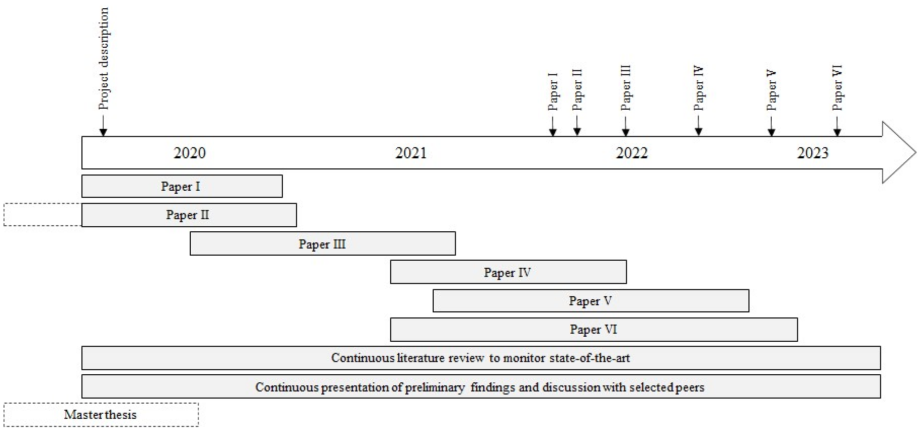


Figure 3-1. Research process for the PhD project.

The research process was highly iterative, and data collected for one study often informed multiple studies.

Continuous monitoring of literature was done parallel to the work on the individual studies over the entire duration of the PhD project. This was done to monitor the state-of-the-art and identify any relevant literature published after the initial exploratory literature review was conducted. In addition, more specific literature reviews were conducted for each paper; these are further described in following subsections. Continuous presentation of preliminary findings and subsequent discussion with selected peers was also conducted in parallel throughout the entire process, with experts from industry and academia. This helped position previous and ongoing studies in the industry and the academic field and further informed the research design of upcoming studies.

The first deliverable was the project description. The project description contained a preliminary outline of deliverables and delivery, including the overall goal and purpose of the project and the intended contribution from the thesis. The description also included a plan of how the work would be conducted in the allotted time. Considerations related to the delivery and the project work were described, including ethical considerations and proposed research methods.

Following the approval of the project description, the work with Paper I and Paper II was initiated in parallel with the finalisation of my master thesis. Findings from the early papers helped inform upcoming research and papers, including the definition of research questions, selection of thematic areas, and research design.

Figure 3-2 shows the research onion (Saunders et al., 2019). The following sections of the chapter will address each of the six layers in the research onion framework. The philosophical position, approach to theory development, methodological choice, strategies, time horizon, techniques and procedures will be presented, and the rationale and implications will each be elaborated upon in turn.

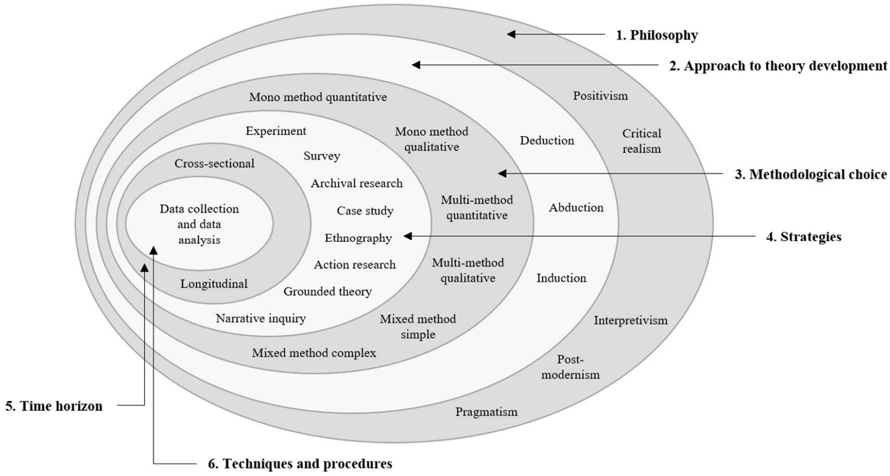


Figure 3-2. The research onion (Saunders et al., 2019).

3.1 Research philosophy

The philosophical worldview of a researcher influences the assumptions brought to a study, the research practice, and the applied strategy (Creswell, 2009). The philosophical worldview of a researcher also influences the shaping of research questions, chosen methodology, and interpretation of data (Saunders et al., 2019).

Three assumptions influencing the research process can be defined (Holden and Lynch, 2004; Saunders et al., 2019). The three are, to some extent, consequential to each other: ontology (nature of reality or being), epistemology (what constitutes acceptable knowledge), and axiology (how the values of the researcher might influence the research). Saunders et al. (2019) define five management philosophies: positivism, critical realism, interpretivism, postmodernism and pragmatism.

Table 3-1 summarises some key characteristics of these philosophical positions and how they relate to each of the three assumptions.

Table 3-1. Comparison of five philosophical positions (Saunders et al., 2019).

	Ontology	Epistemology	Axiology	Typical methods
Positivism	Real, external, independent; One true reality (universalism); Granular (things); Ordered	Scientific method; Observable and measurable facts; Law-like generalisations; Numbers; Casual explanation and prediction as contribution	Value-free research; Researcher is detached, neutral, and independent of what is researched; Researcher maintains an objective stance	Typically deductive, highly structured, large samples, measurement, typically quantitative methods of analysis, but a range of data can be analysed
Critical realism	Stratified/layered (the empirical, the actual and the real); External, independent; Intransient; Objective structures; Casual mechanisms	Epistemological relativism; Knowledge is historically situated and transient; Facts are social constructions; Historical causal explanation as contribution	Value-laden research; Researcher acknowledges bias by world views, cultural experience, and upbringing; Researcher tries to minimise bias and errors;	Retroductive, in-depth historically situated analysis of pre-existing structures and emerging agency; Range of methods and data types to fit subject matter

			Researcher is as objective as possible	
Interpretivism	Complex, rich: Socially constructed through culture and language Multiple meanings, interpretations, realities; Flux of processes, experiences, practices	Theories and concepts too simplistic; Focus on narratives, stories, perceptions, and interpretations; New understandings and worldviews as contribution	Value-bound research; Researchers are part of what is researched, subjective; Researcher interpretations key to contribution; Researcher reflexive	Typically, inductive. Small samples, in-depth investigations, qualitative methods of analysis, but a range of data can be interpreted
Postmodernism	Nominal; Complex, rich Socially constructed through power relations; Some meanings, interpretations, realities are dominated and silenced by others; Flux of processes, experiences, practices	What counts as 'truth' and 'knowledge' is decided by dominant ideologies; Focus on absences, silences, and oppressed/repressed meanings, interpretation, and voices; Exposure of power relations and challenge of dominant views as contribution	Value-constituted research; Researcher and research embedded in power relations; Some research narratives are repressed and silenced at the expense of others; Researcher radically reflexive	Typically, deconstructive – reading texts and realities against themselves; In-depth investigations of anomalies, silences, and absences; Range of data types, typically qualitative methods of analysis
Pragmatism	Complex, rich, external; 'Reality' is the practical consequences of ideas; Flux of processes, experiences, and practices	Practical meaning of knowledge in specific contexts; 'True' theories and knowledge are those that enable successful action; Focus on problems, practices, and relevance; Problem solving and informed future practice as contribution	Value-driven research; Research initiated and sustained by researcher's doubts and beliefs; Researcher reflexive	Following research problem and research Question; Range of methods: mixed, multiple, qualitative, quantitative, action research; Emphasis on practical solutions and outcomes

Saunders et al. (2019) present the reflexive tool, HARP (Heightening your Awareness of your Research Philosophy), to provide the researcher with insights into their philosophical position. The questionnaire is built to score each of the philosophical positions against the views of the researcher. A higher score indicates a higher preference for the position. My results from the HARP test are presented in Table 3-2.

Table 3-2. Results from HARP test (Saunders et al., 2019).

Philosophical position	Score
Pragmatism	15
Postmodernism	11
Critical realism	10
Interpretivism	10
Positivism	7

Naturally, the HARP test is only intended as a starting point for further reflection. However, as this thesis aimed to obtain insights into the practical implications of implementing AI-based tools, a pragmatic worldview concerned with the practical consequences of ideas seems like a natural starting point.

This thesis aimed to obtain insights to support the practical implementation of AI in a construction context, and to enable actors who want to move from ambition to practice. Therefore, this thesis mainly takes a pragmatic philosophical worldview and approach; this is a pluralistic and real-world practice-oriented worldview which allows available approaches to relate to the practical implications of the findings.

3.2 Approach to theory development

Generally, a research approach can be categorised as deductive, inductive, or abductive (Saunders et al., 2019).

In short, an inductive approach can be described to generalise existing ideas, whereas a deductive approach aims to narrow down existing choices. An abductive approach, rather than moving from theory to data (as in deduction) or data to theory (as in induction), moves back and forth, essentially combining a deductive and inductive approach (Suddaby, 2006, cited by Saunders et al., 2019).

The dominant philosophical position of the researcher will influence their choice of approach to theory development. Saunders et al. (2019) note that an abductive approach is typical for postmodernists, critical realists, and pragmatists. Interpretivists tend to use inductive approaches, and positivists deductive approaches.

The research approach applied in this thesis utilises all three of these approaches.

Deductive approaches start by assessing theory, often developed from studying existing literature on the topic and then designing a research strategy to test the theory (Saunders et al., 2019). A deductive approach can be used when building a theoretical framework based on prior theoretical knowledge or testing hypotheses to create new knowledge (Spens and Kovács, 2006). Inductive approaches start by collecting data to explore a phenomenon, and the researcher can then generate or build a theory from this foundation (Saunders et al., 2019). Inductive approaches can be used when empirically validating prior theoretical knowledge by making real-life observations or suggesting hypotheses based on these observations (Spens and Kovács, 2006). Creswell (2009) suggests that qualitative research, by nature, tends to build inductively from particulars to general themes. Induction builds on empirical data and can be described as exploratory research (Tjora, 2017).

Abductive approaches collect data to explore a phenomenon, identify themes, and explain emerging patterns, to generate a new or modify existing theory which is subsequently tested by additional data collection (Saunders et al., 2019). An abductive approach can be used when suggesting hypotheses based on real-life observations, applying and testing hypotheses or propositions, generating new knowledge, or building theoretical frameworks from real-life observations (Spens and Kovács, 2006).

Figure 3-3 illustrates the different approaches to theory development (Spens and Kovács, 2006).

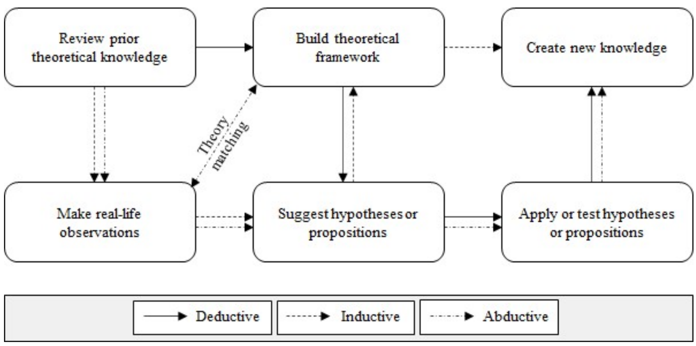


Figure 3-3. Approaches to theory development (based on Spens and Kovács, 2006).

As illustrated in Figure 3-3, different approaches to theory development can be utilised in different stages of a study or a project. Saunders et al. (2019) suggest that a completely inductive design, for instance, is less likely in many situations, and suggests employing a hybrid approach.

Five of the six studies in this thesis utilised a hybrid approach.

The aim of the scoping review in Paper I was to identify research gaps in the literature, so that new ideas and hypotheses for future research could be generated. The three research questions can be categorised as inductive, inductive, and abductive, respectively. Paper I identified patterns and themes within the existing literature on AI in construction projects, ultimately assessing the characteristics of the publications on the dimensions of descriptive features, methodology, areas of application, and the technology used. Paper I can be categorised as abductive.

Paper II focused on identifying specific measures that can be used for waste reduction, and explored how AI can contribute to the effective implementation of these measures. The three research questions can be categorised as deductive, deductive, and abductive, respectively. Paper II can be categorised as deductive because it starts with a specific hypothesis (that AI can help reduce waste on construction sites) and abductive because it seeks to generate hypotheses on how AI can contribute to waste reductions.

Similarly, Paper III starts with a specific hypothesis (that AI can be used to analyse project data and identify success factors in projects); the hypothesis is tested by building an ML algorithm to accomplish this. Hence, there are clear deductive elements to the research design of Paper III. However, the first research question is mainly centred around how this can be done, implying elements of inductive reasoning (seeking to develop a hypothesis based on specific observations – the potential of AI for success prediction). The Paper also utilised a method that had not previously been used for construction project success prediction, requiring a certain degree of abductive reasoning. Paper III, therefore, holds deductive, inductive, and abductive elements.

Paper IV identified and explored the existing barriers related to mapping, collecting, and storing data about materials and products in existing buildings, holding mostly deductive and abductive elements.

The research objectives of Paper V can be categorised as deductive, inductive, abductive, and abductive, respectively. The study can be described as deductive, as the rationale of the study is built with the aim of testing a hypothesis by collecting and analysing data from conducted projects. However, Paper V also incorporates elements of inductive and abductive reasoning, as it draws on existing literature and theories (inductive) while also exploring new insights and further formulating recommendations (abductive).

Similarly, the research questions of Paper VI can be categorised as inductive and abductive; the paper seeks to gather information about the current state of the field and the challenges it faces while also exploring a potential solution to overcome the identified challenges.

As an extensive summary of the conducted studies, the thesis holds deductive, inductive, and abductive elements. In addition, the three overarching research questions defined for the thesis as a whole can be categorised as deductive, inductive, and abductive, respectively.

3.3 Methodological choice

Croom (2010) argues that there is no clear link between epistemology and the choice of method in social science studies. These methods are typically categorised as either qualitative or quantitative. Despite this, Creswell (2009) argues that these approaches should not be viewed as complete opposites, but as representing different areas on a continuum. Both qualitative and quantitative approaches have strengths and weaknesses. Therefore, using mixed methods and combining qualitative and quantitative aspects in a research design can help to improve the quality of the research by overcoming weaknesses related to the individual methods, thus functioning as a means of triangulation (Flick et al., 2004).

Saunders et al. (2019) define the two categories of mono-method research, meaning the use of a single data collection technique and corresponding analysis procedures, and multiple methods. In contrast to mono-method, multiple-method approaches involve using more than one data collection technique and analysis procedure. This could be done by using more than one data collection technique but restricted within either a qualitative or quantitative worldview (multi-method), or by using both qualitative and quantitative methods (mixed methods). Mixed method research can use qualitative and quantitative data collection techniques and analysis procedures at the same time (parallel) or one after the other (sequential), but does not combine them (Saunders et al., 2019). In contrast, mixed model research combines quantitative and qualitative methods; quantitative data can be qualitised, and qualitative data quantised.

The use of mixed methodologies has gained popularity among researchers over the years, especially in social sciences (Creswell, 2009). Multiple methods are useful in the sense that they provide the opportunity for the researcher to evaluate the extent to which the findings from the individual method can be trusted (Saunders et al., 2019) and enable triangulation of findings (Flick, 2004; Denzin, 2012). Different methods can be used for different purposes or stages in the same study (Saunders et al., 2019).

This thesis mainly utilised a mixed research methodology, but with some exceptions.

Paper I is a mono-method study, basing the entire research design on the scoping review framework.

The research design of Paper II is a mixed model design, utilising both qualitative (interviews, document studies, literature review, and site visits) and quantitative methods (quantitative assessment of waste data from construction projects and a questionnaire). The techniques were employed in parallel, and the coding stage of the research included converting qualitative data into quantitative, and vice versa.

Paper III employed a sequential mixed method research design. The study started by conducting a literature review to map previous research conducted on the topic of construction project success, and to explore previous use cases of ML to assess and predict project success. After an extensive data analysis and preparation process, the ML algorithm was built, assessed, and applied.

An initial literature review, followed by a series of interviews, constituted the research design of Paper IV; thus, the study can be categorised as multi-method.

Paper V utilised a wide range of qualitative (interviews, a multiple-case study, document studies, and a literature review) and quantitative (quantitative assessments of case project data) methods. The coding stage of the research included a detailed assessment of the findings across both categories – a mixed model approach.

A range of qualitative methods was chosen for Paper VI, including interviews, a document study, a literature review, and a site visit. The study can be categorised as a multi-method, utilising strictly qualitative methods.

3.4 Strategies

Strategies utilising quantitative methods include experiments and surveys; archival research and case studies can be used in quantitative methods, but also qualitative (Saunders et al., 2019). Ethnography, action research, and grounded theory are most relevant in the use of qualitative methods. Saunders et al. (2019) note that the strategies are not to be thought of as being mutually exclusive. Surveys, case studies, and grounded theory were used in this thesis. Table 3-3 summarises some key characteristics of the three.

Several types of research exist (Fellows and Lui, 2003); among these are descriptive, exploratory, explanatory, and interpretive research methods.

A descriptive research design is used to systematically identify all elements of a phenomenon, process, or system and the relationships between them. Fellows and Lui (2003) recommend that descriptive research is done as objectively and comprehensively as possible. The research can be undertaken in the form of a survey, archival research, or case study work (Saunders et al., 2019). Exploratory research is undertaken to test or explore aspects of existing theory; a central feature is the discovery of processes (Fellows and Lui, 2003). Often, an array of constructs and variables is identified by the research, and further hypotheses are produced to be tested in future research. Exploratory design is generally recommended when previous knowledge is limited, or the problem description is unclear. Case studies, archival research, surveys, and experiments are often employed in exploratory research (Saunders et al., 2019). Explanatory research aims to answer a particular question or explain a specific issue and is often centred around cause-and-effect relationships (Fellows and Lui, 2003). Hypotheses are used similarly to those used in exploratory research. Explanatory research can employ experiments, case studies, and archival research. An interpretive research design fits findings, observations, and experience into a theoretical framework or model (Fellows and Lui, 2003).

Table 3-3. Research sample strategies (from Saunders et al., 2019).

Sampling strategy	Description	Associated with
Survey	A common strategy in management research. Data collected using a survey strategy allows the researcher to suggest possible reasons for relationships between variables and to produce models of these relationships. Data collection methods include questionnaires, structured observations, or interviews.	Quantitative methods Exploratory or descriptive research Deductive approaches Frequently used to answer 'who' 'what' 'where' and 'how' questions

Case study	Provides rich understanding of the context of the research. Single or multiple cases. Data collection methods include interviews, observations, documentary analysis, and questionnaires.	Qualitative or quantitative methods Explanatory or exploratory research Frequently used to answer 'why' 'what' and 'how' questions
Grounded theory	Emphasis on developing and building theory. Data collection starts without the formation of an initial theoretical framework; theory is developed from generated data. Coding of results can be done by open coding, axial coding, or selective coding. Data is continuously analysed against coding concepts and categories until theoretical saturation.	Qualitative methods Inductive or deductive approaches Frequently used to answer 'how' or 'why' questions

Paper I utilises both a survey strategy (in assessing the existing body of publications) and a grounded theory strategy (in building theory based on the findings of assessments). The study can be categorised as descriptive, aiming to provide an overview of recent and current uses of AI; in addition, the identification of research gaps and formulation of recommendations for future research both hold exploratory elements.

Similarly, Paper II holds components of both survey strategy (in assessing current challenges and problem areas) and grounded theory (in presenting a framework of recommendations related to the use of AI for waste reduction). The study is exploratory, examining how AI can help to reduce waste on construction sites, and explanatory, in providing an overview of problem areas and recommendations related to practical implications.

The ML algorithm developed in Paper III is based on data collected through a survey strategy. The study itself also employs grounded theory, in building and advancing theory on the topic of construction project success estimation. The study holds both exploratory and explanatory elements, both employing quantitative assessments to explore how AI and ML can be used to assess and predict project success and, in doing so, they can establish a relationship between the analysis variables.

Paper IV also employs a strategy both in the form of a survey (in collecting data on perceived challenges related to data management) and a grounded theory (in extrapolating how the challenges relate to the hindering of circular economy). The extrapolation of findings to position the perceived barriers in the context of circular economy categorises the study mainly as exploratory.

In examining the potential of using 3D laser scanning, BIM, and AI for Quality Assurance (QA) in construction projects, Paper V utilises both survey, case study, and grounded theory strategies. A survey strategy was employed in the early stages of the research when identifying relevant use cases and case projects. The case study strategy was a large part of the research design, as the case projects constituted a significant portion of the findings. The study had an emphasis on building theory and presenting recommendations for actors seeking to utilise the technology, thus employing a grounded theory strategy. The whole study is exploratory in nature, seeking to provide empirical validation of previous theoretical findings. The study holds elements of several research types, and the four research questions can be described as exploratory, descriptive, descriptive, and explanatory, respectively.

Paper VI holds elements of both survey strategy and grounded theory. The study is exploratory, in mapping the current status in the industry and challenges related to the implementation of AI systems, with an emphasis on the development of theory regarding how development and implementation can be done sustainably.

3.5 Perspective (Time horizon)

Studies can be considered cross-sectional or longitudinal (Saunders et al., 2019). Fellows and Lui (2003) argue that quantitative studies tend to be more cross-sectional by nature, but that qualitative analyses can provide a more longitudinal perspective, introducing longitudinal elements into what originally was cross-sectional findings or data. Both cross-sectional and longitudinal perspectives can represent valuable contributions.

The whole thesis, including the continuous monitoring of literature as indicated in Figure 3-1, can be argued to hold a longitudinal perspective; however, individual studies and papers are mainly cross-sectional. Information acquired from interviewees holds a longitudinal perspective in the sense that the interviewees themselves have acquired the knowledge and experience after a longer time in the industry. Still, the data collected from the interviewees is, per se, cross-sectional. The field of AI is rapidly developing, meaning that a smaller time horizon could be considered longitudinal; meanwhile, the field of project management is, relatively speaking, moving at a much slower pace.

For Papers I through V, the main data collection was conducted over the course of 9-12 months, implying a cross-sectional perspective. This is considered a relatively short span of time in the project management context. Paper I holds a more longitudinal perspective, as the review itself included publications from a span of five years, and part of the objective of the study was exploring the development in the field over time. Similarly, the dataset used for Paper III is the sum of data accumulated by the Nordic 10-10 organisations over several years. However, unlike Paper I, the element of development over time was not crucial for the research objective in Paper III. For Paper VI, the main data collection process was conducted over the course of 18 months. However, like for Paper III, the element of development over time was not of particular interest for the research objectives in Paper VI.

3.6 Techniques and procedures

Techniques and procedures include data collection and analysis (Melnikovas, 2018), meaning the use of primary or secondary data and sources, the crafting of samples, developing content for interview guides and questionnaires, etcetera. All previous layers affect the choice of techniques and procedures, and most of all, as highlighted by Saunders et al. (2019) – the research questions.

This thesis employed literature reviews, interviews, case studies and document studies, among others.

3.6.1 Literature reviews

Literature reviews were conducted for each individual study, in addition to the overall continuous review.

Literature reviews are critical to ensure that research is being conducted on topics that are of relevance, and to confirm that the research questions have not already been answered (Dorussen et al., 2005). An understanding and overview of previously conducted research is essential to make sense of new findings in the context of the field (Tjora, 2017). Literature reviews ensured a relevant and comprehensive foundation for the research conducted in each of the studies.

The literature review in Paper I was conducted according to the scoping review methodology (Arksey and O'Malley, 2005). Reviews within the field of management are often comprised of a process of exploration, discovery, and development (Tranfield et al., 2003); therefore, it was desirable to choose a flexible approach that could be modified throughout the study. The scoping review enables a flexible but systematic approach and is based on five steps: (1) identifying research questions, (2) identifying relevant studies, (3) selecting relevant studies according to formulated criteria, (4) charting the data, and (5) collating, summarising, and reporting results. An additional, parallel element is also described regarding the use of a 'consultation exercise' to inform and validate findings from the main scoping review (Arksey and O'Malley, 2005). For Paper I, the five steps were conducted and presented in the final paper, as the purpose of this paper was the literature review itself. In Papers II through VI, one or more steps were conducted within the research group as a part of the study to improve the context of the research, but not provided in the finalised paper, as this was judged to be out of scope for the studies. Figure 3-4 illustrates the modified scoping review methodology of Paper V.

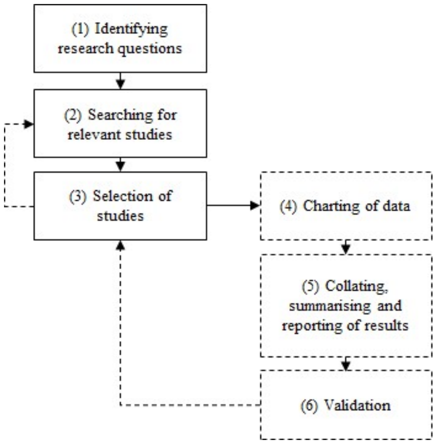


Figure 3-4. Modified scoping review methodology.

To clarify and further evolve the scoping literature review framework, Levac et al. (2010) present specific recommendations for each step. Both in individual studies and for the thesis, the recommendations of choice included linking the purpose of the study to the research questions in the early stages of the process, to facilitate decision-making regarding the inclusion and exclusion of relevant publications as the scoping review proceeded. The nature of the scoping review provides for an emergent and iterative process, meaning that such criteria might not become fully clear until the later stages of the review (Gough, 2007a). The criteria were updated throughout the process to sustain the systematic manner of the review. A more systematic approach helps to provide trustworthiness and accountability for the literature review itself (Gough, 2007b). These criteria were explicitly stated in Paper I, but, as per Figure 3-4, a part of the internal process in the remaining papers.

Since some intersections of the thesis topics are relatively unexplored, field-specific databases gave few hits for certain combinations of keywords. Therefore, Google was used as a supplement to academic databases. Google provides the broadest selection of literature among all search engines. The literature found through Google can provide inspiration or contribute to the discovery of other quality-assured and peer-reviewed sources, but it should not be used uncritically. Whenever possible, original sources were always used.

The continuous literature review was conducted in parallel with the individual studies' respective literature reviews, to monitor the state-of-the-art in the field. This contributed to ensuring the relevance of the individual studies and positioning any preliminary findings both in the context of the thesis and the whole field.

For Papers II through VI, the literature review mainly contributed to the positioning of the respective study, and to supplement any insights provided by interviews or other data sources.

Review process

Levac et al. (2010) recommend measuring the perceived feasibility of the study against the comprehensiveness of the scoping process. This was done through an initial, unstructured literature search.

The purpose of the preliminary search was to produce a literary warrant, establishing a suitable foundation for contextualisation and further definition and indexing of terms and classes during the review. Step 1 in the scoping methodology framework (identifying research questions) was informed by the initial, unstructured search.

To ensure the replicability of the research, Steps 2 (identifying relevant studies) and 3 (selection of relevant studies by formulated criteria) were structured according to the preferred reporting items for systematic reviews and meta-analyses (PRISMA) framework (Moher et al., 2009). Step 2 began by a manual search within selected databases to identify relevant records. Tranfield et al. (2003) emphasise the importance of a well-defined search string to create a replicable and transparent search strategy, ultimately contributing to higher reliability of a study. The definition of search strings was therefore also based on the initial literature search. Searches were filtered on year of publication, publication channels, and so on. Additionally, publications were identified from citation chaining, backward snowballing, or recommendations from personnel involved in other aspects of the study. Citation chaining refers to the use of a central source with multiple citations as a starting point to identify additional sources. Backward snowballing involves the discovery of relevant sources by exploring the references of relevant articles (Wohlin, 2014).

The records were then screened by judging the relevance of titles, keywords, abstracts, and conclusions. The full article was assessed in cases where the initial screening did not provide a sufficient insight into the study. A set of inclusion and exclusion criteria were defined for filtering, to help ensure the relevance and quality of the identified records. AI is rapidly developing; therefore, one inclusion criterion was that the record had to be publicised after 2000. Furthermore, only peer-reviewed articles were included to ensure the inherent quality of the studies. The scoping methodology does not include a formal application of quality assessment criteria, but only selecting peer-reviewed publications contributes to an implicit quality in the chosen records.

A full-text assessment of the remaining records was then conducted, to ensure their eligibility and consider the contribution of each record beyond the initial evaluation. During this process, nine records were deemed out of scope, and five did not provide sufficient detail to provide new insights into the study.

Steps 4 (charting the data) and 5 (collating, summarising, and reporting results) were conducted as part of the coding and triangulation of results. Charting, collating, and summarising were done as a part of the overall coding process of respective studies, where findings were compared against other findings within the same data collection method and across methods. The same approach was chosen to validate the literature review findings, which consisted of validation against the full body of publications and the other utilised methods.

3.6.2 Interviews

Interviews were originally conducted for individual studies, but each interview contributed to broadening the knowledge and perspective on the field, which ultimately informed not only the respective individual studies but the whole thesis. The number of interviews for each study is summarised in Table 3-4.

Table 3-4. Number of interviews in each study.

Paper number	Number of interviews
Paper I	0
Paper II	32
Paper III	0
Paper IV	18
Paper V	9 + 4 case study interviews
Paper VI	36

The novelty of the topics reduced the number of relevant interviewees for each of the studies.

The interdisciplinary nature of the topic meant involving experts from different fields, both in the industry and academia. For the industry interviewees, the aim was to include personnel from all parts of the construction project value chain.

Different sampling strategies were used to recruit interviewees. Paper II, Paper IV, and Paper VI employed a purposive sampling strategy to identify the most relevant interviewees for each study (Robinson, 2014; Saunders et al., 2019). The purposive strategy is traditionally associated with grounded theory (Saunders et al., 2019). Paper V, due to the limited number of available case projects, employed a sampling strategy based on convenience and judgement (Robinson, 2014; Saunders et al., 2019). This meant recruiting interviewees partly based on personal networks and publicly available documents. For each of the sampling strategies, a set of criteria for inclusion and exclusion were defined, to help craft a suitable sample. Additionally, for all studies, a snowball sampling strategy (Bryman, 2016; Tjora, 2017) was used through gathering suggestions from previous interviewees. This was done by including a request for potential future interviewees in the interview guides.

For all four studies collecting data from interviews, one or more pilot interviews(s) were conducted before the initiation of the main interviews, as per the recommendations of Kallio et al (2016).

The interviews followed respective interview guides that were developed after initial literature reviews and (the) pilot interview(s). The interview guides were targeted towards each interviewee to tailor towards their experiences and background and to accommodate the collection of data relevant to their perspective. Over the research period, the interview guides were updated as preliminary findings informed the understanding of the topic further. Interviews were mainly semi-structured in-depth interviews, as this is considered to provide broad and contextual results (Bell and Bryman, 2016). The semi-structured approach allowed the interviewees to elaborate beyond the pre-defined questions, contributing to a more comprehensive understanding of the knowledge and experience of the interviewee, the industry and its dynamics in relation to the topic (Ryen, 2002).

Each interview lasted between 60 and 90 minutes. When possible, two researchers were present during the interview to ensure a higher degree of understanding and reliability in the subsequent coding of the results. Where this was not possible, other researchers or key personnel were involved to a larger extent in the coding stage, and in the presentation of preliminary and final findings. Open-ended questions provided flexibility in the interview approach (Saunders et al., 2019), which gave the interviewees the opportunity to answer in-depth when needed (Tjora, 2017). All interviews were recorded, and transcripts were sent to the interviewees for QA before analysing the data. Follow-up questions were asked where necessary.

All interviewees received written information regarding the study and its focus before the interview. This allowed them to prepare by gathering appropriate documentation and reflecting on any relevant experience or knowledge. Giving the interviewees this opportunity can contribute to increasing the reliability and validity of a study (Saunders et al., 2019).

Thaagard (2013) suggests that the researcher strives to find a selection of interviewees that meets a theoretical saturation point, beyond which adding a new informant would no longer contribute significantly to the research. Saturation was identified in the studies by conducting the coding process iteratively in parallel with the interviews, as recommended by Bell and Bryman (2016). Certain topics reached saturation earlier than others; when this happened, an emphasis was put on the remaining topics in later interviews.

3.6.3 Multiple-case study

Paper V employed a multiple-case study as part of the research design.

Six case projects from two actors constituted the foundation of the case study. The researchers gained access to the QA systems and databases used in the projects, including registers of errors and deviations in the projects. The case study design was chosen as it represented a sound empirical approach to studying lessons learned from 3D laser scanning and BIM for QA. According to Yin (2009), a case study approach is beneficial when the aim is to conduct an in-depth examination of a contemporary phenomenon and explain 'how'. Explorative case studies are appropriate for providing in-depth insights into a phenomenon not previously vigorously examined (Ellram, 1996). The explorative approach was chosen due to the novelty of the intersection between the three topics. Even though previous research recognises the involved tools and their potential, current knowledge of how they can and should be utilised in conjunction is not systematically structured nor developed in large detail.

The case study was a cross-sectional theory-building multi-case study (Dul and Hak, 2008) holding elements from the case study survey framework (Farquhar, 2012). Employing a multiple-case design, the case study set out to explore experiences using 3D laser scanning for QA in six selected case projects. Thus, the study can be described as 'an empirical inquiry that investigates a contemporary phenomenon within its real-life context' where 'the boundaries between the object of study and context are not clearly evident' (Yin, 2009).

Yin (2009) describes six sources of evidence commonly used in case studies, including archival records, direct observation, participant observations, physical artefacts, documentation, and interviews. This study built its multiple-case study upon three main pillars: case documentation, interviews with involved personnel, and presentations provided by involved personnel. The data collection involved a qualitative research approach using semi-structured in-depth interviews to collect primary data. The choice to use semi-structured interviews is attributed to the flexibility this method provides, as previously described. Four semi-structured in-depth interviews were conducted with personnel who had been working on the case projects. Yin (2009) recommends that case study interviews are performed as guided conversations rather than structured interviews. The semi-structured approach was chosen to ensure a certain degree of replicability and increase reliability and validity.

Secondary data were collected from all six projects, including existing plans, project data, and registrations of deviations and errors. Additionally, a document study was conducted to collect secondary data and support and verify the findings from the interviews. With permission from management, several documents of importance were studied, including registers of deviations and errors in the case projects and project-based data such as presentations of key data and characteristics in the projects.

3.6.4 Document studies

Document studies are often found as part of a case study research (Yin, 2009), but can also be used as sources of their own (Bowen, 2009). Document studies involve the analysis of documents created for other use than the research itself (Tjora, 2017) and can be used to verify the data collected through other sources or to acquire new or additional information (Yin, 2009). Documents can provide data on the context within which research participants operate, suggest questions that need to be asked or situations that need to be observed or provide supplementary research data (Bowen, 2009). They can also serve as a means of tracking change and development over time, to verify findings, or corroborate evidence from other sources.

In this thesis, Papers II, V and VI were, partly, built on document studies.

3.6.5 Additional activities

Beyond the four main sources of data, a range of additional activities were performed to add further perspective and increase the understanding of the convoluted dynamics of the topic. Additional activities included courses on the topic of AI, participation in seminars and focus groups, and site visits.

The course Elements of AI was completed over six weeks in the spring of 2020, to obtain a foundational understanding of the concept of AI; this was followed by the course Building AI in the autumn of 2020. The courses are built by Reaktor, MinnaLearn and the University of Helsinki with an aim to make AI knowledge more universally available. They contain a range of modules that provide learners with an understanding of the theoretical and practical aspects of AI (University of Helsinki, 2018). Completion of the courses qualifies the learner for 2 ECTS (European Credit Transfer System) for each course.

Attendance in a wide range of seminars was prioritised throughout the entire duration of the project. The seminars ranged from academically focused seminars with fellow PhD candidates and professors, to seminars targeted towards industry actors, gathering industry experts to showcase successes and lessons learned from industry initiatives and pilots. The latter provided an opportunity to stay in touch with the industry and to follow the development as the project progressed. The seminars also served as an arena to present preliminary and final findings, to open discussions and receive feedback; this proved to be an invaluable contribution to building networks, and maintaining strong ties to the industry throughout, and an important supplement to the interviews. Academic networks included national and international focus groups, working at the intersection between project management and AI. Organised data collection in the form of focus groups, where a group of experts are gathered to discuss one or more topics, is especially effective for the researcher (Tjora, 2017). This is because they allow the researcher to gather a range of insights effectively, and they serve as a form of validation of results upon collection.

As a more practically oriented supplement to other methods, site visits were conducted on three occasions: a construction site visit in the spring of 2020, and two plant site visits hosted by a Construction City member, once in the spring of 2020, and a second time in the spring of 2023. The site visits were combined with interviews of personnel on the sites and planned focus group meetings. The visits aimed to gather in-depth data through observation and interaction with informants in the environment they operate within. Relevant experts conducted tours of the sites based on materials exchanged in advance, and the tours served as a starting ground for subsequent questions and discussions. The construction site tour was mainly related to the inspection of waste stations, while the plant tour was mainly related to the implementation of new and digitalised solutions on the site. The site visits informed the research but were initially conducted for Paper II and VI, respectively.

For Papers II, III, and V, the research design also encompassed continuous management of selected, relevant databases as a part of the quantitative analyses.

3.7 Data analysis and coding

3.7.1 Quantitative analysis

Papers II, III, and V included quantitative analyses, based on data from selected databases.

The quantitative analysis in Paper II was based on a quantitative assessment of waste data in 161 projects. An analysis of the waste disposal in 161 construction projects was conducted to identify any problematic waste fractions, with respect to total volume, environmental impact or impact on project progress, management, or activities. The analysis utilised the tool Grønt Ansvar from Norsk Gjenvinning to provide an overview of disposed waste in terms of volume, weight, degree of sorting, and cost associated with waste management in selected projects (Norsk Gjenvinning, c. 2018). The waste reports are dynamic, and the system allows the user to single out selected fractions, amounts, costs, or projects on-demand. The projects were deemed relevant for inclusion using the following criteria: used Norsk Gjenvinning for waste disposal through the entire production phase; did not use any other providers for waste disposal; and sufficient availability of further documentation, in case of any follow-up questions for the project or its team members. After the initial assessment, all projects meeting the criteria were included, as a bigger sample would make the data foundation more representative. For the analysis, the waste fractions were classified and categorised according to the guidelines provided by Norsk Gjenvinning.

In addition, a distribution analysis was conducted according to Holme and Solvang (1996), to assess both total waste amounts, amounts for each of the registered fractions, and amounts per project phase. The biggest fractions were selected for further assessment.

The ML model in Paper III was built on data from 160 projects in the Nordic 10-10 database. CII 10-10 is a tool for project benchmarking to develop and enhance processes continuously. The database is developed and provided by the Construction Industry Institute at the University of Texas and has later been translated to fit the Norwegian construction industry, resulting in the Nordic 10-10 initiative. Several major construction clients and contractors have since implemented the Nordic 10-10 program in their project organisations. The tool provides the users with a report that evaluates their project and compares it to relevant projects in the database (Nordic 10-10, c. 2020). It is ultimately providing a report serving as a foundation for further discussion and improvements, for individual projects, for a whole organisation, and for the entire body of projects. The questionnaire used to obtain the data constituting the 10-10 datasets is upon input specified by sector (construction, industry, or infrastructure) and project phase (phases 0 through 4). The 10-10 dataset contains several different features, including the four categories of General descriptive data (G), Output ratings (O), Question scores (Q), and Project ratings (I). The Q-attributes are distinct, and closely related to the project sector and phase. Furthermore, they are divided into two categories, those under 40 and those over 100. The sub-40 questions are binary, while the above 100 questions are ranked on a scale from 1 to 5. For each given Q-attribute, they may only relate to one specific sector or phase. However, as there is more than one respondent for each project, the sub-40 Q-attributes will appear in the database as the average of the respondents' answers, resulting in a scale from 0 to 1. The dataset was then loaded into a Python script, where the libraries Pandas, SKLearn, and NumPy were used. When a dataset is loaded into Pandas, it is called a Data Frame (DF). The dataset was processed through an Exploratory Data Analysis (EDA) and preliminary cleaning, resulting in an initial DF. The DF was then split into nine purposed DFs before the next steps were carried out in order: main cleaning, labelling, train-test split, scale, train and fit, classification, and lastly analysis and plot of the results.

For Paper V, the quantitative aspect mainly consisted of data collected in the case studies. Data related to the registration of deviations and errors in the case projects were collected, and the potentially saved risk was assessed based on the three factors: the expected frequency of a given category of deviation or error, the average effect on progress/schedule and cost in the project, and how difficult it would be to discover the deviation or error using traditional methods. Each factor was assigned a number based on available data in case documents and insights from involved personnel. Ultimately the quantified magnitude of the individual factors was based on both qualitative and quantitative factors (Cramer, 2003). Each category of errors and deviations was based on images and data from scans, BIM models, and project data. When the three factors were assessed, the potential risk was evaluated based on (a) these numbers and (b) insights provided through interviews. For instance, findings from the interviews suggested that a higher frequency or more significant consequence should be weighted higher than the difficulty of detection, as this, empirically, had been found to affect the project to a larger extent. The quantitative analysis provided insights into the potential savings related to the implementation of highly effective digital tools to avoid errors and deviations before they arise. The quantitative analysis also provided a greater understanding of which factors would affect the profitability and, therefore, the sustainability of the solution.

3.7.2 Qualitative analysis

The purpose of a qualitative analysis is to concretise each aspect of the collected data to compare the findings against each other (Jacobsen, 2015). All studies utilising qualitative data sources followed the same procedure.

The transcripts of all interviews were stored in a database accessible only by the researchers in in the relevant study, according to requirements from the Norwegian Centre for Research Data (Norsk Senter for Forskningsdata, NSD). Similarly, all written summaries from seminars, focus groups, project and site visits, and courses were stored in corresponding databases. Each study was assigned one database.

Caution was displayed as the data between the sources were analysed, first individually, iteratively, and then against the other sources to ensure high awareness of the context when analysing the data, as per Bryman (2016). The first stage of the coding process was coding by topic. Then, the data were assessed for patterns, and group codes across the interviews were identified and clustered. The emergent patterns and codes generally varied between studies, but some overarching concepts were reoccurring. When new codes emerged, previously coded transcripts were re-analysed with considerations towards the new codes. Assessment of the codes often revealed that some were interrelated; this was seen as a separate finding, informing the research beyond the initial findings.

Case study data were collected in a case study protocol. The protocol included collected documentation, transcriptions from interviews, and codification of the results to enable the comparison to other findings.

As described, literature review findings were coded based on the scoping review framework. Charting, collating, and summarising results were done by collecting all relevant records in the established database. The format of the database varied according to the aim of the review. The contribution of each record to the study was noted in the database, and additional notes concerning the relevance in the context of other findings were made. All records included in the final selection of the literature review were thoroughly assessed according to four criteria: credibility (i.e., authority of author and publication channel), objectivity, accuracy (including currency), and relevance to the study in question.

3.8 Assessment of research design

Table 3-5 summarises the methodological choices for this thesis for each of the layers in the research onion.

Table 3-5. Assessment of research design.

Paper number	I	II	III	IV	V	VI
Philosophy	Pragmatism					
Approach	Abductive	Hybrid Deductive Abductive	Hybrid Deductive Inductive Abductive	Hybrid Deductive Abductive	Hybrid Deductive Inductive Abductive	Hybrid Inductive Abductive
Methodological choice	Mono method	Mixed model	Mixed method	Multi method	Mixed model	Multi method
Strategy	Survey Grounded theory	Survey Grounded theory	Survey Grounded theory	Survey Grounded theory	Survey Case study Grounded theory	Survey Grounded theory
Perspective	Longitudinal	Cross-sectional	Cross-sectional	Cross-sectional	Cross-sectional	Cross-sectional
Techniques and procedures	Scoping review analysing 86 peer-reviewed articles	18 semi-structured in-depth interviews 14 structured interviews Questionnaire with 21 respondents Document study Quantitative assessment of waste data in 161 projects Literature review Project and site visit	Data from 160 project cases in Nordic 10-10 database Literature review	18 semi-structured in-depth interviews Literature review	9 semi-structured in-depth interviews Multiple-case study including 6 projects and 4 case-specific interviews Document study Quantitative assessment of data from 6 case projects Literature review	36 semi-structured in-depth interviews Document study Literature review Site visit

In qualitative studies, criteria for reliability, validity, and generalisability can be used as indicators for the quality of a study (Jacobsen, 2015; Tjora, 2017). The reliability of a study is related to verifiability; reliability can relate to the accuracy of the data being used, how the data is collected and how they are assessed after collection (Johannesen, 2016). Reliability and validity in a study are essential to ensure verifiability and relevance, respectively. For a literature review, this could include both the sources that are being used, and the data collected from the sources that are deemed to be relevant. In an interview, this could include the researcher selecting the right informants and the right questions to ask the informants. Possible sources of errors can lie within the ability of the researcher to validate literary sources, the assessment of relevance in the background and experience of the informants, the formulation of research questions that could be misunderstood or miscommunicated, or the analysis of the data from informants. The selection of interviewees and resources in the study assumes that the experts in the field will have first-hand experience with these tools. The novelty of the topic limits the existing theoretical foundation as well as the number of relevant interviewees for the study. To provide a holistic understanding and ensure sufficient reliability, validity, and generalisability in the study, a compound and comparative research design was developed on the principles of triangulation (Flick, 2004). The generalisability could be restricted, as both qualitative and quantitative considerations are based on a limited number of case projects and interviewees.

The research design utilised a combination of structured and unstructured data collection, primary and secondary data sources, and qualitative and quantitative methods to help overcome limitations associated with the individual methods and sources, thus improving the reliability, validity, and generalisability of the whole study (Love et al., 2002; Flick, 2004).

An abductive research design was employed for theory generation and modification and to incorporate existing theory where appropriate to build and modify the theoretical framework (Saunders et al., 2019). The intention was to include existing theory where applicable, build new theory and modify existing theory, and build upon real-life observations. Therefore, the approach was based on a combination of reviewing previous theoretical knowledge to build a theoretical framework (deductive), constructing hypotheses from real-life observation (inductive, abductive), and theory-matching of real-life observations and theoretical frameworks (abductive). The initial, unstructured literature search, with continuous validation of the findings as previously described, provided a framework and template for the coding, ultimately employing both theory-driven and data-driven codes.

A potential source of inaccuracy lies in the fact that the findings from the interviews were analysed within a framework that had not been presented to the interviewees at the time of the interview. On the other hand, the responses from the interviewees could have become biased if constrained by a previously defined framework. To mitigate the potential source of error stemming from the subjectivity in the data coding and decoding, the results were presented to, and discussed with, a separate group of selected informants, peer academics and practitioners.

The use of primary data sources ensures the quality and relevance of the data (Jacobsen, 2015). Secondary sources can provide a useful addition and extension of the primary sources. However, the use of secondary data sources requires the researchers to be more mindful of how the purpose of collection, methods used, and the focus of the source might differ from the researchers' own work. This became part of the validation process.

In addition to ensuring reliability, validity, and generalisability in the individual studies, the continuous presentation of preliminary findings and following discussions with selected informants, peer academics, and practitioners was done to receive input from relevant actors in academia and the industry and further ensure the validity and reliability of the research and the findings.

Throughout the work with the thesis, selected parts of the research have been presented in a wide range of settings and situations, including two guest lectures at Universidad Politécnica de Madrid, a presentation at the University of Salford Built Environments Summer School Programme, as well as multiple presentations for industry leaders and industry experts, and members of Construction City Cluster. As a result, the research has already been partially applied and evaluated in both academic and industry settings.

In the spring of 2022, a six-month exchange to a research group at the University of Salford in Greater Manchester, United Kingdom, contributed another dimension to the triangulation of methods. The new research groups provided new insights and perspectives into the conducted research and the context it was to be assessed within and provided further direction and perspective for the studies planned through the spring.

3.8.1 Reliability

The reliability of a study is related to the verifiability and replicability of a study (Olsson, 2011).

The research should be transparent enough for it to be replicated. Reliability refers to the accuracy of the data that is being used, how the data is collected and how they are processed (Johannessen et al., 2016). Tjora

(2017) emphasises that qualitative methods often involve a certain degree of subjectivity, which requires the researcher to be mindful of how this might affect the collection and analysis of the data. If many different methods give the same findings, the findings are likely to hold high reliability.

Tjora (2017) emphasises the importance of understanding how the position of the researcher can affect the research itself. To increase the reliability of a study, it is therefore recommended that the researcher reflects on their point of view and expectations for the collection, analysis, and interpretation of data early in the process. In the context of this thesis, earlier experience from the construction industry and previous work with topics related to sustainability in the industry could have led to certain expectations and assumptions related to the topic, but could also lead to a deeper understanding of the findings and the context they should be seen in. Lower levels of previous knowledge in the field of AI contributed to an open and neutral approach to this topic.

For this thesis, triangulation was used to explore if the findings from different sources of data would coincide. Triangulation of methods means combining different methods and is used to compensate for limitations related to the individual methods (Olsson, 2011). Triangulation can contribute to a deeper understanding of a topic and the reliability and validity of a study (Halvorsen, 2008; Denzin, 2012).

3.8.2 Validity

The validity of a study is related to the relevance of the study and whether the study answers the research questions and objectives as defined or not (Olsson, 2011). This means that the chosen method must be relevant to what the researcher intends to measure. For a qualitative study, the validity can be related to the selection of informants and the collection of data from the informants (Dorussen et al., 2005). For a quantitative study, it can be related to selection of projects for monitoring. The literature distinguishes between internal and external validity.

Internal validity is related to whether the collected data provides a good image of reality or not (Jacobsen, 2015). Among the factors that can affect internal validity in a study is, for instance, a lack of common understanding of terminology, which in an interview situation can lead to misunderstandings, and in the worst case, lead to the interviewer and interviewee talking (about) entirely different things. To avoid this, during the data collection process, any terminology and concepts were continuously and continually defined and compared and related to the field of the interviewee to ensure accord. After the interviews, follow-up questions were used to ensure a common understanding between the interviewer and interviewee, for instance, if any uncertainties showed up during the coding of the results.

External validity is related to whether the findings of a study can be generalised or not (Jacobsen, 2015). A factor that could affect external validity is a limited data foundation, as this, in turn, could hinder a representative description of the phenomenon that is being studied. To avoid this, a broad range of methods was used, and actors from all parts of the value chain were involved. This will not guarantee generalisability but can contribute.

3.8.3 Generalisability

Generalisability and external validity are closely related terms.

In this thesis, mostly projects and informants in the Norwegian construction industry are assessed. Some organisations represent a larger portion of the informants in interviews and questionnaires. This means that the contextual quantitative and qualitative findings might not be transferrable to other industries, other countries, other organisations, or other projects.

Jacobsen (2015) distinguishes between intensive and extensive research design. This is related to whether the research is done in depth or breadth, respectively. The qualitative design of the thesis can mainly be categorised as intensive; many variables are examined, with relatively few units. The strength of an intensive research design is linked to generalisation at a theoretical level, where the theory emerges through what the researcher has been told, read, or heard (Jacobsen, 2015). The empirical findings are detailed and nuanced but based on a few units; therefore, the generalisability is generally lower. By using triangulation, different designs can be combined; for instance, in-depth interviews, intensive by nature, can be combined with questionnaires, extensive by nature (Dalen, 2004). Jacobsen (2015) recommends an initial extensive research strategy before starting intensive work. For this thesis, this was done by performing an initial, unstructured literature search and introductory talks with relevant personnel in the early stages of each study. The scoping review presented in Paper I contributed to this. In later stages, in-depth interviews and analyses of data were conducted, built on the initial extensive design. According to Jacobsen (2015), this can increase to increasing generalisability and relevance of a study.

A comparative approach can further contribute to the generalisability of a study (Flick, 2004; Jacobsen, 2015). This can be done by comparing the findings across units, for instance, by 'testing' the findings from one unit by applying the emerging theory from another unit. A comparative approach was implemented in this thesis by utilising a broad selection of informants. Informants were selected from the entire project value chain, from different companies, with different backgrounds and current employers. This has been important to achieve a broad perspective of the study and the findings.

As described in Chapter 3.5, even if the entire thesis can to some extent be considered longitudinal, the individual studies are, first and foremost, cross-sectional studies. This can reduce the generalisability of the study. In the overarching discussions of the topic in Chapter 5, no single finding of any single study is considered an absolute truth; rather, the overarching, emerging themes from the research is examined in detail.

Close collaboration with international research environments (namely the University of Salford in England, and Philadelphia University in Jordan) as well as continuous participation in international expert groups with members from a range of industries and countries, including Switzerland, USA, Spain, Romania, Israel, England, and Norway contributed to increasing generalisability in the research.

3.8.4 Ethical considerations

Access and ethical issues implied by the selected research design should always be considered in preliminary stages of the research (Saunders et al., 2019).

The research conducted in this project is regulated by privacy data acts, and the undertaken studies were submitted to the NSD. Jacobsen (2015) emphasises that the choices that shape the research process must be made based on research ethical principles. Ethical issues can arise when the research directly affects people, and a researcher must therefore tread carefully in an interview situation (Johannessen et al, 2016).

Jacobsen (2015) presents three basic requirements for research ethics, which deal with the relationship between researcher and informant:

- Informed consent
- Requirements for privacy
- Claim to be correctly reproduced

The NSD (2022) also emphasises that the researcher must respect the requirement for free and informed consent and ensure the privacy of the participants. To carry out the research according to these principles, a transparent process was important. Before the informants agreed to participate, a project description was issued, together with a description of how their information would be processed and how the whole study would be carried out. A consent agreement was then signed in accordance with regulations from the NSD. In all published materials, the informant is kept anonymous, and specific statements or experiences are not linked to specific informants; no directly identifiable information is given.

Tjora (2017) recommends communicating the research results back to the informants after completing the study; this is a nice gesture, a thank you for the help, and can, at the same time, give the researcher constructive feedback and reflections beyond the initial contribution and ultimately support in further research.

Respondents who participate in interviews must be treated fairly (Bryman, 2016). The NSD ensures that conducted research is organised in a way that protects the rights of the participants, including confidentiality and privacy. This study was submitted to NSD in the early stages of the research, and data collection was initiated following formal approval.

Documents containing information on the interview process and interview questions were sent to each interviewee prior to the interview itself. The documents described the purpose of the study, the expected contribution from the interviewees, data collection methods, and how anonymity would be ensured in the published version of the script. Each interviewee provided their written consent to participate in the study based on this information. Their identity and organisational affiliation were anonymised to protect the confidentiality and privacy of the interviewees and their participation in the study. Similarly, if the interviewees named specific partners, names, organisations, or in other ways shared confidential information during the interviews, this information was anonymised during the coding stages of the research.

In addition to the anonymisation of involved interviewees and informants, all data collection, processing, analysis, and coding has been conducted neutrally and as transparently as possible to ensure replicability.

4 Findings from Individual Papers

The thesis is built upon the findings from six scientific papers. This chapter presents the findings from each of the individual studies, as summarised in Table 4-1.

Table 4-1. Main findings from each paper.

Paper	Main finding
Paper I	The biggest knowledge gap in the field is related to the practical implementation of the technology, and the implications related to the scalability and robustness of these technologies.
Paper II	Effective measures for waste reduction on construction sites with AI-powered tools, and related practical implications. Defines a possible process and approach for developing a holistic framework, enabling effective use of developed tools and techniques.
Paper III	Meaningful, AI-based analyses can be conducted for low-resolution data. However, more standardisation frameworks for data management in construction projects can enable continuous comparison and tracking between projects, greatly improve project-based benchmarking, support project success prediction, and serve as early warning systems.
Paper IV	The main barriers related to the effective data management for materials and products in existing buildings were identified as lack of data operability, lack of competence, unwillingness to share data, lack of financial incentives, and lack of harmonisation.
Paper V	AI-powered systems can be used to enhance the QA process on the construction site. A five-step standardised process framework is defined, with five main areas affecting the effectiveness and efficiency of the system. Thirteen factors affecting profitability are identified, along with the main challenges perceived to hinder productivity and sustainability in the process.
Paper VI	Developers display more maturity and proficiency in AI than users and implementers. Users are not as proficient as they would like to be. Five factors are central for increasing proficiency and ensuring sustainable implementation of AI: collaboration and stakeholder involvement; access to specialised expertise; sufficient financial support; trust and transparency; awareness and training. A four-step framework is defined.

4.1 Paper I

The purpose of this study was to map the research in the field of AI-based tools in the construction industry. The study focused on the range of applications in the construction context rather than one specific area of application, and thus elaborated on the findings from previous reviews such as Ilter and Dikbas (2009), Martinez and Fernández-Rodriguez (2015), Juszczyk (2017) and Basaif and Alashwal (2018).

The study investigated the current and potential future use of AI in construction projects, and the paper provided an overview of the current state of the field, ultimately giving a sense of direction in a time when academics and practitioners alike are eager to move forward and innovate in the field. Available technology, data access, quality of data, and availability of data are rapidly increasing, while the cost of data processing tools is decreasing equally fast. This creates the possibility for new technologies and applications that were not feasible even a few years ago.

The paper utilised a scoping review methodology and provided an overview of the recent and current uses of AI in construction projects through a descriptive analysis of the characteristics and contents of 86 peer-reviewed articles from 2015 to 2020. The classification framework included descriptive features (year of publication, source, author(s), location, and keywords), method (conceptual, qualitative, quantitative, or mixed methods), areas of application, and technology. Mapping the descriptive features of the publications enabled an extensive analysis of development over time, and the inclusion of bibliometric elements to the analysis.

Publications were categorised according to methodology as either conceptual (40%), qualitative (21%), quantitative (12%), or mixed method (28%), as summarised in Figure 4-1.

The review saw a tendency towards conceptual methodologies. Strictly developmental studies in terms of specific terminology, technical systems, or framework were categorised as conceptual. More than half of the conceptual studies included some qualitative or quantitative testing and validation in the development of the system or algorithm; this was still considered part of the development process, and the studies were therefore still categorised as conceptual. Most developed systems were tested on a PoC scale, and the research did not address whether the systems were further developed or implemented in larger scale or not.

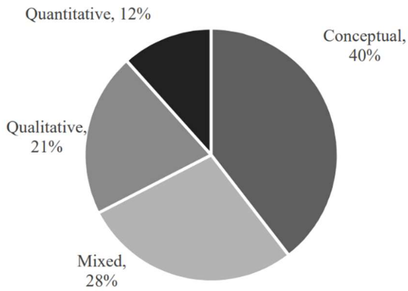


Figure 4-1. Distribution of chosen methodologies.

Publications categorised as qualitative typically addressed aspects surrounding the technology, including potential future areas of application, possibilities, and barriers to the technology itself, related to the soft factors. Notably few studies discussed the use of AI-based systems in the context of people and processes, focusing on technology awareness and digital maturity with an emphasis on AI. This discussion largely appears to be lacking in studies with a focus on more specific solutions and tools – this is also found in previous reviews (Basaif and Alashwal, 2018), and suggests that a gap exists between the potential that the technology constitutes and the evidence of how it is utilised in both practical and academic context. Publications categorised as quantitative involved the testing of previously developed techniques and algorithms and were usually applied to rather limited datasets. This could suggest a low degree of research-based AI implementation, constituting a great potential for future implementation and pilots. Publications were categorised as mixed method when the research design used two of the three aforementioned methodologies equally. Most studies categorised as mixed method were rooted in a conceptual base, but in combination with traditionally qualitative or quantitative methods.

The number of studies conducted within each methodological approach appeared to change between 2015 and 2020, indicating a rapidly developing field. Earlier publications showed a tendency towards mixed or purely quantitative or qualitative studies, whereas later publications were often purely conceptual. An increasing interest in AI within the construction industry becomes apparent; this is confirmed both by the body of publications as a whole and individual studies. However, a higher concentration of conceptual studies could suggest a gap between theory and practice. Many studies seemingly remain in a development phase, and few studies address the practical adoption of AI-based technology in the industry and among practitioners at a larger scale.

To elaborate, most studies illustrate how certain technology can be utilised in different parts of construction projects, for example exploring site layout design (Amiri et al., 2017), or predicting project performance (Mirahadi and Zayed, 2016). However, most studies lack a larger context for the technology – a framework for the technology to operate within. The studies do not discuss organisational or process-oriented considerations in the adaption and adoption of AI in projects. This could, naturally, have many explanations.

For example, a few studies discuss the lack of access to sufficient amounts of quality data. Another possible explanation could lie in the lack of transferability in the developed models and frameworks, meaning that new studies are not necessarily able to build on previous research. This, in turn, could suggest a need for a more standardised framework of technologies and terminology for researchers to operate within when exploring the topic of AI in construction. Challenges concerning transferability could ultimately prevent a model built in one environment from being useful in another environment, due to differences in requirements and prerequisites; it could also prevent one study from effectively building upon the foundational work of another.

This can be understood as a sign that the field itself remains at an emergent stage; at the same time, this provides an understanding of the great potential the field demonstrates. Existing case-based research can, and should, be used as a foundation for developing larger-scale studies.

In terms of areas of application, the research seems to be relatively evenly distributed. There appears to be a predominance of estimation and cost control (22%) and logistics, planning, and scheduling (19%); the two together account for almost half of the body of publications. As mentioned, the availability of a sufficient quantity and quality of data is a challenge in the construction industry. The two predominant areas both lean towards the quantitative and more easily measurable area of the industry; time and money are easily quantifiable. Other areas of application include strategy (12%), health and safety (10%), project performance and success estimation (10%), risk management (8%), reviews and overviews (7%), sustainability (7%), and material properties (5%). Notably, even if a lot of the studies address a certain area of application conceptually or in general terms, relatively few of these studies report on actual implementation and practical use beyond pilots and PoCs. Most focus on the potential use or the development of techniques for future use. No significant links were found in the body of publications between the chosen areas of application and the chosen methodologies.

Figure 4-2 illustrates the distribution of areas of application.

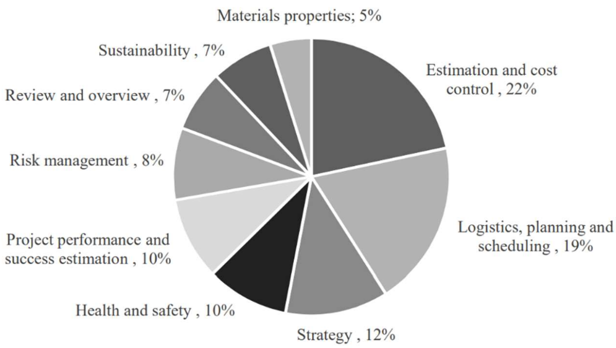


Figure 4-2. Distribution of areas of application.

The framework presented by Akinade (2017) was used for classification of AI systems, meaning systems were categorised as either ML, KBSs, EAs, or hybrid systems. The classification was based upon the description of the techniques provided by the authors themselves. More than a third of the publications (38%) did not explicitly state the nature or class of the technology in question. Some explanations for this were identified during the search. Studies lacking a technical description seemed to mainly focus on implications and effects, or potentials and barriers, rather than the development or use of specific technologies. Hybrid systems (26%) and ML (26%) were the main techniques studied in more than half of the publications. KBSs constituted 6% of the reviewed studies, while EAs constituted 2%. The majority of the hybrid-classed studies describing technology and techniques also utilised ML, mostly supervised ML; a notable number were also based on EAs. Among the publications discussing ML, half of these specifically discussed neural networks. The remainder of the publications showed no significant trend or preferred technique within the category. There appears to be an increase in the application of hybrid models in the later years compared to earlier years (Xiao et al., 2018). This could suggest increased use of more compound systems as technology and industry develop because hybrid systems are able to solve more complex tasks than any single system (Akinade, 2017).

As part of the screening process of the review, a significant number of studies using the terms AI or ML without addressing specific techniques or approaches were discarded; this implies that many use the terminology somewhat loosely. One explanation could be a lack of unambiguously defined terminology and vocabulary in the field, especially in the context of the construction industry. Another explanation could be that these are ‘buzz words’ popularised by the media; this can contribute to the confusion of definitions. Most of the exclusions were caused by the high number of papers discussing technology not explicitly defined as AI.

Figure 4-3 illustrates the distribution of discussed technologies.

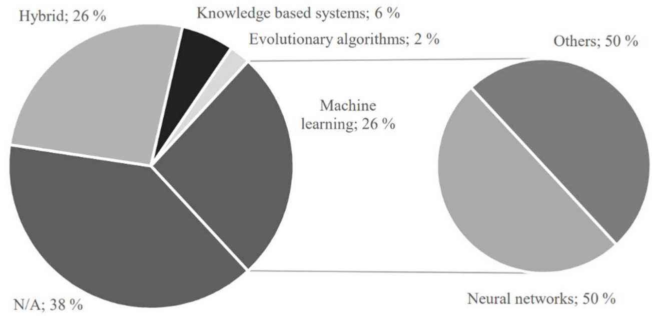


Figure 4-3. Distribution of discussed technologies.

Ultimately, the findings from the literature review became pivotal for the thesis as a whole, making it clear that the biggest knowledge gaps in the field, both in academia and in the industry, were related to the practical implementation of the technology and, by extension, implications related to the scalability and robustness of AI-based technologies.

The field is rapidly evolving, with new technologies, techniques, and tools being developed both inside and outside of the construction context. A visible change in preferred methods, as well as a change in keywords over time, imply that the field is indeed developing. The conceptual methodology seems to be the preferred approach in the field of study. The extensive use of conceptual methodology suggests that this method works in a research context but could, at the same time, suggest a need for other, more practically focused methods to develop the field further. The wide thematic range of previous studies provided a valuable foundation for future research, but the field is assumed to benefit from a shift towards more interdisciplinary studies. Many studies focused purely on the development of algorithms and tools, whereas others focused purely on the expected effects.

It became apparent that AI holds significant potential for increasing productivity and sustainability in construction projects, but the construction industry seems to lack the progress seen in other industries.

The study contributed to the current state of research on AI in construction projects by presenting a state-of-the-art view of the research done in the field from 2015 to 2020. It provided an overview of methodologies used, areas of application, and technologies, ultimately providing a direction for future research. It illustrated possible areas of innovation and application of AI-powered tools and could, in that sense, serve as a tool for benchmarking.

Findings showed a need for future research to focus on developing holistic frameworks to improve scalability and robustness. For this thesis, it meant remaining studies would mainly be centred around systemic, process-oriented, and organisational aspects rather than the technical development of specific tools or algorithms. Through understanding the current status and the main challenges the industry is facing, and mapping the main dimensions of the implementation process, a framework could be developed to help actors move from ambition to practice.

4.2 Paper II

The purpose of this study was to examine and explore through exemplification how AI-based tools, in practice, can be utilised in construction projects. As the findings in Paper I suggested, more research was needed on the practical implications of implementation, and this study sought to contribute to the filling of this gap. To exemplify this, the study explored how AI-based tools can help reduce waste on construction sites.

The construction industry accounts for nearly 40% of worldwide energy consumption and energy-related gas emissions (Global Alliance for Buildings and Construction, 2017). Reduction of waste on construction sites plays an important role in the usage and development of sustainable solutions, and in the ongoing development of a sustainable industry (United Nations, 2021). Studies show that certain waste fractions have very high waste percentages (Hjellnes Consult, 2015; SSB, 2019), meaning that large amounts of such materials pass through the value chain without adding any practical value to a project.

An explorative, mixed method research design was deployed. Qualitative methods were utilised, including a literature review, 32 interviews, a project visit, a site visit, and participation in chosen seminars. In addition, quantitative methods included an analysis of waste quantities in 161 construction projects, selected based on criteria for availability of data, as well as a targeted questionnaire with 21 respondents.

Previous research identifies timber and wood, plaster, cardboard and paper, plastics, and mixed waste as the most significant waste fractions (Rønningen, 2000; Kartam et al., 2004; Osmani, 2012; SSB, 2019). Evaluating the generation of waste in 161 new building projects confirmed previous findings: the most problematic fractions were identified as timber (34.6% of total waste); mixed waste (27.3%); plaster (17.8%); paper and cardboard (2.7%); and plastic (2.3%). The same fractions were confirmed and highlighted by informants in the questionnaire and interviews. Informants identified the activities and processes producing the most waste for each fraction. A range of tools are already established as suitable for construction site waste reduction, including Lean Construction (Womack et al., 1991; Koskela et al., 2002). Other tools include sustainable design choices (Innes, 2004; Zero Waste Scotland, 2016); industrialisation (Tam et al., 2005), and digitalisation (Charef et al., 2018).

The study concluded with 18 proposed measures. Conceptually, the recommendations were constructed by first identifying the main sources of waste, what waste fractions were the largest, and what activities and processes in the project contributed to the generation of waste. Following this analysis, existing measures for waste reduction were assessed, including concepts related to specific frameworks such as Lean Construction, along with concepts related to more general developments in the industry such as industrialisation and digitalisation. Then, AI-based tools and technologies considered relevant were assessed in the context of the identified waste fractions and processes, and the established tools. This conceptual framework is illustrated in Figure 4-4.

Areas that hold potential to be enhanced using AI-based tools should be identified first, and solutions second. This was later confirmed by the findings in Paper VI.

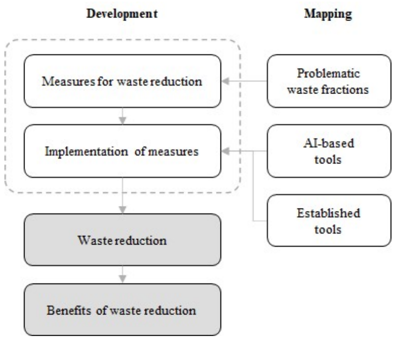


Figure 4-4. Conceptual framework for waste reduction powered by AI.

From this assessment, the study uncovered several possibilities and concluded with the 18 measures for the reduction of waste on construction sites, along with a set of recommendations for practical implementation. The recommended measures were related to the most relevant project phases for implementation, and included definition of appropriate targets for waste production, optimisation of resources, continuous tracking, reporting, and presenting of waste quantities, training, conducting inspections, and implementation of specific routines for warehousing; the recommendations included development and deployment of ML, KBS, and ES systems. It was assumed that most complete AI techniques and tools would comprise more than one form of AI and thus be hybrid models, and so the dominant system or technique was denoted in the recommendations. Recommendations related to the timing of the implementation were proposed based on NS 3467:2023 framework (Standard Norge, 2023).

The recommendations are summarised in Table 4-2.

Table 4-2. Recommendations for implementation of waste reduction measures.

#	Recommended measures for waste reduction	Technique	Phase
1	Early and explicit definition of targets for waste reduction	ML (regression)	4
2	Early and explicit plan for resource optimisation	ML (ANN), EA (GA)	4
3	Continuous tracking of waste quantities	ML (ANN)	5 (3,4)
4	Continuous reporting of waste quantities	ML (ANN)	5 (3,4)
5	Continuous and visual presentation of waste quantities	ML (ANN)	5 (3,4)
6	Defining routines for warehousing on-site	ML (ANN), EA (GA)	4,5
7	Defining routines for ordering materials	ML (ANN), EA (GA)	4,5
8	Training of all involved personnel	ML	3,4
9	Contractual arrangements based on bonus-malus	ML (regression)	3

10	Establishing a digital platform for all actors in the project	ES (RBS)	1,2,3,4,5
11	Establishing a digital platform for experience sharing	ES (RBS)	1,2,3,4,5
12	Inspections during all production phases	ML (ANN), EA (GA)	5
13	Layout planning during all production phases	ML (ANN), EA (GA)	5
14	Increased use of digital tools for ordering accurate quantities	ES (RBS)	5
15	Marking orders and materials arriving on-site	ES (RBS)	5
16	Design for standardised elements	EA (GA)	2
17	Design for the use of cut-offs	EA (GA)	2
18	Design for shared geometry	EA (GA)	2

The study helped to bridge the gap between ambition and practice by highlighting relevant considerations related to the practical implementation of measures for waste management, and by providing an understanding of which AI-based tools and measures are considered effective for waste reduction in construction projects. A range of practical implications were discussed. The increased use of AI in construction projects is expected to require investment, especially during the early phases of implementation and integration. As the cost of data processing continues to decrease and the interest within the field continues to increase – ultimately bringing more available and commercialised solutions – it is reasonable to assume the cost will decrease accordingly.

The findings suggested that, to utilise the potential of AI-based techniques fully, the construction industry should build upon existing methodologies and strategies; however, it is likely that the industry as a whole would need to eventually reinvent and redefine traditional project models, contracts, business models, and enterprises. This is a comprehensive task and should involve key actors in all parts of the value chain.

In the concluding remarks of the study, it was noted that a useful undertaking would be to study in closer detail how data of sufficient quantity and quality can be collected, structured, and utilised to enable effective use of AI; this, in part, inspired the initiation of the two studies resulting in Paper IV and VI. To validate the findings related to the conceptual development of a framework to utilise AI-based tools, it was necessary to explore more than one area of application; later papers explored QA (Paper V) and project success (Paper III).

4.3 Paper III

The purpose of this study was to exemplify an ML application on a limited dataset, as datasets are often limited in a construction context, relatively speaking. In addition, the study gave an opportunity to gain first-hand experience with the process of developing and deploying an AI-based tool in a construction context.

No single definition of project success exists (Bannerman, 2008). One direction of project success research aims to identify the factors that can contribute to project success, project failure, or project risk. Previous research has explored the use of AI to predict project success and examine and identify critical success factors. Several techniques are utilised in previous research (Magaña and Fernández Rodríguez, 2015), including ANNs (Chua et al., 1997; Dvir et al., 2006; Ko and Cheng, 2007; Wang, Yu and Chan, 2012; Jacobsen and Teizer, 2022), EAs (Ko and Cheng, 2007; Cheng et al., 2009), and regression analysis (Dvir et al., 2006).

The study conducted a quantitative analysis on a sample of 160 Norwegian construction projects, building the algorithm with data obtained from a detailed questionnaire delivered to relevant project team members through the Nordic 10-10 initiative. The method utilised ML through a Random Forest Classifier (RFC). The original dataset was loaded into a Python script, where selected libraries were used. One of the selected libraries was Pandas. A dataset loaded into Pandas is a DF. The original datasets were processed through an EDA and preliminary cleaning, resulting in an initial DF. This DF was then split into nine purposed DFs before the next steps were carried out in order: main cleaning, labelling, train-test split, scale, train and fit, classification, and lastly analysis and plot of the results. The process is summarised in Figure 4-5. To keep a low number of DFs and filter out the least relevant, only some combinations were explored further. For instance, if a DF had too few projects, or only either successes or failures, they were dropped. After initial simulations, three DFs yielded more precise results than the remaining six; the main analysis therefore focused on these three.

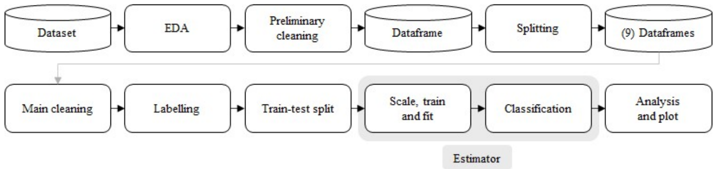


Figure 4-5. Development pipeline.

The findings obtained from the analysis show that it is possible to use AI and ML on a limited, low-resolution dataset. The data in the Nordic 10-10 program are not collected specifically for the utilisation of AI, and therefore the development required a lot of preparatory work. Construction project data can be of high resolution and domain-specific, such as plans for large projects. Low-resolution data, such as the data this study was built upon, are based on qualitative evaluations done by the project organisations themselves. This has advantages; the data describe first-hand experiences from the project team members. Disadvantages include a risk of bias by the staff reporting the scores. The 10-10 database is based on reports from members of the project team in respective projects. This means that there is a possibility of bias or imprecision; consequently, a value could have been put in the wrong place or provide an inaccurate or biased image of the actual situation.

Future analyses would benefit from more consistent registrations of questions and parameters, which is a common issue in ML and other quantitative analyses.

A model or approximation will only ever be as reliable as the data it is based upon. Currently, no standards exist for collection and utilisation of data in construction projects. To a certain extent, this is understandable because all projects are unique. However, it would greatly benefit this type of analysis if some standardisation of data structures would emerge. Some industry-specific standards exist for structuring of data, such as for BIM and standards for data coding such as NORSOK in the Norwegian oil and gas industry. Data that can be consistently compared and tracked between projects has the potential to improve project-based benchmarking, support project success prediction, and perhaps most importantly, serve as early warning systems that can identify potential issues in time for action to be taken.

The findings from the study also demonstrate that it is possible to identify the most important success factors for the projects in question with the developed model. Ultimately, the ML model demonstrated the ability to discover important factors for project success from a limited dataset. Such analyses can be used in early phases of a project to predict project success in later phases, or in the whole project, and could prove to be a useful tool to eventually achieve more project success.

Specifically, the findings suggest that a group of selected processes is more important than others in achieving project success. The identified success factors support the theoretically (and empirically) acknowledged importance of early planning and analysis, managing complexity throughout the project, leadership involvement, and processes supporting project success. The top features (factors) from the best performing DFs with their conceptual meaning is summarised in Table 4-3.

Table 4-3. Top features from the best performing DFs.

Feature	Concept
The complexity was very high due to the progression plan	Complexity
The project had a large quantity of changes in the list of main components	Changes
The project had a large quantity of deviation reports	Deviations
All relevant project members were involved in the uncertainty analysis	Uncertainty
The involvements from project owner were appropriate	Leadership involvement
The project's processes and systems support project success	Project owner process
The project team participated in adequate engineering work training	Training
Suggestions for improved constructability were evaluated and integrated	Planning
Costs to fix potential faults were considered during the engineering phase	Cost of quality

Simultaneously, certain previously acknowledged factors were expected to be among the identified factors; ultimately, these did not appear in any of the algorithm results. These included communication with key personnel and stakeholders, early involvement of key personnel, communication of strategic goals and project goals from the leadership team, among others. Although the factors are not emphasised by the model, they appeared to be important for success in the sample projects. One explanation for this is that the features that are not present are represented and reflected in other features. For instance, the concept of process support success was reflected in three separate features in the analysis, but only one of them was categorised by the algorithm as an important success factor. Therefore, the low occurrence of certain features does not necessarily indicate a lower importance of the feature.

Beyond the findings related to the assessment of project success, several findings could be derived from the development process itself, and the metadata collected during this process.

In developing the algorithm, much of the time was spent on preparing the dataset, meaning splitting, processing, cleaning, and labelling. The data used were originally collected to be read and understood by humans; inevitably, for an algorithm to make sense of the same data when only appraising information as numbers, time and resources must be spent to prepare the dataset. Furthermore, certain entries lacked one or more datapoints, ultimately rendering the whole entry ineffective.

Throughout the process, several decisions were made regarding handling missing values, weighting of DFs, tuning of hyper parameters, and definition of classes. These are all decisions that can, and likely will, affect how the algorithm works. To help both academics and practitioners to continue to build on developed systems and tools, a certain degree of transparency is needed to provide an understanding of how the development can affect the outcome, and how the outcome is to be understood in a larger context.

The overall assessment once again highlighted the importance of an extensive data management strategy, ensuring a high-level collection and storage of relevant data; this was further investigated in Paper IV and VI.

4.4 Paper IV

The purpose of this study was to explore barriers related to mapping, collecting, and storing data about materials and products in existing buildings; in essence, discovering data management as an enabler for circular economy.

A transition to a circular economy is considered essential to sustainable development in the built environment by reducing resource consumption and carbon emissions, and moving away from the traditional, linear economic model (Pomponi and Moncaster, 2016; Cheshire, 2019). The reuse of existing materials is a circular economy practice that can significantly decrease resource consumption and carbon emissions, but one that requires adopting a systemic approach and value chain integration on a large scale (Pomponi and Moncaster, 2016; Munaro and Tavares, 2021; Knoth et al., 2022). Effective data management can enable the utilisation of new tools and technologies and, ultimately, the creation of circular business models in the building industry. To accomplish this, a targeted mapping and collection of data must take place. However, several challenges hinder the exchange of information in a seamless digital flow through the value chain and building life cycle.

This study aimed to bridge the gap in the research on data management, providing an empirically validated and comprehensive overview of existing barriers and prospects related to mapping, collecting, and storing data about materials and products in existing buildings. To provide a construction-relevant context, the topic of circular economy set the basis for the study. An initial literature review confirmed the research gap indicated in previous research and set the basis for two interview cycles, which contained 12 and 6 interviews, respectively.

The insights collected through the interviews acquire both technical and practical connotations, seemingly coinciding with the findings of other studies investigating the link between digitalisation and circular economy, focusing on specific aspects or technologies. Six barriers were identified through 18 semi-structured interviews with industry experts working within the fields of circular economy and digitalisation. Through coding and interpretation of the emerging concepts, the identified barriers were:

- Lack of data availability
- Lack of data interoperability
- Lack of competence
- Unwillingness to share data
- Lack of financial incentives
- Lack of harmonisation

In the circular economy context, lack of data availability is related to data about building materials and products being missing, incomplete, inaccessible, or not digitised. Findings argue that the information should be dynamic, possibly connected in a digital model or a material passport.

Lack of technical interoperability can impede effective data management, and a robust digital infrastructure is highlighted as crucial for effective scaling. Data are often stored in different repositories, in different formats, with varying levels of ownership and accessibility; this is ultimately hindering effective exchange of information between stakeholders through the value chain. Integration with digital tools, such as BIM or material passports, are perceived to simplify this process, given that the platform of choice allows exchange of data in an open format. Transparency and openness of data is considered essential for enabling interoperability. Another vital aspect of improving data interoperability is the collection and storage of data and information in a standardised format. Industry actors noted that regulation standards are still missing, adding another layer to the challenge of coordination. Digital technologies and tools are expected to contribute to the sharing and connection of data between stakeholders in an open, transparent, and standardised way.

Lack of competence is related to collecting, handling, sharing, and managing of data. Some actors note that the competencies adapt over time in an organisation, helped by pilot projects and industry initiatives.

Unwillingness to share data is another challenge, as the perception in the industry today is that actors are not willing to share their information openly across the value chain and between industry actors. Informants note that this unwillingness can ultimately hinder the overcoming of other barriers, such as the lack of interoperability.

A few challenges are associated first and foremost with structural considerations, such as lack of financial incentives. Actors argue that it is difficult to establish a business model for reuse of building materials on a larger scale without financial incentives originating from the market or the authorities. Stricter requirements from project owners and authorities could potentially contribute to solving this barrier and making it financially viable.

Lack of harmonisation across the value chain is mainly related to the lack of cohesion in procedures and processes for data management. This, in turn, can contribute to hindering the exchange of information between stakeholders, making it difficult to achieve circular economy and material reuse. Standardising the processes related to data exchange and management through connecting the value chain and defining the responsibilities and roles of the different stakeholders could help to mitigate these issues. This is expected to also improve the lack of interoperability.

Some identified barriers, such as the lack of data availability and interoperability, lack of competencies and unwillingness to share data, are strongly interrelated. A collaborative approach is required to achieve effective data management, and to ultimately enable a circular economy in the built environment. According to the findings, measures that could contribute to overcoming these barriers include the adoption of a public database to ensure openness and transparency of the data. In addition, to ensure the effective management of large amounts of data, standardised and harmonised procedures and processes for data management and a financially viable model will be necessary. To overcome the barriers, it is essential to strengthen collaboration and trust among key stakeholders.

The study acknowledges the position of AI-based technologies as not the goal itself but a part of a bigger system and picture. It illustrates how the utilisation of AI-based tools extends far beyond developing and building algorithms and how the technology itself is only one part of a much bigger framework that needs to be in place to make use of the technology effectively.

Through exploring previous and ongoing endeavours among academics and practitioners, the research set the basis for developing a holistic framework for data management. This was further explored in Paper VI.

4.5 Paper V

The purpose of this study was to examine how AI can help improve QA on the construction site, specifically used in conjunction with BIM and 3D laser scanning.

Quality in the delivery and deliverables of construction projects has been, and continues to be, identified among the most central factors for project success (Arditi and Gunaydin, 1997; Chan et al., 2004; Bang et al., 2022). Thus, QA plays a vital role in project management (Nguyen et al., 2018). Construction projects often involve complex processes and tasks requiring high levels of accuracy and precision; therefore, QA is critical to ensure that the project can deliver according to the required specifications and standards. Construction projects significantly impact the environment in all stages of their life cycle. Ensuring quality in delivery and deliverables is essential for maintaining social sustainability, reducing costs, and minimising environmental impact.

Laser scanning is identified as a tool to reduce errors and improve the promptness and accuracy of QA processes (Anil et al., 2011; Safa et al., 2013). Previous research demonstrated the strengths of using BIM and 3D laser scanning in conjunction (Kaylan et al., 2016; Liu et al., 2021). As the advances in digital technologies are rapidly increasing, experts argue that the evolution of BIM should be categorised within frameworks factoring in people, processes, and emerging technologies (Kubicki et al., 2019; Boje et al., 2020). Wang et al. (2020) suggest that more case-based research on the implementation and use of new digital technology with BIM can contribute to empirical validation of previously theoretical findings.

This study explored the QA process, how it can be standardised, how it can be advanced by increasing effectiveness and efficiency, and how AI-powered tools can help enhance the process.

A mixed method research design was employed. This was done through nine semi-structured in-depth interviews, where the interviewees had experience from 15 different projects utilising 3D laser scanning for QA; a multiple-case study, investigating case documents and records from six case projects, an additional four interviews with personnel involved in the 6 case projects, as well as presentations from involved personnel; and a literature review, exploring the topic of AI in a BIM and QA context. An initial, unstructured literature search informed the interview guide, and the conducted interviews informed the case study, which again informed the literature review. Since the case projects had not utilised AI in their work, the additional nine interviews, as well as a scoping literature review, were conducted to inform how AI can be used in the BIM and QA context.

A five-step standardised process facilitating the use of AI tools was defined, namely: planning; scanning; data processing; error detection; and distribution and improvement. The framework provided a set of guidelines for the actors in a previously fragmented area of application, to inform future work in academia and industry.

The seven challenges perceived to be the biggest ones hindering productivity and sustainability in the process were identified:

- Time-consuming scanning
- Time-consuming processing
- Time-consuming detection of deviations
- Time-consuming communication of deviations
- Noise in scan
- Lack of interoperability
- Time-consuming updating of BIM model

Recommendations related to how these challenges could be overcome by utilising digital technologies and AI were proposed. The findings from all three research questions informed a proposed system for QA, utilising the potential of 3D laser scanning and AI-based tools, both commercially available or tailored to the project and organisation, built on proposed established data warehouses.

The research discovered five main areas impacting the effectiveness and efficiency of the process:

- The BIM model,
- Competence
- Involvement of subcontractors
- Integration in the company QA system
- Project-specific plans

A series of prerequisite factors were defined for each of the five areas to provide a guideline for validation for the QA system. Thirteen factors affecting the profitability of the system were identified, along with the perceived certainty for cost estimates. The thirteen factors were related to equipment, company-specific factors, project-specific factors, process-specific factors, and factors related to errors.

For academics, the study provided empirical validation of previously identified theoretical findings, and a detailed description of the practical implications related to the use of 3D laser scanning with BIM and AI for QA in construction projects. The study provided a foundation for future research to develop and test AI-based tools to empirically map the effects of these technologies on the QA process. For practitioners, the study provided a set of extensive guidelines to better understand, and more effectively use, 3D laser scanning with BIM and AI for QA in construction projects by proposing a framework for standardisation, along with a set of recommendations for further advancing and enhancing the process.

4.6 Paper VI

The purpose of this study was twofold. Firstly, the study aimed to assess the AI maturity and proficiency among industry actors, namely developers, users, and implementers of digital tools and AI systems. Secondly, the study defined a framework acknowledging challenges related to the development and deployment of AI systems, with recommendations and practical implications for the three groups for each stage of the framework. The framework is intended to facilitate sustainable implementation of digital tools and AI in the construction context and help take the use of AI from an add-on to an integral part of construction projects.

The purpose of this study was twofold. Firstly, the study aimed to assess the AI maturity and proficiency among industry actors, namely developers, users, and implementers of digital tools and AI systems. Secondly, the study defined a framework acknowledging challenges related to the development and deployment of AI systems, with recommendations and practical implications for the three groups for each stage of the framework. The framework is intended to facilitate sustainable implementation of digital tools and AI in the construction context, and help take the use of AI from an add-on to an integral part of construction projects.

Identified barriers for the digital transformation in construction are related to the lack of organisational capabilities (Aghimien et al., 2022; Rajabi et al., 2022; Zhang et al., 2023), collaboration and communication between stakeholders (Bosch-Sijtsema et al., 2021; Xu et al., 2022), availability of expertise (Aghimien et al., 2022; Rajabi et al., 2022), and data collection, storage and sharing (Shahzad et al., 2022; Xu et al., 2022). Construction digitalisation goes beyond acquisition of necessary hardware and software (Akinosho et al., 2020; Adekunle et al., 2021), and there is a need for frameworks facilitating this transition. Data management is identified as a key barrier for scaling and increasing robustness in AI systems in the construction context (Burgess, 2018; Xu et al., 2022). Therefore, this study took on a data management perspective on implementation.

The Pringle and Zoller (2018) maturity model categorise adopters of AI technologies, from ‘novice’ through ‘ready’ and ‘proficient’ to ‘advanced’. The model is summarised in Table 4-4.

Table 4-4. AI maturity model (Pringle and Zoller, 2018).

AI Novice	AI Ready	AI Proficient	AI Advanced
Has not taken proactive steps on the AI journey and at best is in assessment mode	Sufficiently prepared in terms of strategy, organisational setup, and data availability to implement AI	A reasonable degree of practical experience and understanding of how to move forward with AI, but there are still gaps and limitations	A good level of AI expertise and experience, with a proven track record across a range of application cases

An initial literature review confirmed the research gap indicated in previous research and set the basis for empirical data collection through 36 semi-structured in-depth interviews, out of which 14 were developers, 15 were users, and 7 were implementers; a document study; a site visit; and 14 demos, out of which 9 were provided from a developer perspective, while the remaining 5 were provided from the user perspective.

Interviewees were asked to assess themselves and their organisation according to the Pringle and Zoller (2018) maturity model. Only one developer described themselves as ‘novice’ level, while two developers categorised themselves as ‘advanced’, holding experience from application of AI across a range of industries and areas of application. Twelve out of fifteen users categorised themselves as ‘novice’ or ‘ready’, and three as ‘proficient’. Most implementers described themselves as ‘ready’ and only one as ‘proficient’. The final appraisal, as presented in Table 4-5, is based on a qualitative assessment of the interviewees’ descriptions of themselves and their organisation, provided throughout interviews, available documentation, and notes made throughout demos.

Table 4-5. Interviewee assessments according to the AI maturity model.

	AI Novice	AI Ready	AI Proficient	AI Advanced	Total
Developers	1 (7.1%)	3 (21.4%)	8 (57.1%)	2 (14.3%)	14
Users	5 (33.3%)	7 (46.7%)	3 (20.0%)		15
Implementers		6 (85.7%)	1 (14.3%)		7
Total	6 (16.7%)	16 (44.4%)	12 (33.3%)	2 (5.6%)	36

When asked to assess their counterparts, users consistently described developers as more mature, while developers consistently described users as less. Implementers generally described the two other parties closer to their self-assessments. Users acknowledge that they generally do not consider themselves as proficient as they would like to be. Describing proficiency among users, a developer states that there is a very varying degree of proficiency while another developer notes that users do not necessarily need to understand the technology behind a solution to use the system effectively. The consensus among the developers seemed to be that the goal is to develop a tool users can operate with minimal technical knowledge.

Previous research identified the lack of awareness, education, training, and trust as barriers to sustainable construction project implementation (Rajabi et al., 2022; Almakayeel et al., 2023; Kineber et al., 2023b); notably, the same barriers are identified in as barriers for the increased use of digital tools and AI (Burgess, 2018; Darko et al., 2020; Delgado et al., 2020; Goralski and Tan, 2020; Aghimien et al., 2022; Rajabi et al., 2022; Shahzad et al., 2022; Xu et al., 2022; Zhang et al., 2023). This implies that a framework facilitating effective use of digital tools could contain elements that facilitate sustainable construction project implementation. From the findings of the maturity assessment, an implementation framework was developed.

No two interviewees described the same implementation process. However, a common emerging theme was the description of iterative and constantly evolving processes. Every stage of the process provides an opportunity to learn and to generate data and metadata.

The implementation process model is illustrated in Figure 4-6.

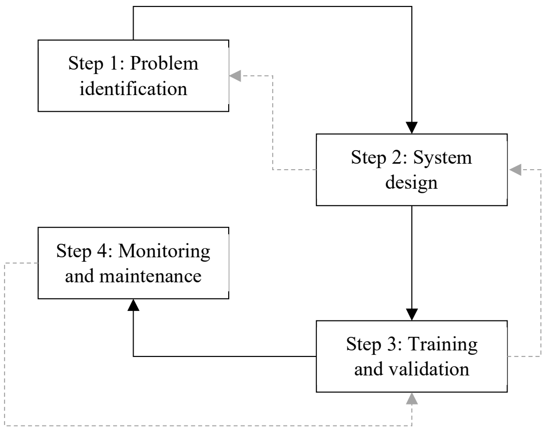


Figure 4-6. Implementation process model.

The first step is problem identification; essentially, identifying areas where AI can add value. Understanding the problem at hand will be essential in making AI a more integral part of a construction project or organisation, rather than an add-on. All users, when asked, expressed an interest to use AI. However, using AI for the sake of AI appears to be one reason why systems are unable to move past the pilot stage. Issues surrounding AI systems and models do not seem to be related to the mathematics of statistics of a model, but rather to the heuristics. Understanding the problem is essential to move past the PoC stage and ensuring sufficient contextualisation.

The second step is system design. This can involve the selection of appropriate AI techniques and models, and plans for integration of the AI system into existing processes. Designing a system that is scalable and robust is identified as one of the most important characteristics of a system. As noted in Paper VI, development and deployment are often done in traditionally academic languages, such as Python or MATLAB. This could contribute to creating a gap between the work done in academia and in the industry, which could, in turn, contribute to further fragmentation in the field. The findings suggest that the fanciest mathematics and most complex models do not necessarily have the biggest impact. Explainable models are seen as easier to deploy and maintain and are generally better received in a project or organisation. The developers emphasise that some problems do not require the use of ML and can be solved or supported by the use of methods that typically require less data, for instance KBS.

The third step is training and validation. While system design focuses on the structure and architecture of a model, the training and validation stage typically involves feeding large amounts of data to the model to learn patterns, make predictions, and perform specific tasks. Availability of data is identified by the interviewees as a central challenge. Construction projects often have fragmented, incomplete, or inaccurate data; a lack of interoperability contributes for complicating data sharing between actors. Developers emphasise the importance of high-quality data and metadata to build high-quality AI systems. Users note that it is necessary to collect data from multiple sources, as there currently exists no single database containing all the necessary data. A potential to improve this could be establishing data warehouses on the organisation level. Similarly, establishing metadata repositories can enable users to easily search, locate, and retrieve relevant data. Data exists in a wide – and unstructured – range of formats, including PDF, JPG, MOV, GIS, CAD, DOC, and, perhaps even more commonly, XLSX format. Data can be summarised in multidimensional data formats, such as NetCDF, JSON, or HDF5. Multidimensional formats allow data to be related to other existing data and metadata, and enables convenient searching, filtering, and extraction of data, and can ensure data quality. One way to increase transferability through the implementation process is standardisation. Standardisation can include systematic alignment of construction or data management processes, and can promote consistency, and interoperability.

The fourth step is monitoring and maintenance. As emphasised in the empirical findings, the final step is to be considered as a continuously ongoing process, rather than a step that is to be finalised upon delivery. The goal is to deliver, and to continue to deliver, a system that works safely and continuously, and works with the user infrastructure. Maintenance can include, but is not limited to, updating the model as new data becomes available, or otherwise adjusting the model after assessment of preliminary available data. It is recommended that users remain an active part throughout the development and implementation process, to ensure an understanding of how this process might affect the system and the output it provides. The findings indicate that involvement, over time, can contribute to increasing trust, competence, and ultimately, proficiency. All actors being experts in all fields is not a goal; experts should continue to foster their core competence, but involvement will be essential to cultivate specialists in the thematic intersection. The implementation process model is illustrated in Figure 4-7.

Figure 4-7 summarises the main contribution and purpose of each of the studies, and how the resulting papers informed subsequent studies.

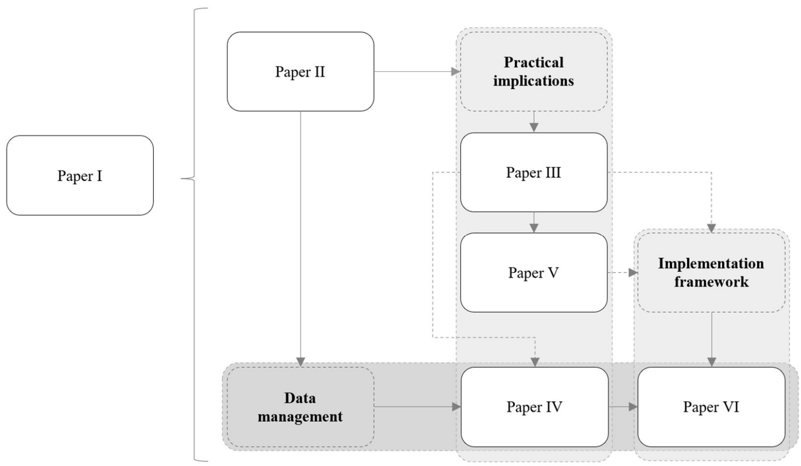


Figure 4-7. Connection between papers.

5 Discussion

The topic of AI in construction has sparked a lot of interest in recent years. Despite the obvious potential for AI systems and models in the industry, a gap remains between the potential the technology holds and its actual implementation at scale; there appears to be more hype than practical application. The six conducted studies saw a range of themes emerge through the research. The following chapter will discuss some main emerging themes in the implementation and integration of AI-based tools in a construction context.

The themes will be discussed in the context of four dimensions. The people, process and technology framework is well established. On the topic of AI, another perspective emerges as equally important: data. The topic of data is often addressed in the context of the technology perspective; however, to utilise AI effectively and efficiently in construction projects, high-quality data and metadata are needed. Data is not only needed in the development of a system or model but on and about the process to understand how the context of the data might affect the output and how the output can be understood. The modified framework is presented in Figure 5-1.

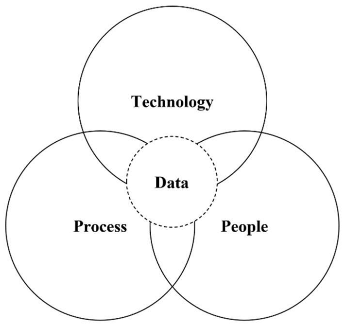


Figure 5-1. Framework for discussion (1).

The construction industry as a whole is generally considered less digitalised when compared with other industries. Still, both research and industry initiatives showcase great results. This thesis aims to enable actors in the industry, with a focus on practical implications contributing to the field. Therefore, the focus of the discussion will be on systems, projects, and organisations, rather than the industry as a whole.

Findings suggest that the industry could benefit from building upon existing methodologies and strategies, but it would eventually need to reinvent and redefine traditional project models, contracts, business models and enterprises. It is believed that change can also be driven by the industry actors themselves.

To enable the use of AI systems in construction projects, relevant infrastructure must be established on the organisation and system levels. Therefore, the following discussion will focus on, and distinguish between, the system, project, and organisation level (Figure 5-2).

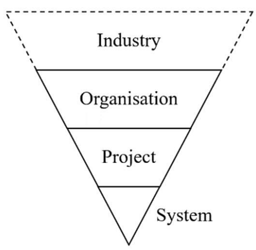


Figure 5-2. Framework for discussion (2).

Based on the two frameworks, the discussion will explore the current state, main challenges, practical implications of implementation and integration, and how actors can work on a system, project, and organisation level to move from ambition to practice. The discussion will be structured according to the frameworks.

5.1 System level

On the system level, a wide range of tools have been developed and successfully applied to estimation and cost control; logistics, planning, and scheduling; strategy; health and safety; project performance and success estimation; risk management; sustainability assessments; and material properties. However, few report on the use of these tools beyond pilots and PoCs; most focus on potential use or the development of techniques.

As illustrated in Paper I, the majority of the research is done on the system level. Consequently, the body of research is lacking on the project level, the organisation level, and on the intersections between the levels.

5.1.1 Technology

The body of research as a whole implies an uneven application of resources to problems as of today, and there is a predominance of applications related to traditionally quantitative areas such as estimation and cost control (Cheng et al., 2009; Shin, 2015; Juszczyk, 2017; Elmousalami, 2019; Yaqubi and Salhotra, 2019; Juszczyk et al., 2019; Juszczyk and Lesniak, 2019; Bilal and Oyedele, 2020; Cheng et al., 2020; Juszczyk, 2020) and logistics, planning, and scheduling (Golparvar-Fard et al., 2015; Podolski, 2016; Xing et al., 2016; de Soto et al., 2017; Camacho et al., 2018; Cheng and Hoang, 2018; Dawood et al., 2019; Hu and Castro-Lacouture, 2019), as noted in Paper I. In this sense, there appears to be a drifting apart between the academic field and the industry.

One explanation could be that some areas of application can more easily yield quantifiable results, meaning these areas gain more attention. Another explanation could be that some areas are still waiting for data. If an area is lacking data of sufficient quality and quantity, the development and employment of an AI system in that area could simply become too resource intensive. Lacking infrastructure could be another contributing factor to this. Different cloud-based systems and applications do not necessarily communicate well – if at all. For any system to work effectively, it should be integrated with other existing infrastructure. This provides a familiar platform for the users and ensures a certain degree of interoperability.

The industry is not currently lacking PoCs, tests, or pilots. This is widely documented in previous research (Golparvar-Fard et al., 2015; Gudauskas et al., 2015; Hajdasz, 2015; Mousavi et al., 2015; Shin, 2015; Kog and Yaman, 2016; Mirahadi and Zayed, 2016; de Soto et al., 2017; Juszczyk, 2017; Pruvost and Scherer, 2017; Samantra et al., 2017; Zou et al., 2017; Ayhan and Tokdemir, 2018; Cheng and Hoang, 2018; Goh et al., 2018; Hanna et al., 2018; Poh et al., 2018; Sharafi et al., 2018; Taherdoost and Brard, 2019; Elmousalami, 2019; Hu and Castro-Lacouture, 2019; Jaber et al., 2019; Juszczyk et al., 2019; Juszczyk and Lesniak, 2019; Vickranth et al., 2019; Yaqubi and Salhotra, 2019; Basaif et al., 2020; Fallahpour et al., 2020; Han et al., 2020; Juszczyk, 2020; Nnaji and Karakhan, 2020; Xu et al., 2020), and confirmed by the findings in Paper I. What appears to be lacking is evidence of scalable and robust systems, of infrastructure that facilitates effective use of the systems, and of organisation structures that preserve the new functions required to operate the systems.

Technology should be designed with the user in mind (Barlett-Bragg, 2017), and to enable streamlined integration with existing processes. Paper II and Paper III illustrated how, on a system level, a process can be deconstructed to identify and understand the problem at hand.

Selecting appropriate models, and further developing these to suit the context that they will operate within, is a central and critical part of the successful utilisation of AI (Russell and Norvig, 2010; University of Helsinki, 2018). Different models will be fit for different types of data, different activities, or different phases in the same construction project. Understanding the problem and the driving forces behind it is essential, and data management plays an important part in this process. As noted in Paper VI, developed models need to be scalable and robust. The AI model must be able to handle potentially large volumes of unstructured data and account for the complex interdependencies between different aspects of a construction project. The model must be capable of adapting to dynamic and rapidly changing environments, and able to identify relevant features and patterns – sometimes from minimal input. Following implementation, the AI model must be monitored and maintained, to ensure continued accuracy and effectiveness. Maintenance can include updating the model as new data becomes available, or otherwise adjusting the model after assessment of preliminary available metadata from the implementation process. To facilitate effective maintenance, maintenance protocols can be established. This can be done on a system level, but it is assumed that an overall organisation level protocol can help reduce the costs and resources needed for maintenance.

5.1.2 Process

On the system level, the process perspective is mainly concerned with the development and implementation process, meaning the development and implementation of the AI system or model.

The findings in Paper VI indicate that fanciest mathematics and most complex models or statistics do not necessarily have the biggest impact. Explainable models will be easier to deploy and maintain and are generally better received in a project or organisation. Advanced ML models might perform better in an isolated context, but a system that is perceived to be more transparent and representative of the actual process can yield better results in a real-life project situation, will long-term build more trust (Sjåstad, 2019; Belle, 2023), and thus, be more sustainable.

Contextualisation

An important first step is to map and understand the construction process that is to be enhanced.

AI systems built and used just for the sake of AI appear to be more likely to be left at a pilot or PoC stage, as noted in Paper VI. This is also indicated from the lack of evidence of scaling (Golparvar-Fard et al., 2015; Gudauskas et al., 2015; Hajdasz, 2015; Mousavi et al., 2015; Kog and Yaman, 2016; Mirahadi and Zayed, 2016; de Soto et al., 2017; Juszczyk, 2017; Pruvost and Scherer, 2017; Samantra et al., 2017; Zou et al., 2017; Ayhan and Tokdemir, 2018; Cheng and Hoang, 2018; Goh et al., 2018; Hanna et al., 2018; Poh et al., 2018; Sharafi et al., 2018; Elmousalami, 2019; Hu and Castro-Lacouture, 2019; Jaber et al., 2019; Juszczyk et al., 2019; Juszczyk and Lesniak, 2019; Taherdoost and Brard, 2019; Vickranth et al., 2019; Yaqubi and Salhotra, 2019; Basaif et al., 2020; Fallahpour et al., 2020; Han et al., 2020; Juszczyk, 2020; Nnaji and Karakhan, 2020; Xu et al., 2020); findings highlighting the need for more system and application-oriented research (Darko et al., 2020; Wang et al., 2020; Xu et al., 2022), and was further indicated by the findings in Paper VI.

Inevitably, this means that time and resources are spent without providing the expected profits and savings. To effectively identify and understand the problem at hand, it is recommended to define the issue and to break complex issues into smaller, more manageable, and comprehensible problems. In Paper II, this was exemplified for construction project waste reduction. Conceptually, the recommendations were constructed by identifying the main sources of waste, and which activities and processes within the project contributed to the generation of waste. Following this analysis, existing measures for waste reduction were assessed, along with concepts related to more general developments in the industry, such as industrialisation and digitalisation. Then, AI-based tools and technologies considered relevant were assessed in the context of the identified waste fractions and processes, and the established tools. When the problem is defined, the goal of the development and deployment of the given tool should be specified. A similar approach was illustrated in Paper III, for the prediction of project success. This type of contextualisation is essential to ensure the relevance of the tool that is developed, and crucial in the next step of the development process, which should be to assess the feasibility of the process.

Given the constraints and available resources in terms of time, personnel, and data, is the development feasible at this stage? If not, can the system boundaries of the defined problem be adjusted to reframe the issue at hand (as discussed in Paper II), or can the goal be modified? Feasibility should be evaluated based on factors such as available data, technical requirements, and organisational readiness.

When the project is deemed to be feasible given the defined scope, data collection should be initiated. The process of data collection can be guided by any existing data management plans and should start by identifying relevant and available data sources. Data could be collected from construction plans, project schedules, equipment usage data, or other relevant documents. Then, the data should be assessed. The data should be assessed according to predefined quality metrics and validation schemes. Based on this data assessment, another assessment of process feasibility is recommended.

After an initial assessment of data (and feasibility), data pre-processing should be initiated. This includes all preparatory activities, such as preliminary cleaning, formatting, filling of missing values, reduction, normalisation, or feature selection. The goal is to prepare the data for model development and ensure accuracy and consistency.

Model development

The model development stage might be considered the most 'technical' stage of the development, and includes model selection, model training, and model validation (Russell and Norvig, 2010). Paper III illustrated how this development stage can look in the construction context. It could be necessary to involve external competence for this stage; however, if the development is outsourced, it becomes crucial to ensure a certain degree of contextualisation for the developing party. Findings in Paper VI imply that most issues surrounding AI systems and models are not related to the mathematics or statistics of a model, but rather to the heuristics. This becomes evident by the number of mathematically successful models that are yet to be scaled and create value in real construction projects.

To fully understand the implications of the output of the model, contextualisation is crucial. The AI model is trained using the pre-processed data. Training will look different for each model. For an ML algorithm, the training stage is where the algorithm learns to identify patterns and relationships in the data that will enable it to make accurate predictions or classifications. The algorithm is then tuned to improve model performance. Validation of the model can, and should, be done in numerous ways. Technical validation of the model can for instance be done through cross-validation, like in Paper III. Validation can also be done based on feedback from stakeholders and results from preliminary testing in a project context.

The findings of Paper VI show that smaller-scale implementation is often done using academic tools, such as Python or MATLAB; this can contribute to creating a gap between the work done in academia and in the industry, and cause fragmentation.

When the model is selected, trained, and validated, a natural next step is prototyping. Developing a prototype using a smaller subset of data allows for testing and refining of the tool before investing in larger-scale implementation. Validation of the prototype can, once again, be based on feedback from stakeholders and results from preliminary testing. Once the prototype has been refined, the model can be scaled up. This should be done by using more data and deploying the model in more than one setting (meaning in more than one project or organisation function), if possible. Including metadata from the initial implementation of the prototype can further help with contextualisation, as noted in Paper VI.

Stakeholder management activities should be prevalent throughout the entire process of development and implementation to facilitate interdisciplinary collaboration (Abioye et al., 2021; Xu et al., 2022) and should be emphasised in the earliest stages of the development. During the identification of the problem, all stakeholders who might affect, or become affected by, the development and implementation should be involved. They can provide insights into opportunities and limitations related to the specific construction process, or how activities in other parts of the project might impact the development and implementation.

On the system level, implementation is more likely to succeed if the groundwork is done in the development process. After refining and scaling the prototype, the next step is integration with existing systems. This could mean assessing the technical compatibility of the AI model with existing technology and infrastructure. The assessment can inform potential modifications of the system to ensure that it can communicate and work seamlessly with other tools and systems already in use in the organisation or project. The model should also be integrated into existing workflows – this could involve modifying existing processes, though, for instance, defining new roles and responsibilities, adjusting timelines, and training staff on the use of the new tool. Based on initial integration, the model can be refined and revalidated.

When the system is integrated, maintenance and continuous monitoring of the system is essential. To do this effectively, performance metrics should be established, and effects of the implementation should be mapped. Based on these findings, the system can be optimised. Maintenance could involve updating the model with new data or upgrading any software or hardware in adjacent infrastructure.

As discussed in Paper VI, it is recommended that users remain an active part throughout all stages of development and implementation. The findings indicate that involvement, over time, can contribute to increasing trust, competence, and ultimately, proficiency.

Much like other relevant stakeholder management activities, actively learning from the development and implementation of the tool is essential throughout the entire process. There is no need to invent the wheel twice, or a hundred times. Learning from best practices is equally as important as learning from missteps.

5.1.3 People

Personnel involved in the implementation and integration of AI-based tools might need training related to the technical use of any new tools or systems; assessment and interpretation of input data, output data, or metadata; or how the system is to be understood in the context of the activity or the whole project.

Implementation and integration might require redefining roles and responsibilities, establishing training programs, mentor-programs, and developing new communication channels to support the use of AI. This is closely linked to the organisational dimension. The element of collaboration will be vital to develop and deploy effective and sustainable systems; this was also indicated by the findings of Paper V, where involvement of subcontractors emerged as one of the main factors impacting effectiveness and efficiency on a digitalised process.

Personnel might be resistant to change. It will be necessary to prioritise building trust in all interactions that are affected by the implementation: human-machine, human-data, and human-human, meaning across the value chain, interdisciplinary fields (such as developer and user, for instance) or organisational silos.

Loukides et al. (2018) define five framing guidelines to help maintain an ethical approach when building data products: consent, clarity, consistency (for trust), control (and transparency), and consequences (and harm). In the construction context, the collection of private data might not be as prevalent as it is in other industries. However, consent can also apply to other aspects of the AI system operations, for instance in a system that uses speech recognition; the user might have to consent before the system can process the voice commands. Clarity in a system could mean ensuring a certain degree of transparency and explainability for users, involved stakeholders, and regulators. Explainability is a central challenge in the development of AI systems, and especially in ML (Abioye et al., 2021). This can lead to a lack of trust in the system (Sjåstad, 2019; Abioye et al., 2021; Belle, 2023), and ultimately aversion. Therefore, a central proactive measure to ensure trust and willingness to use a tool is to build systems that hold a high degree of explainability. Consistency is important to build trust and could mean making sure that the system operates reliably and consistently over time and in different environments. This requires a robust system. Control refers both to the user and stakeholder control over the system, but also to the system operating in accordance with ethical and legal norms. The consequences dimension refers to the potential impact of the AI system on users, stakeholders, and the environment it operates within. Managing this dimension could mean monitoring for deviations or bias in the model. The main reason for algorithmic bias is human bias in the data the algorithm is built upon (University of Helsinki, 2018); therefore, mitigating bias is, to a large extent, data management. Loukides et al. (2018) note that the guidelines should not only dictate the work of the developer, but the entire organisation. For the development and deployment of AI systems to be sustainable long-term and short-term, each of these considerations need to be addressed – on all levels.

There is a talent shortage in the contextual intersection between AI and construction (Abioye et al., 2021), and interdisciplinary collaboration between construction experts and AI experts will be necessary to continue to drive the field forward. Collaboration is needed to generate solutions that can effectively meet the demands of the construction industry. Long-term, interdisciplinary collaboration will contribute to building competence, and ultimately a greater contextual understanding of the potential and limitations of the two fields.

Providing sufficient training in the use of specific systems, software, and in general data management will be of essence. This will provide the personnel interacting with the systems with insights into how systems and algorithm works, beyond the user interface. This is essential to understand the implications of the results the system might produce, and how the input can affect the output from a system. Training should be done for all stages of development and use and extend from data management (how data should be collected and stored), data analytics, and understanding how the context of the input might affect the implications of the output.

The risk of AI systems perpetuating biases and discrimination might not be the most prevalent in the construction context, but development and implementation should still be done with care, and with guidance from ethical principles to ensure fairness and avoid negative consequences.

5.1.4 Data

To defend the investment costs of data collection, storage, and processing, an organisation or project might need results to show – but to achieve results, data is needed. Papers IV and VI noted the importance of holistic frameworks for data management and confirmed the findings from previous research ruling data management among central process-oriented challenges associated with the use of AI (Burgess, 2018; Xu et al., 2022).

A vast amount of data already exists in and on construction projects, as illustrated in Paper II, Paper III, and Paper V. However, metadata providing insights into the quality and characteristics of the data beyond just what they measure is generally lacking. This hinders effective QA and contextualisation and could ultimately render the available data unsuitable for the intended use case. As noted in the concluding discussion of Paper III, data that are not collected specifically for the utilisation of AI require a lot of preparatory work.

Metadata repositories and data warehouses should be established on the organisational level, so data can be traced back to respective projects or actors, and to enable the identification of limitations the data might hold.

As addressed in Paper III, if data is collected to be read by humans, inevitably, for an algorithm to make sense of the same data, time and resources must be invested in preparing the dataset. In an ideal situation, the data would be collected in a way that translates any textual input into numerical data, and relating the data that is input to already existing data. This way, data can be retrieved, read, and understood in the context of other data.

Based on the extensive body of literature on AI development in the construction context (Golparvar-Fard et al., 2015; Gudauskas et al., 2015; Hajdasz, 2015; Mousavi et al., 2015; Shin, 2015; Kog and Yaman, 2016; Mirahadi and Zayed, 2016; de Soto et al., 2017; Juszczyk, 2017; Pruvost and Scherer, 2017; Samantra et al., 2017; Zou et al., 2017; Ayhan and Tokdemir, 2018; Cheng and Hoang, 2018; Goh et al., 2018; Hanna et al., 2018; Poh et al., 2018; Sharafi et al., 2018; Elmousalami, 2019; Hu and Castro-Lacouture, 2019; Jaber et al., 2019; Juszczyk et al., 2019; Juszczyk and Lesniak, 2019; Taherdoost and Brard, 2019; Vickranth et al., 2019; Yaqubi and Salhotra, 2019; Basaif et al., 2020; Fallahpour et al., 2020; Han et al., 2020; Juszczyk, 2020; Nnaji and Karakhan, 2020; Xu et al., 2020) and the findings of Paper VI, three types of data emerge as necessary in the development of a system. Firstly, data on the activity or process being enhanced. This is essential to understand the characteristics of the problem, such as in the case of construction project waste reduction in Paper II, or project success in Paper III. Secondly, data needed for training and validation of the AI model. This can be part of the first group of data. Thirdly, metadata related to the initial data collection, and, eventually, on the implementation process – for instance from PoCs – and related to the mapping of effects after implementation.

A data management plan should be constructed on the organisational level, project level, and system level, as recommended in Paper VI. The plan should contain a detailed overview of the process of data collection and data storage, but also data sharing, and data analysis. The components of the data management plan should be similar at all levels, but the implications of the plans will look different for each level.

At the system level, a data management plan should focus on the specific requirements for the development and deployment of a particular system, and on collecting the three types of data. The plan may include information on the types of data that will be used by the system, how it will be collected and processed, how the system will be tested and validated, and how it will be monitored, maintained, and updated over time.

Data management indicators

A holistic approach to data management is critical to the success of AI implementation in construction (Burgess, 2018; Xu et al., 2022). Prioritising, contextualising, and standardising data management is found to be essential. Emerging from the findings of Paper III, Paper IV, and Paper VI are three key indicators for data management as data quantity, data quality, and data access or availability.

Certain AI techniques, such as ML, require large datasets. The Nordic 10-10 dataset that was used in Paper III was considered very limited in the ML context – despite the underlying data being collected over the course of multiple years, and from multiple companies. If the dataset is too small, users and developers will encounter challenges related to the reliability, validity, and the generalisability of the data. If the reliability, validity, and generalisability can not be guaranteed for the data itself, it therefore can not be guaranteed for the system or model that is being developed, or the results that the system provides. If the output of a tool can not be trusted, the tool can essentially not be used. As noted in the discussion of Paper III, an algorithm and a system will only ever be as good as the data it is built upon. Numerous algorithms, both in research and industry contexts, have provided good results on limited datasets, but neither context have seemingly been successful in scaling these.

AI models require high-quality data to produce high-quality results. As discussed in Paper III, Paper IV, and Paper VI, construction projects often have fragmented, incomplete, or inaccurate data, which makes it hard to build effective AI systems. Data quality can be related to a wide range of indicators, depending on the intended use of the data. To understand what solution will best accommodate the problem, data are needed. Possible tools to help ensure data quality are quality metrics, validation checklists, and quality audits. The validation checklists should be developed based on the quality metrics, and the quality audits should be performed according to the developed validation checklists. The tools can be applied to relevant metadata as well. Relevant quality metrics could be related to the availability of the data; the completeness of the dataset as a whole; the consistency of the data, including data formats, units, and available metadata; and relevance for the system or project in question, and in relation to other existing data. Relevant and applicable metrics and validation criteria will vary depending on project characteristics. Based on the checklist, quality audits should be conducted at a frequency that fits into the data management plan.

The question of data access can be split into two. Firstly, the question is related to the availability of the data for the actor. If the actor does not have access, the data could be produced, or acquired from another industry actor, or projects. Are other actors interested in sharing the data? If yes, are they open to sharing the data material in full, so the reliability, validity, and generalisability of the data can be verified? As discussed in Paper IV, both data availability and willingness to share data can be central enablers – or barriers – for effective data management. Secondly, if the data is accessible for the actor, the question is related to interoperability and cohesion (Paper IV): Can both actors effectively read and utilise the data? This can be related to the availability of necessary software and hardware, and whether the actor will be able to read and display the data effectively or not. Data access is also related to the access to data between software: can the data be transferred between software? If yes, will this be a manual job – and are the necessary resources for such a job available? Paper VI identified the lack of data interoperability as a contributing factor to complicating data sharing between actors.

Software from different suppliers is not always meant to be compatible or allow for seamless integration with other software, or the existing infrastructure of the project or organisation looking to use it.

5.2 Project level

On the project level, in-house and commercially available tools have been applied across a wide range of areas of application. However, this is seemingly done in isolation, meaning that next to no changes are made to how the project is planned or executed. This, in turn, means that the AI system simply becomes an add-on.

As illustrated in Paper V, if a digital tool becomes an add-on, activities related to the active use of the system can become time-consuming, and ultimately hinder productivity in a project.

Recent developments show a trend towards larger and more complex construction projects (Whyte et al., 2016; Fischer et al., 2017), and integration is essential to decrease complexity and increase sustainability.

5.2.1 Technology

On the project level, a wide range of areas of application is displayed in previous research (Ilter and Dikbas, 2009; Martínez and Fernández-Rodríguez, 2015; Juszczyk, 2017; Basaif and Alashwal, 2018; Xiao et al., 2018); this was further illustrated by the findings in Paper I. Paper II indicated a potential for application throughout a project, thus strengthening the findings of previous research, and highlighting the potential that lies within the entire project life cycle (Hossain and Nadeem, 2019; Pan and Zhang, 2021). Paper II also indicated the potential for one area of application to yield benefits across multiple stages of a project.

Taking on the executive perspective from the NS 3467:2023 *Stages and deliverables in the life cycle of construction works* (Standard Norge, 2023); for Phase 1 (P1) Strategic definition, AI-based tools can be used to evaluate project feasibility; prediction of costs and profitability (Cheng et al., 2009; Bilal and Oyedele, 2020), cash flow prediction (Cheng et al., 2015; Cheng et al., 2020), or profit margin estimation (Bilal and Oyedele, 2020); supply chain management and supplier selection (Taherdoost and Brard, 2019); and contractor pre-qualification (Kog and Yaman, 2016). Systems can be built based on internal and external historical project data from similar projects. To enable this type of assessment, a data warehouse should be established prior to the initiation of the analyses.

Possible areas of application for AI systems in (P2) Program and concept development include design optimisation (Liu et al., 2015; Rodriguez-Trejo et al., 2017) to optimise for factors such as cost, energy efficiency, and environmental impact; resource management (Podolski, 2016; Xing et al., 2016; Camacho et al., 2018); utilise AI-based virtual reality to enable stakeholders to experience and provide feedback on preliminary designs and plans; cost prediction and estimation; and tender price evaluations (Bilal and Oyedele, 2020).

For (P3) Development of selected concept and (P4) Detailed design, many AI-related activities coincide. In these phases, relevant use cases include optimisation of construction design and resource allocation (Liu et al., 2015; Xing et al., 2016; Podolski, 2016; Rodriguez-Trejo et al., 2017); validation of change requests (Dawood et al., 2019); assessment of contracts and other legal documents to identify potential risks or issues. As production documentation is established, AI systems can be used for automated clash detection between disciplines (Hu and Castro-Lacouture, 2019). Virtual testing can be used to allow comprehensive testing at an early stage when information and knowledge traditionally is limited.

In (P5) Production and delivery, AI systems can be used for predictive maintenance, to analyse sensor data and predict when equipment is likely to fail, ultimately reducing downtime; quality control (as illustrated in Paper V); quantity control (Nguyen et al., 2020); to predict project success based on preliminary project data (as illustrated in Paper III); for on-site and off-site logistics; to optimise scheduling (de Soto et al., 2017); to reduce waste on-site (as illustrated in Paper II); in automation of robots, for on-site or off-site construction; or for risk and safety monitoring and assessment (Goh et al., 2018; Poh et al., 2018; Han et al., 2020; Xu et al., 2020).

(P6) Handover and commissioning does not hold any obvious potentials for increasing productivity or sustainability using AI systems and has not received significant attention in previous research. However, establishing and maintaining easily accessible systems in early phases of the project can simplify this stage. The focus of this stage should be to transfer any relevant data to the users, the facility manager, and to the organisation database; this can be achieved by AI-based tools, but it might not be the most effective way to do so.

For (P7) Use and management, the main area of application for AI-based systems and tools is facility management, which includes, but is not limited to predictive maintenance; energy management and optimisation; indoor air quality monitoring and correction; security; space planning and optimisation; and cleaning and maintenance. The goal would be to improve the overall efficiency and sustainability of the operation phase.

Like the previous seven phases, (P8) Termination rarely looks the same for two projects. Relevant areas of application could include identification of materials that can be recycled and reused; finalisation of the project database, comparison of available data to previous project data, and identification of opportunities for potential areas of improvement; and ensuring that all documentation related to the termination is complete and accurate.

Figure 5-3 summarises the relevant areas of application per project phase.

	P1. Strategic definition	P2. Program and concept development	P3. Development of selected concept	P4. Detailed design	P5. Production and delivery	P6. Handover and commissioning	7. Use and management	P8. Termination
Areas of application	Evaluate project feasibility Predict costs and profitability Estimate resource demand and potential risk Strategic supply chain management Contractor pre-qualification	Design optimisation Resource allocation Virtual reality Cost prediction and estimation Tender price evaluation	Design optimisation Resource management Document review Virtual testing	Design optimisation Resource management Document review Virtual testing Validation of change requests Site layout design	Predictive maintenance Quality control Quantity control Prediction of project success Logistics and scheduling Waste reduction Automation of robots Risk and safety assessment	Transferring of relevant data	Predictive maintenance Energy management Air quality monitoring Security Space planning Cleaning Logistics	Material repurposing (reduce, reuse, recycle) Identification of areas of improvement Document review

Figure 5-3. Relevant areas of application per project phase.

AI systems and models have demonstrated promising results in construction projects, through all phases of projects. However, the industry has yet to see the larger-scale implementations. For an effective and sustainable scale-up – both on the organisation and industry level – robust infrastructure is needed.

5.2.2 Process

Organisation or project infrastructure must facilitate the effective use of AI for the use of AI to be sustainable long-term (Burgess, 2018; Vinuesa et al., 2020; Xu et al., 2022).

On the project level, infrastructure elements that could be established in (P1) Strategic definition include a centralised project-specific database to store existing internal and external data relevant to the project; an intuitive and easily accessible communication channel for stakeholders; and relevant policies and procedures to ensure quality and accuracy in the data management process and data that will be used to develop and deploy the AI system. This will help facilitate communication and collaboration throughout the project, and ultimately facilitate more effective application of AI systems and tools (Abioye et al., 2021; Xu et al., 2022). If relevant policies and procedures already exist in the organisational context, these should set the basis for project-specific policies and procedures. When a decision is made on a system, available software should be integrated with existing systems and processes. Establishing training programs for involved personnel can be useful to build both trust and technical competence needed to work with the AI systems in later phases. Paper V identified competence as one of the main areas impacting effectiveness and efficiency in a digitalised process, emphasising the importance of sufficient training. In the concluding discussion of Paper II, it was noted that to fully utilise the potential of AI systems, infrastructure should be built upon existing methodologies and frameworks. To utilise existing infrastructure, an existing project BIM model or digital twin can be a good starting point for a project-specific database and communication channel.

Activities in (P2) Program and concept development could include establishing a centralised platform to collect data and metadata on early decisions, and for real-time stakeholder collaboration; decision-making for project-specific software and hardware acquisition to support planned AI systems; and building or otherwise acquiring any additional necessary software. Data and metadata management is an important part of the effective data governance in the project (and organisation) (Al-Ruithe et al., 2018; Burgess, 2018). Established databases and communication-collaboration channels must be maintained throughout (P5) Production and delivery.

In (P3) Development of selected concept and (P4) Detailed design, protocols and procedures for processing and analysis of real-time data generated in the project should be established, along with protocols and procedures for integration with existing systems. In later stages of (P4) Detailed design, the physical software and hardware acquisition should take place.

The focus of (P6) Handover and commissioning should be the transfer of any relevant data to the users, the facility manager, and to the organisation database. Previous research has identified data sharing among the central process-oriented challenges associated with the increased use of AI (Burgess, 2018; Xu et al., 2022). Paper IV confirmed this and identified lack of data interoperability as a central challenge for effective data management in the construction context. Similarly, Paper V identified the lack of data interoperability as a barrier for productivity and sustainability in a digitalised process. Therefore, to ensure effective transfer of data in this phase, the data transfer could be based on the previously established centralised databased.

To utilise AI to improve the aforementioned facility management functions throughout (P7) Use, a range of sensors should be installed to provide data for development prior to deployment, and for feedback post deployment. To protect the devices and the data they produce, an extensive security system should be established.

To facilitate the transfer of knowledge in (P8) Termination, a subsection of the existing project database should be dedicated to the summary of relevant data. This could provide a foundation for future training schemes.

Figure 5-4 summarises relevant elements of infrastructure per project phase.

	P1. Strategic definition	**P2. Program and concept development**	**P3. Development of selected concept**	**P4. Detailed design**	**P5. Production and delivery**	**P6. Handover and commissioning**	**7. Use and management**	**P8. Termination**
Infrastructure	Centralised project-specific database Centralised communication channels Policies and procedures	Centralised database for project-specific metadata Building remaining necessary software	Procedures for processing and analysis of data Procedures for integration with existing systems	Integration with existing systems Software and hardware acquisition	Maintaining databases Maintaining communication-collaboration platforms	Transferring of relevant data	Installing sensors Procedures for data security measures	Transfer-specific databases, communication channels and storage

Figure 5-4. Relevant elements of infrastructure per project phase.

Most infrastructure elements will require the involvement of more than one stakeholder.

5.2.3 People

More collaboration is needed for the continued progress of AI in construction management (Xu et al., 2022). On the project level, stakeholders should be followed closely through all project phases.

An activity that should be prioritised in (P1) Strategic definition is the education of stakeholders on potential benefits and limitations associated with the system. Collaborating with stakeholders to identify areas where AI systems might improve the construction process, and involving stakeholders in the decision-making process, can help build trust and knowledge across the value chain. Long-term, this could help increase the willingness to share data (as illustrated in Paper IV) and help keep stakeholders involved. Continuously interacting with stakeholders to understand their needs and preferences throughout the process of development and deployment will contribute to building this further.

To keep stakeholders involved, informed, and inspired, throughout (P2) Program and concept development, activities should include collaborating with relevant stakeholders to ensure that any AI design choices align with the overall project goals and objectives. For governing bodies in particular, the communication should be centred around the degree to which any AI-based design choices comply with relevant standards and regulations. Clearly establishing roles and responsibilities among stakeholders, related to the management of the AI systems themselves and the output they provide, will be essential.

Throughout (P3) Development of selected concept and (P4) Detailed design it will be essential to continue any conversations with relevant stakeholders regarding the degree to which the chosen AI system does or does not align with the overall project goals and activities, as well as the individual goals and activities of the involved actors. When final decisions are made regarding the involvement of AI-based systems and tools, training should commence. In Paper V, both the involvement of stakeholders and the competence among stakeholders were identified among the main areas impacting effectiveness and efficiency in a project. As discussed in Paper VI, all actors being experts in all fields is not a goal in itself; experts should continue to foster their core competence, but interdisciplinary involvement will be essential to cultivate specialists in the thematic intersection.

In (P5) Production and delivery, the main activities are maintaining a dialogue with actors who affect, and are affected by, the active use of the AI system. This could be due to the chosen methods of data collection or having to adjust their schedules due to waiting for assessments. By extension, it is essential to ensure compliance with other actors on-site. If the use of the system is effectively hindering the work of other actors, any savings made for one actor might not lead to a net positive for the whole project.

The focus of (P6) Handover and commissioning should be to transfer any relevant data to the users, the facility manager, and to the organisation database.

Training of involved and responsible personnel in (P7) Use and management should ideally be conducted prior to the initiation of the phase; however, the phase can provide a good opportunity for 'learning by doing', which some interviewees in Paper VI noted to be an effective approach. Engaging with users can prove useful, both as a part of early design phases, or to understand how the facility management is currently affecting them.

The most important stakeholder activity in (P8) Termination is the transfer of knowledge. Upon completion of the project, efforts should be made to ensure all available information and data is transferred to relevant internal and external stakeholders for future projects. Lack of competence was identified as a key barrier to effective data management in Paper IV, and a structured transfer of knowledge can help minimise this. To facilitate this process, a subsection of the existing project database should be dedicated to the summary of data for this transfer.

Figure 5-5 summarises relevant stakeholder management activities per project phase.

	P1. Strategic definition	**P2. Program and concept development**	**P3. Development of selected concept**	**P4. Detailed design**	**P5. Production and delivery**	**P6. Handover and commissioning**	**7. Use and management**	**P8. Termination**
Stakeholder management	Training related to system benefits and limitations Engaging stakeholders in ideation Engaging stakeholders in development	Alignment in overall project goals Establishing AI-related roles and responsibilities	Alignment of actor-specific project goals Training related to system-specifics (input and output)	Training related to system-specifics (input and output)	Maintaining dialogue Ensuring compliance	Transferring of relevant data	Training related to effective use of system Involving end users	Transfer of knowledge

Figure 5-5. Relevant stakeholder management activities per project phase.

5.2.4 Data

At the project level, a data management plan focuses on the specific data management requirements of a particular project. The plan may include information on the types of data that will be collected, how it will be collected and stored, who will have access to it, and how it will be preserved for long-term use in the organisation.

As discussed in Paper III, no standards currently exist for collection and utilisation of data in construction projects. To a certain extent, this is understandable, because all projects are unique. However, it would greatly benefit the effective development and deployment of AI if some standardisation of data structures would emerge. Some industry-specific standards exist for structuring of data, such as for BIM and standards for data coding such as NORSOK in the Norwegian oil and gas industry. As noted in Paper VI, data currently exists in a very wide range of formats, and these are rarely the same in two projects. Data that can be consistently compared and tracked between projects has the potential to improve project-based benchmarking, support project success prediction, and serve as early warning systems that can identify potential issues in time for action to be taken.

Beyond the aforementioned components for the data management plan, a certain degree of detail is expected and necessary for an effective data management plan. Table 5-1 provides a starting point for a data management plan, including examples of what the plan can contain, and noting how critical components can be included.

The example is not intended to be an ideal data management plan; rather, it is intended to illustrate what a data management plan can look like. In addition to defining the details related to the practical execution of the plan, each post should include an overview of the involved and responsible actors and parties.

Table 5-1. Data management plan.

Project Title: Office Complex		
Project Number: 325061		
1. Data collection		
Data types	Project schedule	Gantt charts detailing the project timeline with milestones, critical paths, and allocation of resources.
	Budget	Spreadsheets tracking project expenses, including labour, materials, and equipment costs.

	Design documents	Architectural and engineering drawings in PDF or CAD format, including floor plans, elevations, sections, and details.
	Construction drawings	Detailed construction drawings in PDF format, including structural, mechanical, electrical, and plumbing drawings.
	Material specifications	Specifications for all materials used in the construction, including manufacturer, model number, and performance requirements.
	Site survey data	Survey reports and maps showing site topography, soil conditions, and other relevant information.
	Photographs, videos, and scans	Digital photographs, videos and scans documenting construction progress and site conditions.
	Metadata	Metadata will be included with all data to provide context and facilitate effective and sustainable data management. Metadata fields will include date of creation, responsible actor, project phase, project location, discipline, file format, file size, keywords, and any additional descriptions.
Data sources	Project team members	Project manager, architects, engineers, and consultants.
	Subcontractors and suppliers	Material suppliers, equipment vendors, and service providers.
	Other external stakeholders	Environmental consultants, geotechnical engineers, and regulatory agencies.
Data collection methods	Existing data	Transferring of existing data from respective software and storage.
	Cameras and drones	Photographs and videos will be taken periodically by project team members and drones for aerial views of the construction site.
	Handheld devices	Field data collection will be done using handheld scanners to record site observations and other relevant information.
Quality control	Quality metrics	The following are defined as main quality metrics: availability, completeness, consistency, and relevance.
	Validation checklist	The quality metrics will be assessed and ensured as per the attached validation checklist.
	Quality audits	To monitor the state and development of the quality metrics, quality audits will be performed regularly. The audits will be conducted every two weeks, or more often if necessary.
2. Data storage		
Data storage location	All project data will be stored in the project cloud-based storage system.	

Data storage format	The preferred format for data storage is a BIM-based digital twin, to enable effective data exchange between relevant stakeholders. The contractor will be responsible for maintaining the model.	
	Project schedule	Gantt chart from Microsoft Project
	Budget	Spreadsheet from Microsoft Excel
	Design documents	CAD files in AutoCAD
	Construction drawings	PDF files in Adobe Acrobat
	Material specifications	PDF files in Adobe Acrobat
	Site survey data	Digital files and GIS formats
	Photographs and videos	Digital files in JPEG and MP4 or MOV formats
Data preservation	Data retention	All project data will be retained for a minimum of 10 years after project completion. The defined retention period complies with legal and regulatory requirements at the time of the project. At the end of the retention period, data will be securely deleted or moved to the permanent organisation data storage. Data that does not require immediate access can be moved to permanent data storage sooner.
	Backup and recovery plan	All project data will be treated according to the organisation data backup and recovery plan.
3. Data sharing		
Data access controls	Project team members will have full access to project data, while external stakeholders will have restricted access based on a role and need-to-know basis. Project team members will have access to relevant data from the organisation data warehouse.	
Data sharing methods	Main data storage	The preferred format for data sharing is the project BIM-based digital twin.
	Project management software	Project data not fit for distribution through the digital twin will be shared and managed through the established project management software, accessible by all project team members.
	Commercial file sharing platforms	Larger files will be shared through secure file sharing platforms, such as Dropbox or Google Drive.
	Email	Smaller files and communications will be shared through email.
4. Data analysis		
Data analysis tools	Statistical software	Project schedule and budget data will be analysed using statistical software, such as R or SPSS.
	Visualisation tools	Project data will be visualised using tools, such as Tableau or Power BI.
	BIM software	Construction data will be analysed using BIM software, such as Autodesk Revit or Navisworks.
Data analysis methods	Schedule and budget analysis	Actual project progress will be compared against the planned schedule and budget to identify potential variances and deviations.

	Resource utilisation analysis	Resource utilisation will be analysed to identify areas of potential optimisation or improvement.

Any project-specific data management plan should be based in the organisation policies and procedures.

5.3 Organisation level

Implementing AI-based tools could require changes in multiple areas of the organisational structures, roles, and responsibilities. Implementation and integration would require training of individuals and personnel involved but could also mean new roles might have to be defined and filled. Whether the responsibility falls on a set role in the project or organisation, or an extended team, this should be clearly defined in the organisational structure.

5.3.1 Technology

Thesis findings indicate that there is a large benefit in approaching new technologies and tools by first initiating tests and pilots. Problems related to scaling seem to, in part, be caused due to a lack of anchoring in strategy and lack of systemic thinking (Darko et al., 2020; Nishant et al., 2020; Xu et al., 2022). This was confirmed by the findings of Paper IV; it is important to think big but start small. Actors should establish an overarching strategy for the development and deployment of technology, and the collection, storage, sharing, and analysis of data. A strategy should include a plan of any data that is needed, what format the data is needed on, and what quantities the data is needed in, among other things.

To some extent, PoCs will be needed to verify the work that is being done. The findings of Paper I suggested that the majority of tools are not currently developed beyond a testing or pilot stage. In Paper VI, both developers and users reported benefits from piloting. However, it is essential for actors to first have a strategy in place, so the pilot does not just become another tombstone in the graveyard of PoCs. Actors should indubitably pilot, but they should pilot with a purpose. An overarching strategy should encompass all dimensions of implementation and integration

As discussed in Paper VI, there are significant costs associated with the implementation of AI systems and digital tools. Paper V identified thirteen factors affecting the profitability of digital systems. The findings showed that equipment costs, company-specific factors, project-specific factors, and process-specific factors all impact the overall profitability. Therefore, it is unlikely that any two systems will have the same cost profile. Thus, to reduce the resource intensity of the implementation process, it can be useful to conduct a profitability analysis prior to implementation and integration. Nevertheless, it seems reasonable to assume that scaling will reduce the cost per use, regardless of any specific characteristics of a system.

5.3.2 Process

Implementing AI-based tools could require changes in multiple areas of the organisational structures, roles, and responsibilities. Change teams should involve team members from the entire organisation (Cameron and Green, 2015). As discussed in Paper VI, interdisciplinary collaboration could contribute to building specialised expertise over time. Implementation and integration would require training of involved individuals and personnel but could also mean that entirely new roles might have to be defined and filled. Whether the responsibility falls on a set role in the project or organisation, or an extended team, this should be clearly defined in the organisational structure – and in an overarching strategy.

Organisational hierarchies and decision-making structures might need to be adjusted to accommodate the development and deployment of AI-based tools and the supporting infrastructure. An arena should be established to keep all relevant actors involved, informed, and inspired throughout the entire process of implementation and integration and beyond.

Certain AI technologies appear to currently have reached the Peak of Inflated Expectation according to the Hype Cycle framework (Fenn, 1995). At this stage, a technology is widely known in an industry, and hype is built around the potential the technology holds. The stage is often characterised of generous media attention, and big expectations are built (Fenn, 1995). However, at this stage, the practical implication of the tool is generally less known. At one point, the market starts to realise that the technology might not meet the initial hype and the perceived potential; at least not in the way it was expected. The field of AI ethics can be argued to have reached this Through of Disillusionment (Fenn, 1995; Dignum, 2017; Dignum, 2018; Hagendorff, 2020). This development indicates a need for more transparency both in AI systems and in the surrounding infrastructure, including procedures and policies. Systematically increasing explainability and transparency can contribute to increased trust in the AI systems and the potential they represent (Abioye et al., 2021).

Using the taxonomy defined by Bosch-Sjitsema et al. (2021), most AI applications in the construction industry appear to have moved past the confusion stage. The majority is still considered to be in the stages of excitement and experimentation, while very few, if any, have reached the integration stage.

Organisation infrastructure must facilitate the effective use of AI for it to be sustainable long-term (Burgess, 2018; Vinuesa et al., 2020; Xu et al., 2022). As the adoption of AI can still be considered at an early stage, a certain degree of organisational change is to be expected. The Lewin Model of Change (Lewin, 1951) is widely used for managing organisational change, and the unfreeze approach is intended to facilitate an iterative change process (Burnes, 2019). The framework is also recognised in the construction context (Hao et al., 2008). In establishing relevant infrastructure to accommodate the implementation and integration of AI systems and models, the change model provides a good starting point. Taking the example of establishing a data warehouse. The unfreeze stage should be used to create awareness to the problem, and to the perceived solution. If the organisation has been purposefully piloting, the unfreeze stage can provide an arena to showcase the results, to provide a deeper understanding of associated benefits or limitations. At the change stage, the data warehouse must be established. This could involve the acquisition of relevant software and hardware, and data. If an external provider is involved in the establishment of the warehouse, they would be involved in the change stage. In the refreeze stage, the warehouse is integrated as a permanent part of the organisation. Relevant personnel receive training, and policies and procedures for governance are established. Involvement is essential to establish ownership. New processes can be stabilised through regular feedback sessions for relevant personnel. New behaviours can be reinforced through recognition programs and celebration of achieved successes. Providing involved personnel with a sense of trust and autonomy will be essential. Over time, this can contribute to embedding the technical and cultural shift as an integral part of the organisation.

Implementation and integration with existing systems in the organisation or project, or the creation of new systems that fit within the existing infrastructure is challenging but important (Xu et al., 2022). Deployment requires careful planning and execution and could mean involving one or more stakeholders to ensure that all needs are being met during and after deployment. The increased efficiency of one actor should not compromise the efficiency of another actor – or the project as a whole. Implementation and integration might require significant changes to the workflow and workforce. As indicated in Paper V and Paper VI, implementation frameworks should provide an overview of practical implications for all actors who might affect or be affected by the process. This way, the frameworks can provide an opportunity to reduce fragmentation.

From a technical perspective, it is essential to ensure interoperability with various software and hardware systems on and off-site, to manage data security concerns, and to deal with any potential physical constraints on the construction site. From a process perspective, implementation and integration might require significant changes to the workflow and workforce. From a people perspective, this means that the personnel working with and around the new system must receive appropriate training prior to implementation, appropriate support during the implementation, and appropriate checks after the implementation. This could, and should, be an integral part of the data mapping of the effects of the implementation, or the continuous monitoring following implementation.

5.3.3 People

According to the Adoption Innovation Curve, actors in the construction industry are often considered to be 'late majority' and 'laggards' in the adoption of digital tools (Rogers, 1995; Ayinla and Aadamu, 2018).

Construction organisations are large and complex, and they can involve many stakeholders. It is likely that different stakeholders will find themselves at different stages on the Adoption Innovation Curve (Rogers, 1995), as indicated by the difference in maturity levels between the groups in Paper VI. It is recommended to involve the entire organisation in development and deployment of new tools. This will make it easier to involve the appropriate knowledge and resources for the issue at hand and is an important starting point to mapping available resources. Active involvement of stakeholders can contribute to closing the adaptation maturity gap, improving AI proficiency among stakeholders, and building trust long-term.

On the organisational level, it is important to map and build knowledge among personnel. As noted in Paper VI, it is not necessarily a goal for everyone to know everything, but rather for each member to have some level of understanding and awareness related to areas where they may require further comprehension. Mapping of knowledge can reveal if the necessary skills and knowledge are available in-house, if a certain process or activity might have to be outsourced, and how necessary knowledge and skills can be built over time. Larger scale implementation of data-based tools and AI systems strongly depends on the human factor. As discussed for the system level, the elements of consent, clarity, consistency, control, and consequences are essential to ensure the scalability and robustness of a solution.

5.3.4 Data

At the organisational level, a data management plan should focus on the overarching policies and procedures for data management that are implemented across the organisation. The plan may include information on the overall approach for the organisation to data management, the roles, and responsibilities of those involved, and how data is collected, stored, shared, and analysed.

It is essential to allocate sufficient resources to ensure the successful development and implementation of the data management plan (Burgess, 2018; Xu et al., 2022). Resources include personnel, equipment, and any required infrastructure that is not already present on the system, project, or organisation level. Lack of competence was identified as a main barrier for effective data management in Paper IV. It is essential that involved personnel receive sufficient training on procedures, policies, and tools used in the data management process.

As an extension of the data management plan, overall data management policies and procedures should be outlined to set the basis for all data activities, to ensure alignment with industry best practices and regulatory requirements. Roles and responsibilities should be defined, identifying individuals and departments responsible for the process of data management, including data collection, storage, sharing, and analysis. A data management plan should ensure at least three types of data: data on the activity or process being enhanced, to provide context; data needed to develop the model, to ensure that the technical requirements are not limiting the system; and metadata, to ease navigation in the human-machine interaction and provide further context.

Currently, no standard exists for data collection, storage, and sharing in the construction context, as found in Paper IV. Standardisation should not necessarily be a goal in itself, seeing as it might not be useful to standardise across all possible processes and activities. However, a certain degree of standardisation can contribute to building systems and tools that require minimal adjustments for good effects. This way, it is not necessary to build one system or interface from scratch for every single construction activity. As suggested by the findings in Paper VI, a system or model will only ever be as good and trustworthy as the data it is built upon; therefore, high-quality data is essential. Standardisation can be related to a wide range of factors, which can be summarised in a data management plan. Some important starting points are related to readability (whether the data is collected to be read and understood by a human or a machine), ownership (who owns the data), and quality.

Ethical considerations must be at the core of any phase or stage of the implementation process (Dignum, 2017; Dignum, 2018; Loukides et al., 2018; Politou et al., 2018), and should therefore be established on the organisation level. Development and deployment of AI models and tools must be done in a responsible and ethical manner, considering privacy concerns and biases. This can mean establishing clear policies and procedures for data collection, storage, use, governance, audits, and ensuring the involvement of relevant stakeholders in all decision-making processes. Systems must be transparent, accountable, and fair to ultimately be sustainable. Developing ethical frameworks, establishing clear policies and procedures, and creating mechanisms for accountability and oversight are some ways to build and increase transparency and trust. Bias is a challenge, especially when AI systems rely on historical data – as they often must. The data foundation needs to be representative. Automated systems such as ML algorithms, which often act as black boxes, must be thoroughly evaluated to ensure that they meet ethical standards; this work starts at the development stage.

Activities related to the development and deployment of AI systems and tools on the organisational level will vary heavily on the area of application and the characteristics of the system in question (Hao et al., 2008; Pan and Zhang, 2021). Therefore, it is challenging, and not necessarily desirable, to define one standardised framework for all activities. However, the organisation could and would benefit from establishing a data warehouse for the management and structuring of data. Data from the data warehouse can be used for analytics, data mining, reports, and development of AI systems. A centralised organisation-wide data storage system integrating data and metadata from all projects and project phases can contribute to increasing productivity and sustainability, not only in the output but in the process of development and use. Ensuring the compatibility of data with AI systems and models is essential. One possible way to structure and systemise data storage is through building a data warehouse.

Data warehouse

Systems and projects depend on data of a certain quality and quantity. As findings indicate that establishing independent databases on every system and project level would be too resource intensive, it is recommended to establish a central system on the organisation level.

To establish the storage system, data should be imported from existing operational systems. This could be operational databases, such as platforms for waste management, deviation reports, project schedules, project design portals, health and safety report systems, or others. Data can also be fetched from so-called flat files, meaning databases storing data in a two-dimensional plain text format. Existing documents, drawings, PDFs, and spreadsheets can also be used, although these often require manual transfer of data, which is time consuming. External data, from subcontractors, suppliers, or other industry-wide initiatives or organisations can also be used, as illustrated in Paper III.

Today, data that are collected in the construction context are rarely collected for the purpose of building and using AI systems and models. Therefore, a certain degree of cleaning will be necessary. Cleaning can involve identifying and removing duplicate data, correcting errors, standardising data and file formats, converting data types, adjusting the resolution of the data, and or filling in any missing data values.

After cleaning, the data can be stored in the data warehouse. The data warehouse should distinguish between at least three types, or levels, of data: raw data, summary data, and metadata. Raw data is the data as it is collected and cleaned. Summary data is aggregated data that allows for quick analysis of relatively large volumes of data and can enable users to identify trends or patterns that might not be apparent in the raw, unstructured data. The metadata provides a broader understanding of the context of the data. Relevant metadata include date of creation, responsible actor, project phase, project location, frequency, discipline, file format, file size, keywords, or any additional descriptions. Metadata repositories can enable users to easily search, locate, and retrieve relevant data, as discussed in Paper VI. Data should be linked to a multidimensional format that allows data to be connected between actors and across project phases, and to metadata. Relevant multidimensional formats identified in Paper VI include NetCDF, JSON, and HDF5. To utilise existing infrastructure, an existing BIM model or digital twin can be a good starting point. As a part of the data management plan, procedures for data preservation and retention should be defined for the data warehouse; this ensures that data is preserved for an appropriate length of time. After the set amount of time, data can be moved from an interface to a permanent data storage. A data backup plan should be developed, to ensure that data is recoverable in the event of data loss. The more actors that are involved and have access to the warehouse, the more important this is.

To retrieve data more effectively from the data warehouse, data marts should be established. A data mart is a substructure that contains the specific data that is relevant for a specific department or team within an organisation or project. Data marts can provide pre-defined data structures and queries, ultimately making data analysis and reporting quicker and more convenient for the end user.

The user interface serves as the primary means for end users to access and interact with the data. The user interface provides access without the need for technical competence beyond standard platforms and portals. Through the user interface, the data can be used for analytics, data mining, or reporting – on project or organisation level. Through this, data could also be accessed for development and deployment of AI systems and models.

The system level, project level, and organisation level are very strongly interlinked, and to fully unlock the potential of effective AI application, the work on all three levels needs to be structured and systemised.

6 Conclusion

The aim of the thesis was to explore the implementation and integration of AI in the construction context and discover how actors can successfully move from ambition to practice. The research questions were as follows:

- RQ1: What is the current state of the field, and what are the main challenges the field is facing?
- RQ2: What are the main dimensions of AI development and deployment in a construction context?
- RQ3: How can industry actors move from ambition to practice – starting today?

This chapter presents the main conclusion of the research conducted in this thesis and answers the research questions as defined. The current state of the field is summarised and identified main challenges are outlined. Seven main dimensions of implementation and integration are defined, and based on these, frameworks are defined on the organisation, project, and system levels.

The research questions are addressed, followed by a brief discussion of the contribution of the thesis for research and practice. Lastly, limitations of the thesis are noted, and opportunities for future research are proposed.

6.1 Current state and main challenges (RQ1)

AI has been around for decades, but recent advances have completely transformed what we can achieve with technology – and advances have enabled areas of application that were not possible before. However, in a rapidly developing field, actors must establish a robust infrastructure to be able to scale and adapt at the same pace.

6.1.1 Current state

There is a lot of talk about the potential that AI holds, and we see impressive, small-scale pilots and examples of the potential it inhibits, but in the construction industry, big-scale implementations are yet to be demonstrated and put into an economically viable and sustainable situation.

The construction industry tends to be considered less digitalised compared to other industries. Still, progress is demonstrated both by researchers and industry actors. There appears to be a divide between the construction industry as a whole, the organisation level, the project level, and the system level. Another divide is found between actors in different parts of the value chain,

The industry could benefit from building upon existing methodologies and strategies but would eventually need to reinvent and redefine traditional project models, contracts, business models, and enterprises to enable room for actors to innovate and create real change, economically and otherwise. This thesis aims to enable actors in the industry, with a focus on practical implications contributing to the field. Therefore, the focus is on organisations, projects, and systems, rather than the industry as a whole. Building on the advances already made in organisations and projects, the thesis provides a framework to continue a pragmatic but ambitious approach to bringing the use of AI-based systems and tools into practice.

On the system level, a wide range of tools have been developed and successfully applied to estimation and cost control; logistics, planning, and scheduling; strategy; health and safety; project performance and success estimation; risk management; sustainability assessments; and material properties. However, few report on the use of these tools beyond pilots and PoCs; most focus on potential use or the development of techniques.

On the project level, in-house and commercially available tools have been applied to one or more activities and processes. However, this is generally done in isolation, meaning that next to no changes are made to how the project is planned or executed, meaning that the AI system simply becomes an add-on. This is hindering effective scaling, and ultimately, effective results for productivity and sustainability.

On the organisational level, many actors are talking about digitalisation and utilisation of AI. Yet, similarly to on the project level, the infrastructure is rarely widely established outside the group or department responsible, this being the IT department or other groups of especially competent personnel. These further decrease scalability and robustness of the system.

6.1.2 Main challenges

A few challenges stand out, both on the system, project, and organisation level, when it comes to explaining why the whole industry is currently lagging. Some main challenges are:

- **Uneven application of resources to problems**. The problems that gain attention are the ones considered to be high value; essentially, for academics, areas that can showcase results and result in publication in the shortest time, and for practitioners, the problems that yield the largest monetary value in the shortest time span. These are not necessarily the areas that can make the greatest difference long-term on efficiency, productivity, or sustainability.
- This is one of a few reasons that **some areas are still waiting for data** – the value of the data collection for these areas might be less apparent, so it is delayed further. The lack of data is considered a major barrier for effective application of AI systems. If you can not measure something, you can not understand it, and, ultimately, you can not build an AI tool to change it.
- **Lack of anchoring in strategy**. This is essential for AI systems to become an integral part of the project or organisation rather than just an add-on, ultimately avoiding graveyards of PoCs.
    - Findings suggest that the responsibility of development and deployment tends to be allocated to one single (relatively small) group; these naturally have limited capacity. If the continuation of the projects falls on a small selection of people, the probability that it can not be continued for practical reasons increases.
    - Projects and organisations should avoid keeping old processes and procedures and simply add the AI system or tool on top; rather, they should aim to rethink and restructure the process to include the system more organically. Adjacent processes directly affecting the system should be adjusted to, for instance, accommodate changes in organisational structure or responsibilities.
- **The work becomes too resource intensive**. A lot of time and effort is spent on activities related to data management, training, follow-ups; when each pilot or PoC is conducted by different actors and personnel, in different departments, a lot of work is, inevitably, done twice. Efforts are currently too fragmented. Conducted tests might not see the greatest effects – which is natural, as the scaling is seen to hold the largest gains. Subsequently, it can be difficult to argue for coverage in the next test.
- There is **a drifting apart between the academic field, and the industry.** A lot of the work conducted in an academic context is centred around smaller use cases, rather than developing scalable and robust tools. Furthermore, many studies utilise traditionally academic ML-development tools. Practitioners may be hesitant to explore areas of application that lack sufficient research, and academics might be hesitant to spend resources on areas that lack commercial interest or immediate effects.
- **Limited transferability**. A model that is developed in one environment, or on one specific dataset can not necessarily be operated in another environment or applied to another dataset; there is a lack of standardisation in both construction and data management activities. This can complicate the collection and sharing of data across the value chain and limit effective development and application of AI tools.
- **Lack of contextualisation**, in data, model, and deployment. There seems to be a lack of understanding of the construction processes themselves; in essence, what the problem really is, what the goal actually is, and how an AI-based tool can actually contribute. Digitalisation and implementation of AI systems and tools should never be the goal, but the means to reach another goal (such as cutting costs, increasing productivity, ensuring safety, or reducing emissions) – AI is only the solution if it is the most effective way to reach this goal.
- **Fragmentation**. Fragmentation is seen both between organisations in the industry, between projects in an organisation, and between actors in a project. It is recommended to involve the entire organisation in the development and deployment; this will make it easier to acquire the appropriate knowledge and resources for the project at hand and is an important starting point for mapping available resources. Reducing fragmentation is essential to overcome challenges related to intersectional talent shortages.

6.2 Main dimensions of implementation and integration (RQ2)

Findings and discussions uncovered seven main dimensions of implementation and integration of AI systems and tools in the construction context.

The identified dimensions are strongly interrelated, and interdependent, and successful implementation and integration of AI systems will require a coordinated effort across all dimensions. However, here, they are defined individually. For academics, this is intended to provide an overview, and a well-defined starting point for future research; for practitioners, this is intended to provide a deeper understanding of the extent of each dimension.

The main dimensions relate to the four previously discussed pillars of technology, process, people, and data; often, multiple at the same time.

6.2.1 Data management

A holistic approach to data management is critical for successful AI implementation. Prioritising, contextualising, and standardising data management is found to be essential. Three key indicators for data management are data quantity, data quality, and data access.

It will be necessary to systemise data collection (such as sources and collection methods), data storage (such as locations and formats), data sharing, data analysis, and standards for how data is used in the development and deployment of AI-based tools. Comprehensive data management plans and infrastructures should be established.

A vast amount of data already exists in and on construction projects; however, metadata providing insights into the quality and characteristics of the data beyond just what they measure is generally lacking. This hinders effective QA of data, and successful contextualisation, and could ultimately render the available data useless. Metadata repositories and data warehouses should be established, so data can be traced back to respective projects or actors, and to enable the identification of limitations the data might hold.

Data should be accurate, relevant, and consistent, to improve the quality of the outcome, and reduce the time and resources needed for processing, cleaning, and transforming in preparation for development. In order to ensure a holistic approach, three types of data are needed:

- Data on the activity or process being enhanced. This is essential to understand the characteristics of the problem, to understand what tool might be useful, how a tool might be useful, and what tool or approach might bring the greatest effects and improvements.
- Data needed to develop the model. Resulting from an initial assessment of the data associated with the process, the developer should get an understanding of what potential an AI-based tool might hold. From this, the developer can decide what data is needed for development. For an ML-based tool, this includes ensuring sufficient quality and quantity of data for development, training, validation, and testing.
- Metadata related to the initial data collection (such as project number, project phase, project location, discipline, file format, file size, or additional characteristics), the implementation process (such as possible downtime, time spent on training), and possible mapping of effects after implementation.

6.2.2 Model

A tool built on AI will use one or more AI models to perform a specific function.

Selecting appropriate models and developing them to suit the construction context is a central and critical part of the successful utilisation of AI. Different models will be fit for different types of data, different activities, or different phases in the same project. Understanding the problem and the driving forces behind it is essential, and data management plays an important part in this process.

Developed models need to be robust and scalable. The AI models must be able to handle potentially large volumes of unstructured data and account for the complex interdependencies between different aspects of a construction project. The models must be capable of adapting to dynamic and rapidly changing environments, and to identify relevant features and patterns. Transferability, trust, transparency, and adaptability are key challenges.

6.2.3 Deployment

Implementation and integration with existing systems in the organisation or project, or the creation of new systems that fit within the existing infrastructure is challenging but important.

Deployment requires careful planning and execution and could mean involving one or more stakeholders to ensure that all needs are being met during and after deployment. The increased efficiency of one actor should not compromise the efficiency of another actor – or the project as a whole. Implementation and integration might require significant changes to the workflow and workforce.

From a technical perspective, it is essential to ensure interoperability with various software and hardware systems on and off-site, to manage data security concerns, and to deal with any potential physical constraints on the construction site. From a process perspective, implementation and integration might require significant changes to the workflow and workforce. From a people perspective, this means that the personnel working with and around the new system must receive appropriate training prior to implementation, appropriate support during the implementation, and appropriate checks after the implementation. This could, and should, be an integral part of the data mapping of the effects of the implementation, or the continuous monitoring following implementation.

6.2.4 Monitoring and maintenance

Following implementation, the AI model needs to be monitored and maintained, to ensure continued accuracy and effectiveness. The performance should, preferably, be monitored in real-time, or close to real-time.

Maintenance can include, but is not limited to, updating the model as new data becomes available, or otherwise adjusting the model after assessment of preliminary available data. To facilitate effective maintenance, maintenance protocols can be established. These can include defining roles and responsibilities, frequency, and key performance indicators. Robust models might be able to, to some extent, autonomously continuously adapt over time; however, the dynamic nature of construction projects might increase the need for manual maintenance, especially at early stages.

6.2.5 The human factor

Personnel involved in the implementation and integration of AI-based tools might need training related to the technical use of any new tools or systems; assessment and interpretation of input data, output data, or metadata; or how the system is to be understood in the context of the activity or the entire project.

Implementation and integration might require redefining roles and responsibilities, establishing training programs, mentor-programs, and developing new communication channels to support the use of AI. This is closely linked to the organisational dimension. The element of collaboration will be vital to develop and deploy effective and sustainable systems. The intersection of fields is currently seeing a talent shortage, and the most important tool in overcoming this will be training of personnel.

Some might be resistant to change. It will be necessary to prioritise building trust in all interactions that are affected by the implementation: human-machine, human-data, and human-human, meaning across the value chain, interdisciplinary fields (such as developer and user, for instance) or organisational silos.

Considering the human factor might require an increased focus on human resources in the organisation.

6.2.6 Organisation

Implementing AI-based tools could require changes in multiple areas of the organisational structures, roles, and responsibilities. Implementation and integration would require training of individuals and personnel involved but could also mean new roles might have to be defined and filled. Whether the responsibility falls on a set role in the project or organisation, or an extended team, this should be clearly defined in the organisational structure.

It is important that the organisational structure facilitates collaboration across the value chain and across different functions in the project or organisation. Organisational hierarchies and decision-making structures might need to be adjusted to accommodate the development and deployment of AI-based tools and the supporting infrastructure.

An arena should be established to keep all relevant actors involved, informed, and inspired throughout the entire process of implementation and integration – and beyond.

6.2.7 Ethical considerations

Ethical considerations must be at the core of any phase or stage of implementation and integration.

Development and deployment of AI models and tools must be done in a responsible and ethical manner, considering privacy concerns and biases. This means establishing clear policies and procedures for data collection, storage, use, governance, audits, and ensuring the involvement of relevant stakeholders in decision-making processes. Systems must be transparent, accountable, fair, and, ultimately, sustainable.

Transparency and trust are two of the major challenges. Developing ethical frameworks, establishing clear policies and procedures, and creating mechanisms for accountability and oversight are some of the possible solutions. Another big challenge is bias, especially when AI systems rely on historical data – as they often must. The data foundation needs to be representative. Automated systems, for instance, ML algorithms which often act as black boxes, must be thoroughly evaluated to ensure that they meet ethical standards.

6.3 Proposed frameworks (RQ3)

Considering the current state of the field, identified challenges for further advancement, and the seven dimensions of implementation and integration, frameworks are defined for the system, project, and organisation levels. The frameworks are expected to improve transferability and contextualisation in development and deployment, and to reduce fragmentation across the value chain, across processes, and in data.

6.3.1 System level

To accommodate the seven dimensions in all stages of development and deployment, the framework illustrated in Figure 6-1 is defined for the system level.

The framework consists of (S1) identifying the problem, (S2) assessment of feasibility, (S3) data collection, (S4) data pre-processing, (S5) model development, (S6) integration, and (S7) maintenance and monitoring. The framework is meant to facilitate a need-based approach to development and deployment, rather than deploying an AI system just for the sake of using AI. Utilising AI should not necessarily be a goal of its own; the goal should be to carry out a process in a more productive and sustainable way – AI systems might offer valuable contributions towards achieving this goal. For certain use cases, employing AI involves reviewing AI-generated examples, providing input, and using the AI system as a platform for experimentation and decision support; a system does not have to be entirely autonomous to create great value.

Each phase of the defined framework is intended as a decision gate, guiding the developer and user through the entire process. Ultimately, the framework provides a standardised process that eases incorporation in overarching strategic plans and goals upon completion of the development process.

The framework aims to facilitate a streamlined integration with established processes and activities, and ultimately ensure that the AI system becomes more than simply an add-on.

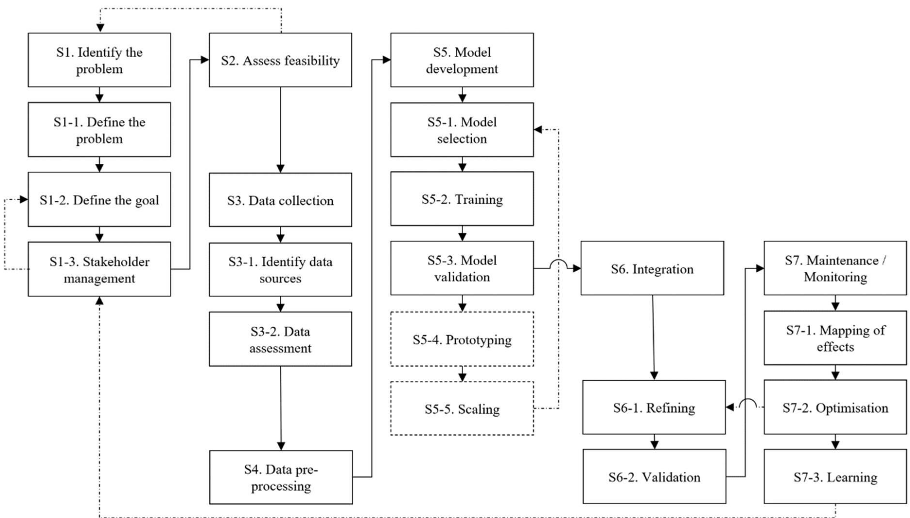


Figure 6-1. System level framework.

6.3.2 Project level

The framework for the project level is based on the NS 3467:2023 *Stages and deliverables in the life cycle of construction works* (Standard Norge, 2023) and outlines relevant AI-related activities for each of the defined project phases. Development and deployment must be an integral part of all phases, rather than an afterthought in the production phase; this will drastically increase scalability and robustness.

A project level framework from the executive perspective is illustrated in Figure 6-2. 'Areas of application' refers to possible areas of application that are relevant for the use of AI systems in the given phase. 'Stakeholder management' refers to recommended activities for stakeholder management in the given phase, and 'Infrastructure' refers to recommended activities for establishing relevant infrastructure to support the use of AI systems in the current and upcoming phases – and projects.

By highlighting potential use cases throughout all project phases, the framework aims to achieve effective distribution of resources to a range of problems. The framework indicates that stakeholder management extends far beyond assigning responsibilities, and outlines relevant activities to contribute to building expertise and trust. Relevant infrastructure must be established to accommodate changes on both the system and organisation levels.

	P1. Strategic definition	**P2. Program and concept development**	**P3. Development of selected concept**	**P4. Detailed design**	**P5. Production and delivery**	**P6. Handover and commissioning**	**7. Use and management**	**P8. Termination**
Areas of application	Evaluate project feasibility Predict costs and profitability Estimate resource demand and potential risk Strategic supply chain management Contractor pre-qualification	Design optimisation Resource allocation Virtual reality Cost prediction and estimation Tender price evaluation	Design optimisation Resource management Document review Virtual testing	Design optimisation Resource management Document review Virtual testing Validation of change requests Site layout design	Predictive maintenance Quality control Quantity control Prediction of project success Logistics and scheduling Waste reduction Automation of robots Risk and safety assessment	Transferring of relevant data	Predictive maintenance Energy management Air quality monitoring Security Space planning Cleaning Logistics	Material repurposing (reduce, reuse, recycle) Identification of areas of improvement Document review
Stakeholder management	Training related to system benefits and limitations Engaging stakeholders in ideation Engaging stakeholders in development	Alignment in overall project goals Establishing AI-related roles and responsibilities	Alignment of actor-specific project goals Training related to system-specifics (input and output)	Training related to system-specifics (input and output)	Maintaining dialogue Ensuring compliance	Transferring of relevant data	Training related to effective use of system Involving end users	Transfer of knowledge
Infrastructure	Centralised project-specific database Centralised communication channels Policies and procedures	Centralised database for project-specific metadata Building remaining necessary software	Procedures for processing and analysis of data Procedures for integration with existing systems	Integration with existing systems Software and hardware acquisition	Maintaining databases Maintaining communication-collaboration platforms	Transferring of relevant data	Installing sensors Procedures for data security measures	Transfer-specific databases, communication channels and storage

Figure 6-2. Project level framework.

6.3.3 Organisation level

Activities related to the development and deployment of AI systems and tools on the organisational level will vary heavily on the area of application and the characteristics of the system in question. Therefore, it is challenging, and not necessarily desirable, to define one standardised framework for all activities.

However, regardless of any area of application or characteristics of a given system, the organisation could and would benefit from establishing a data warehouse for the structuring of data. One such model is illustrated in Figure 6-3. Data from the data warehouse can be used for analytics, data mining, reports, and development.

Data warehouses are expected to be useful on the system and project levels; however, it is considered most resource effective to establish this on the organisation level. This way, the data used on system and project level can be elevated and related to other relevant data. Certain traditionally qualitative areas are still waiting for data. However, this data might already exist in unstructured formats, or exist in databases currently not available to the actor who wishes to access them. This can, in part, be solved by establishing a data warehouse. Ultimately, a data warehouse is expected to contribute to less resource intensive data preparation pipelines.

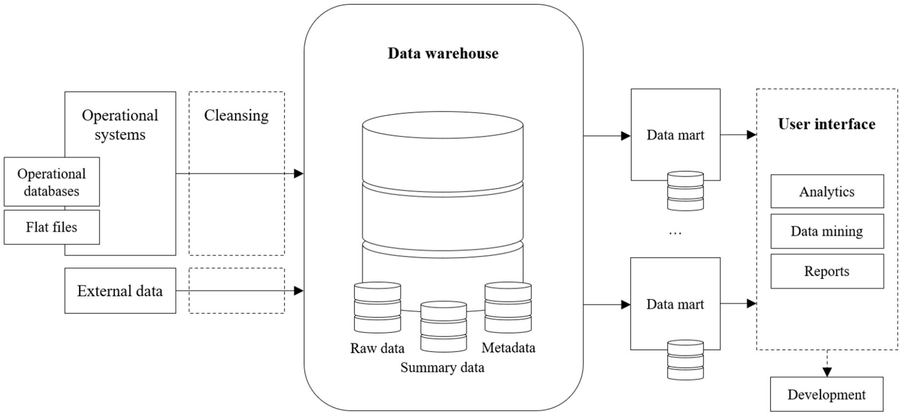


Figure 6-3. Organisation level framework.

6.4 Main contributions

The thesis has outlined the current state of the field, providing a comprehensive and practically oriented overview of recent advances, both from the perspective of academics and practitioners. Key challenges are identified for theory and application in attempts to move the use of AI-based systems and tools from ambition to practice. Based on this, the implementation and integration processes were assessed, and seven main emerging dimensions were mapped. From the seven dimensions, three frameworks were defined for the system, project, and organisation levels. The work is based on insights from previous research and from leading industry actors and experts.

Research mapped experiences and lessons learned from numerous projects to understand how the practical implications of development and implementation actually affect, and are affected by, actors on the system, project, and organisation levels. The thesis helps expand the knowledge within the contextual intersection between project management, AI, and sustainability in the construction context.

The findings provide a sense of direction and highlight current potential and gaps in the research at a time when academics and practitioners alike are eager to move forward. Previous research has emphasised the need for application-oriented research and frameworks (Darko et al., 2020; Wang et al., 2020), and what these might mean for the dimensions of people, processes, and technology (Shen et al., 2010; Nishant et al., 2020; Xu et al., 2022). The frameworks defined in this thesis will contribute to increasing transparency throughout the process, with recommendations related to the standardisation of activities in all three dimensions – and for the dimension of data. Improved standardisation can contribute to comparability and transferability between studies in the academic field, and pilots and PoCs in the industry, and reduce fragmentation.

The thesis provides an application-focused approach to the topic of AI in the construction context, expanding on a people and process-oriented complement to previously technology-focused advances (Ilter and Dikbas, 2009; Martínez and Fernández-Rodríguez, 2015; Juszczyk, 2017; Basaif and Alashwal, 2018). The frameworks address the needs expressed by prior research to facilitate collaboration between stakeholders (Goralski and Tan, 2020), leverage the potential AI systems hold for the entire construction project lifecycle (Pan and Zhang, 2021), and incorporate elements of infrastructure required to support AI technologies and solutions (Agrafiotis et al., 2018; Abraham et al., 2019). As indicated by previous research (Goralski and Tan, 2020; Nishant et al., 2020; Feroz et al., 2021; Pan and Zhang, 2021; Kineber et al., 2023a), the standardised framework is believed to enable increased sustainability in the process output, as well as in the process itself.

Preliminary analyses of existing literature indicated that most of the research in the intersections between the defined topics was primarily grounded in conceptual theory, rather than practical implications. Therefore, the methodology for the studies conducted within this thesis was developed to provide empirical validations.

For academics, the thesis provides a well-defined starting point with many opportunities for future research. The thesis provides empirical validation of findings in a field that has previously been lacking empirical data and research on implementation and performance beyond small-scale testing and PoCs. Previous research in the field was often limited to one specific area of application, or one specific system, and therefore not focused on holistic frameworks (Darko et al., 2020; Wang et al., 2020). Findings are presented with detailed descriptions of practical implications. A significant theoretical contribution is connecting the fields of AI, project management, and sustainability in the context of the implications of technology, process, people, and data. By connecting the fields, the findings identify factors affecting the four dimensions, and how factors in one dimension can affect the remaining three. Consequently, the thesis helps contributes to bridging the research gap existing at the intersection between the topics of AI, project management, and sustainability in the construction context.

For practitioners, the thesis provides a starting point for starting the process of moving from ambition to practice. The frameworks can help enable the shift from small-scale testing to larger scale implementation and integration. For individual actors, establishing frameworks contributes to anchoring in strategy, and a long-term reduction in required resources for effective and sustainable development and deployment of AI tools. The thesis has introduced three frameworks and illustrated the importance of taking a holistic approach, and not only focusing on activities and processes in one dimension, as changes in one dimension affect the three remaining dimensions.

A set of extensive guidelines is defined to help actors understand and more effectively and sustainably develop and deploy AI-based systems and tools. The defined frameworks offer a comprehensive approach for practitioners who want to get started – and want to get started now. Actors do not need to wait for the industry to change to bring ambition into practice, and the thesis provides some of the tools required to start the change. The insights provided can help practitioners identify and overcome some of the key challenges associated with the development and deployment of AI-based systems and tools, to understand the potential it holds and how to effectively unlock it. The findings can help practitioners identify areas of improvement in their own practices.

Actors in the construction industry should be able to apply the findings presented in this thesis by implementing the developed frameworks. Independently, the seven identified dimensions for implementation and integration can serve as a framework of their own right for actors to evaluate their own structures and systems, to ultimately gain insights and perspective into their own practices.

Throughout the work with the thesis, selected parts of the research have been presented in a wide range of settings and situations, including two guest lectures at Universidad Politécnica de Madrid, a presentation at the University of Salford Built Environments Summer School Programme, as well as multiple presentations for industry leaders, industry experts, and members of Construction City Cluster. As a result, the research has already been partially applied and evaluated in both academic and industry settings. Thus, certain aspects of the study have already had the opportunity to be assessed among experts in the fields, and in educational contexts.

6.5 Limitations and opportunities for future research

This thesis provides an enhanced understanding of how the use of AI in construction projects can be taken from ambition to practice. However, the findings presented and discussed in this thesis represent only the beginning of the research in this specific intersection of the field, and thus it provides a starting point for future research.

6.5.1 Empirical context and generalisability

The Norwegian construction industry constituted the main foundation for the conducted studies; the case studies were conducted on Norwegian projects, and most of the interviewees had their experience from the Norwegian setting. Thus, the research can be limited by cultural biases, regional characteristics, or unique circumstances that might not be applicable to other countries or contexts.

Close collaboration with international research environments (namely the University of Salford in England, and Philadelphia University in Jordan) and continuous participation in international expert groups with members from Switzerland, USA, Spain, Romania, Israel, England, and Norway contributed to increasing reliability, validity, and generalisability in the research. All findings were analysed in the context of available international literature exploring adjacent topics. This could improve the generalisability of the study and suggests that the findings can be applicable also outside the empirical context. To empirically validate this, more research is needed.

Future research could further expand the research beyond the Norwegian context and use this thesis as a starting point to strengthen or challenge the findings in the context of other countries and industries. Despite international collaboration providing the opportunity to share insights and findings across countries and industries, conducting research with data and insights predominantly from another country, could be a valuable contribution. It can provide a broader perspective, and allow for a more diverse range of experiences, insights, and practices to be included. Identifying similarities and differences between different countries can help improve generalisability.

By conducting research in an international context, cross-cultural similarities and differences can be identified, which, in turn, can help strengthen the findings. Elements from the defined frameworks could also be extended to facilitate activities in other industries; this could be another opportunity for future research.

Only articles written in English were included in the final literature review samples. This can be addressed in future research by including articles written in other languages, to broaden the scope of the study and potentially provide a more diverse perspective on the topic.

6.5.2 Validation of findings with increasing maturity

Due to the novelty of the topic, the studies conducted within the thesis had a limited number of case projects and informants available. The limited number of relevant informants and experts yielded quantitative methods such as questionnaires inapplicable for parts of the research.

A smaller sample size can reduce the generalisability of the findings. The sample size (and generalisability) was increased by involving informants across the value chain, and with backgrounds from other industries than the construction industry; however, future research can involve an even broader sample of projects and informants. Involving a larger sample of informants for each of the roles in the value chain can help gain a more in-depth understanding of the topic. As the field continues to develop, it seems reasonable to assume that a larger number of relevant projects and informants will become available for future research.

The novelty of the technologies and methods addressed and assessed in the thesis means it might be too early to assess their potential and limitations confidently, this could be confirmed or challenged by future research.

6.5.3 Industry actor perspectives

The project level framework was developed for the executive perspective, in essence, contractors. A valuable contribution for future research could therefore be to develop similar frameworks for owners, subcontractors, advisors, architects, suppliers, and other parts of the value chain. Throughout the research process, actors from across the value chain were interviewed and helped in the validation of findings, but the framework, especially on the project level, was ultimately mainly targeted towards the executive perspective.

6.5.4 Practical implementation of frameworks

Future research could implement the frameworks of this thesis, or elements from the frameworks, and set out to map and quantify the resulting effects on the system, project, and organisation levels. Empirical studies could then see, in practice, how the frameworks affect and are affected by real-life situations. By building on the findings of this thesis, future research could explore identifying even more dimensions of the implementation and integration process and assess how these might affect and be affected by the dimensions identified in this thesis.

The field of AI is developing rapidly, and the state of the field is drastically different upon completion of the thesis (2023) compared to the initiation of the thesis (2020). Therefore, each of the studies can be argued to hold only a cross-sectional view of the topic and the state of the topic. The whole thesis can still be argued to hold elements of a more longitudinal perspective, which can improve the reliability of the research. However, future research can aim to conduct a series of identical studies, to map the changes to a specific dimension or context over time. This will provide an even more longitudinal perspective. Further triangulation of research methods and approaches – especially case-based research – could also strengthen the validity of the findings and provides another opportunity for future research to expand on the preliminary findings of this study.

6.6 Personal reflections

In such a rapidly developing field, it can be hard not to get lost in the jungle of buzzwords and hype.

In order to make real progress, actors need to be pragmatic and put practical considerations and implications first, fancy tools second. Still, there is every reason to be optimistic. The technology, to a large extent, is already here. Tools that are now generating massive hype, and creating significant value, are built on technology that has been around for a while. We are now seeing new combinations of technologies, we have got access to more data than ever before, allowing us to create value for many, many people – that being entertainment value, or value in a construction project or organisation. So, we must be pragmatic, but we also have every reason to be optimistic. There is undoubtedly a big potential, and the industry might soon be ready to move from ambition to practice.

References

Abraham, R., Brocke, J. and Schneider, J. (2019). Data Governance: A conceptual framework, structured review, and research agenda, *International Journal of Information Management*. 49. DOI: 10.1016/j.ijinfomgt.2019.07.008.

Abioye, S. O., Lukumon, O. O., Akanbi, L., Ajayi, A., Delgado, J. M. D., Bilal, M., Akinade, O. O. and Ahmed, A. (2021). Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges, *Journal of Building Engineering*, 44. DOI: 10.1016/j.jobe.2021.103299

Adekunle, S. A., Aigbavboa, C. O., Ejohwomu, O., Adekunle, E. A. and Thwala, W. D. (2021). Digital transformation in the construction industry: a bibliometric review, *Journal of Engineering, Design and Technology*. DOI: 10.1108/JEDT-08-2021-0442

Aghimien, D., Ngcobo, N., Aigbavboa, C., Dixit, S., Vatin, N. I., Kampani, S., and Khera, G. S. (2022). Barriers to Digital Technology Deployment in Value Management Practice, *Buildings 2022*, 12, 731. DOI: 10.3390/buildings12060731

Agrafiotis, I., Nurse, J. R. C., Goldsmith, M., Creese, S. and Upton, D. (2018). A taxonomy of cyber-harms: Defining the impacts of cyber-attacks and understanding how they propagate, *Journal of Cybersecurity*, 4(1). DOI: 10.1093/cybsec/tyy006

Ai, B., Molisch, A. F., Rupp, M. and Zhong, Z. (2020). 5G Key Technologies for Smart Railways, *Proceedings of the IEEE*, 108(6), pp. 856-893. DOI: 10.1109/JPROC.2020.2988595

Akadiri, P. O., Chinyio, E. A. and Olomolaiye, P. O. (2012). Design of A Sustainable Building: A Conceptual Framework for Implementing Sustainability in the Building Sector, *Buildings 2012*, 2(2), pp. 126-152. DOI: 10.3390/buildings2020126

Akinade, O. O. (2017). *BIM-based software for construction waste analytics using artificial intelligence hybrid models*. Doctoral thesis. University of the West of England.

Akinosho, T. D., Oyedele, L. O., Bilal, M., Ajayi, A. O., Delgado, J. M. D., Akinade, O. O. and Ahmed, A. A. (2020). Deep learning in the construction industry: A review of present status and future innovations, *Journal of Building Engineering*, 32. DOI: 10.1016/j.jobe.2020.101827

Al-Fuqaha, A., Guizani, M., Mohammadi, M., Aledhari, M. and Ayyash, M. (2015) Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications, *IEEE Communications Surveys & Tutorials*, 17(4), pp. 2347-2376. DOI: 10.1109/COMST.2015.2444095

Al-Ruithe, M., Benkhelifa, E. and Hameed, K. (2019) A systematic literature review of data governance and cloud data governance, *Pers Ubiquit Comput*, 23, pp. 839–859. DOI: 10.1007/s00779-017-1104-3

Aliu, J., Oke, A. E., Kineber, A. F., Ebekozien, A., Aigbavboa, C. O., Alaboud, N. S. and Daoud, A. O. (2023) Towards a new paradigm o fproject management: A bibliometric review. Sustainability, 15(13), 9967. DOI: 10.3390/su15139967

Allam, Z. and Dhunny, Z. A. (2019). On big data, artificial intelligence and smart cities, *Cities*, 89, pp. 80-91. DOI: 10.1016/j.cities.2019.01.032

Almakayeel, N., Buniya, M. K., Abubakar, A. S., Kamil, S. M., Qureshi, K. M. and Qureshi, M. R. N. M. (2023). Modelling the Construction Projects Implementation Barriers: A Structure Equation Modelling Approach, *Buildings 2023*, 13, 1223. DOI: 10.3390/buildings13051223

Amann, J., Blasimme, A., Vayena, E., Frey, D. and Madai, V. I. (2020). Explainability for artificial intelligence in healthcare: a multidisciplinary perspective, *BMC Medical Informatics and Decision Making*, 20. DOI: 10.1186/s12911-020-01332-6

Amiri, R., Sardroud, J. M., and de Soto, B. G. (2017). BIMbased Applications of Metaheuristic Algorithms to Support the Decision-making Process: Uses in the Planning of Construction Site Layout, *Procedia Engineering*, 196, pp. 558-564. DOI: 10.1016/j.proeng.2017.08.030

Anil, E. B., Tang, P., Akinci, B. and Huber, D. (2011) Assessment of Quality of As-is Building Information Models Generated from Point Clouds Using Deviation Analysis, *Proceedings of SPIE - The International Society for Optical Engineering*. DOI: 10.1117/12.876554

Arditi, D. and Gunaydin, H. M. (1997). Total quality management in the construction process, *International Journal of Project Management*, 15(4), pp. 235-243 DOI: 10.1016/S0263-7863(96)00076-2

Arksey, H. and O'Malley, L. (2005) Scoping studies: towards a methodological framework, *International Journal of Social Research Methodology*, 8(1), 19-32. DOI: 10.1080/1364557032000119616

Ayhan, B. U. and Tokdemir, O. (2018). Predicting the outcome of construction incidents, *Safety Science*, 113, pp. 91-104. DOI: 10.1016/j.ssci.2018.11.001

Ayinla, K.O. and Adamu, Z. (2018). Bridging the digital divide gap in BIM technology adoption, *Engineering, Construction and Architectural Management*, 25(10), pp. 1398-1416. DOI: 10.1108/ECAM-05-2017-0091

Bang, S. and Andersen, B. (2022). Utilising Artificial Intelligence in Construction Site Waste Reduction, *Journal of Engineering, Project, and Production Management*, 12(3), pp. 239-249. DOI: 10.32738/JEPPM-2022-0022

Bang, S. and Olsson, N. (2022). Artificial Intelligence in Construction Projects: A Systematic Scoping Review, *Journal of Engineering, Project, and Production Management*, 12(3), pp. 224-238. DOI: 10.32738/JEPPM-2022-0021

Bang, S., Aarvold, M. O., Hartvig, W. J., Olsson, N. O. E. and Rauzy, A. (2022). Application of Machine Learning to Limited Datasets: Prediction of Project Success, *Journal of Information Technology in Construction (ITcon)*, 27, pp. 732-755. DOI: 10.36680/j.itcon.2022.036

Bannerman, P. L. (2008). Defining project success: a multilevel framework. *PMI® Research Conference: Defining the Future of Project Management*, Warsaw, Poland. Newtown Square, PA: Project Management Institute

Barlett-Bragg, A. (2017). Digital Capabilities: Where People and Technology Intersect, *EDULEARN17 Proceedings*, pp. 14-21. DOI: 10.21125/edulearn.2017.1004

Basaif, A. A. and Alashwal, A. M. (2018). A review of the application of artificial intelligence for risk analysis in construction projects. *Book of Abstracts: ASEAN Post Graduate Conference: Inclusive Built Environment Towards Realising New Urban Agenda*, Kuala Lumpur, Malaysia, 9-9.

Basaif, A. A., Al-Ashwal, A. M., Rahim, F. A., Karim, S. B., and Loo, S. C. (2020). Technology awareness of artificial intelligence (AI) application for risk analysis in construction projects, *Malaysian Construction Research Journal*, 1, pp. 182-195.

Becqué, R., Mackres, E., Layke, J., Aden, N., Liu, S., Managan, K., Nesler, C., Mazur-Stommen, S., Petrichenko, K., and Graham, P. (2016). *Accelerating Building Efficiency. Eight Actions for Urban Leaders*. World Resources Institute. WRI Ross Center for Sustainable Cities.

Bell, E. and Bryman, A. (2015). *Business Research Methods*. Fourth edition. London: Oxford University Press.

Belle, V. Knowledge representation and acquisition for ethical AI: challenges and opportunities, *Ethics and Information Technology 25*, 22(2023). DOI: 10.1007/s10676-023-09692-z

Bellini, A. and Bang, S. (2022). Barriers for data management as an enabler of circular economy: an exploratory study of the Norwegian AEC-industry, SBEfin 2022 – Emerging Concepts for Sustainable Built Environments. Helsinki, 23.-25. November, 2022. Bristol: IOP Publishing. DOI: 10.1088/1755-1315/1122/1/012047

Bilal, M., Oyedele, L. O., Akinade, O. O., Delgado, J. M. D., Akanbi, L. A., Ajayi, A. O., and Younis, M. S. (2019). Design optimisation using convex programming: Towards waste-efficient building designs, *Journal of Building Engineering*, 23, pp. 231-240. DOI: 10.1016/j.jobe.2019.01.022

Bilal, M. and Oyedele, L. O. (2020). Guidelines for applied machine learning in construction industry—A case of profit margins estimation, *Advanced Engineering Informatics*, 43(C), 101013. DOI: 10.1016/j.aei.2019.101013

Blanco, J. L., Fuchs, S., Parsons, M., and Ribeirinho, M. J. (2018). Artificial intelligence: Construction technology's next frontier, *The Building Economist*, pp. 7- 13. DOI: 10.3316/informit.048712291685521

Boje, C., Guerriero, A., Kubicki, S. and Rezgui, Y. (2020) Towards a semantic Construction Digital Twin: Directions for future research, *Automation in Construction*, 114, 103179. DOI: 10.1016/j.autcon.2020.103179

Bosch-Sijtsema, P., Claeson-Jonsson, C., Johansson, M. and Roupe, M. (2021), The hype factor of digital technologies in AEC, *Construction Innovation*, 21(4), pp. 899-916. DOI: 10.1108/CI-01-2020-0002

Bowen, G. (2009) Document Analysis as a Qualitative Research Method, *Qualitative Research Journal*, 9(2), pp. 27-40. DOI: 10.3316/QRJ0902027

Bryman, A. (2016). *Social Research Methods* (5th ed.). London: Oxford University Press.

Burgess, A. (2018). *The Executive Guide to Artificial Intelligence*. London: Palgrave Macmillan

Burnes, B. (2019) The origins of Lewin's three-step model of change, *Journal of Applied Behavioral Science.* 56(1), pp. 32-59. DOI: 10.1177/0021886319892685

Caldas, C. H., Soibelman, L. and Han, J. (2002). Automated Classification of Construction Project Documents, *Journal of Computing in Civil Engineering*, 16(4). DOI: 10.1061/(ASCE)0887-3801(2002)16:4(234)

Camacho, A., Canizares, P.C., Estevez, S., and Nunez, M. (2018). A tool-supported framework for work planning on construction sites based on constraint programming, *Automation in Construction*, 2(86), pp. 190-198. DOI: 10.1016/j.autcon.2017.11.008

Cameron, E. and Green, M. (2015). *Making Sense of Change Management: A Complete Guide to the Models, Tools and Techniques of Organizational Change*. 3rd ed. London: Kogan Page

Chan, A. P. C., Scott, D. and Chan, A. P. L. (2004) Factors affecting the success of a construction project, *Journal of Construction Engineering Management*, 130(1), pp. 153-155. DOI: 10.1061/(ASCE)0733-9364(2004)130:1(153)

Charef, R., Alaka, H. and Emmitt, S. (2018). Beyond the third dimension of BIM: A systematic review of literature and assessment of professional views, *Journal of Building Engineering,* 19(1), pp. 242-257. DOI: 10.1016/j.jobe.2018.04.028

Chen, M., Mao, S. & Liu, Y. (2014) Big Data: A Survey, *Mobile Networks and Applications*, 19, pp. 171–209 DOI: 10.1007/s11036-013-0489-0

Chen, L., Chen, P. and Lin, Z. (2020). Artificial Intelligence in Education: A Review, *IEEE Access*, 8, pp. 75264-75278, DOI: 10.1109/ACCESS.2020.2988510.

Cheng, M.Y and Hoang, N. D. (2014) Interval Estimation of Construction Cost at Completion Using Least Squares Support Vector Machine, *Journal of Civil Engineering and Management*, 20(2). DOI: 10.3846/13923730.2013.801891

Cheng, M. Y. and Hoang, N. D. (2018). Estimating Construction Duration of Diaphragm Wall Using Firefly-Tuned Least Squares Support Vector Machine, *Neural Computing and Applications*, 30, pp. 2489-2497. DOI: 10.1007/s00521-017-2840-z

Cheng, M. Y., Kusoemo, D., and Gosno, R. (2020). Text mining-based construction site accident classification using hybrid supervised machine learning, *Automation in Construction*, 118(1), 103265. DOI: 10.1016/j.autcon.2020.103265

Cheng, M. Y., Hoang, N. and Wu, Y. (2015). Cash Flow Prediction for Construction Project Using a Nobel Adaptive Time-Dependent Least Squares Support Vector Machine Inference Model, *Journal of Civil Engineering and Management*, 6. DOI: 10.3846/13923730.2014.893906

Cheng, M., Tsai, H. and Hsieh, W. (2009). Web-based conceptual cost estimates for construction projects using Evolutionary Fuzzy Neural Influence Model, *Automation in Construction*, 18(2), pp. 164-172. DOI: 10.1016/j.autcon.2008.07.001

Cheshire, D. (2019). *Building Revolutions: Applying the Circular Economy to the Built Environment*. London: RIBA Publishing.

Chua, D., Loh, P., Kog, Y. and Jaelskis, E. (1997) Neural Networks for Construction Project Success, *Expert Systems with Applications*, 13(4), pp. 317-328. DOI: 10.1016/S0957-4174(97)00046-8

Cramer (2003) *Advanced Quantitative Data Analysis*. Philadelphia: Open University Press.

Creswell, J. W. (2009) Research design. *Qualitative, quantitative, and mixed methods approaches*. Third edition. California: Sage Publications.

Croom, S. (2010) *Introduction to Research Methodology in Operations Management.* Researching Operations Management. Oxford: Routledge.

Dalen, M. (2004) *Intervju som forskningsmetode* (Interview as a research method). Oslo: Universitetsforlaget.

Darko, A., Chan, A. P. C., Adabre, M. A., Edwards, D. J., Hosseini, M. R., & Ameyaw, E. E. (2020). Artificial intelligence in the AEC industry: Scientometric analysis and visualization of research activities. *Automation in Construction*, 112. DOI: 10.1016/j.autcon.2020.103081

Dasgupta, D. and Michalewicz, Z. (1997). *Evolutionary Algorithms in Engineering Applications*. Springer, New York.

Dawood, H., Siddle, J., and Dawood, N. (2019). Integrating IFC and NLP for automating change request validations, *Journal of Information Technology in Construction*, 24, special issue, pp. 540-552. DOI: 10.36680/j.itcon.2019.030

de Soto, B. G., Rosarious, A., Rieger, J., Chen, Q., and Adey, B. T. (2017). Using a Tabu-search Algorithm and 4D Models to Improve Construction Project Schedules, *Procedia Engineering*, 196, pp. 698-705. DOI: 10.1016/j.proeng.2017.07.236

Delgado, J. M. D., Oyedele, L., Bilal, M., Ajayi, A., Akanbi, L. and Akinade, O. (2020). Big Data Analytics System for Costing Power Transmission Projects, *Journal of Construction Engineering and Management*, 146(1). DOI: 10.1061/(ASCE)CO.1943-7862.0001745

Denzin, N. K. (2012) Triangulation 2.0, *Journal of Mixed Methods Research*, 6(2), pp. 80-88. DOI: 10.1177/1558689812437186

Dignum, V. (2017). Responsible autonomy. *In Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence* (IJCAI'2017), pp. 4698–4704. DOI: 10.5555/3171837.3171945

Dignum, V. (2018) Ethics in artificial intelligence: introduction to the special issue, *Ethics and Information Technology*, 20, pp. 1–3. DOI: 10.1007/s10676-018-9450-z

Dorussen, H., Lenz, H. and Blavoukos, S. (2005) Assessing the Reliability and Validity of Expert Interviews, *European Union Politics*, 6(3): 315-337. DOI: 10.1177/1465116505054835

Duan, Y., Edwards, J. S. and Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda, *International Journal of Information Management*, 48, pp. 68-71. DOI: 10.1016/j.ijinfomgt.2019.01.021

Dul, J. and Hak, T. (2008) *Case Study Methodology in Business Research*. First edition. Oxford: Routledge.

Dvir, D., Ben-David, A., Sadeh, A., and Shenhar, A. J. (2006) Critical managerial factors affecting defence projects success: A comparison between neural network and regression analysis, *Engineering Applications of Artificial Intelligence*, 19 (5), pp. 535-543. DOI: 10.1016/j.engappai.2005.12.002

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., Medaglia, R. and Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy, *International Journal of Information Management*, 57. DOI: 10.1016/j.ijinfomgt.2019.08.002

Ellram L. M. (1996). The use of the case study method in logistic research, *Journal of Business Logistics*, 17(2), pp. 93-138

Elmousalami, H. (2019). Intelligent methodology for project conceptual cost prediction, *Heliyon*, 5(5), e01625. DOI: 10.1016/j.heliyon.2019.e01625

Energi Norge, Norsk Fjernvarme, Bellona and Enova SF (2017) *Fossil- og utslippsfrie byggeplasser*. (Fossil and emission free construction sites). 2017-0637. 1144USSL-4. [Report]

Fallahpour, A., Wong, K., Rajoo, S., Olugu, E., Nilashi, M., and Turskis, Z. (2020). A fuzzy decision support system for sustainable construction project selection: an integrated FPP-FIS model, *Journal of Civil Engineering and Management*, 26(3), pp. 247-258. DOI: 10.3846/jcem.2020.12183

Fang, W., Luo, H., Xu, S., Love, P.E., Lu, Z., and Ye, C. (2020). Automated text classification of near misses from safety reports: An improved deep learning approach, *Advanced Engineering Informatics*, 44, 101060. DOI: 10.1016/j.aei.2020.101060

Farquhar, J. D. (2012) *Case Study Research for Business*. London: SAGE Publications.

Fellows, R and Liu, A. (2003) *Research Methods for Construction*. Blackwell Science. Second Edition. ISBN 0-623-06435-8

Fenn, J. (1995). *Gartner's hype cycle*. Available at: http://www.out-law.com/page-6043 (Accessed: 29 March 2023)

Feroz, A. K., Hangjung, Z. and Chiravuri, A. (2021). Digital Transformation and Environmental Sustainability: A Review and Research Agenda, *Sustainability 2021*, 13(3). DOI: 10.3390/su13031530

Fischer, M. A., Fosse, R. and Ballard, G. (2017). Virtual Design and Construction: Aligning BIM and Lean in Practice. 25th Annual Conference of the International Group for Lean Construction. Heraklion, Greece. pp. 499-506. DOI: 10.24928/2017/0159

Flick, E. (2004). *A companion to Qualitative Research*. London: Sage Publications

Forbes, L. H. and Ahmed, S. M. (2020). *Lean Project Delivery and Integrated Practices in Modern Construction*. 2nd ed. Oxford: Routledge

Forcael, E. (2020). Construction 4.0: A Literature Review, *Sustainability 2020*, 12(22). DOI: 10.3390/su12229755

Gartner (2023) *What's New in the 2022 Gartner Hype Cycle for Emerging Technologies*. Available at: https://www.gartner.com/en/articles/what-s-new-in-the-2022-gartner-hype-cycle-for-emerging-technologies (Accessed: 22 March 2023).

Ghosh, A., Chakraborty, D. and Law, A. (2018). Artificial intelligence in Internet of things, *CAAI Transactions on Intelligence Technology*, 3(4), pp. 208-218. DOI: 10.1049/trit.2018.1008

Global Alliance for Buildings and Construction (2017) *Global Status Report 2017*. UN Environment and International Energy Agency. ISBN: 978-92-807- 3686-1

Goh, Y. M., Ubeynarayana C.U., Wong K. L. X., and Guo B. H. W. (2018). Factors influencing unsafe behaviors: A supervised learning approach, *Accident Analysis & Prevention*, 188, pp. 77-85. DOI: 10.1016/j.aap.2018.06.002

Golparvar-Fard, M., Peña-Mora, F. and Savarese, S. (2015). Automated Progress Monitoring Using Unordered Daily Construction Photographs and IFC-Based Building Information Models, *Journal of Computing in Civil Engineering*, 29(1). DOI: 10.1061/(ASCE)CP.1943-5487.0000205

Gondia, A., Siam, A., El-Dakhakhni, W. and Nassar, A. H. (2020). Machine Learning Algorithms for Construction Projects Delay Risk Prediction, *Journal of Construction Engineering and Management*, 146(1). DOI: 10.1061/(ASCE)CO.1943-7862.0001736

Goodell, J. W., Kumar, S., Lim, W. M. and Pattnaik, D. (2021). Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters from bibliometric analysis, *Journal of Behavioral and Experimental Finance*, 32. DOI: 10.1016/j.jbef.2021.100577

Goralski, M. A. and Tan, T. K. (2020). Artificial intelligence and sustainable development, *The International Journal of Management Education*, 18(1). DOI: 10.1016/j.ijme.2019.100330

Gough, D. (2007a). Weight of Evidence: a framework for the appraisal of the quality and relevance of evidence, *Research Papers in Education*, 22(2), pp. 213-228. DOI: 10.1080/02671520701296189

Gough, D. (2007b). *Giving voice: Evidence-informed policy and practice as a democratizing process. Marginality and difference in education and beyond*. London: Trentham Books, 31-45.

Grønn Byggallianse and Høgskolen i Østfold (2019) *Merverdien av grønne bygg*. (Added value from green buildings). 2016-18. Available at: https://byggalliansen.no/wp-content/uploads/2019/10/Merverdien-av-gr%C3%B8nne-bygg.pdf (Accessed: 20 November 2019).

Gudauskas, R., Jokubauskiene, S., Zavadskas, E., Kaklauskas, A., Binkyte-Veliene, A., Peciure, L., Budryte, L., and Prialgauskas, D. (2015). Intelligent Decision Support System for Leadership Analysis, *Procedia Engineering*, 122, pp. 172-180. DOI: 10.1016/j.proeng.2015.10.022

Gu, N. and London, K. (2010). Understanding and facilitating BIM adoption in the AEC industry, *Automation in Construction*, 19(8), pp. 988-999. DOI: 10.1016/j.autcon.2010.09.002

Hagendorff, T. (2020). The Ethics of AI Ethics: An Evaluation of Guidelines, *Minds and Machines*, 30(1). DOI: 10.1007/s11023-020-09517-8

Hajdasz, M. (2015). Managing repetitive construction in a dynamically changing project environment: Conceptualizing the system–model–simulator nexus, *Automation in Construction*, 57, pp. 132-145. DOI: 10.1016/j.autcon.2015.05.005

Halliday, S. (2007). *Sustainable Construction*. 1st ed. Oxford: Routledge

Halvorsen, K. (2008) *Å forske på samfunnet. En innføring i samfunnsvitenskapelig metode* (Researching society. An introduction to social science method). Oslo: Cappelen Damm Akademisk.

Han, Y., Yin, Z. Z., Zhang, J., Jin, R., and Yang, T. (2020). Eye-Tracking Experimental Study to Investigating the Influence Factors of Construction Safety Hazard Recognition. *Journal of Construction Engineering and Management*, 146(8), 04020091. DOI: 10.1061/(ASCE)CO.1943-7862.0001884

Hanna, A., Iskandar, K., Lotfallah, W., Ibrahim, M., and Russell, J. (2018). A Data-driven Approach for Identifying Project Manager Competency Weights, *Canadian Journal of Civil Engineering*, 45, pp. 1-8. DOI: 10.1139/cjce-2017-0237

Hao. Q., Shen, W., Neelamkavil, J and Thomas, J. R. (2008). Change management in construction projects. *International Conference on Information Technology in Constructio*n. CIB W78 2008. Santiago, Chile.

Hassan, F. and Le, T. (2020). Automated Requirements Identification from Construction Contract Documents Using Natural Language Processing, *Journal of Legal Affairs and Dispute Resolution in Engineering and Construction*, 12(2). DOI: 10.1061/(ASCE)LA.1943-4170.0000379

Hjellnes Consult (2015). *Plukkanalyser av restavfallskontainere fra byggeplasser* (Analysis of mixed waste containers on construction sites). 20140205. Oslo: Nettverket for Nasjonal Handlingsplan for bygg- og anleggsavfall (NHP-nettverket).

Holden, M. T., and Lynch, P. (2004). Choosing the Appropriate Methodology: Understanding Research Philosophy, *The Marketing Review*, 4(4), DOI: 10.1362/1469347042772428

Holme, I. M. and Solvang, B. K. (1996). *Metodevalg og metodebruk* (Method selection and method use). Otta: Tano.

Hong, T., Wang, Z., Luo, X., and Zhang, W. (2020). State of-the-Art on Research and Applications of Machine Learning in the Building Life Cycle. *Energy and Buildings*, 212(3). DOI: 10.1016/j.enbuild.2020.109831

Hossain, M. A. and Nadeem, A. (2019). Towards digitizing the construction industry: State of the art of Construction 4.0, *Proceedings of the International Structural Engineering and Construction*, 6(1). DOI: 10.14455/ISEC.res.2019.184

Hsu, H. C., Chang, S., Chen, C. C., and Wu, I C. (2020). Knowledge-based system for resolving design clashes in building information models, *Automation in Construction*, 110. DOI: 10.1016/j.autcon.2019.103001

Hu, Y. and Castro-Lacouture, D. (2019). Clash Relevance Prediction Based on Machine Learning, *Journal of Computing in Civil Engineering*, 33(2), 04018060. DOI: 10.1061/(ASCE)CP.1943-5487.0000810

Hussein, B. (2016). *Veien til suksess – fortellinger og refleksjoner fra reelle prosjektcaser*. (The road to success – narratives and insights from real-life projects). Bergen: Fagbokforlaget.

Ilter, D. and Dikbas, A. (2009). A review of the artificial intelligence applications in construction dispute resolution. *Managing IT in Construction/Managing Construction for Tomorrow*, pp. 41-50. DOI: 10.1201/9781482266665-63

Innes, S. (2004). Developing tools for designing out waste pre-site and on-site, *Proceedings of Minimising Construction Waste Conference: Developing Resource Efficiency and Waste Minimisation in Design and Construction*. DOI: 10.1016/j.sbspro.2012.03.158

Irani, Z. and Kamal, M. M. (2014) Intelligent Systems Research in the Construction Industry, *Expert Systems with Applications*, 41(4), pp. 934-950. DOI: 10.1016/j.eswa.2013.06.061

Jaber, F., Al-Zwainy, F. M., and Hachem, S. (2019). Optimizing of predictive performance for construction projects utilizing support vector machine technique, *Cogent Engineering*, 6(1), 1685860. DOI: 10.1080/23311916.2019.1685860

Jacobsen, D. I. (2015). *Hvordan gjennomføre undersøkelser?* (How to conduct surveys?) Third edition. Oslo: Cappelen Damm Akademisk.

Jacobsen, E. L. and Teizer, J. (2022). Deep Learning in Construction: Review of Applications and Potential Avenues, *Journal of Computing in Civil Engineering*, 36(2). DOI: 10.1061/(ASCE)CP.1943-5487.0001010

Johannessen, A., Tufte, P. A., and Christoffersen, L. (2016) *Introduksjon til samfunnsvitenskapelig metode* (Introduction to social science method). Fifth edition. Oslo: Abstrakt forlag.

Johansen, A., Olsson, N., Jergeas, G. and Rolstadås, A. (2019). *Project Risk and Opportunity Management: The Owner's Perspective*. Oxford: Routledge.

Juszczyk, M. (2017). The Challenges of Nonparametric Cost Estimation of Construction Works with the use of Artificial Intelligence Tools, *Procedia Engineering*, 196 (1), pp. 415-422. DOI: 10.1016/j.proeng.2017.07.218

Juszczyk, M. (2020). Development of Cost Estimation Models Based on ANN Ensembles and the SVM Method, *Civil and Environmental Engineering Reports*, 30(3), pp. 48-67. DOI: 10.2478/ceer-2020-0033

Juszczyk, M. and Lesniak, A. (2019). Modelling Construction Site Cost Index Based on Neural Network Ensembles, *Symmetry*, 11(3), 411. DOI: 10.3390/sym11030411.

Juszczyk, M., Zima, K., and Lelek, W. (2019). Forecasting of Sports Fields Construction Costs Aided by Ensembles of Neural Networks, *Journal of Civil Engineering and Management*, 25(7), pp. 715-729. DOI: 10.3846/jcem.2019.10534

Kallio, H., Pietilä, A.-M., Johnson, M. and Kangasniemi, M. (2016) Systematic methodological review: developing a framework for a qualitative semi-structured interview guide, *Journal of Advanced Nursing*, 72(12), pp. 2954– 2965. DOI: 10.1111/jan.13031

Kamble, S. S., Gunasekaran, A., Ghadge, A. and Raut, R. (2020). A performance measurement system for industry 4.0 enabled smart manufacturing system in SMMEs - A review and empirical investigation, *International Journal of Production Economics*, 229. DOI: 10.1016/j.ijpe.2020.107853

Kartam, N., Al-Mutairi, N., Al-Ghusain, I., and AlHumoud, J. (2004). Environmental management of construction and demolition waste in Kuwait, *Waste Management*, 24(10), pp. 1049-1059. DOI: 10.1016/j.wasman.2004.06.003

Kaylan, T. S., Zadeh, P. A., Staub-French, S. and Froese, T. M. (2016) Construction Quality Assessment Using 3D as-built Models Generated with Project Tango, *Procedia Engineering*, 145, pp. 1416-1423. DOI: 10.1016/j.proeng.2016.04.178

Kineber, A. F., Oke, A., Aliu, J., Hamed, M. M. and Oputu, E. (2023a). Exploring the Option of Cyber (Digital) Technology for Sustainable Construction: A Structural Equation Modelling of Critical Success Factors. *Sustainability 2023*, 15(6), 5043. DOI: 10.3390/su15065043

Kineber, A. F., Oke, A. E., Qaralleh, T. J. O., Alaboud, N. S., Alshahrani, A., Alaboud, M. and Daoud, A.O. (2023b). Cyber Technology Implementation Barriers for Sustainable Buildings: A Novel Mathematical Partial Least Square Structural Equa-tion Modelling, *Buildings 2023*, 13, 1052. DOI: 10.3390/buildings13041052

Knoth, K., Fufa, S. M. and Seilskjær, E. (2022). Barriers, success factors, and perspectives for the reuse of construction products in Norway, *Journal of Cleaner Construction*, 337. DOI: 10.1016/j.jclepro.2022.130494

Ko, C. and Cheng, M. (2007). Dynamic Prediction of Project Success Using Artificial Intelligence, *Journal of Construction Engineering and Management*, 133(4). DOI: 10.1061/(ASCE)0733-9364(2007)133:4(316)

Kog, F. and Yaman, H. (2016). A multi-agent systems-based contractor pre-qualification model, *Engineering, Construction and Architectural Management*, 23(6), pp. 709-726. DOI: 10.1108/ECAM-01-2016-0013

Koskela, L. J., Ballard, G., Tommelein, I and Howell, G. (2002). The foundations of lean construction, *Design and Construction: Building in Value*, pp. 211-226.

Kubicki, S., Guerriero, A., Schwartz, L., Daher, E. and Idris, B. (2019) Assessment of synchronous interactive devices for BIM project coordination: prospective ergonomics approach. *Automation in Construction*, 101, pp. 160-178. DOI: 10.1016/j.autcon.2018.12.009

Kuniavsky, M. (2010) *Smart things*. First edition. ISBN: 9780123748997

Ladley, J. (2020). *Data Governance: How to Design, Deploy and Sustain an Effective Data Governance Program*. Second edition. London: Academic Press.

Levac, D., Colquhoun, H., and O'Brien, K. K. (2010). Scoping studies: advancing the methodology, *Implementation Science*, 5(69). DOI: 10.1186/1748-5908-5-69

Lewin, K (1951, 1952) *Field Theory in Social Science*, New York: Harper and Row

Li, J. (2018). Cyber security meets artificial intelligence: a survey, *Frontiers of Information Technology and Electronic Engineering*, 19, pp. 1462–1474. DOI: 10.1631/FITEE.1800573

Lima, L., Trindade, E., Alencar, L., Alencar, M. and Silva, L. (2021). Sustainability in the construction industry: A systematic review of the literature, *Journal of Cleaner Production*, 289, 125730. DOI: 10.1016/j.jclepro.2020.125730

Liu, S., Meng, X., and Tam, C. (2015). Building Information Modelling Based Building Design Optimization for Sustainability. *Energy and Buildings*, 105, 139-153. DOI: 105. 10.1016/j.enbuild.2015.06.037

Liu, J., Xu, D., Hyyppä, J. and Liang, Y. (2021) A Survey of Applications with Combined BIM and 3D Laser Scanning in the Life Cycle of Buildings. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 14, pp. 5627-5637. DOI: 10.1109/JSTARS.2021.3068796

Loukides, M., Mason, H. and Patil, D. (2018). *Ethics and Data Science*. California: O'Reilly Media.

Love, P. E. D., Holt, G. D. and Li, H. (2002). Triangulation in construction management research, *Engineering, Construction, and Architectural Management*, 9(4), pp. 294-303. DOI: 10.1108/eb021224

Magaña, D. and Fernández Rodríguez, J. C. (2015). Artificial Intelligence Applied to Project Success: A Literature Review. *International Journal of Artificial Intelligence and Interactive Multimedia*. 3, pp. 77-84. DOI: 10.9781/ijimai.2015.3510

Martínez, D. M. and Fernández-Rodríguez, J. C. (2015). Artificial Intelligence Applied to Project Success: A Literature Review. *International Journal of Interactive Multimedia and Artificial Intelligence*, 3(5), pp. 77-84. DOI: 10.9781/ijimai.2015.3510

McCarthy, J. (2007) *What is artificial intelligence?* Computer Science Department, Stanford University. Available at: https://www-formal.stanford.edu/jmc/whatisai.pdf (Accessed: 20 July 2023).

Mejlænder-Larsen Ø (2019). *The use of project execution models and BIM in oil and gas projects: searching for relevant improvements for construction*. Doctoral thesis. NTNU

Melnikovas, A. (2018) Towards an explicit research methodology: Adapting research onion model for futures studies. *Journal of Futures Studies*, 23(2), pp. 29-44. DOI: 10.6531/JFS.201812_23(2).0003

Mhlanga, D. (2020). Industry 4.0 in Finance: The Impact of Artificial Intelligence (AI) on Digital Financial Inclusion, *International Journal of Financial Studies*, 8(3). DOI: 10.3390/ijfs8030045

Mirahadi, F. and Zayed, T. (2016). Simulation-based construction productivity forecast using Neural Network-Driven Fuzzy Reasoning, *Automation in Construction*, 65, pp. 102-115. DOI: 10.1016/j.autcon.2015.12.021

Momade, M. H., Durdyev, S., Estrella, D. and Ismail, S. (2021). Systematic Review of Application of Artificial Intelligence Tools in Architectural, Engineering and Construction. *Frontiers in Engineering and Built Environment*, 1, pp. 203-216. DOI: 10.1108/FEBE-07-2021-0036

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., and The PRISMA Group (2009) Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. *PLoS Medicine*, 6(7), e1000097. DOI: 10.1371/journal.pmed.1000097

Mousavi, S., Vahdani, B., Hashemi, H., and Ebrahimnejad, S. (2015). An Artificial Intelligence Model-Based Locally Linear Neuro-Fuzzy for Construction Project Selection, *Journal of multiple-valued logic and soft computing*, 25(6), pp. 589-604. DOI: 10.3233/IFS-120748

Munaro, M. and Tavares, S. F. (2021). Materials passport's review: challenges and opportunities toward a circular economy building sector, *Built Environment Project and Asset Management*, 11(4), pp. 767-782. DOI: 10.1108/BEPAM-02-2020-0027

Nguyen, P. T., Nguyen, T. A., Nguyen, Q. and Huynh, V. (2018) Application of SWOT for Construction Company Quality Management using Building Information Modelling, *Journal of Mechanics of Continua and Mathematical Sciences*, 13(5), pp. 25-33. DOI: 10.26782/jmcms.2018.12.00003

Nguyen, T. A., Nguyen, P. T. and Do, S. T. (2020). Application of BIM and 3D Laser Scanning for Quantity Management in Construction Projects, *Advances in Civil Engineering*, 2020. DOI: 10.1155/2020/8839923

Nishant, R., Kennedy, M. and Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities and a research agenda, *International Journal of Information Management*, 53. DOI: 10.1016/j.ijinfomgt.2020.102104

Nnaji, C. and Karakhan, A. A. (2020). Technologies for safety and health management in construction: Current use, implementation benefits and limitations, and adoption barriers. *Journal of Building Engineering*, 29, 101212. DOI: 10.1016/j.jobe.2020.101212

Nordic 10-10 (c. 2020). *Verktøyet CII 10-10* (The CII 10-10 tool). Available at: https://nordic10-10.org/verktoyet-cii-10-10/ (Accessed: 28 February 2021).

Norsk Gjenvinning (c. 2018). *Grønt Ansvar®*. Available at: https://www.norskgjenvinning.no/bedrift/pakkeloesninger/groent-ansvar/ (Accessed: 7 July 2019).

NSD (2022) *NSD Strategy 2021-2024*. Available at: https://www.nsd.no/en/about-nsd-norwegian-centre-for-research-data/nsd-strategy-20212024 (Accessed: 21 September 2022).

Olsson, N. O. E. (2011) *Praktisk rapportskriving* (Practical report writing). First edition. Trondheim: Tapir akademisk forlag.

Oprach, S., Bolduan, T., Steuer, D., Vössing, M., and Haghsheno, S. (2019). Building the Future of the Construction Industry through Artificial Intelligence and Platform Thinking. *Digitale Welt*, 3, pp. 40-44. DOI: 10.1007/s42354-019-0211-x

Pan, Y. and Zhang, L. (2021). Roles of artificial intelligence in construction engineering and management: A critical review and future trends, *Automation in Construction*, 122. DOI: 10.1016/j.autcon.2020.103517

Perrier, N., Bled, A., Bourgault, M., Cousin, N., Danjou, C., Pellerin, R. and Roland, T. (2020). Construction 4.0: a survey of research trends, *Journal of Information Technology in Construction*, 25, pp. 416-437. DOI: 10.36680/j.itcon.2020.024

Pinto, J. K. and Prescott, J. E. (1988) Variations in Critical Success Factors Over the Stages in the Project Life Cycle. *Journal of Management*, 14(1). DOI: 10.1177/014920638801400102

PMI (2021). *A Guide to the Project Management Body of Knowledge* (PMBOK® Guide) Seventh edition 2021PMBOK® Guide (2021).

Podolski, M. (2016). Management of resources in multiunit construction projects with the use of a tabu search algorithm, *Journal of Civil Engineering and Management*, 23(2), pp. 1-10. DOI: 10.3846/13923730.2015.1073616

Poh, C. Q. X., Ubeynarayana, C. U., and Goh, Y. M. (2018). Safety leading indicators for construction sites: A machine learning approach, *Automation in Construction*, 93. DOI: 10.1016/j.autcon.2018.03.022

Politou, E. Alepis, E. and Patsakis, C. (2018). Forgetting personal data and revoking consent under the GDPR: Challenges and proposed solutions, *Journal of Cybersecurity*, 4(1), tyy001. DOI: 10.1093/cybsec/tyy001

Pomponi, F., & Moncaster, A. (2016). Circular economy for the built environment: A research framework. *Journal of Cleaner Production*, 143, pp. 710-718. DOI: 10.1016/j.jclepro.2016.12.055

Pringle, T. and Zoller, E. (2018) *How to achieve AI maturity and why it matters*. Report. London: Ovum TMT intelligence.

Pruvost, H. and Scherer, R. (2017). Analysis of risk in building life cycle coupling BIM-based energy simulation and semantic modelling, *Procedia Engineering*, 196, pp.1106-1113. DOI: 10.1016/j.proeng.2017.08.068

Pylyshyn, Z. W. (2010). Computation and cognition: issues in the foundations of cognitive science, *Behavioral and Brain Sciences*, 3 (1), pp. 111 – 132. DOI: 10.1017/S0140525X00002053

Qadri, Y. A., Nauman A., Zikria Y. B., Vasilakos A. V., and Kim S. W. (2020). The Future of Healthcare Internet of Things: A Survey of Emerging Technologies, *IEEE Communications Surveys & Tutorials*, 22(2), pp. 1121-1167. DOI: 10.1109/COMST.2020.2973314.

Rahimian, F. P., Seyedzadeh, S., Oliver, S., Rodriguez, S. and Dawood, N. (2020). On-demand monitoring of construction projects through a game-like hybrid application of BIM and machine learning. *Automation in Construction*, 110, DOI: 10.1016/j.autcon.2019.103012

Rajabi, M. S., Radzi, A. R., Rezaeiashtiani, M., Famili, A., Rashidi, M. E. and Rahman, R. A. (2022). Key Assessment Criteria for Organizational BIM Capabilities: A Cross-Regional Study, *Buildings 2022*, 12, 1013. DOI: 10.3390/buildings12071013

Rezvani, A. and Khosravi, P. 2018. A comprehensive assessment of project success within various large projects, *The Journal of Modern Project Management*, 6(1), pp. 115-123. DOI: 10.19255/JMPM01612

Robinson, O. (2014) Sampling in Interview-Based Qualitative Research: A Theoretical and Practical Guide, *Qualitative Research in Psychology*, 11(1). DOI: 10.1080/14780887.2013.801543

Rodriguez-Trejo S., Ahmad A.M., Hafeez M.A., Dawood, H., Vukovic V., Kassem M., Naji K.K., and Dawood N. (2017). Hierarchy based information requirements for sustainable operations of buildings in Qatar. *Sustainable Cities and Society*, 32, 435-448. DOI: 10.1016/j.scs.2017.03.005

Rogers, E. M. (1995). *A Diffusion of Innovations*. Fourth edition. New York: Free Press.

Russell, S. J. and Norvig, P. (2010) *Artificial Intelligence. A Modern Approach*. Third edition. Upper Saddle River, New Jersey: Pearson Education.

Russell, S. J. (1997). Rationality and intelligence, *Artificial Intelligence*, 94(1-2), pp. 57-77. DOI: 10.1016/S0004-3702(97)00026-X

Ryen, A. (2002) *Det kvalitative intervjuet: fra vitenskapsteori til feltarbeid* (The qualitative interview: from scientific theory to fieldwork). Bergen: Fagbokforlaget.

Rønningen, O. (2000) *Bygg- og anleggsavfall. Avfall fra nybygging, rehabilitering og rivning. Resultater og metoder.* (Construction waste. Waste from new buildings, rehabilitation and demolition. Results and methods). Oslo: Statistisk Sentralbyrå (Statistics Norway).

Safa, M., Nahangi, M., Shahi, A. and Haas, C. (2013) An Integrated Quality Management System for Piping Fabrication Using 3D Laser Scanning and Photogrammetry. *30th International Association for Automation and Robotics in Construction*. Montreal. DOI: 10.22260/ISARC2013/0073

Samantra, C., Datta, S., and Mahapatra, S.S. (2017). Fuzzy based risk assessment module for metropolitan construction project: An empirical study. *Engineering Applications of Artificial Intelligence*, 65(C), pp. 449-464. DOI: 10.1016/j.engappai.2017.04.019

Saunders, M., Lewis, P. and Adrian, T. (2019) *Research Methods for Business Students*. Eighth edition. Harlow, UK, Pearson Education.

Sawhney, A., Riley, M. and Irizarry, J. (2020). *Construction 4.0: An Innovation Platform for the Built Environment.* Oxford: Routledge.

Shahzad, M., Shafiq, M. T., Douglas, D., and Kassem, M. (2022). Digital Twins in Built Environments: An Investigation of the Characteristics, Applications, and Challenges, *Buildings 2022*, 12, 120. DOI: 10.3390/buildings12020120

Sharafi, P., Rashidi, M., Samali, B., Ronagh, H., and Mortazavi, M. (2018). Identification of Factors and Decision Analysis of the Level of Modularization in Building Construction. *Journal of Architectural Engineering*, 24(2). DOI: 10.1061/(ASCE)AE.1943-5568.0000313

Shen, L., Tam, V. W. Y., Tam, L. and Ji, Y. (2010). Project feasibility study: the key to successful implementation of sustainable and socially responsible construction management practice, *Journal of Cleaner Production*, 18(3), pp. 254-259. DOI: 10.1016/j.jclepro.2009.10.014

Shin, Y. (2015). Application of Boosting Regression Trees to Preliminary Cost Estimation in Building Construction Projects. *Computational intelligence and neuroscience*, 2015(4), 149702. DOI: 10.1155/2015/149702

Singh, P., Dulebenets, M. A., Pasha, J., Gonzalez E. D. R. S., Lau, Y. and Kampmann, R. (2021). Deployment of Autonomous Trains in Rail Transportation: Current Trends and Existing Challenges, *IEEE Access*, 9, pp. 91427-91461. DOI: 10.1109/ACCESS.2021.3091550

Sjåstad, H. (2019) *Algoritme-aversjon* (Algorithm aversion). MAGMA, 8-2019, 63-70. ISSN 1500-0788.

Sowa, J. F. (2000) *Knowledge representation*. First edition. Pacific Grove: Brooks.

Spens, K., and Kovács, G. (2006). A Content Analysis of Research Approaches in Logistics Research, *International Journal of Physical Distribution & Logistics Management*, 36 (5), pp. 374-390. DOI: 10.1108/09600030610676259

Standard Norge (2023). *NS 3467:2023 Steg og leveranser i byggverkets livsløp*. (Stages and deliverables in the life cycle of construction works). Available at: https://www.standard.no/no/Nettbutikk/produktkatalogen/Produktpresentasjon/?ProductID=1512402 (Accessed: 15 May 2023)

Stanford University (2020) *Artificial intelligence definitions*. Available at: https://hai.stanford.edu/sites/default/files/2020-09/AI-Definitions-HAI.pdf (Accessed: 20 July 2023)

Statistisk sentralbyrå (SSB) (Statistics Norway) (2018). *Produktivitetsfall i bygg og anlegg* (Reduced productivity in construction). Available at: https://www.ssb.no/bygg-bolig-og-eiendom/artikler-og-publikasjoner/produktivitsfall-i-bygg-og-anlegg (Accessed: 15 February 2020)

Statistisk sentralbyrå (SSB) (Statistics Norway) (2019). *Avfall fra byggeaktivitet* (Waste from construction activities). Available at: https://www.ssb.no/avfbygganl (Accessed: 14 June 2019).

Statistisk sentralbyrå (SSB) (Statistics Norway) (2022). *Utslipp fra norsk økonomisk aktivitet* (Emissions from Norwegian economic activity). Available at: https://www.ssb.no/natur-og-miljo/miljoregnskap/statistikk/utslipp-fra-norsk-okonomisk-aktivitet (Accessed: 15 March 2021)

Suddaby, R. (2006). From the Editors: What grounded theory is not, *Academy of Management Journal*, 49(4), pp. 633–642. DOI: 10.5465/amj.2006.22083020

Taherdoost, H. and Brard, A. (2019). Analysing the Process of Supplier Selection Criteria and Methods. *Procedia Manufacturing*, 32, pp. 1024-1034. DOI: 10.1016/j.promfg.2019.02.317

Tam C. M., Tam V. W. Y., Chan J. K. W., and Ng W. C. Y. (2005). Prefabrication to minimise construction waste—a case study approach, *International Journal of Construction Management*, 5(1), pp. 19-101. DOI: 10.1080/15623599.2005.10773069.

Thaagard, T. (2013) *Systematikk og innlevelse. En innføring i kvalitativ metode*. (Systematics and empathy. An introduction to qualitative method). Fourth Edition. Bergen: Fagbokforlaget.

Tidemann, A. (2023). *Kunstig intelligens* (Artificial Intelligence). *Store Norske Leksikon* (SNL). Great Norwegian Encyclopaedia. Available at: https://snl.no/kunstig_intelligens (Accessed: 23 March 2023).

Tidemann, A. and Elster, A, C. (2022). *Maskinlæring* (Machine learning). *Store Norske Leksikon* (SNL) Great Norwegian Encyclopaedia. Available at: https://snl.no/maskinl%C3%A6ring (Accessed: 23 March 2023).

Tjernshaugen, A. (2022). *Bærekraft* (Sustainability). *Store Norske Leksikon* (SNL). (Great Norwegian Encyclopaedia). Available at: https://snl.no/b%C3%A6rekraft (Accessed: February 28 2020).

Tjora, A. (2017) *Kvalitative forskningsmetoder i praksis* (Qualitative research methods in practice). Third edition. Oslo: Gyldendal Akademisk.

Tranfield, D., Denyer, D., and Smart, P. (2003). Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review, *British Journal of Management*, 14(3), pp. 207-222. DOI: 10.1111/1467-8551.00375

Tørresen, J. (2013). *Hva er kunstig intelligens?* (What is Artificial Intelligence?) Oslo: Universitetsforlaget.

United Nations Department of Economic and Social Affairs. (2023). *Sustainable Development*. Available at: https://sdgs.un.org/goals (Accessed: 21 March 2023).

United Nations. (2021). *The Sustainable Development Goals Report 2021*. Available at: https://unstats.un.org/sdgs/report/2021/ (Accessed: 14 April 2023).

University of Helsinki (2018). Introduction to AI. *How should we define AI? Elements of AI*. Available at: https://www.elementsofai.com/ (Accessed: 23 March 2023).

Vickranth V., Bommareddy S. S. R., and Premalatha V. (2019). Application of lean techniques, enterprise resource planning and artificial intelligence in construction project management, *International Journal of Recent Technology and Engineering*, 7(6C2), pp. 147-153.

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S. D., Tegmark, M. and Nerini F. F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals, *Nature Communications*, 11(1). DOI: 10.1038/s41467-019-14108-y

Wang, M., Wang, C. C., Sepasgozar, S. and Zlatanova, S. (2020) A Systematic Review of Digital Technology Adoption in Off-Site Construction: Current Status and Future Direction towards Industry 4.0, *Buildings*, 10(11), 2014. DOI: 10.3390/buildings10110204

Wang, Y., Yu, C. and Chan, H. (2012) Predicting construction cost and schedule success using artificial neural networks ensemble and support vector machines classification models, *International Journal of Project Management*, 30(4), pp. 470–478. DOI: 10.1016/j.ijproman.2011.09.002

Wernicke, B., Stehn, L., Sezer, A. A. and Thunberg, M. (2021). Introduction of a digital maturity assessment framework for construction site operations, *International Journal of Construction Management*, 23(5), pp. 898-908. DOI: 10.1080/15623599.2021.1943629

Whyte, J., Stasis, A. & Lindkvist, C. (2016). Managing change in the delivery of complex projects: Configuration management, asset information and 'big data', *International Journal of Project Management*, 34, pp. 339-351. DOI: 10.1016/j.ijproman.2015.02.006

Winston, P. H. (1992) *Artificial intelligence*. Third edition. Addison-Wesley publishing company.

Wohlin, C. (2014) Guidelines for Snowballing in Systematic Literature Studies and a Replication in Software Engineering. *Proceedings of the 18th International Conference on Evaluation and Assessment in Software Engineering*. London, United Kingdom, 13. - 14. May 2014. New York: Association for Computing Machinery, pp. 1-10. DOI: 10.1145/2601248.2601268

Womack, J. P., Jones, D. T. and Roos, D. (1991) *The Machine That Changed the World: The Story of Lean Production*. New York: MacMillan Publishing.

Wooldridge, M. and Jennings, N. R. (1995). Intelligent agents: theory and practice, *The Knowledge Engineering Review*, 10(2), pp. 115-152. DOI: 10.1017/S0269888900008122

Xiahou, X., Wu, Y., Duan, T., Lin, P., Li, F., Qu, X., Liu, L., Li, Q. and Liu, J. (2022). Analyzing Critical Factors for the Smart Construction Site Development: A DEMATEL-ISM Based Approach, *Buildings 2022*, 12, 116. DOI: 10.3390/buildings12020116

Xiao, C., Liu, Y., and Akhnoukh, A. K. (2018). Bibliometric Review of Artificial Intelligence (AI) in Construction Engineering and Management, *International Conference on Construction and Real Estate Management 2018*. Charleston, South Carolina, 9.-10. August 2018. Reston, Virginia: American Society of Civil Engineers, pp. 32-41. DOI: 10.1061/9780784481721.004

Xing, Y., Song, Z., and Deng, X. (2016). Optimizing the schedule of dispatching construction machines through artificial intelligence, *Chemical Engineering Transactions*, 51, pp. 493-498. DOI: 10.3303/CET1651083

Xu, H., Chang, R., Pan, M. and Li, H. (2022). Application of Artificial Neural Networks in Construction Management: A Scientometric Review, *Buildings*, 12(7). DOI: 10.3390/buildings12070952

Xu, J., Zheng, J., Zhao, B., and Gong, D. (2020). Application of remote electron microscope technology in construction management of building engineering. Acta Microscopica, 29(1), pp. 328-337

Yaqoob, I., Hashem, I. A. T., Gani, A., Mokhtar, S., Ahmed, E., Anuar, N. B. and Vasilakos, A. V. (2016). Big data: From beginning to future, *International Journal of Information Management,* 36(6B), pp. 1231-1247. DOI: 10.1016/j.ijinfomgt.2016.07.009

Yaqubi, M. K. and Salhotra S. (2019) The automated cost estimation in construction, *International Journal of Innovative Technology and Exploring Engineering*, 8(7), pp. 845-849.

Yin, R. K. (2009) *Case Study Research: Design and Methods*. Fourth edition. Applied social research methods series. Sage: Thousand Oaks, California, United States of America.

Zero Waste Scotland (2016) *Designing out Construction Waste*. European Regional Development Fund. Available at: https://www.zerowastescotland.org.uk/sites/default/files/Designing%20Out%20Construction%20Waste%20Guide_0.pdf (Accessed: 22 February 2022).

Zhang, K. and Aslan, A. B. (2021). AI technologies for education: Recent research & future directions, *Computers and Education: Artificial Intelligence*, 2. DOI: 10.1016/j.caeai.2021.100025

Zhang, N., Ye, J., Zhong, Y., and Chen, Z. (2023). Digital Transformation in the Chinese Construction Industry: Status, Barriers, and Impact, *Buildings 2023*, 13, 1092. DOI: 10.3390/buildings13041092

Zou, Y., Kiviniemi, A., and Jones, S. (2017). Retrieving similar cases for construction project risk management using Natural Language Processing techniques, *Automation in Construction*, 80, pp. 66-76. DOI: 10.1016/j.autcon.2017.04.003

Zuhang, Y., Cai, M., Li, X., Luo, X., Yang, Q. and Wu, F. (2020). The Next Breakthroughs of Artificial Intelligence: The Interdisciplinary Nature of AI, *Engineering*, 6(3), pp. 245-247. DOI: 10.1016/j.eng.2020.01.009

Çınar, Z. M., Abdussalam Nuhu, A., Zeeshan, Q., Korhan, O., Asmael, M. and Safaei, B. (2020). Machine Learning in Predictive Maintenance towards Sustainable Smart Manufacturing in Industry 4.0. *Sustainability*, 12. DOI: 10.3390/su12198211

APPENDIX

Appendix I

Paper I

«Artificial Intelligence in Construction Projects: A Systematic Scoping Review»

Published in: Journal of Engineering, Project, and Production Management
ISSN: 2223-8379

Journal of Engineering, Project, and Production Management
2022, 12(3), 224-238

Artificial Intelligence in Construction Projects: A Systematic Scoping Review

Sofie Bang[1] and Nils Olsson[2]

[1]Ph.D. Candidate, Department of Mechanical and Industrial Engineering, Norwegian University of Science and Technology, Richard Birkelands vei 2B, 7034 Trondheim, Norway, E-mail: sofie.bang@ntnu.no (corresponding author).
[2]Professor, Department of Mechanical and Industrial Engineering, Norwegian University of Science and Technology, Richard Birkelands vei 2B, 7034 Trondheim, Norway, E-mail: nils.olsson@ntnu.no

Project Management
Received December 7, 2021; revised March 31, 2022; April 19, 2022; accepted May 14, 2022
Available online June 13, 2022

Abstract: The use of artificial intelligence (AI) in construction projects has surged in recent years and is believed to represent a significant potential for increasing productivity and efficiency in the industry. The purpose of this paper is to present a state-of-the-art view of the field by conducting a review of publications concerning the topic of AI in construction and comparing the findings to previously conducted reviews. This paper provides an overview of the recent and current uses of AI in construction projects, through a descriptive analysis of the characteristics and contents of 86 peer-reviewed articles from 2015 to 2020. Although the application of AI in the industry is not entirely new, construction appears to currently be behind other industries in terms of adopting and adapting to AI. The results show that a wide range of research is conducted on AI in construction projects. A limited number of publication channels and authors stand behind a significant part of the reviewed publications. Most studies are conceptual or use a mixed-methods research design. The research addresses several areas of application, but there is a predominance of quantitatively based subfields of construction, such as estimation and cost control, logistics, planning, and scheduling. Future research should focus on developing holistic and process-oriented frameworks for projects to move from ambition to practice. Findings can inform the future development and implementation of AI in the construction industry context. For researchers, this study identifies areas in need of further attention and examines possibilities for future exploration of multidisciplinary approaches that combine construction engineering, project management, AI, and social science. For practitioners, the study highlights current trends and work within the field, providing an overview of the potential for pilot studies, tests, and innovations.

Keywords: artificial intelligence, construction projects, literature review, scoping review.

DOI 10.32738/JEPPM-2022-0021

1. Introduction

The construction industry is complex; conflicting objectives contribute to this complexity, as demands for productivity, resource efficiency, sustainability, and advances in technology continue to develop rapidly (Wood and Gidado, 2008; Luo et al., 2017). In the past, the construction industry has been considered rather traditional and, although it is currently experiencing a digital shift, it remains behind the curve compared to other sectors in implementing AI-based solutions (McKinsey Global Institute, 2015). Thus, the practical implementation of artificial intelligence (AI) in construction is still considered a rather unexplored topic.

The concept of AI is broad, but it can be defined as a system or a structure that has 'the ability to perform tasks in complex environments without constant guidance by a user' (University of Helsinki, 2018). AI is believed to enable an increase in productivity throughout the entire construction project lifecycle chain, ultimately improving the sustainability of environmental, economic, and social factors (Blanco et al., 2018; Oprach et al., 2019). Benefits are expected at the project level, the organisational level, and for the industry as a whole. The construction industry remains a significant contributor to the gross domestic product of many countries. However, it also heavily contributes to resource usage, energy consumption, and waste production, and the sector suffers several occupational fatalities every year (Barker et al., 2007; Becqué et al., 2016; Dong et al., 2019). AI is believed to impact how the industry approaches sustainability, policies on health and safety, risk assessment, planning and scheduling, strategy, project performance, cost control, and calculations for operations and lifecycles (Hossain and Nadeem, 2019).

AI is a highly interdisciplinary field, comprising elements from computer science, logic, mathematics, psychology, and neuroscience (Tidemann, 2020; Tørresen, 2013). In the construction context, AI systems can be grouped into four categories: machine learning techniques, knowledge-based techniques, evolutionary algorithms, and hybrid systems (Akinade, 2017). Machine learning algorithms have the ability to learn from data (Tidemann, 2019); in the construction industry, neural networks, support vector machines, and fuzzy logic seem to be the most widely used machine learning techniques (Akinade, 2017). Knowledge-based systems mimic the problem-solving expertise of humans to identify solutions for complex problems (Sowa, 2000). Frequently utilised knowledge-based approaches include expert systems, rule-based systems, case-based reasoning, and semantic networks (Akinade, 2017). Evolutionary algorithms are based on biological evolution (Russel and Norvig, 2010); evolutionary AI techniques optimise factors and possible scenarios to find the most suitable outcome (Dasgupta and Michalewicz, 1997) – such algorithms can cover broad territory, from genetic algorithms to ant colony optimisation, particle swarm optimisation, and artificial bee colonies (Akinade, 2017). Hybrid systems combine two or more AI approaches to maximise the strengths and overcome the weaknesses of individual approaches (Russel and Norvig, 2010).

This study investigates the current and potential use of AI in construction projects, through a scoping review of 86 articles from peer-reviewed journals. Providing an overview of the available research will indicate which knowledge exists in the field, and where further research is required. Specifically, the study addresses the following research questions (RQs):

- RQ1: What research has been carried out on AI in construction projects?
- RQ2: What research approaches have been used in studies on AI in construction projects?
- RQ3: What gaps exist in the research?

The first research question will be answered through a descriptive analysis of the selected publications. For this purpose, the following data will be collected: title; author(s); year of publication; study location; and keywords. The second research question will be answered through a more extensive analysis of the research design of each study, assessing and classifying the chosen methodology as conceptual, qualitative, quantitative, or mixed. Last, the third research question will be answered by assessing the overall purpose of each study, its focus of attention, significant results, and conclusions; this stage also includes assessing the answers to the two previous research questions.

Several literature reviews on the topic of AI in construction projects have previously been conducted. For example, Ilter and Dikbas (2009) reviewed AI applications in construction dispute resolution; Martínez and Fernández-Rodríguez (2015) reviewed AI as a tool for estimating project success and identifying critical success factors; Juszczyk (2017) reviewed the use of AI for cost estimation in construction projects; Basaif and Alashwal (2018) reviewed AI applications for risk analysis in construction projects; Xiao et al. (2018) conducted a bibliometric review of AI in construction engineering and management, providing an overview of the most influential studies of AI in construction between 2007 and 2017; and Darko et al. (2020) conducted a scientometric analysis of research activities related to the use of AI in the architecture, engineering, and construction (AEC) industry.

This review examines a range of relevant articles published between 2015 and 2020 to provide a state-of-the-art perspective of the available technology and its current areas of application in construction projects. Reviews conducted by Ilter and Dikbas (2009), Martínez and Fernández-Rodríguez (2015), Juszczyk (2017), and Basaif and Alashwal (2018) considered AI applications in specific areas. Xiao et al. (2018) conducted a bibliometric review on publications up to 2017. Darko et al. (2020) mapped research interests and themes in the AEC industry, identifying topics such as optimisation, simulation, and decision-making. This study will contribute to the research field by examining and assessing the body of literature dating from 2015 to 2020, focusing on the variety of practical applications of AI in construction projects. The study targets use cases and applications as well as the research activity itself. Ultimately, this study provides a state-of-the-art overview for reference to future research endeavours, highlighting relevant resources, potential collaborators, and areas in need of more work. For practitioners who wish to implement AI-powered tools in their projects, it provides a sense of direction for AI-powered innovation, a resource for identifying potential AI solutions for their problems, and an opportunity to benchmark their work against previous undertakings in the field.

The remainder of the study is organised as follows: the next section explains the methodology of the review process; the Results section presents and discusses the main findings of the review; the Conclusion section answers the research questions as defined and summarises the qualitative characteristics of the body of publications, the research approaches used, and the gaps identified within the field. The last section reflects upon the possibilities this study provides for future research, as well as the limitations of the conducted review.

2. Method

2.1. Unstructured Literature Search

The perceived feasibility of the study was measured against the comprehensiveness of the scoping process, following the recommendations by Levac et al. (2010). This provided the main motivation for an initial, unstructured literature search. Conducting this initial search in an explorative manner provided a broad knowledge of the field, and ultimately created a foundation for the literature review. The purpose of the preliminary search was to produce a literary warrant, thereby establishing a suitable foundation for further definition and indexing of terms and classes during the review. The search provided an overview of the topic and contributed to an initial understanding of the development of the field and related key concepts.

2.2. Systematic Scoping Review

To answer the research questions, a scoping review was conducted according to the preferred reporting items for systematic reviews and meta-analyses (PRISMA) framework (Moher et al., 2009) and the scoping methodology framework presented by Arksey and O'Malley (2005). Reviews within the field of management are often considered to be comprised of a process of exploration, discovery, and development (Tranfield et al., 2003); therefore, it is desirable to choose a flexible approach that can be modified throughout the study. The scoping review enables such a flexible but systematic approach and comprises five steps:

1. Identifying research questions
2. Identifying relevant studies
3. Selection of relevant studies by formulated criteria
4. Charting the data
5. Collating, summarising, and reporting results

To clarify and further evolve the framework, Levac et al. (2010) present some specific recommendations for each step. For the methodological approach of this review, the recommendations employed included linking the purpose of the study to the research questions early in the process, in order to facilitate decision-making regarding the inclusion and exclusion of relevant publications as the scoping review proceeds. The nature of the scoping review provides for an emergent and iterative process, meaning that such criteria might not become fully clear until the later stages of the review (Gough, 2007a). In this review, the inclusion and exclusion criteria as presented produced the final selection of publications. The criteria were updated throughout the process to sustain the systematic manner of the review; a more systematic approach helps to provide trustworthiness and accountability for the literature review (Gough, 2007b).

The next step was to initiate a manual search of selected databases. The databases were chosen as they were known to include significant topics and authors, as identified through the preliminary search. Additionally, the selected databases were deemed especially suitable due to their interdisciplinary nature, and their position as well-recognised databases for academic articles and publications. The selected databases were Scopus, ScienceDirect, and Web of Science, each of which provides an advanced search function that allows the user to customise their search preferences. Identification and selection of relevant studies – steps two and three of the scoping review framework – were structured according to the PRISMA framework (Moher et al., 2009), as illustrated in Fig. 1.

Tranfield et al. (2003) emphasise the importance of a well-defined search string in order to create a replicable and transparent search strategy. During the first, unstructured search, several search strings were explored. For example, TITLE-ABS-KEY (construction and artificial intelligence). This search resulted in 60,398 hits across the three databases. Even after further restrictions, such as year, language, and document types, this search string yielded an unmanageable number of publications. Moreover, the initial search proved that several terms, including expert systems, knowledge engineering, and even artificial intelligence, seem to lack a single definition within the field. Therefore, the final search string needed to be open enough to include possible variations of such words but narrow enough to exclude the most peripheral subjects. For the scoping search, the string was modified to TITLE-ABS-KEY ('construction project*' AND 'artificial intelligence*'), which resulted in a far more relevant selection of publications and 1,608 hits. An additional 21 publications were reviewed upon request from scholars involved in the study.

A set of inclusion and exclusion criteria were defined for filtering, to help ensure the relevance and credibility of the sources for the review. Decisions regarding inclusion and exclusion criteria remain relatively subjective (Tranfield et al., 2003); this strengthens the need for a transparent and verifiable process of inclusion and exclusion. Thus, one criterion used was that the inspected studies must deal with technology that could be considered AI. For example, studies were excluded that simply discussed challenges of construction projects, or the construction industry, without any explicit mention of specific solutions. The field and definitions of AI are rapidly changing; the availability and accessibility of data and technology are rapidly increasing, while the cost of data processing tools is rapidly decreasing. This enables applications that were not possible just a few years ago. Therefore, in order to ensure and capture a state-of-the-art view of the topic, this review only included literature from 2015 to 2020. Furthermore, the document type was limited to include only peer-reviewed articles. As the scoping methodology itself does not include a formal application of quality assessment criteria, strictly including publications from peer-reviewed sources contributes to an implicit quality in the chosen body of publications.

The main targets of this analysis were studies of conceptual or practical cases of AI in construction projects; however, studies discussing AI in the construction industry in a more general fashion were also included, as long as the technology was not explicitly targeted toward infrastructure or industrial construction – such articles were excluded. Studies without mention of any specific technologies or techniques were also excluded. If a publication discussed a specific technology with an explicit functionality but did not name the technology, it was included. Finally, the search was limited to only include publications written in English; any duplicates were also removed during this process. Following this, manual screening of titles, abstracts, and keywords was conducted to assess the relevance of the remaining publications in the selection; 481 records were screened, and 374 were excluded. A full-text assessment of the remaining 107 records was then conducted, to ensure their eligibility and to evaluate the contribution of each study beyond its title, abstract, and keywords. Twenty-one articles were found to be out of scope, and seven lacked sufficient detail to provide an accurate assessment. Eighty-six articles remained to be included in the review.

2.3. Classification Framework

To answer the research questions, several dimensions were defined along which the selected articles were analysed; together these constituted the assessment framework and provided a foundation for the fourth and fifth steps of the scoping review framework. The classification framework was structured to enable a holistic and comprehensive analysis of the field of AI in the context of construction projects and provide a descriptive presentation of the body of publications, according to the recommendations by Arksey and O'Malley (2005). The descriptive features of each publication were collected directly from each database and included the year of publication, source journal, author(s), location, and keywords. Table 1 describes the classification framework.

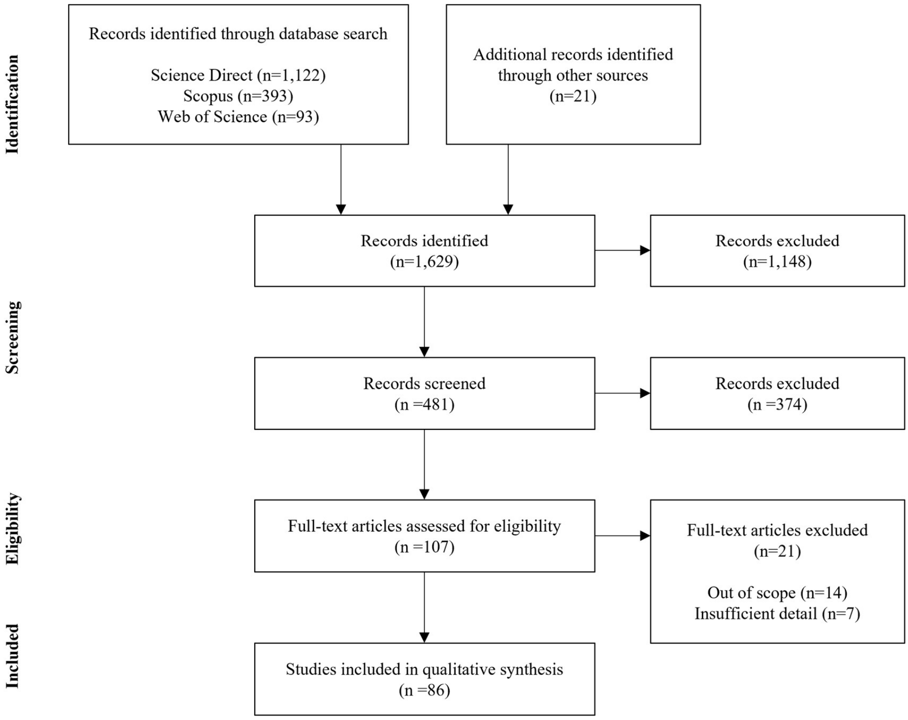


Fig 1. PRISMA flow diagram describing the review process

The publication methodology was classified as either conceptual, qualitative, quantitative, or mixed-method. Some publications did not offer a definitive description of their research methodology; in these cases, the chosen methodological approach needed to be interpreted from any direct or indirect descriptions provided by the author(s) themselves. Where the approach of the publication was strictly developmental in terms of, for example, a specific terminology, system, or framework, the methodology was considered to be conceptual. A publication was considered to be qualitative if it addressed the subject in a qualitative manner, such as by discussing certain soft factors regarding the implementation of AI, its potential or non-quantifiable implications, or the effects of its implementation. Meanwhile, publications considered quantitative addressed the more quantifiable effects of implementation, or the applications of the tools themselves; use of specific algorithms, for example. Publications were assessed to be using mixed methods when the research design appeared to use two of the three aforementioned methodologies equally.

The categorisation of areas of applications comprised four steps:

1. Identifying common applications
2. Clustering similar applications
3. Filtering out rarely mentioned applications
4. Sorting applications by categories

This procedure resulted in nine categories that summarised the grouped findings of the literature search: logistics and scheduling, estimation and cost control, health and safety; project performance and success estimation, strategic design, risk management, material properties, reviews, and implementation, and sustainability. The contents of the publications in each of these categories are further addressed in Section 3.3.

The initial search uncovered countless definitions and descriptions of AI-powered technologies and techniques. Thus, the framework defined by Akinade (2017), as described in the introduction, was used for classification and categorisation: machine learning, knowledge-based systems, evolutionary algorithms, or hybrid systems. The classification presented in Section 3 was based upon the description of the techniques provided by the authors themselves and how these compared to the categories in the chosen framework. Where the authors did not provide a sufficient description of the technique being used or discussed, the technology was labelled N/A.

3. Results

3.1. Descriptive Analysis

Fig. 2 shows the number of publications in each year for the review selection. Although the sample is small, the trend line indicates a steady increase in publications from 2015 to 2020; Xiao et al. (2018) noted a gradual increase in publications on AI in construction up to 2017, and the increase seems to hold for later years. The years 2016 and 2017 appear to show dips in development; during the review, it was noted that many of the publications from 2016 and 2017 were related to infrastructure, roads, and tunnels. The differences in this sample of publications and the full body of publications from the same years could be due to several reasons. One explanation is that the focus could have shifted over the years; whereas a certain area of the industry was more concerned with the use of AI in earlier years, other areas seem to have experienced an increased interest in AI as time progressed. Another possible explanation lies in the selection of studies provided by the chosen databases – using other databases could potentially have yielded additional or different results.

The most frequent publication channels are charted in Fig. 3. A significant portion (15%) of the publications were published in the Automation in Construction, followed by procedia engineering (8%) and the Journal of Building Engineering (6%). The findings of Xiao et al. (2018) and Darko et al. (2020) confirm that the Automation in Construction has been the leading publisher in construction-related research in AI for a significant period. This observation is of interest to anyone involved in the field, as it provides a suggestion of both where to read and where to submit research. There is a clear tendency for the conceptual and technically focused studies to be published in journals such as the Automation in Construction and the Journal of Computing in Civil Engineering, whereas qualitative studies, assessing the potential, barriers, and effects of the implementation of AI are more common in such journals as the Journal of Civil Engineering and Management and the Journal of Construction Engineering and Management. Certain journals, such as Safety Science and Energy and Buildings, are more targeted toward specific areas of AI application.

Table 1. Literature classification framework

Grouping	Collected data	Purpose
Descriptive features	1.1 Year of publication 1.2 Source 1.3 Author(s) 1.4 Location 1.5 Keywords	Describe the characteristics of the selected articles.
Method	2.1 Conceptual 2.2 Qualitative 2.3 Quantitative 2.4 Mixed methods	Classify the chosen methodology in the field of study.
Area of application	3.1 Estimation and cost control 3.2 Health and safety 3.3 Logistics and scheduling 3.4 Material properties 3.5 Project performance and success estimation 3.6 Reviews and implementation 3.7 Risk management 3.8 Strategic design 3.9 Sustainability	Explore the area of application and utilisation of the technology or technique at issue.
Technology	4.1 Machine learning 4.2 Knowledge-based systems 4.3 Evolutionary algorithms 4.4 Hybrid systems 4.5 N/A	Explore which specific technology or technique is being utilised or discussed. Based on the framework presented by Akinade (2017).

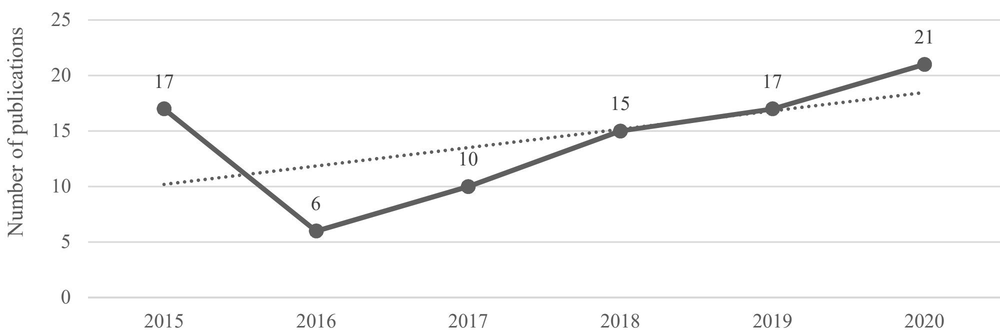


Fig. 2. The number of publications per year

Fig. 4 shows the most prolific researchers within the field. It appears that a limited number of researchers and authors are involved in a significant amount of the research conducted.

As Fig. 5 shows, the main contribution to the body of publications comes from the United Kingdom, followed by China, Taiwan, the United States, and Australia. This could be explained by a higher concentration of researchers within the field in these countries, but it seems reasonable to assume that this could also be due to the fact that this review only included publications written in English. Other countries could be publishing research within the field but in their languages. In total, 21 countries were represented. A low representation of countries can imply that the field is somewhat immature. However, the field appears to be evolving, as additional scientific environments seem to be emerging.

All keywords, meaning not only author keywords, were assessed, as author keywords are largely reliant on authors' experience, interests, and knowledge. In total, 441 keywords were defined, out of which 354 were distinct. However, certain keywords were found to be used more frequently (Fig. 6). To provide a better understanding of keyword frequency, interchangeable keywords were grouped. For instance, 'artificial intelligence' and 'AI' were simply grouped into 'artificial intelligence', as were 'construction project' and 'construction projects', and 'building information model' and 'building information modelling'. 'Artificial intelligence' appearing as the most frequent keyword seems reasonable, as does 'construction project(s)' as the second most frequent keyword. 'Construction management' and 'decision support systems' as the third and fourth most often used reflect, to some extent, the focus of the current research. The high frequency of 'machine learning' and 'neural networks' reflects what appears to be the rather predominant position of these techniques.

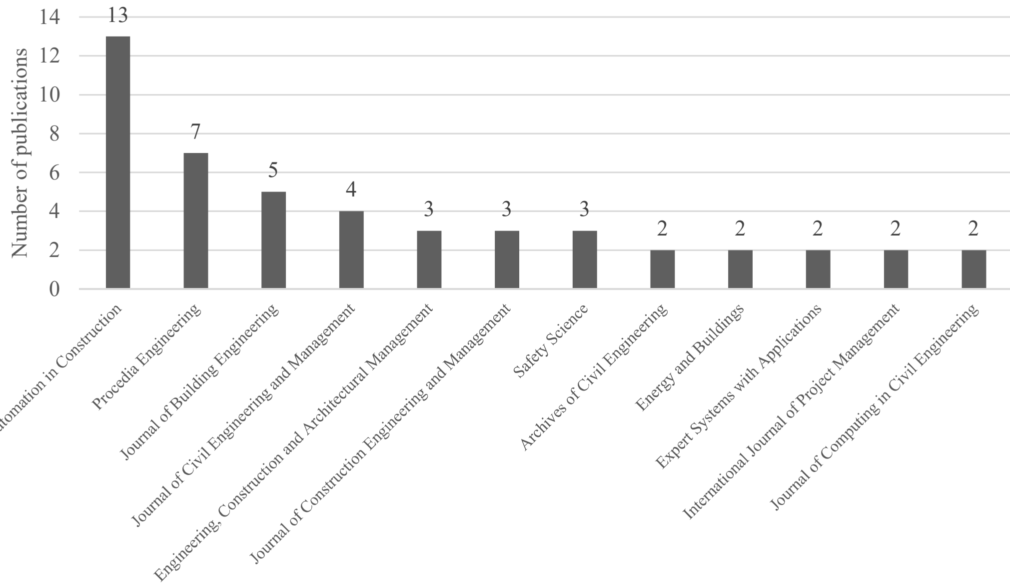


Fig. 3. Most frequent publication channels

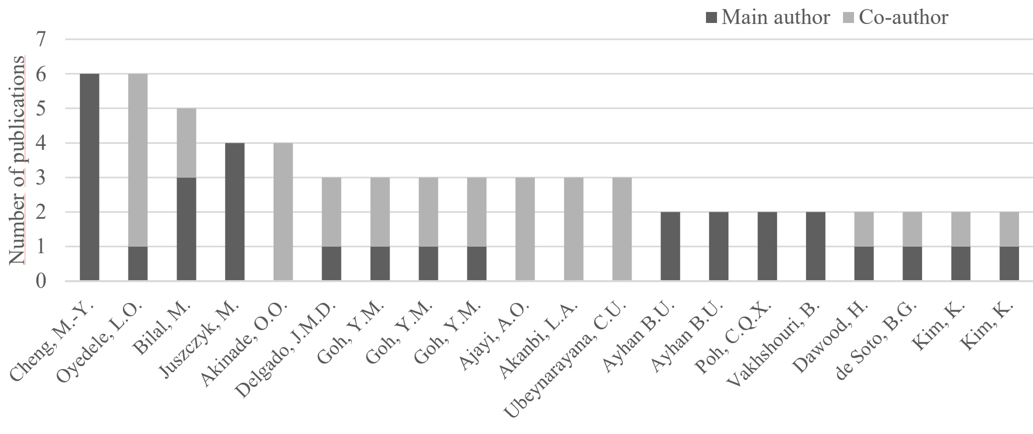


Fig. 4. Most frequent authors with two or more publications

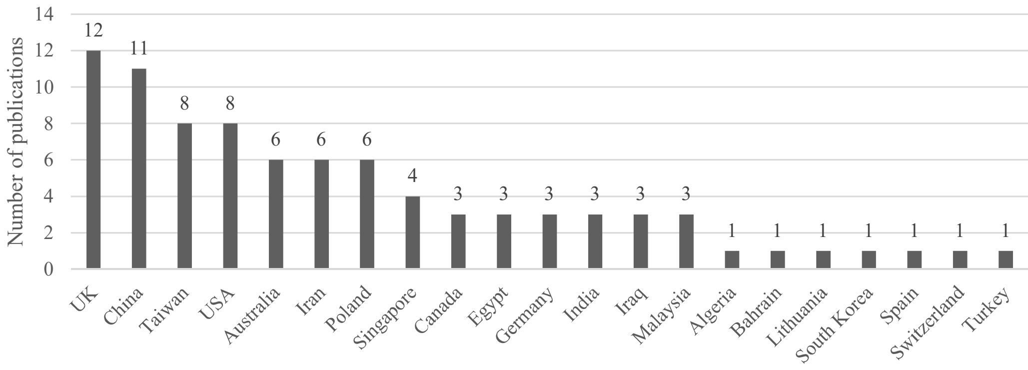


Fig. 5. Most frequent countries of main authors

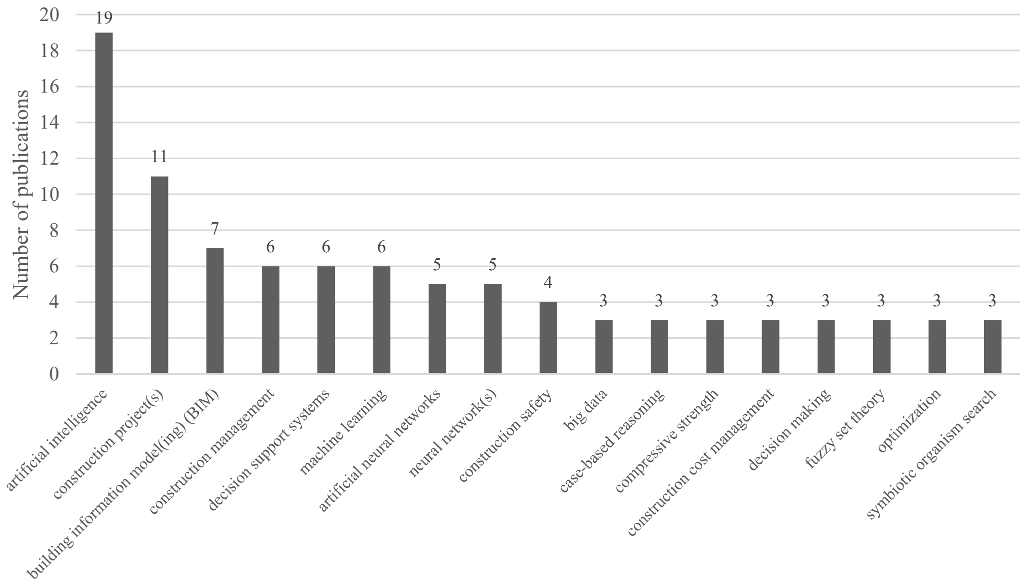


Fig. 6. Most frequent keywords

3.2. Methods

Since not all the studies explicitly described their chosen methodology, it is possible that this data may contain errors. To elaborate, certain publications do not label their own methods within the framework defined for this study. Here, the descriptions of the method provided by the authors of the individual studies are used as the reference when categorising each study. There seems to be a slight tendency towards a conceptual methodology (40%), as Fig. 7 illustrates, which can also be seen in previous literature reviews (Juszczyk, 2017). Most of the studies based on a conceptual methodology are concerned with developing specific AI-powered tools and techniques. More than half of the conceptual studies include some quantitative testing and validation in the development of the technique; this is still to be considered part of the development process itself and thus accounted for as conceptual. Several of the conceptual studies provide specific solutions or algorithms tailored toward certain areas of application. Most were tested on a proof-of-concept scale, and the research does not explicitly state whether or not it was developed further or implemented on a bigger scale.

The mixed method is the second most frequently used methodology (28%). Most of the studies classified as mixed methods are rooted in a conceptual base, but in combination with traditionally qualitative or quantitative methods, for example, the observation of specific case projects or the use of questionnaires. Purely qualitative studies account for a slightly smaller proportion (21%) of the body of publications. These studies are mainly concerned with the prospects surrounding the technology, which include potential future areas of application, possibilities, and barriers to the technology itself, related to soft factors, people, and processes. Very few discuss the use of AI in the context of people and processes, focusing on technology awareness and digital maturity with an emphasis on AI. However, this discussion seems to be lacking in the studies that discuss more specific solutions and tools. This synthesis is supported by previous reviews, such as the one undertaken by Basaif and Alashwal (2018), which suggests that a gap exists between the potential that the technology constitutes and the evidence of how it is utilised both in practical and academic contexts. Other studies compare different techniques and tools in a qualitative frame of reference. Purely quantitative studies account for only 12% of the body of publications. These studies involve the testing of previously developed techniques and algorithms and are usually applied to rather limited datasets. This could suggest a relatively low degree of research-based AI implementation, constituting a great potential for future implementation and pilots.

Another observation is that to some extent, the number of studies conducted within each methodological approach can be observed to change over the years; this suggests a shift not only in the focal area, as already mentioned, but possibly also in the methodological stance. Earlier publications show a tendency towards mixed or purely quantitative or qualitative studies, whereas later publications are more often purely conceptual. This could further suggest a field undergoing change. An increasing interest in AI within the construction industry becomes apparent; this is confirmed both by the body of publications as a whole and individual studies. However, the high concentration of conceptual studies could suggest a gap between theory and practice.

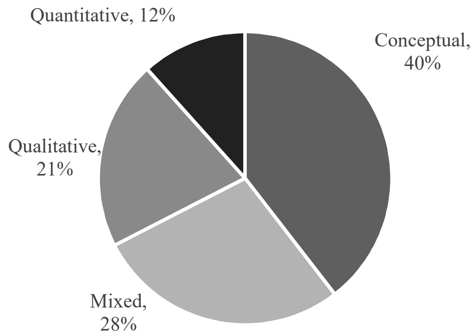


Fig. 7. Distribution of chosen methodology

Many studies appear to remain in a development phase while very few address the practical adoption of AI-based technology in the industry and among practitioners at a larger scale. To elaborate, most studies illustrate how certain technology can be utilised in different parts of construction projects, for example exploring site layout design (Amiri et al., 2017), or predicting project performance (Mirahadi and Zayed, 2016). However, the majority of studies lack a larger context for the technology – a framework for the technology to operate within. The studies do not discuss organisational or process-oriented considerations in the adaption and adoption of AI in projects. This could, naturally, have many explanations. For example, a few studies discuss the lack of access to sufficient amounts of quality data. Another possible explanation could lie in the lack of transferability in the developed models and frameworks, meaning that new studies are not necessarily able to build on previous research. This could suggest a need for a more standardised framework of technologies and terminology for researchers to operate within when exploring the topic of AI in construction. Challenges concerning transferability could ultimately prevent a model built in one environment from being useful in another environment, due to differences in requirements and prerequisites; it could also prevent one researcher from effectively building upon the work of another. There is no simple solution to such a complex problem, but it seems reasonable to assume that an increased degree of transparency and communication, both in the research field as a whole and in individual studies, would be beneficial.

3.3. Areas of Application

In terms of areas of application, the research seems to be relatively evenly distributed, as Fig. 8 shows. There appears to be a predominance of estimation and cost control (22%) and logistics, planning, and scheduling (19%); the two together account for almost half of the body of publications. As mentioned, the availability of a sufficient quantity and quality of data is a challenge in the construction industry. The two predominant areas both lean towards the quantitative and more easily measurable area of the industry; time and money are easily quantifiable.

- A third of the studies categorised under *estimation and cost control* examine the application of AI to cost prediction and estimation (Shin, 2015; Juszczyk, 2017; Elmousalami, 2019; Yaqubi and Salhotra, 2019; Juszczyk et al., 2019; Juszczyk, 2020). Other applications in the category include tender price evaluations (Zhang et al., 2015; Bilal and Oyedele, 2020a; Mehrabani et al., 2020), cash flow prediction and mapping (Cheng et al., 2015; Cheng et al., 2020a), and cost-effectiveness analysis (Wang et al., 2019). Furthermore, publications categorised as estimation and cost control include assessment of profitability (Oyedele et al., 2019), profit margin estimation (Bilal and Oyedele, 2020b), and prediction of project award price (Chou et al., 2015). Similarly, studies explore the selection of optimal construction bid price (Aboelmagd, 2018), the setting of baseline rates (Shahtaheri et al., 2015), and the calculation of the construction site cost index (Juszczyk and Leśniak, 2019).

- The category of *logistics, planning, and scheduling* includes publications discussing applications of AI to improve construction project schedules (de Soto et al., 2017), estimation of construction project schedules (Cheng and Hoang, 2018; Cheng et al., 2020b) progress monitoring (Golparvar-Fard et al., 2015), and prediction of risk delay (Yaseen et al., 2020). Other studies discuss the topic of clash relevance prediction (Hu and Castro-Lacouture, 2019), resolving design clashes (Hsu et al., 2020), and validation of change requests (Dawood et al., 2019). Publications focused on logistics include the utilisation of AI in resource management (Xing et al., 2016; Podolski, 2016; Camacho et al., 2018), resource-constrained scheduling (Li and Womer, 2015; Zheng and Wang, 2015), and the resource-levelling optimisation (Iyer et al., 2015). For the physical construction site, material layout planning (Cheng and Chang, 2019), and site layout design (Amiri et al., 2017) are explored.

- In the category of *strategy* strategic matters such as project selection (Mousavi et al., 2015; Fallahpour et al., 2020), contractor pre-qualification (Kog and Yaman, 2016), and strategic supply chain management & supplier selection (Taherdoost and Brard, 2019) are examined. More specific endeavours are also found, in publications studying the utilisation of AI in relating organisational characteristics and project delivery methods (Gazder et al., 2018) and enhancing communication between actors (Khosrowshahi, 2015). Appraisal of decision support systems for modularisation (Sharafi et al., 2018) and prefabrication (Arashpour et al., 2017; Li et al., 2018; Zhou and Ren 2020) are also seen from a strategic perspective.

- In the category of *health and safety* (10%) all studies explore AI utilisation in safety, while two focus specifically on the interaction between health and safety (Ayhan and Tokdemir, 2018; Nnaji and Karakhan, 2020). Safety applications include the identification of factors indicating and influencing safety on the construction site (Poh et al., 2018; Goh et al., 2018; Xu et al., 2020, Han et al., 2020), safety planning of temporary structures (Kim et al., 2018), planning of safe construction site layouts (Ning et al., 2018) and safety assessment (Ayhan and Tokdemir, 2019).

- Publications examining *project performance and success estimation* (10%) are generally targeted toward project management, the majority focusing on decision support for the project manager, or the discipline and process of project management itself (Hajdasz, 2015; Gudauskas et al., 2015; Hanna et al., 2018; Mahfouz et al., 2018; Vickranth et al., 2019). Other studies focus on predicting and optimizing project performance, time, and cost (Mirahadi and Zayed, 2016; Jaber et al., 2019) or project evaluation (Erzaij et al., 2020).

- Topics related to *risk management* (8%) include risk analysis (Pruvost and Scherer, 2017; Basaif et al., 2020), risk assessment (Samantra et al., 2017) and risk prediction (Zou et al., 2017). Other publications categorised as risk management include studies examining the identification of critical risks in projects (Qazi et al., 2016), forecasting of project status based on threats-opportunities and strength-weaknesses (Boughaba and Bouabaz, 2020), and construction site accident classification (Cheng et al., 2020c).

- One group of articles provides an overview of the current situation in the construction industry and maps possibilities, barriers, and implications within the field through *reviewing* the existing body of publications. Identified reviews explore the use of relevant technology in construction projects: machine learning (Hong et al. 2020), deep learning (Akinosho et al., 2020) and automation (Faghihi et al., 2015). Eber (2020) investigates the potential of AI, and Delgado et al. (2019) investigate industry-specific challenges in the implementation of AI; both in the context of the construction industry. Chen et al. (2015) investigate the use of BIM in conjunction with AI.

- Only one of the publications assessed in the category of *sustainability* (7%) is concerned with social sustainability, specifically dispute resolution (Elziny et al., 2016). The remaining studies mainly explore environmental sustainability, while a few are centred around sustainability in broader terms. These publications examine design optimization for sustainability (Liu et al., 2015; Rodriguez-Trejo et al., 2017), assessing and classifying sustainability in a project (Akbari et al., 2018), or waste reduction (Banihashemi et al., 2017; Bilal et al., 2019).

- Publications categorised in *materials properties* (5%) are related to the quantitative assessment of construction materials, predicting properties of concrete (Vakhshouri and Nejadi, 2015; Zhang et al., 2020), specific construction elements (Qi et al., 2018) and using remote electron microscope technology to monitor the composition of materials (Xu et al., 2020).

Notably, even if a lot of the studies address a certain area of application conceptually or in general terms, relatively few studies report on actual implementation and practical use beyond pilots and proofs-of-concept. Most focus on the potential use or the development of techniques for future use. No significant links were found in the body of publications between the chosen areas of application and the chosen methodologies.

An overwhelming majority of the studies examine the use of AI first and foremost as a decision support tool, implying that the human decision-maker is still seen as an essential part of the project, the project processes and activities; this could suggest a low degree of maturity in the implementation of AI in the industry.

3.4. Technology

Fig. 9 shows the distribution of technology discussed in the publications, based on the authors' own descriptions, categorised by the framework presented by Akinade (2017); the distribution shows a clear tendency. More than a third of the publications (38%) do not explicitly state the nature or class of the technology in question. Some explanations for this were identified during the search. Studies lacking a technical description seem to mainly focus on implications and effects, or potentials and barriers, rather than the development or use of specific technologies. Hybrid systems (26%) and machine learning (26%) were the main techniques studied in more than half of the publications. Knowledge-based systems constituted 6% of the reviewed studies, despite case-based reasoning, a type of knowledge-based system (Akinade, 2017) being identified as one of the most frequently used tools in dispute resolution in projects (Ilter and Dikbas, 2009). However, the limited use of case-based reasoning is also seen in previous reviews (Xiao et al., 2018). Similarly, evolutionary algorithms only constituted 2% of the studies, despite previously being identified as one of the most frequently used tools in AEC (Darko et al., 2020). However, Darko et al. (2020) suggest that genetic algorithms might be more widely utilised as a part of hybrid systems. Akinade (2017) suggests that the strength of hybrid systems lies in their capability to overcome weaknesses related to single AI techniques or algorithms, which makes them a useful option in complex and dynamic construction projects. The majority of the hybrid-classed studies describing technology and techniques also utilised machine learning, mostly supervised machine learning; a notable number were also based on evolutionary algorithms. Among the publications discussing machine learning, half specifically discussed neural networks. The frequent use of neural networks is also confirmed in previous reviews (Ilter and Dikbas, 2009; Martínez and Fernández-Rodríguez, 2015; Juszczyk, 2017; Darko et al., 2020). The remainder of the publications showed no significant trend or preferred technique within the category. There appears to be an increase in the application of hybrid models in the later years compared to the earlier years (Xiao et al., 2018). This could suggest increased use of more compound systems as technology and industry development because hybrid systems are able to solve more complex tasks than any single system (Akinade, 2017).

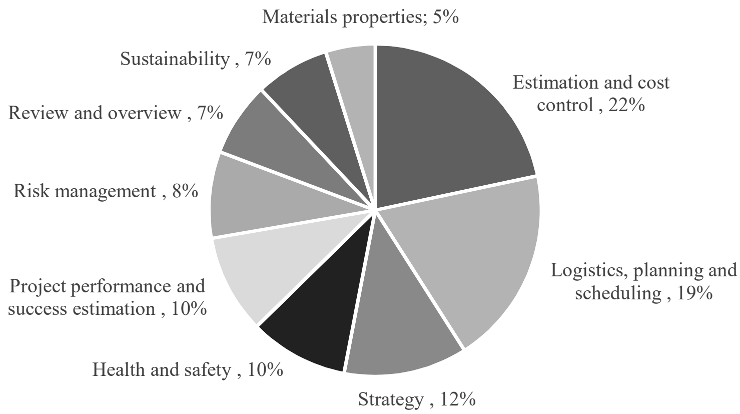


Fig. 8. Distribution of areas of application

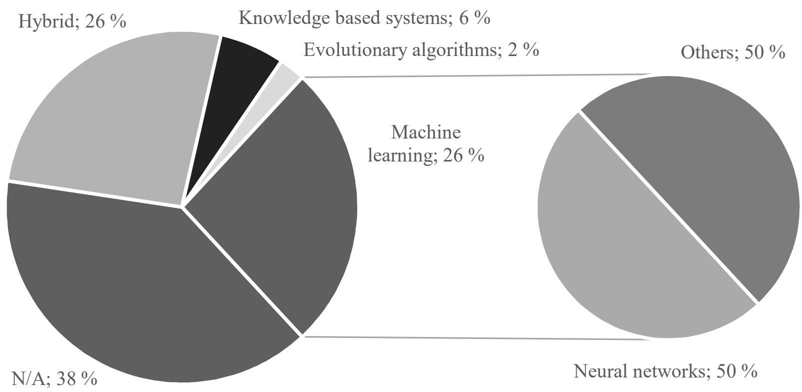


Fig. 9. Distribution of discussed technology

As part of the screening process, studies using the term AI without addressing specific techniques or technology were discarded. This was warranted for a significant number of studies, which implies that many authors use 'AI' somewhat loosely; the same can be said for machine learning. One explanation could be a lack of unambiguously defined terminology and vocabulary in the academic field, especially in the context of the construction industry. Another explanation could lie in the fact that these are 'buzz words', popularised by the media; this can contribute to the confusion of definitions. This observation is to some extent validated by the high number of exclusions required during the screening process (Fig. 1); a majority of the exclusions were caused by the high number of papers discussing technology not explicitly defined as AI.4. conclusion

This paper contributes to the current state of research on AI in construction projects by presenting a state-of-the-art view of the field of AI in construction. For researchers, it provides an overview of the most influential publication channels, authors, methodologies used, and areas of application, ultimately providing a direction for future research. For practitioners, it illustrates possible areas of innovation and application of AI-powered techniques and serves as a tool for benchmarking.

The findings of this study indicate a versatile body of literature, with a few characteristics that stand out. There seems to be a steady increase in the number of publications from the years 2015 to 2020. Three journals, Automation in Construction, Procedia Engineering, and the Journal of Building Engineering amount account for a quarter of the publications, with the rest of the articles being distributed evenly among the remaining 48 publication channels. A limited number of authors produced the majority of the publications; correspondingly, a limited number of countries are also far more prominent than others.

The preferred approaches in the field have changed during the last few years, indicating a rapidly developing field. Studies are often descriptive in nature, due to the lack of empirical evidence. Purely conceptual studies constitute almost half of the reviewed publications, suggesting a theoretical foundation, but a lack of practical implementation beyond small-scale testing and proofs-of-concept. This can be taken as a sign that the field itself remains at an emergent stage, but at the same time, this provides an understanding of the great potential the field demonstrates. Existing case-based research can and should be used as a foundation for larger-scale studies.

The field is rapidly evolving, together with new technologies, techniques, and tools being developed both in and out of the construction context. A visible change in preferred methods, as well as a change in keywords over time, implies that the field is indeed developing. The conceptual methodology seems to be the preferred approach in the field of study. The extensive use of conceptual methodology suggests that this method works in a research context but could at the same time suggest a need for other, more practically focused methods to further develop the field. The wide thematic range of previous studies has provided a valuable foundation for future research, but the field is assumed to benefit from a shift toward more interdisciplinary based studies. Among the barriers to practical implementation is the lack of sufficient quantity and quality of data, as well as transferability among developed models and frameworks. This could be due to the immaturity of certain technologies within the industry context, posing problems in practical implementation, testing and surveying. This is supported by the findings, specifically the limited extent of big-scale experimental and practical implementations. It has been shown that AI has been applied to several areas, and the body of evidence is relatively evenly distributed thematically, with a slight predominance of more quantitatively focused areas of application. This highlights the need for a degree of standardisation and structure in the field, allowing researchers to assess and compute both the qualitative and quantitative areas of the industry. Standardisation of collected data, process-oriented frameworks, industry wide definitions of terminology and technology are believed to enable a greater degree of transparency and interdisciplinary collaboration in the field, ultimately contributing to the research field evolving. The identified research appears to have focused mostly on the technology itself, and less on the context the technology would be operating within; this suggests that the field could benefit from an increased focus on organisational and process-oriented research in the context of AI and construction

5. Limitations and Future Research

For future research, this study provides a sense of direction and highlights where current gaps in the research are to be found. It becomes apparent that AI holds significant potential for increased productivity and sustainability in construction projects, but the construction industry seems to lack the progress seen in other industries. For the future of the field, transparency and explicit definitions across all sub-fields will be of particular importance for the field as a whole to mature and develop – and to a greater extent to ensure comparability and transferability among studies and findings. The research currently lacks empirical data and research on implementation and performance beyond small-scale testing and proof-of-concepts. Research mapping the effects of the increased use of AI also seems to be lacking. Pilots and testing are important first steps in a developing field; however, in order to truly change deliveries and deliverables through the use of AI future research must focus on developing holistic frameworks for projects to move from ambition to practice.

A few limitations can be associated with this study. First, the research may be limited by deficiencies in data collection and analysis, as a limited number of sources were reviewed. Second, limitations could be associated with the chosen framework for the review. For example, only articles written in English were included in the final sample; therefore, the chosen publications are not necessarily conclusively representative of the field of AI in construction projects. Another possible limitation is the organisation of the search as a manual search of chosen databases. This may have led to some relevant studies being missed, thereby possibly under-estimating or wrongly assessing the extent of research regarding AI in construction projects.

Furthermore, limitations are associated specifically with the scoping review methodology itself: the scoping review does not formally evaluate the quality of the publications reviewed and relies on the implicit quality of the publication sources. The descriptive nature of the methodology can result in broader, less defined searches; however, it also ensures flexibility and resilience in the study and allows for more rapid mapping which is beneficial for an expanding research field.

References

Aboelmagd, Y. M. R. (2018). Decision support system for selecting optimal construction bid price. *Alexandria Engineering Journal*, 57(4), 4189-4205. doi: 10.1016/j.aej.2018.11.007

Akbari, S., Khanzadi, M., and Gholamian, M. (2018). Building a rough sets-based prediction model for classifying large-scale construction projects based on sustainable success index. *Engineering, Construction and Architectural Management*, 25(4), 00-00. doi: 10.1108/ECAM-05-2016-0110

Akinade, O. O., (2017). *BIM-based software for construction waste analytics using artificial intelligence hybrid models*. Doctoral dissertation. University of the West of England.

Akinosho, T. D., Oyedele, L. O., Bilal, M., Ajayi, A. O., Delgado, M. D., Akinade, O. O., and Ahmed, A. A. (2020). Deep learning in the construction industry: A review of present status and future innovations. *Journal of Building Engineering*. 32, 101827. doi: 10.1016/j.jobe.2020.101827

Amiri, R., Sardroud, J. M., and de Soto, B. G. (2017). BIM-based Applications of Metaheuristic Algorithms to Support the Decision-making Process: Uses in the Planning of Construction Site Layout. *Procedia Engineering*. 196, 558-564. doi: 10.1016/j.proeng.2017.08.030

Arashpour M., Bai Y., Aranda-mena G., Bab-Hadiashar A., Hosseini R., and Kalutara P. (2017). Optimizing decisions in advanced manufacturing of prefabricated products: Theorizing supply chain configurations in off-site construction. *Automation in Construction*,84, 146-153. doi: 10.1016/j.autcon.2017.08.032

Arksey, H. and O'Malley, L. (2005) Scoping studies: towards a methodological framework. *International Journal of Social Research Methodology*, 8(1), 19-32. doi: 10.1080/1364557032000119616

Ayhan, B. U. and Tokdemir, O. (2018). Predicting the outcome of construction incidents. *Safety Science*, 113, 91-104. doi: 10.1016/j.ssci.2018.11.001

Ayhan, B. U. and Tokdemir, O. (2019). Safety assessment in megaprojects using artificial intelligence. *Safety Science*, 118, 273-287. doi: 10.1016/j.ssci.2019.05.027

Banihashemi, S., Tabadkani, A., and Hosseini, M. R. (2017). Modular Coordination-based Generative Algorithm to Optimize Construction Waste. *Procedia Engineering*, 180, 631-639. doi: 10.1016/j.proeng.2017.04.222

Barker, T., Bashmakov I., Alharthi, A., Amann, M., Cifuentes, L., Drexhage, J., Duan, M., Edenhofer, O., Flannery, B., Grubb, M., Hoogwijk, M., Ibitoye, F. I., Jepma, C. J., Pizer, W. A., and Yamaji, K. (2007). *Mitigation from a cross-sectoral perspective. Proceedings of the Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Basaif, A. A., Al-Ashwal, A. M., Rahim, F. A., Karim, S. B., and Loo, S. C. (2020). Technology awareness of artificial intelligence (AI) application for risk analysis in construction projects. *Malaysian Construction Research Journal*, 1, 182-195.

Basaif, A. A. and Alashwal, A. M. (2018). A review of the application of artificial intelligence for risk analysis in construction projects. *Book of Abstracts: ASEAN Post Graduate Conference: Inclusive Built Environment Towards Realising New Urban Agenda*, Kuala Lumpur, Malaysia, 9-9.

Becqué, R., Mackres, E., Layke, J., Aden, N., Liu, S., Managan, K., Nesler, C., Mazur-Stommen, S., Petrichenko, K., and Graham, P. (2016). *Accelerating Building Efficiency. Eight Actions for Urban Leaders*. World Resources Institute. WRI Ross Center for Sustainable Cities.

Bilal, M. and Oyedele, L. O. (2020a). Big Data with deep learning for benchmarking profitability performance in project tendering. *Expert Systems with Applications*, 147, 113194. doi: 10.1016/j.eswa.2020.113194

Bilal, M. and Oyedele, L. O. (2020b). Guidelines for applied machine learning in construction industry—A case of profit margins estimation. *Advanced Engineering Informatics*, 43(C), 101013. doi: 10.1016/j.aei.2019.101013

Bilal, M., Oyedele, L. O., Akinade, O. O., Delgado, J. M. D., Akanbi, L. A., Ajayi, A. O., and Younis, M. S. (2019). Design optimisation using convex programming: Towards waste-efficient building designs. *Journal of Building Engineering*, 23, 231-240. doi: 10.1016/j.jobe.2019.01.022

Blanco, J. L., Fuchs, S., Parsons, M., and Ribeirinho, M. J. (2018). Artificial intelligence: Construction technology's next frontier. *The Building Economist*, 7-13. doi: 10.3316/informit.048712291685521

Boughaba, A. and Bouabaz, M. (2020). Identification and risk management related to construction projects. *Advances in Computational Design*, 5(4), 445-465. doi: 10.12989/acd.2020.5.4.445

Camacho, A., Canizares, P.C., Estevez, S., and Nunez, M. (2018). A tool-supported framework for work planning on construction sites based on constraint programming. *Automation in Construction*, 2(86), 190-198. doi: 10.1016/j.autcon.2017.11.008

Chen K., Lu W., Peng Y., Rowlinson S., and Huang G. Q. (2015). Bridging BIM and building: From a literature review to an integrated conceptual framework. *International Journal of Project Management*, 33(6), 1405-1416. doi: 10.1016/j.ijproman.2015.03.006

Cheng, M. Y. and Chang, N. W. (2019). Dynamic construction material layout planning optimization model by integrating 4D BIM. *Engineering with Computers*, 35(3), 703-720. doi: 10.1007/s00366-018-0628-0

Cheng, M. Y., Kusoemo, D., and Gosno, R. (2020a). Text mining-based construction site accident classification using hybrid supervised machine learning. *Automation in Construction*, 118(1), 103265. 10.1016/j.autcon.2020.103265

Cheng, M. Y., Cao, M. T., and Herianto, J. G. (2020b). Symbiotic organisms search-optimized deep learning technique for mapping construction cash flow considering complexity of project. *Chaos, Solitons & Fractals*, 138, 109869. doi: 10.1016/j.chaos.2020.109869

Cheng, M. Y., Chang, Y.-H., and Korir, D. (2020c). Novel Approach to Estimating Schedule to Completion in Construction Projects Using Sequence and Nonsequence Learning. *Journal of Construction Engineering and Management*, 145(11), 04019072. doi: 10.1061/(ASCE)CO.1943-7862.0001697

Cheng, M. Y. and Hoang, N. D. (2018). Estimating Construction Duration of Diaphragm Wall Using Firefly-Tuned Least Squares Support Vector Machine. *Neural Computing and Applications*, 30, 2489-2497. doi: 10.1007/s00521-017-2840-z

Cheng, M. Y., Hoang, N.-D., and Wu, Y.-W. (2015). Cash Flow Prediction for Construction Project Using a Novel Adaptive Time-Dependent Least Squares Support Vector Machine Inference Model. *Journal of Civil Engineering and Management*, 21(6), 679-688. doi: 10.3846/13923730.2014.893906.

Chou, J., Lin, C. W., Pham, A.-D., and Shao, J.-Y. (2015). Optimized artificial intelligence models for predicting project award price. *Automation in Construction*, 54, 106-115. doi: 10.1016/j.autcon.2015.02.006

Darko, A., Chan, A. P. C., Adabre, M. A., Edwards, D. J., Hosseini, M. R., and Ameyaw, E. E. (2020). Artificial intelligence in the AEC industry: Scientometric analysis and visualization of research activities. *Automation in Construction*, 122, 103081. doi: 10.1016/j.autcon.2020.103081

Dasgupta, D. and Michalewicz, Z. (1997*). Evolutionary Algorithms in Engineering Applications*. Springer, New York.

Dawood, H., Siddle, J., and Dawood, N. (2019). Integrating IFC and NLP for automating change request validations. *Journal of Information Technology in Construction*. 24, special issue, 540-552. doi: 10.36680/j.itcon.2019.030

de Soto, B. G., Rosarious, A., Rieger, J., Chen, Q., and Adey, B. T. (2017). Using a Tabu-search Algorithm and 4D Models to Improve Construction Project Schedules. *Procedia Engineering*, 196, 698-705. doi: 10.1016/j.proeng.2017.07.236

Delgado, J. M. D., Oyedele, L., Ajayi, A., Akanbi, L., Akinade, O., Bilal, M., and Owolabi, H. (2019). Robotics and automated systems in construction: Understanding industry-specific challenges for adoption. *Journal of Building Engineering*, 26, 100868. doi: 10.1016/j.jobe.2019.100868

Dong, X. S., Jackson, R., Varda, D., Betit, E., and Bunting, J. (2019). *Trends of Fall Injuries and Prevention in the Construction Industry*. The Center for Construction Research and Training (CPWR). Data report.

Eber, W. (2020). Potentials of artificial intelligence in construction management. *Organization, Technology and Management in Construction: An International Journal*, 12, 2053-2063. doi: 10.2478/otmcj-2020-0002

Elmousalami, H. (2019). Intelligent methodology for project conceptual cost prediction. *Heliyon*, 5(5), e01625. doi: 10.1016/j.heliyon.2019.e01625

Elziny, A. A., Mohamadien, M. A., Ibrahim, H., and Fattah, M. K. (2016). An expert system to manage dispute resolutions in construction projects in Egypt. *Ain Shams Engineering Journal*, 7(1), 57-71. doi: 10.1016/j.asej.2015.05.002

Erzaij, K. R., Rashid, H. A., Naji, H. I., and Ali, R. H. (2020). Projects evaluation in construction industry. *Periodicals of Engineering and Natural Sciences*, 8(3), 1808-1816.

Faghihi, V., Nejat, A., Reinschmidt, K., and Kang, J. (2015). Automation in construction scheduling: a review of the literature. *The International Journal of Advanced Manufacturing Technology*, 81(9), 1845-1856. doi: 10.1007/s00170-015-7339-0

Fallahpour, A., Wong, K., Rajoo, S., Olugu, E., Nilashi, M., and Turskis, Z. (2020). A fuzzy decision support system for sustainable construction project selection: an integrated FPP-FIS model. *Journal of Civil Engineering and Management*, 26(3), 247-258. doi: 10.3846/jcem.2020.12183.

Gazder, U., Shakshuki, E., Adnan, M., and Yasar, A.-U.-H. (2018). Artificial Neural Network Model to relate Organization Characteristics and Construction Project Delivery Methods. *Procedia Computer Science*, 134, 59-66. doi: 10.1016/j.procs.2018.07.144

Goh, Y. M., Ubeynarayana C.U., Wong K. L. X., and Guo B. H. W. (2018). Factors influencing unsafe behaviors: A supervised learning approach. *Accident Analysis & Prevention*, 188, 77-85. doi: 10.1016/j.aap.2018.06.002

Golparvar-Fard, M., Peña-Mora, F., and Savarese, S. (2015). Automated Progress Monitoring Using Unordered Daily Construction Photographs and IFC-Based Building Information Models. *Journal of Computing in Civil Engineering*, 29(1), 04014025. doi: 10.1061/(ASCE)CP.1943-5487.0000205

Gough, D. (2007a). Weight of Evidence: a framework for the appraisal of the quality and relevance of evidence. *Research Papers in Education*, 22(2), 213-228. doi: 10.1080/02671520701296189

Gough, D. (2007b). *Giving voice: Evidence-informed policy and practice as a democratizing process*. Marginality and difference in education and beyond. London: Trentham Books, 31-45.

Gudauskas, R., Jokubauskiene, S., Zavadskas, E., Kaklauskas, A., Binkyte-Veliene, A., Peciure, L., Budryte, L., and Prialgauskas, D. (2015). Intelligent Decision Support System for Leadership Analysis. *Procedia Engineering*, 122, 172-180. doi: 10.1016/j.proeng.2015.10.022

Hajdasz, M. (2015). Managing repetitive construction in a dynamically changing project environment: Conceptualizing the system–model–simulator nexus. *Automation in Construction*, 57, 132-145. doi: 10.1016/j.autcon.2015.05.005

Han, Y., Yin, Z. Z., Zhang, J., Jin, R., and Yang, T. (2020). Eye-Tracking Experimental Study to Investigating the Influence Factors of Construction Safety Hazard Recognition. *Journal of Construction Engineering and Management*, 146(8), 04020091. doi: 10.1061/(ASCE)CO.1943-7862.0001884

Hanna, A., Iskandar, K., Lotfallah, W., Ibrahim, M., and Russell, J. (2018). A Data-driven Approach for Identifying Project Manager Competency Weights. *Canadian Journal of Civil Engineering*, 45, 1-8. doi: 10.1139/cjce-2017-0237

Hong, T., Wang, Z., Luo, X., and Zhang, W. (2020). State-of-the-Art on Research and Applications of Machine Learning in the Building Life Cycle. *Energy and Buildings*212(3). doi: 10.1016/j.enbuild.2020.109831

Hossain, M. A. and Nadeem, A. (2019). Towards digitizing the construction industry: State of the art of Construction 4.0. *Proceedings of the International Structural Engineering and Construction*, 6(1). doi: 10.14455/ISEC.res.2019.184

Hsu, H. C., Chang, S., Chen, C. C., and Wu, I C. (2020). Knowledge-based system for resolving design clashes in building information models. *Automation in Construction*, 110. doi: 10.1016/j.autcon.2019.103001

Hu, Y. and Castro-Lacouture, D. (2019). Clash Relevance Prediction Based on Machine Learning. *Journal of Computing in Civil Engineering*, 33(2), 04018060. doi: 10.1061/(ASCE)CP.1943-5487.0000810

Ilter, D. and Dikbas, A. (2009). A review of the artificial intelligence applications in construction dispute resolution. *Proceedings of the Managing IT in Construction. 26th International Conference*, 41-50. doi: 10.1201/9781482266665-63

Iyer, P., Liu, Y., Sadeghpour, F., and Brennan, R. W. (2015). A Fuzzy-Logic based Resource Levelling Optimisation Tool. *IFAC-Papers OnLine*, 48(3), 1942-1947. doi: 10.1016/J.IFACOL.2015.06.371

Jaber, F., Al-Zwainy, F. M., and Hachem, S. (2019). Optimizing of predictive performance for construction projects utilizing support vector machine technique. *Cogent Engineering*, 6(1), 1685860. doi: 10.1080/23311916.2019.1685860

Juszczyk, M. (2017). The Challenges of Nonparametric Cost Estimation of Construction Works with the use of Artificial Intelligence Tools. *Procedia Engineering*, 196 (1), 415-422. doi: 10.1016/j.proeng.2017.07.218

Juszczyk, M. (2020). Development of Cost Estimation Models Based on ANN Ensembles and the SVM Method. *Civil and Environmental Engineering Reports*,30(3), 48-67. doi: 10.2478/ceer-2020-0033

Juszczyk, M. and Lesniak, A. (2019). Modelling Construction Site Cost Index Based on Neural Network Ensembles. *Symmetry*, 11(3), 411. doi: 10.3390/sym11030411.

Juszczyk, M., Zima, K., and Lelek, W. (2019). Forecasting of Sports Fields Construction Costs Aided by Ensembles of Neural Networks. *Journal of Civil Engineering and Management*, 25(7), 715-729. doi: 10.3846/jcem.2019.10534

Khosrowshahi, F. (2015). Enhanced project brief: Structured approach to client-designer interface. Engineering, *Construction and Architectural Management*, 22(5), 474-492. doi: 10.1108/ECAM-10-2014-0128

Kim, K., Cho, Y., and Kim, K. (2018). A BIM-Driven Automated Decision Support System for Safety Planning of Temporary Structures. *Journal of Construction Engineering and Management*, 144(8). doi: 10.1061/(asce)co.1943-7862.0001519

Kog, F. and Yaman, H. (2016). A multi-agent systems-based contractor pre-qualification model. *Engineering, Construction and Architectural Management*, 23(6), 709-726. doi: 10.1108/ECAM-01-2016-0013

Levac, D., Colquhoun, H., and O'Brien, K. K. (2010). Scoping studies: advancing the methodology.

Implementation Science, 5(69). doi: 10.1186/1748-5908-5-69

Li, H. and Womer, N. K. (2015). Solving stochastic resource-constrained project scheduling problems by closed-loop approximate dynamic programming. *European Journal of Operational Research*, 246(1), 20-33. doi: 10.1016/j.ejor.2015.04.015

Li, Y. S., Hwang, B. G., Shan, M., and Looi, K. Y. (2019). Developing a Knowledge-based Decision Support System for Prefabricated Prefinished Volumetric Construction. *IOP Conference Series: Earth and Environmental Science*, 385, 012002. doi: 10.1088/1755-1315/385/1/012002

Liu, S., Meng, X., and Tam, C. (2015). Building Information Modeling Based Building Design Optimization for Sustainability. *Energy and Buildings*, 105, 139-153. doi: 105. 10.1016/j.enbuild.2015.06.037

Luo, L., He, Q., Jaselskis, E. J., and Xie, J. (2017). Construction Project Complexity: Research Trends and Implications. *Journal of Construction Engineering and Management*, 143(7), 04017019. doi: 10.1061/(ASCE)CO.1943-7862.0001306

Mahfouz, T., Kandil, A., and Davlyatov, S. (2018). Identification of latent legal knowledge in differing site condition litigations. *Automation in Construction*, 94(C), 104-111. doi: 10.1016/j.autcon.2018.06.011

Martínez, D. M. and Fernández-Rodríguez, J. C. (2015). Artificial Intelligence Applied to Project Success: A Literature Review. *International Journal of Interactive Multimedia and Artificial Intelligence*, 3(5), 77-84. doi: 10.9781/ijimai.2015.3510

McKinsey Global Institute (2015). *Digital America. McKinsey & Company. MGI Industry Digitization Index.* Retrieved from https://www.mckinsey.com/ on February 28, 2020

Mehrabani, M. N., Golafshani, E. M., and Ravanshadnia, M. (2020). Scoring of Tenders in Construction Projects Using Group Method of Data Handling. *KSCE Journal of Civil Engineering*, 24(3), 1996–2008. doi: 10.1007/s12205-020-1537-5

Mirahadi, F. and Zayed, T. (2016). Simulation-based construction productivity forecast using Neural-Network-Driven Fuzzy Reasoning. *Automation in Construction*, 65, 102-115. doi: 10.1016/j.autcon.2015.12.021

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., and The PRISMA Group (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. *PLoS Medicine*, 6(7), e1000097. doi: 10.1371/journal.pmed.1000097

Mousavi, S., Vahdani, B., Hashemi, H., and Ebrahimnejad, S. (2015). An Artificial Intelligence Model-Based Locally Linear Neuro-Fuzzy for Construction Project Selection. *Journal of multiple-valued logic and soft computing*, 25(6), 589-604.

Ning, X., Qi, J., Wu, C., and Wang, W. (2018). A tri-objective ant colony optimization-based model for planning safe construction site layout. *Automation in Construction*, 89, 1-12. doi: 10.1016/j.autcon.2018.01.007

Nnaji, C. and Karakhan, A. A. (2020). Technologies for safety and health management in construction: Current use, implementation benefits and limitations, and adoption barriers. *Journal of Building Engineering*, 29, 101212. doi: 10.1016/j.jobe.2020.101212

Oprach, S., Bolduan, T., Steuer, D., Vössing, M., and Haghsheno, S. (2019). Building the Future of the Construction Industry through Artificial Intelligence and Platform Thinking. *Digitale Welt*, 3, 40-44. doi: 10.1007/s42354-019-0211-x

Oyedele, L. O., Kusimo, H. O., Owolabi, H. A., Akanbi, L. A., Ajayi, A. O., Akinade, O. O., and Delgado, J. M. D. (2019). Investigating profitability performance of construction projects using big data: A project analytics approach. *Journal of Building Engineering*, 26, 100850. doi: 10.1016/j.jobe.2019.100850

Podolski, M. (2016). Management of resources in multiunit construction projects with the use of a tabu search algorithm. *Journal of Civil Engineering and Management*. 23(2), 1-10. doi: 10.3846/13923730.2015.1073616

Poh, C. Q. X., Ubeynarayana, C. U., and Goh, Y. M. (2018). Safety leading indicators for construction sites: A machine learning approach. *Automation in Construction*, 93. doi: 10.1016/j.autcon.2018.03.022

Pruvost, H. and Scherer, R. (2017). Analysis of risk in building life cycle coupling BIM-based energy simulation and semantic modelling. *Procedia Engineering*, 196, 1106-1113. doi: 10.1016/j.proeng.2017.08.068

Qazi, A., Quigley, J., Dickson, A., and Kirytopoulos, K. (2016). Project Complexity and Risk Management: Towards modelling project complexity driven risk paths in construction projects. *International Journal of Project Management*, 34, 1183-1198. doi: 10.1016/j.ijproman.2016.05.008

Qi, C., Fourie, A., Ma, G., and Tang, X. (2018). A hybrid method for improved stability prediction in construction projects: A case study of stope hangingwall stability. *Applied Soft Computing*, 71, 649-658. doi: 10.1016/j.asoc.2018.07.035

Rodriguez-Trejo S., Ahmad A.M., Hafeez M.A., Dawood H., Vukovic V., Kassem M., Naji K.K., and Dawood N. (2017). Hierarchy based information requirements for sustainable operations of buildings in Qatar. *Sustainable Cities and Society*, 32, 435-448. doi: 10.1016/j.scs.2017.03.005

Russell, S. J. and Norvig, P. (2010). *Artificial Intelligence. A Modern Approach*. Third edition. Upper Saddle River, New Jersey: Pearson Education.

Samantra, C., Datta, S., and Mahapatra, S.S. (2017). Fuzzy based risk assessment module for metropolitan construction project: An empirical study. Engineering *Applications of Artificial Intelligence*, 65(C), 449-464. doi: 10.1016/j.engappai.2017.04.019

Shahtaheri M., Nasir H., and Haas C. T. (2015). Setting baseline rates for on-site work categories in the construction industry. *Journal of Construction Engineering and Management*, 141(5), doi: 10.1061/(ASCE)CO.1943-7862.0000959

Sharafi, P., Rashidi, M., Samali, B., Ronagh, H., and Mortazavi, M. (2018). Identification of Factors and Decision Analysis of the Level of Modularization in Building Construction. *Journal of Architectural Engineering*, 24(2). doi: 10.1061/(ASCE)AE.1943-5568.0000313

Shin, Y. (2015). Application of Boosting Regression Trees to Preliminary Cost Estimation in Building Construction Projects. *Computational intelligence and neuroscience*, 2015(4), 149702. doi: 10.1155/2015/149702

Sowa, J. F. (2000). *Knowledge representation*. First edition. Pacific Grove: Brooks.

Taherdoost, H. and Brard, A. (2019). Analyzing the Process of Supplier Selection Criteria and Methods. *Procedia Manufacturing*, 32, 1024-1034. doi: 10.1016/j.promfg.2019.02.317

Tidemann, A. (2020). *Kunstig intelligens (Artificial Intelligence). Store Norske Leksikon (SNL). Great Norwegian Encyclopedia*. Retrieved from https://snl.no/kunstig_intelligens on February 28, 2020.

Tidemann, A. (2019). *Maskinlæring (Machine learning). Store Norske Leksikon (SNL). Great Norwegian Encyclopedia.* Retrieved from https://snl.no/kunstig_intelligens on February 28, 2020.

Tranfield, D., Denyer, D., and Smart, P. (2003). Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. *British Journal of Management*, 14(3), 207-222. doi: 10.1111/1467-8551.00375

Tørresen, J. (2013). *Hva er kunstig intelligens? (What is Artificial Intelligence?)* Oslo: Universitetsforlaget.

University of Helsinki (2018). *Introduction to AI. How should we define AI? Elements of AI*. Retrieved from https://www.elementsofai.com/ on March 24, 2021

Vakhshouri, B. and Nejadi, S. (2015). Predicition of Compressive Strength in Light-Weight Self-Compacting Concrete by ANFIS Analytical Model. *Archives of Civil Engineering*, LXI(2), 53-72. doi: 10.1515/ace-2015-0014

Vickranth V., Bommareddy S. S. R., and Premalatha V. (2019). Application of lean techniques, enterprise resource planning and artificial intelligence in construction project management. *International Journal of Recent Technology and Engineering*, 7, 6C2.

Wang D., Liu J., Wang X., and Chen Y. (2019). Cost-effectiveness analysis and evaluation of a 'three-old' reconstruction project based on smart system. *Cluster Computing*, 22, 7895-7905. doi: 10.1007/s10586-017-1490-3

Wood, H. and Gidado, K. (2008). An Overview of Complexity Theory and its Application to the Construction Industry. *Proceedings of 24th Annual Conference of the Association of Researchers in Construction Management*, 677-787.

Xiao, C., Liu, Y., and Akhnoukh, A. K. (2018). Bibliometric Review of Artificial Intelligence (AI) in Construction Engineering and Management. *International Conference on Construction and Real Estate Management 2018*, 32-41. doi: 10.1061/9780784481721.004

Xing Y., Song Z., and Deng X. (2016). Optimizing the schedule of dispatching construction machines through artificial intelligence. *Chemical Engineering Transactions*,51, 493-498. doi: 10.3303/CET1651083

Xu, J., Zheng, J., Zhao, B., and Gong, D. (2020). Application of remote electron microscope technology in construction management of building engineering. *Acta Microscopica*, 29, 1. 328-337

Yaseen, Z., Ali, Z., Salih, S., and Al-Ansari, N. (2020). Prediction of Risk Delay in Construction Projects Using a Hybrid Artificial Intelligence Model. *Sustainability*, 12(4), 1-14. doi: 10.3390/su12041514

Yaqubi, M. K. and Salhotra S. (2019) The automated cost estimation in construction. *International Journal of Innovative Technology and Exploring Engineering*. 8(7), 845-849.

Zhang, J., Huang, Y., Ma, G., Sun, J., and Nener, B. (2020). A metaheuristic-optimized multi-output model for predicting multiple properties of pervious concrete. *Construction and Building Materials*, 249, 118803. doi: 10.1016/j.conbuildmat.2020.118803

Zhang, Y. and Luo, H. and He, Y. (2015). A System for Tender Price Evaluation of Construction Project Based on Big Data. *Procedia Engineering*, 123, 606-614. doi: 10.1016/j.proeng.2015.10.114

Zheng, X. L. and Wang, L. (2015). A multi-agent optimization algorithm for resource constrained project scheduling problem. *Expert Systems with Applications*. 42(15-16). doi: 10.1016/j.eswa.2015.04.009

Zhou, J. and Ren, D. (2020). A hybrid model of external environmental benefits compensation to practitioners for the application of prefabricated construction. *Environmental Impact Assessment Review*, 81, 106358. doi: 10.1016/j.eiar.2019.106358

Zou, Y., Kiviniemi, A., and Jones, S. (2017). Retrieving similar cases for construction project risk management using Natural Language Processing techniques. *Automation in Construction*, 80. doi: 10.1016/j.autcon.2017.04.003

Sofie Bang is a Ph.D. Candidate at the Norwegian University of Science and Technology. The Ph.D. is conducted in collaboration with Construction City Cluster, and explores and maps the opportunities, challenges, and future outlooks associated with the increased use of artificial intelligence in construction projects. Bang holds an MSc in Mechanical Engineering, with a specialization in Project and Quality management. Her research interests include artificial intelligence, construction, project management and sustainability.

With a Ph.D. from the Norwegian University of Science and Technology (NTNU) and an MSc from Chalmers in Sweden, Olsson is a full professor in project management at the department of production and quality engineering at NTNU in Trondheim, Norway. He has served as research coordinator for the Concept research programme on large governmental projects and has had a professorship in facilities management. Olsson has extensive experience as a consultant, research scientist and manager. His consulting experience includes Ernst & Young and DNV (Det Norske Veritas). Current research is focused on emerging aspects of project management and railway traffic management.

Appendix II

Paper II

«Utilising Artificial Intelligence in Construction Site Waste Reduction»

Published in: Journal of Engineering, Project, and Production Management
ISSN: 2223-8379

Journal of Engineering, Project, and Production Management
2022, 12(3), 239-249

Utilising Artificial Intelligence in Construction Site Waste Reduction

Sofie Bang[1] and Bjørn Andersen[2]

[1]Ph.D. Candidate, Department of Mechanical and Industrial Engineering, Norwegian University of Science and Technology, Richard Birkelands vei 2B, 7034 Trondheim, Norway, E-mail: sofie.bang@ntnu.no (corresponding author).
[2]Professor, Department of Mechanical and Industrial Engineering, Norwegian University of Science and Technology, Richard Birkelands vei 2B, 7034 Trondheim, Norway, E-mail: bjorn.andersen@ntnu.no

Project Management
Received December 6, 2021; revised March 3, 2022; accepted May 21, 2022
Available online June 13, 2022

Abstract: The purpose of this study is to examine how artificial intelligence (AI) can help reduce waste on construction sites. An explorative, mixed-method research design is deployed. Qualitative methods were utilised, including an extensive literature search, 32 interviews, a project visit, and participation in chosen seminars. Additionally, quantitative methods included an analysis of waste quantities in 161 construction projects, selected based on criteria for availability of data, as well as a targeted questionnaire with 21 respondents. Several methods were employed as means of triangulation, to increase the validity and reliability of the data in a complex and rapidly developing field. The study uncovers several possibilities and concludes with 18 proposed measures for waste reduction on a construction site, along with a set of recommendations for practical implementation. The recommended measures include defining appropriate targets for waste production, optimising resources, tracking continuously, reporting and presenting waste quantities, training, conducting inspections, and implementing specific routines for warehousing. The study helps bridge the gap between ambition and practice by highlighting considerations related to the practical implementation of measures for waste management and providing an understanding of which AI-based tools and measures are considered effective for waste reduction in construction projects.

Keywords: artificial intelligence, construction projects, sustainability, waste, waste reduction.

DOI 10.32738/JEPPM-2022-0022

1. Introduction

The ever-growing construction industry is accountable for nearly 40% of worldwide energy consumption and energy-related gas emissions (Global Alliance for Buildings and Construction, 2017), while the need for more sustainable solutions is growing just as swiftly. Implementing circular thinking and optimal waste management will be among the most important courses of action to fulfil national and international ambitions to reduce emissions (Avfall Norge, 2016; Olerud, 2019). A significant potential to increase productivity and sustainability is widely assumed to lie in the utilisation of new technology, digitalisation, and artificial intelligence (AI) (Becqué et al., 2016; Moen, 2017; Mejlænder-Larsen, 2019).

Construction waste can be defined as ‘a material or product which needs to be transported elsewhere from the construction site or used on the site itself other than the intended specific purpose of the project’ (Skoyles and Skoyles, 1987 as cited in Osmani, 2011). Reduction of waste on construction sites plays an important role in the usage and development of more sustainable solutions, and in the ongoing development of a sustainable industry; therefore, waste reduction is an important means to reach the 13th sustainability goal related to climate action (United Nations, 2021). Studies show that certain waste fractions have very high waste percentages (Hjellnes Consult, 2015; SSB, 2019), meaning that large amounts of such materials pass through the value chain without adding any practical value to a project. Existing literature identifies wood, plaster, cardboard and paper, plastics, and mixed waste as problematic waste fractions (Rønningen, 2000; Kartam et al., 2004; Osmani, 2012). However, a recent development with practical implications for sustainability is the increased use of AI in the industry, as data become more available and data processing capacity grows more affordable.

The purpose of this study was to examine how AI can help reduce waste on construction sites. An unambiguous definition of AI is currently lacking, especially in a construction context. Adio-Moses and Asaolu (2016) describes AI-based tools as tools capable of ‘reasoning, planning, learning, natural language processing (communication), perception, and the ability to move and manipulate objects.

Three research questions are answered through a mixed-methods research design, providing quantitative data collected from the contractor and qualitative considerations from other parts of the value chain. Specifically, the study answers the following research questions:

- RQ1: Which measures are suitable for waste reduction on the construction site?
- RQ2: How can the identified measures be implemented?
- RQ3: How can AI contribute to the implementation of the measures?

The remainder of this article is organised as follows. The next section explains the review methodology. The results section presents findings from all described methods. These findings are further assessed, discussed, and summarised in 18 specific measures for utilising AI to improve waste reduction. The final section provides the conclusion, along with the implications of the study and avenues for future research. The conclusion also answers the research questions as defined, summarises the conducted research, and reflects upon the possibilities the study provides for future research, as well as the current study's limitations.

2. Method

To answer the research questions, the explorative research design combines quantitative and qualitative methods; methodological triangulation contributes to the inherent quality of the findings of the study (Love et al., 2002). Table 1 illustrates the research design, with its five phases of data collection and analysis. Each methodological technique is described and elaborated.

Initial research comprised a thorough literature search on the topic of waste reduction and the use of AI in the construction industry. In parallel, a document analysis of available material was conducted, to ensure the relevance of theoretical findings. Other qualitative methods utilised were semi-structured in-depth interviews, structured interviews, a project visit, a tour of the Norsk Gjenvinning plant, as well as participation in chosen seminars and webinars. Quantitative methods utilised include an analysis of data on waste disposal in 161 construction projects and a questionnaire distributed among the personnel responsible for waste management of ongoing projects in Skanska Norway. Further research was carried out by analysis and compilation of the collected data.

Criteria such as validity, reliability, and generalisability can indicate the quality of a study (Tjora, 2017). Validity is related to the relevance of the study itself, as well as the relevance of collected data; reliability is related to verifiability (Denzin, 2012). The literature search included an assessment of the relevance of the sources themselves in addition to the collected data. Similarly, in interviews, the relevance of both the interviewees and the questions themselves was assessed. Generalisability could be restricted, as the quantitative aspects of the study are based on projects from one contractor, and on new construction projects specifically; the results are not necessarily transferable to other actors or projects. However, reduced generalisability can be compensated for via a comparative research approach.

Table 1. The five phases of data collection and analysis.

	Phase 1: Framing the problem	Phase 2: Mapping of waste, causes, and effects	Phase 3: Mapping of techniques based on AI	Phase 4: Triangulation of data	Phase 5: Validation
Performed activity	Definition of purpose and aim; conceptualisation of problem statement in the context of the field	Identification of problematic waste fractions, activities, and processes	Identification of available techniques based on AI	Assessment of findings and the intersection between the two areas	Validation and refinement
Methodological technique	Review of previous research through literature search; document analysis; introductory conversations with relevant personnel	Mapping and evaluation of waste in 161 construction projects; questionnaire; targeted interviews; project visit; participation in chosen seminars	Mapping literature and lessons learned in pilots and case studies; targeted interviews; participation in chosen webinars	Combining evidence from the previous investigations, theoretical and practical findings; targeted interviews	Consulting informants, peer academics, and practitioners
Analysis	Assessment of early findings	Problematic waste fractions identified in quantitative analysis; cross-checked with existing literature and informants, summarised; causes of waste and effects of waste reduction mapped	Estimation of available technology and techniques enabling potential measures for waste reduction; mapping was done with the help of informants	Iterative assessment of findings in Phase 2 and 3; discussions with selected informants	Discussions with selected informants, peer academics, and practitioners; presentation of findings
Contribution to paper	Section 1 Section 2	Section 3 Section 4 RQ1 RQ2	Section 3 Section 4 RQ3	Section 4 Section 5 Section 6	All sections

For this study, this entailed using multiple methods and involving actors from various parts of the value chain in interviews and reviews throughout the process, as well as a validation of results in the final research phase.

The literature search was conducted to obtain insights into current and previous studies on waste reduction in the construction industry, as well as AI in the construction industry. The search commenced by selecting databases considered appropriate for finding studies on waste reduction and AI in the construction industry. The Scopus and Oria databases were chosen, due to their coverage of engineering-based publications. Search strings such as [waste AND (reduction OR minimisation) AND construction AND (project* OR industry)] as well as [artificial intelligence OR machine learning AND construction AND (project* OR industry)] were used to identify relevant literature. To ensure the provision of a state-of-the-art view of the topics, publications from 2000 or later were examined. Suggestions given by interviewees were also reviewed

Over the course of a year, 18 semi-structured in-depth interviews were conducted in person and via computer; in addition, 14 structured interviews were conducted in written form. The interviewees were actors from every stage of the construction project supply chain. Selection of the interviewees was based on inclusivity of different roles and perspectives throughout a project and its value chain, as well as suggestions from previous interviewees, building a strategic selection according to the recommendations of Dalland (2012). Interviewees included personnel with experience from waste management and general interest in environmental initiatives, as well as those with experience in the use of AI both within and outside the construction industry. The semi-structured approach facilitates a set structure for the conversation but provides paths for input from the informants themselves (Johannessen et al., 2016).

Where informants were unable to participate in the in-depth interviews, or for various reasons preferred another format, an additional 14 structured interviews were conducted in a written format. Challenges associated with this approach include fewer reflections from the interviewees and the increased possibility of misunderstanding; this was accounted for largely by asking follow-up questions. An overview of the background and contributions of the interviewees is summarised in Table 2. The total of certain characteristics may be greater than 18 or 14, respectively, as some informants fell into two or more of the defined categories.

The interviews followed one of two interview guides, developed after the initial literature search and document analysis. The first guide was structured to gather perspectives on problematic waste fractions, the origin of the identified fractions, suggested solutions, and challenges related to the reduction of the identified fractions. The second guide was structured to gather perspectives on the role of AI in waste reduction on construction sites. The interviews were recorded, transcribed, and categorised for further analysis. Thaagard (2013) suggests that the researcher strives to find a selection of interviewees that meets a theoretical saturation point, beyond which adding a new informant would no longer add anything significantly new to the research. Saturation was identified in this study by continuously assessing and comparing responses from the conducted interviews. Certain topics reached saturation point earlier than others; in these cases, an emphasis was placed on the unsaturated topics in any follow-up questions and further choices of interviewees.

Table 2. Interviewees.

	Semi-structured interviews		Structured interviews	
Characteristics	N	%	N	%
Total	18	100.0%	14	100.0%
Current title				
Architect	2	11.1%	3	21.4%
Client	0	0.0%	3	21.4%
Project manager	4	22.2%	1	14.3%
Project engineer	3	16.7%	3	21.4%
	2			
Purchasing	2	11.1%	0	0.0%
Skilled worker	1	11.1%	0	0.0%
Supplier	4	0.06%	2	14.3%
Researcher		22.2%	2	14.3%
Current field of work				
Academic	4	22.2%	2	14.3%
Practitioner	14	77.8%	12	85.7%
Previous experience				
Construction	10	55.6%	8	57.1%
AI	4	22.2%	6	42.9%
Both	4	22.2%	0	0.0%
Other	2	11.1%	0	0.0%

Additional observations were made during a project visit, a tour of the Norsk Gjenvinning plant, and participation in chosen seminars and webinars on the topic of waste reduction and/or AI. These further observations provided an additional understanding of the topic and contributed to the continuous validation of the results.

An analysis of the waste disposal in 161 construction projects was conducted to identify any problematic waste fractions, with respect to total volume, environmental impact or impact on project progress, management, or activities. The analysis utilised the tool *Grønt Ansvar* from Norsk Gjenvinning to provide an overview of disposed waste in terms of volume, weight, degree of sorting, and cost associated with waste management in selected projects (Norsk Gjenvinning, c. 2018). The waste reports are dynamic, and the system can single out selected fractions, amounts, costs, or projects on demand. The projects were deemed relevant for inclusion using the following criteria: used Norsk Gjenvinning for waste disposal through the entire production phase; did not use any other providers for waste disposal; and sufficient availability of further documentation, in case of any follow-up questions for the project or its team members. After this assessment, all projects meeting the criteria were included, as a bigger sample would make the data foundation more representative. For the analysis, the waste fractions were classified and categorised according to the guidelines provided by Norsk Gjenvinning. In addition, a distribution analysis was conducted according to Holme and Solvang (1996), to assess both total waste amounts, and amounts for each of the registered fractions. The biggest fractions were selected for further assessment.

The questionnaire distributed among those responsible for waste management and disposal in construction projects confirmed the findings from the waste-disposal analysis.

The questionnaire contained 25 questions in total, of which 15 were considered open, and 10 closed. The questions were tested before the final distribution. Of the 105 potential respondents who received the questionnaire, 21 of them answered, yielding a response rate of 20%.

Finally, as the study continued to develop, presentation of findings and targeted discussions with selected informants and peer academics were conducted, in order to validate and refine the findings and place them within the context of the field as a whole.

3. Results

3.1 Construction Waste

In many cases, production of waste is the result of inefficient use of materials. Waste production is also costly in terms of both financial concerns and environmental issues. The construction industry is affected by an inherent resistance to change, which could prove to be a significant challenge in the work towards waste reduction (Teo and Loosemore, 2001). The waste management hierarchy (Fig. 1) illustrates the preferred means for reducing waste in the construction industry (NSW EPA, 2014). The hierarchy consists of five levels: prevent, reduce, reuse, recycle, and disposal. The hierarchy is designed to be read from the top down: a measure assigned higher in the hierarchy implies a more sustainable solution. Concepts of the waste hierarchy appear to represent a significant potential for sustainability in the industry.

Several informants emphasise the importance of moving from a cradle-to-grave to a cradle-to-cradle approach and embracing concepts from circular economy in order to truly improve the handling of waste production in the construction industry.

3.1.1 Problematic waste fractions

The most significant waste fractions for the construction industry are cardboard and paper, plastic, and timber, plaster, and mixed waste (Kartam et al., 2004; SSB, 2019). Evaluating the generation of waste in the 161 new building projects confirmed previous findings: the largest or most problematic fractions were identified as timber (34.6% of total waste); mixed waste (27.3%); plaster (17.8%); paper and cardboard (2.7%); and plastic (2.3%). Paper, cardboard, and plastic do not account for large proportions of the total weight, but considering the low material densities of these fractions, it is reasonable to assume their volumes will be significant. The same fractions were also confirmed and highlighted by informants, in interviews and through the questionnaire.

Different amounts and fractions of waste arise in different phases of a project (NHP Network, 2016; Nordby and Wærner, 2017). 'Neste Steg' is a Norwegian framework for construction projects defined by Bygg21 (2015), similar to the RIBA Plan of Work (RIBA Architecture, 2020). Neste Steg specifies eight phases of a construction project: strategic definition; concept development; refining of concept; programming; production; delivery; operation and maintenance; and disposal of the facility. Furthermore, six sub-phases of the production phase can be defined (NHP Network, 2016): excavation; groundworks; framing; exterior finishing; internal finishing and fitting; and furnishing. The two classifications constitute the implementation framework of this study as summarised in Fig. 2.

3.1.2 Perceived potential for waste reduction

Interview informants were asked to identify the activities and processes producing timber waste. Some respondents reported answering the question based on their available statistics on a current project, while others answered based on their experience from previous projects. Carpentry, formwork, deliveries and rig work were identified as the activities that produce the largest amounts of timber waste. Similarly, informants were asked to identify perceived sources of plaster waste. The responses indicated that carpentry and the installation of inner and outer walls are the activities producing the largest amounts of plaster waste.

Most of the waste fractions were reported as arising from large portions of the production phase of a project. The interviewees suggested that to effectively reduce waste, not only should there be a focus on each of the fractions, but also on entire projects. Respondents generally considered large amounts of waste to be unnecessary, and some suggested that the problem is due to a lack of will, motivation, or knowledge.

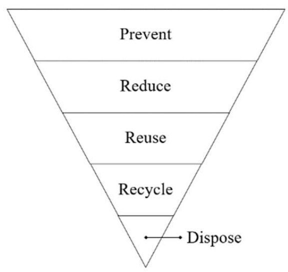


Fig. 1. The waste management hierarchy.

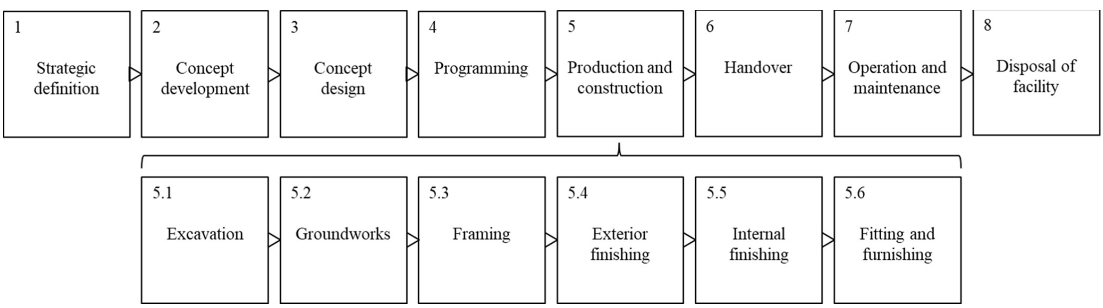


Fig 2. Phases of a construction project (Bygg21, 2015; NHP Network, 2016)

Most of the interviewees highlighted setting out clear objectives as important to create both engagement and a willingness to change. One interviewee believed that such objectives would be particularly valuable if combined with economic incentives, such as bonus-malus.

Incentive schemes that reward good actors and fines that deter careless actors were another measure suggested by numerous interviewees. Economic incentives are seen to be important both in the selection and implementation of measures in all levels of the project organisation and are supported by research (Azizi et al., 2015). One interviewee suggested that such a scheme could be used to reward measures for innovation in waste reduction, while another suggested that bonus-malus in contracts be allocated according to predefined objectives for waste reduction on site. Both emphasised the importance of involving all actors in the development of such solutions and saw a transparent process as essential.

A further general perception among the informants was that there is great value in establishing contact between all involved actors, and start-up meetings and joint reviews of the waste plans for the project or resource optimisation were mentioned as possible supplements to existing project waste plans. Strategically working towards a more collaborative project execution during the earliest project phases was also identified as of particular importance. Unfinished and imprecise contracts, as well as differing expectations between parties, were additionally highlighted as especially challenging with respect to waste reduction. The interviews further revealed that resistance to change is a major challenge on site.

In addition, most respondents mentioned the use of pre-cuts, prefabrications, and modular elements as possible measures. The resulting reduction of cut-offs was considered to be the greatest benefit, especially for timber and plaster. In this context, an interviewee stressed the importance of collaborative strategies in the early phases of a project to ensure it could meet the needs of all involved actors.

One informant emphasised the difference between preventing the production of waste and taking measures to utilise construction site resources after waste had been produced. Other interviewees argued that certain measures could reduce the construction waste on individual sites but would not be effective at the industry level.

Most respondents agreed on the importance of having a tidy, accessible waste station on site, with several interviewees mentioning the sufficient availability of containers as being especially important. The deterioration of materials on site because of weather, vandalism, or theft was also mentioned as a possible source of waste, while others considered the conscious or unconscious neglect of materials by workers to be of greater importance.

The design of a building itself was considered especially important. One informant mentioned late changes in design as one main reason that processes and activities must be repeated, or materials and elements discarded. This can happen due to late availability of information, or late change requests from the customer. Another interviewee mentioned complexity in the design of the building. Furthermore, unclear instructions and specifications were highlighted as problematic.

When asked which measures they believed to hold the most potential for waste reduction, interviewees responded that prefabrication, increased awareness, targeted building design, and contractual demands were among the greatest contributing factors to waste reduction on a construction site.

The systematic shift towards a more sustainable industry has led to an increasing number of techniques, tools, and solutions with the potential for waste reduction.

3.2 Established Tools for Waste Reduction

Certain tools are already established in the industry as suitable for construction site waste reduction. Lean construction, which draws concepts from lean methodology (Koskela et al., 2002; Womack et al., 1991), is a system that aims to maximise value by enhancing quality, improving efficiency, and reducing waste.

Conscious and sustainable design choices contribute to the reduction, and potentially, the avoidance, of waste – use of durable materials, standard sizes, and systems for increased adaptability, disassembly or reuse (Innes, 2004; Zero Waste Scotland, 2016). Measures built on the concepts of circular economy are seen to be an important factor also beyond specific design choices (NSW EPA, 2014). Reuse can be done on site, or elsewhere.

Research suggests a correlation between the level of collaboration in projects, and project performance in terms of cost, time, and quality, implying significant benefits in the use of collaborative strategies for waste reduction (Haaskjold et al., 2020). Increased industrialisation, for instance in the form of prefabrication has also proved to provide benefits in terms of reduced waste quantities on site (Tam et al., 2005).

Digitalisation is considered an important piece in the waste reducing puzzle, especially when aiming to realise the increased use of AI. An important part of the digitization process is the continuous development of tools such as building information models, that can store and display big amounts of data, even beyond the three dimensional digital twin (Charef et al., 2018).

3.3 AI in Construction Projects

Four categories of AI tools in the construction industry can be defined: machine learning (ML), knowledge-based systems, evolutionary algorithms (EAs), and hybrid systems (Akinade, 2017).

ML describes AI techniques that can learn from data (Tidemann, 2019). In the construction field, the ML approaches of artificial neural networks (ANN), support vector machines (SVM), and fuzzy logic (FL) appear to be the most widely employed (Akinade, 2017). Their main strength lies within their ability to handle uncertainty, and work efficiently with incomplete data. Knowledge-based systems mimic human problem-solving expertise to find solutions to complex problems, and possess strong explanation abilities (Sowa, 2000; Akinade, 2017). Commonly employed techniques include expert systems (ES), rule-based systems (RBS), case-based reasoning, and semantic networks (Akinade, 2017). EAs are based on biological evolution (Russel and Norvig, 2010); the techniques utilise an optimisation approach to find the most suitable solution (Dasgupta and Michalewicz, 2013). Among EAs are genetic algorithms (GA), ant colony optimisation (ACO), particle swarm optimisation (PSO), and artificial bee colonies (ABC) (Akinade, 2017). Hybrid systems combine two or more AI techniques to utilise the strengths and overcome the weaknesses of the individual techniques (Russel and Norvig, 2010). Robotics is a fifth, adjacent field. The techniques can all be employed for similar purposes, and can to some extent be said to, for instance, provide support for the human decision maker in design, scheduling, monitoring of progress, or assessing risks; the main difference lies within how the systems are developed, and the input they require.

Previous studies have been conducted on the use of AI in several areas: analysing, forecasting, and managing waste; examining the use of AI supporting the selection of an optimal landfill site and a waste-flow-allocation pattern, to minimise the total system cost related to waste disposal (Cheng et al., 2003); forecasting the generation of municipal solid and mixed waste (Abbasi and Hanandeh, 2016); developing a framework for an AI-based construction waste management system (Ali et al., 2019); and examining how the application of AI in the construction industry can be supported, highlighting the need for laying a sustainable foundation for advanced technologies in buildings (Adio-Moses and Asaolu, 2016).

A recent surge of interest in the topic of AI in construction has also led to an increased number of pilots and proofs of concept in the industry, both on the national and international scales. Experience and lessons learned have been further mapped through interviews, seminars, and discussions.

3.3.1 Waste reduction powered by AI

The interviews conducted illustrate a lack of common understanding and terminology, especially relating to certain technologies and techniques regarding the field of construction and information technology in general, and AI in particular. This can be observed in the informants having highlighted the need to establish unified terminology for effective communication. A general perception among respondents was that there is considerable potential in utilising AI in construction projects and on construction sites, but only two interviewees could point to concrete examples of this being conducted in practice at a larger scale. The interviewees had expectations of increased productivity, increased quality, and savings in time and cost, as well as waste reduction.

Problems with obtaining enough data, as well as data of sufficient quality, were identified as one of the barriers to increasing the use of AI. The relationship between the people involved and the technology was also considered to be critical for the successful implementation of AI-based techniques. One interviewee was especially interested in the potential of virtual reality and augmented reality. Relevant areas of use included tours and inspections; communication and cooperation among the actors in a project; preparation and training; and the possibility for consultants and specialists to visit a site before completion of the project. The majority of interviewees stated that the implementation process is particularly important, as it represents an important transition from traditional to more innovative methods. Fig. 3 illustrates the strategic framework developed for waste reduction powered by AI, drawn from all the findings of this study and validated through interviews, seminars, and discussions.

4. Discussion

The aforementioned techniques and tools can be utilised in new ways, enabling the reduction of previously challenging waste fractions. The following chapter will present the findings yielded from the methodological framework as described in the previous chapter, summarised in 18 recommendations for practical implementation of AI-focussed measures.

Early and explicit definition of appropriate targets for waste production seems to represent significant potential for waste reduction. At present, projects often define targets for sorting degrees; therefore, defining targets should be attainable for waste quantity, by volume or weight. Such a defined target could, for instance, be based on the indicator of kilograms waste per square inch. The indicator could then be divided among the project phases, among construction stages, among buildings within the same site, or within the same building. Including all actors in the project is recommended, for example, by utilising partnering elements such as start-up meetings and physical co-location; these can contribute to the development of a common culture and 'language' among the members of a project team. The target could be measured against other targets within the organisations of the involved actors, or those of other actors within the industry, which would potentially contribute to improved motivation. Appropriate targets could be defined through the utilisation of ML, specifically techniques for regression. An ML algorithm could estimate an appropriate value based on data from previous, comparable projects. Ideally, the algorithm would have access to sufficient amounts of good quality data. In theory, this could be conducted in the very early stages of a project, or during the concept design phase; however, to ensure the greatest possible amount of data, it is recommended that it be implemented during the programming phase (4).

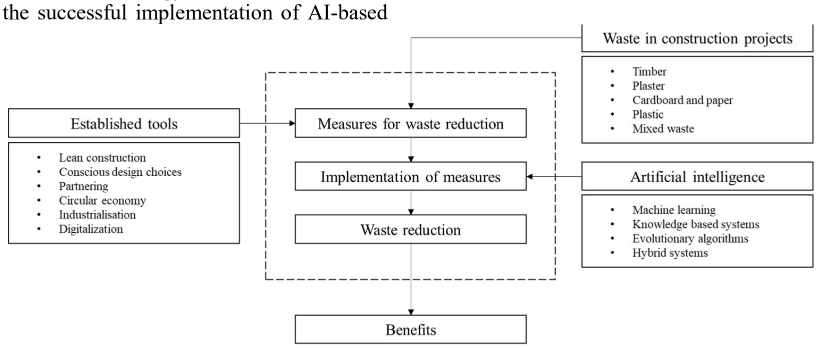


Fig. 3. Strategic framework for waste reduction powered by AI.

Similarly, an early and explicit plan for resource optimisation could be an important step towards more sustainable waste management. A resource optimisation plan should include an overview of which materials each actor plans to work with, an appraisal of potential sources of surplus material, and the ways in which any surplus material could be utilised by other actors on site –and it should be formed in the early stages of the project. A resource optimisation plan would provide benefits in the form of both increased awareness on the topic, and savings of time and money due to the presence of a dynamic plan. Plan development could employ such techniques as generative design in the form of GA, supported by ML, or ANN specifically, to evaluate and choose between alternative plans. The simplest form of generative design is topology optimisation, but more advanced algorithms are built around the same framework. Designs generated by such algorithms have been found to be far more efficient than those created by humans (McKnight, 2017), and are produced in a fraction of the time it takes for humans to create them. Nevertheless, algorithms rely on the quality of the input provided by the user. Furthermore, such an approach would, again, require access to sufficient amounts and quality of data, and it is therefore recommended that the approach be implemented during the programming phase (4).

In order to keep track of and create an understanding of, the full extent of a project's on-site waste production, continuous tracking of waste quantities is desirable. Tracking of waste quantities produced allows on-site production to be adjusted along the way, as a project approaches the defined target for waste production. This would be an important element in a holistic and integral waste management system, as production often happens simultaneously and in parallel at different physical locations. If a project succeeds in the tracking of waste quantities, continuous reporting of waste quantities should be next. Reporting could happen internally to the project team, or externally to staff members in other parts of the business. Similarly, to fully utilise the potential of tracking waste quantities, a project should strive to render a continuous visual presentation of waste quantities on site. Such a presentation could be displayed near any safety, health, and environment boards, in common areas, or near the site entrance. The goal would be to display the numbers to every worker on site, to provide an understanding of the size and scope of the current waste production. Presenting these numbers would be an important step in raising awareness and developing knowledge among personnel on site. For the continuous tracking of waste quantities, ML could be employed to manage sensors and computer vision. These tools could be installed inside and close to any waste stations and containers on site, and could contribute by weighing the waste or visually estimating remaining space. The biggest perceived benefit from such a system would be its ability to communicate with other systems, such as the project schedule system. A hybrid system based on ML and EAs could help estimate the next necessary emptying of containers and alert the responsible parties. For obvious reasons, this would need to be performed during the production phase (5). However, the system reports could be used for reference in future projects, to enable the knowledge to be utilised in earlier project phases. Existing, established tools – fuelled by AI or not – could be used to generate the reports and presentations.

To enable the reuse of materials and on site, defined routines for warehousing on site are recommended. The construction site needs sufficient capacity to maintain intermediate storage; tidy storage would also reduce the need for the placement of unnecessary orders, as it would be easier to track any already-available materials on site. Thus, defined routines for ordering materials would also be beneficial. A lean approach to the ordering of materials is one of many ways a lean mindset can be brought to construction sites. Maintaining such functions and routines may require significant resources. Similarly, increasing volumes and frequency of orders will increase transport emissions; therefore, such conditions should be considered for each project. Routines for warehousing on site could be designed based on information gathered by ML-supported sensors and computer vision. Moreover, routines could, again, be established based upon generative design techniques, such as utilising decision support in determining storage unit layout. The measure should be initiated during the programming phase (4) and continued through production (5). The ordering itself could technically be done by AI-powered tools, for example, based upon natural language processing. However, the results of this study suggest the more expedient option is likely utilising AI to estimate appropriate timing for the next order placement.

Training of all involved personnel seems to represent a significant potential for waste reduction. Proper training could reduce wasted time and potential savings in materials. Tools such as virtual and augmented reality, combined with a digital twin, enable virtual visits to the finished building – and the construction site itself – in advance. This could, for example, be utilised to instruct skilled workers in specific processes that are known to produce waste. Combining virtual and augmented reality with ML allows visitors to interact with their surroundings when exploring a digital twin. Ideally, the training of actors on all levels would happen independently of the individual project; if this is not the case, it is desirable to start the training as soon as all subcontractors and suppliers are procured, in the concept design (3) or programming (4) phases.

Several respondents pointed to the need for economic motivations, such as contractual arrangements based on bonus-malus, especially during the early stages of a waste reduction initiative. In such an arrangement, desirable performance and results are rewarded, whereas the actors who do not meet the required targets or expectations must pay. The biggest potential for AI utilisation would be using ML and generative design to identify fitting targets and prerequisites for such an arrangement. This would need to be implemented and established before contractual arrangements are finalised.

To fully benefit from all the benefits expected of digitalisation, and facilitate the increased use of AI, it is recommended to establish a digital platform for all actors in a project. This could serve as a platform for communication among all involved actors, but also as a hub for assembling all available information. Every actor should have access to any information relevant to their field. Establishing a digital experience-sharing platform in the early stages of a project would enable increased use of previous information and experience; this could become an important tool for the assembly and assessment of data from previous projects. Such a digital platform should be linked to a digital twin, as established in the design phases of a project. Ideally, the platform would be able to communicate with other systems, models, sensors, and programs within the project environment; this could make the platform an invaluable tool in the work towards a more sustainable operation. Such a platform would, naturally, be very complex, and built upon several tools; however, the foundational lines of communication could be built on a set of ES or RBS. The platform should be established as soon as all subcontractors and suppliers are procured, continued through the production phase—and brought into future projects, where it can be utilised as early as in the strategic definition (1) or concept development (2) phases.

Carrying out inspections during all phases of production (5) is desirable, as some type of surveillance will be crucial in the implementation and auditing of any other recommended measure. Inspections could also prove critical, to avoid faults resulting from a lack of communication among involved actors. During the early phases of the project, inspections could be executed with virtual and augmented reality, supported by AI. This could prove especially valuable in the earliest phases, as concepts, design, and plans appear the most distant in these stages. Such environments can also be used during later phases, provided the digital twin is updated throughout the project. This could reduce, or even eliminate, the need for physical inspections on site, as could the use of autonomous robots, computer vision, and sensors.

Functional layout planning of a construction site can increase efficiency and decrease faults, and can be achieved in numerous ways: defining areas for deliveries; establishing functional production lines for certain processes and activities; planning according to the availability of waste stations and containers; and planning according to the area covered by cranes. Layout planning should be powered by the use of generative design.

Increased use of digital tools to order more accurate quantities of materials is especially relevant for such waste fractions as wood and plaster and should be implemented as part of the concept design (3). These fractions are dictated by the design and architectural choices, to a greater extent than fractions like plastic. This measure, once again, depends on the continuous revision and availability of the digital twin. By marking orders and materials arriving on site according to the digital twin, waste could, potentially, be reduced even more drastically. Marking could, for example, be performed using barcodes, perhaps in collaboration with relevant suppliers. Such a system could be built upon a set of ES or RBS.

Several interviewees highlighted the potential of certain design choices during the early phases of project development. This is supported by the literature (Innes, 2004; Zero Waste Scotland, 2016). One approach would be to design for standardised elements, in which the building itself is designed to fit standard sizes of materials, such as given lengths of wood, or given areas of plasterboards. Another approach would be to design for the use of cut-offs, in which the possibility to use cut-offs produced on site is examined in the design phase. A third approach would be to design for shared geometry, in which several areas or sections of buildings are designed according to the same geometrical properties; this could even reduce the risk of wrongly manufacturing materials and elements, even further decreasing the amount of waste produced. These design approaches are especially relevant for such fractions as wood and plaster, as these materials are often delivered in standard sizes.

Table 3. Recommendations for implementation of waste reduction measures.

#	Recommended measures for waste reduction	Technique	Phase
1	Early and explicit definition of appropriate targets for waste reduction	ML (regression)	4
2	Early and explicit plan for resource optimisation	ML (ANN), EA (GA)	4
3	Continuous tracking of waste quantities		
4	Continuous reporting of waste quantities	ML (ANN)	5 (3,4)
5	Continuous and visual presentation of waste quantities on site		
6	Defining routines for warehousing on site	ML (ANN), EA (GA)	4,5
7	Defining routines for ordering materials		
8	Training of all involved personnel	ML	3,4
9	Contractual arrangements based on bonus-malus	ML (regression)	3
10	Establishing a digital platform for all actors in the project	ES (RBS)	1,2,3,4,5
11	Establishing a digital platform for experience-sharing		
12	Inspections during all production phases	ML (ANN), EA (GA)	5
13	Layout planning during all production phases		
14	Increased use of digital tools for ordering more accurate quantities of materials	ES (RBS)	5
15	Marking orders and materials arriving on site		
16	Design for standardised elements		
17	Design for the use of cut-offs	EA (GA)	2
18	Design for shared geometry		

According to interviewees, generative design has proven efficient in the design phase. The field of design seems to be of particular interest, both among academics and practitioners. The traditional design process is described by the informants as linear, reliable, and robust but with several drawbacks; for practitioners, one of the more obvious shortcomings is the use of cost and time resources.

A few interviewees suggested that time pressure in early project phases is problematic, as this often forces a project team to make decisions based on relatively little information. In this regard, techniques based on AI would be especially helpful, as, given the necessary input, they can swiftly generate hundreds of possible solutions. Some suggest that this could also help avoid certain late design changes that traditionally follow shifts in user demands. Decisions on the design of a building itself should be implemented as soon as all necessary information is available; this will naturally vary among individual projects, but concept development (2) could provide a basis.

Table 3 summarises the 18 recommended measures and their implementation. The recommended phases are numbered as per the framework in Fig. 2. Because most complete AI techniques and tools would comprise more than one form of AI and thus be hybrid models, the dominant system or technique is denoted.

An important topic of discussion when considering waste reduction is the definition of system boundaries for the analysis; for example, if the waste production is to be assessed for each project, or as a part of a bigger system and cycle. For a given analysis, certain measures will yield benefits depending on the system boundaries chosen for analysis. Such measures may reduce the amount of waste reduced on site, but not necessarily do so from a holistic perspective. One such measure is an increased degree of waste sorting on site, which will, naturally, reduce the amount of mixed waste, but not necessarily contribute to reducing the total amount of waste in the project. It will enable an increased degree of recycling, the second to last level in the waste hierarchy. Other examples include returning packaging to the respective suppliers following deliveries, and the increased use of prefabricated and pre-cut elements. The volumes of waste fractions such as timber and plaster will benefit from such on-site measures, but the waste will simply be moved elsewhere – even if the evidence suggests that the total amounts of waste will be reduced compared to production by more traditional methods.

Initially, the implementation of new measures and technology will require an investment cost. However, the consensus is that the savings provided by the same measures and techniques will exceed the costs within a relatively short timeframe. Implementation of such measures should be based on the assessment of expected benefits for each project.

5. Conclusion

The purpose of this study was to examine how AI can reduce waste on construction sites. The recommendations provide a practical approach to reducing waste, complementing the existing body of more theoretically based assessments. Through a broad research design based on analysis of existing literature, waste data, and involvement of actors from multiple parts of the value chain, the study identifies 18 recommended measures, presented in Table 3, for construction site waste reduction.

Benefits regarding increased sustainability are expected. A decreased carbon footprint, and decreased consumption of resources, are direct consequences of reducing waste on site. To accurately assess and understand the benefits associated with specific measures or combinations thereof, a mapping of actual implementation is recommended.

The increased use of AI in construction projects will require investment, especially during the early phases of implementation and introduction. As the cost of data processing continues to decrease and interest within the field continues to increase – bringing more available and commercialised solutions – it is reasonable to assume the cost will decrease dramatically.

The findings suggest that to fully utilise the potential of AI-based techniques, the construction industry would need to build upon existing methodologies and strategies; however, it would need to eventually reinvent and redefine the most traditional project models, contracts, business models, and enterprises. This is a comprehensive task and should involve key actors in all parts of the value chain. Another useful undertaking would be to study in closer detail how data of sufficient quantity and quality should be collected and structured to enable AI to efficiently utilise it.

A valuable option for further work could be to examine the implications that identified measures will have for other actors: for example, how certain design choices may affect other architectural principles and solutions. Another extension of the theoretical approach of this study could be a case study to further investigate the identified measures and test them in practice. Finally, the measures for certain processes or activities could also be selected for testing, providing an opportunity to vet any effects of each measure – or combinations of measures – before the measures are implemented on a larger scale.

6. Acknowledgements

The authors would like to thank Professor Nils Olsson at the Norwegian University of Science and Technology for support during this research. The authors are also grateful for the support provided by personnel from Skanska Norge and Construction City Cluster.

References

Abbasi, M. and Hanandeh, A. E. (2016). Forecasting municipal solid waste generation using artificial intelligence modelling approaches. *Waste Management*. 56, 13-22. DOI: 10.1016/j.wasman.2016.05.018

Adio-Moses, D. and Asaolu, O. S. (2016). Artificial Intelligence for Sustainable Development of Intelligence Buildings. 9th cidb Postgraduate Conference.

Akinade, O. O. (2017). *BIM-based software for construction waste analytics using artificial intelligence hybrid models*. Doctoral thesis. University of the West of England.

Ali, T. H., Akhund, M. A., Memon, N. A., Memon, A. H., Imad, H. U., and Khahro, S. H. (2019) Application of Artificial Intelligence in Construction Waste Management. 8th International Conference on Industrial Technology and Management, 50-55.

Avfall Norge (2016). Avfalls- og gjenvinningsbransjens veikart for sirkulærøkonomi (The waste and recycling roadmap to circular economy). Report. Retrieved from https://s3-eu-west-1.amazonaws.com/avfall-norge-no/dokumenter/2016-XX-Avfalls-og-gjenvinningsbransjens-veikart-for-en-sirkulaer-okonomi_2021-01-25-211229.pdf?mtime=20210125221229&focal=none on August 17, 2019.

Azizi, N. Z. M., Abidin, N. Z., Raofuddin, A. (2015). Identification of soft cost elements in green projects: exploring expert's experience. *Procedia—Social and Behavioural Sciences*. 170. 18-26. DOI:10.1016/j.sbspro.2015.01.009.

Becqué, R., Mackres, E., Layke, J., Aden, N., Liu, S., Managan, K., Nesler, C., Mazur-Stommen, S., Petrichenko, K., and Graham, P. (2016). Accelerating Building Efficiency. Eight Actions for Urban Leaders. World Resources Institute: WRI Ross Center for Sustainable Cities.

Bygg21. (2015). Veileder for fasenormen 'Neste Steg'. Et felles rammeverk for norske byggeprosesser (Guide for the phase norm 'Next Step'. A common framework for Norwegian construction processes).

Charef, R., Alaka, H. and Emmitt, S. (2018). Beyond the third dimension of BIM: A systematic review of literature and assessment of professional views. *Journal of Building Engineering*. 19(1), 242-257. DOI: 10.1016/j.jobe.2018.04.028

Cheng, S., Chan, C. W., and Huang, G. H. (2003). An integrated multi-criteria decision analysis and inexact mixed integer linear programming approach for solid waste management. *Engineering Applications of Artificial Intelligence*. 16(5-6), 543-553. DOI: 10.1016/S0952-1976(03)00069-1

Dasgupta, D. and Michalewicz, Z. (2013). Evolutionary algorithms in engineering applications. Springer: Berlin.

Dalland, O. (2012). Metode og oppgaveskriving (Method and assignment writing). Oslo: Gyldendal akademisk.

Denzin, N. K. (2012). The logic of naturalistic inquiry. Sociological methods: a sourcebook. Second edition. New York: McGraw-Hill.

Global Alliance for Buildings and Construction (2017) Global Status Report 2017. UN Environment and International Energy Agency. ISBN: 978-92-807-3686-1

Haaskjold, H., Andersen, B., and Langlo, J. A. (2020). In search of Empirical Evidence for the Relationship Between Collaboration and Project Performance. *The Journal of Modern Project Management*. 22(7).

Hjellnes Consult (2015). Plukkanalyser av restavfallskontainere fra byggeplasser (Analysis of mixed waste containers on construction sites).

Holme, I. M. and Solvang, B. K. (1996). Metodevalg og metodebruk (Method selection and method use). Otta: Tano.

Innes, S. (2004). Developing tools for designing out waste pre-site and on-site. Proceedings of Minimising Construction Waste Conference: Developing Resource Efficiency and Waste Minimisation in Design and Construction. DOI: 10.1016/j.sbspro.2012.03.158

Johannessen, A., Tufte, P. A., and Christoffersen, L. (2016). Introduksjon til samfunnsvitenskapelig metode (Introduction to social science method). Fifth edition. Oslo: Abstrakt forlag.

Kartam, N., Al-Mutairi, N., Al-Ghusain, I., and Al-Humoud, J. (2004). Environmental management of construction and demolition waste in Kuwait. *Waste Management*. 24(10): 1049-1059. DOI: 10.1016/j.wasman.2004.06.003

Koskela, L. J., Ballard, G., Howell, G., and Tommelein, I. (2002). The foundations of lean construction. *Design and Construction: Building in Value*. 211-226.

Love, P. E. D., Holt, G. D. and Li, H. (2002). Triangulation in construction management research. *Engineering, Construction, and Architectural Management*. 9(4). 294-303. DOI: 10.1108/eb021224

McKnight, M. (2017). Generative Design: What it is? How is it Being Used? DesTech Conference Proceedings. 259-261. DOI: 10.18502/keg.v2i2.612

Mejlænder-Larsen Ø. *The use of project execution models and BIM in oil and gas projects: searching for relevant improvements for construction*. Doctoral thesis. Norges teknisk-naturvitenskapelige universitet.

Moen, J. R. (2017). Article: Avfallsfrie byggeplasser (Waste-free construction sites). Retrieved from http://www.bygg.no/article/1325023 on June 20, 2019.

NHP Network. Nettverk for gjennomføring av Nasjonal handlingsplan for bygg- og anleggsavfall (Network for National Action Plan implementation for construction and demolition waste) (2016) Avfallshåndtering på byggeplass (Waste Management on Construction Site)

Norsk Gjenvinning (c. 2018). Grønt Ansvar. Retrieved from https://www.norskgjenvinning.no/bedrift/pakkeloesninger/groent-ansvar/ on July 7, 2019.

Nordby, A. S. and Wærner, E. R. (2017). Hvordan planlegge for mindre avfall. En veileder for å redusere avfallsgenerering i byggeprosjekter.

New South Wales Environment Protection Authority (NSW EPA) (2014). EPA Waste Delivery Plan. Retrieved from https://www.epa.nsw.gov.au/-/media/epa/corporate-site/resources/wastestrategy/140876-warr-strategy-14-21.pdf on February 22, 2022.

Olerud, K. (2019). Grønt skifte. Store norske leksikon. Retrieved from https://snl.no/gr%C3%B8nt_skifte on September 15, 2019.

Osmani, M. (2011). Waste. A Handbook for Management. Chapter 15. Construction Waste. DOI: 10.1016/B978-0-12-381475-3.10015-4

Osmani, M. (2012). Construction waste minimization in the UK: Current pressures for change and approaches. *Social and Behavioral Sciences*. 40. 37-40. DOI: 10.1016/j.sbspro.2012.03.158

RIBA Architecture. (2020). *RIBA Plan of Work 2020 Overview*. RIBA: London.

Russel, S. J. and Norvig, P. (2010) *Artificial Intelligence. A modern approach.* Third edition. Upper Saddle River, New Jersey: Pearson Education.

Rønningen, O. (2000) Bygg- og anleggsavfall. Avfall fra nybygging, rehabilitering og rivning. Resultater og metoder. (Construction waste. Waste from new buildings, rehabilitation and demolition. Results and methods). Statistisk Sentralbyrå (Statistics Norway): Oslo.

Skoyles, E. R. and Skoyles, J. R. (1987) Waste prevention on site. Mitchell: London.

Sowa, J. F. (2000) Knowledge representation. First edition. Pacific Grove: Brooks.

SSB. (2019). Avfall fra byggeaktivitet (Waste from construction activities). Retrieved from https://www.ssb.no/avfbygganl on June 14, 2019.

Sørnes, K., Nordby, A. S., Fjeldheim, H., Hashem, S. M. B, Mysen, M., and Schlanbusch R. D. (2014). Anbefalinger ved ombruk av byggematerialer.

Tam C. M., Tam V. W. Y., Chan J. K. W., and Ng W. C. Y. (2005). Prefabrication to minimise construction waste—a case study approach. *International Journal of Construction Management*. 5(1): 19-101. doi:10.1080/15623599.2005.10773069.

Teo, M. M. and Loosemore, M. (2001). A theory of waste behaviour in the construction industry. *Construction Management and Economics*. 19(7), 741-751. DOI: 10.1080/01446190110067037

Thaagard, T. (2013) Systematikk og innlevelse. En innføring i kvalitativ metode. (Systematics and empathy. An introduction to qualitative method). Fourth Edition. Fagbokforlaget: Bergen.

Tidemann, A. (2019). Maskinlæring (Machine Learning). Retrieved from https://snl.no/maskinl%C3%A6ring on February 18, 2020.

Tjora, A. (2017). Kvalitative forskningsmetoder i praksis (Qualitative research mehods in practice). 3rd edition. Oslo: Gyldendal Akademisk.

United Nations. (2021). *The Sustainable Development Goals Report 2021*.

Womack, J. P., Jones, D. T., and Roos, D. (1991). The Machine that Changed the World: The Story of Lean Production. New York: MacMillan Publishing.

Zero Waste Scotland (2016) Designing out Construction Waste. Report. European Regional Development Fund. Retrieved from https://www.zerowastescotland.org.uk/sites/default/files/Designing%20Out%20Construction%20Waste%20Guide_0.pdf on February 22, 2022.

Sofie Bang is a Ph.D. Candidate at the Norwegian University of Science and Technology. The Ph.D. is conducted in collaboration with Construction City Cluster and explores and maps the opportunities, challenges, and future outlooks associated with the increased use of artificial intelligence in construction projects. Bang holds an MSc in Mechanical Engineering, with a specialisation in Project and Quality management. Her research interests include artificial intelligence, construction, project management, and sustainability.

Bjørn Andersen is a professor of quality and project management at the Norwegian University of Technology and Science. He has authored/co-authored around 20 books and numerous papers for international journals and conferences, in total more than 300 publications. He has managed and been involved in several national and international research and implementation projects. He serves as Director of Project Norway, is an Academic in the International Academy of Quality, is co-editor of the journal Production Planning & Control and reviewer for several other journals and conferences and directs the NTNU master program in mechanical engineering.

Appendix III

Paper III

«Application of Machine Learning to Limited Datasets: Prediction of Project Success»

Published in: Journal of Information Technology in Construction
ISSN: 1874-4753

www.itcon.org - Journal of Information Technology in Construction - ISSN 1874-4753

APPLICATION OF MACHINE LEARNING TO LIMITED DATASETS: PREDICTION OF PROJECT SUCCESS

SUBMITTED: February 2022
REVISED: June 2022
PUBLISHED: July 2022
EDITOR: Žiga Turk
DOI: 10.36680/j.itcon.2022.036

Sofie Bang, PhD Candidate,
Norwegian University of Science and Technology (NTNU);
sofie.bang@ntnu.no (corresponding author)

Magnus O. Aarvold, Researcher,
Norwegian University of Science and Technology (NTNU)

Wilhelm J. Hartvig, Researcher,
Norwegian University of Science and Technology (NTNU)

Nils O. E. Olsson, Professor,
Norwegian University of Science and Technology (NTNU)

Antoine Rauzy, Professor,
Norwegian University of Science and Technology (NTNU)

SUMMARY: *Much research is conducted on the importance of success factors. This study contributes to the body of knowledge by using artificial intelligence (AI), specifically machine learning (ML), to analyse success factors through data from construction projects. Previously conducted studies have explored the use of AI to predict project success and identify important success factors in projects; however, to the extent of the authors' knowledge, no studies have implemented the same method as this study. This study conducts quantitative analysis on a sample of 160 Norwegian construction projects, with data obtained from a detailed questionnaire delivered to relevant project team members. The method utilises ML through a Random Forest Classifier (RFC). The findings obtained from the analysis show that it is possible to use AI and ML on a limited dataset. Furthermore, the findings show that it is possible to identify the most important success factors for the projects in question with the developed model. The findings suggest that a group of selected processes is more important than others to achieve success. The identified success factors support the theoretically acknowledged importance of thorough and early planning and analysis, complexity throughout the project, leadership involvement, and processes supporting project success.*

KEYWORDS: *artificial intelligence; limited datasets; machine learning; predictive modelling; project management success; project success; random forest classifier; success factors*

REFERENCE: *Sofie Bang, Magnus O. Aarvold, Wilhelm J. Hartvig, Nils O. E. Olsson, Antoine Rauzy (2022). Application of machine learning to limited datasets: prediction of project success. Journal of Information Technology in Construction (ITcon), Vol. 27, pg. 732-755, DOI: 10.36680/j.itcon.2022.036*

1. INTRODUCTION

Over the recent years, AI has made a significant impact in the industries where it is applied; including manufacturing (Lee et al., 2018), energy (Sozontov, Ivanova and Gibadullin, 2019), agriculture (Misra et al., 2020), and petroleum (Rahmanifard and Plaksina, 2019), among others. The construction industry has increasingly applied new technology to digitise and digitalise the workflow but remains in a nascent stage (Oliver Wyman, 2018). This study explores how AI can be utilised to analyse a selection of project data to identify important success factors in a project and addresses the following two research questions:

- RQ1: How can AI, specifically ML, be applied to analyse limited datasets from project evaluations?
- RQ2: Based on such an analysis, what are the most important factors for project success?

Project success is fundamental to the competitiveness of a company. Multiple definitions of project success exist, and there are different types of success within one project (Hussein, 2016). Despite the potential that is demonstrated to lie within AI, evidence shows that the construction industry lags behind other sectors, both in terms of productivity and the adoption of new technology (McKinsey Global Institute, 2017). New technology and tools, along with new areas of applications are constantly delivered to the market, and AI-based technology has recently regained momentum (Loureiro, Guerreiro and Tussyadiah, 2020). The industry operates with small margins, and the need to implement new, smart technology to accommodate the market is recognised (Deloitte AI Institute, 2020). Research suggests that technology and areas of applications becoming more common could contribute to the adoption in the industry, as well as increased digital maturity (Cubric, 2020).

Success factors relate to different aspects of a project - certain success factors relate to organisational complexity, others to the experience level of the project manager, coordination, or productivity (Chua et al., 1997; dos Santos et al., 2019).

Both academics and practitioners are exploring the use of AI to predict project success and identify critical success factors. Several techniques are utilised in previous (Magaña and Fernández Rodríguez, 2015) including neural networks (Chua et al., 1997; Wang, Yu and Chan, 2012) and regression analysis (Dvir et al., 2006).The body of knowledge on project success and the use of AI in the construction industry is growing. This study will build on the existing body of knowledge to explore the application of ML to a limited dataset and how it can be used to identify critical success factors.

The paper is divided into the following sections. First, the theoretical framework is presented, covering relevant aspects of the three topics of project management, project success and AI in construction. The following section describes the methodology of the study, including an analysis of the utilised dataset, insights, cleaning, splitting of data, and ultimately implementation of ML. Subsequently, the findings are presented, followed by a discussion of the model itself and its findings. Limitations of the study are evaluated, and suggestions for further research are presented. The last section concludes with an assessment of all previous sections.

2. THEORY

2.1 Project Management

A Guide to the Project Management Body of Knowledge (PMBOK) defines a series of knowledge areas that should be inherent in a project (Project Management Institute, 2017): the management of integration, scope, time, cost, quality, human resources, communication, risk, procurement, and stakeholders. Hwang and Ng (2012) identify schedule management and planning, cost management, quality management, human resources management, and communication management as the most important areas. At the same time, the field is constantly developing, and the knowledge requirements for project managers are changing with it, along with fundamental roles and functions in the project team (Russel, Jaelskis and Lawrence, 1997; Edum-Fotwe and McCaffer, 2000). A shift can be seen from the traditional responsibility of technical content of the project, the reliability of the facility and within-cost performance to include additional responsibility in non-engineering knowledge to meet expectations and demands for professionalism and expertise.

The majority of projects experience cost and time overruns to some extent, despite the availability of project control techniques and the increased utilisation of digital tools (KPMG, 2015; Project Management Institute, 2018). A report from McKinsey Global Institute (2017) indicates that the rate of productivity in the construction industry has been stagnant and thus remained at the same level for decades. Nationally, the Norwegian construction industry has seen a 10% decrease in productivity from 2000 to 2016, whereas the total productivity in mainland Norway has increased by 30% in the same period (Todsen, 2018). This evidence supports the need to elevate the efficiency of these sectors, and research suggests the field and the industry is ready for disruption (Agarwal et al., 2016; Assaad, El-Adaway and Abotaleb, 2020).

Increased digitalisation and introductions of new technology are already making waves in the industry (Vikan, 2018; Brekkhus, 2017). Adapting to new conditions and circumstances is crucial to maintaining a lasting and sustainable industry.

2.2 Project Success

According to Ika (2009), the research on project success can be divided into project success criteria or critical success factors (CSFs). The findings suggest that the definition of project success has evolved. Definitions have traditionally been based on the iron triangle, including time, cost, and quality. Later definitions are seen to include more dimensions of the projects, such as their relation to stakeholders, project team, and end-user, as well as strategic objectives.

Hussein (2016) suggests a difference between the factors necessary to achieve project management success, project success, and long-term strategic success. The same distinction between project management success and strategic success seems to be supported by the literature in general, among others, Samset and Volden (2016). Project management success is generally seen to relate to the fulfilment of project objectives (de Wit, 1988) and traditional measurements of time, cost, and quality (Radujkovic and Sjekavica, 2017). These are easily quantifiable. Therefore, project management success (hereby referred to as 'project success') constitutes the foundation for this study.

A success factor is, by definition, a condition, event, or circumstance that contributes to project success. Certain success factors are attributed to specific project characteristics (Hussein, 2016); for instance, if there is organisational complexity in the project structure, the project will need (1) a good flow of information, (2) clear roles and responsibilities, and (3) project manager authority in order to achieve success. Chua et al. (1997) identified eight significant success factors for predicting success, in descending order of significance:

- Number of organisational levels between project manager and craftsmen
- Percentage of the detailed design completed at construction start
- Frequency of control meetings during the construction phase
- Number of budget updates per year
- Implementation of constructability program
- Project-team-turnover rate
- Control system budget
- Project manager's technical experience in a project with similar technology

2.3 AI in Projects

The concept of AI has been around for decades (Russell and Norvig, 2003), often associated with science fiction and human-like robots; this has created an inaccurate picture of what AI is. Numerous definitions exist, recent ones including 'the science and engineering of making intelligent machines' (ScienceDaily, 2020) and 'the field of computer science dedicated to solving cognitive problems commonly associated with human intelligence, such as learning, problem-solving and pattern recognition (Marr, 2020). The field experienced a renaissance around 2000 and has since sparked the debate on whether the increased interest is a 'hype' or a necessary step for businesses to maintain a competitive advantage (Walch, 2020). In the construction context, AI systems can be grouped into four categories: machine learning, knowledge-based systems, evolutionary algorithms and hybrid systems (Akinade, 2017).

Automated project management (APM) is the automation of software development tasks, typically organised as software projects (Campbell and Terwilliger, 1986). In general terms, APM contains all approaches for automating project management tasks and activities (Auth, Jokisch and Dürk, 2019). The expectations of what AI can do still exceed the current possibilities that lie within the technology, and the broad and dynamic field of tasks of a project manager can currently only be automated in limited, clearly defined areas. Niu et al. (2019) highlight the potential of using AI for project managers to be more accurate, precise, and swift, and argue that smart construction objects can be effective tools for data collection, information processing, and decision support. In addition to characteristics that differ between individual projects, such as planning and reporting, the project manager relies on knowledge from previous projects. This information can be categorised as tacit knowledge. To utilise such knowledge in an AI context, the information contained needs to be made explicit. Kowalski et al. (2012) explore the use of AI as a tool for decision-making with input of know-how in the form of natural language.

Among the major challenges seen in overrun construction projects is delay risk, the time overrun from the date agreed upon for delivery (Assaf and Al-Hejji, 2005). Yaseen, Salih and Al-Ansari (2005) analysed prediction of risk delay using a hybrid AI model, using genetic algorithms and a Random Forest model. The model was proved to handle the nonlinearity and complexity of data used and demonstrated that such models can be utilised in the construction industry. Another demonstration is provided by Worldsensing (2020), connecting civil infrastructures to the Internet of Things (IoT) to continuously monitor assets and analyse risks. Project managers and decision-makers can receive insights into local operations, track relevant key indicators and use gathered information for analyses. Ultimately, these insights can be used to detect anomalies or anticipate needs. GHD (2020) has successfully applied ML on information collected from projects, to provide a dashboard of key measures for the project manager.

3. MATERIALS AND METHODS

This study is based upon a quantitative analysis of data obtained from construction projects, through the tool CII 10-10. The database is built through the project team members' submission of a questionnaire after chosen project phases. The theoretical framework presented in the previous section formed the basis for the preparation of the dataset, to ensure that no data was lost in the process.

The dataset was then loaded into a Python script, where the libraries Pandas, SKLearn, and NumPy were used. When a dataset is loaded into Pandas, it is called a data frame (DF). Figure 1 illustrates the steps of the analysis. First, the original dataset is processed through an exploratory data analysis (EDA) and preliminary cleaning, resulting in an initial DF. This DF is then split into nine purposed DFs before the next steps are carried out in order: main cleaning, labelling, train-test split, scale, train and fit, classification, and lastly analysis and plot of the results.

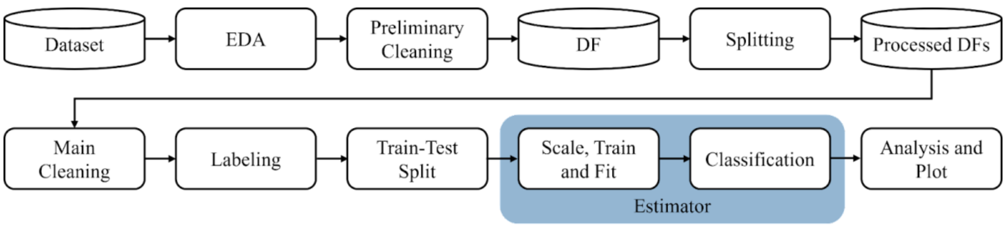


FIG. 1: Flow chart of the utilised methods in this study.

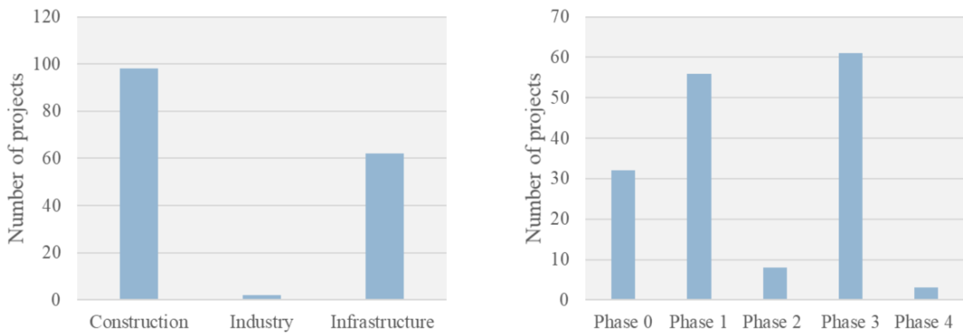
3.1 Dataset

The model was built on data from the CII Nordic 10-10 database. CII 10-10 is a tool for project benchmarking to develop and enhance processes continuously. It is developed and provided by the Construction Industry Institute at the University of Texas and has later been translated to fit the Norwegian construction industry, resulting in the Nordic 10-10 initiative. The tool provides the users with a report that evaluates their project and compares it to relevant projects in the database (Nordic 10-10, 2020). It is ultimately providing a report serving as a foundation for further discussion and improvements, for individual projects, and for the organisation as a whole. It has been proven that participating companies perform better than the industry average (Prosjekt Norge, 2017). The questionnaire used to obtain the data constituting the 10-10 datasets is upon input specified by sector (construction, industry, or infrastructure) and project phase (phases 0 through 4). Consequently, some data points are only relevant to certain sectors or phases. To maximise the number of useful columns within each DF, it was decided to split up the DF.

The 10-10 dataset contains several different features, including the four categories of General descriptive data (G), Output ratings (O), Question scores (Q), and Project ratings (I). The Q-attributes are distinct, and closely related to the project sector and phase. Furthermore, they are divided into two categories, those under 40 and those over 100. The sub-40 questions are binary, while the above 100 questions are ranked on a scale from 1 to 5. For each given Q-attribute, they may only relate to one specific sector or phase. However, as there is more than one respondent for each project, the sub-40 Q-attributes will appear in the database as the average of the respondents' answers, resulting in a scale from 0 to 1.

3.2 Exploratory Data Analysis

A preliminary EDA confirms that the sample of projects comes from three sectors: construction, industry, and infrastructure. The EDA also shows that there were only two projects registered from the industry sector, illustrated in Figure 2(a). This is not enough data points for a meaningful analysis, and the projects contained in the category will consequently be discarded. What remains is the distribution of the remaining 160 projects and their phases, illustrated in Figure 2(b).



(a) Sector count plot. Before discarding industry projects. **(b)** Phase count plot. Sectors combined.

FIG. 2: Count plots, aggregated on sector and phase.

3.3 Preliminary Cleaning

Algorithms for ML only appraise information as numbers. Consequently, columns and rows with a high percentage of missing data must be discarded. The dataset contains nominal numbering, for instance, the number corresponding to the respective phase and sector. In the original dataset, the construction sector is assigned the value '0' and the infrastructure sector is assigned the value '2' in the column called 'G1_Project-Category'. To avoid the inherent sense of scale, being that '2' is bigger than '0', dummy variables were introduced. The mentioned column would be split, where all projects originally assigned '0' would be assigned '1' in a new column called 'G1_Construction'; correspondingly, the projects originally assigned '2' would be assigned '1' in a column called 'G1_Infrastructure'. This procedure is illustrated in Figure 3.

G1_Project-Category
0
2

G1_Construction	G1_Infrastructure
1	0
0	1

G1_Construction
1
0

FIG. 3: Illustration of one-hot-encoding.

The two new columns will contain the same information, only in reverse. This allows for deleting the second of the two columns, while keeping the information contained; this process is called one-hot-encoding. The same procedure is done on the columns corresponding to the phases of the project. As a part of the preliminary cleaning, a few columns were discarded for further analysis, this included columns with a particularly high percentage of missing data, columns containing nominal data types, or deemed irrelevant for the analysis.

3.4 Splitting

The dataset was split between sectors and phases. More precisely, the split first made a copy of the sector DF and split it into each of the project phases. This way, it was not necessary to fill in the missing values, not available (NA) or not a number (NaN). This produced 12 DFs, one for each sector, and one for each of the five phases of each sector. The process is illustrated in Figure 4.

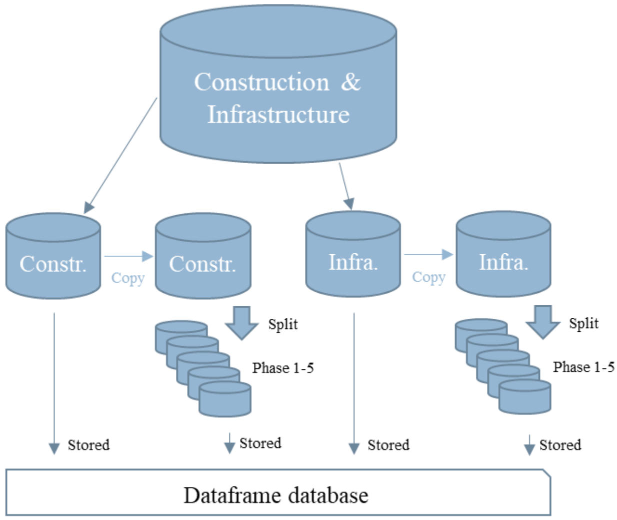


FIG. 4: Splitting and storing of the dataset illustrated.

Subsequently, various combinations of the DFs were evaluated. For instance, one combination was that the same phase from different sectors was joined together, or that phases 1 and 3 within a sector were combined. To keep a low number of DF and sort out the least relevant, only some combinations were further assessed. For example, if a DF had too few projects, or only successes or failures, they were discarded.

3.5 Main Cleaning

Several values were still missing in the DFs, and the next step consisted of investigating the percentage of missing values in each column of each sub-DF. It became apparent that some DFs had one projects missing a substantial number of columns, ultimately polluting the whole DF. A clean DF is one where all cells of the table are filled with legal values. If one cell is missing, the cell can be filled or the whole row or column can be removed. Three options were considered. Firstly, discarding the occurrence that polluted the columns; secondly, discarding the polluted columns; thirdly, filling the gap with an educated guess for the missing value. The third option was undesirable, as it would mean to temper with the datapoint on a limited foundation. Since a big number of different DFs were to be generated from the dataset, the second option was chosen for this model.

Then, a function was made to look for columns where all entries were of the same value. These columns would have provided no value to the estimator; thus, analysing these would mean wasting processing power and time. Therefore, if the function found one or more of these columns, it would remove these from the DF. The model approach to outliers is particularly important, especially for outliers classified as failures. The outliers represent projects that have gone far beyond budget or estimated time.

3.6 Defining Success and Labelling

A scoring system was established. Since project success is being predicted and evaluated, this feature must be explicitly quantified. The theoretical framework suggests that project success as defined in this study is threefold and based upon the three dimensions of 'the iron triangle': time, budget and quality, or specifications. The dimensions reflect whether the project is delivered within the set time frame, and similarly within the set budget and agreed-upon project specifications. The time and cost dimensions are well documented in the 10-10 dataset, in the columns O_01 and O_02 respectively. The values correspond to the percentage increase in cost and time for the given project, summarised in Equations 1 and 2 respectively.

$$\frac{G20\_PhaseRealCost\_MNOK}{G19\_PhaseEstCost\_MNOK} - 1 = O\_01 \quad [1]$$

$$\frac{G22\_RealVarFase}{G21\_EstVarFase} - 1 = O\_02 \quad [2]$$

The resulting output columns will be positive if the real value succeeds the estimated value, and negative otherwise. To quantify the specifications, and whether they were met, the column in the dataset 'Q149' was used. This column reflects the level of customer satisfaction regarding the deliveries of the specified phase on a scale from 1 to 5, as submitted by the questionnaire respondents. This feature was chosen based on the PMI definition of quality, which sees quality as 'how the inherent characteristics actually fulfil the set requirements, and to which degree this occurs' (Project Management Institute, 2017). Customer satisfaction is related to meeting specifications; however, it is not necessarily equivalent, as there could exist scenarios where the customer fails to specify exactly what they need.

The dataset also contains a feature labelled 'I7_Pr', in the CII system denoted 'Quality', which is deducted from other available features. However, the resulting 'Quality' feature is a conglomeration and can therefore be seen as less precise than the 'Q149', as different projects might utilise different combinations of features to determine the 'I7_Pr', even within the same sector and phase. The reason for this choice is further elaborated on in Section 3.7.

To make the scoring of the customer satisfaction compatible with the other two dimensions, the scoring had to be standardised. Therefore, the mean of the column was subtracted from each row, and then divided by the maximum score, which was 5. Equation 3 was used for all rows, in which *i* represents a single row.

$$\frac{Q149_i - Q149_{AVG}}{Q149_{MAX}} = customer\_satisfaction_i \quad [3]$$

The next step was to decide how the three dimensions should be combined to reflect project management success. Three solutions were considered, labelled A, A_fillNA and B.

3.6.1 Project success definition – Solution A

Solution A would quite simply be a summation of the three dimensions. The values of the three dimensions would at this point be of the same magnitude and could therefore be summated. However, positive values of the first two dimensions would negatively impact project success, as they reflect overruns in time and cost. The summation approach stems from the idea that if a project lasted 15% longer than estimated, and the cost was 15% less than estimated, the deviations would cancel each other out. Since positive cost and time dimensions imply longer and more costly projects than estimated, these were summed as a negative value. If the value for customer satisfaction was high, i.e., a value above 3 on the scale from 1 to 5, a good score would be positive after standardisation. Therefore, for the quality dimension, the value was kept positive for the summation. Solution A is illustrated in Equation 4.

$$-O\_01_i - O\_02_i + customer\_satisfaction_i = success\_score\_A_i \quad [4]$$

The next step would be to make the score binary. If the score was higher than 0, the binary score would become 1. Otherwise, it would become 0. A weakness of this method lies within the fact that if one of these features were missing from the dataset, the summation would become NaN, and thus useless. Consequently, many projects would have to be removed if one or more values were missing. One way to combat this would be by the use of the 'fillNa'-function in Pandas. The 'fillNa' function replaces the NaN with a value, so the project does not have to be discarded. Possible values to replace the NaN with are the overall mean, the mean of similar projects, or simply 0. For this examination, the latter was chosen. The 'fillNa' was not taken any further in this study but constitutes a potential for future studies and research. For this model, another solution was chosen.

3.6.2 Project success definition – Solution B

Solution B was classifying the projects through a two out of three (2oo3) voting system. To do this, a function that takes in variables for voting had to be implemented. This function took three arguments: a DF, a list of wanted columns, and a limit. First, the columns of interest, the three aforementioned dimensions, were located in the DF. Second, the function counted the number of not-NaN values in each column. Then, the value of cost and time was compared to the limit value. Different values for the limit were tested and the resulting success and failure counts of each DF were inspected; ultimately, 0 was chosen as the most objective and balanced limit. Successful projects had values equal to or higher than the set value. For the last column, the customer satisfaction, the value was compared with the weighted mean, 3. In this column, the successful projects would have a value equal to or higher than the resulting limit. The next step was to identify the outliers. To do this, the 'empirical two-sigma rule' was utilised, as illustrated in Equation 5.

$$Pr(\mu - 2\sigma \leq X \leq \mu + 2\sigma) \approx 0.9545 \qquad [5]$$

In short, this rule says that an interval containing two standard deviations, σ, away from the mean, μ, covers approximately 95% of the distribution. Thus, the confidence interval will be $\bar{X} \pm 2 \sqrt{\sigma}$ n where n is the sample size which yield the average $\bar{X}$. So, if either the cost or time dimensions value deviated more than 2σ over the mean, the project was classified as an 'outlier - failure'. The second classification was is a 2oo3; if two or more of the dimensions have satisfactory values, the project is classified as a success. After this point, the unassigned projects either have two or more NaNs, or one NaN; this would lead to a tie. If two or more NaN values were found, the project was classified as a '2 or more nan'. These projects werediscarded, as they did not provide enough data points for a 2oo3 voting system to be implemented.

Furthermore, if the function found a NaN value, it investigated how to rule the tie. It checked which dimension were NaN, and the values of the two remaining dimensions. If the NaN value was customer satisfaction, and the remaining two values were of different signs, i.e., '+' and '-' it was classified as a 'tie - 1v1'. Since this is inconclusive, the project was discarded in further analysis. However, if the NaN value was only one of the dimensions, the function investigated the other dimension and compared this to the set limit. If the present dimension was considered satisfactory, meaning negative or 0, the project was classified as a success. If not, the project was classified as a 'tie - 1v1 - failure'. This classification was regarded as a 'failure' later in the function. Lastly, if two or more dimensions are higher than the limit, the project will be classified as a 'failure'. The count plots of all the categories are illustrated in Figure 5.

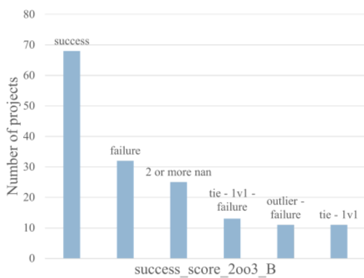


FIG. 5: Before discarding categories '2 or more NaN' and 'tie - 1v1'.

Subsequently, another function inspected the columns produced by solution A, A_fillNA and B. The function translated the classifications into a binary system where '1' denotes a successful project and '0' a failed project. Binary classification was chosen, as the dataset was small and preliminary analysis using regression yielded less than wanted accuracy. Table 1 summarises the count of the remaining projects of each solution. Solution A_fillNA and Solution B has the most remaining projects. Figure 6 illustrates this, showing the 41 projects that are retained within Solution B, but discarded in Solution A due to NaN values. In a small dataset, every project matters, and contributes to providing the model a more stable foundation for training and testing.

TAB. 1: Labels of the different solutions.

Solution	Success	Failure	Total
A	51	30	81
A_fillNA	75	49	124
B	68	56	124

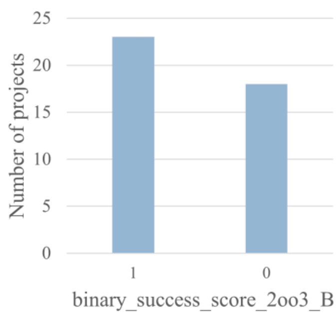


FIG. 6: Count plot of the projects that were 'saved' by switching to Solution B.

A confusion matrix (CM) is plotted in Figure 7. The matrix corresponds to a sensitivity analysis where the two different solutions of labelling are shown. On one axis, the labels from Solution A are plotted; on the other axis, Solution B is plotted. On the main diagonal are the number of projects the two solutions labelled the same. High numbers on the diagonal implies that the solutions agree, which strengthens the reliability and validity of the models. The top right square (1,2) shows the number of projects that are deemed a success by Solution A, and a failure by Solution B; a false positive. The bottom left (2,1) square shows the opposite, false negatives. Solution B appears to be stricter than Solution A and Solution A_fillNA. However, this may not be entirely true, as the matrix only displays the projects that Solution A actually did label.

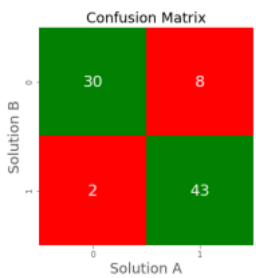


FIG. 7: CM of projects labelled by both solutions A and B.

3.7 Train-Test Split

Following the preceding steps, the DF was cleaned and ready for further analysis. First, the projects were shuffled to remove a possible bias in the original ordering. For the analysis itself, the Python library, SciKit

Learn (SKLearn), was utilised. The set of columns describing the DF labels were discarded, because they are mutually correlated, including the three success dimension columns, the resulting success column, all columns I1-I10 and the four columns on which O_01 (cost) and O_02 (time) are based on.

Already having a small DF to base the model on, the split between train and test data is of even bigger importance. The split process divides the labelled data in two: training and testing. After preliminary testing, an 80-20 split was chosen. It is desirable to retain as much data as possible to train the model, while leaving the model with enough data for testing, and scoring.

There are more successes than failures in the dataset, making the DF unbalanced - it is therefore necessary to stratify the data split. Stratifying ensures that the split of each set is approximately the same as the split of the complete set; if the complete set contains 20% of class 0, both the training and test split will have about 20% samples of class 0.

3.8 Estimator

The choice of an estimator for the model depends on whether the issue at hand is considered a regression or classification problem. Determining if a project is a success or not is a classification problem. The argument could be made that success is a subjective and continuous characteristic, but this model defines success based on the iron triangle, and thus as a binary factor of fail or success.

3.8.1 Scale, train and fit

Since the columns of the data set were of different magnitudes, a scaler was used to scale all columns. For this model, the MinMaxScaler was utilised. The MinMaxScaler scales all features sequentially, to a number between 0 and 1. The scaler was fit based on the training set, and subsequently transformed the test set.

3.8.2 Classification

For classification, several classifiers were tested, including LinearSVC, KNeighbors Classifier, MLPClassifier and Random Forest Classifier (RFC), which was ultimately chosen. A RF model uses multiple decision trees (DT) as the base learner. An inherent attribute of a DT is low bias but high variance. However, as the model aggregates over several DTs, and proceeds to calculate the mean of the DTs, the input variance decreases. The R2 score, the accuracy score, tends to overfit on the training data, yielding a score of 0.90 and higher. It is not desirable for the model to overfit, as this reduces the generalising properties of the model. RF is an ensemble method, meaning that the overfitting is reduced with a higher number of estimators. In this model, 100 DTs are used in each iteration. Additionally, the RFC provides an insight into the attributes of highest importance for the model to find the proposed label, increasing the transparency of the model. This enables an investigation of importance of the individual attribute, on a scale from 0 to 1.

In modelling, the simulated results become more accurate to the true result if the model is run a high number of times (Schwarz, 2015). It was therefore decided to run Monte Carlo Simulations (MCS) on this classifier. MCS introduces randomness to the variables, as well as a high number of iterations to create a nominal distribution of results (Oberle, 2015). From this distribution, a mean can be calculated. A higher number of iterations yields higher quality in the results, ultimately resulting in a higher quality of the mean. The model iterated 10 000 times over each DF. The law of large numbers (Kent State University, 2021) then states that the measured accuracy trends toward a number that is sufficient to use as the true value.

To balance the initially unbalanced datasets, selected functions in the SKLearn library were utilised. First, the built-in parameter called class_weight was set to 'balanced'. Next, the code implemented the built-in function of random search and grid search with cross-validation to find the best hyper parameters, such as max depth and number of estimators. No random state was set since this would counterweigh the effect of the MCS.

Then, the process of fitting was initiated. The fit function further contributed to decreasing the effects of an unbalanced dataset through sample weight. The argument for the sample weight of a function is another function using the training values; this is done to find a balanced class, and thus, sample weight. Upon completion of the fit process, the predicting could commence.

Predictions were stored as the variable 'y_pred' for further analysis. Both the f1-scoring method as well as the CMs use this variable. The built-in method RFC.score() function does not; thus, it does not catch, for instance, true and false-positive predictions. RFC.feature_importances_ were utilised to retrieve the importance score of the features, and then stored in an appropriate format as a new DF. Consequently, this DF was sorted and sliced. Contributors with an importance score below 0.01 were discarded. Based on the f1-score of the prediction, the top five entries from this DF were stored in different tiers of lists. More precisely, if the f1-score was higher than 0.5, it was appended to a specified list. Similarly, if the score was higher than 0.7, 0.8 and 0.9, it was appended to other, respectively specified lists. If the score was higher than 0.8, the CM was also appended , into a list called 'cm_over_80'. When one MCS had reached its set number of iterations, all the lists were saved into another list as a list of top entries. This list, containing up to 10 000 entries, was stored as a single element in a new list; this originated the wording list of lists, as seen in Figure 8. Other lists were also established, summarised in Figure 8.

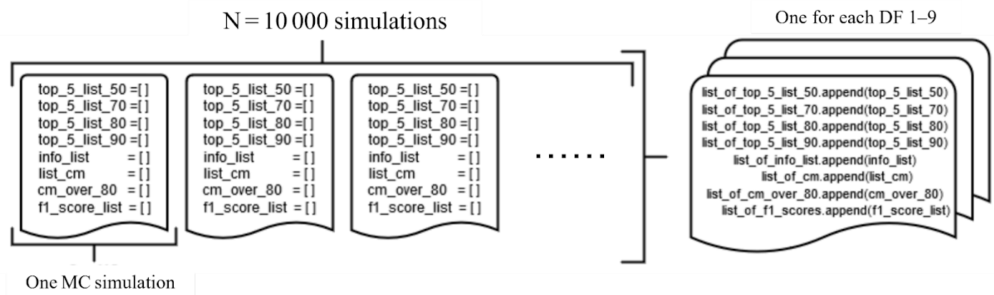


FIG. 8: Illustration of how lists, and lists of lists, are made.

Figure 9 outlines the method in its entirety. Every DF is simulated 10 000 times. In each of these 10 000 iterations, 100 DTs were made. The most accurate tree was used for further analysis, to determine whether the f1-score, the predictive performance of the model, was sufficiently high.

4. RESULTS

Important findings and characteristics of the models are presented in Table 2.

TAB. 2: DF splits and respective characteristics.

DF#	Split	Shape (row,col)	Shape after NaN discards (row,col)	# success	% success	Mean accuracy	Mean f1-score	Mean CM
0	Whole construction sector	(47,296)	(47,51)	28	60	0.54	0.62	[[1.5 2.5] [2.1 3.9]]
1	Whole infrastructure sector	(77,296)	(77,38)	41	53	0.7	0.72	[[4.8 2.2] [2.66 6.34]]
2	Construction phase 1	(22,296)	(22,86)	12	55	0.55	0.62	[[0.75 1.25] [1.01 1.99]]
3	Construction phase 3	(16,296)	(16,105)	12	75	0.69	0.8	[[0.01 0.99] [0.26 2.74]]
4	Infrastructure phase 1	(32,296)	(32,79)	14	44	0.73	0.64	[[3.32 0.68] [1.17 1.83]]
5	Infrastructure phase 3	(28,296)	(28,99)	20	71	0.73	0.81	[[0.83 1.17] [0.45 3.55]]
6	Both sectors only phase 0	(17,296)	(17,80)	7	41	0.48	0.05	[[1.82 0.18] [1.92 0.08]]
7	Both sectors only phase 1	(54,296)	(54,296)	26	48	0.67	0.64	[[3.93 2.07] [1.6 3.4]]
8	Both sectors only phase 3	(44,296)	(44,92)	33	75	0.67	0.78	[[0.45 1.55] [1.44 5.56]]

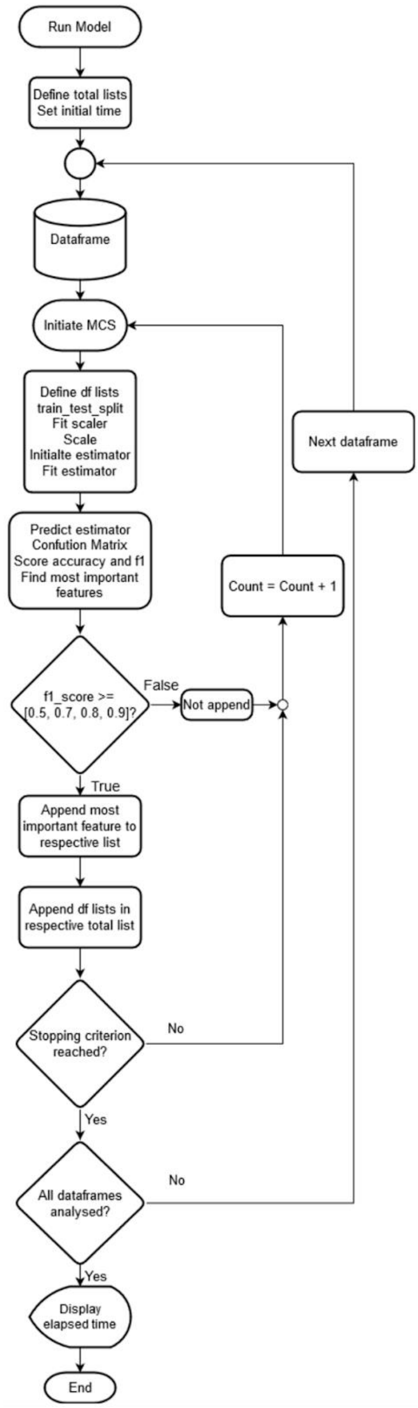


FIG. 9: Flow chart of the MCS and classifier.

The analysis will primarily focus on DFs 1, 4 and 7. These DFs were the ones that yielded the best results from the simulations, as described in the previous section, and are highlighted in Table 2. Since the dataset was limited, it is reasonable to assume not all DFs would be correctly predicted by the base model, even after implementing remedies such as built-in functions like sample weights, stratify and choice of classifier.

As illustrated in Table 2, DF 1, 4 and 7 were the only DFs in which 'Mean F1-score' are relatively large as compared to '% success'. This is further illustrated in Figure 10, where the subtraction of 'Mean F1-score' and '% success' in decimal form is illustrated. The '% success' column shows what a baseline classifier would get as accuracy, if the predictions were purely based on guesses; this means that the proficiency of the developed model will be implied by the Delta, the difference, between these two columns.

Figure 10 illustrates the difference between '% success' and 'Mean f1-score', the Delta. The Delta is the difference between the respective Mean f1-scores and %-success. Worth noting, the Delta score of DF 6 is -0.36, but is cropped out to illustrate the differences of the Delta scores more accurately in the remaining DFs.

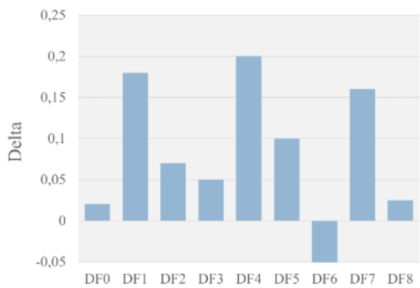


FIG. 10: Bar plot of Delta, converted to decimal value.

The first metrics that were analysed further were the CMs. As mentioned, a high number in the main diagonal is desirable. Element (1,1) is the true negative location in the matrices, and element (2,2) is the true positive location. In the off-diagonal, an as-low-as-possible value is preferable. Only the matrices of DFs 1, 4 and 7 showed a clear connection with this principle and were therefore selected for further analysis. The DFs are illustrated in Figures 11(a)-(c).

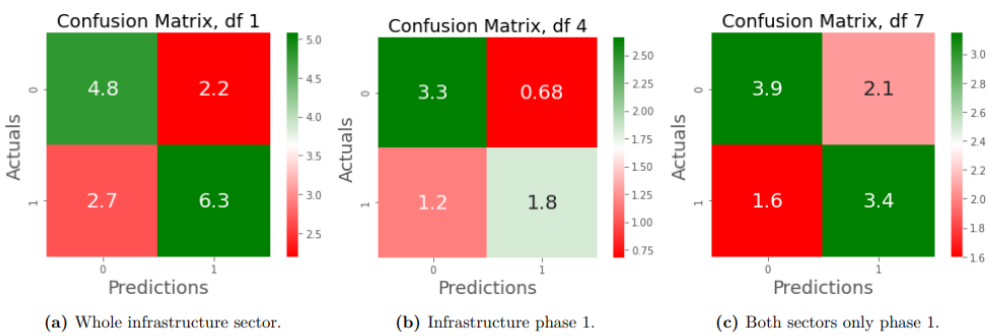
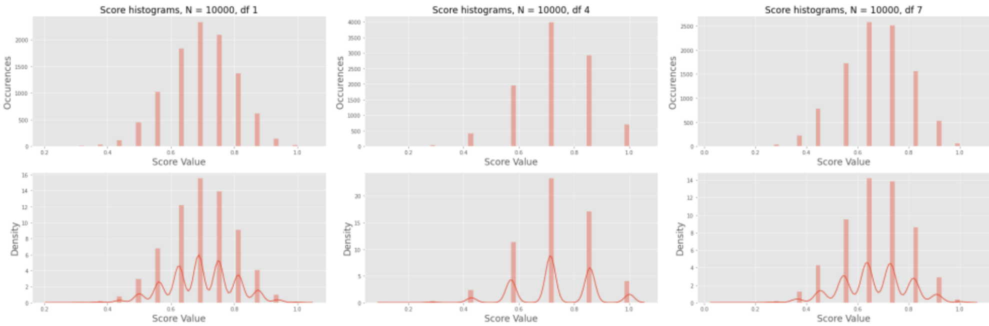


FIG. 11: CMs for DFs 1, 4 and 7.

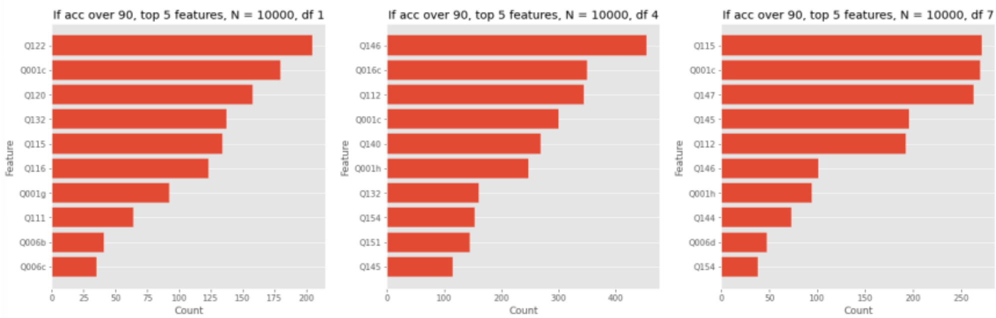
Count- and density plots of the DFs are presented in Figure 12(a)-(c). It becomes apparent that the mean score is quite high. Moreover, the distribution of the bars looks to resemble a bell curve, referring to the inherent characteristics of an MCS (Oberle, 2015). From Table 2, we know that these DFs had a '% success' score of 50 ± 6% as their base score.



(a) Whole infrastructure sector. **(b)** Infrastructure phase 1. **(c)** Both sectors only phase 1.

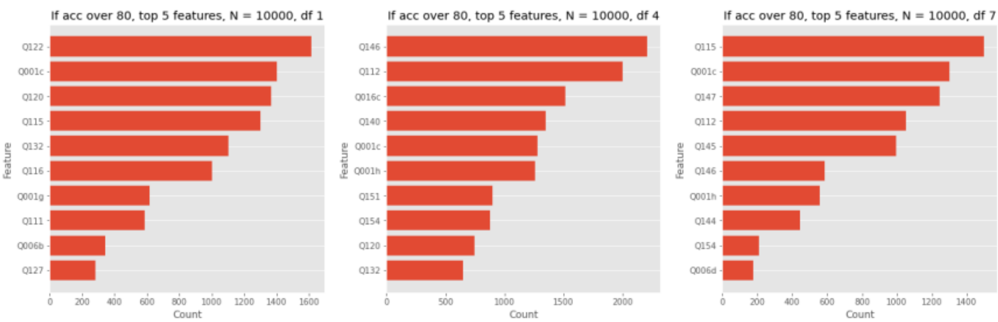
FIG. 12: Count and density plot of DFs 1, 4 and 7.

Figure 13(a)-(c) shows the top five most important features for the three DFs, only collected if the f1-score for the feature was above 80. The count along the x-axis provides an insight into how frequently this occurred during the iterations. For instance, Figure 13(b) shows that both features ‘Q146’ (planning) and ‘Q112’ (planning) was in the top five more than 2000 out of 10 000 times. Similarly, in Figure 14, the highest count is that of Figure 14(b). For these, the threshold for features to be appended is a f1-score of 90; this increase in the threshold limit results in a drastic decrease in the count, approximately five times as low as for DF 4.



(a) Whole infrastructure sector. **(b)** Infrastructure phase 1. **(c)** Both sectors only phase 1.

FIG. 13: Top occurring features from MCS, f1-score over 80 for DFs 1, 4 and 7.



(a) Whole infrastructure sector. **(b)** Infrastructure phase 1. **(c)** Both sectors only phase 1.

FIG. 14: Top occurring features from MCS, f1-score over 90 for DFs 1, 4 and 7.

For Figure 15, the top 10 features of all nine DFs were aggregated and plotted against the number of times the respective feature appeared in all the DFs. The blue bar indicates the number of times the feature appeared in the top 10, and the red bar how many possible times the same feature could have been chosen. The relationship between the two bars is of importance. For instance, the ratio between the bars of ‘Q001c’ (complexity) is the same as the ratio of ‘Q146’ (planning), ‘Q017a’ (measure progression) and ‘Q047’ (cost of quality). Therefore, one could argue that the better features are located on the left side of the plot.

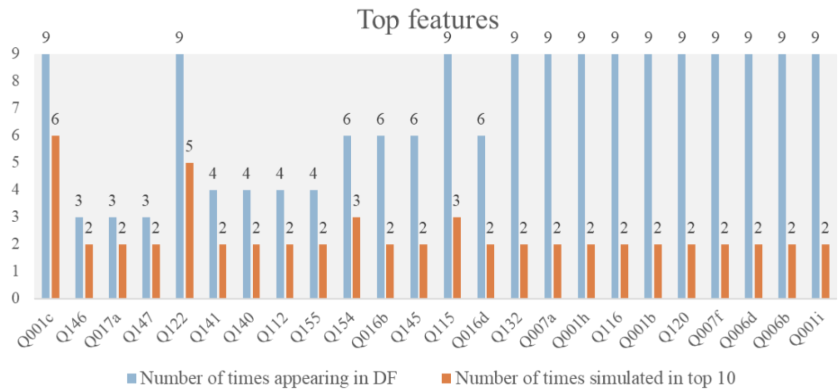


FIG. 15: Top features of top 10, sorted on the ratio between the bars.

Figure 15 illustrates the correlation (Pearson’s r score) between the 24 most occurring features, meaning the features that occurred more than twice in the top 10 in all DFs. In this plot, red indicates a strong positive correlation, while blue indicates a strong negative correlation between the two. The dimmer the colour, the closer the absolute value is to 0, meaning no correlation in either direction. A small correlation is defined as an r score between 0.1 and 0.3 in absolute value. Similarly, a medium correlation is defined between 0.3 and 0.5, and a large correlation over 0.5.

Figure 16 illustrates an example of a DT. This specific tree is collected from one of the many trees in the RF when trying to model DF 1. As the dataset is relatively small, the model can only produce a small tree before the gini value becomes 0.

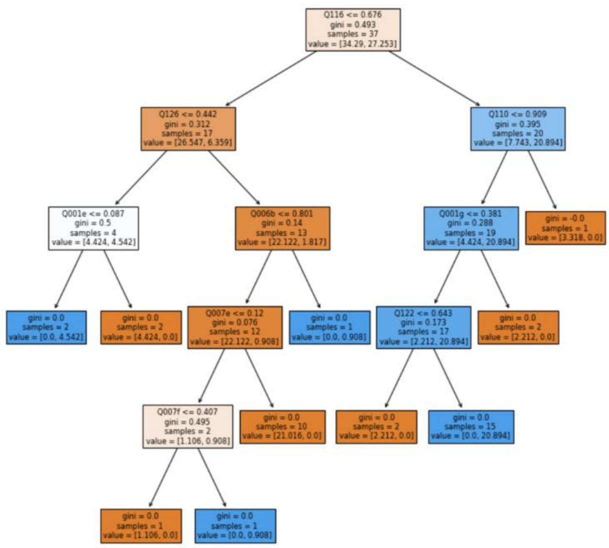


FIG. 16: A single decision tree from the RF for DF 1. Colours indicate which class is in majority of the leaf.

5. DISCUSSION

5.1 ML Model Development

As mentioned, DFs 1, 4 and 7 shows better results in terms of accuracy, representing the infrastructure sector, infrastructure phase 1, and both sectors in phase 1, respectively. Table 2 shows that these DFs are closest to an equilibrium between the number of successes and failures. Worth noting is that infrastructure phase 1 appears in all the top-performing DFs. Therefore, the two other DFs could possibly perform well because they also contain infrastructure 1. However, by inspecting Figure 13, it becomes evident that the most frequently appearing Q-attributes have some differences. For instance, 'Q146' (constructability) is the single most appearing in infrastructure phase 1 but does not appear among the top 10 features in infrastructure as a whole. The same applies in reverse; the most occurring in infrastructure as a whole does not appear in infrastructure phase 1. The top feature for both sectors in phase 1 is 'Q115' (uncertainty analysis); this feature is not among the top 10 in infrastructure phase 1 but appears as the fourth feature for infrastructure as a whole.

Choosing Solution B over Solution A_fillNA may have affected the results. Solution B labelled fewer projects as successful. This could mean that this was a stricter solution. At the same time, this solution labelled 12 projects that would have been discarded by Solution A_fillNA as failures.

The CM of the two solutions A_fillNA and B has been plotted in Figure 17. Comparing this to the CM in Figure 7, it becomes apparent that the two solutions A_fillNA and B share characteristics. Of the 41 gained projects by filling in the NaN, only five are labelled differently. This is found by subtracting the numbers in the off-diagonal, top-right to bottom-left, in the two CMs in question; (11-8) + (4-2) = 5.

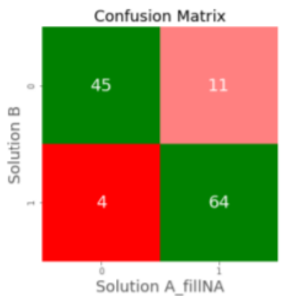


FIG. 17: CM of projects labelled by both solutions A_fillNA and B.

5.2 Identified Success Factors

5.2.1 Most occurring features

Table 3 presents the top features – and by extension, success factors – from DFs 1, 4 and 7. Several features are appearing in two or more DFs. All DFs contain five features of the ten listed. This suggests that certain success factors are of importance both across different project phases and different sectors. For instance, the schedule ('Q001c') leads to high complexity in the engineering phase in both infrastructure and construction, and this appears to be a problem in the infrastructure as a whole. The results in Table 3 illustrates that the top features in DF 7, also appears in DF 1, 4 or in both - the exception is 'Q147' (cost of quality). This could be because the data points in DF 7, as mentioned, also appear in DF 1 and 4. DF 7 could therefore be argued to be a duplicate of the two others. Alternatively, it may indicate that the top features for the engineering phase across all sectors are the same as the top features for engineering in infrastructure, and for infrastructure as a whole.

All features presented in Table 3 seem reasonable in regard to the theory presented in Section 2.2.2. Similarities can be seen in factors addressing involvement from leadership, early planning, structured risk-handling, and implementation of a constructability program. The similarities indicate that it is possible to use ML to obtain the most important success factors, and that the model is performing well.

Multiple listed features relate to the early phases of the project, such as planning, analysis and engineering. This suggests that it could be possible to predict success at an early phase in the project by measuring, reporting, and assessing these features at early stages. Choosing another definition for project success could have yielded different results – and the inability of an owner or a customer to specify their wants and needs explicitly and correctly poses a potential challenge. Additionally, it could be argued that the project quality is in fact the ex-post value created (Haddadi and Johansen, 2019).

TAB. 3: Top features from the best performing DFs with their conceptual meaning.

Feature	Description	Concept	DF
Q001c	The complexity was remarkably high due to the schedule	Complexity	1,4,7
Q016c	The project had a large number of changes in the list of main components	Changes	4
Q112	The tender plan was developed and communicated to the project team during the engineering phase	Planning	4,7
Q115	All necessary and relevant members of the project team were involved in the process of uncertainty analysis	Uncertainty	1,7
Q120	Involvement from the project owner was appropriate	Leadership involvement	1,4
Q122	The project processes and systems support project success	Project owner's process	1
Q132	Members of the project team participated in adequate professional training directly associated with their engineering work	Training	1
Q146	A rich supply of suggestions for improved constructability was evaluated and integrated during the engineering phase	Planning	4,7
Q147	Cost to fix potential faults were considered during the engineering phase	Cost of quality	7

5.2.2 Correlation matrix

Upon inspection of the bivariate correlation matrix in Figure 18, a few observations can be made. The most important features can be compared with the correlation score r to determine if it is a positive or negative attribute, a '+' or '-' correlation. 'Sol B' in this plot is an abbreviation of 'binary_success_score_2oo3_B'. Feature 'Sol B' is seen to have two medium correlations, with the remaining classified as small correlations, if numbers are rounded down (Kent State University, 2021). The features 'Q001c', 'Q016c' and 'Q016e' reflect complexity and uncertainty and are negatively correlated to the 'Sol B' label. This seems reasonable, as a high value of one of these features, like 1, usually means that the 'Sol B' is low, like 0, and therefore classified as a failure. Similarly, features 'Q112', 'Q132', 'Q146' and 'Q147' reflect adequate early analysis and processes and show a positive correlation with the label feature. The same holds true for 'Q120', reflecting leadership involvement, and 'Q122', relating to the extent to which the work processes in the project supports project success.

Figure 18 further illustrates how 'O_01', known as the cost growth, is slightly positively correlated with 'Q001c' (complexity) and 'Q016c' (changes) respectively. Upon investigating 'Q115' (uncertainty) and 'Q120' (leadership involvement) there is a medium-large correlation with the cost growth and customer satisfaction score, 'Q149'. Both are negatively correlated with the cost, which deducts that inclusion of key personnel and project owner aided the project to keep its budget. Furthermore, both features are positively correlated with the customer satisfaction score, suggesting that the customer was happier with the result if these inclusions were present.

Similarly, both 'Q122' (project owner success) and 'Q132' (training) are correlated positively to both cost and customer satisfaction. 'Q122' (project owner success) only has a correlation score of 0.17 with 'Sol B'. This could indicate that the extra cost this causes, deducted from the positive cost growth, does not do as much for the overall project success as defined for the framework of this study. However, it becomes apparent that this affects the customer satisfaction score, with a correlation score of 0.47. The same argument can be made for the 'Q132' feature, which relates to the training of the project team before the engineering phase.

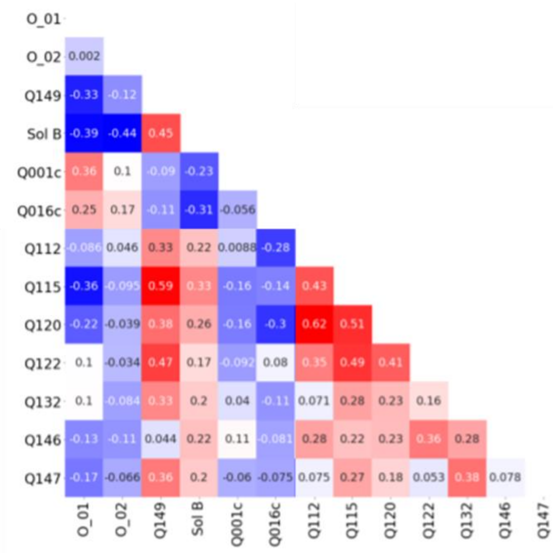


FIG. 18: Correlation matrix of top three features from DFs 1, 4 and 7.

5.2.3 Features between phases

As there is some overlap in the DFs, it is interesting to compare infrastructure as a whole with the single, separate phases of 1 and 3, which infrastructure as a whole is based upon. The correlation of top features between the infrastructure DFs is presented in Table 4.

TAB. 4: Correlation of top features between DFs.

Feature	Infrastructure	Phase 1	Phase 3	Concept
Q001	x	x	x	Complexity
Q122	x	-	x	Project owner's process
Q132	x	x	-	Training
Q115	x	-	-	Uncertainty
Q120	x	x	-	Leadership involvement
Q016	-	x	x	Changes
Q154	-	x	x	Deliver on time
Q146	-	x	-	Planning
Q112	-	x	-	Planning

Some similarities are seen between phases 1 and 3. 'Q154', 'Q001' and 'Q016' are appearing in both top features; however, the dataset shows that they contain different aspects of 'Q001' and 'Q016'. In phase 1, the high complexity is due to the progression plan and diversity in the project team. In phase 3, the complexity is mainly linked to the ability of the supplier to deliver on time.

Five of the top 10 features in phase 3 mainly relate to three features but concern different aspects, namely 'Q016', 'Q001' and 'Q014'. Of these, 'Q016' (numerous deviation reports) occurs over 1000 more times than the runner up. This implies that the quantity of deviation reports is indubitably more important than other features during the building phase of infrastructure projects. Considering that phase 1 represents engineering, it seems reasonable that engineering to a bigger extent is more associated with complexity due to schedule, team diversity, and changes of main components. As phase 3 represents the building phase, it seems reasonable that it is associated with complexity due to the ability of the supplier to deliver on time, along with numerous deviation reports.

As illustrated in Table 4, the top 10 features are mostly reflected in phases 1 and 3, but some are solely in the infrastructure as a whole. These features include ‘Q115’ (uncertainty), ‘Q116’ (changes), ‘Q001g’ (complex scope), ‘Q111’ (trust), ‘Q006b’ (effective meetings), and ‘Q127’ (team aware of goals). In short, these regard the uncertainty analysis, trust and respect across the team, and an adequate flow of information in the project. Even though these only appear in the infrastructure as a whole, they are more conceptual in nature, which is reasonable when analysing multiple project phases. Keeping in mind that 60 of 77 projects in infrastructure are from phases 1 and 3, one could expect more of the same features. However, four of the top five features in infrastructure as a whole also appear in phases 1 and 3. The three most occurring features in infrastructure as a whole are ‘Q122’, ‘Q001c’ and ‘Q120’, representing processes that support project success, complexity due to the schedule, and involvement of the project owner.

Another observation that can be made is that certain top features in phases 1 and 3 do not appear in infrastructure as a whole. As explained, this could be due to the fact that infrastructure as a whole to a bigger degree contains features that are wider in scope.

5.2.4 Theoretical features compared to model findings

The 10-10 dataset contains more than 100 questions touching on the many aspects of project management. Based on the literature addressing project success and success factors, certain questions and features were expected to be among the factors identified as the most important for project success. Ultimately, some of these did not appear as success factors in any results, including*:*

- Q013a-c: Did the main goal of the project change during engineering/procurement/construction?
- Q103: The project team was aware of the project goals, requirements, and project owner expectations.
- Q105: Communication with key personnel was handled in a satisfactory manner.
- Q111: There was a high degree of trust, respect, and transparency between the actors in the project.
- Q113: The execution plan supports the goal of the project.
- Q114: Key members of the team understood the owner’s goal and scope of this project.
- Q126: The leadership communicated strategic goals, project goals in an effective manner.
- Q139: Key personnel were identified and adequately included in an early phase.

Among the listed features, only ‘Q013’, ‘Q105’, ‘Q111’, ‘Q114’ and ‘Q126’ had a sufficiently low percentage of missing datapoints to be used in this analysis. Although these success factors are not emphasised by the model, they appear to be important for success in the sample projects. One possible explanation for this is that the concepts they represent are reflected in other, appearing features. For instance, ‘Q113’, ‘Q114’ and ‘Q122’ (processes support success) all relate to project success, but only ‘Q122’ appears as an important success factor. The same holds true for ‘Q013’, ‘Q105’, ‘Q111’ and ‘Q126’, as they can be related – some more strongly than others – to the most important features. This means that the low occurrence of certain features not necessarily implies that the features are of smaller importance, but that they are reflected in other features that are seen to occur more frequently.

5.3 Construction Project Datasets

In construction projects, dimensions such as time, cost, quality, scope, benefits, and risk are all indicators of primary importance for classifying and quantifying project success. Construction projects data can be of high resolution and domain specific, such as plans for large projects. This study is based on what can be described as low-resolution data, as they are based on qualitative evaluations done by the project organisations themselves. This has advantages; the data describe what the projects experienced themselves, for instance. Disadvantages include a risk of bias by the staff reporting the scores. However, we believe that the 10-10 data are interesting. Future analyses would benefit from more consistent registrations of the questions and parameters, a common issue in machine learning and other quantitative analyses.

A model or approximation will only ever be as reliable as the data it is based upon. Currently, no standards exist for collection and utilisation of data in construction projects. To a certain extent, this is understandable, because all projects are unique. However, it would greatly benefit this type of analysis if some standardisation of data structures would emerge. Some industry-specific standards exist for structuring of data, such as for Building information Models (BIM) and standards for data coding such as NORSOK in the Norwegian oil and gas industry.

Data that can be consistently compared and tracked between projects has the potential to improve project-based benchmarking, support project success prediction, and perhaps most importantly, serve as early warning systems that can identify potential issues in time when it still possible to do something about it.

6. LIMITATIONS AND FUTURE RESEARCH

The 10-10 data is based on reports from members of the project team in respective projects. This means that there is a possibility that some of the data points are biased or imprecise; consequently, a value can have been put in the wrong place or provide an inaccurate or biased image of the actual situation.

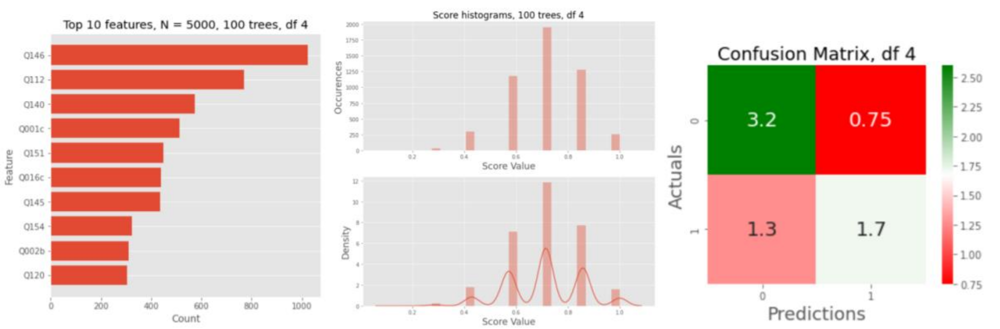
6.1 Handling Missing Values

When developing the model in this study, several solutions were tested. The model did not implement a function to remove dirty projects within a selected phase; in mixed phase DFs, this would not have worked, while it could have in single phase DFs. The idea is that a single-phase DF, in theory, should include all the same features. This means that no missing values unless all the projects in the DF are missing the same values. With the chosen method, if one project was missing a value in a column the entire column would be discarded.

Analyses showed that if the DF has some missing values where it should not be, it is often one or two projects that are the cause of this. One method to keep more information in the DFs could be to fill missing values in the cleaning; this was deemed undesirable, as it would mean to temper with the available data, inserting values that could be wrong, and ultimately yield imprecise results. A complete DF is always preferred.

Alternatively, a method to keep more information in the DFs could be to discard the projects with missing data, instead of discarding entire columns with missing data.

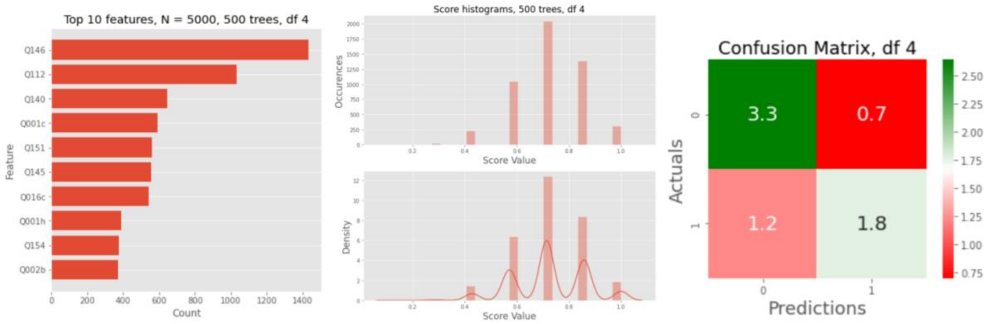
An alternative sensitivity analysis was performed on DF 4 (infrastructure phase 1), by using a model that discarded the polluted projects. One project in particular had several missing data points. Originally, DF 4 had 32 projects, and 79 non-NaN columns after cleaning and discarding. By discarding the project in question, 31 projects and 109 non-NaN columns remained, leaving 30 more columns for the model to analyse. One project constitutes 3% of the DF, meaning one contaminated project would contaminate the entire DF. As illustrated in Figure 19, only one out of these 30 features show up among the most important features. This feature is ‘Q002b’, concerning the classification of the level of difficulty of the project. Also worth noting, is that none of the additional features regarding BIM, ‘Q031’ (BIM used), ‘Q032’ (who used BIM), and ‘Q033’ (reason BIM was used), is among the most important features; this is shown in Figure 19(a).



(a) Top 10 features. (b) Histogram. (c) Confusion matrix.

FIG. 19: After discarding the polluted project. N = 5000, 100 estimators/trees for DF 4.

The same DF was tested with a higher value for the number of estimators, meaning DTs in the RF. However, no correlation between higher estimator count and f1-score was found. The result is illustrated in Figure 19 and can be compared with the CM in Figures 11 and 19.



(a) Top 10 features. (b) Histogram. (c) Confusion matrix.

FIG. 20: After discarding the polluted project. N = 5000, 500 estimators/trees for DF 4.

6.2 Weighting of DFs

The weighting of DFs posed a challenge in constructing the model. Using Python built-in parameters and functions, such as stratify, class_weight, and sample_weight, the model became more equipped to handle the troubles of a small, unbalanced DF. Alternatively, the parameters could have been weighted manually and individually; this could have yielded a different result. Certain DFs could potentially have performed differently with a different split than the 80/20 split chosen in this model.

6.3 Tuning of Hyper Parameters

This study was intended as a pilot analysis of the Nordic 10-10 dataset, limiting the allocated time and scope for the development of the model. The tuning of DFs was done by searching for global best parameters; another potential approach for future studies would be to analyse one DF at a time and subsequently tune hyper parameters through RandomSearchCV or GridSearchCV functions in SK Learn. Recommended hyper parameters for further analysis and assessment are ccp_alpha, class_weight and sample_weight. This model only utilised the built-in 'balanced' arguments in the two latter.

Furthermore, for a corresponding model, the test size for each DF can be explored further, along with the different paths in the cleaning procedure. Another potential lies within the assessment and comparison of the performance of different ML algorithms on the same dataset.

6.4 Classes

For this model, two classes were defined: success or failure. Further work could look into the possibility of using additional categories, for instance success, failure, and outlier failure. An outlier failure category could provide interesting insights into the identification of the most important features for these projects. Alternatively, classes such as success outliers, neutral projects and failure outliers could be defined. As previously discussed, choosing a non-binary approach would heighten the importance of an unambiguous definition of project success.

Due to the small size of the dataset, manual inspection of the individual projects, specifically outliers, could be yet another option - such inspections could provide unique insights, and prove valuable for further categorisation and classification.

7. CONCLUSIONS

The first research question, regarding how AI, and ML specifically, can be applied to analyse limited datasets from project evaluation has been answered through the description and demonstration of the developed model. However, as the results indicate, only a few DFs display high enough accuracy to facilitate a constructive discussion of the identified features. This indicates that the dataset may have been too limited to provide high-quality statements. Results provided by the DFs displaying high accuracy suggests that the proposed method is indeed useful for limited datasets.

The second research question was answered through the demonstration of the developed model. The model presented top features for each sector, and for each phase in the two sectors. Among the DFs displaying the highest accuracy, the top features identified align with established success factors in project management theory. Ten features appear more frequently than the others. These features relate to complexity, number of design changes, adequate training and knowledge in the project team, early planning including uncertainty analyses, involvement from top management, and whether or not the processes in the project are perceived to support project success. At the same time, success factors highlighted in literature did not appear as significant in this analysis, and the reasons for this have been discussed.

Ultimately, the ML model demonstrates the ability to discover important factors for project success. Such analyses can be used in early phases of a project to predict project success in later phases, or in the project as a whole, and could prove to be a useful tool in order to eventually achieve more project success.

REFERENCES

Agarwal, R., Chandrasekaran, S. and Sridhar, M. (2016) Imagining construction's digital future. Accessed from https://www.mckinsey.com/industries/capital-projects-and-infrastructure/our-insights/imagining-constructions-digital-future on 14th of August 2021.

Akinade, O. O. (2017) *BIM-based software for construction waste analytics using artificial intelligence hybrid models*. Doctoral dissertation. University of the West of England.

Assaad, R., El-Adaway, I. H. and Abotaleb, I. S. (2020) Predicting Project Performance in the Construction Industry. Journal of Construction Engineering and Management. 146(5). Doi: 10.1061/(ASCE)CO.1943-7862.0001797.

Assaf, S. and Al-Hejji, S. (2005) Causes of delay in large construction projects. International Journal of Project Management. 24(4): 349-357. Doi: 10.1016/j.ijproman.2005.11.010.

Auth, G., Jokisch, O. and Dürk, C. (2019) Revisiting automated project management in the digital age - a survey of AI approaches. Online Journal of Applied Knowledge Management. 7(1). Doi: 10.36965/OJAKM.2019.7(1)27-39.

Brekkhus, A. (2017) Den fulldigitale byggenæringen kommer stadig nærmere. Accessed from http://www.bygg.no/article/1323049 on 13th of October 2020.

Campbell, R. and Terwilliger, R. (1986) The SAGA Approach to Automated Project Management. *Computer Science*. 244. Doi: 10.1007/3-540-17189-4_95.

Chua, D., Loh, P., Kog, Y. and Jaelskis, E. (1997) Neural Networks for Construction Project Success. Expert Systems With Applications. 13(4): 317-328. Doi: 10.1016/S0957-4174(97)00046-8.

Cubric, M. (2020) Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study. Technology in Society. 62. Doi: 10.1016/j.techsoc.2020.101257.

de Wit, A. (1988). Measurement of project success. Project Management Journal. 6(3). 164–170. Doi: 10.1016/0263-7863(88)90043-9.

Deloitte AI Institute (2020) Deloitte Survey: State of AI in the Enterprise, Third Edition: Thriving in the Era of Pervasive AI. Accessed from https://www2.deloitte.com/us/en/pages/about-deloitte/articles/press-releases/deloitte-survey-state-of-ai-in-the-enterprise-third-edition.html on 15th of September 2020.

dos Santos, I., Barriga, G., Jugend, D. and Cauchick-Miguel, P. (2019) Organizational factors influencing project success: an assessment in the automotive industry. Production. 29(5). Doi: 10.1590/0103-6513.20180108.

Dvir, D., Ben-David, A., Sadeh, A., and Shenhar, A. J. (2006) Critical managerial factors affecting defense projects success: A comparison between neural network and regression analysis. *Engineering Applications of Artificial Intelligence*. 19 (5): 535-543. Doi: 10.1016/j.engappai.2005.12.002

GHD (2020) Using instant intelligent insights to revolutionise major infrastructure construction. Accessed from https://www.ghd.com/en/projects/using-instant-intelligent-insights-to-revolutionise-major-infrastructure-construction.aspx on 27th of October 2020.

Ika, L. (2009) Project Success as a Topic in Project Management Journals. Project Management Journal. 40(4). 6–19. Doi: 10.1002/pmj.20137.

Haddadi, A. and Johansen, A. (2019) Value Proposition in Different Types of Buildings- Characteristics and Means. The Journal of Modern Project Management. 6(3). Doi: 10.19255/JMPM01805.

Hussein, B. (2016) Veien til suksess. Fagbokforlaget: Bergen.

Hwang, B. and Ng, W. (2012) Project management knowledge and skills for green construction: Overcoming Challenges. International Journal of Project Management. 31(2): 272-284. Doi: 10.1016/j.ijproman.2012.05.004.

Kent State University (2021) SPSS Tutorials: Pearson Correlation. University Libraries. Accessed from https://libguides.library.kent.edu/SPSS/PearsonCorr on 11th of December 2021.

Kowalski, M., Zelewski, S., Bergenrodt, D. and Klüpfel, H. (2012) Application of new techniques of artificial intelligence in logistics: An ontology-driven case-based reasoning approach. The European Modelling and Simulation Conference. 323-328.

KPMG (2015) Global construction survey 2015: Climbing the curve. KPMG international. Accessed from https://assets.kpmg/content/dam/kpmg/pdf/2015/05/construction-survey-201502.pdf on 23rd of September 2021.

Lee, J., Davari, H., Singh, J. and Pandhare, V. (2018) Industrial Artificial Intelligence for industry 4.0-based manufacturing systems. Manufacturing Letters. 18: 20-23. Doi: 10.1016/j.mfglet.2018.09.002.

Loureiro, S., Guerreiro, J. and Tussyadiah, I. (2020) Artificial intelligence in business: State of the art and future research agenda. Journals of Business Research. 129: 911-926. Doi: 10.1016/j.jbusres.2020.11.001.

Magaña, D. and Fernández Rodríguez, J. C. (2015). Artificial Intelligence Applied to Project Success: A Literature Review. *International Journal of Artificial Intelligence and Interactive Multimedia*. 3: 77-84. Doi: 10.9781/ijimai.2015.3510.

Marr, B. (2020) The key definitions of artificial intelligence (AI) that explain its importance. Accessed from https://www.forbes.com/sites/bernardmarr/2018/02/14/the-key-definitions-of-artificial-intelligence-ai-that-explain-its-importance/?sh=14dcaf9f4f5d on 9th of October 2020.

McKinsey Global Institute. (2017) Reinventing Construction: a Route to Higher Productivity. Executive Summary. McKinsey & Company.

Misra, N. N., Dixit, Y., Al-Mallahi, A., Bhullar, M.S, Upadhyay, R. and Martynenko, A. (2020) IoT, big data and artificial intelligence in agriculture and food industry. IEEE Internet of Things Journal. Doi: 10.1109/JIOT.2020.2998584.

Niu, Y., Lu, W., Chen, K., Huang, G. and C. Anumba (2019) Smart Construction Objects. Journal of Computing in Civil Engineering. 30(4). Doi: 10.1061/(ASCE)CP.1943-5487.0000550.

Nordic 10-10 (2020) *Hvordan bruke CII 10-10*. How to use CII 10-10. Accessed from https://nordic10-10.org/hvordan-bruke-cii-10-10/ on 11th of November 2020.

Oberle, W. (2015) Monte Carlo Simulations: Number of Iterations and Accuracy. Technical note. US Army Research Laboratory.

Oliver Wyman (2018) Digitalization of the Construction Industry: the Revolution is Underway. Marsh & McLennan Companies. Oliver Wyman.

Project Management Institute (2017) A guide to the Project Management Body of Knowledge. PMBOK® GUIDE. Sixth Edition. Project Management Institute.

Project Management Institute (2018) Success in disruptive time: Expanding the value delivery landscape to address the high cost of law performance. Accessed from https://www.pmi.org/-

/media/pmi/documents/public/pdf/learning/thought-leadership/pulse/pulse-of-the-profession-2018.pdf on 14th of August 2021.

Prosjekt Norge (2017) Bli med på å fremme benchmarking i prosjektledelse som gulloppskrift for BAE-bransjen. Contribute to promotion of benchmarking in project management as the golden standard for the AEC-industry. Accessed from https://www.bnl.no/siteassets/dokumenter/rapporter/invitasjon_prosjektnorge_screen.pdf on 11th of November 2020.

Radujkovic, M. and Sjekavica, M. (2017) Project Management Success Factors. Procedia Engineering. 196: 607–615. Creative Construction Conference 2017. Doi: 10.1016/j.proeng.2017.08.048.

Rahmanifard, H. and Plaksina, T. (2019) Application of artificial intelligence techniques in the petroleum industry: a review. Artificial Intelligence Review. 52. 2295-2318. Doi: 10.1007/s10462-018-9612-8.

Ramos, M., Tacla, C., Sato, G., Paraiso, E. and Barthès, J. (2010) Dialog Construction in a Collaborative Project Management Environment. International Conference on Computer Supported Cooperative Work in Design. Doi: 10.1109/CSCWD.2010.5471963.

Russell, S. J. and Norvig, P. (2003) Artificial Intelligence: A Modern Approach. Second Edition. Upper Saddle River, New Jersey: Prentice Hall, ISBN 0-13-790395-2.

Samset, K. and Volden, G. (2016) Front-end definitions of projects: Ten paradoxes and some reflections regarding project management and project governance. International Journal of Project Management. 34(2): 297–313. Doi: 10.1016/j.ijproman.2015.01.014.

Schwarz, J. (2015) Implementation of artificial intelligence into risk management decision-making processes in construction projects. Universität der Bundeswehr München. Institut für Baubetrieb.

ScienceDaily (2020) Artificial intelligence. Accessed from https://www.sciencedaily.com/terms/artificial_intelligence.htm on 9th of October 2020.

Sozontov, A., Ivanova, M. and Gibadullin, A. (2019) Implementation of artificial intelligence in the electric power industry. International Conference of Young Scientists Energy Systems Research 2019. 114. Doi: 10.1051/e3sconf/201911401009.

The Economist (2020) An understanding of AI's limitations is starting to sink in. Accessed from https://www.economist.com/technology-quarterly/2020/06/11/an-understanding-of-ais-limitations-is-starting-to-sink-in on 9th of October 2020.

Todsen, S. (2018) Produktivitetsfall i bygg og anlegg. Statistisk Sentralbyrå.

Vikan, J. (2018) Digitalisering gir store muligheter - og store utfordringer. Accessed from http://www.bygg.no/article/1365237 on 19th of October 2020.

Walch, K. (2020) Is AI overhyped? Accessed from https://www.forbes.com/sites/cognitiveworld/2020/06/04/is-ai-overhyped/?sh=1a5e35fb63ee on 9th of October 2020.

Wang, Y., Yu, C. and Chan, H. (2011) Predicting construction cost and schedule success using artificial neural networks ensemble and support vector machines classification models. International Journal of Project Management. 30(4): 470–478. Doi: 10.1016/j.ijproman.2011.09.002.

Witten, I. H. (2016) Data Mining: Practical Machine Learning Tools and Techniques. Elsevier Science & Technology.

Worldsensing (2020) Smart construction powered by onemind. Accessed from https://www.worldsensing.com/one-mind-smart-construction/ on 27th of October 2020.

Appendix IV

Paper IV

«Barriers for Data Management as an Enabler of Circular Economy: An Exploratory Study of the Norwegian AEC-Industry»

Published in: IOP Conference Series: Earth and Environmental Science
ISSN: 1755-1315

Presented at: SBEfin2022 Emerging Concepts for Sustainable Built Environment

IOP Conf. Series: Earth and Environmental Science 1122 (2022) 012047 doi:10.1088/1755-1315/1122/1/012047

Barriers for data management as an enabler of circular economy: an exploratory study of the Norwegian AEC-industry

A Bellini and S Bang

Department of Mechanical and Industrial Engineering, Norwegian University of Science and Technology, 7491 Trondheim, Norway

Email: alessia.bellini@ntnu.no

Abstract. Effective data management can enable the utilisation of new tools and technologies and, ultimately the creation of circular business models in the building industry. To accomplish this, a targeted mapping and collection of data must take place. However, several challenges hinder the exchange of information in a seamless digital flow through the value chain and building life cycle. This exploratory study contributes to bridging the gap in the research, providing an overview of existing barriers related to mapping, collecting, and storing data about materials and products in existing buildings. The findings are obtained through 18 semi-structured interviews with experts working with circular economy and digitalisation in the Norwegian AEC-industry. Some of the identified barriers, such as the lack of data availability and interoperability, lack of competencies and unwillingness to share data, are strongly interrelated; a collaborative approach will be essential across the value chain. The research sets the basis for developing a framework for data management that can facilitate the reuse of materials and products from a building at the end of life to new construction or refurbishment projects. Ultimately, effective data management opens for developing and implementing innovative circular business models, enhancing strategic data-based asset management.

1. Introduction

The construction industry is responsible for consuming almost 40% of the natural resources and generating circa 40% of the total waste in Europe [1,2]. Therefore, a transition to a circular economy is considered essential to sustainable development in the built environment by reducing resource consumption and carbon emissions and moving away from the so-called linear economic model [2,3,4]. Reusing existing materials and products is an example of circular economy practices that can significantly decrease resources consumption and carbon emissions but requires adopting a systemic approach and value chain integration on a large scale [4,5,6].

Like other industries, the construction industry has seen a surge in digitalisation over the last years, despite remaining one of the least digitally advanced industries [7]. The sector has already been positively affected by some technologies, enhancing efficiency in processes and communication [8], but the rapid advancement in digital technologies, such as Building Information Modelling (BIM), digital twins, blockchain, Internet of Things (IoT), and Artificial Intelligence (AI), is an essential means to achieve the potential of a more sustainable and circular industry [9,10,11].

Digitally enabled solutions can support the implementation of circular economy strategies, like the reuse of building materials and products, by helping to map, trace, and provide information about the availability, location, condition, and durability of a product [12]. A standardized information exchange is one of the means for a more circular and sustainable sector [5] and implementing a seamless data flow can facilitate sharing information about reusable materials, from an existing building to a potential new construction or refurbishment project. However, the lack of information and data about the existing built environment is often one of the main challenges for material reuse [5,9,12]. Greater knowledge of existing buildings and materials, greater visibility and transparency of data, and improved construction products information management across the value chain are essential to enable business model opportunities and accelerate the circular transition [12,13,14].

Although several studies, like Knoth et al. [6], Nordby [15], Sandberg and Kvellheim [16], investigates the barriers for materials reuse in the AEC-industry, the research on digitalization connected with circular economy is relatively limited and it often fails to address the topic from a systemic point of view [11, 17,18]. Kovacic et al. [9] underlined that a framework for information management that supports a continuous and standardized data flow for a circular economy is still lacking.

The research conducted by Çetin et al. [10] is one of the few contributions that investigates which digital technologies can potentially enable circular economy in the built environment, also presenting some of the challenges connected with these specific technologies. Similarly, Chan et al. [19] addresses the question of the digital potential in advancing circular economy in the construction industry. The results show how digital technologies (digital twins, BIM, material passport, and digital platforms), can help to create a viable digital marketplace for circular products and services. More specifically, Debacker [20] looks at the challenges for the implementation of *material passports*, underlying the need for a digital and centralized management of building and material information. A material passport can be defined as a tool that helps to document and track circular materials and products, providing accurate information for recovery and re-use [5].

Others research looks at the connection between digital technologies and circular economy but are not exclusively limited to the AEC-industry. De Felice and Petrillo [17] recognizes the lack of interoperable solutions and communication protocols as the main factor hindering innovation and circularity. The authors suggest an integrated approach, that combines technology, legislation, and cooperation among the value chain. Similarly, the research from Mulhall et al. [21] underlines that a standardized data format for storing product information is necessary for circular economy, both in the construction, textile, and batteries sector. Moreover, the newly published report by Ellen Mac Arthur Foundation underlines that data on materials and products are essential to promote circular business models and identifies the barriers that hinder data sharing, across different sectors [22].

When it comes to specifically investigate the barriers for circular economy and reuse of materials in the AEC-industry, several studies have been conducted which do not necessarily focus on the digitalization perspective. Kirchherr and Piscicelli [23] and Munaro and Tavares [24] look at the cultural barriers, such as lack of awareness and holistic thinking, and they underline that the lack of information and the fragmentation of the value chain can hinder the introduction of circular practices and understanding of circular thinking. Norby [15] analysed the technical, legislative, environmental, and market barriers to reusing materials in Norway. Similarly, Sandberg and Kvellheim [16] conclude that the lack of economic incentives and requirements limits the reuse of materials on a bigger scale. Knoth and Fufa [6] analyse perceived challenges, barriers, and opportunities for material reuse from different stakeholders. Finally, it is worth mentioning how Moscati and Engström [25] and Redwood and Thelning [26] look at the barriers for digitalization in the AEC-industry in a general context and they underline how the most significant barriers lie in the organisational aspects rather than technical ones.

The effective and sustainable utilisation of new digital technologies and tools requires effective data management, and this study contributes to bridging the current gap in the research, by providing a comprehensive overview of the existing barriers, related to mapping, collecting, and storing of data on materials and products in existing buildings. The results are obtained through a review of the existing literature and 18 semi-structured interviews with experts in circular economy and digitalisation in the

Norwegian AEC-industry. Specifically, the study will be answering the following research question: *What are the existing barriers for digitalization of data management as an enabler of circular economy in the Norwegian AEC-industry?*

The remainder of this paper is organised as follows; first, the research method adopted in this study is described. Then, findings are presented and discussed. Finally, the last section summarises and concludes based on the previous results, providing an overview and recommendations for practitioners and researchers who wish to explore the topic further.

2. Research method

The research design for this study is exploratory because the topic of digitalization and data management in the context of circular economy is relatively unexplored, and the intention is to clarify the understanding of the problem and seek for new insights [27]. The research started with an initial literature search in three chosen databases (Scopus, Web of Science, Science Direct). This revealed that a research gap exists in the nexus between the topic of data collection and management, and circular economy, as stated in the introduction.

To support the search of the literature and to fully answer the research question, semi-structured interviews were identified as the preferred research method, following the recommendation by Bell and Bryman [27]. This method was seen to provide more broad and contextual results, as compared to more quantitively oriented methods such as questionnaire and surveys. The semi-structured approach allows the respondents to elaborate beyond pre-defined questions, contributing to a comprehensive understanding of the industry and its dynamics in relation to the topic [28].

The interview guide was sent to the interviewees in advance to ensure the alignment of expectations and topics between interviewers and interviewees and it included a series of open-ended questions such as: *'what is the role of data management for facilitating the implementation of circular economy?'*; *'how can the circular data flow for the reuse of materials be structured through the value chain and throughout the life cycle?'* and *'what are the main barriers that hinder the digitalization of the materials data flow?'*.

In total, 18 semi-structured in-depth interviews were conducted, over the course of two interview cycles. The interviewees in the first cycle (12 interviews) were selected based on their experience and involvement in relevant projects and initiatives. Inclusion criteria included experience working with digitalization, digital technologies, and processes in the AEC industry in Norway, as well as the participation in pilot projects, workshops, and networks connected with circular economy and materials reuse. All the interviewees have more than five years of experience working within the AEC industry in major and well-known organizations in Norway, as well as software developers working with circular platforms and solutions. To ensure valid and relevant results, a broad sample of stakeholders, representing the different roles across the value chain was involved.

The interviewees in the second cycle (6 interviews) were selected based on the specific recommendations from the first group of interviewees and from other practitioners and academics. The authors evaluated the suggestions to ensure that the respondents fit the inclusion criteria defined for the first cycle. The final selection of respondents and their role in the value chain is illustrated in Table 1.

Table 1. Number of respondents by role in the value chain.

Role	Number of respondents
Manufacturer	1
Project owner (public & private)	3
Architect	1
Research institute and university	2
Not-for-profit organisation and network	2
Software provider	3
Engineering & sustainability consultant	4
Contractor	2

Each interview lasted for approximately one hour and was conducted as a video call over Microsoft Teams due to the current Covid-19 regulations in Norway. Both authors were attending during the interviews to ensure a higher degree of understanding and reliability in the subsequent coding of the results. The interviews were recorded, and the transcriptions were sent to the interviewees for quality assurance before analysing the data. The interviews were conducted in Norwegian and subsequently translated to English to ensure accuracy and avoid misinterpretation of the information.

The coding process was done iteratively in parallel with the interviews, as recommended by Bell and Bryman [27]. Although interviewees used different terminology when asked to define existing barriers, emerging themes were identified and categorised. This was done through the utilisation of industry-specific knowledge as well as common understanding and asking follow-up questions where necessary. The process resulted in the classification of six main barriers that represent the findings of this research. Both authors took part in coding and analysis, first individually and then comparing and discussing the results, to ensure increased validity and understanding of the findings. As the coding was conducted, it became evident that the interviewees' answers and views on certain aspects of the topic seemed to be converging; this could suggest a higher degree of relevance of the findings.

3. Findings

Six themes emerged from the interviews, resulting in six (6) explicitly defined barriers for data management as an enabler of a circular economy. The barriers are described in the following chapters and summarised in Table 2.

Table 2. Identified barriers for each interviewee's role

	Interviewees roles							
	Manufacturer	Project Owner	Architect	Research	Org. / network	Software	Consultant	Contractor
Lack of data availability	1/1	3/3	1/1	1/2	2/2	2/3	3/4	2/2
Lack of data interoperability	1/1	3/3	1/1	1/2	2/2	2/3	3/4	1/2
Lack of competences	1/1	2/3	1/1	2/2	1/2	3/3	2/4	1/2
Unwillingness to share data	1/1		1/1			2/3	2/4	1/2
Lack of financial incentives	1/1	2/3		2/2	1/2	3/3	2/4	2/2
Lack of harmonisation		2/3		1/2	1/2	2/3	1/4	1/2

3.1. Lack of data availability

As several interviewees underlined, it will not be possible to enable circular economy and reuse of building materials unless the data is available or accessible. One of the main challenges today is that the data about building materials and products are often missing, not complete, not accessible, or not digitised. An interviewee highlighted: *'if one looks ten years back, for example, there is very little documentation available [about buildings and materials]. And when available, it is often buried in archives at the manufacturers' or project owners' offices'.* Another interviewee underlined that: '*to decide to reuse a [building] product, you need certain information about that product'*. It is necessary to collect information about the quantity, properties, characteristics, physical location in the building, quality and current maintenance state, how they can be reused, repaired, or disassembled, which certifications are required, etc. The interviewees recommend this information to be dynamic, possibly connected in a digital model or a material passport. The material passport is a digital register that follows the building and products through all the life cycle, describing defined characteristics of materials – ultimately providing value for recovery and reuse [5]. Collecting and making information available and accessible increases the possibility to reuse existing materials on a larger scale: *'to achieve a sort of industrialisation for materials reuse, then one needs enough information to evaluate if a product could be suitable for the [new] use'*.

3.2. Lack of data interoperability

Lack of technical interoperability can, according to interviewees, impede effective data management and consequently slow down the practices of materials reuse in the construction industry. As an interviewee stated: '*it is impossible to achieve a circular economy in the building industry without a robust digital infrastructure'*. Data are often stored in different repositories, in different formats, with varying levels of ownership and accessibility. This hinders the exchange of information between the stakeholders through the value chain, so, ideally: *'one should get a seamless data flow that can be triggered automatically because there are a lot of information and products in a building or construction project'*.

The integration with digital tools, such as Building Information Modelling (BIM) or material passports, can simplify this process, given that this platform can exchange information in an open format: *'there are several digital solutions that can simplify data management, for example, only in Norway there are about 30 different software that are designed for the operation & maintenance phase, but none of them is [currently] communicating and none of them is connected with software for circular material reuse either'*. The openness of data is considered essential for enabling interoperability, and some concerns emerged during the interviews: *'what is an open solution [for data collection and sharing], actually? What does it mean to handle the data openly? We need a discussion about this concept'*.

Some interviewees expect governmental initiatives that could promote the adoption of a public database to ensure data openness and transparency on a higher level: *'the access to information is a problem today. Establishing a central system, like a central database or marketplace, where you can gather and collect all the information would be great. Right now, everybody is developing a marketplace of their own, and everyone has their systems. A centralisation of the information is incredibly important'*. One of the interviewees suggested that the requirements for data openness should be regulated at the European or global level to avoid the data being limited in proprietary systems: *'we need guidelines about the requirements for [data] openness and this should be regulated with an EU Directive at least, or a global requirement'*.

Another vital aspect to improving data interoperability is to collect and store data and information about the products and materials in a standardised way: '*when [one] has mapped the existing building materials then these data are updated in a [digital] system. But for this information to be exchanged with another stakeholder [that uses another digital system], they must be in the same format and mapped with the same purpose'*. According to some interviewees, standards that regulate how circular properties for materials and products should be classified and described are still missing. It is challenging to coordinate data management to reuse materials without common standards; as one interviewee mentioned, '*data will have little value if different actors do not use a common language when describing products and materials.* With the support of digital technologies and tools, this data can be shared and connected between the different stakeholders in an open, transparent, and standardised way.

3.3. Lack of competences

Another barrier for data management as an enabler of circular economy in the AEC-industry is the lack of competencies among the different stakeholders. The interviewees refer to this as the competencies on collecting, handling, sharing, and managing the data about the building materials and a broader understanding of the value of this information to accommodate circular principles. As one interviewee mentioned: '*what is missing is the common understanding of the value of data and information (...) in a life-cycle perspective'*. According to some of the interviewees, data management competencies will be acquired over time by gaining experience from projects and initiatives based on circular principles and thinking: '*while we go through more mappings of building materials, we get a bigger understanding of which [data] is necessary (...)'*.

3.4. Unwillingness to share data
Unwillingness to share data among the parties in the value chain is a barrier for data management and, consequently, hinder materials reuse in the AEC-industry. As one interviewee mentioned, the challenge is that *'there are too few [actors] in the industry that are willing to share the information'*. According to some of the interviewees, the unwillingness of stakeholders to share available data and information ultimately means that other barriers, such as the lack of interoperability, cannot be solved. This aspect impacts the collaboration between the stakeholders, who are unwilling to work together to enable the circular economy in the AEC-industry.

3.5. Lack of financial incentives
Collecting, digitising, and managing data from existing buildings and materials can be quite resource intensive. The interviewees underlined that the lack of financial incentives represents a significant barrier for enabling effective data management. A sustainable circular economy and effective reuse of building materials will require managing a large amount of data. Without financial incentives, originating from the market or the authorities, it is difficult to establish a business model for reuse of building materials on a larger scale, as one of the interviewees mentioned: '*if we manage to collect more data for material reuse, then the market will be much bigger and so the volume of materials and products [available] for reuse'*. Several interviewees claimed that stricter requirements from project owners and authorities could potentially contribute to solving this barrier and make the process financially viable.

3.6. Lack of harmonisation across the value chain
It emerges from the interviews that harmonized procedures and processes for data management across the value chain in a circular economy context are still missing. This represents a barrier to practical implementation because the lack of organizational processes and standardized data management procedures hinder the exchange of information between the different stakeholders, making it difficult to achieve circular economy and materials reuse. According to the interviewees, it is therefore relevant to structure the processes for data exchange and management, by connecting the value chain and defining the roles of the different stakeholders. Combined with the lack of data interoperability, as another barrier for data management (as underlined in Section 3.2), it is even more important to make data available through the life cycle and create mechanism to match the supply and demand of reusable existing products and materials, as one interviewee underlined: *'in a reuse-project (...) you need actors and businesses that can collect information about existing products, re-test the materials etc. All the value chain should be connected'*

4. Discussion
Creating a functional framework for information management, to support a continuous and standardised data flow for circular economy, will be essential to enable the implementation of big-scale circular principles. A comprehensive understanding of the barriers that hinder data management in the circular economy context is consequently a significant step for the definition of this framework.

Previously conducted studies discover the barriers related to digitalisation in the construction industry [25,26] or to circular economy and reuse of materials [6,15,16], but not many studies address the intersection between these two, specifically digitalisation of data collection and management as an enabler of a circular model. Thus, this research contributes to empirical validation of the perceived barriers to this process of digitalisation in connection with circular economy in the AEC-industry.

To enhance the reuse of materials and products from end-of-life buildings to new buildings or refurbishment projects and, in turn develop circular business models, it is decisive to exchange data and information about the reusable materials in a seamless and digital data flow through the entire value chain and building life cycle; this perception was shared by most interviewees. Collaboration and sharing of data between the stakeholders during the building life cycle is perceived as a critical factor for enabling circular economy and it is also recognized in the literature, despite in connection with different contexts [10,22]. This seems to hold true for the process of digitalisation of data management in the same context, as seen in the identification of unwillingness to share data as one of the critical barriers to this.

The findings show that the lack of interoperability, intended as the ability of different digital systems to coordinate and communicate with one another, still hinders effective data management as an enabler for the circular economy. To overcome this barrier, interviewees suggest that information about building materials could be collected through mapping, stored in a database, and available and accessible through the entire life cycle of the asset; this is in line with findings of studies exploring the barriers of more analogue circular concepts and principles [7,5,14]. The same can be said about the perceived opportunity for increased openness to enable interoperability [19,21,22].

According to interviewees, most material mapping today takes place at the end-of-life phase before a building must be deconstructed or rehabilitated. The findings suggest that the prospect for a circular AEC industry depends on the availability of data and the adoption of material passports or digital inventories, both for new and existing buildings. This is in line with the literature that specifically investigate the implementation of materials passports in the AEC-industry [5,19,20]. As several interviewees emphasised, to make the process of reusing materials viable, the data should be accessible, preferably in an open public database, that could be centrally governed. Precise requirements for data openness and transparency should be regulated at the European level, to avoid data loss through the building life cycle, across borders and industries. In March 2022, the European Commission published the proposal for a revised Construction Products Regulation (CPR) which, among other aspects also suggest the adoption of a centralized database for product information management.

The barriers identified in this study appear to be strongly interrelated. For example, the understanding and definition of the barrier *lack of interoperability* to some extent overlaps with the concept of data openness and standardisation. Some of the identified barriers, such as the *lack of data availability* and *interoperability* involve both technical and organisational connotations. While some barriers could be addressed by implementing new technologies and tools, organisational and managerial efforts are ultimately required to establish a seamless data flow across the value chain. This is particularly true for the barrier *lack of harmonization*, which entails the adoption of processes and procedures for data management to facilitate the exchange of information across the value chain. The idea is that harmonized and standardised processes for data management could be adopted in different projects, helping to achieve materials reuse and circular economy on a larger scale. In addition, competencies, collaboration, and willingness to share data are identified as crucial factors for the industry to move forward and overcome the barriers.

The purpose of this study was to empirically validate and provide a comprehensive overview of the barriers for digitalisation of data management, as an enabler of circular economy in the AEC industry. The insights collected through the interviews acquire both technical and practical connotations, seemingly coinciding with the findings of other studies investigating the link between digitalization and circular economy, focusing on specific aspects or technologies [10,12,13,19]. Ultimately, this study provides also an organisational and procedural perspective to the barriers to data management; it represents a point of reference and perspective of what it entails to digitalize the information required to enable circular economy and material reuse. The interview-based research design was an essential tool to increase understanding of the problem. The findings illustrate how the topic is still in an emerging phase and it requires great engagement both from the industry and the academia.

5. Conclusion and recommendations

This study is, to the best of the authors' knowledge, the first empirical validation of previously theoretically based hypotheses related to the barriers to data collection and data management in a circular economy context. This exploratory study contributes to bridging the gap in the research by concretizing existing barriers for digitalisation of data management as an enable for circular economy. Coding and evaluation of the emerging concepts identified the following barriers:

1. Lack of data availability
2. Lack of data interoperability
3. Lack of competences
4. Unwillingness to share data
5. Lack of financial incentives
6. Lack of harmonisation across the value chain

Some of these barriers, such as lack of availability and interoperability, are deeply interrelated. A collaborative approach is required to achieve effective data management and ultimately enable a circular economy in the AEC industry. According to the findings, measures that could contribute to overcoming these barriers, include the adoption of a public database to ensure openness and transparency of the data. Regulations should set specific requirements for how data related to the circular properties of products and materials is stored and exchanged across the value chain. In addition, a sustainable circular economy requires effective management of a large amount of data, and this could not be achieved without standardised and harmonized procedures and processes for data management, and without a financially viable model. Finally, to overcome the barriers to data management, it is essential to strengthening collaboration and trust among the stakeholders.

5.1. Limitations of the study

To overcome the limitation of this study, a broader sample of interviewees could be involved, including respondents from several roles and positions across the value chain. The findings show that there is a general agreement among the practitioners in Norway regarding the challenges of data management in the context of a circular economy, and the research opens for further implementation and analysis on the topic.

This study was conducted within a Norwegian context, providing insights from practitioners with expertise and experience from the Norwegian AEC industry. The local context in which the research developed could potentially influence the results, therefore it has been important to analyse the findings also with regards with the international literature that explore adjacent topics such as digitalisation or circular principles in general. This suggest that the findings can be applicable also outside the empirical context and will find a valid application in other countries, considering regional trends and opportunities for the circular economy. To empirically validate this, similar studies of the AEC industry in other countries should be undertaken.

5.2. Future research

In terms of research methodology and in order to validate the applicability of the results, it might be relevant to conduct a similar analysis in other contexts and countries. In addition, future studies could include a larger sample of respondents for each of the roles in the value chain, especially include several manufacturers, contractors, and architects.

In terms of thematic, several potentials lie within this topic. This study identified the existing barriers for digitalisation of data management; future research could analyse each of these barriers, identifying how those can be overcome and concretizing prospects and plans.

An organizational framework supporting a continuous and standardized data flow is still missing in the AEC context; this could be a central topic for future studies. The qualitative and empirical identification of perceived barriers for effective information management could and should be used as a foundation in the development of such a framework. Future research should analyse necessary data and information for the reuse of building materials, and how digital solutions can support the exchange of this information across the value chain. Effective data management can open for the creation of innovative circular business models, and it could enhance strategic data-driven asset management.

References

[1] European Commission 2020 *Circular economy action plan: for a cleaner and more competitive Europe*
[2] MacArthur E 2013 Towards the circular economy *J. Ind. Eco.* **2** 23-44
[3] Cheshire D 2019 *Building revolutions: applying the circular economy to the built environment* Riba publishing
[4] Pomponi F and Moncaster 2017 A Circular economy for the built environment: a research framework J. Clean. Prod. 147 710-8
[5] Munaro M R and Tavares S F 2021 Materials passport's review: challenges ad opportunities towards a circular economy building sector *Buil. Env. Proj. and Ass. Mana.* **11**(4) 767-782
[6] Knoth K, Fufa S M and Seilskjær E 2022 Barriers, success factors, and perspectives for the reuse of construction products in Norway *J. of Clea. Prod.* **337** 130494
[7] Sezer A A, Thunberg M, Wernicke B 2021 Digitalization index: developing a model for assessing the degree of digitalization of construction projects *J. Const. Eng. Manag.* **147**(10) 04021119
[8] Parusheva S and Aleksandrova Y 2021 Technologies, tools, and resources-driving forces in construction sector digitalization *Int. Conf. on Inte. Comp. and Info. Syst.* 219-23
[9] Kovacic I, Honic M and Sreckovic M 2020 Digital platform for circular economy in AEC industry *Eng. Proj. Organ. J.* **9**
[10] Çetin S, De Wolf C and Bocken N 2021 Circular digital built environment: an emerging framework *Sust.* **13**(11) 6348
[11] Chiaroni D, Orlandi M and Urbinati A 2021 *The role of digital technologies in business model transition towards circular economy in the building industry* Springer
[12] Honic M, Kovacic I, Sibenik G and Rechberger H 2019 Data and stakeholder management framework for the implementation of BIM-based material passport *J. of Buil. Eng.* **23** 341-50
[13] Mêda P, Sousa H and Hjelseth E 2020 *Data templates – product information management across project life cycle* Springer 117-33
[14] buildingSMART International 2021 *Digitizing construction for better product exchange, identification and transparency*
[15] Nordby A S 2019 Barriers and opportunities to reuse of building materials in the Norwegian construction sector *IOP Conf. Series* **225** 012061
[16] Sandberg E and Kvellheim A K 2021 *Ombruk av byggematerialer – marked, drivere og barrierer*
[17] De Felice F and Petrillo A 2021 Green transition: the frontier of the Digicircular economy. Evidenced from a systematic literature reviee *Sustainability* **13** (19) 11068
[18] Antikainen M, Uusitalo T and Kivikytö-Reponen P 2018 Digitalisation as an enabler of circular economy *Procedia CIRP* **73** 45-9
[19] Chan P et al. 2020 The digital potential in creating a circular construction economy *Technische Universitetit Delft, The Netherlands*
[20] Debacker W et al. 2017 Circular economy and design for change within the built environment: preparing the transition *International HISER conference on advances in recycling and management of construction and demolition waste* 114-117
[21] Mulhall D et al. 2022 The product circularity data sheet: a standardized digital fingerprint for circular economy data about products *Energies* **15** 9-3397
[22] MacArthur E 2022 *Looping on data*
[23] Kirchherr J, Piscicelli L, Bour R, Kostense-Smit E, Muller J, Huibrechtse-Truijens A et al. 2018 Barriers to the circular economy: evidence from the European Union *Ecol. Econ.* **150** 264-72
[24] Munaro M R, Tavares S F and Bragança L 2020 Towards circular and more sustainable buildings: a systematic literature review on the circular economy in the built environment *J. of Clea. Prod.* **260** 121134
[25] Moscati A and Engström S 2019 *Digitalisation and industrialisation: exploration of the current and future challenges in the Swedish built environment sector*
[26] Redwood J, Thelning S, Elmualim A and Pullen S 2017 The proliferation of ICT and digital

technology systems and their influence on the dynamic capabilities of construction firms *Procedia Eng.* **180** 804-11
[27] Bell E and Bryman A 2015 *Business research methods* Oxford University Place (Oxford)
[28] Ryen A 2002 *Det kvalitative intervjuet: fra vitenskapsteori til feltarbeid* Fagbokforlaget

Appendix V

Paper V

«Construction Project Quality Assurance with AI-powered 3D Laser Scanning and BIM: A Standardised Framework»

Submitted to: Construction Innovation
ISSN: 1471-4175

This paper is submitted for publication and is therefore not included.

Appendix VI

Paper VI

«Sustainable Implementation of AI in Construction: Challenges and Opportunities for Data Management»

Submitted to: Buildings
ISSN: 2075-5309

This paper is submitted for publication and is therefore not included.

ISBN 978-82-326-7552-4 (printed ver.)
ISBN 978-82-326-7551-7 (electronic ver.)
ISSN 1503-8181 (printed ver.)
ISSN 2703-8084 (online ver.)

NTNU

Norwegian University of
Science and Technology