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.

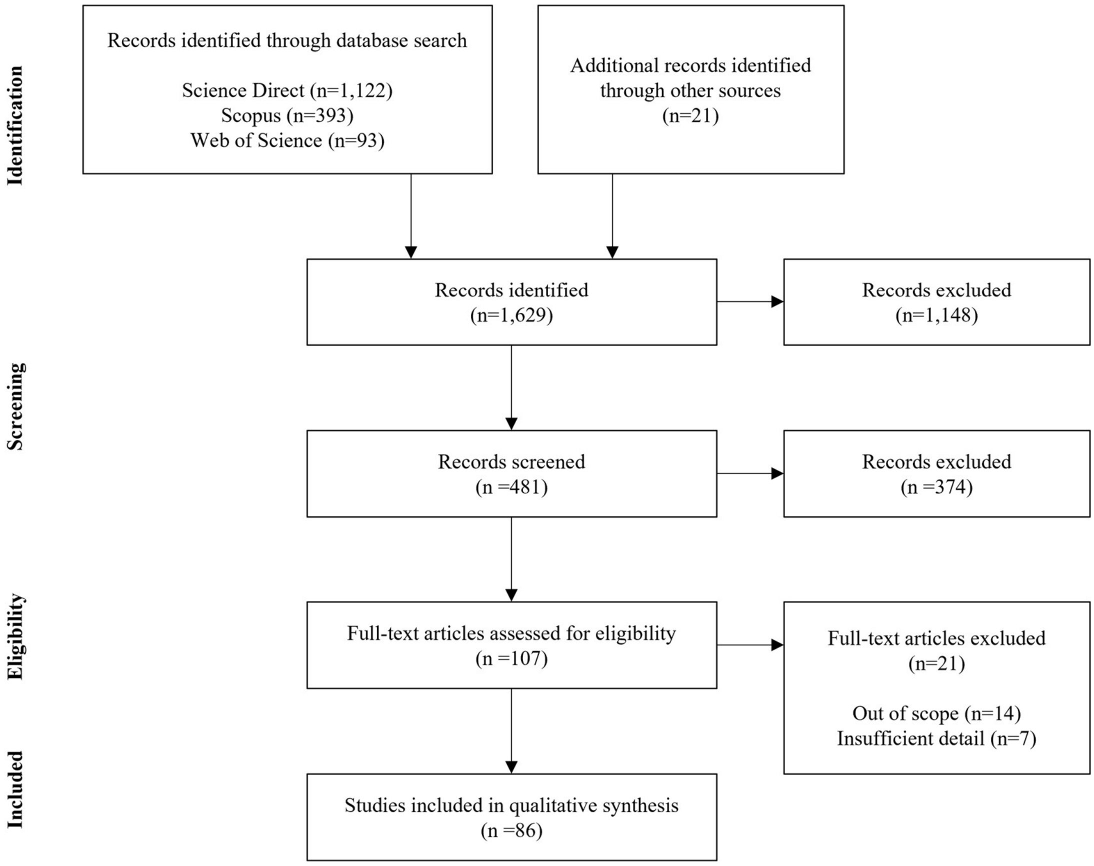

Fig 1. PRISMA flow diagram describing the review process

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).

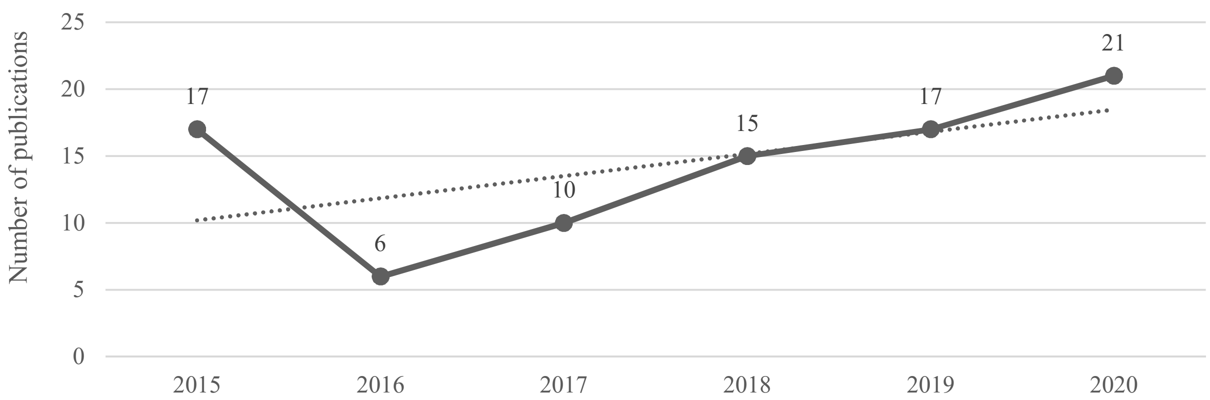

Fig. 2. The number of publications per year

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.

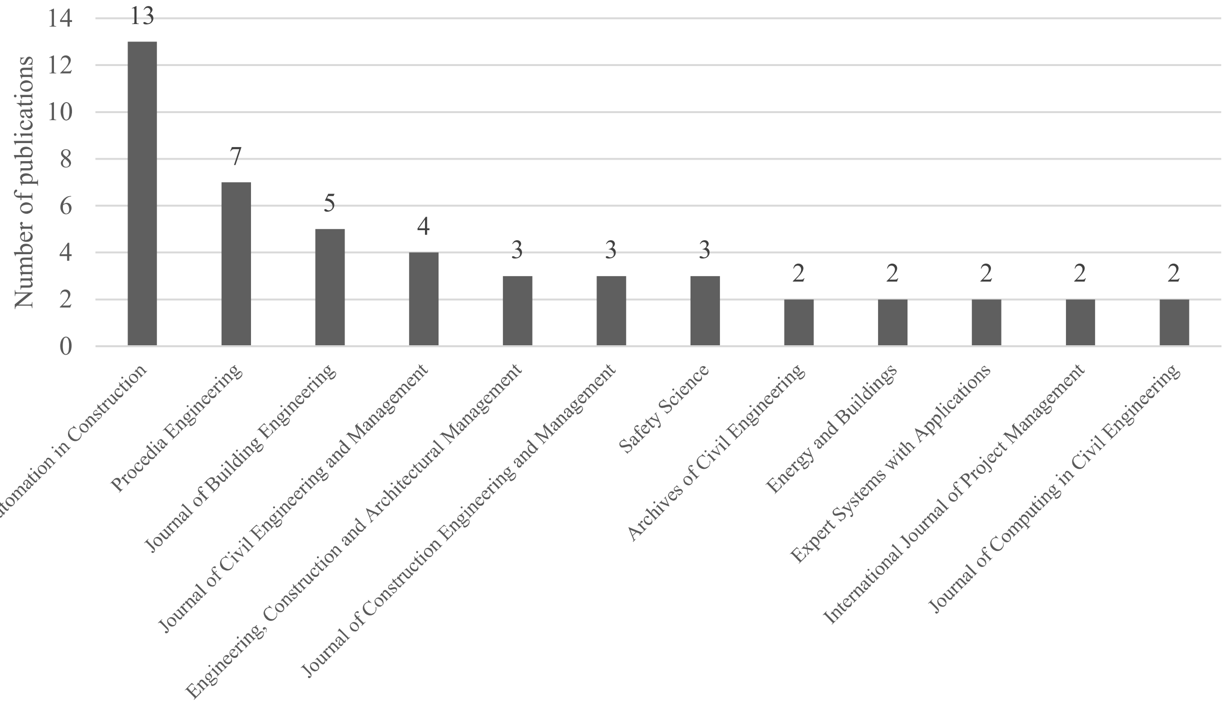

Fig. 3. Most frequent publication channels

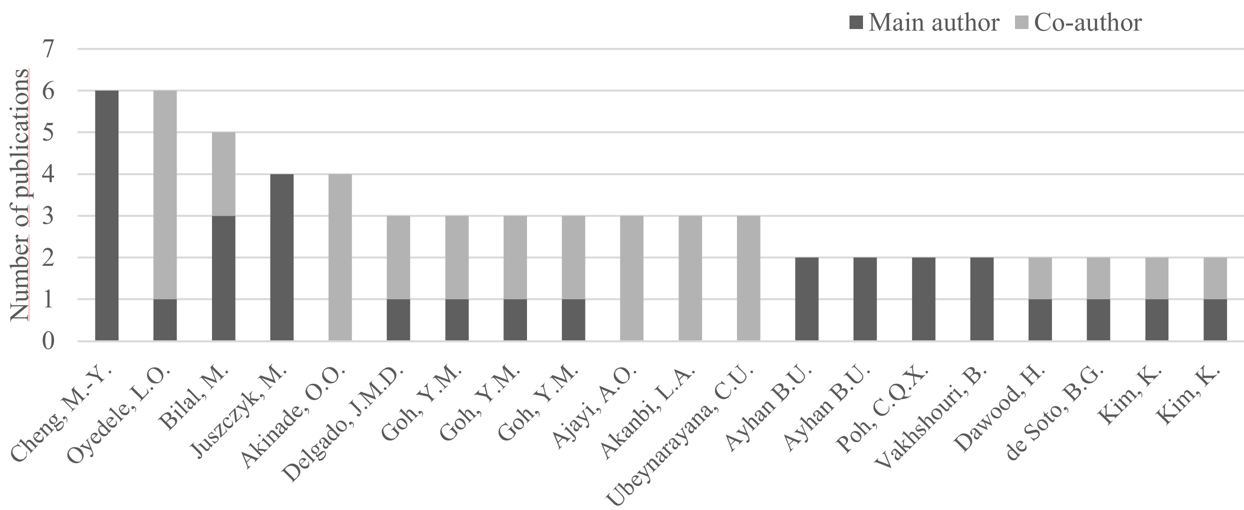

Fig. 4. Most frequent authors with two or more publications

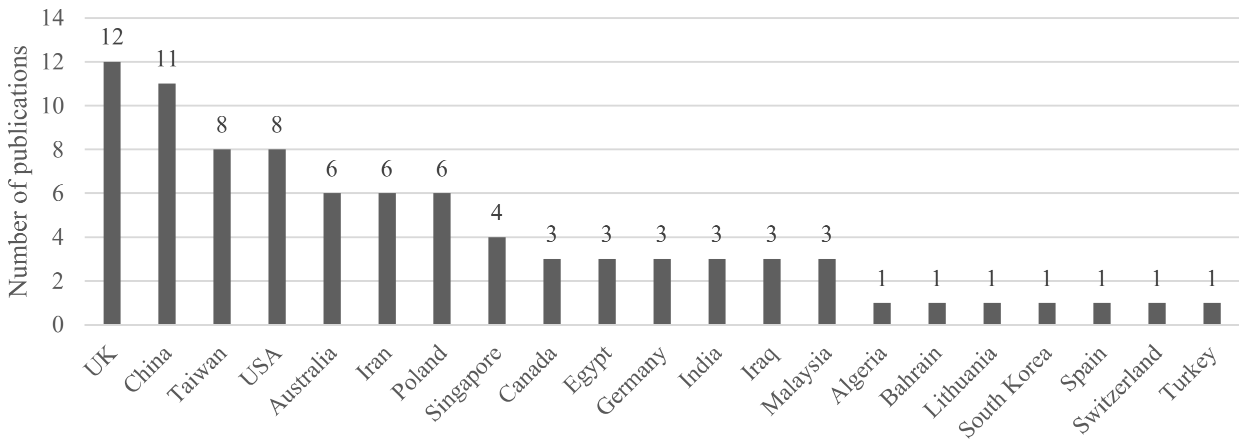

Fig. 5. Most frequent countries of main authors

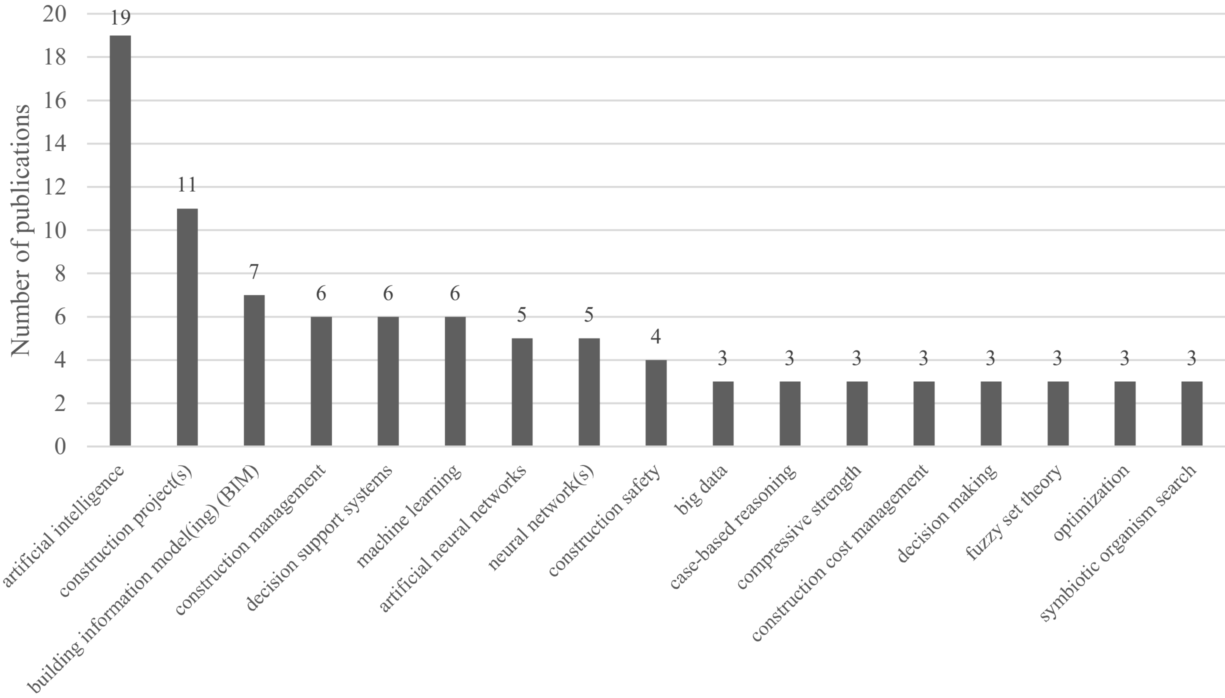

Fig. 6. Most frequent keywords

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.

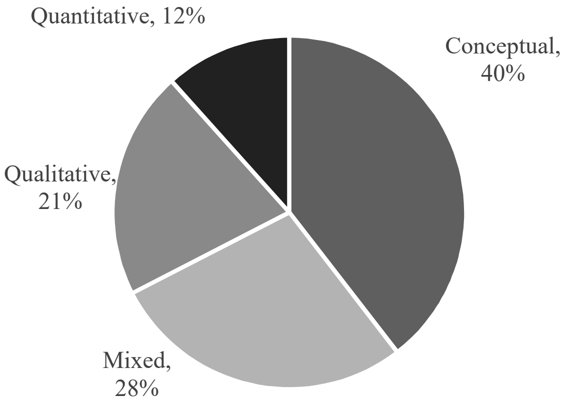

Fig. 7. Distribution of chosen methodology

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).

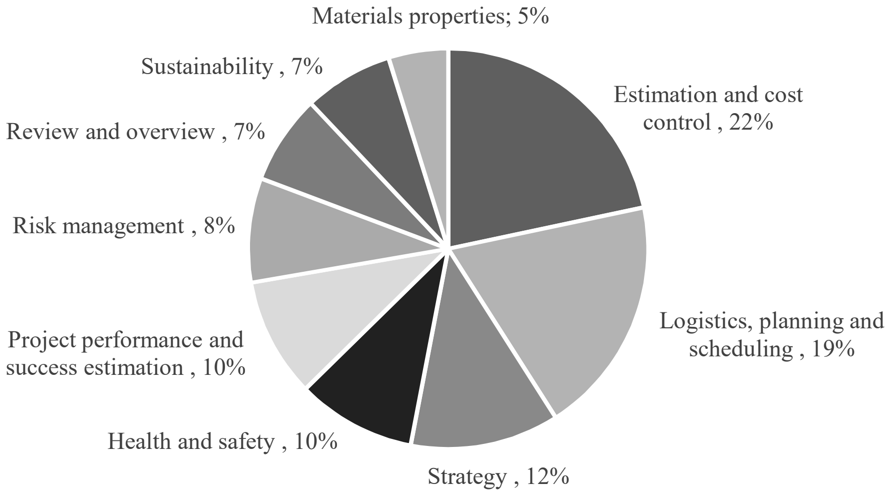

Fig. 8. Distribution of areas of application

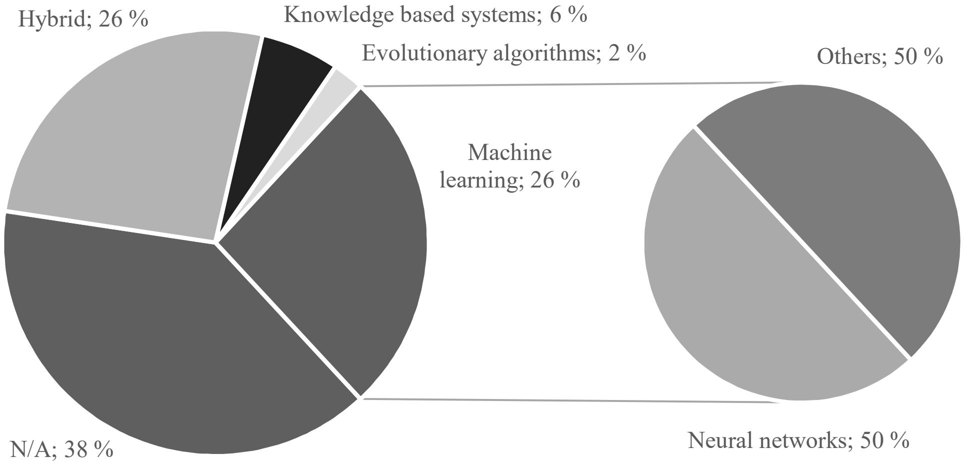

Fig. 9. Distribution of discussed technology

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.