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Review

Trustworthy AI and robotics: Implications for the AEC industry

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ABSTRACT

Human-technology interaction is concerned with trust as an inevitable user acceptance requirement. As the applications of artificial intelligence (AI) and robotics emerge in the architecture, engineering, and construction (AEC) industry, there is an immediate need to study trust in such systems. This paper presents the results of a systematic review of the literature published in the last two decades on (1) trust in AI and AI-powered robotics and (2) AI and robotics applications in the AEC industry. Through a thorough analysis, common trust dimensions are identified and the connections to the existing AEC applications are determined and discussed. Furthermore, major future directions on trustworthy AI and robotics in AEC research and practice are outlined. Findings indicate that although AEC researchers and industry professionals increasingly study and deploy AI and robotics, there is a lack of systematic research that studies key trust dimensions such as explainability, reliability, robustness, performance, and safety in the AEC context

1. Introduction

The growing sociotechnical influence of Artificial Intelligence (AI) and AI-powered robotics is nowadays realized in various industrial and organizational processes. As the role of AI in our lives becomes more prominent, and with the emergence of autonomous and intelligent agents in industrial settings, the need to build trust towards these agents by their human counterparts is becoming ever more apparent [1].

A report published by the National Academies of Science, Engineering, and Medicine together with the Royal Society identified trust, transparency, and interpretability as some of the key sociotechnical challenges in designing, evaluating, and deploying AI systems [2]. Research has consistently shown that an explainable and transparent decision-making process can help users gain an appropriate level of trust in intelligent agents [3]. However, the algorithmic complexity and abstraction of AI-based processes makes it challenging to provide straightforward and comprehensible explanations for such decisions [4]. Additionally, while transparency is one of the key factors, it is not the only element that affects trust in AI and robotics [5]. For example, in the context of AI-enabled robots, it was shown that new technology is more trusted when it functions reliably and safely as we expect other humans to do [6].

Over the past two decades, the architecture, engineering, and construction (AEC) industry has shown significant potential to widely deploy robotics and AI technologies. However, the industry practitioners are generally reluctant to trust new technologies, and the use of antiquated work processes is prevalent [7–10]. Small businesses comprise the vast majority of the industry with a share of 82.3% (compared to 44.4% for manufacturing and 35.1% for retail) [11] and smaller companies are known to be often the "late majority" and "laggards" in technology adoption [12]. Additionally, a typically very small profit margin (i.e., 3-5%) makes AEC practitioners more hesitant to adopt new technologies with unproven cost-saving prospects and expensive ownership cost for programming and maintenance. Research has shown that building a culture of trust in the potential and reliability of AI-powered systems and robotics can play a key role in enhancing adoption levels within the AEC industry [13].

In this study, a thorough systematic review of the literature on (1) trustworthy AI and AI-powered robotics, and (2) AI and AI-powered robotic applications in the AEC is presented to prime this area of research for future studies. It is important to note the twofold scope of this research project as illustrated in Fig. 1.

2. Research background

2.1. Definitions

Trust is defined as "*the attitude that an agent will help achieve an*

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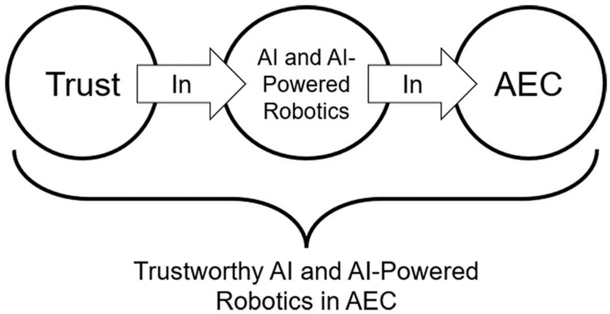

Fig. 1. The two-fold focus of this study and interconnection of the scopes

individual's goals in a situation characterized by uncertainty and vulnerability" [14], and as "*the reliance by an agent that actions prejudicial to their well-being will not be undertaken by influential others*" [15]. AI and AI-powered robotics belong to interdisciplinary fields that include computer science, engineering, mathematics and statistics, and psychology that enable learning from existing data and past experience to perform tasks that typically require humans' intellectual processes [4,16,17]. AI and AI-powered robotics applications studied in this research include embodied intelligence (e.g., a robot) and software or hardware that can be used stand-alone or distributed through computer networks.

2.2. Previous systematic reviews in this area

Trustworthy AI and AI-powered robotics, have been previously the subject of systematic literature review articles [18,19]. Such studies often describe the factors that increase the acceptability and reliability of these technologies [18] and define trust in the context of those factors [19]. A widely acknowledged fact in studies of trust in AI and AI-powered robotics is the importance of contextualized research with a special focus on the culture of the environment in which the technology is adopted [20]. Similarly, the technology acceptance behavior and technical background of the end users have shown to be highly consequential on the level of trust in AI and AI-powered robotics [9]. Trust factors often have different interpretations in different contexts (or industries). For example, security or reliability in the banking industry are among critical trust dimensions with clear definitions [21] that are different from what they mean in a construction project or architectural design task. In the AEC industry, with a considerable heterogeneity of work conditions and stakeholders in a typical project, such contextualization considerations deserve even more attention. Nevertheless, to the best of the authors' knowledge, there has been no systematics review effort to identify AI and robotics trust factors in the AEC industry and consolidate publication records in this area. A limited number of papers that studied AI and robotics in AEC have only discussed the challenges, limitations, and benefits of using these technologies in this industry, without offering practical solutions to address trust issues. This paper consolidates the records of research published on the topics of trust in AI and AI-powered robotics as well as AI and AI-powered robotics in AEC to create a comprehensive picture of trust requirements and dimensions conducive to this industry.

3. Systematic review methodology

In this study, a systematic literature review (SLR) approach developed by Lockwood and Oh (2017) is used to illustrate a comprehensive picture of the literature and review the most relevant publications. Fig. 2 presents a schematic overview of the review approach adopted in this research.

3.1. Establishing a research question

The first step in the SLR is to set up its focus through framing clear research questions to be addressed in the review. Well-formulated questions can guide the direction of the review by determining what studies should be included/excluded in the research, how these studies should be identified, and what information should be extracted from them [22,23]. The research questions in this study follow the same twofold structure of "trust in AI and AI-powered robotics" and "AI and AI-powered robotics in the AEC industry". Specifically, this study seeks to answer two questions: (1) What are the key and common drivers (i.e.,

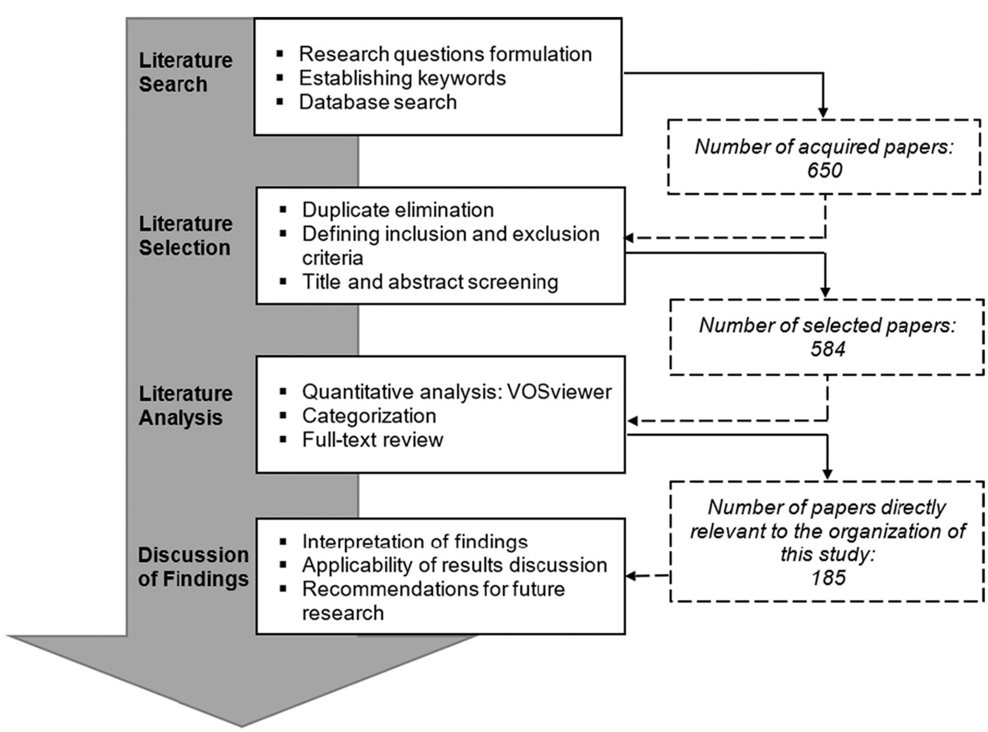

Fig. 2. Schematic overview of the SLR approach used in this research study

dimensions) of human trust in AI and AI-powered robotics? (2) What are the connections, similarities, and differences between the identified dimensions and the existing/potential applications of AI and AI-powered robotics in AEC?

3.2. Database search

A comprehensive literature search was conducted in Scopus, Google Scholar, Web of Science, and PsycInfo databases to find articles, primarily published in peer-reviewed journals and conference proceedings. The first three databases were selected because they are among the most comprehensive and up-to-date sources of publications [24]. PsyInfo was also selected because human trust is in essence a psychology topic and this database is the primary reference source in the psychology research disciplinary area. Therefore, the selected four databases collectively form a comprehensive resource of the pertinent studies in this research. After a preliminary analysis of the literature [25], a list of search keywords was created, which was further refined as the searching process progressed. Particularly, the keywords were selected to cover all three main areas of Purpose, Process, and Performance during the two stages of "building initial trust" and "continuous trust development" as identified in previous research in this area [26]. The set of keywords and key phrases used to search in titles, abstracts and keywords included "Trust in AI", "Trustworthy AI", "Acceptance modeling for AI", "Ethical AI", "Transparent and explainable AI", "Interpretable AI", "Reliable AI", "Safe AI", "Privacy in AI systems" and "Human-robot interaction", to find papers on trust in AI and robotics domain. To collect papers related to the use of AI and robotics in AEC, keywords and key phrases including "Artificial Intelligence in construction management", "AI in construction management", "AI-enabled systems in construction management", "Robotics in construction management", and "Construction automation" were used. Furthermore, single words of these phrases were combined using the + operator (for example: "AI+construction+trust" or "AI+intrepretability") to expand the search results. In total, the search resulted in 650 preliminary publications including journal and conference papers, theses, and book chapters that were collected for review and imported to a reference managing software EndNote [27].

3.3. Literature selection

At this stage of the SLR, abstracts, highlights, and key words were retrieved, analyzed, and reviewed, and those studies that met the inclusion criteria were selected for a full review. The inclusion criteria were: (1) papers must be peer-reviewed and published after 2000 (papers published prior to 2000 were not included due to the fast pace of AI and robotics research advancement in the last two decades); (2) papers must be written in English language; and (3) the study subject of the papers must be either on trust (or its dimensions) in AI and robotics, or the applications of AI and robotics in the AEC industry, or both. This literature selection and screening process reduced the total number of articles to 584.

3.4. Literature analysis

This stage involved creating a metadata spreadsheet describing these papers (i.e., title, authors, publication year, and keywords) and a detailed review of the content. Among the total of 584 selected publications, 361 papers were written by authors affiliated with the United States institutions, 47 papers were written by authors affiliated with institutions in China, and 29 papers were written authors affiliated with European institutions, as the top three geographical regions producing 75% of the publications in this field. The top 10 sources in this review with the highest number of published articles in the field of trustworthy AI and robotics or AI and robotics in AEC are presented in Table 1. Also, Table 2 shows the vast majority of these articles were published as journal papers.

Table 1
The top 10 publication venues with the highest number of publications reviewed

Venue Name	Number of Publications
Automation in Construction	56
arXiv Preprint	28
Journal of Construction Engineering and Management	14
Journal of Computing in Civil Engineering	12
International Symposium on Automation and Robotics in Construction (ISARC)	11
International Journal of Social Robotics	8
Nature Machine Intelligence	7
Energy and Buildings	7
Artificial Intelligence	7
Computers in Human Behavior	6

Table 2
Distribution of publication source types

Source	Number of Publications
Peer-Reviewed Journals	407
Conference Proceedings	131
Book Chapters	39
Theses	11
Online Articles/Reports	4

Furthermore, the result of a temporal bibliographic analysis is shown in Fig. 3. In this Figure, a publication date histogram of the articles reviewed in this study is presented in two categories; those discussing trust in AI, and the ones focused on developing or adopting AI models for AEC applications. Fig. 3 shows that the number of articles published in these two areas of research has grown significantly since 2016. It is also noteworthy that this growth has been slower in the AEC industry. Additionally, the histogram is heavily skewed to the right which indicates the significant traction that has been gained by these two topics in the past five years. As the AI and robotics research community's interest grow in the area of trust, research in AI and AI-powered robotics in AEC is also growing by a considerable margin. This observation emphasizes the necessity and significance of research on trustworthy AI and robotics in the context of AEC applications.

Finally, an analysis of keyword co-occurrences has been conducted to create a concise grouping of trust dimensions that is used to organize this literature review. This analysis was conducted using VOSviewer software [28] and the map of the co-occurrences is shown in Fig. 4.

The size of the nodes is proportionate with the frequency of the keyword occurrence and the distance between each two nodes is inversely proportionate with the number of the keywords co-occurrences in the literature analyzed. This Figure serves two purposes. First, it clearly depicts the trust dimensions (identified in Section 4) in the context of AI-enabled systems and robotics in the literature. They stand out as larger nodes, in the close proximity of the words "AI", "machine learning", and "trust" nodes. Second, it elaborates on these dimensions by showing the related factors (or sub-dimensions) that affect trust in AI and AI-powered robotics systems. Fig. 4 implies that factors such as explainability or security have been frequently cited in the literature as they demonstrate a relatively larger node size compared to other nodes (not considering AI, trust, and robotics, as they are the subject keywords). However, some factors, such as cyber security, have not been subject to as many studies. A preliminary conjecture solely based on such analysis could be that factors such as explainability have a much greater impact on the level of trust in AI and AI-powered robotics, even though such arguments must be evaluated through much rigorous analysis. It is equally likely that smaller nodes belong to trust factors that are as important as the larger ones in the AEC context, but they have not been yet studied sufficiently. This highlights the synergistic effect of all these dimensions and subdimensions and the fact that a comprehensive investigation must take all these dimensions and sub-dimensions into

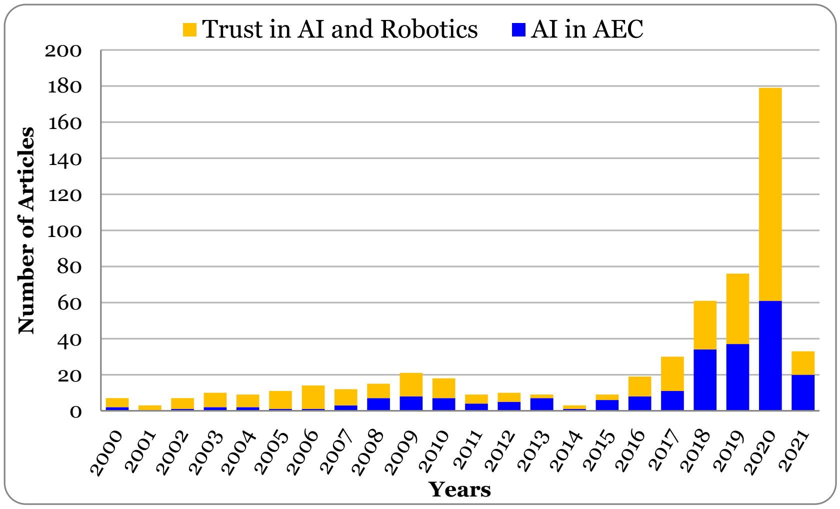

Fig. 3. Histogram of the reviewed papers associated with the two topics of AI in AEC and Trustworthy AI and Robotics from 2000 to early 2021

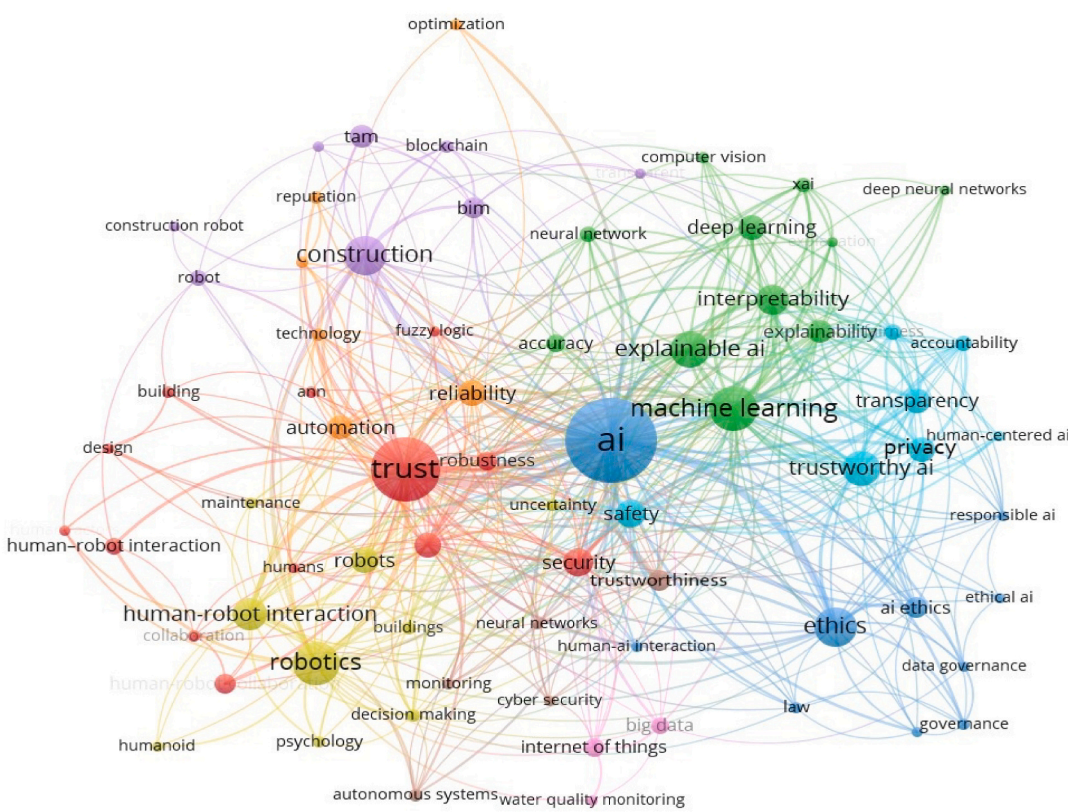

Fig. 4. Map of keyword co-occurrences

considerations. Thus, Fig. 4 as a whole, can help in developing a roadmap for trust in AI and robotics research in the AEC industry. The next Section describes a framework of trust dimensions based on the co-occurrence analysis here, which in turn provides an organization for further discussion.

4. Trust dimensions

State-of-the-art research has used different taxonomic categorizations to classify factors influencing trust in AI and robotics [4,29–33]. A notable study in this area suggests that different trust dimensions affect human trust regardless of whether AI is deployed as a robot, virtual assistant, or embedded in a software [4]. Therefore, an integrated but compartmentalized review approach can provide a comprehensive view of trust in AI within a specific disciplinary field. To identify the key trust dimensions most applicable to AEC projects and applications, the authors have initially conducted a thematic analysis to identify the key relevant trust dimensions [25]. Inspired by the findings of that study and the literature on trustworthy AI and robotics, in this research common trust dimensions are used to organize a comprehensive and systematic review of the literature. The eight dimensions identified are Explainability, Interpretability, Reliability, Safety, Performance, Robustness, Privacy, and Security. Considering semantic similarities and in order to create a more focused discussion for AEC applications, the eight dimensions are presented in four pairs for the purpose of this review. Each pair is formed by grouping two dimensions that according to the authors' analysis, have appeared more frequently, studied together in trust in AI and robotics research, and are related in the context of AEC research [25]. Therefore, a total of four key trust dimension pairs are used to review empirical research on trustworthy AI and robotics and implications for AEC research. Fig. 5 illustrates the four trust dimensions used to organize this paper and a brief description of each dimension is provided in the following subsections.

4.1. Explainability and interpretability

In AI and robotics applications, explainability is often related to the concept of interpretability, where the operations of a system can be understood by a human through introspection or explanation [34,35]. In computer science, explainable AI (XAI) is a trending research topic [36]. In AEC, it is especially important since technologies are often not developed in-house. Therefore, the end-users may need to understand workflow between the input and output (i.e., explainability) and the output should be understandable and meaningful to them (i.e., interpretability).

4.2. Reliability and safety

Reliability is concerned with the capacity of the models to avoid failures or malfunctions and exhibit the same and expected behavior over time [37]. It can be seen from both technical and cognitive/psychological (e.g., affect) perspectives [38]. As a related dimension, and in the context of adopting AI and robotics in AEC, safety also has to be studied from both technical (i.e., avoiding accidents with heavy-duty construction robots) and psychological (i.e., AI and robotics applications seen as job companions, not competitors) viewpoints [39,40].

4.3. Performance and robustness

Ability, accuracy, or competence are similar concepts used in the AI and robotics literature to refer to the importance of performance indicators in gaining human trust [26,29,41]. These indicators (collectively referred to as performance in this study) play a key role in trust trajectories. Research has shown that humans have some preliminary performance expectations toward AI-enabled robots and failing to satisfy that expectation (or exceeding it) after interaction with the system has a major effect on trust [4,42]. A related concept in this realm is robustness. Robustness refers to performance consistency in different situations where the AI model or the robotic system is deployed [29]. This is particularly important in AEC applications as the environment and workflows are ever-changing within and between projects and failure to adapt to the new setting would result in reduced levels of trust.

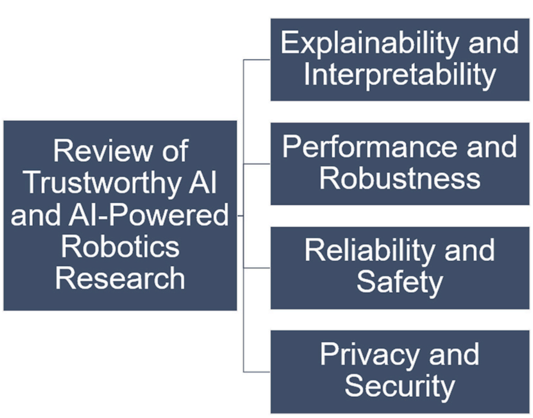

Fig. 5. Trust dimensions selected for a systematic review of trust in AI and AI-powered robotics in the AEC industry

4.4. Privacy and security

Humans' trust in technology is highly influenced by the levels of privacy and security involved in technology implementation [38]. Both dimensions fall under the category of ethical or responsible AI where the protection of human identity and sensitive data as well as the vulnerability (i.e., security) of the system against attacks that breach privacy are known as leading trust (or distrust) drivers [43]. In the AEC literature, workers and clients' sensitive data vulnerable to privacy leaks [44] as well as cybersecurity issues pertaining to the use of cameras, drones, and other sensing devices have been widely regarded as barriers to technology adoption [44,45]. Privacy and security issues in AEC are prone to be exacerbated by the growth of automated and intelligent agents and have to be addressed in the context of AI-based systems and robotics.

5. AI and robotics adoption in the AEC industry

Notwithstanding the recent surge in industrial technology advancements and innovations, technical processes and workflows in the AEC industry have been long criticized for inefficiency, safety hazards, and workforce issues [9,46–49]. In other industries such as automotive, health care, and manufacturing, AI-enabled systems and robots helped alleviate such challenges [50,51]. Similarly, digital transformation is set to revolutionize the AEC industry and AI and robotics play a critical role in this major transformation [52]. Many researchers have studied and explained the potential improvements made by AI-based technologies and robots for different phases of construction projects [9,20,53–58]. Nevertheless, a one-size-fits-all study of AI and robotics adoption does not do justice in the AEC field due to the multifaceted nature of construction projects involving multiple stakeholders, decentralized production, extensive use of subcontractors in different trades, lack of standard workflows, and various project types. Therefore, researchers have used various classification schemes to categorize technology adoption approaches, drivers, or barriers in the AEC fields. For example, Hatami et al. (2019) focused on construction manufacturing systems and categorized the use of AI in this area into four main applications of planning and design, safety of autonomous equipment, and monitoring and maintenance [59]. In another study, a systems-framework was presented by Pan et al. (2020) to identify key factors influencing the future implementation of construction robotics in Hong Kong. They identified eleven interrelated factors, critical for shaping the future trajectory of construction robotic applications, including construction costs, government support, and the scale of prefabrication, and suggested that implementation of robots in construction suffers from lack of interdisciplinary and non-technical studies [60]. The four main factors hindering the adoption and acceptance of robotics and automated systems in the construction industry were identified in another study as (1) contractor-based financial factors, (2) client-based financial factors, (3) technical and work-culture factors, and (4) weak business case factors [9]. In another scientometric study and using a science-mapping method, it was concluded that genetic algorithms, neural networks, fuzzy logic, fuzzy sets, and clustering have been the most widely used AI methods in AEC to address topics and issues such as optimization, simulation, uncertainty, project management, and cash flow analysis [52,61]. Sacks et al. (2020) described AI fields such as machine learning, deep learning, and computer vision as top AEC-supporting technologies besides more established technologies such as BIM, 3D printing, and Simultaneous Localization and Mapping (SLAM). With respect to adoption driver and barriers, research has identified three key parameters of (1) promotion and support of research and evolution of supporting technologies, (2) simultaneous or non-simultaneous developments in various fields of application, and (3) interdisciplinary collaboration between AEC industry and technology companies as key drivers of Research and Development (R&D) in construction robotics

[62]. Additionally, Sacks et al (2020) indicated that lack of complete and accessible information in models is a major hindrance to broad adoption of BIM and AI technologies in the construction industry that prevents effective exploitation of the information they provide [63].

6. Discussion of trust dimensions and implications for the AEC Industry

As stated in Section 4, a thorough scrutiny of the collected papers reveals that a series of factors contribute to the "attitude" or "reliance" (see the definition of trust in Section 2) in a multi-dimensional space. These factors or dimensions have been presented with different names, manifested in different characteristics of the human-technology system, and categorized based on their semantics and functionality towards trust building. The dimensions identified in Section 4 are used in this section to present a review of their characteristics, applications in different disciplinary research fields, and implications for the AEC industry. A wide variety of other factors pertinent to these four (as shown by connected nodes in Fig. 4) are also considered here to depict a complete picture of trust as a multi-dimensional space.

6.1. Explainability and interpretability

As suggested by the panel on the One Hundred Year Study on Artificial Intelligence: Artificial Intelligence and Life in 2030 [64]: "well-deployed artificial intelligence prediction tools have the potential to provide new kinds of transparency about data and inferences, and may be applied to detect, remove, or reduce human bias, rather than reinforcing it." Technologies that involve obscure processes between the input fed to the system and the generated output are generally less trustworthy than those with transparent and interpretable inner-workings [65]. The lack of a common language is a key barrier to achieving transparency in AI as varying dentitions exist across disciplines [2]. "Openness" and "explainability" are two neighboring terms that are commonly used in the literature to refer to the transparency and interpretability concept in AI systems and address the notions implied by "black box" terminology [66]. In particular, the concept of XAI has recently gained tremendous momentum in computer science research [34,67,68]. This research trend is motivated by intriguing results of deep learning (e.g., mistakenly labeling a tomato as a dog [69]) to provide an overview on transparency and interpretability of data-driven algorithms [34,70–73].

XAI is in essence an initiative to transform black-box to white-box AI, where the process by which the algorithms and models arrive at an output could be intuitively interpreted by humans. A white-box model is explainable by design and does not require additional processes to be explained. In other words, XAI allows AI systems to operate in a glass box, enabling computers to understand the context in their operational environment while keeping humans in their decision loop [74]. Similarly, knowledge representation and reasoning are the types of AI models that develop knowledge-based systems using a symbolic representation of domain knowledge and pre-defined rules rather than complicated algorithms or statistics [75]. As a result, computers can reasonably comprehend the knowledge, facts, and beliefs that exist in the actual world, and then use them to derive accurate conclusions and promote logic inference in a clear and efficient manner. Pan and Zhang (2021) identify structural equation modeling (SEM) and Bayesian networks, as two easy and useful tools for establishing measurement models for knowledge representation.

Particularly in robotics, explainable agents (e.g., autonomous robots) are capable of providing explanations about their actions and the rationale behind their decisions [76]. Understanding the behaviors of robots that result in perceiving their actions is known as mentalizing or mindreading which is derived from the Theory of Mind (ToM). According to the ToM, humans estimate the actions of other humans by observing their behavior and attributing mental states thereby attempting to understand their own perspective [77,78]. Research studies in the field of human-robot interaction (HRI) have confirmed that humans show a similar to non-human objects and robots [77,79]. More generally, and to gauge humans' trust in applied AI, it is important to account for how ordinary users understand explanations and assess their interactions with the system (e.g., tool, service) [80]. Developing higher extents of explainability and interpretability equips users with higher levels of understanding of and thereby trusting in the intelligent agents or AI models [81–83].

In industrial applications, explainability and interpretability can be viewed as the most important factor in determining the level of trust in AI and robotics given the fact that such systems are often designed and developed by companies external to the end-user organization [84]. This is particularly true for AEC companies where technologies are not always developed in-house, and they are sometimes purchased or licensed from outside developers. In such cases, the obscure nature of decisions made by AI-based systems and robots make practitioners even more hesitant to trust them [85]. From an HRI standpoint, transparency and interpretability in construction robotics can be achieved if the robot is flexible in the type and extent of help it offers. The level of collaboration may differ as some tasks are structured and specified to be completely performed by a robot, while some other tasks may require human engagement (i.e., human-in-the-loop) [86]. In construction, human-in-the-loop applications comprise the majority of the current applications. In one example, Follini et al. (2020) proposed a collaborative robotic platform focused on human-in-the-loop applications considering the unstructured, dynamic job site environment. Their proposed platform is programmed to follow the operator while it carries heavy materials and equipment and stops when its sensors detect the close distance to the operator or any obstacles. Additionally, the robot can navigate through the site based on known geometric and semantic information of the building project by connecting the Robot Operating System (ROS) the BIM [87].

Very little research has been explicitly devoted to the role of explainability and interpretability in AI-based AEC applications. Researchers have examined the potential of Blockchain technology to increase transparency and simplify interpretably in different phases of construction [88,89]. Blockchain technology promotes peer-to-peer digital transaction management which can be used as a secure and transparent method among users. In simple words, Blockchain can add value to AI by explaining AI decisions, mitigating AI risks, increasing AI efficiency, and improving data accessibility and decentralization [90]. In one study, a framework was proposed based on Blockchain technology to facilitate the use of BIM, and improve data transparency and security in construction projects [91]. In another study of the use of Blockchain in AEC industry, researchers proposed 3 Blockchain-based applications for construction projects, namely Blockchain-based contract management, Blockchain-based supply chain management, and Blockchain-based equipment leasing which can be utilized by AEC professionals [92].

In the context of knowledge representation, construction safety management is an area of application for SEM which is frequently combined with exploratory factor analysis (EFA). Zaira and Hadikusumo [93], for example, used SEM to identify the most effective intervention-related safety practices for improving workers' safety behavior. Similarly, Liu et al. used a combination of SEM and EFA to identify the critical risk factors and advise safety control in a complex metro construction project [94]. Zhang et al. created a SEM-based strategy to determine dynamic safety leadership roles during different phases of a construction project, which enabled stakeholders to better assign responsibility for safety management [95]. There is also a different strategy that can be used for reasoning. The fuzzy cognitive map (FCM) is constructed using data or expert opinions. This type of fuzzy graph structure interprets complex relationships and allows systematic causal propagation using a combination of fuzzy logic and cognitive map, which can provide immediate understanding and identification of root causes of a risk event even under complicated, uncertain, and subjective conditions [96].

The aforementioned examples and applications highlight the importance of explainability and interpretability to generate trust in AI and AI-powered robotics in any field including AEC. The term "comprehensibility" (which includes transparency, explainability, traceability, and consequently interpretability aspects) with regards to AI's decisions has emerged recently in the literature to cover a wide range of important concepts in this context. With the fast pace of technology advancements in the areas of AI and robotics, the social science literature emphasizes the need for research related to the interconnection between trust and the transparency of AI's decision. Moreover, since explainability and interpretability are qualitative phenomena and can be subjectively interpreted, concepts such as the limits of interpretability in AI and robotics and relative transparency of AI and robotics in the AEC industry are yet to be better investigated.

6.2. Reliability and safety

Reliability and safety are two cornerstones of trust in AI-powered systems [97]. Both concepts are related to trust from a performance (rather than a moral) angle [98] and are interconnected paradigms in the context of trust between the human user and a robot agent. On the one hand, safe interaction with robots make them more reliable and thus trustworthy [99]. On the other hand, increased reliability may lead to overtrust and higher potential complacency when the robots act unsafely [100,101]. This tradeoff highlights the importance of a process called trust calibration within a human-robot team to achieve an appropriate level of trust given both human and robot capabilities. Trust calibration process enables a human to accurately recognize the risks associated with trusting a person or machine [14]. In this process, the human user learns the abilities, reliability, and failure modes of the agent to avoid overtrust and undertrust [102]. If the user undertrusts the intelligent agent, trust calibration helps them to gradually build trust in the system with experience and iterative interactions [103]. Whereas in an overtrust situation, the user accepts too much risks as they believe that the system will mitigate those risks [104].

Another tradeoff that affects trust from a reliability and safety perspective, is the amount of human effort versus robot autonomy. Reliability is an HRI variable that needs to be evaluated as a function of robot autonomy. Beer et al. (2014) discussed this concept by proposing levels of robot autonomy (LORA) for HRI [105]. Their proposed LORA classification starts at a stage where the human is in full control and the process is Manual and continues with similar approximations of a robot's autonomy along a continuum that ends with Full Autonomy as illustrated in Fig. 6.

All these classifications are analyzed based on the engagement of the human, robot, or both in sensing, planning, and acting. Besides LORA, there are other similar widely influential taxonomies of automation levels such as the classic Sheridan-Verplank levels of automation [106] and recent classification schemes for self-driving cars levels of autonomy [107,108]. However, a common criticism of all these taxonomies is the fact that they only represent situations in which boosted levels of automation will certainly result in restricted and limited human control (i.e., one-dimensional levels of automation). In an effort to address these constraints, Shneiderman (2020) proposed the Human-Centered Artificial Intelligence (HCAI) framework to produce designs that are reliable, safe, and trustworthy and not a zero-sum game in terms of the robot and human levels of control. HCAI indicates that despite what one-dimensional taxonomies suggest, achieving high levels of human control, and at the same time, high levels of automation (i.e., two-dimensional HCAI) is possible and in fact, leads to increased human performance levels [109]. This two-dimensional HCAI toward reliable, safe, and trustworthy AI is shown in Fig. 7.

The construction industry deals with major safety and health problems, and many technology tools have been developed to alleviate this grand challenge [110]. As such, addressing safety issues using AI is a popular research topic in construction [111–113]. Construction tasks that should be carried out at a high altitude, over extended periods of overtime work, or under any hazardous condition are desired to be delegated to AI-controlled systems or robots to increase efficiency and eliminate accidents [86]. Systems that use hazard proximity monitoring are among the most common applications of AI for construction safety. For example, researchers have implemented a system which sends images from trucks, cranes, and other construction machinery to a database via 5G wireless networks and utilizes AI to evaluate the interactions between workers and equipment [114]. AI can also be used to predict safety measures such as injury severity, injury type, body part impacted,

Level	Description
Full Autonomy	Robot performs all aspects of a task autonomously
Supervisory Control	Robot does all aspects of task, but human continuously monitors the process. Human can override and set new goals
Executive Control	Human sets an abstract high-level goal. Robot autonomously senses environment, sets the plan, and takes action.
Shared Control with Robot Initiative	Robot does all aspects of the task and can ask human for assistance in setting new goals and plans, if there are difficulties and ahcllenges.
Shared Control with Human Initiative	Robot autonomously senses the environment, develops plans and goals, and takes actions. Human monitors the process and may intervene and set new goals and plans if the robot is facing challenges.
Decision Support	Both the human and robot sense the environment and generate a task plan. Human makes the final choice and commands robot to execute tasks.
Batch Processing	Both the human and robot monitor and sense the environment. Only human sets the goals and plans for the task. Robot executes the assigned tasks.
Assisted Teleoperation	Robot senses the environment and chooses to intervene with task that human assist with all aspects of it.
Teleoperation	Human is responsible for sensing and planning. Robot assists the human with task execution.
Manual	Human does all aspects of the task with no involvement of robot.

Fig. 6. One-Dimensional levels of robot involvement in operations (modified from Beer 2014)

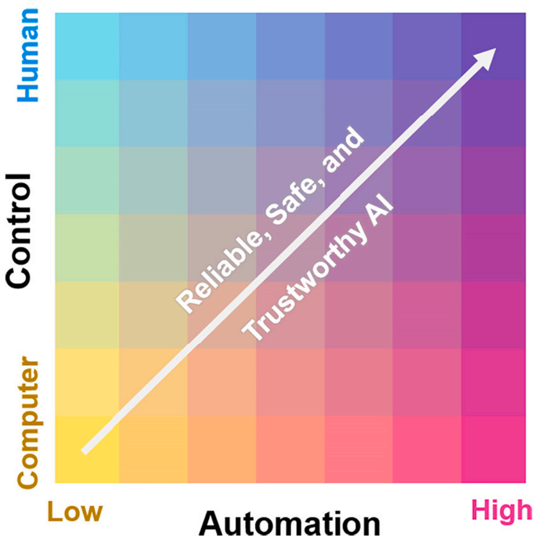

Fig. 7. Two-dimensional framework for HCAI (modified from Shneiderman 2020).

and incident type in a construction project [115]. In building construction, a dynamic BIM can provide AEC project teams with insights for better planning and more efficient design, construction, and operation/maintenance. This can be improved by BIM and AI-based software packages that use machine learning algorithms to analyze all aspects of a proposed design (or an altered design) to ensure it does not interfere with other systems in the building, thus enhancing the reliability of design [10]. As an example, the usefulness of AI in designing smart homes has been extensively discussed by Augusto and Nugent [116].

However, regardless of whether the ultimate goal is to address a safety challenge or not, newly introduced AI-enabled systems and robotics will be less trusted if they pose new safety threats. Research has shown that any technologically advanced system must exhibit reliability and safety to be acceptable in construction [117]. Human safety while working with intelligent robots in industrial applications is an important consideration since the type of robot hardware is usually rugged, large, or manipulation-enabled and humans often feel unsafe working around such robots [118,119]. Fig. 8 shows a few examples of using such robotics systems in building construction.

The study of reliability and safety in human-robot interaction in construction is often conducted with two validation approaches. In one approach, robot prototypes operate in physically simulated working environments to identify robot weaknesses in reliability and safety and enhance its functionality. Another approach is to develop predictive models to explicate the perceived reliability and safety of robots and their influence on humans [124,125]. Models such as the Robot Acceptance Safety Model (RASM) have been developed using the second approach in the construction robotics literature. RASM is a model that integrates Immersive Virtual Environments (IVEs) to analyze the perceived safety of collaborative work between humans and robots. This was done by inviting participants to a laboratory to collaborate and work with a 3D simulated robot regarding a construction-related task using a head-mounted display. According to the IVE results, segregation of human and robot working areas leads to accelerated perceived safety as it facilitates team identification and fosters trusting robots gradually. Moreover, it was deduced that the improved safety feeling and comfort of simulation attendees while working with robots signifies their willingness to work with robots in the future [126]. Collaboration and efficiency of human and robot work in industrial settings can be hindered by collisions and other types of accidents [127]. Active vision-based safety systems have been reported to be one of the best solutions to mitigate collisions and consequently, boost trust in humans to work alongside robots and automation systems. Recent methodologies and advances in vision-based technologies and alarming systems including various methods, sensor types, safety functions, and static/dynamic action of robots to work in their zones have been reviewed and analyzed technically in the literature [128].

The literature reviewed in this research suggests that the applications of AI and its subfields (e.g., machine learning, computer vision,

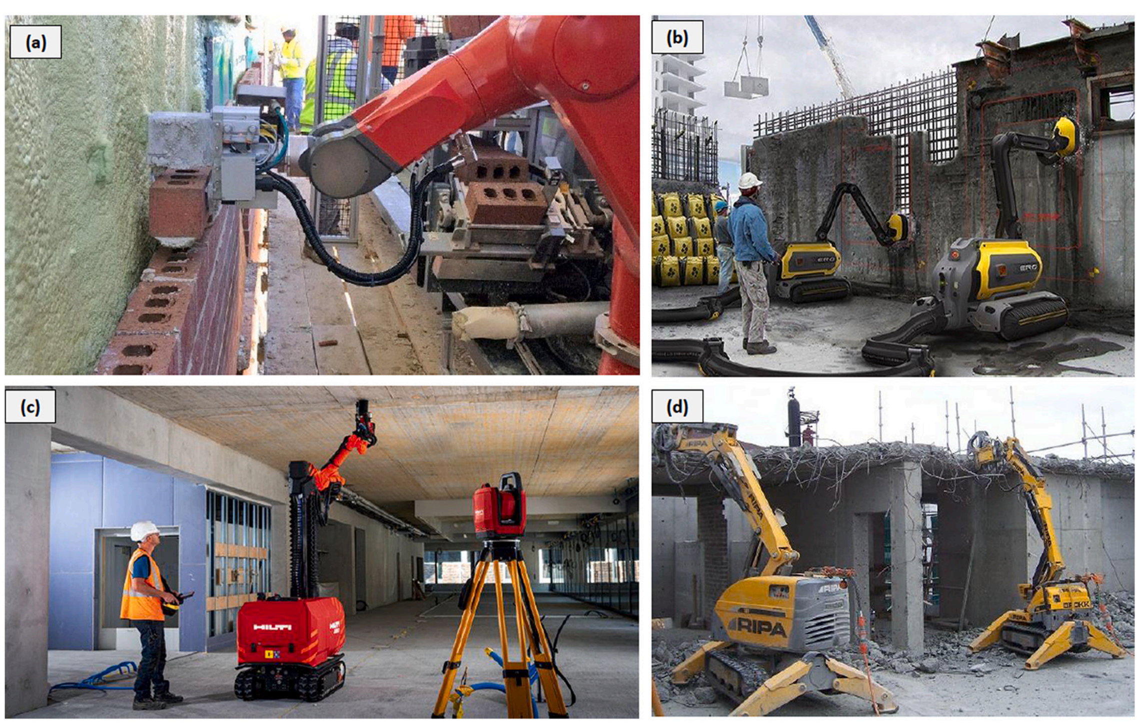

Fig. 8. Examples of application of robotics in building construction: (a) Architecture-related, façade installation [120]; (b) Structure-related, shotcrete for shear walls [121]; (c) Interior layout-related, BIM-enabled mobile ceiling-drilling robot [122]; (d) Demolition of buildings and existing structures [123]

knowledge-based systems, and natural language processing) as well as AI-powered robotics in construction often aim at promoting health and safety which can in turn improve reliability and trust. However, regardless of the end goal, the role of reliability and safety of AI systems and AI-powered robots in developing cognitive trust is crucial and deserves further explorations.

6.3. Performance and robustness

Machine competence, which manifests itself in technical performance and ability, is a leading driver of trust in human-machine teaming literature [14,15,129]. To assess the performance of an AI system, measures such as accuracy are commonly used. Accuracy is a gold standard of machine learning models that contributes to the trustworthiness of the AI system [29]. Also, AI robustness refers to the ability of AI developed in one context to be transferred to a wide range of problems (within and outside that context) in a systematic way while demonstrating a similar level of performance [130]. Theoretically, the two concepts of performance and robustness can be at odds with each other since imperceptible perturbations of the test data (i.e., adversarial examples) may result in incorrect misclassification with high confidence [131–134]. However, they are both commonly used to describe the technical reliability of AI systems in the context of trustworthiness. For example, the Ethics Guidelines for Trustworthy AI prepared by the European Commission in 2018 defines robustness as “resilience, accuracy, reliability of AI systems” and lists it as one of the seven broad key requirements that contribute to trustworthiness [38,135]. Explicit training against known adversarial examples, as well as techniques such as regularization and robust inference are methods to produce robust machine learning models with acceptable accuracy [136,137]. One way that laypeople trust AI models is based on performance metrics such as accuracy. Such accuracy-based trust can be achieved by knowing the stated performance of the system or direct observation or perception of the model’s performance in practice. However, if a model’s observed accuracy is low, the effect size of the stated accuracy on people’s trust is very low, meaning that people’s trust in a model is significantly affected by its observed accuracy regardless of its stated accuracy [138].

Regardless of the source of where the performance accuracy comes from, people stop trusting an algorithm as soon as they observe it makes a mistake [139,140]. Laypeople stabilize their trust to a level correlated with the perceived accuracy [141], although system failures have a stronger impact on trust than system successes [142]. While performance and robustness have shown to have a significant effect on user’s trust in an AI system, there are other machine learning performance metrics such as precision and recall that have been shown to be effective in terms of trust-building. For example, users tend to put more weight on a classifiers’ recall rather than its precision when deciding whether the classifiers’ performance is acceptable, although the application can make a difference in terms of the weight [143].

AEC use cases are not different from other applications in that the performance of the technology tool plays a key role in trusting and ultimately adopting it. Almost all performance measures in construction ultimately target a metric related to the cost or schedule of the project [88,144,145]. However, immediate gains represented by factors such as quality, safety records, sustainability measures, productivity metrics, and inspection outcomes are as important as ultimate cost and schedule benefits in adopting innovations and trusting new technologies in construction [146–148]. Regarding performance optimization and assessment in construction projects, there is a huge advantage in using BIM, big visual data, and modeling construction performance analytics [149] in conjunction with AI systems. Digitizing construction site layout planning process in BIM and training models to be used in future projects, can enable project teams to significantly increase their performance and efficiency. As suggested by [150], a holistic real-time site analytics tool using AI as well as cloud-based data analytics of the data collected on the site can be developed to facilitate reaching performance targets and quality standards. For example, the project management team can take advantage of an AI chatbot which can be utilized on the job site to receive, process, and share activities and updates.

Construction is a multi-sector, project-based industry where in a typical project, multiple specialty trade contractors are involved. Heterogeneity in projects means that the applications and algorithms of AI and machine learning systems can vary widely from one project type to the other or even within one project [151]. Thus, robustness in construction AI translates to the ability to successfully transfer models between different projects, sectors, trades, and even geographic locations considering the uniqueness of any given project without compromising the user’s trust in the system’s ability. For example, a 334 meter-wide dam construction work in Japan used robots for tasks such as pouring concrete, brushing uneven layers, and dismantling forms [152]. Also, within tunnel construction projects, applications such as inspection, maintenance, and health monitoring benefit from AI [153–155]. Robust AI models developed for these tasks in the dam construction project should be effectively transferred and reused in the tunneling project if certain project-specific risk, quality, and inspection considerations are programmed into the design of the model. It is also important to note that performance and robustness must manifest themselves in both the technical construction work and the business aspects. In other words, trust cannot be generated if the models have acceptable technical abilities in performing trade work but ignore variables related to business and management processes [156].

6.4. Privacy and security

Privacy and security are among the most important socio-technical considerations pertinent to the use of AI and robotic technologies. Privacy is defined as the right not to be observed. Nevertheless, the nature of AI necessitates observing various phenomenon to learn and improve where human is involved [157]. Ethical AI (a.k.a. responsible AI) is an enabler of engendering trust and scaling AI with confidence [158]. Data security is the most basic and common requirement of responsible AI. Although AI privacy and security are interconnected in most cases, they should not be confused with each other or used interchangeably. Security in AI can be associated with ensuring the confidentiality of data, preserving information integrity, and guaranteeing immediate data availability when desired. However, privacy is often tied to acquiring, processing, and using personal data. Preventing data breaches by accident and/or improper system engineering and design, ensuring unplanned data corruption, and obstructing outsider’s intention to hinder or limit user’s access to the system or portal are undoubtedly essential to make sure a designed AI-based system or product cannot be hacked or breached (Wu 2020). The majority of the recent topics regarding ethical AI in the literature are focused on opacity of AI systems, privacy and surveillance, machine ethics (or machine morality), ethical decision-making effect of automation on employment, manipulation of behavior, human-robot interaction, bias in decision-makings, control of autonomous systems, artificial moral agents, and singularity [159,160].

In the context of human-robot interaction, privacy and security have also been identified as a relevant risks to trust [161]. Privacy depends on the protection of cybersecurity systems and is directly related to engendering trust in robots [162]. There are two types of risks to trust from privacy and security perspective. “Privacy situational risk” is the belief that a human-robot task or activity will likely expose personal information about the user or their surroundings. “Privacy relational risk” is the belief that a human-robot task will expose the team or their environment to unauthorized observation or disturbance. “Security situational risk” is the belief that a human-robot task or situation could make the team vulnerable to crime, sabotage, attack, or some other threat to safety. “Security relational risk” is the belief that a human-robot could be vulnerable to being misused for crime, sabotage, attack, or some other threat to safety [161].

There are limited studies on the ethical challenges caused by using AI and robotics in the AEC industry. AI and robotics applications require monitoring construction tasks in order to collect data using telecommunications devices, wearable devices (such as VRs, smart hard hat cameras, and sensors), GPS, CCTV cameras, drones, or smartphones [163–165]. While applications vary from worker safety [166] to equipment emission monitoring [167], worker performance and contextual information are involved in one way or the other regardless of the application. Some researchers believe that worker monitoring methodologies that are often used to train machine learning models fail to consider the worker's natural consciousness, intentionality, and free will [168]. Another pervasive technology in the AEC domain that enables AI and robotics applications is cloud computing [169]. Industrial applications of cloud computing involve privacy and security challenges for data security, access control, and intrusion prevention [170,171], but specific solutions for data security in construction projects should be further studied and analyzed [169]. Data security is particularly important for projects related to the construction of buildings and infrastructures associated with the military, government, public sector and public service. AEC project data including contracts information, blueprints, photos, and project personnel data, are considered confidential and careful attention must be paid to prevent data leaks.

7. Future research

With the observations outlined in the comprehensive review of the literature on trust in AI presented in Section 6, the authors have identified the following future directions for the AEC research in this area.

7.1. Integrated and interdisciplinary studies

There are various lenses through which the trust dimensions identified in this paper can be seen. For example, the explainability and interpretability concept is sometimes seen as a technical issue and sometimes as a legal or social issue [2]. Dimensions such as reliability and safety can be studied from both the cognitive and emotional perspectives, and humans trust phenomena that do not require social or emotional intelligence [4]. Therefore, regardless of the application area and technology implementation, it is important to study trust in AI and robotics as an interdisciplinary field of research involving researchers with a variety of related backgrounds. In AEC, various engineering and management aspects of the projects also affect this conglomerate of fields. Depending on the project phase (e.g., pre-construction, construction, post-construction), project type (e.g., building construction, horizontal construction), application objective (e.g., safety, productivity, sustainability, scheduling), and specific technology being leveraged (e.g., BIM, teleoperated robots, mobile computing, blockchain), different trust elements can hinder or drive adoption of AI in AEC projects. A previous study by the authors indicated that regardless of the project phase, type, application, and technology, all the identified trust dimensions in this study (i.e., Explainability and interpretability, Reliability and safety, Performance and robustness, and Privacy and security) are key in generating trust in AI and robotics for AEC applications [25].

7.2. Trust calibration

Adjusting human trust levels with the actual abilities of the AI and robotics is a key process to eliminate overtrust and undertrust [14,172]. Research has shown that creating transparency about an AI or a robot's abilities significantly increases the likelihood of building calibrated trust and increasing adoption levels [173]. However, similar to the dearth of research in trusting and adopting AI-enabled systems and robotics in the AEC industry, determining the adequate level of trust that is justified and can be adjusted based on real technical capabilities (i.e., trust calibration) has received very little attention. Also, as Desai et al. (2009) mentioned in their study, research should be conducted to develop trust models that are particularly aimed at human-robot systems since trust calibration is a critical topic in human-centered robotics. As such, trust calibration analysis through empirical studies, particularly relating to factors unique to robotics (and not general AI or automation), deserve further investigations [174].

7.3. Human-centered AI and robotics

In AEC, it is vital to promote research that focuses on AI and robotics as an enabler for transitioning workers' role to higher-level tasks as opposed to eliminating large segments of the workforce. Research has shown that to initiate trust between humans and AI, AI systems should prove human-centered and a means to serve humankind, upskill workers, and promote human values [175,176]. Another concept in human-centered research towards trust in AI and robotics that received major attention in fields other than AEC, is the importance of anthropomorphism. Anthropomorphism refers to human-likeness and the perception of technology or an object as having human qualities, such as feelings [177,178]. For an industry that still relies on labor as the primary production source, designing tools and approaches without the human as a centerpiece is doomed to failure in many fronts including trust. Therefore, future research should recognize the importance of human-centered design for AI- enabled systems and robots in AEC adoption studies.

7.4. Enhancing explainability and interpretability on value and mechanism

In order to secure management buy-in and establish trust among end-users, the value of adopting AI and robotics should be clearly identified [179]. In addition, the mechanism by which AI enhances the workflows should be clear to those who make adoption decisions as well as the end-users [180]. Addressing these two issues can address the explainability and interpretability requirement identified in this research in a substantial way. Previous research has demonstrated the significance of presenting benefits in terms of key performance indicators (KPIs) such as time, cost, safety, and sustainability added values [181]. In construction, many studies have shown that perceived added value of new technologies in terms of safety, efficiency, and gains in cost or time saving have a substantial impact on adoption levels of those technologies [182–185]. The important role of workforce training and education in establishing the "what" (i.e., value) and "how" (i.e., mechanism) of introducing new technologies have also been highlighted in the literature [186]. Further research can determine what approaches best demonstrate the added values and adequately explain the inner-workings of AI and robotic technology to construction professionals.

7.5. Intuitiveness and familiarity

A recent survey on human-robot collaboration emphasizes the fact that intuitive interfaces drive adoption levels [187]. In the AEC applications, this translates to human-technology interaction mechanisms that do not entail sophisticated programming or require complex computer skills. For example, advances in natural language processing (NLP) [188], learning from demonstration (LfD) [189], and active learning [190] have emerged in computer science to simplify the ways humans interact with AI-enabled applications or robots, thus making them easier to adopt. By the same token, a familiar interface results in a more welcoming appearance for the end-user and thus increased levels of trust and adoption [191]. In AEC applications, it is vital to design AI and robotic technologies that are compatible with the traditional workflows and reinforce best practices as opposed to replacing them. Furthermore, leveraging technologies such as BIM that have become industry standard as a familiar interface can create the intuitiveness and familiarity effects. Future research can explore possibilities that NLP, LfD, active learning, and familiar technologies such as BIM can offer to further grow the adoption levels of AI and robotics applications.

8. Conclusion

In this paper, a comprehensive review of research on (1) human trust in AI and AI-powered robotics as well as (2) the role of these technologies in the AEC research and industry practice was presented. The concept of trust was broken down into four main dimensions (i.e., explainability and interpretability, reliability and safety, performance and robustness, and privacy and security) to organize the presentation of the review. For each dimension, the literature published between years 2000 and 2021 in two categories of trust in "AI and AI-powered robotics", and "AI and AI-powered robotics applications in AEC", totaling 584 peer-reviewed scholarly papers, were thoroughly reviewed. A thorough analysis of the literature in this study indicates that although the AEC research and practice increasingly study and deploy AI and robotics, no systematic effort is focused on investigating trust in these technologies. This is while the literature in fields such as computer science and psychology emphasize on building appropriate levels of trust and acceptance between the AI systems and the end-user as a first step to increase adoption and utilization. This study also found that explainable and transparent AI systems that are built to have understandable operations and outputs are more trustworthy. Also, the level of privacy involved in technology implementation was shown to have a big impact on human's trust in it. It was confirmed that AI systems must also be safe, reliable, and secure against unauthorized actions in order to be trusted. While embodied intelligence (e.g., intelligent robots) may require presenting more indications of safe behavior in the presence of human users, software and computer networks will be distrusted as well if they show indications of safety and security hazards. Additionally, the ability of AI and AI-powered robots to prevent malfunctions or harm the user is directly linked to their reliability. Performance inaccuracies and flaws can result in distrust, and technological or behavioral interventions must be considered by design to ensure that autonomous systems that show instances of inaccuracy of malfunction can regain user's trust. Finally, based on presented literature analysis, five directions for the future of research in trust in AI and robotics for AEC applications were proposed. The authors believe that the collection and critical reviews presented in this paper can guide the work of researchers, scholars, and practitioners in this area to contextualize their methods within the state-of-the-art.

The presented study has three limitations. While the four dimensions presented in this research are the main trust paradigms identified in the literature, other dimensions such as fairness [192], tangibility [4], and availability [29] can be included in future reviews. Second, the literature prior to 2000 was not reviewed, thus a more comprehensive review can also include those publications. Third, the proposed framework for the literature review only considered robots that are powered by AI. A standalone review on trusting robots in AEC may also include robotic systems that are not intelligent or do not use AI to function.

Declaration of Competing Interest

The authors have no competing interest to declare.

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