State-of-the-Art Review

Toward a Framework for Trust Building between Humans and Robots in the Construction Industry: A Systematic Review of Current Research and Future Directions

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Abstract: With the construction sector primed to incorporate such advanced technologies as artificial intelligence (AI), robots, and machines, these advanced tools will require a deep understanding of human–robot trust dynamics to support safety and productivity. Although other disciplines have broadly investigated human trust-building with robots, the discussion within the construction domain is still nascent, raising concerns because construction workers are increasingly expected to work alongside robots or cobots, and to communicate and interact with drones. Without a better understanding of how construction workers can appropriately develop and calibrate their trust in their robotic counterparts, the implementation of advanced technologies may raise safety and productivity issues within these already-hazardous jobsites. Consequently, this study conducted a systematic review of the human–robot trust literature to (1) understand human–robot trust-building in construction and other domains; and (2) establish a roadmap for investigating and fostering worker–robot trust in the construction industry. The proposed worker–robot trust-building roadmap includes three phases: *static trust* based on the factors related to workers, robots, and construction sites; *dynamic trust* understood via measuring, modeling, and interpreting real-time trust behaviors; and *adaptive trust*, wherein adaptive calibration strategies and adaptive training facilitate appropriate trust-building. This roadmap sheds light on a progressive procedure to uncover the appropriate trust-building between workers and robots in the construction industry.
DOI: 10.1061/JCCEE5.CPENG-5656.

Author keywords: Human–robot teaming; Trust; Construction sites; Future work.

Introduction

Increasing automation and the incorporation of state-of-the-art technologies into workplaces may be akin to an evolutionary jump in occupational domains, and the interactions between humans and these technologies will play a substantial role in advancing these working environments. With the presence of varying robots, machines, and automated systems, humans remain in the loop to work alongside different forms of robotic partners at workplaces (Janssen et al. 2019; Stern and Becker 2017).

Consequently, it becomes vital to boost a harmonious teaming relationship by cultivating appropriately leveled trust between humans and their robotic partners (Hu et al. 2019). Trust-building is challenging and vulnerable to influential factors such as user experience, robot capabilities, and situational contexts (Billings et al. 2012; Choi and Ji 2015). To address this challenge, trust-building has been explored in various arenas, including transportation (e.g., trust between drivers and autonomous vehicles) (Lee et al. 2021; Raats et al. 2019), manufacturing (e.g., trust between employees and industrial robots) (Jiao et al. 2020), and agriculture (e.g., trust between farmers and automated machines) (Sanchez et al. 2014; Vasconez et al. 2019). Although these domains highlight opportunities for trust-building between human and technological partners, questions remain about how broadly previous findings can cross-pollinate in different situations.

Over the last decade, the construction industry has demonstrated growing interest and potential for deploying robotics and machines. However, because construction sites feature safety-critical, dynamic, and complex situations involving assorted equipment, crews, and concurrent construction tasks (Chua and Goh 2004; Wanberg et al. 2013), the construction sector has been slower to incorporate advanced/artificial intelligence (AI) technologies into the real-world jobsites (Pan and Pan 2020; Wisskirchen et al. 2017). Although incorporating robots has a notable potential to establish intelligent jobsites, newly introduced technologies might add extra uncertainties to the already-hazardous construction jobsites. For instance, drones can be helpful in delivering heavy materials for workers, but they may also physically collide with workers and draw their attention away from construction tasks (Chang et al. 2023b; Jeelani and Gheisari 2022). In respect of robots' benefits and uncertainties, workers must establish an appropriate level of trust, neither excessive nor insufficient, in robots to reach their full potential and beware of their risks.

Given construction workplace's dynamic nature, discussing trust within the construction industry presents greater complexity compared to other sectors. Although static workplace settings such as offices allow for more consistent task performance by robots, the dynamic environment on construction sites may complicate the operation of robots and provoke their unstable performance. As explained in the literature, trust has a dynamic nature, meaning that the trust level in robots can be changed continuously due to various factors, especially the robot's performance. Accordingly, workers observing robots' behaviors in various contexts may update their trust levels, raising the need to monitor workers' trust changes to prevent improper trust-building.

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Note. This manuscript was published online on March 6, 2024. Discussion period open until August 6, 2024; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Computing in Civil Engineering***, © ASCE, ISSN 0887-3801.

However, the present study discerned a research gap in the paucity of discussing workers' trust-building in their robotic counterparts on dynamic and hazard-rich construction jobsites. Therefore, this systematic review paper aims to (1) interrogate trust development between humans and varying robots/machines during teaming activities in construction and other domains; and (2) propose a roadmap for exploring worker–robot trust within the construction industry.

The driving research questions this study considers are as follows:

- What are the antecedents of trust in the interaction between humans and robots?
- Which widely used measurement methods can gauge human trust?
- How do humans calibrate/recalibrate their trust levels when teaming with robots?
- What is the current state of investigating trust within construction?
- Which opportunities manifest for exploring the trust between workers and robots/machines on future construction sites?

The findings here (1) provide recent insights about research regarding human trust-building in robots; and (2) identify research routes for examining and fostering human–robot trust-building within construction studies.

Background

Human–Robot Teaming in the Current Construction

Although the implementation of robotics/machines in the construction industry is still in its infancy compared to other industries (e.g., manufacturing), a variety of technologies have been progressively incorporated into construction to team up with workers (Janssen et al. 2019; Stern and Becker 2017). A recent study presented a taxonomy to categorize the varying types of robots applied to the jobsites: (1) off-site automated prefabrication systems, (2) onsite automated and robotic systems, (3) drones and autonomous vehicles, and (4) exoskeletons (Davila Delgado et al. 2019).

The first category refers to the systems that help automatically produce building components to facilitate prefabrication. These systems are motivated by the industrial robots in the manufacturing sector and are primarily represented by three-dimensional (3D) printing techniques in recent construction literature (e.g., Wu et al. 2016; Zhang et al. 2018). For example, a critical review of 3D printing in construction reported the associated benefits (e.g., reduced schedule growth and reduced worker power) and challenges (e.g., large-scale building and mass customization) (Wu et al. 2016). Unlike off-site systems, onsite automated and robotic systems are embodied on the jobsites to help execute repetitive tasks and perform risky tasks (Bock 2015). For example, robotic arms are usually mounted on movable platforms to paint walls, spray concrete, handle tasks, assemble and disassemble tasks, and form processes (e.g., Ardiny et al. 2015; Dritsas and Soh 2019; Prasath Kumar et al. 2016; You et al. 2018).

The third category denotes the vehicles that can be either piloted remotely or autonomously (e.g., drones and unmanned ground vehicles). These systems are usually utilized for accessing dangerous and unreachable environments (e.g., mud eruption zones), exploring spaces to survey/monitor (e.g., automate bridge inspection), excavating, drilling, demolishing, or transporting materials (e.g., Li and Liu 2019; Peel et al. 2018; Rakha and Gorodetsky 2018). Lastly, exoskeletons are wearable systems that augment the capabilities of workers (Ajoudani et al. 2018; Li and Ng 2018). Exoskeletons can help workers with high-impact jobs, improve their productivity, and reduce fatigue and injuries (Kim et al. 2019).

Human–robot teaming depicts that workers and robotic technologies work interdependently and value common goals (Johnson et al. 2012). Many studies have emphasized the necessity of trust-building between two entities for teaming. Nonetheless, most construction studies paid attention to the technical aspects of technologies (Chen et al. 2022; Hsu et al. 2021) but disregarded the importance of trust development.

Trust Definition

Various definitions have been suggested for trust. At its simplest, trust can be viewed merely as an interrelation between a trustor (i.e., humans) and a trustee (e.g., robots and machines). From a deeper perspective, one generally accepted definition is "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (Lee and See 2004, p. 51). From this definition, uncertainty—which refers to the possibility of a mismatch between the trustee's behaviors and the trustor's goal—and vulnerability—which denotes a latent loss hidden in this interrelation between the trustor and trustee—can be extracted and emphasized (Khavas 2021).

In particular, most studies endeavored to either reduce the uncertainty (e.g., provide the trustor with more information regarding the trustee) or lower the potential loss underlying this trust relationship (e.g., avoid overreliance on the trustee) (Kraus et al. 2020; Kunze et al. 2019). However, mitigating the uncertainty and vulnerability is challenging because trust is a multifaceted and dynamic concept, depending on different contexts, trustee partners, and trustor's affective and cognitive features (Hancock et al. 2011b).

Previous Review on Trust between Humans and Robots in Architecture, Engineering, and Construction

As the research on human–robot trust becomes mature in varying domains, previous studies have conducted a systematic review of relevant literature (e.g., Brzowski and Nathan-Roberts 2019; Emaminejad and Akhavian 2022; Khavas 2021; Schaefer et al. 2016). Most of the previously published review papers summarized the influential factors in trust while, more importantly, highlighting that trust-building is a context-dependent concept (i.e., the differences among domains would also influence trust). That is, the workplaces where the interaction occurs should play a significant role in reshaping the trust-building between humans and robots. Especially in such high-risk workplaces like construction sites, their dynamic and unpredictable natures must affect trust development compared to other workplaces (e.g., offices and factories). Unfortunately, construction-related features have not been attenuated by most of the trust review papers.

To address this limitation, a recently published paper systematically reviewed the trust-related literature in architecture, engineering, and construction (AEC) and other domains (Emaminejad and Akhavian 2022). Those authors classified the concept of trust into four dimensions: explainability and interpretability, reliability and safety, privacy and security, and performance and robustness. Explainability and interpretability represented whether users could comprehend how AI systems generate output from input data and whether the output results were intelligible to users. Reliability and safety are related to an AI's ability to continuously manifest expected behaviors to prevent incidents (e.g., accidents, failures, or malfunctions). Performance and robustness refer to whether the robotic systems exhibit consistent performance across various deployment environments. Privacy and security denoted whether robotic systems would raise concerns about a privacy breach and/or protect users' identities or any sensitive information.

Although that paper provided insights into the importance of the trustworthiness of AI and technologies, there are a few limitations in the paper that need to be addressed in future studies. First, the proposed dimensions were still associated with the influential factors in trust instead of involving different aspects of trust (e.g., trust calibration and trust measurement). It is worth noting that this review also suggested future work to discuss workers' trust calibration process. Second, the authors did not propose step-by-step directions for future research to follow. A progressive roadmap could serve as an efficient guide to accelerate the explorations of trust in construction. Third, because trust-building has increasingly gained research interest in recent years, multiple trust-related studies in construction were recently published but they were not included in previous review papers. Therefore, it is critical to conduct a comprehensive literature review on published papers and propose a roadmap for establishing trust in future construction where workers need to team up with robots.

Research Methodology

To answer the aforementioned research questions, the present study used Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), which provides evidence-based protocol guidelines for systematic reviews, to search and select literature (Moher et al. 2009) (Fig. 1).

Eligibility Criteria

Before searching the literature, eligibility criteria (i.e., inclusion and exclusion criteria) were defined to determine the scope of this review paper and to find the most relevant literature. The following criteria were considered: (1) must be published between 2010 and 2023; (2) must be written in English; (3) only journal papers and conference proceedings are included; and (4) must be related to the humans' trust-building in robots/machines/automation. This study established a publication year limitation due to the growing emphasis on trust-building between humans and robots in the Industry 4.0 era, which emerged in the 2010s. Besides, it was assumed that the findings of the included publications were highly built upon the literature predating 2010. On the other hand, only journal and conference papers were considered because of their high credibility and validation supported by a peer-reviewed process. These sources of publications usually disclose detailed experiment methodologies that represent an essential part of trust-related research.

Information Sources and Search Strategy

Afterward, a systematic search of the literature was conducted to gather relevant publications in construction and other domains within the databases of Scopus, IEEE Xplore, Elsevier, Springer Link, and Google Scholar. The definition of search queries is an integral part of the search strategy. Hence, a couple of search queries were delineated and adopted, as follows: "Human-machine trust" AND ("factor" OR "measurement" OR "calibration"); "Human-automation trust" AND ("factor" OR "measurement" OR "calibration"); and "Human-robot trust" AND ("factor" OR "measurement" OR "calibration"). Based on the eligibility criteria and keywords search in article title, abstract, or keywords, a total of 3,802 publications were identified.

Selection Process

Three rounds of review were conducted to choose the optimal papers for answering the aforementioned research questions. For the first-round literature selection, the process involved skimming the titles of the literature gathered using predefined queries to roughly screen the irrelevant papers. The second-round selection focused on scanning the abstracts of the literature that passed the first-round selection. Scanning abstracts enabled examining the paper's relevance and removing the literature that did not meet the eligibility criteria. In the third-round selection, the research team thoroughly read the papers and documented a summary of each paper, including

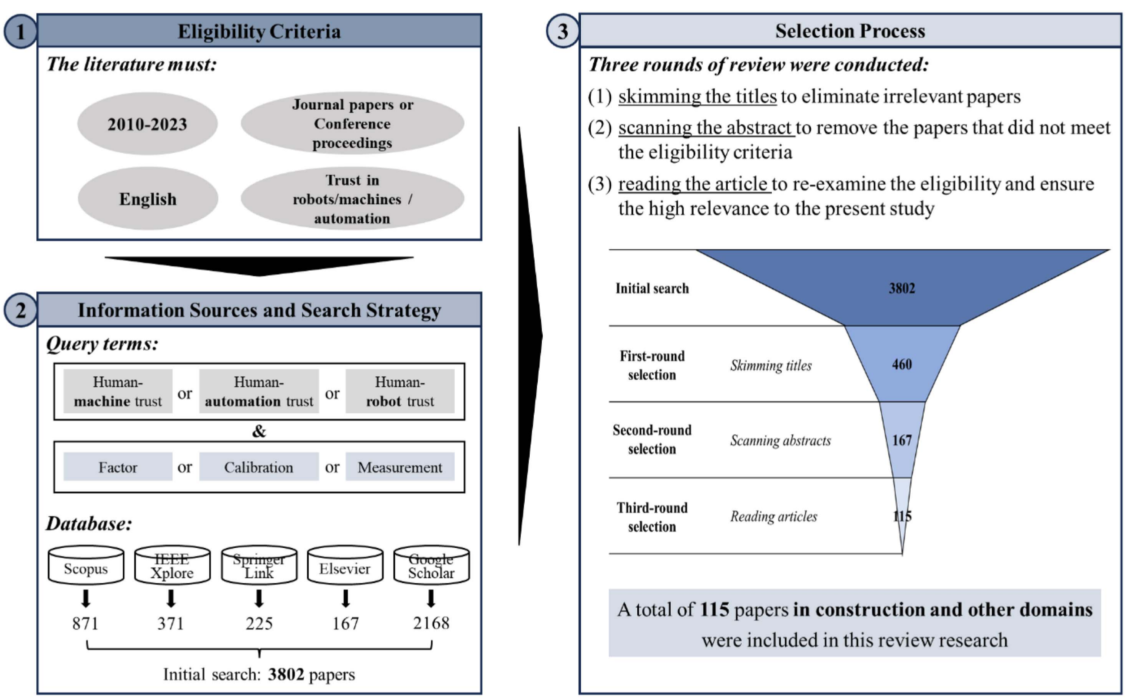

Fig. 1. Research framework of the present review paper.

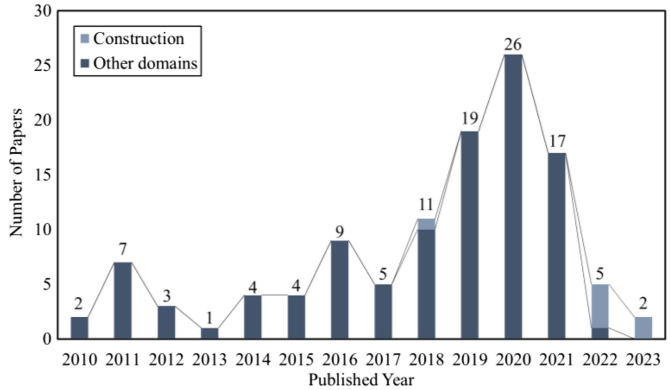

Fig. 2. Distribution of publication year for the papers.

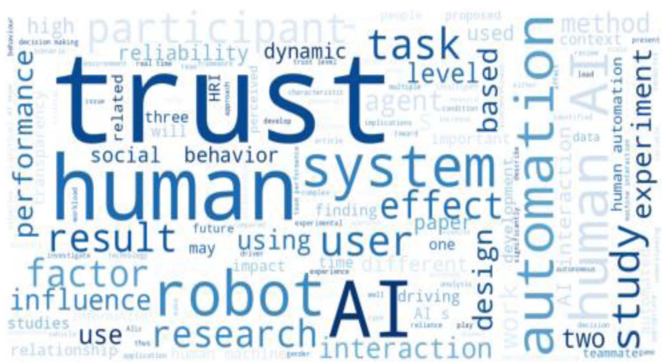

Fig. 3. Word cloud of the papers included in this review paper.

information regarding the studied problem, methodology, objectives, findings, and conclusions of the study. The obtained information was then organized based on the research questions: (1) antecedent of trust, (2) trust calibration, and (3) trust measurement. The studies only proposed assumptions or frameworks without any data or validations were eliminated from this review. This comprehensive review of the papers helped reexamine whether inclusion conformed to the eligibility criteria and whether selected papers were sufficiently relevant to the scope of this study.

A total of 3,802 papers (IEEE Xplore = 371, Scopus = 871, Elsevier = 167, Springer Link = 225, Google Scholar = 2,168) were initially identified. In the first-round selection, 460 papers were selected after removing irrelevant studies identified when skimming the titles. After scanning abstracts during the second-round selection, 293 papers outside the eligibility criteria were removed. In the third-round selection, 52 papers were eliminated by thoroughly reading articles due to their insufficient relevance to the research questions. Ultimately, 115 studies were included in the present review paper. Fig. 1 shows a schematic paradigm of the entire literature-selection process.

The publication years of the studies appear in Fig. 2. The increasing number of papers across the years indicates an upward trend in trust-related explorations in construction and other domains.

The word cloud in Fig. 3 provides a visualization of the valuable information within the papers. Trust, Human, AI, and Robot are the most conspicuous terms shown by the word cloud, and they perfectly coincide with the focal point of this study (i.e., trust between humans and technologies).

Findings

Current State of Worker–Robot Trust in the Construction Industry

To better understand the current state of the literature discussing the trust-building between construction workers and robotic technologies, published papers have been thoroughly reviewed and analyzed. To date, only seven studies investigated the trust-building between workers and robots in the construction contexts (Adami et al. 2022; Chang et al. 2023a, b; Emaminejad and Akhavian 2022; Shayesteh et al. 2022; Shayesteh and Jebelli 2022; You et al. 2018). Table 1 provides detailed descriptions of each literature and organizes their information based on the antecedent of trust, measurement method, and calibration process.

As presented, most of the literature focused on investigating the effect of a single factor on trust, and trust was regarded as a static concept. However, trust is a dynamic and complex phenomenon (de Visser et al. 2014), and it is critical to review the related literature regarding trust changes and calibration. Additionally, the majority of the published papers (71%) within construction utilized self-report to assess workers' trust levels in the robotic technologies (e.g., Chang et al. 2023a; Shayesteh and Jebelli 2022; You et al. 2018). However, various objective measures that have been discussed for trust measurement in other domains need to be explored further in the construction. In conclusion, although these studies have contributed to exploring human–robot trust in construction, it is valuable to delve into the rich literature to deeply study (1) antecedents of trust, (2) trust calibration, and (3) trust measurement concepts. Fig. 4 illustrates an overview of the findings that have been proposed by literature in other domains.

Antecedents of Trust in Human–Robot Teaming

Due to the importance of developing trust in human–robot interactions, previous studies have increasingly explored the factors that affect trust. Most of the studies categorized related factors based on the following taxonomy: (1) human properties factors (i.e., trustor), (2) robotic system properties factors (i.e., trustee), and (3) environmental factors (Hancock et al. 2011b) (Table 2).

Human Properties

Scholars started paying more attention to human trust in technology when needing to interact and collaborate with various robots in future work. The human factors have primarily been discussed in three subcategories: (1) dispositional factors, (2) situational factors, and (3) learned factors (Marsh and Dibben 2003) (Table 2).

Dispositional Factors. Dispositional factors are related to demographics and psychographic factors representing individuals' overall propensity to trust their partners. Regarding demographics, previous studies showed that gender and nationality could impact trust-building (Ghazali et al. 2018; Hu et al. 2019). In the study conducted by Hu et al. (2019), a higher tendency to trust robots was observed in males rather than females. Similarly, Ghazali et al. (2018) found that male participants trusted the advice provided by a physical robot more than female participants. Nationality, which is correlated with cultural background, also plays a nonnegligible role in human–robot trust (Hu et al. 2019). For example, in the study examining how passengers trust autonomous vehicles, US passengers showed a lower trust level than Indian ones (Rice et al. 2014).

Moreover, the impacts of psychographic factors (e.g., personality traits) on human–robot trust have been discussed in the literature (Rossi et al. 2018; Zhou et al. 2020). For instance, several studies used the Big Five personality traits questionnaire (i.e., extroversion, agreeableness, conscientiousness, neuroticism, and openness) to

Table 1. Human–robot trust-related literature in the construction industry

Related references	Description	Methodology	Antecedent	Measurement
You et al. (2018)	This study examined the effect of work area separation between workers and robots by developing a masonry experiment in a virtual reality (VR) environment. They found that work separation can increase trust and perceived safety toward the task.	Mixed methods (experiment and survey)	Perceived safety (higher perceived safety because there was a work area separation between workers and robots)	Self-reporting [5-point Likert scale from Jian et al. (2000)]
Adami et al. (2022)	This study compared VR-based and in-person training for a remotely operated demolition robot. Their results indicated that the VR-based training enhanced workers' trust in the robot and helped workers pay attention to the training-related information and familiarize themselves with the operation.	Mixed methods (experiment and survey)	Familiarity	Self-reporting [5-point Likert scale from Jian et al. (2000)]
Emaminejad and Akhavian (2022)	This study reviewed the papers related to trustworthy AI or AI-powered robotics and proposed dimensions to be considered in the AEC industry. Four dimensions were identified as key factors to enhance the trustworthiness of AI.	Literature review	Explainability and interpretability; reliability and safety; performance and robustness; privacy and security	—
Shayesteh and Jebelli (2022)	This study created a VR bricklaying experiment to investigate the impact of automation level on trust [i.e., building a masonry wall in collaboration with a semiautonomous robot (i.e., human intervention included) versus a fully autonomous robot (i.e., human intervention excluded)]. The results indicated a higher robot automation level reduced workers' trust.	Mixed methods (experiment and survey)	Robot automation level	Self-reporting [14-item subscale of the trust scale from Schaefer et al. (2016)]
Shayesteh et al. (2022)	This study investigated using EEG signals for trust measurement in a VR future bricklaying training platform. The results supported that EEG signals could function as an indicator of workers' trust levels in construction robots.	Mixed methods (experiment and survey)	—	EEG signals
Chang et al. (2023a)	This study examined the effect of robot failure and time pressure on workers' trust and performance. Although the failure would force workers to reduce their trust and pay more attention to robots, the results revealed a dominating role of time pressure in quickly recovering their trust.	Mixed methods (experiment and survey)	Robot's failures, time pressure	Self-reporting [5-point Likert scale adapted from Muir (1994)]
Chang et al. (2023b)	This study investigated the effect of responsibility attribution on trust when robot failures occurred. The outcomes showed the workers who perceived themselves as responsible for robot failures retained trust in robots whereas the ones who blamed robots reduced their trust.	Mixed methods (experiment and survey)	Responsibility attribution for failures (workers or robots took responsibility for robot failures)	Self-reporting [5-point Likert scale adapted from Muir (1994)]

investigate the effect of human traits on trust in human–robot teaming. In the research carried out by Zhou et al. (2020), the results indicated individuals with lower openness revealed a higher trust level in an robot. Those authors speculated low openness was related to careful reasoning, which is helpful for individuals to comprehend robotic technology and increase their trust. Regarding extroversion, Rossi et al. (2018) reported extroverted participants manifested a higher trust in a household robot. Although these studies showed correlations, there is minimal evidence in the literature concerning any causative effects of personality traits on trust levels toward robots, which has large potential for future research in the construction domain.

Situational Factors. Apart from dispositional factors that are not restricted to specific situations, the context-dependent characteristics of humans (i.e., situational factors) might influence human trust (Hoff and Bashir 2015). Situational factors have been exemplified by emotion, self-confidence, and attentional control in previous studies. Emotion has demonstrated its influence on such human cognitive processes as decision-making. Stokes et al. (2010) found emotion mainly affected the initial trust level prior to the interaction with an automated system. The effect declined as the interaction began because users can evaluate the system by observing its performance (Stokes et al. 2010). Further, humans manifested a higher trust level in automation owing to happiness (Merritt 2011).

On the other hand, self-confidence, which stems from sufficient domain knowledge or work experience, also exerts an impact on human trust in robots. For instance, experienced farmers were less willing to trust the automated alarm system on an agricultural machine than novices (Sanchez et al. 2014). Notably, the experience that results in self-confidence is not the same experience as that of

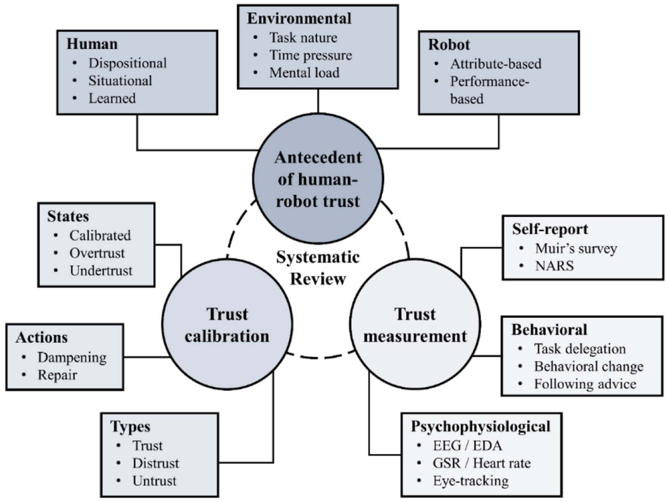

Fig. 4. A graphical overview of the subsections explored in the systematic review.

interacting with robots; instead, the self-confidence experience represents how long the users have deployed conventional approaches and consequently become reluctant to accept innovation.

Attentional control, which includes attention focus and shifting, was also recognized as one of the situational factors affecting human trust. In research that studied multitasking in the military (i.e., managing a group of ground robots), participants with lower attentional control were observed to trust more in the aids provided by an intelligent agent (Chen and Barnes 2012).

Learned Factors. Learned factors (e.g., experience, expectancy, and involvement) pertain to an individual evaluation of the robot that is being interacted with, based on prior or ongoing interactions (Clare et al. 2015; Lee et al. 2021; Lyons and Guznov 2019; Sanders et al. 2017; Yin et al. 2019). Experiences refer to the prior interactions with identical or similar robots that considerably impact the individual's trust in the current interaction (Hoff and Bashir 2015). Positive previous experiences result in a higher initial trust rating and a tendency to rely on the partners (Lee et al. 2021). Likewise, users who had game-playing experience tended to trust unmanned vehicles/systems (Clare et al. 2015).

Similarly, expectancy, which is shaped based on prior experiences or high performance (e.g., accuracy), exerted an effect on trust (Lyons and Guznov 2019; Sanders et al. 2017; Yin et al. 2019). Studies have shown that the effect of the stated accuracy (i.e., expectancy) became less impactful after users had opportunities to observe the performance of robots (Sanders et al. 2017).

The involvement factor relates to the extent to which users feel engaged in the interaction with robots (i.e., be a passive or active member of this interaction). Involvement also resembles cognition absorption, a state of deep involvement with new technologies comprised of five dimensions: temporal dissociation (i.e., an engaged interaction makes users unable to register the passage of time), focused immersion (i.e., an immersed interaction makes users ignore other attentional demands), heightened enjoyment (i.e., capturing the pleasurable aspect of the interaction), curiosity (i.e., an interaction raises users' cognitive curiosity), and control (i.e., users perceive being in charge of the interaction) (Agarwal and Karahanna 2000). In construction research discussing the effect of "human-in-the-loop" on workers' trust, research found that humans' involvement in the task facilitated their higher trust in robots (Shayesteh and Jebelli 2022). Likewise, Ullman and Malle (2016) reported users displayed a higher trust level when believing that they could influence the robot (i.e., control). Future research can conduct further explorations on the impact of cognitive absorption on trust.

Robotic System Properties

Because enhancing the functional capabilities of robotic systems has been the primary focus of design and development in the trust-related research area, the majority of the previously published studies have explored robotic system factors, specifically attribute-based characteristics (e.g., gender, appearance, and personality) and performance-based characteristics (e.g., transparency, competence, and reliability) (Hancock et al. 2011a). Attribute-based factors represent the characteristics inherent to robots before the interaction begins. Performance-based factors refer to the behaviors or outcomes that will directly affect users' perception of the trustworthiness of robots during or after the interaction (Oleson et al. 2011).

Attribute-Based Factors. Social cues embedded in a robot's appearance influence how individuals may interact with robots and perceive the robot's capability (Charalambous et al. 2016). Previous literature showed that most attribute-based factors are related to anthropomorphism, which involves external and internal human-likeness features (e.g., such external features as gender, appearance, communication style, and voice, and such internal features as intelligence, emotion, and personality) (Kim et al. 2020; Law et al. 2021; Torre et al. 2018). Anthropomorphism aims to instill a perception into human users that they are teaming with a humanlike agent. Nevertheless, there are contradictory results regarding the effect of anthropomorphic approaches. Some of the research supported the idea that anthropomorphism (e.g., robot personality) was beneficial to increase human trust (Kulms and Kopp 2019; Natarajan and Gombolay 2020). However, other studies refuted this statement because anthropomorphism would distract users from the primary task (Onnasch and Hildebrandt 2022).

The influence of communication style on human trust has also been investigated by previous studies (Ezer et al. 2019; Hamacher et al. 2016; Natarajan and Gombolay 2020; Sanders et al. 2014). In the experiment undertaken by Hamacher et al. (2016), users were less likely to reduce their trust in the robot with the ability to communicate (i.e., ask users questions) than the robot without the ability to communicate when both robots were misbehaving (i.e., dropping an egg to the ground). In another interesting study that examined the effect of different communication channels (i.e., text, audio, and graphic) on trust, participants perceived the robot that delivered messages by using graphic information as more trustworthy (Sanders et al. 2014).

Performance-Based Factors. Performance-based factors—such as error alarm sequence, adaptation, transparency, competence, predictability, proximity, and reliability—can directly influence trust development (Desai et al. 2012; Kunze et al. 2019; Nothdurft et al. 2012; Przegalinska et al. 2019; Sanders et al. 2014). Among these factors, transparency—which denotes the user's comprehension of the robot's intention, decision-making process, current/future actions, and limitations—has been the most investigated factor. For example, the provision of information regarding the current action of an unmanned vehicle can increase pedestrians' trust level compared to when no information was provided (Liu et al. 2021).

Also, if users were informed of the limitation of an automated car (i.e., transparency) before the interaction, the decrease in trust level would be mitigated when malfunctions occurred (Kraus et al. 2020). With such information, humans will have a holistic understanding of robot partners and anticipate their behaviors in advance. Although these benefits are intuitive, transparency may also provoke an adverse reaction because additional information may cause an increase in human cognitive load (Akash et al. 2020). Balancing these dynamics remains challenging but important.

Table 2. Antecedents of trust in human–robot interaction identified in this systematic review

Entity	Category	Factor	Description	Related references
Human factors	Dispositional	Gender	Male/female	Ghazali et al. (2018) and Hu et al. (2019)
		Nationality	Values and social norms embedded in a nation	Hu et al. (2019)
		Personality traits	Behaving in identical ways across diverse situations	Salem et al. (2015), Yan et al. (2011), and Zhou et al. (2020)
	Situational	Emotion	A state of physiological arousal and of cognition appropriate to this state of arousal	Merritt (2011) and Stokes et al. (2010)
		Attentional control	The ability to focus and switch attention	Chen and Barnes (2012)
		Self-confidence	Individuals' belief in successfully executing desired behaviors	Sanchez et al. (2014)
	Learned	Expectancy	A belief that a particular outcome can be produced	Lyons and Guznov (2019) and Yin et al. (2019)
		Experience	Prior interactions with robots	Clare et al. (2015), Lee et al. (2021), and Sanders et al. (2017)
		Involvement	The extent to which users feel engaged in the interaction with robots	Balakrishnan and Dwivedi (2021) and Ullman and Malle (2016)
		Enjoyment	Capturing the pleasurable aspects of interactions	Aroyo et al. (2018) and Hegner et al. (2019)
Robotic system factors	Attribute-based	Gender	Male/female	Ghazali et al. (2018), Law et al. (2021), Simon et al. (2020), and Tay et al. (2014)
		Appearance	Outward aspects of robots	Arts et al. (2020), Calhoun et al. (2019), Ghazali et al. (2018), and Hamacher et al. (2016)
		Personality traits	Behaving in identical ways across diverse situations	Tay et al. (2014)
		Communication	The way that robots impart information to users	Ezer et al. (2019), Hamacher et al. (2016), Natarajan and Gombolay (2020), and Sanders et al. (2014)
		Voice	The sound produced by robots	Torre et al. (2018)
		Emotion	A state of physiological arousal and of cognition appropriate to this state of arousal	Law et al. (2021)
		Intelligence	The ability to learn or understand	Barczak et al. (2010), Kim et al. (2020), Law et al. (2021), and Rheu et al. (2020)
		Automation level	The extent of how automated robots are	Schaefer et al. (2016) and Shayesteh and Jebelli (2022)
	Performance-based	Transparency	The user's comprehension of the robots' intention, decision-making process, current/future actions, and limitations	Akash et al. (2019, 2020), Cai and Lin (2010), Calhoun et al. (2019), Choi and Ji (2015), Clare et al. (2015), Du et al. (2020), Kaniarasu et al. (2013), Kraus et al. (2020), Kunze et al. (2019), Liu et al. (2021), Matthews et al. (2020), Maurtua et al. (2017), Sanders et al. (2014), Sucameli (2021), and Wang et al. (2016)
		Reliability	The consistency of robots' functions	Calhoun et al. (2019), Charalambous et al. (2016), Daronnat et al. (2020), Desai et al. (2012), Huang et al. (2021), Volante et al. (2016), and Wright et al. (2020)
		Predictability	The extent to which robot's performances are consistent with users' expectation	Simon et al. (2020)
		Proximity	The physical closeness between robots and users	Charalambous et al. (2016), Simon et al. (2020), and You et al. (2018)
		Competence	Robots' ability to meet performance standards (Merritt and Ilgen 2008)	Abd et al. (2017), Choi and Ji (2015), and Desai et al. (2012)
		Adaptation	Robots can change their mode of operation dynamically	Ezer et al. (2019), Nothdurft et al. (2012), and de Visser and Parasuraman (2011)
		Blame	The cause of a negative outcome	Kaniarasu and Steinfeld (2014)
		Alarm sequence	The sequence of false alarms (e.g., errors are followed by a series of correct behaviors/a series of correct behaviors is followed by errors)	Lu et al. (2020)
Environmental factors	—	Mental workload	The amount of mental capacity required during task(s)	Ahmad et al. (2019), Akash et al. (2019, 2020), Gupta et al. (2020), Kunze et al. (2019), Wright et al. (2020), Yamani et al. (2020), and Zhou et al. (2020)
		Mental model	Individuals' internal representation of robots	Matthews et al. (2020) and Schaefer et al. (2016)
		Time pressure	The interaction should be executed in a given limited time	Robinette et al. (2017)
		Task nature	The characteristics of the task itself	Salem et al. (2015) and Sanders et al. (2019)

Competence, which means the perceived abilities of a robot to execute tasks, is another broadly studied performance-based factor (Fiske et al. 2007; Kulms and Kopp 2019). For instance, van den Brule et al. (2014) revealed users reduced their trust levels if observing the robot trembling (i.e., incompetent) when executing a pick-up task. Likewise, a navigation robot that guided participants with an efficient route was perceived as more trustworthy than the robot guiding with a circuitous path (Salem et al. 2015).

Adaptation represents whether a robot can adjust its mode of operation dynamically based on humans' demands and contexts (Scerbo et al. 2003). For example, de Visser and Parasuraman (2011) designed an adaptive system that was only activated when participants were suffering from a high workload. Under their study, participants were asked to control three (i.e., low workload) or six (i.e., high workload) unmanned vehicles to execute a reconnaissance mission with the aid of an automated system that detected targets. The participants reported higher trust when the aid was implemented in a context-dependent manner than in a static manner. More details on performance-based factors and related papers are tabulated in Table 2.

Interestingly, human and robot factors could be combined to discuss their (in)equivalent impacts on trust. For example, in recent construction research examining workers' trust in a bricklaying robot, both robot failures (robot factor) and responsibility attribution for the failures (human factor) were considered in the discussion (Chang et al. 2023b). The results indicated the workers who perceived themselves as responsible for robot failures retained trust in robots, whereas the ones who blamed robots reduced trust.

Environmental Factors

Environmental factors relate to the operational environment in which the interaction occurs and can be represented by mental workload, mental models, the nature of the task, risk, and time pressure (Robinette et al. 2017; Salem et al. 2015; Sanders et al. 2019; Yamani et al. 2020). For instance, users experiencing higher mental workload may misperceive the behaviors of automated systems because of the insufficiency of their attentional resources, which further caused a decline in trust levels (Yamani et al. 2020). Also, in the research conducted by Matthews et al. (2020), individuals' differences in mental models resulting from observation and expectations affected trust.

On the other hand, trust is a task-dependent construct and can be impacted by task-related factors. For example, previous studies indicated that humans preferred robots to be responsible for time-critical evacuation tasks (i.e., finding an exit in a mazelike space) (Robinette et al. 2017) and for dangerous tasks (e.g., improvised explosive device technicians) instead of safe tasks (e.g., warehouse technicians) (Sanders et al. 2019).

Although abundant papers have investigated the factors impacting trust, there are a few research gaps that can be filled by future scholars. First, there are discrepancies between the findings proposed by different papers. These inconsistencies might be related to the small sample size and the nature of the different studied problems. Therefore, further investigation of various factors (e.g., validating the effect of factors on trust or examining the mediators and moderators in human–robot trust) is still needed.

Second, it remains unclear whether previous findings can be replicated in the construction domains. Due to the distinctiveness of this industry, the effects of previously proposed influential factors on trust should be reexamined within construction, and more importantly, more construction-related variables should be taken into consideration.

Trust Calibration

Considering trust is a multifaceted and dynamic phenomenon changing over time, individuals decide how to adjust their trust level (i.e., trust calibration) based on various human, robot, and environmental factors (Demir et al. 2021). Therefore, trust calibration is defined as a process in which humans continuously update the trust in their partner by aligning the perceived trustworthiness (i.e., the perceived capability of executing a specific task) with its actual trustworthiness (i.e., the actual capability of executing a specific task) (Lee and See 2004; de Visser et al. 2020).

However, this alignment mechanism is challenging for individuals to accomplish. Misalignment between these two variables would compromise the interaction performance and even provoke negative consequences. For example, the malfunction of an autonomous vehicle system (i.e., an autonomous overtaking without permission) may temporarily decline users' trust level because its actual capability was lower than its perceived capability (Kraus et al. 2020). Therefore, this section examines the different trust conditions and actions during the calibration process during the interaction between humans and robots.

Calibrated Trust versus Overtrust versus Undertrust

Fig. 5 provides a schematic overview of three conditions in the trust calibration process. Calibrated trust refers to the condition that a human's trust level exactly corresponds with the actual capability of robots. Humans may manifest neither excessive nor inadequate trust in their partners (Demir et al. 2021). Calibrated trust is the optimal circumstance of the trust calibration process and a vital component for people to use their robotic partners appropriately. Facilitating appropriate trust-building is crucial to preventing the misuse (overtrust) and disuse (undertrust) of robots and exploiting their full potential while preventing adverse effects on their performance (Ullrich et al. 2021).

Overtrust (the region above the line in Fig. 5) represents the state when the perceived trustworthiness is higher than the actual trustworthiness. This misalignment would cause humans' overreliance on robots because the established trust exceeds system capability: robots are perceived to be more competent, reliable, and trustworthy than their actual state, leading to misuse (Aroyo et al. 2021; Inagaki and Itoh 2013). Overtrust is seemingly challenging to evade; it would also be exacerbated by specific contexts (e.g., time pressure, mental workload, and prior positive experiences) (Itoh 2012; Li et al. 2014; Robinette et al. 2016; Ullrich et al. 2021).

In a study examining an emergency evacuation scenario, a robot was used to guide participants to a meeting room with either an efficient or a circuitous path (Robinette et al. 2016). In the case of fire in the building, having most participants trust (i.e., overtrust) the evacuation paths provided by the robot demonstrated that time

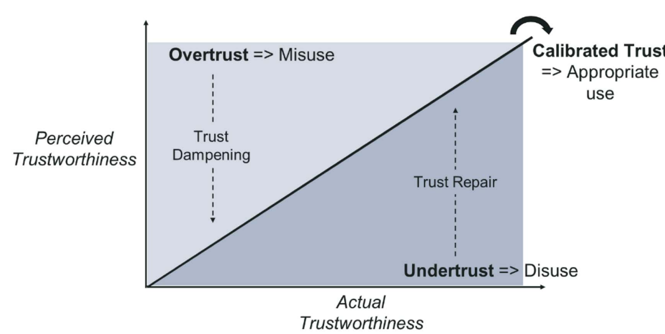

Fig. 5. Three trust conditions in the trust calibration process.

pressure is one of the factors that cause overtrust. Also, Li et al. (2014) conducted an experiment in which participants were required to execute a computer-based moving task with a robot, including controlling a robotic arm, planning trajectories, selecting desired camera views, and monitoring camera views while an automated system helped them plan the trajectories (Li et al. 2014). The results indicated participants tended to overrely on the system and failed to recognize its failures due to the higher mental workload of the task.

Moreover, other studies presented four latent reasons for overtrust in robots: instant rewards (e.g., immediate benefits of reducing workload from humans by releasing tasks), inappropriate generalization (e.g., generalizing from a positive experience of using a robot in one task to another success in a different task, e.g., a ripple effect), transfer of social concepts from human-human interaction to human–robot interaction, and wishful thinking (e.g., believing the robot is perfect when using it) (Itoh 2012; Ullrich et al. 2021). Although these factors were frequently mentioned in the previous literature, there is a paucity of reliable empirical evidence to validate their effects on overtrust.

Undertrust stands for the conditions where perceived trustworthiness is lower than the actual trustworthiness, leading to disuse (Fig. 5). Trust-related research has generally assumed that humans are capable of independently and accurately completing tasks without the assistance of robots. In fact, this assumption might be controversial because human errors have been regarded as one primary reason for compromising human–robot interaction (Honig and Oron-Gilad 2018). In other words, a robot may perform functionally (e.g., warning about a potential car collision) but human users consider not trusting it (e.g., ignoring the warning). This paradigm of undertrust could engender an adverse consequence (e.g., collision) or even a considerable loss for humans (e.g., injury or fatality).

Undertrust has also been mainly discussed alongside the "trust violation" concept due to its causal relationship (Khavas 2021). Trust violation was defined as "unmet expectations concerning another's behavior or when [the trustee] does not act consistent with one's values" (Bies and Tripp 1996, p. 248). Even though technological advancements have tremendously improved the quality of robots, their performances are far from ideal, and trust violations are inevitable (Baker et al. 2018). The trust violation can be categorized into (1) competency-based violations (e.g., a robot fails to execute a task); and (2) integrity-based violations (e.g., a robot intentionally does something contrary to human interest) (Lee et al. 2021; Salem et al. 2015).

For example, Salem et al. (2015) found that participants were unwilling to follow a robot's instructions after it executed faulty navigation. This incorrect behavior is a typical competency-based violation that lowers users' trust levels. Further, Sebo et al. (2019) provided examples of a competency-based violation (i.e., a robot mistakenly hitting a wrong button) and an integrity-based violation (i.e., a robot intentionally hitting a wrong button), and suggested the importance of two types of trust violations. Notably, although competency-based violations happen more commonly to traditional automated partners (e.g., robots without AI) that only execute predefined actions, integrity-based violations will be more prevalent in robots that can intelligently make their own decisions (de Visser et al. 2018). Therefore, both violations might exert an effect on undertrust and should be taken into consideration.

Given that overtrust and undertrust could jeopardize human–robot teaming, improving calibrated trust plays an important role in the entire trust calibration process. A recent study developed a framework based on relationship acts, regulation acts, and net victim effects to depict the trust calibration cycle (de Visser et al. 2020). Specifically, the relationship act represents the acts (undertaken by the trustee) that the trustor considers as either harmful (e.g., trust violation) or beneficial (e.g., superior performance) to trust, causing either undertrust or overtrust. Relationship regulation acts denote the acts that provide corrective actions (i.e., trust repair and dampening) for the relationship acts to encourage calibrated trust. Finally, the net victim effect combines the effects of the relationship act and the related regulation acts (i.e., the updated trust).

This framework aligns with a recent narrative study viewing trust as a sociocognitive concept (Chiou and Lee 2023). In their study, Chiou and Lee (2023) emphasized that the actions performed by either humans or robots in a relationship will dynamically influence trust. Previous literature identified trust repair and dampening as the behaviors undertaken by robots to address overtrust (i.e., decreasing perceived trustworthiness) and undertrust (i.e., increasing perceived trustworthiness), respectively (Fig. 5) (Chancey and Politowicz 2020).

Trust Repair versus Trust Dampening

There are various trust repair approaches such as (1) commitment to change (e.g., promise), (2) apology, (3) denial, and (4) trustworthy actions, which can ameliorate undertrust and which are adopted from human–human interaction (Baker et al. 2018; Khavas 2021). Baker et al. (2018) proposed that the repair strategies for the interactions between humans could be applicable to the trust between humans and robots, based on the premise that robots were perceived as humanlike. Specifically, commitment to change refers to the promise made by robots to perform well in the following tasks. For example, an automation system would say, "I promise to do better," after breaking human trust through unpredictable behaviors (Albayram et al. 2020).

Furthermore, whereas apology represents the robot confessing a mistake and asking for forgiveness from the human, denial conversely indicates the robot desires to convince the human of its innocence by providing explanations (Fratczak et al. 2021; Sebo et al. 2019). In trustworthy actions, the trustee (robot as violator) demonstrates a series of reliable actions to restore trust. Denial was recommended for integrity-based violations, and others were suitable for competency-based breaches (Kim et al. 2004; Kohn et al. 2018; Sebo et al. 2019). For example, Sebo et al. (2019) observed that competency-based violations (i.e., a wrong button was hit by a robot mistakenly) could be effectively fixed by an apology and promise (i.e., apologizing for the error and promising not to make a mistake again) whereas integrity-based violation (i.e., the robot intentionally hit the wrong button) can be better addressed by a denial (i.e., denying hitting the wrong button).

To alleviate overtrust, recent studies have mainly explored two trust-dampening strategies: (1) confidence score; and (2) trust calibration cue. The confidence score represents the chances that robots perform correctly (Desai et al. 2013; Helldin et al. 2013; Zhang et al. 2020). It is still impossible to guarantee the perfection of robots because their actions correspond to probabilistic models. Individuals might be prone to overtrust in robots when ignoring this uncertainty (Tomsett et al. 2020). Therefore, the confidence score provides information about uncertainty for human users to avoid overtrust. For example, in the study investigating the trust calibration in a driving task, Helldin et al. (2013) mentioned that providing the confidence score of a car automation system (i.e., whether automation is reliable under the current condition) was beneficial for drivers to appropriately calibrate their trust.

Compared to proactively providing a confidence score, the trust calibration cue is a reactive strategy, activated when human overtrust is detected (de Visser et al. 2014). For instance, Okamura and Yamada (2020) utilized four types of cues (i.e., visual, auditory, verbal, and anthropomorphic) in an experiment where participants were asked to execute a pothole inspection task with a drone. Participants needed to determine either to use the autonomous inspection provided by the drone—which might not always be accurate—or to inspect the pothole manually. If an algorithm identified the users' overtrust (i.e., users' perceived capability of the drone was higher than its actual capability), one of the four cues was presented for them to reduce their trust level. The results support the benefits of the cues to mitigate overtrust.

The detection of overtrust (or undertrust) is an integral part of using trust calibration cues. Until now, two challenges complicate this detection: non-real-time judgment and nonobservable property of overtrust (Liu and Hiraoka 2019). Non-real-time judgment means we can identify the situation of human overreliance on robots/machines only after the situation already happened (i.e., the feedback is already known). That is to say, real-time identification of overtrust is difficult to achieve when the situation is happening because the accuracy of robots is still unknown. The nonobservable property of overtrust refers to the difficulty of understanding a human's trust state. Researchers should predefine a behavioral pattern (e.g., following a robot's advice right after it erred) or an algorithm (e.g., users' perceived capability of a drone was higher than actual capability) to discern human overtrust, but both responses might be subjective and unreliable (Okamura and Yamada 2020; Robinette et al. 2016). Therefore, more studies are needed to investigate the real-time approaches to authentically detect human overtrust/undertrust.

Although several trust repair and dampening methods have been proposed, a follow-up issue would be whether the methods could be equivalently effective across a variety of individuals. For example, the provision of additional information (e.g., confidence score) can improve the calibrated trust, but the information might not be understandable to some target users (e.g., children, workers, and people with disabilities) (Wagner and Robinette 2021). On the other hand, trust resilience, which represents human resistance to losing trust when encountering a trust violation, could provide an example that a trust repair method might be more useful for people with higher trust resilience (de Visser et al. 2016). Hence, this paper recommends future studies to consider how to make these methods more adaptive for individuals.

Trust versus Distrust versus Untrust

Previous studies argued that there are three types of trust: (1) trust, (2) distrust, and (3) untrust (Fig. 6). Most of the studies would presume a dichotomy between trust and distrust, but distrust is just an adverse form of trust rather than a negation of it (Abdul-Rahman 2005). For example, when the trustor says, "I do not trust the information provided by the trustee," more evidence would be needed for the trustor to manifest trust or distrust. Thus, there is a gap between trust and distrust, called "untrust" (Fig. 6) (Marsh and Dibben 2005). When trust conditions (i.e., calibrated trust, overtrust, and undertrust) and trust-related actions (i.e., trust dampening and trust repair) were explored by previous studies, the main focus was on trust and distrust. Consequently, untrust remains understudied in human–robot trust studies.

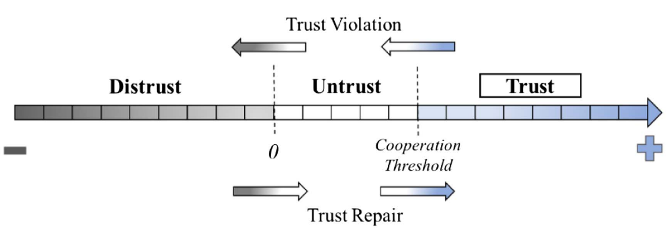

Fig. 6. Schematic framework of trust calibration.

Distrust refers to a situation where a human's trust level is below zero. When the trust level exceeds the cooperation threshold (i.e., humans believe robots will be of any help in this situation)—a threshold that varies among individuals—the human is willing to cooperate with the robot (i.e., trust). Untrust is when the trust level is higher than zero but not high enough to achieve the cooperation threshold; this span between distrust and the cooperation threshold indicates that the human needs more evidence to adjust their trust level (Marsh and Dibben 2005). The trust level may fluctuate among the three types of trust during the interaction due to violations and recovery by trust repair methods.

As highlighted previously, trust calibration has been unexamined by previous construction literature. This dynamic process will be decisive in establishing a successful human–robot teaming on future jobsites. Because workers are still unfamiliar with working alongside robotic technologies, correctly calibrating their trust in robots will be challenging for them, imposing some latent safety issues. Thus, it is critical to further explore the issues with trust calibration in future construction workplaces and develop effective interventions to better prepare the next generation of the workforce.

Trust Measurement Methods

Understanding the calibration process entails an effective and reliable trust measurement. To gauge the trust between humans and robots, several methods have been used in the literature: (1) self-reports, (2) behavioral methods, and (3) psychophysiological methods.

Self-Report Trust Measurement

Self-reporting is the most used method for measuring trust between humans and robots. Previous studies have either applied preexisting trust scales or developed a customized questionnaire for measuring trust after the primary experiments were completed (e.g., Chang et al. 2023b; Shayesteh and Jebelli 2022; You et al. 2018). The widely used trust scales include the Negative Attitudes toward Robot Scale (Nomura et al. 2006), Trust in Automation Scale (Jian et al. 2000), and Muir's questionnaire (Muir 1994).

The main benefit of using self-reporting is its ease of use (Khavas 2021), but some limitations and biases also undermine the reliability of this method (Hu et al. 2016; Lu and Sarter 2020): (1) these questionnaires are post trials, and subjects need to respond to questions based on their perceptions and attitudes toward partners after completing the designated task (Brzowski and Nathan-Roberts 2019); and (2) the reliability of subjective reports might be impacted by participants forgetting details or intending to align their answers to what experimenters anticipate (Khavas 2021). Therefore, more objective trust measurement methods have been proposed to address the limitations of the self-report methodology.

Behavioral Trust Measurement Methods

An alternative for measuring trust is the behavioral method, which observes specific humans' behaviors during the interaction to understand their trust. Behavioral trust can be measured through three metrics: (1) task delegation, (2) behavioral change, and (3) following advice (Law and Scheutz 2021).

Task delegation represents human participants who are willing to defer their task to robots or to take back the task. The trust level of humans can be measured by the user's willingness to release/retrieve tasks—a potential distrust in the robot can be implied by humans' unwillingness to assign the task to their partners. For example, although a robot performed flawlessly in feeding pets regularly, pet owners still tended to prepare food themselves (Ullrich et al. 2021).

Behavioral change is another fruitful metric when people cannot control the behaviors of robots (e.g., shutting down the machine or taking over the task again) (Law and Scheutz 2021). People may undertake behavioral adjustments to correspond with their trust levels. For instance, participants may place both hands underneath an object that was being delivered by a robot to take a precaution against a latent fall (Onnasch and Hildebrandt 2022). Similarly, observing the frequency that humans ask for robot help can indicate their trust level (Ghazali et al. 2018).

Trust can also be measured based on an individual's decision to follow the advice provided by robots during the interaction or not. Regardless of the accuracy of the provided advice, the determination to adopt or disregard the advice (Aroyo et al. 2018) and response time (Lu et al. 2020) are rooted in users' trust. Specifically, a shorter time for deciding to follow the advice implies a higher trust level than a longer response time.

Compared to self-reports, the behavioral method is less biased and more accessible in real-time (Akash et al. 2020). Trust levels can be derived from the observation of subjects' particular behaviors during the experiment instead of collecting data at the end of the experiment. This method is highly based on the premise that those behaviors correctly reflect humans' trust level or attitude (Khavas 2021), so it might become controversial if the premise is not supported. Furthermore, it is challenging to generalize the relationship between those behaviors and trust across varying individuals. Therefore, an alternative method can be utilized or combined with this method to collect relatively implicit trust data.

Psychophysiological Methods

The psychophysiological method is an unobtrusive and objective approach. Unlike the behavioral method, which explicitly observes behaviors, this method implicitly measures trust by examining human psychological states and physiological responses and by identifying psychophysiological patterns. With the advancement of sensing technologies, psychophysiological responses have recently been used for trust measurement purposes.

The common psychophysiological methods used in the selected trust-related studies include electroencephalogram (EEG) (e.g., Akash et al. 2018; Gupta et al. 2020; Hu et al. 2016; Shayesteh et al. 2022), electrodermal activity (EDA) (e.g., Cominelli et al. 2021), galvanic skin response (GSR) (e.g., Akash et al. 2018; Gupta et al. 2020; Hu et al. 2016), heart rate (e.g., Gupta et al. 2020; Kunze et al. 2019; Lu et al. 2020), and eye-tracking (e.g., Kunze et al. 2019; Lu and Sarter 2020; Lu et al. 2020). For instance, signals from central regions of the brain (e.g., C3 and C4) collected by EEG sensors were discovered to be related to human trust. In an experiment, participants were required to determine whether to trust the detection results provided by an obstacle detection system, and EEG sensors identified trust metrics (Akash et al. 2018). Also, using eye-tracking sensors, Lu et al. (2020) measured human trust by conducting a multitasking experiment (i.e., a searching task assigned to a drone and a tracking task assigned to participants). The results indicated that participants with higher trust in the drone allocated more attention to the drone-irrelevant area, which was an interface for participants to execute the tracking task.

Although these findings are promising, an evident challenge in the psychophysiological method is the ambiguity of the correlation between trust and psychophysiological signals. Specifically, instead of a one-to-one correlation (i.e., one psychophysiological signal corresponding to one trust state), this correlation is analogous to a one-to-many relationship (i.e., one trust state affects several psychophysiological signals) (Ajenaghughrure et al. 2020). Therefore, there is still a paucity of a comprehensive understanding of psychophysiological responses as trust metrics.

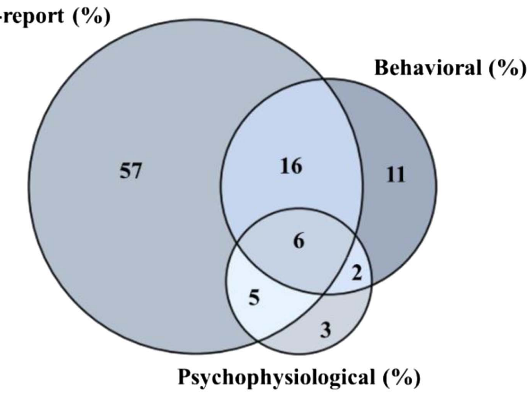

Fig. 7. Measurement methods distribution within the reviewed papers.

Each trust measurement method has its advantages and limitations. Instead of gauging trust by a single method, many studies recommended incorporating two or more methods together (e.g., Salem et al. 2015), shown in Fig. 7. Incorporating different methods can facilitate cross-validation and consolidate the reliability of findings. Among the reviewed papers using any measurement methods, 6% of papers combined all three methods (i.e., Dizaji and Hu 2021; Gupta et al. 2020; Kunze et al. 2019; Lu et al. 2020; Zhou et al. 2020). It is worth noting that measuring trust in human–robot teaming is not a straightforward task. Most of the previous studies measured a momentary state of trust rather than its prolonged changes over time. In addition, trust data were mainly collected in a structured experiment instead of in natural and realistic scenarios.

Previous construction literature primarily focused on deploying self-reports as the trust measurement method; however, this subjective method suffers from some limitations (e.g., non-real-time and biased). Although behavioral and psychophysiological methods could provide a real-time and objective understanding of trust, construction-related features might complicate their deployment. For example, construction is a physically demanding industry in which workers inevitably make physical movements that may lead to additional artifacts in psychophysiological signals. Hence, finding a suitable trust measurement in the construction domain deserves more researchers' attention.

Discussion

Synthesis and Prospects for Trust-Building between Humans and Robots in Construction

Although the previous literature contributed to portions of the trust-related body of knowledge, the findings of this comprehensive literature review demonstrated that its construction exploration is still nascent compared to other industries. Specifically, Fig. 8 presents the body of knowledge in construction and other domains. The synthesized comparison illustrates multiple research areas still unexplored by the current construction literature. The primary research gaps are (1) the effect of environmental factors on trust has not been examined, (2) the dynamic nature of trust-building has not been considered, and (3) trust calibration and effects of that are not investigated by construction literature (Fig. 8). Thorough understanding of workers' dynamic trust levels can be obtained from environmental and other human–robot-related factors, and the selection of strategies can be built upon the knowledge of workers' dynamic trust levels.

J. Comput. Civ. Eng., 2024, 38(3): 03124001

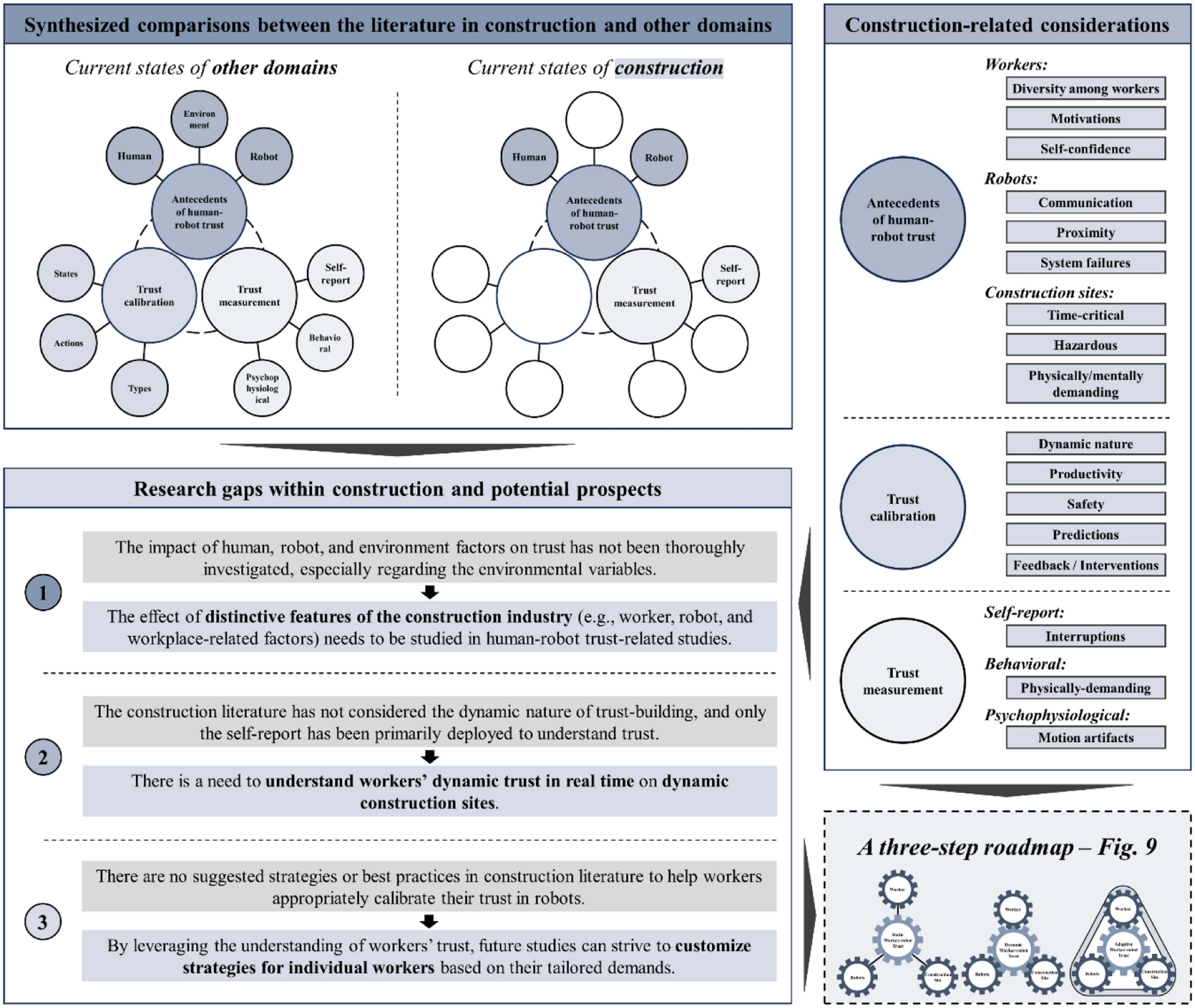

Fig. 8. Summary of the findings and the major research gaps in construction identified by this study.

A Framework toward Worker–Robot Trust in Future Construction Industry

Although the findings from research in other domains could provide valuable insights, construction-related factors must be considered to further discuss human–robot trust in construction (Chua and Goh 2004; Wanberg et al. 2013), as shown in Fig. 8. Due to the special considerations of the construction industry and the complexity of trust-building, it is crucial to establish guidance for prospective construction researchers to accelerate advances in these research areas. Taking advantage of this systematic review, the present study builds a three-phase roadmap for researching worker–robot trust in construction (Fig. 9).

Phase I: Static Worker–Robot Trust

Prior studies have verified trust is affected by three entities: humans, robots, and the environment (Hancock et al. 2011b). In construction, the entities become workers, robots, and the construction site. The first phase (i.e., static worker–robot trust) investigates the static relationship between three entities (i.e., the effect of a single entity on trust):

Worker-Related Factors. The construction industry is characterized as labor-intensive compared to other industries, and various worker crews concurrently execute tasks on jobsites. Given the variety of workers, it is readily expected that human factors (Table 2) will influence workers' trust in robots. However, previously published papers in the construction domain mainly focused on system properties. Thus, future studies into worker-related factors are recommended to highlight and explore the importance of such factors as self-confidence, motivation, and disability.

Self-confidence (i.e., complacency) is estimated to seriously impact workers' trust-building in robots, and individuals with more self-confidence were observed to manifest less trust in their partners (Sanchez et al. 2014). Similarly, construction workers who have worked in the construction sector for decades might be unwilling to relinquish their work because they feel confident in performing better than robots. Additionally, the capability of robots to execute

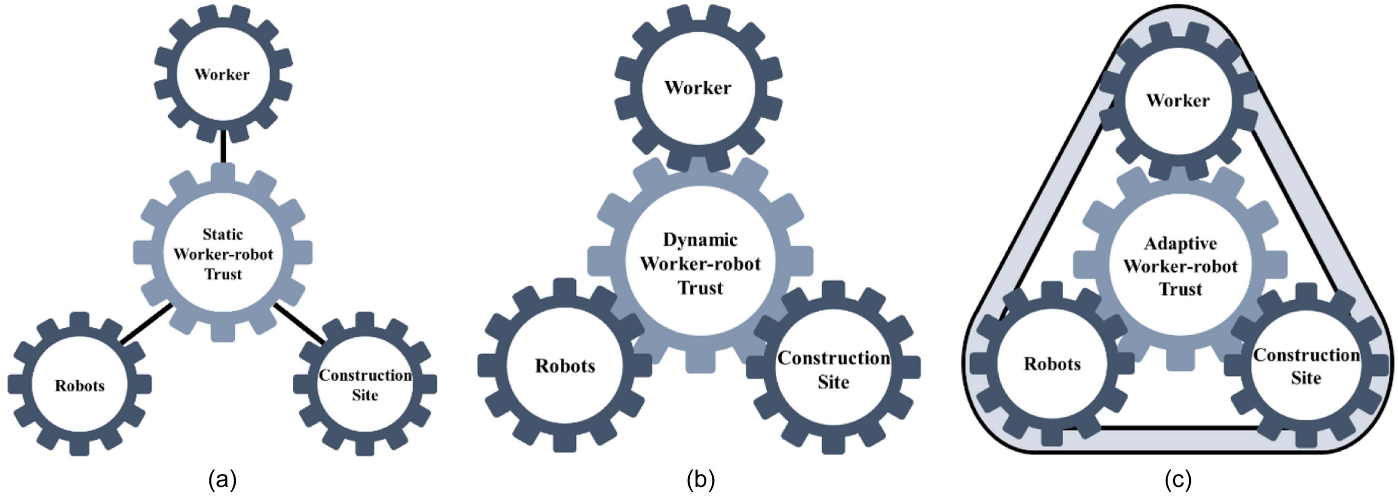

Fig. 9. Three-step framework for studying worker–robot trust in the construction industry: (a) static; (b) dynamic; and (c) adaptive.

dynamic and unpredictable construction tasks might be underestimated by workers. This unwillingness could pose an underlying issue for the jobsites, so a further investigation into the effects of construction workers' self-confidence in trust building is needed.

Another notable factor is workers' motivations to build their trust in robots. As highlighted, the construction sector is labor-intensive, so it offers considerable job opportunities for construction workers. The incorporation of robots into construction sites may indirectly reduce the demand for workers because portions of construction tasks can be taken over by robots. The fear of job loss was mentioned to be one influential factor that may undermine the interaction between workers and robots (Kopp et al. 2021). Therefore, providing adequate motivation for workers to embrace and trust the robot in the construction sector needs to be prioritized.

The consideration of disability in human–robot trust has been an understudied research area. A survey found approximately 26% of US adults reported any disability (e.g., mobility, cognition, hearing, or vision) (Okoro et al. 2018), which was a statistic that should draw the attention of any human-related research. With automated technologies becoming increasingly prevalent in daily lives and workplaces, the discussion of how individuals with different mental and physical disabilities may build trust in their robot teammates in the future workplace becomes vital and urgent. Although no studies proposed a specific ratio of construction workers with disability, it is estimated that the portion should be nonnegligible based on the aforementioned percentage. In parallel, the construction industry could conceivably become more inclusive with the incorporation of robots because these technologies may offset workers' physical or cognitive constraints. Teaming with robots provides an opportunity for workers with disabilities to use their strengths when robots can compensate for their limitations. In this case, these workers could comprise a part of the future workforce on future construction sites.

Jobsite-Related Factors. This category of factors is highly related to the characteristics of construction sites as identified in the previous literature: time pressure, task safety, mental workload, and physical fatigue (Ahmad et al. 2019; Robinette et al. 2016; Sanders et al. 2019). Future researchers may wish to expand this category by examining additional construction-related factors.

Time pressure has been proposed as an influential factor for increasing human trust, and even overtrust, in robots (Robinette et al. 2016). Construction projects are time-critical, and workers are responsible for completing construction tasks on schedule to meet delivery requirements and avoid financial penalties regulated in contracts. Time pressure inflicts invisible stress on humans, causing workers to abandon or diminish situation awareness of surrounding dynamic objects and accelerate decision-making (Chang et al. 2023a). In this case, workers may inevitably make a trade-off between (1) manifesting overtrust in robots to accomplish tasks on time; and (2) manifesting appropriate trust in robots to carefully finish tasks despite potential delays. On future jobsites, workers may place disproportionate trust in robots to relieve time pressure stress. Accordingly, time pressure should be further explored by future researchers.

Construction is one of the most hazardous industries worldwide because of its dynamic and uncertain working environment (Wanberg et al. 2013). Construction workers are frequently exposed to varying hazards throughout their construction tasks (Chua and Goh 2004). Task safety has been recognized as a factor to impact workers' trust in robots, and previous studies discerned a preference for assigning dangerous tasks to robots (Sanders et al. 2019). Even though this task transfer might enhance workers' safety, workers may misuse a robot that is not developed for executing dangerous tasks, or workers assign robots tasks that are more suitable for humans. Hence, it is crucial that the capabilities of the robots are fully understood by workers to put them into appropriate use.

Mental workload has been presented as an environmental factor by human–robot trust literature (e.g., Akash et al. 2020; Gupta et al. 2020; Wright et al. 2020; Yamani et al. 2020) because excessive mental workload may cause misplaced trust due to human limited attentional and cognitive resources (Yamani et al. 2020). Construction workers already endure a copious amount of mental workload due to their multitasking across assigned tasks and safety tasks. Additional imposed load involved in using robots also consumes attentional and working memory resources. This overload might further lead to inappropriate trust-building and trust miscalibration. Research will need to explore to what extent human–robot trust causes workers to pay insufficient attention to their interaction with robots and/or have an inclination to overtrust them.

Physical fatigue caused by physically demanding construction tasks is another peculiar factor to be considered. Physical fatigue could provoke decreased productivity, poor judgment, inattention, accidents, and injuries (Abdelhamid and Everett 2002; Aryal et al. 2017). Workers experiencing severe physical fatigue might build inappropriate trust in robots due to their impaired judgment, which needs to be studied further.

Robot-Related Factors. An abundance of these factors has been studied in other research domains, as detailed in Table 2, as well as in a few published papers within the construction domain. Their findings provide valuable insights into how this category of factors would impact workers' trust in the construction industry. Due to the distinctiveness of the construction industry, construction research in this vein would particularly need to accentuate the explorations of communication and proximity for construction worker–robot trust.

Communication has been identified as a crucial component of teaming, and studies have also emphasized its influence on trust (Ezer et al. 2019; Hamacher et al. 2016). Communication between entities refers to the exchange of information through explicit or implicit modalities that enable behaviors, thoughts, and emotions (Lackey et al. 2011), all of which facilitate transparency and trust-building. Therefore, selecting an efficient and proper communicative modality is integral to information exchange. However, a few challenges complicate communication on construction sites. For example, the high level of noise generated by construction activities on the jobsites (Suter 2002) inevitably creates a barrier to verbal communication between robots and workers. Alternatively, nonverbal communication (e.g., gesture) could be a satisfactory approach for noisy worksites and its effectiveness in the construction domain could be further researched. Thus, investigating proper communication modality for the construction industry is essential to enhance worker–robot trust.

Proximity, representing the physical distance between entities, would also affect workers' trust-building on jobsites. Previous studies revealed a bidirectional relationship between proximity and trust. Specifically, individuals with sufficient trust level are more willing to approach a robot, and, appropriate proximity to robots would encourage them to build trust (Charalambous et al. 2016; Simon et al. 2020). However, unlike other sectors (e.g., manufacturing), construction sites are a dynamic and uncontrollable environment, so maintaining a fixed distance between workers and robots is arduous. Although it was discussed in the literature that separating a robot by a fence may increase workers' perceived safety and trust (You et al. 2018), the ultimate expectation for worker–robot teaming on future construction sites is a shared workplace. To fulfill this expectation, it is necessary to further investigate the strategies to maintain comfortable proximity between workers and robots to garner appropriate trust-building.

In summary, the first phase of the roadmap delves into worker–robot trust as built by the static relationships among workers, robots, and construction-site factors. These static relationships refer to the causal factors contributing to increased or decreased trust levels. Although such an exploration is beneficial to reshaping the development of robots for the construction industry, the dynamic nature of trust-building (i.e., trust calibration) is ignored here. Exploring the evolving trust levels between workers and robots is especially necessary within the dynamics of construction because worker–robot trust is not steady during an entire interaction and must be expected to fluctuate as the teaming advances.

Phase II: Dynamic Worker–Robot Trust

Dynamic worker–robot trust represents the changes in workers' trust levels toward the robot in the construction context. The literature showed that humans continuously update and calibrate their trust based on their perceptions of their present situations (Lee and See 2004; de Visser et al. 2020). Workers need to efficiently and safely complete tasks, and their inappropriate levels of trust in robots might compromise productivity and safety performance. Accordingly, a real-time understanding of workers' trust is essential in future construction to facilitate worker–robot interaction. This understanding helps predict trust in advance and, in the case of inappropriate trust, provide real-time feedback and interventions for workers. Thus, adding to the causal static relationships discussed in the first phase, the second phase of the framework strives to address this ongoing calibration process. In particular, three arenas for interrogation were highlighted: trust measurement, dynamic model development, and trust-condition interpretation.

Trust Measurement. An understanding of dynamic trust necessitates a suitable measure to gauge workers' trust levels during teaming. Although prior studies have broadly applied self-report, behavioral, and psychophysiological methods in other domains, their applicability to the construction domain should be reexamined by construction researchers. Specifically, a self-report would not be a suitable option because it cannot provide real-time trust data without interrupting the teaming (Khavas 2021); in the context of a dynamic setting, such interruptions would obscure real-time measurements. The first step toward a more reliable measurement is to establish a well-accepted definition of trust, mitigating the possibility that workers view the questions of trust differently.

Although the objective methods—behavioral and psychophysiological—can be used for real-time understanding of trust, a few difficulties that might weaken the effectiveness of methods should be tackled in advance. As mentioned in the previous section, the challenges of the behavioral method lie in predefining which behaviors reveal human trust level and in generalizing these definitions across individuals (Khavas 2021). These challenges might be amplified by the excessive behaviors exhibited by workers and the diversity of workers on jobsites. For the psychophysiological methods, previous literature indicated that a one-to-one correlation between psychophysiological signals and trust had not been corroborated (Ajenaghughrure et al. 2020).

Additionally, physically demanding construction tasks might generate excessive artifacts to psychophysiological signals—for example, EEG signals have been used as a metric to evaluate human trust levels, but this metric is susceptible to physical movements (Alomari et al. 2013), leading to massive artifacts and unreliable data, especially for construction research. Due to the limitations of each trust measurement method in the construction context, exploring an adequate construction-specific measure (or combination of methods) for an understanding of dynamic trust is still needed and essential. Further, given the novelty of robots for the majority of the construction community, it is critical to perform long-term studies to examine the transient nature of trust measurement.

Dynamic Model Development. Rather than directly measure trust, researchers have considered developing a dynamic model to estimate and predict trust (e.g., Akash et al. 2017; Huang et al. 2021). The formulation of such a model is founded on the concept of inputting the influential factors of trust and outputting the resulting trust level, given a specific context. For example, based on the experimental context, Akash et al. (2017) selected previous experiences, cumulative trust, and expectation as inputs to evaluate participants' trust in an autonomous obstacle-detection system. Similarly, depending on the various contexts of application space, researchers could choose different factors as the inputs for their model to generate an output (Khavas 2021). Moreover, in the study conducted by Li et al. (2023), the proposed trust dynamics model argues that users' trust will be updated based on their capability, valence, arousal, and system's capability. Although such an approach could benefit an understanding of human–robot trust, to date, dynamically estimating worker trust in robots on construction sites is understudied.

One option for achieving trust estimation is to harness machine learning and deep learning techniques with enormous potential to discern patterns from an abundance of data and make accurate future predictions. Recently, machine learning models have been applied to predict trust levels (e.g., Ajenaghughrure et al. 2019; Akash et al. 2018; Hu et al. 2016). In particular, psychophysiological data (e.g., EEG and GSR) were used to train models to estimate the real-time trust level. Capturing such data into models and applying machine/deep learning tools may provide a means for pursuing dynamic models within a construction setting.

Trust-Condition Interpretation. Once the trust level has been estimated, another challenging issue is how to interpret current trust conditions—calibrated trust, overtrust, undertrust, untrust, or distrust—based on quantitative trust levels. Although this research area has been covered in other domains, until now, most of the literature considered a binary classification (i.e., 1 = trust and 0 = distrust) for human–robot trust instead of a spectrum of trust conditions. Moreover, previous studies mostly relied on the predefinition of specific behaviors to identify overtrust and undertrust, without quantitative analyses. For example, Robinette et al. (2016) recognized overtrust when participants followed the route provided by a navigation robot that just erred. A research gap that should be filled by future research is to quantitatively analyze the interpretation of various trust conditions. This interpretation is important for all domains because it expedites the real-time identification of inappropriate trust conditions.

In summary, the second phase of the roadmap tackles the dynamic nature of worker–robot trust by investigating trust measurement, dynamic model development, and trust-condition interpretation. It is anticipated that the outcome of this phase would be a real-time understanding of workers' trust conditions during teaming. Although this understanding of trust condition could indicate increasing or decreasing trust levels and quantify trust calibration, the ultimate goal of stimulating workers' appropriate trust-building remains unaddressed. Accordingly, the next phase focuses on investigating strategies to facilitate proper worker–robot trust.

Phase III: Adaptive Worker-Robot Trust

Adaptive worker–robot trust represents adjusting trust-building procedures to facilitate workers' appropriate trust during the teaming by leveraging workers' real-time trust conditions. The published studies in other domains have suggested the positive effect of adaptation on human trust (Ezer et al. 2019). This adjustment should be accentuated in the construction context because their unexpected trust conditions might provoke safety concerns to the construction sites that have been remarkably hazardous. Effective strategies to help workers appropriately calibrate their trust in robots deserve investigation to ensure construction safety. To achieve this goal, the present study proposes two innovations: an adaptive calibration strategy for robots, and adaptive training for workers.

Adaptive Calibration Strategy for Robots. The adaptive calibration strategy refers to the specific actions executed by robots to restore appropriate trust during or after unexpected conditions. According to the systematic review, trust dampening and repair strategies have been applied to address overtrust and undertrust, respectively (Chancey and Politowicz 2020; de Visser et al. 2020). Although the strategies can incentivize humans to adjust their trust, the previous literature suggested that selecting a proper strategy is context-dependent (Kim et al. 2004; Kohn et al. 2018). Moreover, previous studies also emphasized that strategies may need to adjust to address the diversity among individuals (Naiseh et al. 2021; Wagner and Robinette 2021). As a result, to select adaptive actions robots must comprehend the human users and perceive the circumstances.

However, the diversity of workers and the dynamic nature of jobsites complicate these two procedures, and robots need to have a comprehensive understanding of workers, construction sites, and even themselves to determine the most suitable adaptive calibration strategy for the present context. Accordingly, researchers should investigate the effectiveness of various strategies under different teaming contexts on construction sites and should consider how robots can comprehend contexts to select the proper adaptive calibration strategy to enable workers to maintain the appropriate trust during teaming.

Adaptive Training for Workers. Providing training has been proposed to help users familiarize themselves with robots to build appropriate trust (Adami et al. 2022). However, individuals' differences can impact their learning and overall experience. Effective training needs to be customized to accommodate the broad variability between humans. Previous education studies have suggested a two-step adaptive training approach (Landsberg et al. 2012; Tennyson and Christensen 1988). Herein, the trainees are initially placed in a proper level of training based on their inherent differences (intellectual ability, cognitive style, and so on), followed by a second step wherein the training is tailored to trainees' needs by assessing their real-time performances during the training (Shute and Towle 2003). This hybrid approach is based on the concept that real-time performance (i.e., the second step) plays a dominating role in predicting future performance compared to inherent differences (i.e., the first step) (Park and Tennyson 1980). This two-step training approach ideally includes the elements proposed in Phases I and II; hence, it is suitable for workers to learn how to build appropriate trust in robots.

Future studies must consider developing adaptive training for construction workers: First, researchers should examine the critical variables that could be used as a reference to determine the initial training. Second, researchers should investigate how a real-time understanding of trust can help tailor the training to workers' needs. Such multistep training will better prepare workers for appropriate trust-building and provide foundational data points for robots to adapt their calibration over time.

The present study introduces a three-step framework for investigating worker–robot trust in the construction industry (Fig. 9). Furthermore, as the number of robots increases in the construction field and operation and hardware costs decrease, workers will interact with a larger number of robots to accomplish complex construction tasks. This three-step framework can be extended from a single loop (i.e., one worker, one robot, and one construction site) to multiple loops (i.e., multiworkers, multirobots, and multisites) (Fig. 10). Therefore, multiworker–robot-teaming is anticipated to be the dominant working mode on future construction sites. However, no comprehensive work in the construction domain has investigated how multiple workers working with multiple robots affect each other's trust levels. It is hoped that this framework provides an insightful guideline for scholars to explore this understudied research area.

Conclusion

The pervasive incorporation of robots into construction sites is imminent, necessitating rapid preparation for construction workers to embrace, team up with, and build the appropriate trust in the robots that will become their teammates. Consequently, the contributions of the present study lie in (1) systematically reviewing and categorizing the up-to-date trust-related literature about human–robot teaming, and (2) presenting a framework for researching worker–robot trust in the construction domain. The findings of this systematic review present not only the convergence and divergence of research domains outside construction with those topics relevant to construction workers, but also a systematic pathway for exploring

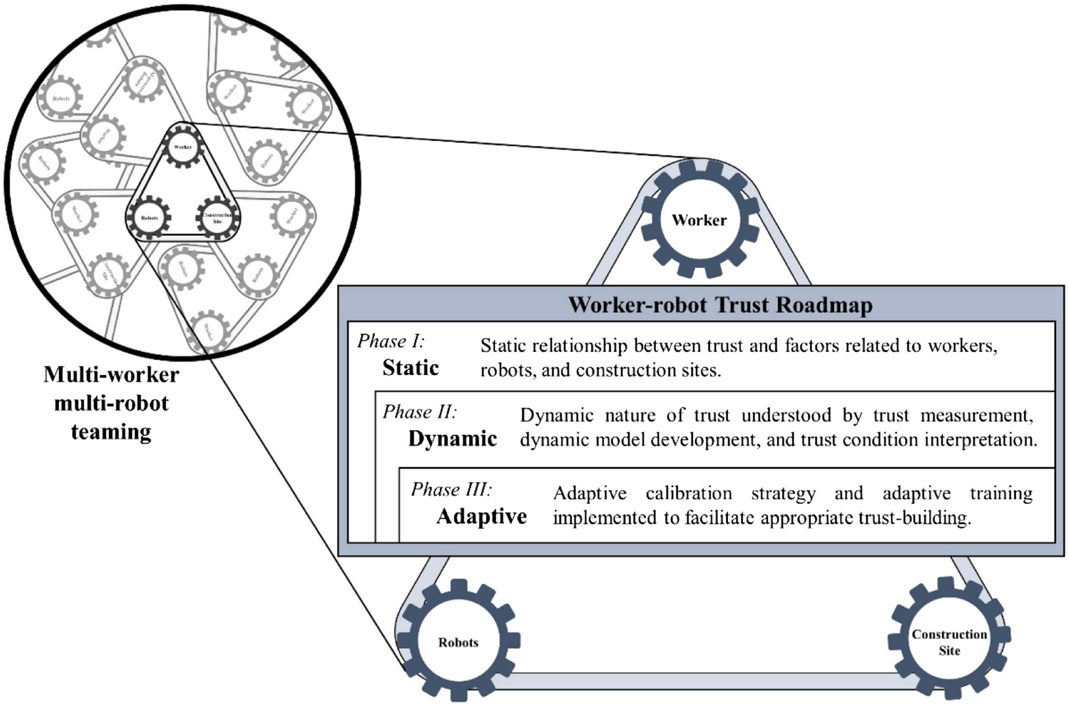

Fig. 10. Proposed framework of worker–robot trust research directions in the future construction.

static, dynamic, and adaptive trust-building between workers and their robotic partners.

Although the construction industry is still nascent in robotic technology adoption compared to other sectors, it is anticipated that workers will need to work alongside robots, communicate with drones, and build a team with robots on future jobsites. Trust is an integral component of establishing successful human–robot teaming, but the explorations of worker–robot trust in construction are just emerging. Therefore, this review paper proposed a roadmap for exploring construction worker–robot trust by systematically reviewing relevant literature across domains. This review categorized the antecedents of trust, trust measurement, and trust calibration, revealing opportunities for a three-phase research roadmap that explores static, dynamic, and adaptive worker–robot trust. This roadmap sheds light on a progressive procedure to uncover the appropriate trust-building between workers and robots in the construction industry. As such, the research presented here will facilitate technological emergence and adoption for researchers and practitioners in the near and long term.

Although the breadth of topics handled here reveals rich outcomes for construction worker–robot trust studies, given the criteria used to develop this paper, the presented review has a few limitations. First, this proposed roadmap was designed especially for the construction industry by incorporating several contexts within authentic construction sites. Although the workflow of the three phases could also be applied to other domains, the details of each phase should be reexamined by researchers. Second, this study concentrated on the trust-building in human–robot teaming under the premise that humans (or workers) should still be in the loop to team up with robots, instead of being out of the loop to merely supervise robots. The interaction between humans and fully autonomous agents was not the primary focus of this review paper.

Data Availability Statement

The data (i.e., reviewed papers and organized information) that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments

This work was supported by the National Science Foundation Future Work-Human Technology Frontier (FW-HTF) (2 2128970). Any opinions, findings, and conclusions or recommendations in this material are those of the authors and do not reflect the views of the National Science Foundation.

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