Assessing Trust in Construction AI-Powered Collaborative Robots Using Structural Equation Modeling

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Abstract: This study aimed to investigate the key technical and psychological factors that impact the architecture, engineering, and construction (AEC) professionals' trust in collaborative robots (cobots) powered by artificial intelligence (AI). This study seeks to address the critical knowledge gaps surrounding the establishment and reinforcement of trust among AEC professionals in their collaboration with AI-powered cobots. In the context of the construction industry, where the complexities of tasks often necessitate human–robot teamwork, understanding the technical and psychological factors influencing trust is paramount. Such trust dynamics play a pivotal role in determining the effectiveness of human–robot collaboration on construction sites. This research employed a nationwide survey of 600 AEC industry practitioners to shed light on these influential factors, providing valuable insights to calibrate trust levels and facilitate the seamless integration of AI-powered cobots into the AEC industry. Additionally, it aimed to gather insights into opportunities for promoting the adoption, cultivation, and training of a skilled workforce to effectively leverage this technology. A structural equation modeling (SEM) analysis revealed that safety and reliability are significant factors for the adoption of AI-powered cobots in construction. Fear of being replaced resulting from the use of cobots can have a substantial effect on the mental health of the affected workers. A lower error rate in jobs involving cobots, safety measurements, and security of data collected by cobots from jobsites significantly impact reliability, and the transparency of cobots' inner workings can benefit accuracy, robustness, security, privacy, and communication and result in higher levels of automation, all of which demonstrated as contributors to trust. The study's findings provide critical insights into the perceptions and experiences of AEC professionals toward adoption of cobots in construction and help project teams determine the adoption approach that aligns with the company's goals workers' welfare. **DOI: 10.1061/JCCEE5.CPENG-5660.** © *2024 American Society of Civil Engineers.*

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Introduction

Traditional construction production methods rely heavily on human workers, require substantial, arduous effort, and can pose safety and health risks to workers due to exposure to demanding physical work and dangerous substances. Instances of physical hazards that can lead to injuries or long-term damage to the body include being subjected to vibrations or loud noises, as well as exposure to chemical hazards such as vapors, dust, or fumes (Kulkarni 2007). Although the construction industry has attempted to improve productivity by using powered hand tools and more recently prefabrication, it is still lagging behind other industries in their embrace of automation (De Valence and Abbott 2015). Additionally, the industry has been facing a labor shortage, which has further slowed progress toward increased productivity (Bahr and Laszig 2021). According to the Associated Builders and Contractors, the construction industry will have to attract around 546,000 extra workers in 2023, in addition to the regular hiring pace, to meet the labor demand. This shortfall in workers is due to multiple factors, including an aging workforce, a lack of interest among younger generations to enter the industry, and immigration policies that limit the availability of foreign workers (ABC 2023).

Therefore, the industry needs to improve productivity and construction time while addressing workers' safety concerns and cost overruns. This can be achieved by developing new solutions to carry out labor-intensive tasks using artificial intelligence (AI) and robotics, thus freeing up workers to focus on more technical jobs, reducing the risk of injuries caused by physical hazards and exposure to harmful substances, improving productivity and efficiency, and reducing labor costs (Baduge et al. 2022; Darko et al. 2020; Javaid et al. 2021). To automate repetitive and linear tasks such as bricklaying, demolishing, and welding, AI and robotics have shown great promise in the execution phase of a project (Manzoor et al. 2021; Saidi et al. 2016).

Studying collaborative robots, or cobots in the industrial applications is receiving increasing attention from both engineering and social science research communities (Kluy and Roesler 2021). AI-powered cobots are robots designed to collaborate alongside human workers. They are equipped with varying levels of intelligence offered by AI and sensors that enable them to autonomously perceive and interpret their environment. The combination of this perception and AI capabilities allows them to make informed decisions and adapt to dynamic conditions without the need for explicit human instructions. This autonomy enhances their ability to work harmoniously with human counterparts in shared workspaces (Meziane et al. 2017; Müller et al. 2016). Construction tasks are

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often too complex for full automation, and robots require collaboration with humans. Thus, cobots are gaining popularity in the AEC industry and are expected to play a significant role in the future of construction (Gambao et al. 2012).

However, the widespread adoption of cobot applications on construction sites has been limited due to various factors, such as lack of research, high initial costs, technical complexity, health and safety concerns for human–robot collaboration, potential job displacement, and non-compliance with building regulations (Gharbia et al. 2020; Holder et al. 2016; Rosenberg et al. 2015). Furthermore, existing commercially available solutions for physically demanding tasks such as automated masonry [FBR (FBR 2023), material unit lift enhancer (MULE), and semi-automated mason (SAM) (SAM 2023)] and multifunctional robots such as Baubot, which can perform tasks such as milling, drilling, sanding, and laser marking (Printstones, Vienna, Austria) (Printstones 2023) or rebar laying and tying (Advanced Construction Robots 2023a, b) may raise the concern of limiting the involvement of the human worker in the loop, which exacerbates the concerns associated with robots taking over workers jobs.

To address these unique aspects of the construction industry, establishing trust between human workers and cobots is imperative. The level of trust that humans have in cobots is a key consideration that impacts the success and effectiveness of human–robot teams. Insufficient trust can result in disuse, where individuals are unwilling to use the cobots and do not recognize their abilities (Kok and Soh 2020). Conversely, excessive trust can lead to overreliance on the cobots, potentially causing failures in critical situations. Therefore, it is essential to have a calibrated level of trust in cobots for successful human–robot interaction at construction sites. This study aims to investigate the technical and psychological factors that may influence the establishment and reinforcement of trust among AEC professionals when working with AI-powered cobots to enable major future work on trust calibrations.

Research Background

The literature on the implementation of collaborative robots (cobots) in the context of Industry 5.0 emphasizes the significance of sociotechnical factors. Prassida and Asfari (2022) presented a conceptual model grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) and Sociotechnical Systems theory (STS) to understand the acceptance of cobots in the manufacturing industry, which forms the basis of the Industry 5.0 by adding the human edge to the Industry 4.0 phenomenon. Their model underscores the importance of early human involvement, considering elements such as safety and trust assurance, which are discussed among the hypotheses of this research (Prassida and Asfari 2022).

Some of the other hypotheses tested in this research have also been discussed in other prior studies. For example, Libert et al. (2020) introduced a conceptual framework, connecting human resource management (HRM) practices, technology adoption, and human–robot collaboration (HRC) determinants. They stressed the need for commitment to change, change management, and interdisciplinary work in cobot integration (Libert et al. 2020). Oberc et al. (2019) highlighted the challenges of integrating cobots into manufacturing and emphasized the lack of methodology and simulation tools for assessing workplace readiness for robots (Oberc et al. 2019). Bi et al. (2021) delved into the safety assurance mechanisms of cobots in manufacturing and the importance of HRC for enterprise competitiveness (Bi et al. 2021). Heo et al. (2019) introduced a collision detection framework using deep learning to ensure the safety of human workers in real-time scenarios. Malik and Bilberg (2019) developed an architecture for human–robot collaboration in manufacturing based on team composition, engagement, and safety dimensions, offering a unified taxonomy for balanced automation (Malik and Bilberg 2019). Ogenyi et al. (2019) conducted a survey on robotic systems for physical human–robot collaboration (pHRC), emphasizing human factors, progress in robot design, and the need for standardization and safety regulations (Ogenyi et al. 2019).

These studies collectively offer valuable insights to practitioners, policymakers, and researchers in enhancing the acceptance and successful integration of cobots in various domains, spanning safety, HRM practices, technology adoption, and human–robot collaboration (Kluy and Roesler 2021; Kok and Soh 2020; Meziane et al. 2017; Müller et al. 2016). However, not all the trust dimensions in the HRC have been previously explored in the literature. In addition, the current research landscape has primarily focused on cobots within manufacturing, with limited attention to their use in construction (Calitz et al. 2017; Gualtieri et al. 2021). Safety remains a central concern, but other factors affecting worker trust and adoption progress require exploration, particularly in the unique context of construction.

The presented research aims to identify these factors and gather practical insights by involving workers and end-users, whose perspectives are underrepresented. It is crucial to gain buy-in from construction leaders and instill worker confidence in cobot reliability because negative perceptions can hinder adoption. The study recognizes that end-users possess practical expertise and their inclusion in decision-making positively impacts job satisfaction. Additionally, key decision makers' perspectives, including company owners and leaders, are essential because cobots represent a substantial investment for construction firms. Therefore, in previous steps of this research program, a comprehensive literature review as well as interviews with AEC practitioners were conducted (Emaminejad and Akhavian 2022, 2023; Emaminejad et al. 2021), and several factors about gaining users' trust in robots were identified. As shown in Fig. 1, a set of 13 factors influencing trust were established.

Among these, seven were directly derived from the initial stage of the current research, which involved a systematic literature review (Emaminejad and Akhavian 2022, 2023; Emaminejad et al. 2021). Subsequently, an additional six factors were defined based on insights gathered from interviews conducted with construction practitioners, constituting the second stage of the research (Emaminejad and Akhavian 2022, 2023; Emaminejad et al. 2021). These 13 factors are as follows:

1. Reliability: In the context of cobots, reliability refers to their capacity to carry out their designated tasks consistently and predictably without experiencing any malfunctions, failures, or unexpected interruptions (Kluy and Roesler 2021).
2. Safety: In cobots, safety encompasses the process of designing and deploying cobots to ensure the well-being and protection of human workers who collaborate with them. Because cobots are specifically designed to operate alongside humans, they must incorporate essential safety measures that minimize the risk of accidents, injuries, and damage to property (Askarpour et al. 2019).
3. Transparency: In cobots, transparency pertains to their capacity to offer feedback regarding their operations and performance, enabling human workers to observe and comprehend the actions of the robot. This transparency ensures that external observers can easily understand how the system generated its outcomes (Kluy and Roesler 2021).

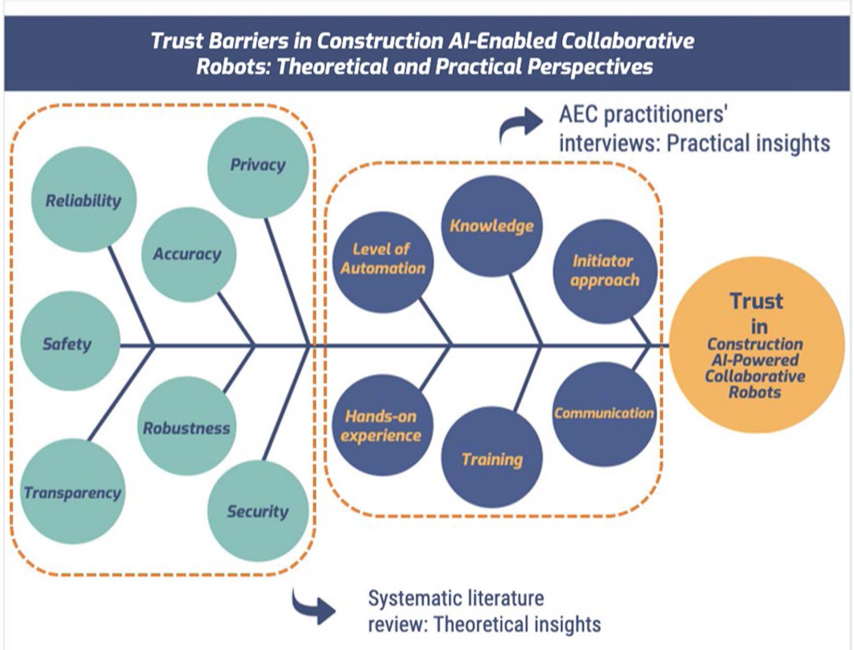

Fig. 1. Trust barriers in construction AI-powered collaborative robots: theoretical and practical perspectives.

4. Robustness: In cobots, robustness refers to their capacity to function efficiently and consistently across diverse conditions, without being negatively impacted by variations in the environment or task demands (Wang et al. 2021).
5. Accuracy: In cobots, accuracy pertains to the capacity of these robots to execute their designated tasks with exceptional precision and minimal margin of error (Rekleitis et al. 2002).
6. Privacy: In cobots, privacy refers to the protection of personal information and data that may be collected or processed by collaborative robots (Li and Zhang 2017).
7. Security: For cobots, security entails safeguarding the cobot and its related systems and construction workflows against unauthorized access, malicious attacks, and other potential security risks (Li and Zhang 2017).
8. Level of automation (LOA): In cobots, LOA pertains to the extent to which cobots can independently carry out their assigned tasks, without requiring human intervention or control. This level of automation is influenced by the complexity of the tasks cobots can handle and their ability to adjust to dynamic conditions or inputs (Michaelis et al. 2020).
9. Hands-on experience: In the context of cobots, hands-on experience involves actively engaging workers with cobots in real-world scenarios. This encompasses tasks such as programming, operation, and maintenance across diverse construction environments. Hands-on experience fosters a profound comprehension of cobots' capabilities, constraints, and the wide range of potential applications they offer.
10. Having general knowledge: Having general knowledge about cobots involves possessing a basic understanding of cobots and their applications, even without hands-on experience. This includes being familiar with cobot features, components, and capabilities, as well as their potential benefits and limitations in various construction contexts. Several factors can influence the acquisition of this knowledge:
    a. Level of education: The educational background can shape individuals' understanding of cobots and provide a basis for comprehending their principles and applications.
    b. Years of experience: The amount of time individuals' have spent working in the construction industry can contribute to their exposure to cobots and related technologies.
    c. Familiarity with relevant technologies: Being acquainted with the technologies that enable cobots functionalities, can influence workers basic understanding of cobots.
    d. Awareness about construction robotics: Being informed about the current use of robots in construction contributes to individuals' knowledge of cobots potential in projects.
11. Training: In cobots, training involves participating in a structured program aimed at acquiring the skills to operate, program, and maintain cobots in a safe and efficient manner. The training curriculum generally encompasses key areas such as safety protocols, cobot programming, operation and maintenance procedures, troubleshooting techniques, and fault diagnosis. It often incorporates a blend of theoretical and practical instruction in simulated or real-world settings.
12. Initiator approach of trust in cobots: This refers to the individual or group that takes the initial action to establish trust in cobots within a specific context or environment. This initiator can be a union, a company's CEO, a manager, an engineer, or any other person accountable for the implementation and operation of these robots in a particular workplace or industry.
13. Communication: Communication with cobots entails the capability for humans to engage with cobots through diverse approaches, including voice commands, having two-way conversation, gestures, cobot size or shape, touchscreens, or alternative interfaces.

Factors 1–8 pertain to the cobot's system and configurations, 9–12 refer to user's perception, and 13 is related to the environmental conditions. In addition to defining these trust factors, the literature review and interviews informed several hypotheses about them.

This paper describes the results of a nationwide survey to determine their relevance and applicability in practical perspectives (summarized in Fig. 2) through testing the following hypotheses:

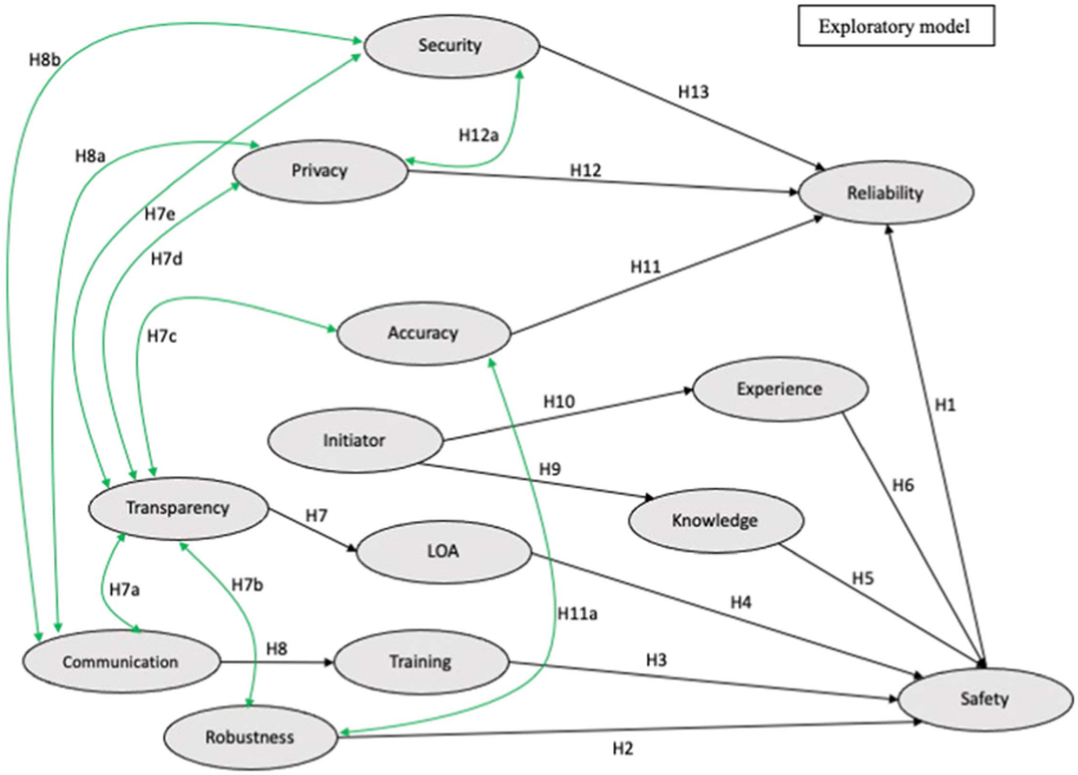

Fig. 2. Proposed exploratory model.

H1: The perceived reliability of cobots is significantly affected by their safety value, including the reduction of potential harm and the overall safety improvement compared with noncobot operations.

H2: The safety of cobots is significantly influenced by their robustness and ability to perceive and understand the environment.

H3: Training directly influences the perception of safety regarding cobots. In other words, well-trained individuals are expected to have a higher perception of safety regarding cobots compared with those who have received less or no training.

H4: The level of automation in cobots has a direct impact on how individuals perceive their safety. It suggests that as the level of automation increases, individuals' perception of safety regarding cobots will also increase.

H5: Sufficient knowledge about cobots, their capabilities, and limitations positively influences how they are embraced by workers and organizations.

H6: Individuals who have firsthand experience of working directly with cobots are more likely to embrace these robots compared with those who have not interacted with them in this manner.

H7: The transparency of cobots' inner workings and decision-making processes plays a significant role in determining the acceptable level of automation.

H7a: The level of transparency in the decision-making process of cobots is significantly correlated to their communication capabilities. When cobots have a transparent decision-making process, they can effectively convey their actions and intentions to users, resulting in clearer and more efficient communication.

H7b: The degree of transparency in the decision-making process of cobots is correlated with their robustness. A more transparent decision-making process is expected to lead to a higher level of robustness because it allows for better monitoring and understanding of the cobots' actions, enabling them to adapt and handle various situations more effectively.

H7c: The transparency of the decision-making process in cobots is correlated with their accuracy. When cobots' decision-making processes are transparent, their actions and outputs are more aligned with the intended tasks, resulting in higher accuracy.

H7d and H7e: The transparency of the decision-making process in cobots is significantly related to their privacy and security measures. When the decision-making process is transparent, it is easier to assess the privacy implications and security vulnerabilities in cobots' operations.

H8: The communication style of cobots directly influences workers' understanding of training content and significantly impacts the effectiveness of the received trainings.

H8a and H8b: The communication of cobots with users has a significant correlation with privacy and security. A strong correlation suggests that clear and informative communication fosters a greater sense of trust and confidence in the privacy and security practices implemented in cobots.

H9: The initiator's approach has a direct effect on workers' knowledge regarding cobots. The initiator's efforts to disseminate information, provide training, and raise awareness about cobots are expected to result in a higher level of trust among workers regarding these cobots.

H10: The initiator's approach has a direct effect on workers' hands-on experience with cobots. By facilitating practical interactions and opportunities to work directly with cobots, the initiator can foster trust and confidence in these cobots among workers.

H11: The level of accuracy exhibited by cobots directly influences their overall reliability. A higher degree of accuracy is expected to result in a more reliable performance of cobots, as their actions and outputs align closely with the intended tasks and objectives.

H11a: There is a positive correlation between the accuracy and robustness of cobots. This means that when cobots are more precise in their actions and outputs, they are likely to exhibit a higher level of adaptability in various operating conditions.

H12: Ensuring a high level of privacy protection in cobots directly influences their reliability. By safeguarding sensitive data and user information, cobots are less susceptible to privacy breaches and potential data manipulations that could compromise their functioning.

H12a: The security and privacy levels of data collected by cobots from jobsites are significantly correlated.

H13: The level of security measures implemented in cobots directly impacts their reliability. When cobots are equipped with robust security features, they are better protected against potential cyber threats and unauthorized access.

The path diagram (Fig. 2) summarizes these hypotheses and adheres to conventions regarding the representation and labeling of variables. One-headed arrows signify hypothesized causal relationships, pointing from the cause to the effect. When variables are only correlated without assumed causal connections, a double-headed, curved arrow is used.

It is important to account for residual error in predictions, representing the impact of unmeasured predictors in the model. In this research, structural equation modeling (SEM) was employed as a powerful analytical tool to examine the complex relationships among various factors in the context of applied science, particularly in research areas involving complex and multifaceted constructs like organizational psychology and social psychology (Baumgartner and Weijters 2021). The utilization of SEM allowed for a deeper understanding of how these factors influenced and interacted with each other (Hoyle 2012). Through SEM, the intricate dynamics between different variables were quantitatively assessed, offering quantifiable insights into the strength and direction of relationships between these variables. These variables (called latent) are theoretical constructs that cannot be directly measured but are believed to influence attitudes and behaviors and are defined by multiple observed variables (Hoyle 2012). These quantitative findings were deemed valuable for identifying the most influential factors within the studied context, enabling the development of targeted strategies to enhance outcomes.

SEM also enabled a nuanced exploration of indirect effects and the underlying mechanisms at play, providing a richer understanding of the factors affecting the studied outcomes. In SEMs, these error terms, referred to as disturbances, are depicted by arrows (sometimes with dotted lines). These disturbances are identified with numbered subscripts (e_1, e_2, e_3, and so on) to indicate their involvement in predicting values for specific variables (Reinard 2006).

Methodology

Procedure

To accomplish the goals outlined in the preceding section, this research employed a Qualtrics (Tharp and Landrum 2017) survey to individuals who met at least one of the following criteria: working in the AEC sector, having relevant technology experience in the AEC industry, or having conducted research related to the integration of intelligent cobots/robots in the AEC industry. The survey was distributed using two methods: posting on LinkedIn and recruiting participants through the Prolific survey panel (an online participant platform) (Palan and Schitter 2018).

To recruit participants from the construction industry, a specific selection process was employed via Prolific, filtering out individuals whose professional background aligned with the research focus. In this process, Prolific confirmed that they had 483 potential active participants who met the criteria. Additionally, a prescreening procedure was implemented by posing a question that asks about the industry where the participant is involved in, by presenting AEC among choices such as healthcare, restaurants, and automobiles, to explicitly filter out non-AEC participants.

Subjects

To determine the necessary sample size for conducting an SEM analysis, this study relied on proven approaches in the literature. For example, the online statistics calculator developed by Daniel Soper was employed to estimate the sample size needed for the required SEM analysis. This calculator takes into account factors such as the expected effect size, desired statistical power level, the number of latent variables, the number of observed variables, and the probability level (Soper 2023).

Also, a power analysis was carried out to calculate the minimum sample size needed to detect the anticipated effect size of 0.3, with a desired statistical power level of 0.8, a probability level of 0.05, and considering the study's 13 latent variables and 80 observed variables (detailed calculations are available upon request from the corresponding author). The selection of an expected effect size of 0.3 is a common and well-accepted practice in research design (Hoyle 2012). It strikes a balance between being large enough to detect practical significance and small enough to maintain statistical power. This choice ensures that the study is designed to identify meaningful relationships between variables while avoiding the risk of overlooking potentially important effects. The results indicated that a minimum of 204 participants would be needed to detect the effect, and at least 225 participants would be necessary for model structure testing. Therefore, a total of 300 participants were chosen to perform each of the two SEM analyses. This also aligns with the sample size used in prior successful studies on trust toward technology integration in construction (Joshi 2005; Son et al. 2012).

Those who completed the survey via the Prolific survey panel received compensation of $12 per hour, whereas participants who joined through other channels had a chance to win a $100 gift card. The incentive amounts were chosen carefully: insufficient incentives could lead to low participation and disinterested participants, leading to a biased sample. On the other hand, excessive incentives might attract individuals primarily motivated by the reward rather than a genuine interest in the study's topic (Deutskens et al. 2004). The research was approved by San Diego State University's Institutional Review Board (IRB protocol HS-2022-0258) for adhering to ethical guidelines.

Measurement

The survey (full survey available upon request from the corresponding author) started with five multiple-choice demographic questions. Afterward, participants were given the opportunity to watch a short video demonstrating seven construction cobots in action, aimed at improving their understanding of what cobots are and how they might be used in the construction industry. To ensure clarity and consistency in conveying the definitions and concepts related to this study, a table was included in the informed consent form presented to the participants, defining essential terms, such as "robot," "intelligent robot," "AI," "cobot," and "AI-powered cobots."

Following that, there were 28 Likert-scale questions to gauge participants' opinions about factors that might have impact on their level of trust in cobots. Additionally, three rank-order questions were included to assess preferences for the situations in which

J. Comput. Civ. Eng., 2024, 38(3): 04024011

cobots are more likely be embraced. In the final section of the survey, participants were requested to rate their assessment of various attributes such as safety, reliability, inner-workings transparency, security, privacy, robustness, and accuracy on a scale of 1 = Strongly Disagree to 5 = Strongly Agree for seven different cobot applications. The survey questions can be found in the Supplemental Materials.

The questions with varying response scales have been normalized or standardized for consistency. Regarding the preference questions, each question has been disaggregated into separate observed variables, with labels assigned based on their positions in the ranking. For instance, for Question P1, participants were asked to arrange five options in their preferred order. The options in the first place were assigned a score of five, second place received a score of four, third place was given a score of three, fourth place received a score of two, and fifth place got a score of one. Similarly, to mitigate the impact of outliers, for Questions P2 and P3 with three options (instead of five) the options in first place were scored as five, second place as three, and third place as one. This conversion facilitates a more standardized and quantifiable assessment of participants' preferences.

The questions concerning the level of education and years of experience in the construction industry were also scored using a standardized scale (Questions D2 and D4 in Table S1). For the level of education, the options "High school or below," "Two-year college," "Four-year college," "Master's degree," and "Doctorate" were converted to scores of one, two, three, four, and five, respectively.

Similarly, for years of experience in the construction industry, the options "1–5," "6–10," "11–15," "16–20," and "More than 20" were converted to scores of one, two, three, four, and five, respectively. Regarding Question D5, the scoring process was as follows: If participants selected all three options, their response was converted to a score of five. If they chose robots along with either drones or unmanned machinery, their response was converted to a score of four. Choosing only robots resulted in a score of three. Opting for drones, unmanned machinery, or both led to a score of two. Lastly, responses indicating "none" or "others" were assigned a score of one. This scoring approach was implemented because the research emphasizes robotics, and therefore, responses involving robots, were given higher scores to reflect the focus on this aspect.

However, converting categorical values to numerical ones may raise a concern, given that SEM relies on regression, which is founded on the assumption of normality. As cited by Bollen (1989), early studies indicated that Pearson correlations may tend to have underestimated the strength of association for continuous constructs underlying categorical variables, potentially leading to parameter estimate attenuation. The Shapiro-Wilk tests were conducted to assess the normality of these converted variables. For the "Edu" variable, although the test suggested a marginal departure from normality (p-value $= 0.065$), the W value of 0.975 indicated proximity to a normal distribution, particularly with a larger sample size. Both the "Exp" and "Tech" variables exhibited no significant evidence of departure from normality, with W values of 0.9551 and 0.9998 and p-values of 0.112 and 0.234, respectively.

A descriptive analysis was conducted on seven demonstrated cobot applications in AEC projects. The rationale for selecting these cobots for the survey was based on their common and familiar use cases in the construction industry. In other words, the functionalities of these seven cobots were available for demonstration to participants at the time when this research was under way. The research team believed that such demonstrations were essential to ensure participants had a comprehensive understanding of the study's focus, the varying levels of automation, and the unique aspects they represent. These robots are as follows:

- The HRP-5P humanoid (National Institute of Advanced Industrial Science and Technology, Hokkaido, Japan) robot specializes in heavy labor and autonomous operations in hazardous areas, focusing on gypsum board installation (Humanoid Robot Prototype HRP-5P).
- The SAM100 (semiautomated mason) (Construction Robotics, Victor, New York) lays bricks at an impressive rate, enhancing worker safety and efficiency.
- TyBot (TyBot, Allison Park, Pennsylvania), an automated steel-tying robot, employs computer vision for rapid installation on construction sites.
- The robust Husqvarna DXR 305 (Husqvarna group, Stockholm, Sweden) demolition robot precisely handles demanding tasks in both industrial and construction settings.
- Boston Dynamics' Spot robot (Boston Dynamics, Waltham, Massachusetts) autonomously navigates construction sites, capturing comprehensive 360° images for project documentation.
- Okibo's autonomous wall plastering technology (Okibo, Petah Tikva, Israel) combines AI, three-dimensional (3D) scanners, and sensors to efficiently apply coatings on walls.
- ERO Concrete Recycling Robot (Atlas Copco, Nacka, Sweden) contributes to sustainable construction by safely demolishing concrete buildings for recycling, reducing waste in the process.

The purpose was to determine whether the approach to establishing trust should vary depending on the specific cobot application. The analysis also aimed to identify which dimensions are perceived as more crucial from the participants' perspective in overall cobot trust. It is worth mentioning that the standard errors for all attributes in each cobots were implied a similar level of consensus among the participants in their expectations. The relatively low standard error (~0.03) suggests a high level of agreement among the participants regarding the cobots' attributes.

A thorough examination of the data was conducted to handle missing data and outliers; however, given that the survey solely consisted of Likert scale questions (ranging from 1 = Strongly Disagree to 5 = Strongly Agree) and multiple-choice questions, no outliers were detected, and the potential problem of missing data was mitigated by enforcing completion of all survey questions. The responses were filtered based on the response duration, excluding those below 10 min, in order to look for insufficient effort responding or people who were just picking answers to try to get their money as quickly as possible. Additionally, the email addresses were screened, and surveys were excluded where participants selected the same rating (e.g., three) for all questions.

Reliability pertains to the consistency of results obtained from a measurement instrument, whereas validity relates to how accurately a measure or instrument assesses the intended construct. Table 1 presents the results of various indices, including construct reliability (CR), average variance extracted (AVE), maximum shared squared variance (MSV), and average shared squared variance (ASV), along with their acceptable ranges. It is demonstrated in the table that all the measures fall within the acceptable range, indicating satisfactory reliability and validity.

The researchers employed SEM, a statistical technique that enables researchers to investigate and test hypotheses concerning the connections between observed and unobserved (i.e., latent) variables (Gerow et al. 2011). Unlike other statistical approaches that focus on a single dependent variable and a set of independent variables, SEM permits the modeling of intricate relationships between latent (unobserved) and observed variables (Hoyle 2012). Latent variables are theoretical constructs that cannot be directly measured but are believed to influence attitudes and behaviors

Table 1. Reliability and validity assessment

	Model							
	Exploratory				Confirmatory			
Latent variable	CR	AVE	MSV	ASV	CR	AVE	MSV	ASV
Knowledge	0.922	0.646	0.591	0.117	0.843	0.745	0.614	0.137
LOA	0.710	0.678	0.082	0.010	0.712	0.891	0.136	0.021
Transparency	0.885	0.786	0.743	0.157	0.928	0.732	0.705	0.145
Communication	0.741	0.535	0.255	0.052	0.758	0.659	0.284	0.089
Initiator	0.703	1.658	0.931	0.145	0.701	0.597	0.469	0.121
Privacy	0.708	0.624	0.443	0.163	0.721	0.652	0.471	0.134
Robustness	0.910	0.709	0.637	0.104	0.848	0.508	0.352	0.096
Experience	1.678	3.397	0.931	0.169	1.017	0.932	0.904	0.166
Security	0.828	0.580	0.511	0.102	0.830	0.564	0.552	0.098
Accuracy	1.014	1.039	0.937	0.104	1.027	0.767	0.716	0.115
Acceptable range	>0.7	>0.5	<AVE	<AVE	>0.7	>0.5	<AVE	<AVE

and are defined by multiple observed variables (Sardeshmukh and Vandenberg 2017). SEM is a valuable tool, particularly in research areas involving complex and multifaceted constructs, like psychology (Baumgartner and Weijters 2021).

To evaluate the validity of the measurement constructs in the model, a confirmatory factor analysis (CFA) was performed. CFA is a statistical technique within structural equation modeling that examines the extent to which a group of observed variables (indicators) effectively measures a set of latent variables (factors) that are presumed to exist based on theory or previous studies (Wang and Wang 2019). The outcomes of the CFA provide insights into whether the items truly capture the same underlying construct. After conducting the CFA, any observed variables with a factor loading below 0.5 were omitted from the analysis. Specifically, five observed variables from Question P1, with factor loadings approximately around 0.2, were excluded from further consideration in the analysis.

Results

Demographic Results

Figs. 3(a and b) provide insights into the distribution of job positions and education levels of participants in the AEC industry. The Prolific group is primarily composed of foremen and laborers, with a majority having completed high school or earned bachelor's degrees. In contrast, the LinkedIn group includes a higher proportion of higher-level managers, company leaders, and academic individuals, with more participants holding graduate degrees. Figs. 3(c and d) offer information about participants' work experience in the AEC industry and their familiarity with industry-related technologies. Both groups, LinkedIn and Prolific, exhibit similar work experience patterns. However, LinkedIn participants demonstrate a higher level of familiarity with robots. When asked whether they had encountered such technologies in their projects, the results show that robots are not yet widely utilized in construction. Among Prolific participants, 18% chose "other," whereas 16% indicated "none." Some mentioned limited use of laser scanners and building information modeling (BIM).

Descriptive Analyses

These results (Table 2) indicate the participants' perceptions and attitudes toward adopting AI-powered cobots in the construction industry. On average, the participants indicated moderate awareness of cobots (Item 1), but relatively few had direct experience with robots in construction projects (Item 2). The participants' perceptions and attitudes toward adopting AI-powered cobots in the construction industry were evident from their responses. Trust emerged as a crucial factor, showing strong agreement among participants (Item 3). Additionally, peer recommendations held significant weight in embracing AI-powered cobots, closely followed by company recommendations (Items 4 and 5). Union recommendations seemed to have a slightly lower impact in comparison (Item 6).

On average, participants highly valued direct experience with the cobot, emphasizing hands-on interaction (Item 8). They also stressed the importance of transparency in the cobot's decision-making process and appreciated understanding this process, while valuing recommendations from those who had worked directly with the cobot (Items 7, 9, and 10). Participants had a neutral perception of the cobot's physical appearance (Item 11), showing moderate interest in two-way conversations (Item 12), but a mixed response to a humanoid appearance (Items 13 and 16). Participants displayed a modest preference for smaller cobots, while variability in responses suggests varying opinions (Item 14). They also generally expressed reservations about trusting AI-powered cobots, indicating some safety concerns without extreme mistrust, because responses showed variability (Item 15). Regarding trust in cobot autonomy, participants were somewhat hesitant to fully trust autonomous cobots (Item 17) and they preferred cobots to be under human supervision (Item 18). Participants on average rated the importance of the cost of purchasing and maintaining the cobot as significant for adoption (Item 20). They also on average, highly valued responsive and responsible customer support services (Item 21).

Similarly, on average, participants showed a strong inclination to embrace cobots that included a training package (Item 22). Participants on average rate the desire for cobots leading to upskilled workers moderately high (Item 23). Recommendations from well-established construction companies were also considered important, with participants expressing a relatively high rating for this factor (Item 24). The majority of participants (77.66%) ranked "Real-world hands-on" training as their top choice, indicating a strong preference for practical, hands-on experience with the cobots in real-world settings. "Demonstration videos" were ranked second by 35.58% of participants, suggesting that visual demonstrations and instructional videos are also valued as effective training methods. Meanwhile, "Simulations (e.g., games)" was the second choice for 50.39% of participants, indicating a preference for interactive and gamified training experiences. Participants on average considered having global/national standards for implementing

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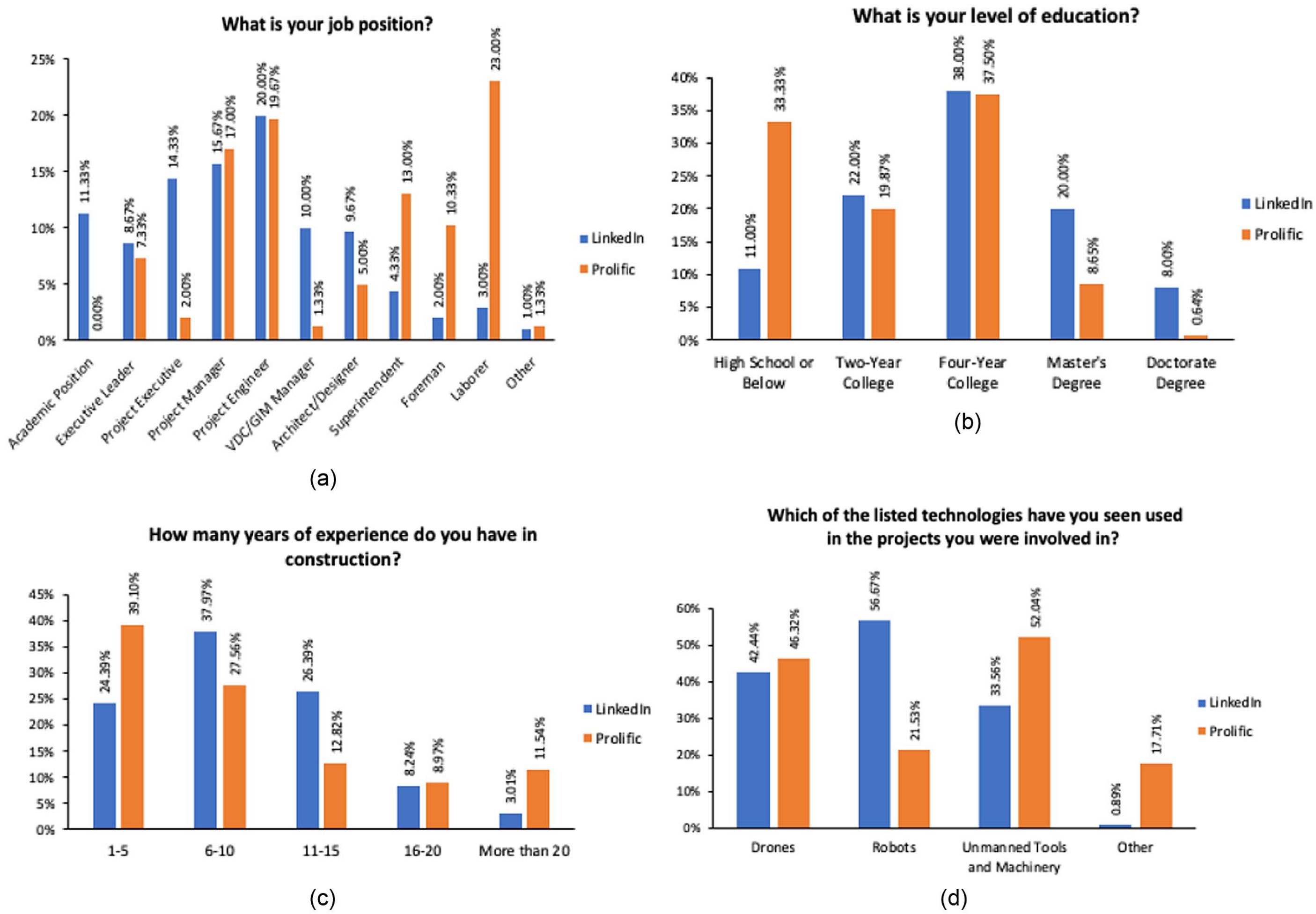

Fig. 3. Distribution of (a) different job positions; (b) different education levels; (c) duration of the participants' work experience; and (d) percentage of each technology being seen utilized in construction projects by participants.

cobots as essential, and emphasized the importance of advanced privacy and security systems (Items 25 and 26). The majority of them believed that the cobot's ability to perceive the environment impacted their level of trust (Item 27). However, most of them indicated that if they encountered problems or errors during hands-on experience, they were less likely to trust and rely on cobots for future tasks (Item 28).

Exploratory Model

The proposed model (Fig. 2) was tested using a randomly selected 300 participants from the overall sample, which included a total of 600 participants. Fig. 4 illustrates the results of the proposed model test. The standardized regression coefficients or path coefficient for each path are represented by the numbers on the arrows, which reflect both the magnitude and direction of the relationships between the variables. There are many indices for determining whether the data fit the model, and it is important to consider multiple fit indices rather than relying on a single index. In the next paragraph, recommended cutoffs are described and the results for the exploratory model test for the current study will be indicated in parentheses.

The minimum discrepancy divided by its degrees of freedom (CMIN/df) should typically be below 3 (2.38). The goodness-of-fit index (GFI) is often considered acceptable when around 0.90 or higher (0.75), and the adjusted goodness-of-fit index (AGFI) is expected to fall within the range of 0.85 or higher (0.78). The root-mean square error of approximation (RMSEA) is generally considered acceptable when below 0.08 (0.06). Incremental fit indices, such as the comparative fit index (CFI), incremental fit index (IFI), Tucker-Lewis index (TLI), and the relative fit index (RFI), are considered indicative of a good fit when above 0.90 (CFI 0.87, IFI 0.87, TLI 0.86, and RFI 0.73). Parsimonious fit indices, such as the normed fit index (NFI), the parsimonious normed fit index (PNFI), and the parsimonious comparative fit index (PCFI), should ideally be around 0.50 or higher (NFI 0.75, PNFI 0.53, and PCFI 0.65) (Hair et al. 2009).

Because all incremental fit indices, GFI, and AGFI scores were below the acceptable threshold, it was concluded that the proposed model did not fit well. Consequently, the exploratory model was revised in an attempt to achieve a better fit. The modification indices were employed to incorporate these relationships, but only those that had a logical basis and were supported by prior research and interview data were included. This means that the added correlations were in line with existing literature and interview findings, as suggested by Cho et al. (2009).

The results indicated that hypotheses H4, H6, H7, H8, H7b, and H7c were rejected due to their respective *p*-values being 0.649, 0.212, 0.079, 0.058, 0.611, and 0.145. These findings suggest that there were no significant effects or correlations observed for these

Table 2. Descriptive analysis for the seven demonstrated cobots

Cobot	Descriptive statistics	Trust factors						
		Safety	Reliability	Transparency	Security	Privacy	Robustness	Accuracy
HRP-5P	Mean	4.0544	4.0177	3.5063	3.8342	3.7418	3.9127	4.1063
	Standard error	0.0371	0.0341	0.0381	0.0372	0.0373	0.0348	0.0333
	Median	4	4	4	4	4	4	4
	Mode	5	5	4	4	4	4	5
	SD	1.0432	0.9591	1.0701	1.0448	1.0497	0.9769	0.9372
SAM100	Mean	4.0051	4.0177	3.6051	3.7367	3.6759	3.8152	4.0987
	Standard error	0.0368	0.0341	0.0372	0.0379	0.0383	0.0370	0.0324
	Median	4	4	4	4	4	4	4
	Mode	5	5	4	4	3	4	5
	SD	1.0330	0.9591	1.0445	1.0652	1.0757	1.0398	0.9120
TYBOT	Mean	3.9570	3.9544	3.5709	3.7266	3.6620	3.8203	4.1152
	Standard error	0.0368	0.0353	0.0384	0.0385	0.0397	0.0361	0.0321
	Median	4	4	4	4	4	4	4
	Mode	5	4	4	4	3	4	5
	SD	1.0334	0.9920	1.0796	1.0816	1.1172	1.0148	0.9010
DXR-305	Mean	3.9481	3.9823	3.6443	3.7253	3.6810	3.9342	4.0709
	Standard error	0.0378	0.0343	0.0378	0.0375	0.0386	0.0357	0.0323
	Median	4	4	4	4	4	4	4
	Mode	5	4	4	4	4	5	5
	SD	1.0638	0.9630	1.0615	1.0545	1.0843	1.0035	0.9077
Spot	Mean	3.9519	3.9405	3.4810	3.7570	3.7392	3.8823	4.0443
	Standard error	0.0369	0.0352	0.0395	0.0385	0.0385	0.0365	0.0335
	Median	4	4	3	4	4	4	4
	Mode	5	5	3	5	4	4	5
	SD	1.0368	0.9906	1.1106	1.0818	1.0835	1.0257	0.9402
Okibo	Mean	3.9253	3.9747	3.5722	3.6797	3.7013	3.8886	4.0848
	Standard error	0.0373	0.0353	0.0383	0.0388	0.0380	0.0352	0.0326
	Median	4	4	4	4	4	4	4
	Mode	5	5	4	4	4	4	5
	SD	1.0492	0.9914	1.0771	1.0903	1.0677	0.9880	0.9155
ERO	Mean	3.9190	3.9367	3.5873	3.7253	3.6519	3.9165	4.0835
	Standard error	0.0390	0.0353	0.0384	0.0372	0.0386	0.0350	0.0319
	Median	4	4	4	4	4	4	4
	Mode	5	5	3	4	3	4	5
	SD	1.0955	0.9935	1.0795	1.0461	1.0841	0.9843	0.8953

Note: SD = standard deviation.

hypotheses. Following the utilization of the modification indices and further exploration of the literature, a few additional hypotheses were incorporated into the model:

H14: Maintaining a high level of privacy in cobot operations directly influences their safety.

H15: The level of security measures implemented in cobots has a direct impact on their safety.

H16: The reliability of cobots has a direct impact on the level of automation that can be achieved. More reliable cobots are better equipped to perform tasks consistently and accurately, enabling higher levels of automation with increased confidence in their capabilities.

H17: The level of experience with cobots directly influences the degree of automation that individuals and organizations are willing to implement. Greater experience and familiarity with cobots lead to increased trust in their abilities, which, in turn, facilitates higher levels of automation.

H7f: There is a significant correlation between the initiator of cobot usage and the level of transparency provided in the cobots' operations. A transparent approach to cobot functionalities, guided by the initiator's initiatives, is expected to contribute to better understanding and acceptance of cobots by users and organizations.

H8c: There is a significant correlation between the communication style of cobots and the effectiveness of training sessions. It suggests that effective and clear communication between cobots and users during training enhances the learning experience and improves the overall effectiveness of the training process.

H8d: There is a significant correlation between the communication style of cobots and the party responsible for initiating their usage.

H11b: There is a significant correlation between the accuracy of cobots and the effectiveness of training provided to users. It suggests that cobots with higher accuracy are more likely to facilitate successful and impactful training sessions for users.

Confirmatory Model

The revised model (Fig. 5) was tested using the remaining 300 participants from the overall sample. This validation process aimed to verify the relationships and assumptions proposed in the model using an independent set of data. Fig. 6 illustrates the results of the proposed model test. Again, the recommendations for fit indices are described subsequently, with observed values in parentheses. The minimum discrepancy divided by its

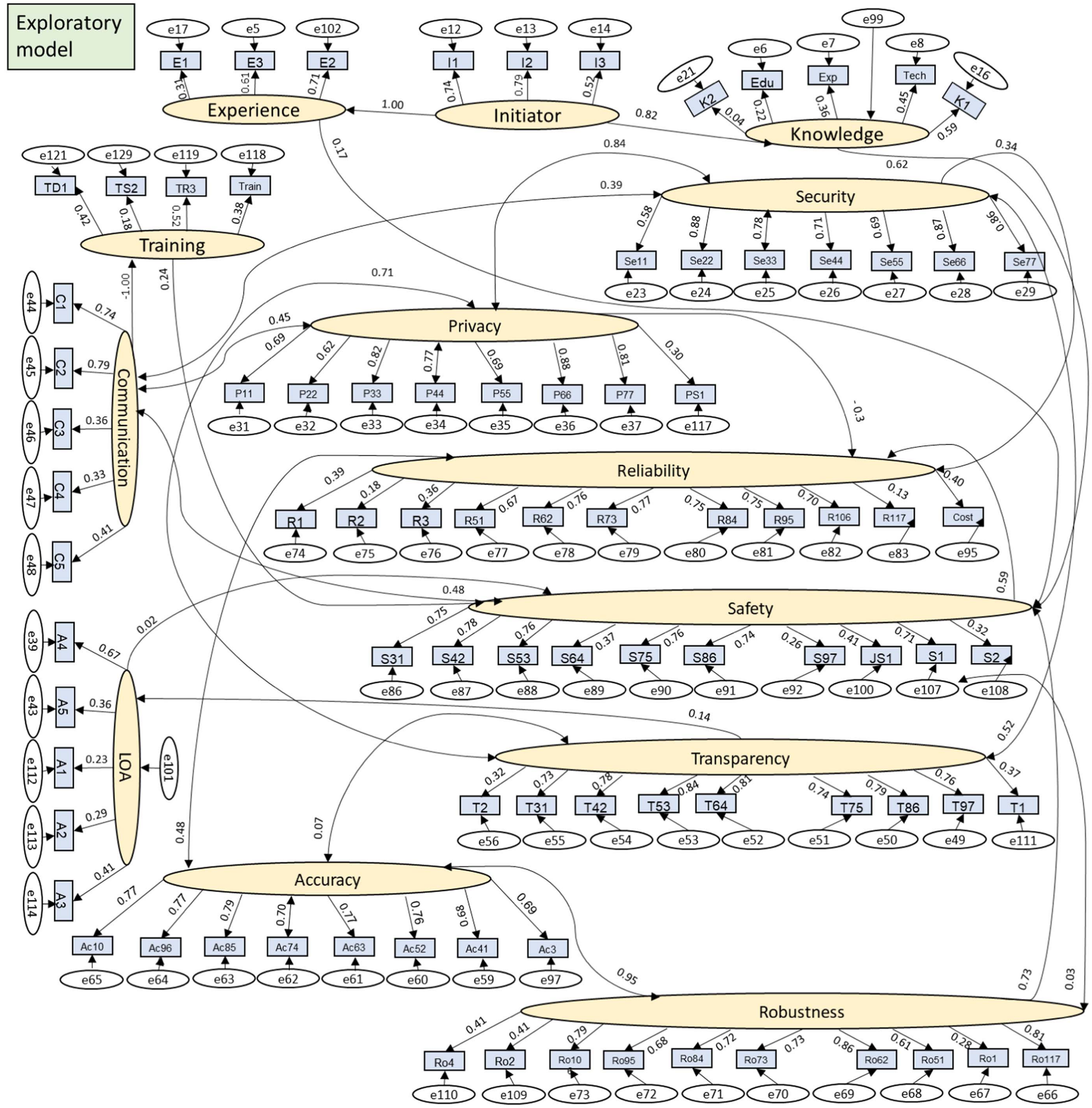

Fig. 4. Exploratory model results.

degrees of freedom (CMIN/df) should typically be below 3 (2.20). GFI is often considered acceptable when around 0.90 or higher (0.84), and the AGFI is expected to fall within the range of 0.85 or higher (0.82). The RMSEA is generally considered acceptable when below 0.08 (0.05). Incremental fit indices, such as CFI, IFI, TLI, and RFI, are considered indicative of a good fit when above 0.90 (CFI 0.90, IFI 0.93, TLI 0.91, and RFI 0.83). Parsimonious fit indices, such as NFI, PNFI, and PCFI, should ideally be around 0.50 or higher (NFI 0.84, PNFI 0.82, and PCFI 0.84) (Hair et al. 2009). Although the GFI and AGFI are still below the acceptable range, the incremental fit indices are largely above the recommended value, indicating the data fit the model reasonably well.

Perceptions about Seven Construction Cobots in Action

Table 2 presents the descriptive statistics on the survey participants' perceptions about these cobots. Across the seven cobots, different attributes seemed to hold varying levels of importance. HRP-5P and SAM100 prioritize safety and accuracy, with reliability also valued highly. Transparency received lower ratings for both. TyBot values accuracy the most, followed by reliability, but safety received a slightly lower rating. For DXR-305, robustness and transparency are crucial, whereas safety and security received slightly lower ratings. Spot values safety and accuracy but rated transparency and privacy lower. Robustness and accuracy are highly valued by Okibo, while safety and security received relatively

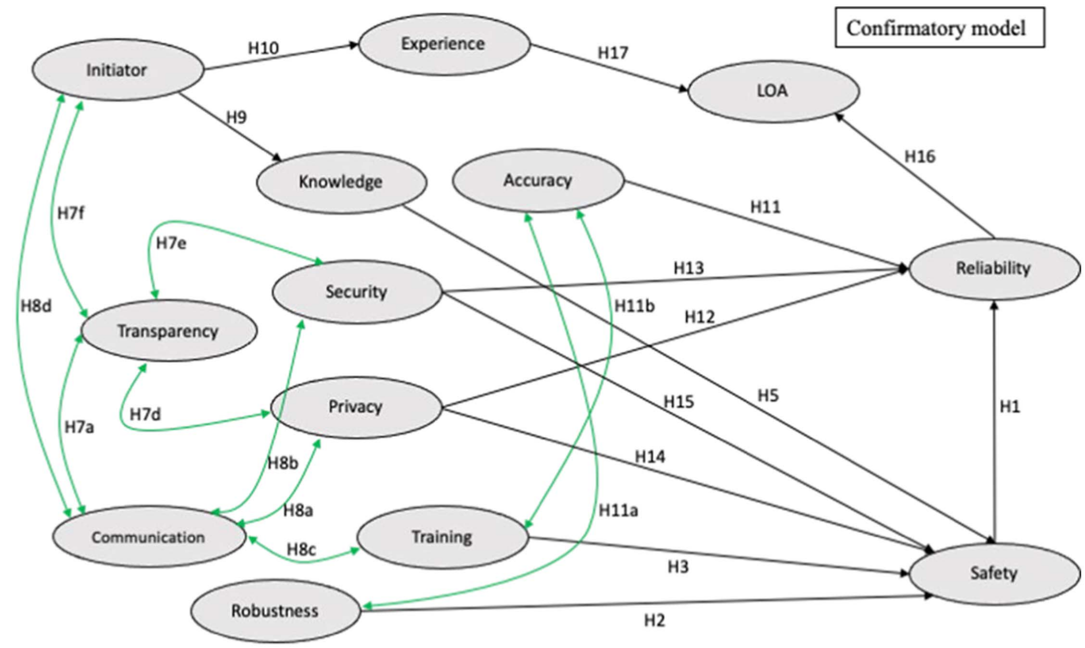

Fig. 5. Proposed revised (confirmatory) model.

lower ratings. ERO places significant importance on robustness and accuracy, but safety, reliability, and privacy received lower ratings. The cobot type and application likely influence the perceived importance of different attributes. For example, safety and accuracy are consistently considered major factors in building trust, whereas the effects of attributes such as robustness, privacy, and security are not as significant.

Conclusion

The study's findings revealed several significant factors that influence trusting cobots by construction workers. Specifically, this study highlighted the role of perceived safety and reliability of AI-powered cobots toward establishing trust. Training and robustness were identified as key direct contributors to safety perceptions, indicating that providing workers with adequate training and ensuring that cobots can effectively perceive their environment will foster a sense of safety and confidence in their operation. The study also emphasized the importance of proper communication between workers and cobots, which positively affected accuracy, robustness, security, privacy, and the level of automation in the conducted analysis.

Additionally, the research highlighted the role of initiators in influencing trust, with their knowledge and experience impacting users' understanding and perceptions of cobots. Recommendations from peers, companies, and individuals who have worked with cobots were also proven influential in shaping their trust. Participants showed some hesitancy in fully trusting fully autonomous cobots, preferring them to operate under human supervision. The results underscored the importance of perceived reliability in gaining trust in cobots, with factors like accuracy and security playing crucial roles. The cost of purchasing and maintaining cobots, along with the availability of responsive customer support and training packages, were also significant factors impacting willingness to adopt the technology.

Transparency was also found to be significant in building trust, but its importance varied across different cobot applications. Participants placed a high importance on trust in cobots, emphasizing the need for transparent decision-making processes and the value of hands-on experience with the technology. Privacy and security were ranked as essential factors, emphasizing the need for robust measures to safeguard data and ensure a reliable and trustworthy cobot system. The study revealed that direct experience and hands-on involvement with cobots positively influenced trust, leading to increased knowledge and confidence in their capabilities. The provision of comprehensive training, particularly through simulations and real-world experiences, was seen as essential for encouraging cobot acceptance and adoption.

In conclusion, this research provides valuable insights into the multifaceted factors that contribute to trust in AI-powered cobots within the construction industry. By understanding and addressing these factors, stakeholders can create a conducive environment for successful cobot integration, fostering user confidence and maximizing the potential benefits of this advanced technology.

Discussion

Perceived Safety and Reliability

Safety and reliability are foundational for establishing trust in cobots. Users must have confidence in the safety measures and the reliability of these machines. Effective training programs and robustness in cobot performance are essential for ensuring safe and dependable operation. For practitioners, this means prioritizing comprehensive safety training for their workforce and investing in cobots with advanced sensory capabilities to enhance safety perceptions. Policymakers should develop regulations that emphasize safety standards and support the creation of standardized training programs. Researchers can explore the interplay between safety culture within construction companies and trust development, as well as the influence of safety measures on projects of varying complexity.

Effective Communication

Effective communication between workers and cobots is integral in building trust. Communication positively impacts accuracy,

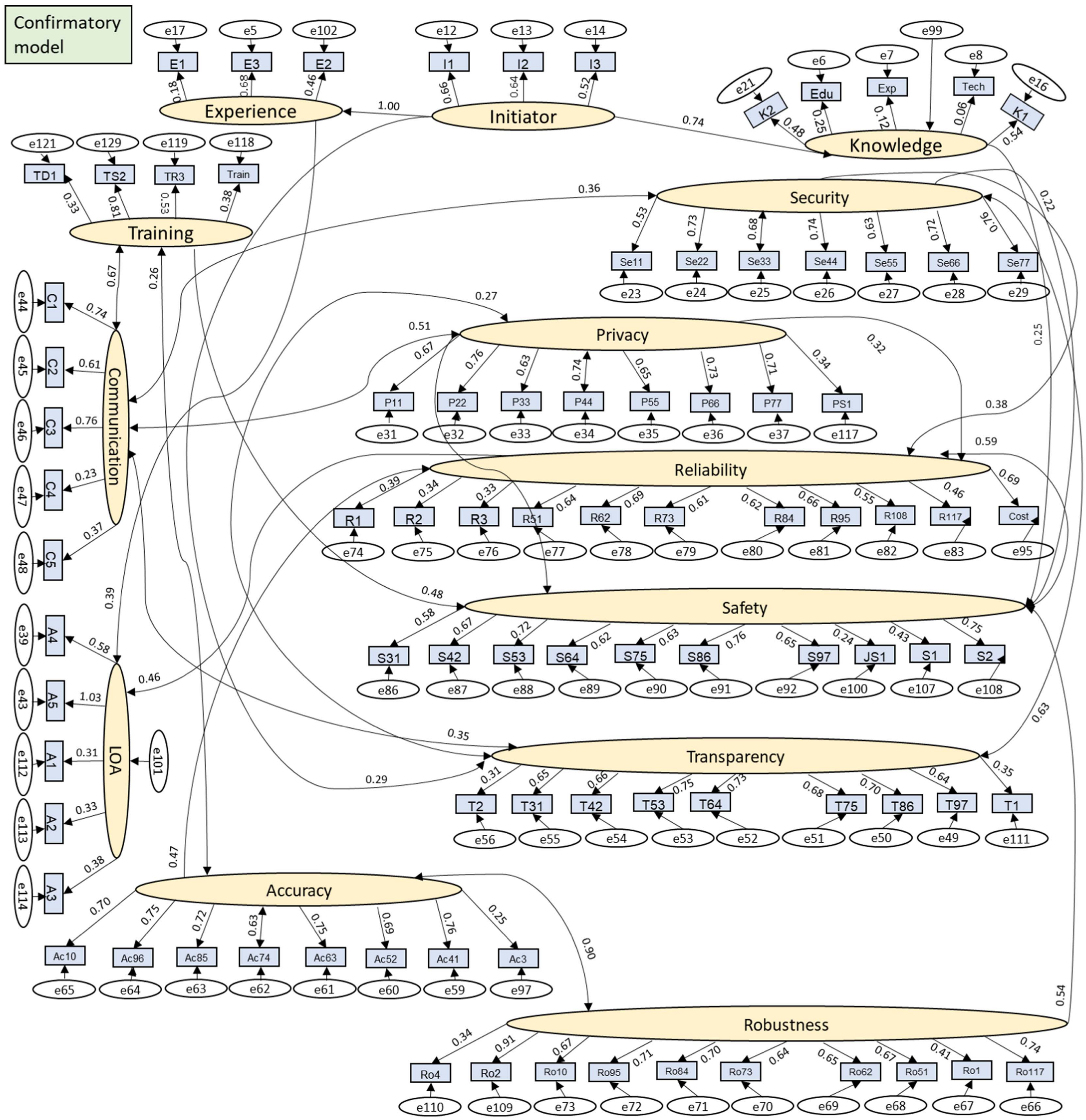

Fig. 6. Confirmatory model results.

robustness, security, privacy, and the level of automation, all of which contribute to trust. Practitioners should encourage open channels of communication between human workers and cobots to foster mutual understanding. Policymakers can promote guidelines for transparent communication practices in cobot deployment. Researchers have an opportunity to study the long-term effects of communication strategies on trust development, exploring how effective communication can be sustained and improved over time.

Role of Initiators

Initiators, individuals with prior experience and peer recommendations, play a significant role in shaping trust perceptions among users. They act as bridges between the technology and the workforce, influencing trust development. For practitioners, active engagement with initiators is key to facilitating knowledge sharing and addressing concerns. Policymakers can support mentorship programs and peer support networks to enhance the role of initiators in the workplace. Researchers can delve into the dynamics of initiator influence in more depth, examining how initiators shape perceptions, their credibility, and how their role evolves over time.

Transparency

Transparency in decision-making processes and hands-on experience with cobots is vital in trust-building. For practitioners, fostering a culture of transparency in cobot deployment is crucial. Policymakers should tailor transparency regulations to different cobot applications to ensure the right level of transparency is maintained. Researchers can investigate how transparency impacts trust in diverse cobot contexts, helping to refine transparency practices.

Privacy and Security

Privacy and security measures are essential for trust-building, emphasizing the need for robust data protection. Practitioners must prioritize data security and implement robust privacy measures. Policymakers should develop and enforce data protection regulations to safeguard sensitive information in cobot use. Researchers can examine the effectiveness of privacy and security measures in enhancing trust, studying how these measures impact user confidence.

Direct Experience and Training

Hands-on involvement with cobots and comprehensive training positively influences trust. Practitioners should invest in continuous training initiatives, providing opportunities for direct cobot experience. Policy makers can promote standardized and accessible training programs to ensure that workers at all levels of expertise can benefit. Researchers should explore the long-term effects of training on trust development, focusing on how training impacts worker competence and user confidence over time.

Cost and Support

The cost of cobots, along with the availability of customer support and training, impact willingness to adopt the technology. Practitioners should consider cost-effective cobot solutions and ensure robust customer support to address user needs. Policymakers should support initiatives that make cobots more affordable and enhance the support infrastructure. Researchers can investigate the cost-effectiveness of cobot adoption and its impact on trust, helping to identify cost-effective solutions for the construction industry.

Limitations

Although this study represents an important endeavor to explore the factors influencing the adoption of cobots in construction from a trust-building perspective, it does have certain limitations. First, although attempts have been made to involve a diverse range of construction practitioners, such as project laborers, foremen, engineers, managers, and leadership, it is important to examine the distinct viewpoints of each group individually. The introduction of cobots into construction projects can have diverse implications for these stakeholders, and conducting separate analyses of their perspectives can help identify specific challenges or concerns. Therefore, it is vital to investigate the unique outlooks of these various parties in order to gain a comprehensive understanding of the impact of cobots in the construction industry. Understanding the similarities among and differences between these groups will help establish a better understanding of the generalizability of these results.

Second, there was no empirical study conducted by researchers to assess trust in cobots in either controlled experimental environments or real-world field settings where a cobot is deployed. Therefore, conducting real-world investigations to examine the trust dimensions identified in this research, as well as those validated through interviews and surveys, would provide additional confirmation regarding the reliability and validity of the research findings. Most specifically, experimental studies would help establish the true causal directions among our variables and would reduce concerns about endogeneity bias (Antonakis et al. 2014). Our models imply that one factor causes another, but the study design does not support strong conclusions with regards to the directionality of these relationships. Most often, the relationships are found to be more complex, including reciprocal causality. Ideally, not only would future research include experiments, but they would also include the examination of these factors over time. The workplace is dynamic, and the development (or decay) of trust is especially so. A study of this type only provides a snapshot of what is going on at a single moment in time.

Third, the level of trust can be influenced by the type and size of construction projects. The type of project determines the complexity and range of tasks that cobots are expected to perform. In smaller construction projects, cobots may handle simpler responsibilities like material transportation or basic assembly. Conversely, larger projects may require cobots to engage in more intricate activities such as welding, cutting, and drilling. The complexity of these tasks can impact workers' trust in cobots because they may be hesitant to rely on them for more demanding duties. In smaller projects, the presence of a cobot may disrupt the workflow and draw more attention, leading to increased wariness and reduced trust from workers. However, in larger projects with multiple workers and machinery, cobots may integrate more smoothly into the workflow and be more widely accepted.

Additionally, the project size can influence the extent of training and supervision provided to workers collaborating with cobots. Smaller projects may prioritize less training and supervision, which could increase the risk of accidents and errors, thus diminishing workers' confidence in the safety of cobots. Conversely, larger projects may emphasize comprehensive training and supervision to minimize risks, thereby enhancing overall trust in cobots.

Finally, although our model includes a large number of variables, it is possible that some important variables have been omitted. We based this model on a literature review and input from subject matter experts, but there may be factors that we overlooked. Omitted variables can lead to endogeneity bias (Antonakis et al. 2014), and conducting experimental studies, as well as staying alert to the potential for omitted variables, can help reduce/eliminate this bias, leading to better estimates of true relationships among variables.

Future Work

Besides addressing the limitations outlined previously, the future directions of this work encompasses specific research efforts that currently pursued by the research team. Measurement of specific trust factors can be accomplished using physiological data collected from workers who are involved in construction robotics activities. Furthermore, future research can explore the factors that affect overtrust and undertrust to establish procedural requirements that result in proper trust calibration. Pilot or case study projects that incorporate real or simulated cobots and actively working with AI-powered cobots can better help in understanding the system (i.e., cobot), user, and environmental characteristic that influence trust. This approach allows for a more comprehensive assessment of the worker–robot collaboration requirements, considering factors such as potential malfunctions or the need for maintenance that may arise over time. Furthermore, long-term utilization of cobots enables a more precise and realistic evaluation of their capabilities. Hence, the authors suggest longitudinal experiments that allow for long-term worker–robot interaction tests.

Finally, the study did not differentiate between diverse professional roles and experience levels within the ACE industry in collecting opinions and perceptions. Although the research intentionally targeted a diverse population of the industry in a uniform fashion to capture the heterogeneity of the data and diversity of the workforce, future research could evaluate and model the perceptions and acceptance of cobots separately among various ACE professional groups, including frontline workers, managers, and individuals new to the field. Such an approach would offer a more nuanced understanding of the unique requirements and challenges faced by each group, thereby enabling more tailored and effective implementation strategies for AI-driven collaborative robots in real-world ACE projects. This avenue of investigation represents an important next step in advancing the understanding of technology adoption in the ACE sector.

Data Availability Statement

All data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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Supplemental Materials

Tables S1 and S2 are available online in the ASCE Library (www.ascelibrary.org).

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J. Comput. Civ. Eng., 2024, 38(3): 04024011