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Examining Factors of Human-AI Trust: Comparing Human- and AI-Related Factors

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Abstract

With the development of artificial intelligence (AI) technology, human-machine collaboration (HMC) plays an important role in enhancing construction safety. Human trust in AI is the key to the successful implementation of HMC. In this study, the effects of human-related factors (gender, technology acceptance) and AI-related factors (accuracy) on trust were measured and analyzed with controlled experiments simulating a tower crane operation scenario. Twenty-four college students were recruited for the experiment and randomly assigned to two false alarm rate conditions. A remote-controlled tower crane model toy was be used to simulate a lifting task. A tablet computer was be used to simulate an intrusion alarm monitoring system. Users' initial technical acceptance of the system was assessed via a questionnaire. Subjects' trust scores at the end of each alarm were measured using a trust rating scale. The statistical methods of t-test and two-way ANOVA were used to test the significant relationship between false alarm rate, gender, technology acceptance and trust score. The results show that the false alarm rate is a key factor affecting trust, while gender and technology acceptance and their interaction effects with the false alarm rate are not significant. The study emphasizes the importance of reducing false alarms and improving AI accuracy to enhance user trust.

1 Introduction

With the rapid development of AI, deep learning, big data, and other information technologies (Duan et al., 2019), machines have transitioned from mechanization and automation to intelligence over the past few decades. With the continuous penetration of intelligent technologies in the construction field, intelligent innovations such as drones, sensors, and smart visualization cameras provide new solutions for remote safety monitoring at construction sites. They play an important role in reducing operator workloads and compensating for the limitations of operator capabilities. However, during hazardous inspections of image data, monitors may face several challenges, including fatigue, stress, and

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distraction which results in up to half of the potential hazards being overlooked (Chen et al., 2016). To overcome the shortcomings of manual monitoring, advanced computer vision techniques have been developed to enable situation recognition, reasoning, diagnosis, and decision support (Paneru & Jeelani, 2021). Although high levels of automation and intelligence continue to evolve and improve, their value lies in assisting rather than completely replacing human operators. As a result, human-machine collaborative (HMC) systems have emerged as a key factor in improving construction safety and efficiency and play an important role in hazard detection. Among them, human trust in AI is essential for the successful implementation of HMC strategies to improve construction safety (Paneru & Jeelani, 2021).

It has been shown that trust is influenced by both human and AI influences. Human influences often include gender, technology acceptance, and experience. Gender differences may influence how much an individual trusts AI (Hu et al., 2019). The technology acceptance model provides a useful theoretical framework to validate the importance of trust in AI to predict acceptance of AI (Choung et al., 2023). Experience, on the other hand, influences an individual's judgment of the reliability of AI-related influences focusing on accuracy, predictability, and transparency. Accuracy refers to the precision and reliability of the AI in performing a task. Predictability refers to the stability of the AI's behavior and outcomes within the expected range. Transparency refers to the visibility and understandability of the AI's workings and decision-making process to the user (Parasuraman & Riley, 1997). Together, these factors determine user trust in the AI. Therefore, to enhance users' trust in AI systems, these factors need to be considered and analyzed comprehensively to ensure that the system's performance and user experience are optimized.

Intelligent monitoring and alerting systems are one of the important applications of AI in the construction field. When an intelligent monitoring and alerting system detects unsafe human behavior or an unsafe state of a machine, it issues an alert prompting the operator to take corrective action. However, differences in individual human characteristics and biases against AI may trigger human-machine trust issues, resulting in the misuse or abandonment of intelligent systems. In addition, most alert systems set low thresholds because the cost of missed alarms (e.g., casualties) is usually much higher than the cost of false alarms. This results in most alerts being "false alarms" with negative consequences. (Zhou & Liao, 2023). First, because the final decision is made by humans, frequent false alarms cause humans to double-check the information to ensure that the alarm is indeed false, which can be distracting and consume unnecessary energy (Okpala et al., 2020). Second, after frequent false alarms, people may experience "crying wolf" syndrome, which can lead them to ignore alarms (including true alarms), ultimately resulting in fatal accidents and system abandonment (Woods, 2019). Therefore, to prevent potential problems, AI should not only be used as a tool to assist humans but also to support the process of human trust.

Therefore, this study conducted a human-machine trust experiment for a remotely controlled tower crane hoisting task by simulating a tower crane hazardous area intrusion alarm system scenario. The human-related factors in this research focused on gender and technology acceptance. The AI-related factors are focused on accuracy. Through controlled experiments, the factors were analyzed and compared. The AI accuracy information is provided in the form of "alarm + monitoring", where the alarm system provides immediate warning and the monitoring system continuously provides real-time operating environment data, which closely fits the operating scenarios of tower crane drivers under intelligent technology. Statistical analysis methods including T-test and two-way ANOVA are used. This study aims to reveal the factors of that influence human-machine trust and provide a new perspective on human-machine trust in Chinese HMCs in the construction industry.

2 Literature Review

All forms of interaction between humans and machines are collectively referred to as human-machine interaction. The machine can refer to automated or autonomous systems, autonomous agents, robots, algorithms, or AI (Xiong et al., 2022). For example, in order to improve the safety of tower crane operations, an intelligent identification and warning system that realizes accurate monitoring and real-time warning of dangerous areas through image acquisition, intelligent identification, coordinate warning, and other technologies (WU et al., 2024). The system is a new type of robot that can be used to perform a single task. Many construction robots are manufactured to perform a single type of work, such as autonomous excavators (Kim et al., 2019). Human-robot collaboration, as a type of human-robot interaction, can be used to perform complex tasks through physical contact or non-contact collaboration between humans and machines (Hentout et al., 2019). In this process, humans are responsible for exercising dexterity and making decisions, while machines take on tasks that are not suitable for direct human execution, such as high-precision manipulation (Yang et al., 2022) In the construction industry, this type of human-machine interaction can be utilized in a variety of ways. This cooperation between humans and machines is particularly important in the construction industry, as it involves complex task execution and risk management (Janssen et al., 2019). As the level of AI increases, so does the autonomy of smart machines, which may affect the trust of workers, making it particularly important to study trust in the built environment (Alikhani et al., 2023).

Trust can be defined as a strong belief in another person's intentions or will, by following their words, expressions, decisions or actions (Gupta et al., 2020). As humans are increasingly required to interact with AI, automated systems, trust becomes an important factor in synergistic interrelationships. In this context, sufficient trust can mediate the relationship between humans and automated systems (Yagoda & Gillan, 2012). Trust is a subjective experience with three components: dispositional trust, situational trust, and learned trust (Hopko et al., 2023). Dispositional trust is influenced by demographic, personality, and social characteristics. Previous research has shown that gender may influence trust building, with males being more inclined than females to trust robots (Hu et al., 2019). Acceptance and perception of robot behaviors are influenced by operator gender (Kuo et al., 2009). Venkatesh has emphasized the important role of gender differences in technology acceptance research in several empirical studies, where men are more sensitive to the perceived usefulness of technology while women value the perceived ease of use of technology, as well as significant gender differences in subjective normative factors in technology acceptance (Venkatesh et al., 2000). Low acceptance reduces human-computer collaboration and team performance. Acceptance is related to many factors in human-machine collaboration, such as machine performance, transparency, interpretability, and human characteristics (Gursoy et al., 2019; Kraus et al., 2020). Situational trust includes internal human factors (e.g., fatigue) and external factors (e.g., accuracy). The higher the system accuracy, the more operators trust the automated system and the higher the human-machine collaboration performance (Hoesterey & Onnasch, 2023). Acquired trust is related to the operator's expertise and past experience, and this trust changes dynamically (Hoff & Bashir, 2015). Thus, the overall perception of trust in a human-machine collaborative environment depends on human-related factors, AI-related factors, and the interactions between them.

Although there are many papers studying the factors influencing trust, there are still some research gaps. First, there are discrepancies between the findings presented in different papers. These inconsistencies may be related to the small sample size and the nature of the different research questions. Therefore, further research on various factors (e.g., the effect of validation factors on trust or examining mediators and moderators in human-computer trust) is needed. Second, it is unclear whether the results of previous studies can be replicated in the construction field. Due to the specific nature of the industry, the effects of previously proposed influences on trust need to be revisited during the construction process and, more importantly, more construction-related variables need to be considered.

Therefore, research on the effects of human and AI influences on trust in human-machine collaboration in the construction domain is still in its infancy. There is a gap in the understanding of the impact of gender, technology acceptance and system accuracy on dynamic trust, and in this context, the focus of this study is to understand how gender, technology acceptance and system accuracy as human-AI factors affect trust in human-computer collaboration, and to explore the impact of different factors on dynamic trust.

3 Methodology

3.1 Subjects

Twenty-four undergraduate and graduate students, 12 males and 12 females, with an age range of 20 to 25 years (M = 23.2 years, SD = 1.4 years) were openly recruited for this experiment at Chang'an University. All subjects had normal hearing, normal or corrected-to-normal vision, and were in good health. All subjects were randomly assigned to one of two false alarm rate (33.33% and 66.67%) experimental conditions, with 12 subjects in each condition, including 6 males and 6 females. There was no significant difference in the age of the subjects between the two experimental conditions and they had never participated in a similar experiment. All subjects received a gift in return at the end of the experiment.

3.2 Equipment and Materials

The remote-control tower crane model toy used in this experiment is mainly composed of a lifting arm, balance arm, luffing trolley, lifting hook, and workbench (as shown in Figure 1a). The total height of the model is 132cm, the arm length is 90cm, and the working table rotates 360°. Using 2.4GHz wireless remote control can control the front and rear movement of the luffing trolley, the rotation of the lifting arm and the up and down of the rope. In this experiment, the remote-controlled tower crane model toy was used to simulate the operation of a tower crane in a real construction site. Subjects used the remote control to control the tower crane to complete the tasks of handling objects and placing objects. The model can help the subjects establish a connection with the actual situation. Test and record their behavioral responses and trust scores when performing the tasks under different experimental conditions.

A HUAWEI MatePad tablet with a screen size of 11.5 inches was used to play the tower crane hazardous area intrusion alarm simulation monitor. The tablet was placed in front of the operator's right-hand side, simulating the placement of an actual tower crane hook monitoring panel. The clips and alarm tones for the tower crane hazardous area intrusion alarm simulation monitoring were publicly available on the Internet. The video clips were segmented using the Python programming language and related libraries. The true and false alarms were randomly reorganized according to the experimental condition ratios (33.33% and 66.67% false alarm rate). The generated long video consists of 10 video clips, of which 6 video clips are alarm clips, with a total duration of 4 minutes and 32 seconds.

Two false alarm rate conditions, 33.33% and 66.67%, were selected in this study based on a review of the existing literature and an understanding of the practical application context. Wang et al. study human-machine trust in the aircraft engine fire alarm system scenario with a false alarm rate set to 33.33% and all alarm sequences considered (Wang et al., 2022). Many studies do not have a uniform and fixed standard for setting the false alarm rate and accuracy of the system but rather set the relative ratios according to the needs of the study (Li et al., 2023). In complex environments such as construction sites, security monitoring systems often need to set lower thresholds to avoid major accidents that may be caused by missed alarms, which also leads to higher false alarm rates. In this experiment, the number of alarms in one experiment is 6. The ratio of the number of false alarms is 1/3 for a low false alarm rate and 2/3 for a high false alarm rate. Therefore, these two ratios represent relatively low and high false alarm scenarios, respectively. These ratios were chosen to simulate different scenarios in the real world, where 33.33% of the false alarm rates are closer to good performance under ideal conditions, while 66.67% reflect some of the challenges that may exist under current technological conditions. By comparing the user responses in these two extreme scenarios, it is possible to better understand how the false alarm rate affects trust building during human-computer interaction.

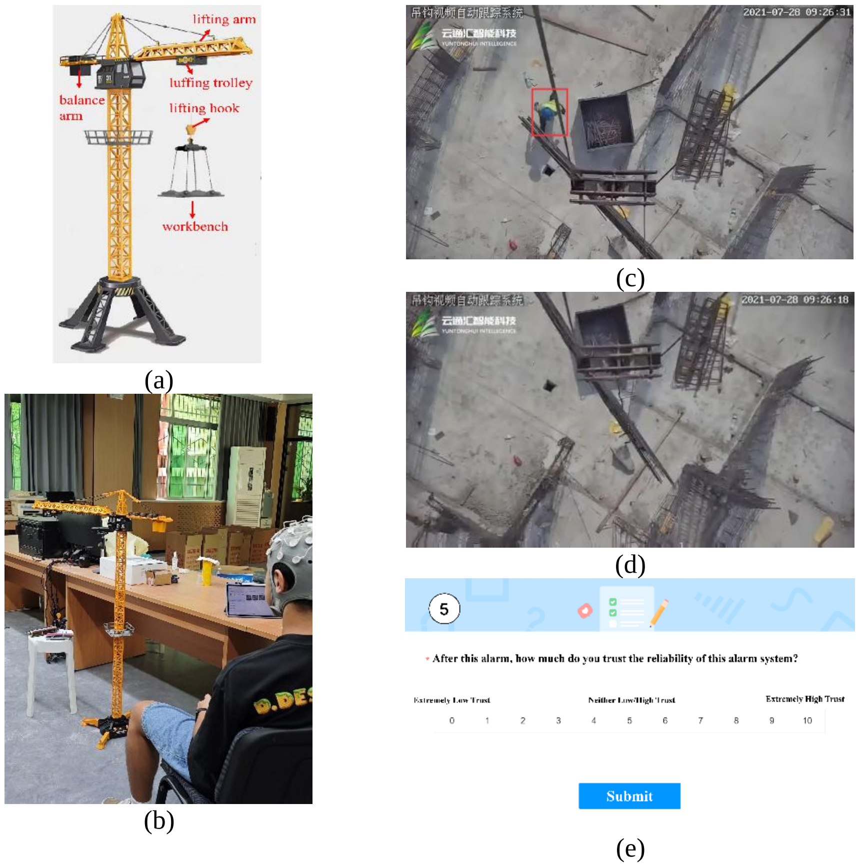

Figure 1: (a) Remote-control tower crane model (b) Experiment setup (c) True alarm (d) False alarm (e) Trust rating scale

3.3 Trust Measures

Self-report (questionnaire and trust rating scale) was used in this study. The "Tower Crane Hazardous Area Intrusion Alert System Technical Acceptance" questionnaire was used to collect demographic information prior to the experiment and to assess the initial technical acceptance of the system by the subjects. This acceptance was based on the system's performance, reliability, and the user's perception of the system's usefulness, ease of use, and behavioral attitudes and intentions. For the experiment, subjects verbally reported trust ratings after determining the authenticity of each alert to measure the subjects' trust scores at the end of each alert.

3.4 Experimental Design

This experiment utilized a 2 (gender) × 2 (false alarm rate) between-subjects design. All subjects were required to sign an informed consent form and divided into two groups by random draw for the experiment with different false alarm rates, with a balanced gender ratio in each group. Subsequently, subjects were asked to complete a questionnaire on the technical acceptability of the tower crane hazardous area intrusion alarm system. Prior to the official start of the experiment, subjects were informed in detail about the experimental procedure and precautions, and familiarized with the operation of the remote-control handle of the remote-controlled tower crane model toy, which lasts for 3 to 5 minutes.

At the beginning of the experiment, subjects were required to maneuver a remote-controlled tower crane for the task of lifting objects, which were loaded and unloaded by the experimenter. An analog monitor of the tower crane's hazardous area intrusion alarm was randomly played. When the simulated monitor sounded an alarm, subjects were required to check the monitor screen. It was a true alarm if the monitor screen showed that a worker was passing by (as shown in Figure1c), and a false alarm if the monitor screen showed that no worker was passing by underneath the crane hook (as shown in Figure1d). A trust rating scale then appeared on the screen and subjects were asked, "After this alarm, how much do you trust the reliability of this alarm system?" (as shown in Figure1e). To avoid a lengthy question, it was explained to subjects prior to the experiment that the trust rating would be based on cumulative alarm experience as a whole, not just the current alarm. Ratings ranged from 1 (extremely low trust) to 10 (extremely high trust). Subjects were required to verbally report the results of the ratings. After completing one rating, the lifting task was continued. Subjects need to wait for the next alarm until the end of this experiment.

This study utilized a multiple-experiment approach. Each subject was required to complete three experiments in order to extend the total experimental duration and to ensure that more data points were collected, thereby increasing the reliability and validity of the results and reducing errors arising from the influence of chance factors (e.g., mood swings and distraction of the subjects) on the results of a single experiment. The length of each experiment was approximately 5 minutes. There was a 2-minute break between each experiment in which subjects were asked to relax. The total duration of the experiment was approximately 30 minutes.

3.5 Data Analysis

(1) Technology Acceptance

Before the experiment, subjects completed a 13-item questionnaire on "Technical Acceptance of Tower Crane Hazardous Area Intruder Alert Systems". The items included five dimensions: knowledge of the system (e.g., "I understand how the intrusion alarm system works"), perceived ease of use (e.g., "The interactive information of the intrusion alarm system is clear and easy to understand"), perceived usefulness, behavioral attitudes, and behavioral intentions. To ensure the quality of the questionnaire, after the initial design of the questionnaire, a small sample was collected for Cronbach's coefficient alpha reliability analysis and Bartlett's spherical test validity analysis. In this study, a technology acceptability score was obtained by summing all scores for each item and dividing by the total number of items. The mean value of technology acceptance was calculated for all subjects, and based on this mean value, the subjects were categorized into "high technology acceptance" and "low technology acceptance" groups.

Dimension	Cronbach Alpha	Normalized term-based clone Bach Alpha	Item count
Knowledge of the system	.861	.866	2
Perceived ease of use	.855	.855	2
Perceived usefulness	.820	.828	3
Behavioral attitudes	.833	.834	3
Behavioral Intentions	.885	.889	3

Table 1: Results of reliability analysis

(2) Trust Score

The average score of all trust ratings in the three experiments was used as the trust score for each subject as in Equation (1) (Chauhan et al., 2024). Where r_{ij} denotes the j_{th} trust rating in the i_{th} experiment.

$$\text{Trust score} = \frac{\sum_{i=1}^{3}\sum_{j=1}^{6} r_{ij}}{3\times 6} \qquad (1)$$

(3) Methods of Analysis

The dataset was grouped according to false alarm rate, gender, and technology acceptance, respectively. After the Shapiro-Wilk test was used to initially assess the normal distribution information of the dataset, the significance of each of the three for the difference in the trust scores was compared using the two-independent samples t-test. The dataset was divided into two subgroups according to gender and technology acceptance under two groups of false alarm rates, representing the male and female groups, the high technology acceptance group and the low technology acceptance group, respectively. The significance of the differences in trust scores by gender and technology acceptance under the two types of false alarm rates was compared using two-way ANOVA, respectively.

4 Results

The results in Table 1 show that the questionnaire exhibited good reliability (Cronbach's alpha>0.8) and validity (p<0.001). The mean value of technology acceptance for all subjects was 4.05 with a standard deviation of 0.55. Based on the grouping, 12 data were available for the high and low technology acceptance groups respectively.

The Shapiro-Wilk test performed on the data sets indicated that all data sets satisfied normal distribution. Across the datasets, high and low false alarm rates were significantly different from trust scores as shown in Table 2. The t-test results showed that trust scores in the low false alarm rate group (7.107 ± 1.493) were significantly higher than trust scores in the high false alarm rate group (5.116 ± 0.725), t = 4.155, p < 0.001, 95% CI (0.975 ~ 3.007). This suggests that false alarm rate is an important factor influencing trust scores and that low false alarm rate may be associated with higher perceptions of trust. This may be due to the fact that a low false alarm rate reduces false alarms and improves the accuracy of the system, which in turn enhances the user's trust in the system.

There was no significant difference between gender and trust scores, as shown in Table 3. The t-test results showed that the difference was not statistically significant at t = －0.717, p = 0.481. The interaction effect between false alarm rate and gender was not significant, as shown in Table 5. The results of two-way ANOVA test showed that the main effect of the false alarm rate was significant (F=16.366, p<0.001, partial η2=0.450). In contrast, the main effect of gender was not significant (F=0.850, p=0.368), nor was the interaction effect between false alarm rate and gender (F=0.006, p=0.941). This suggests that gender may not be a significant factor influencing trust scores in this sample. This result may be due to the more balanced distribution of gender in the sample and the fact that gender differences may have less of an effect on technology trust in the student population.

There was no significant difference between technology acceptance and trust scores, as shown in Table 4. The t-test results showed that the difference was not statistically significant at t=0.145 and p=0.886. The interaction effect between false alarm rate and technology acceptance was not significant, as shown in Table 5. The results of the two-way ANOVA test showed that a significant main effect of false alarm rate (F=16.232, p<0.001, partial η2=0.448), while the main effect of technology acceptance was not significant (F=0.238, p=0.631). The interaction of false alarm rate and technology acceptance effect was also not significant (F=0.189, p=0.669), suggesting that initial technology acceptance had little effect on trust scores in this study. It indicates that the effects of these two factors on trust scores are independent. This may be related to the fact that the experimental subjects, who were all students and had no experience with the tower crane hazardous area intrusion alarm system, did not differ significantly in initial technology acceptance and therefore had a limited effect on trust scores.

Human trust measure	Low false alarm rate		High false alarm rate		T value	p value	95%CI
	Mean	SD	Mean	SD			
Trust score	7.107	1.493	5.116	0.725	4.155	p＜0.001*	0.975～3.007

Table 2: Difference in human trust score between low false alarm rate and high false alarm rate

Human trust measure	Male		Female		T value	p value	95%CI
	Mean	SD	Mean	SD			
Trust score	5.884	1.603	6.338	1.495	- 0.717	0.481	- 1.766~0.858

Table 3: Difference in human trust score between male and female

Human trust measure	High technology acceptance		Low technology acceptance		T value	p value	95%CI
	Mean	SD	Mean	SD			
Trust score	6.157	1.660	6.065	1.468	0.145	0.886	- 1.234~1.419

Table 4. Difference in human trust score between high technology acceptance and low technology acceptance

Variable: trust score

	Sum of squares	Degree of freedom	Mean squares	F	p value
False alarm rate *Gender	0.008	1	0.008	0.006	0.941
False alarm rate *Technology acceptance	0.280	1	0.280	0.189	0.669

Table 5. Two-way ANOVA analysis

5 Discussion

This study provides insights into the factors influencing human-machine trust by simulating a tower crane hazardous area intrusion alarm system scenario. The finding indicates that AI accuracy, especially false alarm rate, was shown to be a significant factor affecting trust scores. The experimental results showed that the false alarm rate was significantly correlated with trust scores, and the trust scores of the low false alarm rate (33.33%) group were significantly higher than those of the high false alarm rate

(66.67%) group. This may be due to the fact that the low false alarm rate reduces false alarms and improves the accuracy of the AI, which in turn enhances the user's trust in the AI. This finding emphasizes the importance of reducing false alarms and improving AI accuracy when designing and implementing tower crane alarm systems.

Gender is not a significant factor in trust scores, which may be related to the balanced gender distribution in the sample and the low impact of gender differences in the student population on technology trust. This finding contradicts some previous studies that suggest that gender may play an important role in technology trust (Hu et al., 2019). Potential reasons for this difference may include factors such as sample composition and experimental design characteristics. The participants in this experiment were all in the college student population, and the age range was concentrated between 20 and 25 years old. The younger generation is generally open to new technologies, which may have attenuated the effect of gender differences in the traditional sense. In addition, none of the subjects had prior exposure to similar tower crane hazardous area intrusion alarm systems, implying that their initial technology acceptance was more consistent, further minimizing the differences due to gender. Although no significant gender effect was observed in this study, this does not mean that the same conclusion would be reached in other populations or different application scenarios. Future research should consider expanding the sample size and examining more diverse contextual factors to fully assess how gender and other personal characteristics work together to shape trust formation during human-computer collaboration.

The main effect of technology acceptance was not significant, which may be related to the fact that the experimental subjects were all students and had no experience with tower crane hazardous area intrusion alarm systems. The difference in initial technology acceptance was not significant and therefore had a limited effect on trust scores. The interaction effect between false alarm rate and technology acceptance was also not significant, suggesting that these two factors had independent effects on trust scores. This result suggests that the effect of false alarm rate on trust may be consistent across levels of technology acceptance.

This experiment also recorded the subconscious behavior of whether subjects chose to believe after hearing an alarm, while EEG signals were collected as subsequent analysis data. Objective data from EEG were used to further analyze the dynamics and neural mechanisms of trust.

6 Conclusions

This study reveals that the false alarm rate is a key factor influencing tower crane drivers' trust in man-machines, while gender and technology acceptance have insignificant effects in this study. These findings provide new perspectives on the study of human-machine trust in the construction industry, especially in the scenario of tower crane drivers' operations with intelligent technology. The findings emphasize the importance of focusing on reducing false alarms and improving system accuracy when designing and implementing tower crane alarm systems in order to enhance users' trust in the system. In addition, the effects of gender and technology acceptance on trust may vary depending on sample characteristics, and future research needs to validate this in a wider population and explore other factors that may affect trust, such as individual experience, cultural background, etc. With further research, we can better understand the dynamics of human-machine trust and provide more effective strategies for safety management in the construction industry.

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