

The Importance of Situational Awareness in Future Construction Work: Toward the Effects of Faulty Robot, Trust, and Time Pressure

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ABSTRACT

Introducing robots to future construction sites will impose extra uncertainties and necessitate workers' situational awareness (SA) of them. While previous literature has suggested that system errors, trust changes, and time pressure may affect SA, the linkage between these factors and workers' SA in the future construction industry is understudied. Therefore, this study aimed to fill the research gap by simulating a future bricklaying worker-robot collaborative task where participants experienced robot errors and time pressure during the interaction. The results indicated that robot errors significantly impacted subjects' trust in robots. However, under time pressure in time-critical construction tasks, workers were tended to recover their reduced trust in the faulty robots (sometimes over-trust) and reduce their situational awareness. The contributions of this study lie in providing insights into the importance of SA in future jobsites and the need for investigating effective strategies for better preparing future workers.

INTRODUCTION

Robots will be an integral part of the future construction industry, while workers will be in the loop to interact with robots. Although robots could enhance automation in construction, this incorporation might impose extra uncertainties (e.g., workers struck by a robot) in the workplace (e.g., Jeelani and Gheisari 2022). To ensure the safety of future construction sites, workers should perform situational awareness (SA) of newly-introduced robots during human-robot interaction. However, the present study discerned a research gap of insufficient discussion on the factors affecting workers' SA in the future construction industry.

Literature has proposed a few factors that could potentially impact workers' SA on future construction sites. For example, in the study investigating human-drone interaction, Lu and Sarter found that participants would decrease their trust in drones and pay more attention to them after knowing drones made mistakes in detection tasks (Lu and Sarter 2020). Hence, the errors of robots and changes in trust levels might affect workers' attention allocation and SA of robots. On the other hand, in the research examining the effect of time pressure on workers' risk-taking behaviors, Pooladvand and Hasanzadeh identified their tendency to overlook potential hazards under stress (Pooladvand and Hasanzadeh 2022). That is, time pressure might force workers to focus on tasks while disregarding being situationally aware of robots. However, the linkage between these factors and SA has not been investigated in the context of the future construction industry. Therefore, this

study aims to examine two factors (i.e., robot error with safety incident and time pressure) that can affect workers' SA on future construction jobsites where they need to team up and work alongside robots. The findings of this study provide insights into the influential factors on human-robot teaming on future jobsites.

BACKGROUND

SA and Attention. The widely-accepted definition of SA was the perception of dynamic elements, the comprehension of their meaning, and the projection of their status in the future (Endsley 1988). Maintaining a high SA in dynamic environments can facilitate a rapid and accurate situation assessment that is assistive to safe decision-making. Previous studies have confirmed the linkage between SA and attention, and highlighted attention is an indispensable element for human information processing (Wickens et al. 2008). In other words, human attention reflects the information that is being sensed, processed, and interpreted (Hasanzadeh et al. 2018). In dynamic environments (e.g., construction sites), humans have to allocate their limited attentional resources to the information that should be perceived, comprehended, and projected to perform SA (Kaber et al. 2016). Humans' SA can be indicated by understanding their attentional allocation, and previous literature has suggested eye-tracking is a reliable metric to measure an individual's attention in the construction domain (e.g., Hasanzadeh et al. 2018). On future jobsites where the workers are required to work alongside robots and communicate with drones continuously, it is important to maintain SA, ensuring their safety. Accordingly, the present study used eye-tracking metrics to evaluate workers' SA on future jobsites.

Human-Robot Trust and SA. Previous studies have mentioned the importance of trust-building in human-robot interaction and highlighted the multifaceted and dynamic nature of human trust (e.g., Demir et al. 2021). Humans would continuously calibrate their trust levels in robots based on human (e.g., gender), robot (e.g., transparency), and environmental (e.g., time pressure) factors (Hancock et al. 2011). During the trust calibration process, the trust level would fluctuate between different trust conditions, such as calibrated trust (ideal trust), overtrust (overreliance on robots), undertrust (under reliance on robots), untrust (information is needed to trust robots), and distrust (believing robots are unreliable) (de Visser et al. 2020). These trust conditions might compromise human-robot interaction. Moreover, literature has proposed the difference in trust levels would impact human attentional management and SA (e.g., Kunze et al. 2019). For example, in the study investigating the effect of transparency on drivers' trust in an automated system, Kunze and his colleagues reported that drivers with a lower trust level would distribute much attention to the driving environment, maintaining their SA (Kunze et al. 2019). Extending to the future construction sector, workers with less trust might need to allocate more attentional resources to the robots. However, the effect of trust in robots on workers' SA has not been sufficiently explored by construction studies yet.

Time pressure and SA. The time-critical, demanding, and complicated construction tasks impose time pressure on workers to complete missions within a limited time. Literature has highlighted the importance of time pressure and productivity demand in construction and supported their adverse influence on workers' SA (Pooladvand and Hasanzadeh 2022). Time pressure refers to the differences between the given amount of time for finishing a task and the required amount. This scheduling contradiction would drive the acceleration of human information processing and all the

steps of SA while compromising quality (Nepal et al. 2006). The embedded scheduling stress/productivity demand will still play an important role in the future construction industry. Therefore, this study considered the time pressure with productivity demand as an influential factor affecting workers' SA on future jobsites.

METHODOLOGY

Experimental design. This study developed an immersive mixed-virtual-reality bricklaying task to simulate worker-robot teaming in future construction. Subjects had to execute bricklaying in collaboration with a bricklaying cobot (a.k.a. MULE), drones, and an AI assistant. MULE was designed to help workers with lifting/dropping heavy concrete blocks while human intervention was still necessary (i.e., workers must apply mortar and move MULE to the correct position). Three types of drones were involved in this experiment: (1) surveillance, (2) delivery, and (3) inspection drones. The surveillance drone aimed to either examine the status of the jobsite by surveying the environment or to convey a message to the worker (e.g., change orders). The delivery drone was employed to deliver materials (i.e., a new mortar bucket in this experiment) for the workers in an elevated workplace. The inspection drone helped monitor workers' progress, safety behaviors, and productivity and reported to the manager. AI-assistant can provide information on dynamic objects (i.e., the type and direction of drones) to prepare workers for their approach. This research undertook a within-subject study in which participants were asked to complete three modules: (i) Baseline, (ii) Error, and (iii) Time Pressure modules. Each module would take approximately 7 mins. In the Error module, an inspection drone struck participants, and a delivery drone struck a co-worker. In addition, in the Time Pressure module, participants were informed that extra compensation would be available if finishing 25 blocks in 7 mins, referring to the combination of scheduling stress and productivity demand in construction. Figure 1 shows the research framework of this experiment.

Experimental procedure. After signing a consent form, participants were asked to complete a demographic pre-survey, followed by an introduction to the experiment. Then, participants were equipped with a VR headset, two controllers, three motion trackers, and neuro-psychophysiological wearable sensors. The training was provided for subjects to practice bricklaying in an immersive environment. Participants were then asked to complete three designated modules (i.e., Baseline, Error, and Time Pressure modules). A widely-used 5-point Likert-scale trust questionnaire (Muir 1994) was used to gauge the trust in drones at the beginning of the experiment (t_i = initial trust before the Baseline module) and after each module (t_b = trust after Baseline module; t_e = trust after Error module; t_t = trust after Time Pressure module). The questionnaire included predictability (i.e., to what extent the drones' behavior can be predictable), dependability (i.e., to what extent can you depend on the drones to do their job), and faith (i.e., what degree of faith do you have that the drones will be able to cope with similar situations in the future) to assess trust levels. During the experiment, eye-tracking data was collected to measure the SA of drones. This study focused on drones as the area of interest (AOIs) since they were the dynamic agents of which workers should be situationally aware. Dwell time (i.e., the total amount of time spent looking at an AOI) and run count (i.e., the number of times that participants returned their attention to an AOI) were selected as eye-tracking metrics to conduct the analysis. Finally, a

brief interview was used to obtain participants' feedback on the experimental design. All the procedures were approved by the Purdue Institution Review Board (IRB).

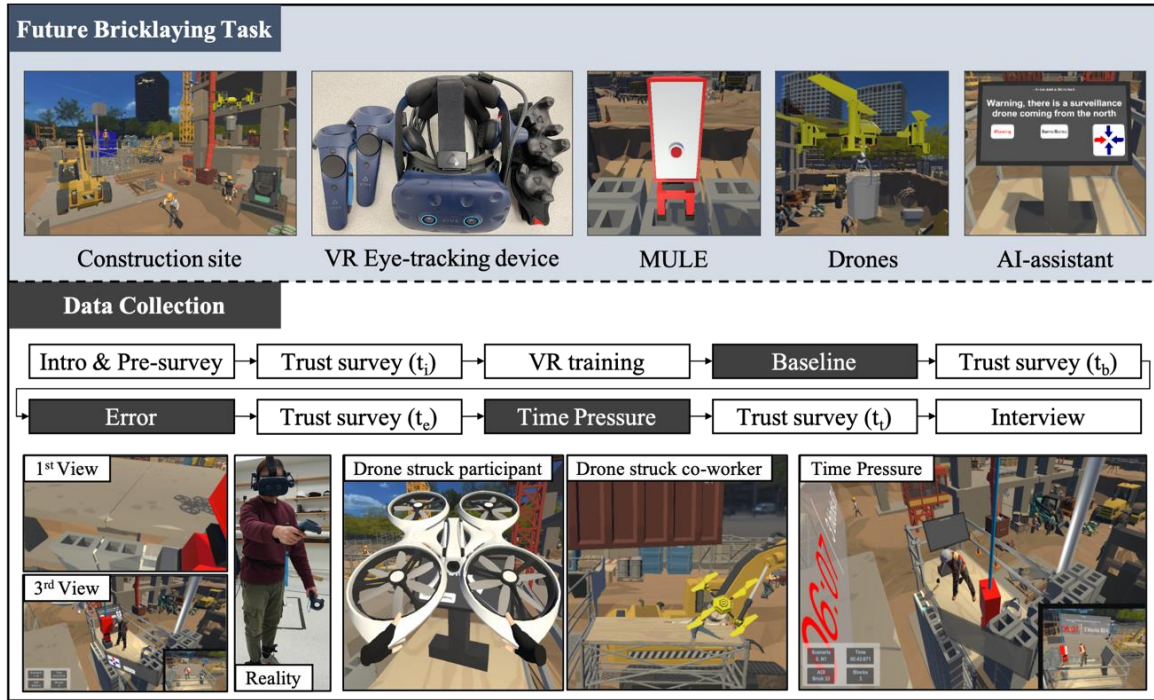


Figure 1. Research framework.

Participants. In total, 36 healthy subjects (23 males and 13 females, aged between 19 and 31, $M=23.19$, $SD=3.0$) were recruited to participate in this study. All the subjects were qualified as the construction industry's future workforce and were recruited from Civil Engineering and Construction Engineering and Management programs with work experience. All the subjects had normal or corrected-to-normal vision.

Apparatus. HTC Vive Pro Eye (manufactured by HTC Corporation, Taoyuan, Taiwan) was employed in this study as the VR device because of its built-in Tobii eye-tracker with a refresh rate of 90 Hz and a field of view of 110°. The developed system in HTC Vive can calibrate eye-tracking for each user to improve the accuracy of data. An Alienware PC with an AMD Ryzen 9 5950X 16-Core processor and an NVIDIA GeForce RTX 3090 graphics card was used to execute this user study.

RESULTS

During the experiments, subjects were asked to report their trust level in drones in different modules, including t_i ($M=3.717$, $SD=0.671$), t_b ($M=4.165$, $SD=0.705$), t_e ($M=3.160$, $SD=1.070$), and t_f ($M=3.958$, $SD=0.715$). Figure 2 shows a graphical overview of the changes in trust. According to the self-report, 72% of subjects (26 subjects) reduced their trust after Error module compared to the initial trust (i.e., $\Delta T = t_e - t_i < 0$). This study conducted a mixed-design analysis of variance (ANOVA) to examine (1) the effect of system error on workers' SA, (2) the effect of time pressure on workers' SA, and (3) the effects of the interaction of trust change and time

pressure on workers' SA. The data conformed to the assumptions of normality and homogeneity. Figure 3 provides an overview of the variables used in the hypotheses, and Table 1 presents the summary of the results.

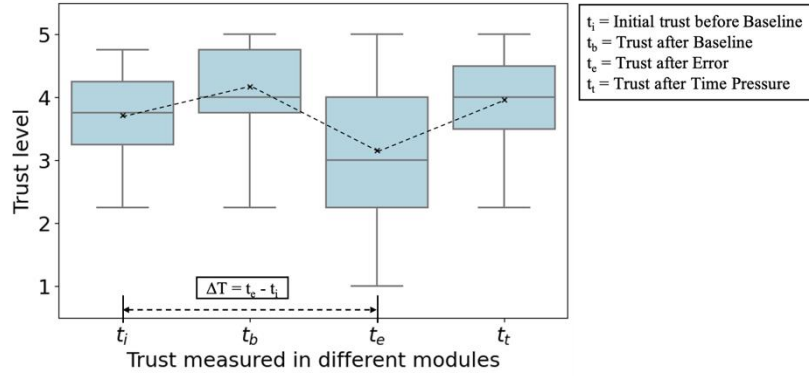


Figure 2. Graphical overview of trust changes in different modules.

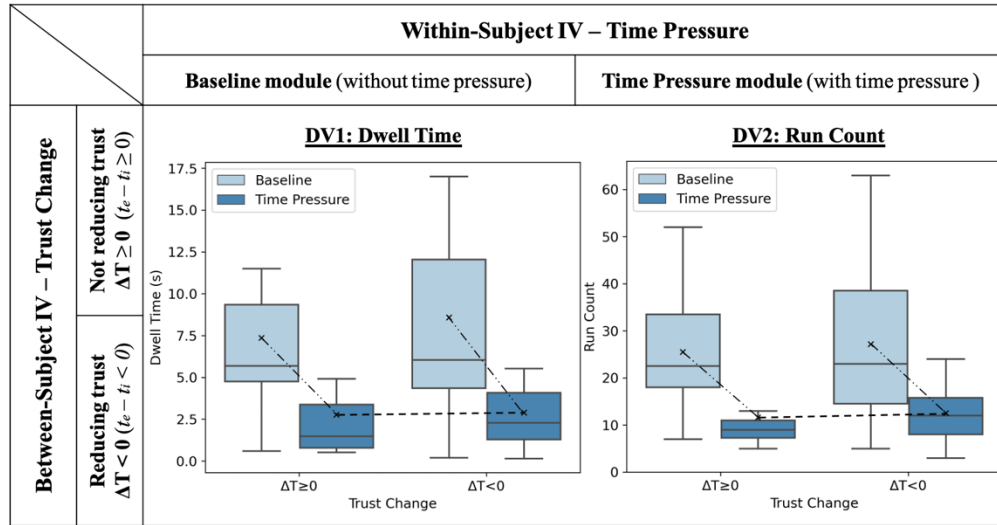


Figure 3. Overview of variables used in the mixed-design ANOVA.

First, a t-test was carried out to support a significant difference between t_i and t_e ($t=3.211$, $p=0.002<0.05$), caused by the system error. Further, to test the effect of system error on SA, a comparison between the subjects who reduced their trust in drones ($\Delta T < 0$) and the subjects without reducing their trust ($\Delta T \geq 0$) was conducted. For the trust-reducing group, the mean and standard deviation (STD) of dwell time were 2.885s and 2.383s in Time Pressure module, while the counterparts for run count were 12.538 and 5.901. For the non-trust-reducing group, these values were 2.760s, 3.233s, 11.600, and 9.264, respectively. The result of ANOVA revealed that the system error (leading to trust change) did not significantly impact dwell time ($f=0.161$, $p=0.691>0.05$) and run count ($f=0.132$, $p=0.719>0.05$). Second, a within-subject comparison between Baseline and Time Pressure modules was undertaken to examine the effect of time pressure on SA. In Baseline module, subjects' mean and STD of dwell time were 8.232s and 7.314s, while the counterparts for run count were 26.694 and 15.120. In Time Pressure module, these values were 2.850s, 2.598s, 12.278, and 6.864, respectively. The statistical outcome indicated the significant effects of time pressure on dwell time ($f=24.750$, $p=0.000<0.05$) and run

count ($f=37.649$, $p=0.000<0.05$). Last, because there was no interaction effect between trust change and time pressure on dwell time ($f=0.206$, $p=0.653>0.05$) and run count ($f=0.019$, $p=0.892>0.05$), this study focused on the individual effect of two independent variables.

Table 1. Results of hypotheses tests.

Variable	Dwell time (s)				Run count (times)			
	SS	MS	F	P	SS	MS	F	P
Trust change	6.536	6.536	0.161	0.691	24.269	24.269	0.132	0.719
Time pressure	521.402	521.402	24.750	0.000*	3741.125	3741.125	37.649	0.000*
Interaction	4.331	4.331	0.206	0.653	1.848	1.848	0.019	0.892

* $p<0.05$; SS=sum of squares; MS=mean squares

DISCUSSION

Introducing robots (especially different types of drones) to future construction sites will create new challenges and uncertainties that the future workforce needs to be ready for. Specifically, robot errors might unintentionally happen to future jobsites and jeopardize construction safety so that workers will have to maintain their SA of robots. One of the uncertainties is how the robot errors will impact workers' trust in robots. The results supported a significant effect of drone errors on decreasing trust levels, which aligned with previous studies reporting trust violation (i.e., unmet expectations concerning robot's behaviors) (e.g., Salem et al. 2015). For example, Abd and his colleagues found subjects reduced their trust in a bottle-delivery robot once the robot dropped a bottle (Abd et al. 2017). This violation could influence trust change and workers' SA because more attentional resources should be allocated to robots to guarantee their safety.

While the findings showed no significant impacts of trust changes after interacting with the faulty robot (safety incidents of drone striking workers) on subjects' SA, Figure 3 (dash lines) presents that the trust-reducing subjects tended to spend more attentional resources (higher dwell time and more frequent run count) to scan the surrounding environment after experiencing the errors to maintain their SA. Previous literature argued the linkage between trust in automation and SA (e.g., Kunze et al. 2019; Lu and Sarter 2020; Lu et al. 2020). For instance, the study conducted by Lu and Sarter demonstrated that subjects allocated more attentional resources to a detection drone after discerning its errors and decreasing their trust levels (Lu and Sarter 2020).

In the future construction industry, workers will need to calibrate their trust in robots during interactions while experiencing different construction contexts. Although it is readily assumed that workers with a lower trust level will allocate much attention to robots, this assumption might be violated by some task stressors, such as time pressure/productivity demand, which are integral business aspect of the construction. Further, the results supported a dominating role of time pressure in influencing workers' SA over the trust change. This finding could be explained by previous literature suggesting time pressure would provoke attentional tunneling (i.e., allocating attention to a single goal, given the potential cost of ignoring other events) and overtrust (i.e., overreliance on robots after experiencing errors) (Wickens 2005; Robinette et al. 2017). Specifically, in this study, the extra compensation available in the Time Pressure module could encourage participants to concentrate more on the bricklaying for completing the mission (i.e., a single goal) while disregarding checking drones' behaviors (i.e., potential cost). On the other hand, in the study examining overtrust in a faulty robot, Robinette and his colleagues found participants

tended to overtrust the faulty robot in a time-critical scenario (i.e., evacuation) (Robinette et al. 2017). This finding can explain that time pressure helped subjects quickly recover their trust in (even overtrust) faulty drones, leading to a lower SA of drones. This explanation was endorsed by an increasing trust of t_i , as shown in Figure 2.

While the findings contributed greatly to the body of knowledge, there are some limitations worth noting. First, this research only focused on participants' SA toward drones. Due to the dynamic and complex nature of the construction environment, the overall SA of workers toward all surrounding environment workers is worth exploring in future studies. Second, all the recruited subjects in this experiment were students because they referred to the next generation of construction workforces. However, the current workers are recommended to be considered as subjects of future studies because they might manifest different propensities to interact with robots.

CONCLUSION

While robots (drones) are set to have tremendous potential to revolutionize the construction industry, human-robot interactions and influential factors need to be further studied. The findings of this study demonstrated that the robot's system errors might impose extra hazards (e.g., workers struck by drones) on future jobsites and adversely affect workers' trust levels in robots. Their decreasing trust led to more checking on drones to ensure their safety. However, the results demonstrated that time pressure might cause attentional narrowing, reflecting on over-focusing on the bricklaying task and their prompt recovery from reduced trust in drones after observing the errors. This outcome supported a dominating role of time pressure in affecting workers' SA over the trust change in human-robot interaction. The findings of this paper shed light on (1) factors that can affect worker performance and safety in human-robot teaming, including trust in robots and time pressure; (2) factors that may be influenced by the adoption of robots on construction sites, e.g., workers' SA. Also, this study provided insights into the need to explore more effective strategies for training and preparing future workers to maintain their SA in time-critical construction tasks.

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