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Exploring Worker-Drone Interaction in Mixed Reality: Balancing Distraction and Situational Awareness

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Fig. 1. Experimental design framework.

Abstract

Mixed-reality (MR) technology has been widely used to simulate high-risk workplaces in order to minimize safety concerns. However, its use in understanding worker attentional allocation during interactions with drones in future construction environments remains underexplored. This study developed a futuristic bricklaying MR environment, where human-drone interaction was mandatory, to capture participants' naturalistic behaviors (i.e., attention, productivity, and distraction) across different interaction levels (i.e., no interaction, coexistence, and collaboration). The core research question explored whether workers maintained situational awareness of the drones or were distracted by them. The results confirmed that participants experienced a high sense of presence in the MR environment, driven by the use of environmental modalities, passive haptics, and drones' sounds and spinning blades. Moreover, the findings demonstrated that participants were distracted by the drones during coexistence, as evidenced by lower productivity and reflections indicating they felt they were over-allocating attention to the drones. Conversely, participants exhibited situational awareness of the drones during collaboration, deliberately allocating attention to ensure safety, despite a reduction in productivity. These findings highlight the value of immersive technology in investigating workers' naturalistic behaviors in future construction scenarios where workers and robots must function as teammates.

Index Terms: Mixed Reality (MR), worker-drone interaction, situational awareness, distraction, future construction.

1 Introduction

As advanced technologies (e.g., artificial intelligence and robots) are promising to revolutionize various industries, the potential of Unmanned Aerial Vehicles (a.k.a. drones) to improve the construction sector has been emphasized by previous studies [1]. In recent research reviewing the application of drones in the construction domain, the authors summarized monitoring, inspection, and photography as the most common examples of drone applications on jobsites [2,3]. While drones exhibit the capability to take over some construction tasks, they remain insufficiently intelligent to handle all unpredictable situations

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in construction. This fact sheds light on the necessity of workers' presence on future jobsites to collaborate with drones (i.e., worker-drone interaction) and complete tasks as a team [4]. Literature has categorized the varying roles (e.g., operator, supervisor, collaborator, and bystander) that workers will serve during worker-drone interaction [5]. The workers' roles in this relationship can be affected by their interaction levels with drones (e.g., coexistence and collaboration).

While the incorporation of drones into construction jobsites facilitates automation, previous research has highlighted potential adverse effects on workers, including safety concerns [6] and distraction [7]. Specifically, drones, representing flying robots, might collide with workers on dynamic jobsites, so workers must maintain situational awareness (SA) to ensure safety [8]. In other words, workers need to properly allocate their limited attentional resources to drones while executing their primary tasks [9]. On the other hand, being an unfamiliar entity to the workers, drones might distract and divert their attention. Although both SA and distraction depend on attentional allocation, the key difference is that SA is considered positive, while distraction is viewed as unfavorable. Distinguishing between these two attention-related situations remains understudied.

To address this gap, the study developed a mixed-reality (MR) environment simulating future construction sites - Fig. 1, capturing workers' naturalistic behaviors during worker-drone interactions. The key contribution of this study lies in its ability to differentiate between situational awareness and distraction in a real-world-inspired setting, providing valuable insights into optimizing worker safety in drone-integrated jobsites.

2 Background

2.1 Situational Awareness (SA) Vs. Distraction

The importance of SA has been accentuated in such dynamic workplaces as construction sites to guarantee occupational safety [10]. The broadly adopted definition of SA was the perception of dynamic elements, the comprehension of their meaning, and the projection of their status in the future [11]. Workers' high SA of dynamic hazards on jobsites enables their accurate assessment of the current situation and their rapid decision-making, leading to construction safety [12]. Moreover, the relationship between SA and attention has been established because attention refers to an essential element for human information processing [10]. That is, human attentional allocation implies the information that is being sensed, perceived, and interpreted [13]. Maintaining SA of dynamic objects necessitates attentional resources allocated to those objects. Therefore, workers' attentional allocation to drones might result from their intention to maintain SA of drones.

The measurements of SA assessment can be categorized into subjective and objective approaches. Subjective approaches typically rely on self-reported methods, such as questionnaires or interviews, where participants provide their perception of SA. The broadly used methods include Situation Awareness Global Assessment Technique (SAGAT) [14], Situation Awareness Rating Technique (SART) [15], and NASA Task Load Index (NASA-TLX) [16]. SAGAT involves pausing tasks to ask participants specific questions about the situation, while SART uses self-rating scales to evaluate an individual's perceived SA across demand, supply, and understanding dimensions. NASA-TLX measures mental workload, which is often linked to SA in complex tasks. All these three methods have been applied to understand users' SA performance in applications of immersive technology [17,18].

On the contrary, objective approaches assess situational awareness by analyzing measurable behavioral or physiological indicators, often focusing on attention-related metrics. These include eye-tracking measures such as dwell time [8], run count [19], and saccade patterns [9], which provide insights into how users allocate their attention in dynamic environments. Compared to subjective approaches, objective measurements exhibit the ability to capture users' real-time performance during experiments without any interruptions. As multiple commercially available head mount devices (HMD) have built-in eye-trackers, these objective approaches become prevalent in immersive environments.

On the other hand, distraction occurs when attention is diverted from primary tasks due to external stimuli or internal thoughts that compete for cognitive resources [20]. In dynamic workspaces, distraction can compromise productivity, increase human errors, and pose safety concerns[21,22]. Unlike focused attention, which enhances performance, distractions might interrupt information processing and undermine decision-making [23]. Understanding the sources of distraction on construction sites is critical for minimizing interruptions and facilitating workers' sustained attention on primary tasks. Moreover, previous literature suggests that workers could be visually, auditorily, and cognitively distracted by drones on future jobsites [7], supporting that drones should be considered a latent source of distraction.

Although SA and distraction are associated with attentional allocation, the main difference between them lies in three perspectives: (i) productivity, (ii) intention, and (iii) risk levels. First, while distraction typically compromises human productivity, the effect of SA on productivity might be neutral or even positive [24], [25]. Second, SA refers to an intentional behavior focusing on dynamic elements to ensure safety, whereas distraction can be regarded as an intentional or unintentional behavior [26]. Third, the risk level associated with interacting with drones is a key criterion for differentiating SA from distraction. If the risk is high, attentional allocation to drones is necessary and represents SA. Conversely, if the risk is low, such attentional allocation is unnecessary and can be considered a distraction. Therefore, these three perspectives were involved in this study to make the discussion comprehensive.

2.2 Immersive Technology Applications in Construction

As construction is one of the most hazardous workplaces, immersive technology, especially virtual reality (VR), provides researchers and practitioners with a platform to observe workers' naturalistic behaviors and responses without compromising their safety. A recent review categorized the majority of immersive technology applications in construction into three groups: (i) hazard identification, (ii) safety training and education, and (iii) safety inspection and instruction [27]. Specifically, the first group of research refers to developing an immersive construction site to capture workers' realistic hazard identification behaviors [28,29]. In addition, the use of immersive technology for training has been recognized as an effective method to enhance the cognitive learning of workers and to offer them an opportunity to learn from an experienced professional through virtual cues [30,31]. Augmented reality (AR) devices have been also utilized to inspect the alignment between drawings and the built construction on physical jobsites [32,33]. Recently, immersive technology has been increasingly applied to understand how workers will interact with robotic partners in future construction [4,34]. As future construction sites do not yet exist, it is impossible to study them directly. Immersive technology offers a practical solution by creating realistic simulations that enable researchers to explore worker-robot interaction.

2.3 Human-Drone Interaction Levels

While the risks of human-drone interaction are crucial in determining SA and distraction, previous studies have shown that these risks are directly influenced by interaction levels (e.g., coexistence and collaboration), as each level involves specific patterns of interaction between humans and drones [35,36]. Specifically, *coexistence* refers to a scenario where humans and drones maintain a shared workplace without a shared goal [37]leading to limited-to-no direct communication between humans and drones. Worker-drone coexistence in construction is often represented by the cases of on-site safety inspection and monitoring [38]. *Collaboration* denotes scenarios wherein humans and drones simultaneously work on a shared object, toward a shared goal, and in a shared space, and the action executed by any of the agents has immediate consequences on the other entity [39]. Worker-drone collaboration in construction has been commonly found in material delivery and installation tasks [2,40,41]. Compared to drones merely flying around jobsites without sharing workspace with workers, human-drone coexistence may pose a higher risk, with human-drone collaboration posing the highest risk, as workers must be close to drones to share an object. The risks would justify whether workers' attentional allocation to drones across different interaction levels is necessary.

3 Point of Departure

While drones have been recognized as potential robotic teammates to be incorporated into jobsites and revolutionize the construction industry, their presence will impose extra uncertainties on workers in future construction, including risks and distractions. While the concept of robot/no-robot and its impacts on human SA and productivity have been explored in the literature, the nature of human-drone interaction—ranging from no interaction to coexistence and collaboration—significantly determines how workers share workspaces with drones, and primarily remained understudied. The degree of workspace sharing directly influences the risks associated with each interaction level. Fig. 2 presents a graphical overview of the relationship between interaction levels and risks. Given that drones should be perceived as a hazard due to their latent collision with humans, workers must continuously perceive drones' risks and maintain their SA of drones, ensuring their safety on jobsites. Conversely, drones can act as distractions due to their physical presence, spinning blades, and noise, diverting workers' attention from primary tasks and potentially compromising productivity. Given that both SA and distraction stem from attentional allocation, this raises a question: Across different levels of interaction, are workers maintaining situational awareness of drones, or are they being distracted by them?

This study addresses the research question by utilizing mixed reality (MR) technology to simulate future construction job sites where drones are integrated. The MR environment immerses workers in a projected but realistic job site, allowing them to interact with drones in scenarios that closely resemble real-world conditions. The use of a simulated MR environment is essential for several reasons: First, construction is a safety-critical environment, and conducting an experiment on an actual jobsite would expose workers to unnecessary risks, potentially endangering their lives. Alternatively, the MR environment provides a controlled and realistic environment where naturalistic worker behaviors can be observed without compromising safety. Second, this study mainly discussed the future construction where the presence of drones will be prevalent, and MR offers a platform to accurately simulate this future landscape. Third, by leveraging the authenticity of MR, workers' perception of drone risks across different interaction levels, attention allocation, productivity, and subjective distraction assessment can be realistically captured.

To answer the above research question, this study examines the following hypotheses to assess participants' sense of presence in MR environments and its applicability for studying their naturalistic behaviors within different worker-drone interaction levels:

H_1: The developed MR environment with passive haptics and drone-related features (i.e., actual dimension, spinning blades, and sounds) strengthens workers' sense of presence and interaction with drones, ensuring their correct risk perception of drones.

H_2: Varying levels of interaction with drones significantly influences risk perception, attentional allocation, productivity, and subjective assessment of distraction, leveraging the heightened presence to capture workers' realistic metrics.

The MR approach ensures that the study's findings are grounded in realistic scenarios, making them more applicable to future jobsite environments. The findings of this study aim to offer insights into distinguishing distraction from SA across different levels of worker-drone interaction.

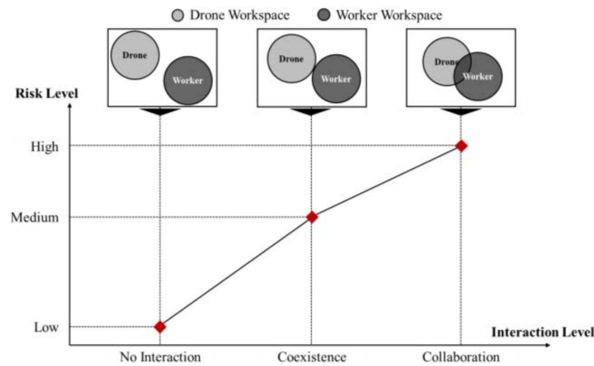


Fig. 2. Schematic representation of risks associated with worker-drone varying interaction levels.

4 Methodology

4.1 Experimental Design

To simulate worker-drone interaction in future construction, an MR bricklaying experiment in which workers were asked to team up with drones at different interaction levels was developed, as illustrated in Fig. 1. In the simulated experiment, workers completed a 7-min bricklaying task with MULE, which is a real-world bricklaying robot, while interacting with inspection and delivery drones, with these drones representing human-drone coexistence and collaboration, respectively. The MULE was designed to mitigate workers' physical burden by automatically lifting/dropping heavy concrete blocks while workers manually applied mortar and moved MULE to the correct positions. The sequential procedure that participants followed to complete the bricklaying involved manually applying mortar, moving the MULE to lift a block, and then placing the block onto the brick wall. These procedures must be repeated until the end of the experiment. The selection of this bricklaying task in this study stems from its representativeness of other construction activities that, traditionally, entail workers' physical effort, but the physical burden can be relieved from workers by incorporating robots, such as drywall panel installation [42].

In the simulated context, the inspection drone *coexisted* with workers by hovering overhead and following workers to examine the environment and the workers' progress for one minute. The coexistence nature of this interaction lay in the fact that workers only shared a workplace with the inspection drone without any shared goal or object. On the other hand, the delivery drone *collaborated* with workers by delivering a new mortar bucket to the workers on a scaffold when the old mortar bucket was empty. During the interaction with the delivery drone, the participants had to be in close proximity to the drone and pick up the new mortar bucket to continue the bricklaying task. Participants were given one minute to finish picking and returning the bucket. Thus, this collaborative relationship was built on the shared workplace, goal, and object between the workers and the delivery drone.

It is worth noting that, apart from the inspection and delivery drones, there were other irrelevant drones flying around the construction sites without any interaction with participants. All the drone-related interaction behaviors and flight paths were pre-defined and implemented to control all participants experiencing identical interactions with drones. Therefore, this study considered three interaction levels: *no interaction* (i.e., the drones on the background without any interaction with workers), *coexistence* (i.e., interaction with the inspection drone), and *collaboration* (i.e., the interaction with the delivery drone).

To promote realism of the MR environment, the simulated construction workplaces involved not only bricklaying-related objects (e.g., concrete blocks, shovels, and mortar buckets) but also various dynamic construction machinery (e.g., excavators), materials (e.g., rebar and concrete), and co-workers who were executing different tasks to represent the dynamic nature of construction jobsites, heightening the sense of presence. Additionally, the MR model was enhanced with environmental modalities (i.e., construction background sounds and wind simulated by a fan) and passive haptics (i.e., physical guardrail of a scaffold) to enhance participants' sense of presence. To increase the sense of presence of the simulated drones, the developed scenario included spinning blades and increasing drone sounds as they approached.

4.2 Participants

This study recruited 105 healthy participants (71 males and 34 females) who were aged from 18 to 36 years (Mean= 22.857, STD= 3.404). All the subjects were current students with construction work experience at Purdue University, representing the next generation of workforce in construction. Having such work experience would ensure their understanding of the responsibility for being a construction worker. However, none of them possessed drone experience within construction based on their self-report. A lack of experience with drones would reflect the actual situation where drones or other technologies are just introduced to jobsites.

4.3 Experimental Procedure

The experiment was initialized with participants signing a consent form and filling out a demographic pre-survey. Subjects were provided with a 10-minute training to familiarize themselves with the bricklaying task and the functionalities of each drone. Then, participants were equipped with a VR HMD with a built-in eye tracker, two hand controllers, three motion trackers, a medical wristband, and a functional near-infrared spectroscopy (fNIRS) cap.

Thereafter, they completed the 7-min bricklaying experiment, experiencing both the coexistence and collaboration interaction conditions with drones once, while the order of two conditions was counterbalanced to prevent order bias in within-subject analyses. As the no-interaction condition represented drones flying around the construction site, durations without interaction with drones were considered part of this condition. Finally, a post-survey was conducted to understand their sense of presence and subjective distraction assessment. The entire experiment approximately took one hour, and a $40 Amazon gift card was offered as compensation for completing the experiment. All the procedures were approved by the Purdue Institutional Review Board (IRB).

4.4 Apparatus

HTC Vive Pro Eye (manufactured by HTC Corporation, Taoyuan, Taiwan) was selected to present the developed bricklaying experiment. It has a built-in Tobii eye-tracker with a refresh rate of 90 Hz and a 110^o field of view. The MR environment was developed in Unity, and the experiment was run on an Alienware PC with an AMD Ryzen 9 5950X 16-Core processor and an NVIDIA GeForce RTX 3090 graphics card. Furthermore, the Empatica E4 wristband (manufactured by Empatica, Boston, United States) was deployed to collect real-time physiological data (e.g., electrodermal activity (EDA)), and a fNIRS cap (Brite 23, Artinis, Netherlands) was used to capture human brain activation. Due to the page limit and scope of this paper, we mainly discuss eye-tracking findings and distraction-related reporting.

4.5 Performance Metrics and Statistical Tests

4.5.1 Sense of Presence

This study developed a MR environment to simulate the futuristic bricklaying task where workers needed to interact with drones at different levels. Since workers' naturalistic behaviors and responses are crucial for the analyses, ensuring their high sense of presence in the MR environment is essential. Therefore, this study examined the sense of presence of the MR environment from two perspectives: Place Illustion (*PI*) and Plausibility Illusion (*Psi*). *PI* refers to the sense of being in a place that is not the physical location of the user. In the developed MR environment, participants should feel as if they are working on an elevated scaffold rather than in an office. On the other hand, *Psi* represents the extent to which the events, interactions, and objects within the environment are believable and consistent with the users' expectation based on real-world experiences. In this experiment, participants should experience their interactions with drones as realistically as they would in an actual construction site. By ensuring both PI and Psi perspectives, the MR environment aims to foster realistic immersion, and to make it suitable for studying worker behaviors in drone-integrated jobsites.

In the 7-point Likert post-survey, participants were asked to subjectively report their sense of presence by answering four main questions, as shown in Fig. 3. The first two questions addressed the evaluation of PI in the MR environment, while the other question focused on Psi.

4.5.2 Attentional Allocation

The participants' visual attention toward each area of interest (AOI) (i.e., different drones) was monitored to calculate two commonly used eye-tracking metrics: dwell time and run count. Dwell time represents the total time a subject fixated on an AOI, while run count denotes the number of times a subject returned their attention to each AOI. Specifically, this study utilized dwell time percentage (i.e., dwell time/total duration of each condition) and run count per second (i.e., run count/total duration of each condition). This processing mitigated the bias resulting from the varying duration of different conditions.

4.5.3 Bricklaying Productivity

In the developed MR experiment, while participants might maintain their SA of drones or be distracted by drones, the bricklaying task represented the primary task that they should concentrate on. More importantly, the productivity of the primary task is a key indicator that provides insights into whether workers are being distracted. Consequently, the bricklaying productivity rate (i.e., the number of blocks laid by participants per second) across three different interaction levels was calculated to mitigate the impact of varying durations.

4.5.4 Distraction

In addition to productivity, workers' subjective distraction assessments provided insights into how they memorized and perceived their distraction-related behaviors at different interaction levels. As introduced, this study considered *recall* (i.e., the extent to which subjects exhibited any distraction-related behaviors, such as looking at drones) and *reflection* (i.e., the extent to which participants felt it was necessary to exhibit distraction-related behaviors, such as looking at drones) into the distraction assessment in a 5-point Likert scale. The distraction questionnaire was developed by a well-cited study [43].

4.5.5 Statistical Tests

Apart from descriptive analyses, this study executed multiple repeated measure analysis of variance (RMANOVA) to conduct within-subject analyses by comparing the difference in attentional allocation, productivity, and distraction across three levels of human-drone interactions. This approach ensures that individual differences

#	Description	Type
Q1	To what extent you felt present in the virtual environment, as if you are really there and everything you saw was real?	PI
Q2	To what extent you felt standing on a scaffold rather than an office during the experiment?	PI
Q3	To what extent the visual aspects (e.g., virtual workers, equipment, and spinning blades) of the environment immerse you?	Psi
Q4	To what extent the auditory aspects (e.g., background sound and drone sound) of the environment immerse you?	Psi

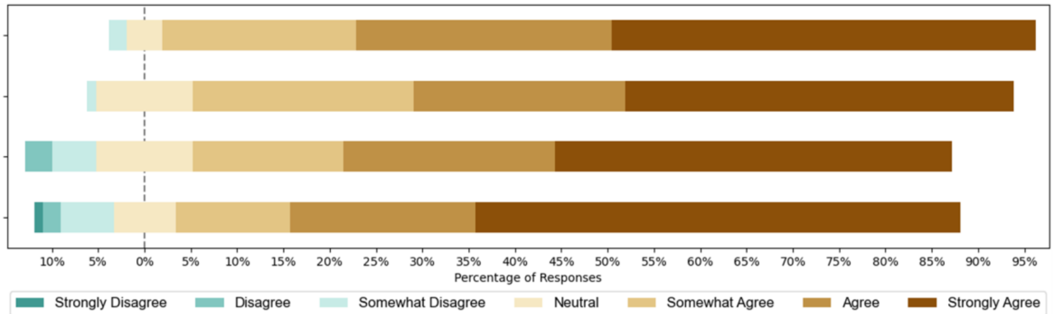


Fig. 3. Participants' sense of presence.

are controlled, allowing for a more precise analysis of the effects of the interaction conditions on the measured variables.

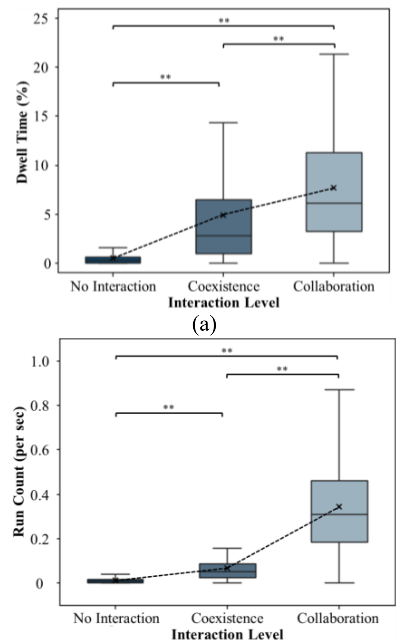
5 Results

5.1 Sense of Presence in MR Environment

Participants' high sense of presence in this MR environment can be verified by the high PI (Q_1: Mean ± STD = 6.114 ± 0.993, Median = 6.0; Q_2: Mean ± STD = 5.943 ± 1.082, Median = 6.0) and Psi (Q_3: Mean ± STD = 5.800 ± 1.369, Median = 6.0; Q_4: Mean ± STD = 5.974 ± 1.411, Median = 7.0) values, supporting the first hypothesis (H_1). Fig.3 illustrates the distribution of participants' responses to individual questions. The results provided a reliable foundation, showing that the MR environment accurately reflected future construction sites and that the collected data captured workers' naturalistic behaviors during their interactions with drones.

5.2 Worker Attentional Allocation across Different Interaction Levels

This study considered two eye-tracking metrics (i.e., dwell time percentage and run count per second) to understand how participants allocated their attentional resources on drones across different interaction levels. Fig. 4a shows a graphical overview of the relationship between dwell time percentage and three interaction levels: no interaction (Mean ± STD = 0.461 ± 0.803), coexistence (Mean ± STD = 4.864 ± 7.087), and collaboration (Mean ± STD = 7.675 ± 6.175). The results from ANOVA analysis showed that the impact of interaction levels on dwell time percentage was significant (F(2,312)=46.777, p=0.000<0.05, η^2=0.403). The post-hoc Turkey tests confirmed the significant difference between each pair of interaction levels: (i) no interaction vs. coexistence ($t(312)$= 5.856, p= 0.000<0.05, d= 5.113), (ii) no interaction vs. collaboration ($t(312)$= 9.595, p= 0.000<0.05, d= 1.637), and (iii) coexistence vs. collaboration ($t(312)$= 3.739, p= 0.000<0.05, d= 0.637).



(b)

Fig. 4. Changes in worker attentional allocation toward drones across three Interaction Levels. (** p<0.05)

Moreover, Fig. 4b presents how subjects' run count per second varied according to the conditions of no interaction (Mean ± STD = 0.014 ± 0.018), coexistence (Mean ± STD = 0.067 ± 0.059), and collaboration (Mean ± STD = 0.343 ± 0.220). The ANOVA test indicated a significant effect of interaction levels on run count (F(2,312)= 188.351, p= 0.000<0.05, η^2=0.522). Similarly, the post-hoc analyses showed the significant difference between each pair of interaction levels: (i) no interaction vs. coexistence ($t(312)$= 2.909, p= 0.011<0.05, d= 0.735), (ii) no interaction vs. collaboration ($t(312)$= 18.073, p= 0.000<0.05, d= 2.081), and (iii) coexistence vs. collaboration ($t(312)$= 15.164, p= 0.000<0.05, d= 1.646). The findings supported the second hypothesis (H_2).

5.3 Worker Productivity across Different Interaction Levels

As highlighted, productivity is critical in identifying human distraction at work. Therefore, subjects' bricklaying productivity rates across different interaction levels were recorded, including no interaction (Mean ± STD = 3.246 ± 1.020), coexistence (Mean ± STD = 2.805 ± 1.032), and collaboration (Mean ± STD = 2.258 ± 1.292), Fig. 5. The outcome of the ANOVA test revealed that interaction levels significantly influenced workers' productivity rate ($F(2,312)=20.449$, $p=0.000<0.05$, $\eta^2=0.103$). Additionally, the post-hoc analyses demonstrated the significant difference between each pair of interaction levels: (i) no interaction vs. coexistence ($t(312)=2.849$, $p=0.013<0.05$, $d=0.377$), (ii) no interaction vs. collaboration ($t(312)=6.383$, $p=0.000<0.05$, $d=0.862$), and (iii) coexistence vs. collaboration ($t(312)=3.534$, $p=0.001<0.05$, $d=0.430$). These outcomes aligned with the second hypothesis (H_2).

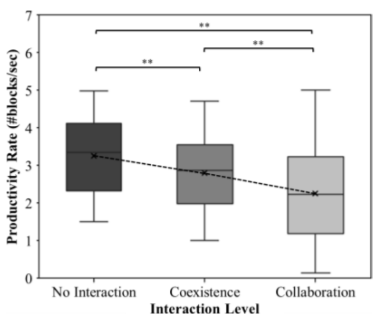


Fig. 5. Changes in worker productivity across three levels of interaction with drones. (** $p<0.05$)

5.4 Worker Subjective Distraction Assessment across Different Interaction Levels

Fig. 6 presents a graphical overview of these two metrics across different interaction levels. Specifically, participants' recall scores were low, medium, and high under the conditions of no interaction (Mean ± STD = 2.305 ± 1.194, Median = 2.0), coexistence (Mean ± STD = 2.800 ± 1.577, Median = 2.0), and collaboration (Mean ± STD = 3.533 ± 1.442, Median = 4.0), respectively. This result aligned with the findings derived from eye-tracking metrics (i.e., dwell time and run count).

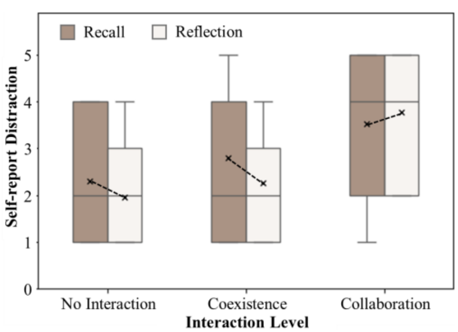


Fig. 6. Changes in worker distraction recall and their reflections on necessity of allocating attention toward drones at three interaction levels.

On the other hand, regarding the reflection, a similar trend was observed, where participants exhibited low scores under no interaction (Mean ± STD = 1.952 ± 1.086, Median = 2.0) and medium scores under coexistence (Mean ± STD = 2.257 ± 1.101, Median = 2.0). Their high score was identified at the collaboration level (Mean ± STD = 3.771 ± 1.288, Median = 4.0). It is worth highlighting that the comparisons between the recall and reflection scores indicated dissimilar patterns across different interaction levels. Overall, participants felt that the number of distraction-related behaviors they exhibited was unnecessary under the no interaction and coexistence levels. By contrast, they felt it was vital to maintain their situational awareness by checking the drone status frequently at the collaboration level. These findings confirmed the second hypothesis (H_2).

6 DISCUSSION

Although drones display huge potential to improve construction efficiency and automation, previous studies have already mentioned that drones could become a hazard (i.e., workers should maintain SA) or a distractor for workers [7]. However, given that SA and distraction relate to visual attention, it remains unknown whether workers are situationally aware of drones, which is a *positive* statement, or distracted by drones, which is a *negative* statement. Therefore, this study aims to address this issue by developing MR environment to capture workers' naturalistic behaviors across different levels of interaction with drones. Based on participants' self-report in the post-experiment interview, the passive haptics (i.e., physical guardrails) and environmental modality (i.e., wind and construction sound) facilitated their high sense of presence in the MR environment. Moreover, the manipulated visual (i.e., spinning blades) and auditory (i.e., drone sound) aspects of drones enhanced participants' perception of interacting with real drones. This finding was consistent with a recent study investigating whether drones trigger user stress and discomfort [44]. The authors corroborated that the ecological validity of the virtual environment was strengthened by adding spinning blades and unpleasant drone sound. To summarize, participants' high sense of presence in the MR environment ensured that their risk perception of drones at different interaction levels was realistic and as expected (see Fig. 2).

Given that participants' high sense of presence and interaction has been validated by their self-report, it is reliably anticipated that they should perceive the risk levels of no interaction, coexistence, and collaboration as low, medium, and high. The discussion would consider the condition of no interaction as a baseline to evaluate whether workers were situationally aware of drones or distracted by drones. Regarding attention, the results derived from eye-tracking metrics indicated that participants allocated significantly more attentional resources to drones in coexistence and collaboration. This finding confirms our premise that human-drone interaction captures worker attention, regardless of whether it stems from SA or distraction [45,46], necessitating the consideration of other performance metrics.

During worker-drone coexistence, the analysis shows that workers exhibited significantly lower productivity than their counterparts for no interaction. This phenomenon suggests the possibility of workers being distracted by drones; however, as previously mentioned, assessing their intention is also important in drawing a conclusion. Based on participants' subjective distraction assessment, they felt the number of distraction-related behaviors under coexistence was unnecessary. This reflection challenges the notion that workers intentionally focus on the drones during coexistence, instead indicating that their attention is being diverted involuntarily by the drones, leading to distraction.

Further, workers' significantly lower productivity was found during human-drone collaboration, indicating the possibility of distraction. Nevertheless, the subjective distraction assessment reflects that the participants felt it was necessary to allocate more attention to the drones. This reflection supports participants intentionally allocated attention and maintained *situational awareness* of drones during collaboration, which, in turn, impacted their productivity.

Although this research has exhibited considerable contribution to the body of knowledge and practice, there remain some limitations worth noting. First, this study recruited current students who represent the next generation of the workforce in the experiment; however, more experienced workers can also be recruited to replicate this study. Second, apart from attentional allocation, other human psychophysiological responses can be included in the analysis to explore different aspects (e.g., cognition and stress) of SA and distraction. Third, while this study included larger number of male participants compared to female ones, reflecting the current male-dominated demographic in the construction industry, it is worth examining the potential impact of gender on workers' behaviors during human-robot interactions. Fourth, this study concentrates on the situation where workers remain unfamiliar with robotic technologies at the beginning, while how the findings will be changed by their long-term exposure must be addressed.

7 Conclusions

This research conducted a user study examining the potential of deploying the MR environment to understand whether workers were situationally aware of drones or distracted by drones across different interaction levels. This potential has been validated by participants' self-report of their high sense of presence in the MR environment and of interaction with drones, providing a reliable platform to capture workers' naturalistic behaviors across different levels of human-drone interaction in future construction. Moreover, the findings illustrated that workers were *distracted* by drones during coexistence according to their decreasing productivity and subjective distraction assessment. However, workers were more situationally aware of drones during collaboration, supported by their intention to allocate attention to drones. To summarize, this study contributed to (i) verifying the robustness of the MR environment in simulating human-drone interaction on future jobsites, and (ii) distinguishing situational awareness and distraction based on multidimensional performance metrics across different interaction levels. Further, this MR approach ensures that the study's findings are grounded in realistic scenarios, making them more applicable to future jobsites.

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