

Using gesture and speech communication modalities for safe human-drone interaction in construction

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ABSTRACT

Drones are increasingly being used in the construction industry for numerous applications. However, their presence poses safety risks to construction workers who work around them but have limited control and information about these drones. To ensure safety, general construction workers who are not part of the pilot teams should also be able to communicate their concerns with drones effectively and naturally. Despite its importance, research on human-drone communication within construction for non-operator workers is scarce. This study developed and evaluated communication protocols using gesture and speech modalities to ensure safe human-drone interactions for non-operator workers in construction environments. An immersive VR environment replicating construction site dynamics was developed, enabling workers to utilize gesture or speech communication protocols while working with drones. A total of 100 participants were recruited for the user-centered study analysis on an immersive VR construction site, and the safety implications and cognitive loads of both protocols were assessed both quantitatively and qualitatively. The findings suggest that gesture-based communication is more effective than speech-based communication in mitigating risks and alleviating the negative impacts of drones without imposing additional cognitive strain on users on construction sites.

1. Introduction

Advanced technologies have become widely adopted and implemented in the construction industry to enhance safety, quality, schedule, and cost performance [1]. Specifically, drones, also known as unmanned aerial vehicles (UAVs), have gained popularity in construction projects due to their numerous advantages. According to DroneDeploy, construction is already the largest adopter of drones among the US industries, with 94 % of respondents using drones as their primary tool for digitizing construction sites [2]. A recent industry report shows that 88 % of drone users in the construction industry intend to either increase or maintain their investment in drone technology [3]. According to another industry report, the size of the worldwide market for construction drones is projected to increase to \$11,968.6 million by 2027, with a compound annual growth rate of 15.4 % from 2020 to 2027 [4]. More than half of the drone users in the construction industry believe that drones are expected to become even more common in the near future compared to their current usage, with 21 % holding the opinion that they will be ubiquitous [2]. Drones have been employed in the construction industry for numerous applications, such as building

inspection [5,6], damage assessment [7,8], site surveying and mapping [9,10], progress monitoring [11,12], and safety inspection [13]. Moreover, they are being explored for more active roles in applications beyond data collection, such as improving operations, reducing cost, and increasing safety [2], including assembling construction components [14].

However, since the construction industry revolves around human labor, drones must operate in close proximity to human workers, impacting each other significantly. As drones evolve from passive observers to active participants in construction projects, human workers must adapt their behavior to collaborate with these aerial agents. Similarly, drones must adjust their flight paths to ensure human safety. The presence of drones alongside various construction crews, even those unrelated to drone operations, poses physical risks to workers and affects them psychologically. Given that the construction industry is already considered one of the most dangerous [15], a rising risk of unintended contact between drones and workers [16] poses new safety challenges and increased cognitive loads for the workers [17].

To mitigate safety risks associated with drones in construction, active engagement between construction personnel and drones via various

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communication methods is crucial. Effective communication holds paramount importance in an industry prone to accidents and fatalities. It aids in reducing uncertainty [18], perceived threat, and lack of control [19,20], which are known stressors in construction work. By facilitating effective communication, workers can actively exchange information and influence drone behavior. For instance, if workers feel unsafe due to drones' proximity, they should be able to redirect drones to prevent collisions. Human-to-drone communication should also be intuitive and natural to foster trust [21], build confidence, and establish a connection between workers and drones [22] to improve performance consequently [23] and enhance productivity [24]. Conversely, inadequate communication may impair human judgment and decision-making, making drone interaction more challenging and less safe for construction workers [13,25].

This study's primary objective is to establish and assess a safety communication protocol utilizing natural interaction methods, specifically speech and gestures, for general workers (those who possess limited knowledge of drone operations but work within drone-inhabited construction sites). Virtual reality (VR) technology was employed to investigate the efficacy of gestures and speech for human workers to express their safety requirements. Protocols for human-drone communication via gestures and speech were developed and validated within a virtual construction environment. Additionally, a user-centered study, coupled with safety performance assessments in the virtual setting, was conducted to evaluate the effectiveness and distinctions qualitatively and quantitatively between gesture and speech communication modalities in facilitating safe human-drone interactions.

2. Background

2.1. Safety challenges of human-drone interaction in construction

The construction industry, already known for its high risk, has seen over 5,000 fatal work injuries in the United States in the past five years, as reported by the Bureau of Labor Statistics [15]. Beyond fatalities, the industry also recorded over 174,000 non-fatal injuries and illnesses in 2020 alone [26]. These non-fatal incidents can result in severe disability, income loss, chronic pain, and ongoing medical expenses, significantly impacting workers' quality of life. Even minor injuries can lead to missed workdays, reduced productivity, and increased medical costs [27]. As the integration of drones in construction grows, it introduces additional safety challenges, potentially heightening the danger on construction sites, particularly for workers exposed to hazardous conditions, such as working at heights, handling dangerous tools, or operating near heavy equipment.

Integrating drones in construction presents various safety challenges encompassing physical risks, psychological impacts, and negative perceptions. Physical risks are multifaceted and involve potential hazards such as collisions with flying drones, the danger of being struck by falling drones or their components, entanglement in drone rotors and moving parts, and exposure to dust emissions generated by swiftly spinning drone rotors [28]. The growing prevalence of drones on construction sites has amplified concerns regarding physical risks, with expectations of increased incidents, including near-miss events and more hazardous accidents that could result in severe or fatal injuries [16]. Psychological impacts emerge in the form of acute stress, which elevates cognitive load and sensory saturation, culminating in negative emotional states and potential fatigue. While the previous study [29] did not find statistical evidence to associate drone presence with changes in physiological and emotional states, as the methods and metrics used in experimental settings may not fully capture the complexities of real-world construction sites, this result is not equivalent to drones having no psychological effects. Therefore, further research should be conducted to explore potential safety implications in practical significance or other psychological impacts, especially when designing training programs or tools to facilitate safe human-drone interaction. For instance, the

presence of drones can introduce noise and visual distractions, triggering adverse emotional responses among workers laboring near drones and potentially provoking a sense of little or no personal control [30]. Working alongside drones can also intensify the fear of errors, as employees perceive the need for flawless execution, straining their capabilities further in already demanding construction environments [31]. It should be noted that construction workers' negative perception of drones may lead to the fear of working with or around drones [32]. These concerns include a lack of perceived safety, where workers have doubts about the reliability or precision of drones, consequently avoiding working with these flying robots. Furthermore, workers might exhibit negative attitudes toward drones, viewing them as a threat rather than a helpful tool or friendly co-worker. Privacy concerns may exacerbate these negative perceptions as workers perceive surveillance, leading to cognitive distraction and heightened accident risks [28].

Previous research has extensively recognized the safety challenges inherent in human-drone interaction within construction sites and the consequential impact on worker safety and well-being. While previous literature [28] has proposed various conceptual frameworks and recommendations for integrating UAVs safely into construction environments, there is a notable lack of empirical studies and tested solutions that address the specific communication protocols and safety needs of workers. This study endeavors to bridge this void by crafting a comprehensive communication protocol to empower human workers with active and effective means of communication with drones, ultimately serving as a safeguard against physical risks, particularly accidents stemming from drone collisions. It is envisioned that such a human-to-drone communication protocol will not only mitigate psychological impacts by cultivating positive emotional states among workers and alleviating cognitive burdens but also reshape worker perceptions by bolstering their sense of safety and countering negative attitudes. Ultimately, this endeavor aims to foster a safer and more harmonious work environment.

2.2. Human-robot communication for safe co-existence

People use communication to exchange information and reduce uncertainty [33]; positive communication leads to positive relationships that can enhance trust, satisfaction, and comfort. Effective communication is essential in the construction industry to ensure occupant safety, given the industry's high risk of accidents and fatalities, and communication among team members improves safety outcomes and promotes worker safety [34–36]. Communication between humans and robots also provides similar benefits by creating meaning and exchanging information to achieve better performance [37]. Effective communication between humans and robots can give robots the intelligence to understand the situation [24] and the respective responsibilities [38]. It also helps to develop common ground and a shared understanding, especially the decision-making in complex environments [39], such as construction sites. The modes of human-robot communication applied in construction include direct physical interaction, remote contactless interaction, and message exchange through interfaces [40].

Human-robot communication also has essential safety implications that can help react to unexpected or potentially unsafe situations [41,42]. For example, effective human drone communication extends the capability of individuals who were previously outside the drone operation team to also be able to intuitively engage with the drone system and address safety concerns in potentially hazardous situations [43,44]. Establishing such effective communication channels empowers drones to grasp the contextual situation, comprehend their responsibilities, rectify errors, and ensure human worker safety [24,38]. Furthermore, employing natural communication modalities is pivotal for fostering trust between humans and co-robots [21], enhancing performance in time-sensitive environments [23], optimizing productivity and resource utilization [24], instilling confidence in interactions, and even nurturing a sense of personal connection or companionship

between workers and drones [22].

As the adoption of drones in construction tasks continues to grow, there is a pressing need to enhance their operational intelligence to meet performance requirements and ensure worker safety. The conventional remote control method for drones is cumbersome and unnatural, especially for individuals engaged in multiple on-site tasks [45]. Notably, construction workers performing construction activities and sharing the same space with drones often struggle to express safety concerns directly. Instead, they must rely on other personnel to communicate with drone operators, whose lack of hazard recognition and safety identification may lead to drone incidents in construction [46]. This lack of direct communication methods with drones may hinder workers' ability to address potential risks. Ideally, general construction workers who were previously uninvolved in drone operations could benefit from effective direct communication with drones, allowing them to redirect the drones when they feel unsafe in close proximity. This proactive approach could prevent potential hazards and create a safer on-site working environment. To realize this vision, innovative communication methods are essential to empower human workers to communicate effectively and actively with drones, especially addressing safety challenges in human-drone interaction within construction. Enabling active communication with drones holds the potential to reduce miscommunication and misunderstandings, ultimately mitigating the adverse effects of human-drone interaction while simultaneously enhancing workers' safety.

2.3. Communication modalities in human-drone interaction

Extensive literature has explored a range of natural communication modalities intuitively suited for humans, including gestures, speech, gaze, touch, movements, and body postures, with the aim of enhancing human-drone communication [47–53]. Among the modalities commonly employed in human-robot interaction, visual and voice commands have gained prominence due to their user-friendly nature, requiring minimal additional tools or training [54]. In the context of human-drone communication, a previous elicitation study revealed that the majority of users favored gestures to command drones and complete tasks, followed by speech or a combination of both modalities [45].

Previous studies underscore the remarkable simplicity of natural gestures, enabling individuals to convey a wide range of ideas with ease [55]. Consequently, human-drone interaction necessitates only a concise set of gestures to effectively transmit information, as both their execution and recognition prove sufficient. Several gesture-focused studies have endeavored to determine the naturally employed gestures by individuals when interacting with drones [45,56,57]. Existing research demonstrates that gesture can be used to control flight motion (e.g., 'Closer,' 'Further,' 'Stop,' 'Go Away' commands) [58–67], define figural trajectories (e.g., 'Circle,' 'Spiral' commands) [68], and manipulate visual sensors of drones (e.g., 'Take Picture,' 'Record Video' commands) [56,69]. Notably, commercial drone manufacturers like DJI have also ventured into developing gestural languages (e.g., 'Launch' and 'Follow' commands) for user interactions [70].

Previous studies also underscore the uncomplexity of speech communication medium for human interaction with drones or other robots, as users need only remember voice commands, requiring a shorter training period [71]. It's noteworthy that certain research endeavors have explored both gesture and speech communication modalities utilizing similar sets of commands. For instance, some studies have investigated how individuals naturally employ speech to command drones (e.g., 'Up,' 'Down,' 'Closer,' and 'Further' commands) [45,69]. Specifically, research on the development of gesture recognition systems has delved into creating fusion communication systems that combine gesture and speech (e.g., 'Go Forward,' 'Go Back,' and 'Go away' commands) [58,60,62,65,67]. Some other studies have exclusively concentrated on developing speech recognition systems and commands capable of altering drones' general motions (e.g., 'Up,' 'Down,' and 'Stop'

commands) [72–75]. Additionally, commercial drone manufacturers have introduced speech-controlled drones, allowing speech commands to govern both general motions (e.g., 'Takeoff,' 'Land,' 'Stop' commands) and sensors (e.g., 'Take a Picture' command) [76]. The collective body of research on gesture and speech communication furnishes invaluable insights that inform the design and implementation of the proposed protocol for ensuring safe human-drone interaction.

3. Research gap and point of departure

The majority of the studies on human-drone communication primarily focused on technical development, which enabled humans to communicate with drones through different commands, such as changing the drone's motions or trajectories and controlling the embedded sensors on the drone (see section 2.3). Since these studies center solely around the operational needs of drone operators [45,56,57,69] rather than non-operators who share the same environment and need to work safely around drones, the proposed commands of these existing studies communication only focus on operator-task-related and tend to overlook the pivotal role of communication in ensuring safety. Although communication has been proven effective in enhancing safety between human workers or in human-robot interaction (see section 2.2), no safety-oriented communication commands have been designed and evaluated between drones and non-operators working around them.

Despite the increasing integration of drones in the construction industry, no studies have addressed empowering human-drone communication for non-operator construction workers, especially in the context of their safety. Consequently, a comprehensive understanding and practical solutions concerning effective safety communication between drones and general workers have yet to be established. Our preliminary study has demonstrated that gesture-based communication has great potential for human-drone interaction in construction environments [77]. However, a research gap still exists concerning how different communication modalities can impact the safety and well-being of general construction workers when they are empowered to actively convey their safety needs to drones operating in close proximity. To bridge this gap, this study focused on addressing the increasing safety challenges of drone presence on the construction site by developing a communication protocol tailored for general workers outside the drone operating team who possess limited drone-related information. The study encompasses user-centered investigations designed to assess the effectiveness and differences of gesture and speech communication modalities to ensure safe human-drone interaction.

4. Research objectives and methodology

This research aims to develop and assess the effectiveness of gesture-based and speech-based communication protocols to facilitate safe human-drone interaction on construction sites. The main goal of this study is to enable workers to communicate their safety needs to drones while understanding the impact of these protocols on workers' safety and their overall experience during interactions with drones. To achieve this goal, the study pursued the following objectives:

- (1) Development of gesture-based and speech-based communication protocols for facilitating safe human-drone interaction on construction sites,
- (2) Evaluation of the influence of these communication protocols on physical risks, psychological impact, and worker perceptions during human-drone interactions.

VR as a methodological tool Given the challenges and potential risks associated with conducting such research on real construction sites, which could expose participants to actual dangers, this study employed VR technology to simulate work scenarios, on-site drone operations, and

human-drone interactions. VR offers a safe and cost-effective platform for testing and evaluating scenarios that may involve potential hazards or uncertainty [78]. It ensures worker safety while still enabling realistic simulations and visualizations, allowing participants to engage with digital objects and virtual spaces, and creating a realistic and interactive virtual world [79]. VR can also evoke lifelike responses at both behavioral and psychophysiological levels [80], enabling the reproduction of a realistic human-robot interaction experience in complex scenarios [81]. The use of VR technology has been prominent in several facets of the construction industry, including simulation [82–84], education [85], training [86], and visualization [87,88], and as a reliable tool to assess human-robot interaction under construction environments [89]. Existing studies also explored utilizing VR to simulate drone operating environment and provide operator training [90–92], simulate drone-related safety risks [84,93], and assess the human-drone interaction in response to drone proximity [94–96], flight characteristics [97], and the perception of drone social companionship [98].

Therefore, to assess communication protocols that facilitate safe human-drone interaction on construction sites, a virtual construction site environment was developed in this study to replicate and visualize potential interactions between workers and drones. This virtual environment aims to represent construction workers performing general construction activities in hazardous environments and facing additional safety risks related to drones. The VR construction scenario serves as a platform that seamlessly integrates the proposed communication protocol. It also creates situations where participants need to utilize the communication protocol, evoking realistic responses, including behavioral, psychophysiological, and perceptual reactions, when interacting with drones.

Fig. 1 illustrates the three phases required to complete this study:

- (1) **Protocol Development:** This phase focused on identifying the safety needs of workers who work around drones on sites and establishing communication protocols using gestures and speech to communicate those safety needs to drones.
- (2) **VR Development:** This phase focused on creating a virtual environment to mimic a realistic drone-populated construction site where workers and drones can interact using the developed communication protocols.
- (3) **Experimental Assessment:** This phase of the study focused on a user-centered experiment to assess the influence of these communication protocols on physical risks, psychological impact, and worker perceptions during human-drone interactions.

5. Protocol development

Considering previous literature on gesture- and speech-based communication modalities, this phase focused on the development of

a communication protocol for safe human-drone interaction. The protocol was designed to utilize either modality to cater to the safety needs of construction workers operating around drones on construction sites. The primary objective was to empower workers to engage with drones actively, ensuring their safety and well-being during construction tasks, particularly in potentially hazardous scenarios. Instead of serving as passive observers, workers gained the capability to issue commands, actively influencing drone behavior and potentially augmenting their safety perception about drones. For instance, workers could halt drones when they felt unsafe in close proximity or direct them away to prevent potential collisions. In this phase, the initial critical commands for human-drone communication were identified, serving as the foundation for workers to communicate their safety requirements effectively. These commands were then utilized to develop both gesture-based and speech-based communication protocols to facilitate safe human-drone interaction.

6. Identification of critical commands to communicate safety needs

In this phase, the safety communication needs of construction workers to interact with drones were thoroughly assessed. This entailed gaining a comprehensive understanding of the specific challenges and concerns faced by workers when working in close proximity to drones. While empowering workers to communicate their safety requirements to drones was a primary focus, it was equally important to establish boundaries to prevent potential misuse or interference with drone operations. Therefore, the development of the communication protocol was carefully tailored to address workers' safety needs without granting excessive control over drone operations.

As discussed in section 2.1, the potential safety challenges were categorized into three key areas: physical risks, psychological impacts, and worker perceptions [28,99]. The safety requirements for workers to safely interact with drones should be not only maintaining physical safety but also ensuring that the proximity is comfortable for humans [100]. To mitigate physical risks, it was imperative for workers to maintain a safe working distance between themselves and the drones. Despite the presence of obstacle detection features in commercial drones, the dynamic and complex working environment of construction sites could still lead to potential collisions [84]. Thus, enabling workers to actively communicate with drones and keep a safe distance to prevent potential collisions was deemed essential for ensuring their safety. Providing collision avoidance is not sufficient as when robots share the same workspace with humans, they also need to be able to stay within a specified distance without causing discomfort [101]. Additionally, to address safety risks associated with psychological impacts, such as negative emotional states and increased cognitive loads when working closely with drones, workers needed the ability to redirect drones from their predetermined flight paths if they felt uncomfortable or unsafe,



Fig. 1. Research methodology.

and this could have a potentially positive impact on workers' perceptions regarding drones and their overall sense of safety on the job site. Therefore, drones must meet safety requirements by maintaining or adjusting a safe distance to prevent potential physical contact. They must also allow workers to alter the drone's flight path if they feel uncomfortable while still enabling the drone to continue its task. In light of these safety requirements, four critical commands were identified:

- (1) *Stop Task*: Workers could command the drone to stop or halt its movement.
- (2) *Keep Distance*: Workers could command the drone to adjust the distance between them.
- (3) *Change Path*: Workers could command the drone to alter its flight path.
- (4) *Resume Task*: Workers could command the drone to continue its flight task from a stopped position.

6.1. Proposed gesture- and speech-based communication protocol

This step involved the integration of the previously identified critical commands into the framework of gesture- and speech-based communication modalities as part of the communication protocol for safe human-drone interaction. Beyond merely incorporating the four critical commands, several additional considerations shaped this integration process. Firstly, ensuring compatibility and comparability between the gesture- and speech-based modalities was paramount for the upcoming experiment. Secondly, the design of gesture and speech commands required them to be natural, consistent, safe, and easily executable within the construction site context. Lastly, it was imperative that the commands within each modality maintained their distinctiveness to prevent any potential interference.

Building upon the critical commands identified in the previous step and drawing insights from the existing literature on gesture- and speech-based communication modalities, a communication protocol for safe human-drone interaction was devised. The existing gesture and speech commands found in the literature were aligned with the identified critical commands that enable drones to meet the safety requirements of workers, including not only maintaining physical safety but also ensuring that robot proximity is comfortable for them to share the same work environment. These commands should be effectively utilized in construction environments where typical construction activities occur. The commands should also have minimal training requirements for workers, as they already perform construction tasks in complex site environments. Workers should only need to remember and familiarize themselves with the most natural and accessible commands to stay safe. Specifically, four speech commands were established: "Stop," signifying the Stop Command to halt or pause drone movement; "Back," employed for the Keep Distance Command to modify the distance between human workers and the drone; "Go Away," serving as the Change Path Command to redirect the flight path; and "Keep Going," functioning as the Resume Task Command to continue flying from a stopped position.

Table 1

Proposed Gesture- and Speech-based Communication Protocol.

Critical commands	Stop Task	Keep Distance	Change Path	Resume Task
Speech-based Commands	"Stop"	"Back"	"Go Away"	"Keep Going"
Gesture-based Commands				

Additionally, gesture commands were developed, featuring a closed fist gesture for "Stop," a flat palm extended away from the face for "Back," an index finger pointing outward for "Go Away," and a flat palm directed toward the face for "Keep Going." These gestures were intentionally designed to be distinct from one another, ensuring unambiguous communication between humans and drones. A comprehensive overview of the communication needs, and specific commands is presented in [Table 1](#).

7. VR development

This phase aimed to immerse users in an interactive experience where they could apply the proposed communication protocol for safe human-drone interaction while performing construction tasks in close proximity to virtual drones on a construction site. This section delves into the design of the VR scenario, detailing how users engaged with virtual drones on the construction site and the technical developments necessary to facilitate this scenario and implement various communication modalities.

7.1. Scenario design

The goal of this phase was to design a scenario in a virtual construction site that would allow users to apply communication modalities while simulating increased risks typically encountered in a construction setting. Given that interactions with drones can introduce additional safety risks, particularly in hazardous environments, the scenario needed to replicate these risks accurately. An analysis of construction accident data consistently highlights falls from heights as a leading cause of death and injury in the construction industry. In 2020, falls, slips, and trips accounted for 46.1 % of fatal injuries and 31.4 % of non-fatal injuries recorded in the construction sector [15]. According to the Center for Construction Research and Training (CPWR), injuries resulting from falls to lower levels represented 34.7 % of all construction fatalities, making it the most perilous hazard for workers [102]. A closer examination of fall accidents revealed that roofs, ladders, and scaffolding were the primary work locations contributing to fatal falls in the construction industry [103].

To authentically replicate these hazardous conditions encountered on construction sites, a scenario focused on working at heights was devised. In this scenario, participants found themselves positioned near scaffolding and assigned inspection tasks while a construction crew worked on the slab, engaged in various tasks such as binding rebars and delivering and setting up scaffolds. To comprehensively simulate realistic drone applications in construction and account for various interaction possibilities, two generic quadcopter drones, the most popular and widely used drones in the construction industry [104], were used in the scenario, which was modeled to resemble popular drones used in construction [105]. They were equipped with easily accessible cameras that can accommodate different types of popular construction sensors, such as LiDAR and laser scanning devices [106], while offering operational flexibility with vertical takeoff and landing [104,106]. For the

purpose of this experiment, the drones were pre-programmed to fly a particular flight path for construction tasks along designated paths or positions. All workers, including participants, were non-operators who needed to perform their construction activities continually and were not operating or controlling the drones for the tasks. However, participants could use designated commands to communicate with the drones to slightly adjust the drones' flight paths if they felt unsafe or uncomfortable or if a drone came too close to them. One drone, the inspector drone, was responsible for inspecting the progress of the work around the virtual site by flying along a predefined path. The other, the delivery drone, was tasked with picking up toolboxes and delivering them to designated positions on the slab. Furthermore, environmental and drone noises were integrated into the scenario contents to replicate the realistic site environment and drone operations.

7.2. Technical development

After finalizing the scenario design, the subsequent step centered on two key technical developments. Firstly, the creation of the virtual construction site aimed to accurately simulate a realistic construction environment, encompassing various structural elements, dynamic objects, equipment, and construction workers engaged in their tasks. Secondly, gesture and speech recognition systems were implemented to enable communication between humans and drones within the virtual environment (as illustrated in Fig. 2).

The initial phase of VR development focused on constructing a virtual construction site with all the elements outlined in the designed scenario. This involved procuring 3D game objects relevant to the virtual construction site and converting them into the FBX file format for Unity® integration. These objects encompassed a wide range, including buildings, equipment, temporary structures, virtual construction workers, and drones. To add realism, 3D models of construction workers were generated using Daz 3D® and then programmed and animated using Adobe® Mixamo's exported animations. This allowed for the simulation of actual workers engaged in various construction tasks within the scenario, creating an immersive environment for users to interact with drones as they performed construction-related activities.

The second phase of technical development was dedicated to creating the gesture and speech recognition systems, pivotal components enabling the implementation of the proposed protocol for safe human-drone interaction. The gesture recognition system leveraged the Open XR plug-in within Unity, a widely utilized application interface for head-mounted devices, and the Meta Quest interaction SDK [107]. This

SDK, associated with Meta Quest, introduced the hand tracking feature, which allowed hands to serve as input methods for the headsets. Utilizing this feature, alongside various components and configurators, facilitated the detection of hand poses. The four gestures devised for the gesture-based communication modality were defined using hand shapes, finger positions (e.g., curl, flexion, abduction, opposition), and transforms (employing wrist, palm, and finger positions as 3-axis representations) [107]. Once detected by the Unity game engine, these gestures acted as inputs to scripts governing drone behavior and triggering corresponding responses.

Moreover, the speech recognition system was established by utilizing the Windows speech recognition system API within the Unity game engine [108]. This implementation facilitated the integration of voice input from the Meta Quest 2 headset into the application. The system operated through two distinct processes: keyword recognition and dictation recognition. Keyword recognition enabled the system to actively listen for predefined phrases spoken by the user. This approach ensured that the system exclusively processed specific voice inputs, as delineated in the protocol, rather than analyzing all spoken content. Subsequently, the dictation recognizer translated the identified speech commands into text, thus triggering corresponding responses from the drones.

After the completion of the gesture and speech recognition systems, they were seamlessly integrated into the virtual construction site, enabling users to immerse themselves in the virtual environment and experience the gesture and speech interaction modalities for controlling drone behaviors.

8. Experimental assessment

This study employed a user-centered quasi-experiment with a between-subjects design to investigate whether the developed communication protocol, utilizing communication modalities of gesture and speech, can enhance worker safety and well-being on construction sites when working with or near drones. The study adopted a between-subject design to minimize the time participants spent wearing VR headsets, thereby avoiding potential negative feelings like nausea and headache [109] and potential carry-over or learning effects [110], such as becoming familiar with the presence of drones, which could lead to biased responses to safety risks.

The experiment consisted of three conditions:

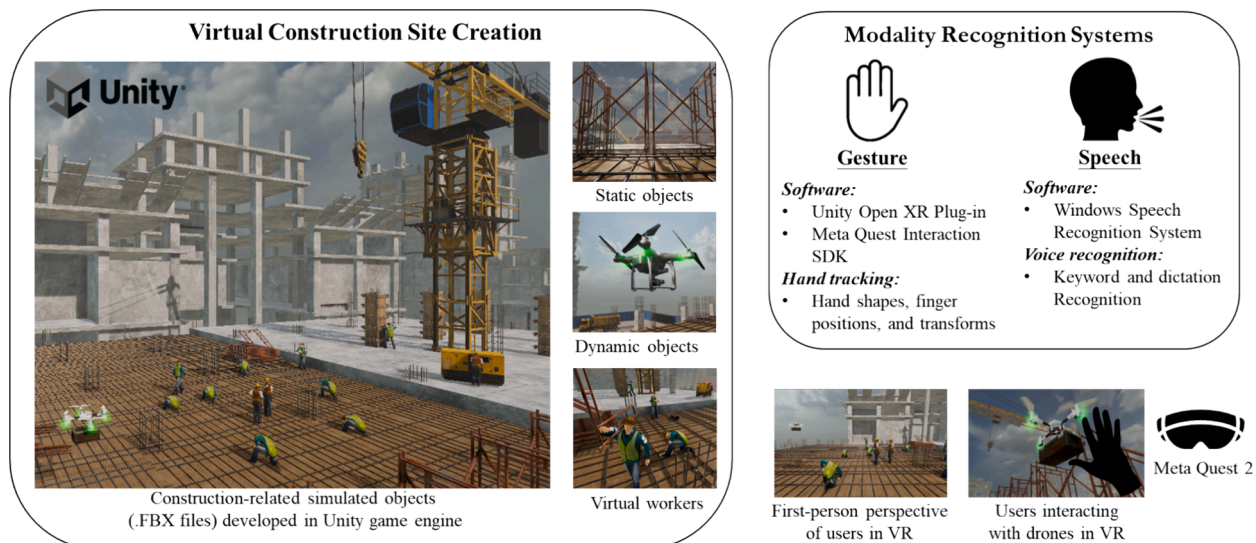


Fig. 2. Technical development.

- (1) **Control Condition:** Subjects were not able to use any communication modalities to interact with drones.
- (2) **Gesture Condition:** Subjects were able to use gesture-based communication modality to interact with drones.
- (3) **Speech Condition:** Subjects were able to use speech-based communication modality to interact with drones.

The assessment protocol received approval from the University of Florida Institutional Review Board (IRB #202300203). An a priori power analysis was performed using G*Power v. 3.1.9.7 [111]. The analysis, utilizing an effect size f^2 of 0.40 [112], a significance level α of 0.05, and a desired power of 0.80 [113], with a group number of 3 for a between-subjects design, showed that a total sample size of 66 participants would be required. Considering potential participant dropouts in addition to other technical and external factors, a total of 100 participants were recruited in this study. The following subsections will outline the experiment procedures and study metrics.

8.1. Experiment procedures

In this experiment (Fig. 3), participants initially reviewed and consented to the study by completing a consent form. Subsequently, they provided demographic information and then randomly assigned to one of three conditions: Control, Gesture, or Speech. Before starting the experimental conditions, each condition viewed an instructional video outlining their tasks within the virtual environment. As described in scenario design (see Section 6.1), during the experiment, participants were assigned an inspection task on top of an ongoing structure, where they needed to stand near scaffolding and inspect a construction crew working on the slab. The crew was engaged in various tasks, such as binding rebar, delivering, and setting up scaffolds. All workers, including participants, were non-operators who needed to continually perform their construction activities and were not operating or controlling the drones for the tasks. To ensure participants continued to pay attention to the site situation and engage with the scenario during the inspection task, they were required to report on the scenario's activities and the crew's safety after the inspection task. For the purpose of this experiment, the drones were pre-programmed to fly a particular flight path for construction tasks along designated paths or positions. Participants were required to remain vigilant about all activities on the site and ensure site safety. They could change their standing positions or move around during the inspection if they felt unsafe or uncomfortable or if a drone came too close. In the Gesture and Speech condition, participants were informed that they could utilize gestures or speech to command the drones if they felt unsafe or uncomfortable, to slightly adjust the drones' flight path (e.g., stop momentarily, fly around the work area), and they could practice the commands in VR before the experiment task. The participants in the Control condition could not communicate with the drones or adjust their flight paths at all (Fig. 3). Once they clearly understood their responsibilities, participants were placed in a learning scene tailored to their assigned condition, where they familiarized themselves with the available communication modality. After confirming their command familiarity, participants proceeded to engage in the actual experimental conditions. Throughout the experiment, data logs from the VR environment were collected to record

their interactions and behaviors, including near-miss incidents, for further analysis. Upon completing the experimental tasks, participants filled out four post-experiment surveys: NASA TLX, SAM, Safety Risk Perception Scale, and NARS: interaction subscale. The following section will provide a detailed discussion of all the study measures employed in this experiment.

8.2. Study metrics

The study employed the following metrics to assess three aspects of physical risks, psychological impact, and worker perceptions:

- Physical Risks of Drones on Workers:
 - *Near-Miss Incidents* [114]: A near-miss incident was defined as a potential hazard where no property damage or personal injury occurred but had the potential to occur with slight changes in time or position, as defined by OSHA [114]. The analysis of near-miss incident data is commonly used to assess safety performance [115] and conduct risk assessment [116]. Within this experiment, we programmed in Unity3D game engine to classify and record events as near-miss incidents when the distance between the human and the drone reached an intimate distance of 1.5 feet [117]. After each experiment, the total number of near-miss incidents was extracted from project log files.
- Psychological Impacts of Drones on Workers:
 - *Cognitive Workload by NASA-TLX* [118]: NASA-TLX is a widely used instrument for assessing cognitive and mental workload during or immediately after performing a task, which has demonstrated reliability and effectiveness in investigating the psychological load of individuals performing different activities [119,120]. It comprises a multidimensional score based on a weighted average of ratings on six subscales: mental demand, physical demand, temporal demand, performance, effort, and frustration level [121]. In this study, each subscale was scored on a seven-point scale from very low to very high.
 - *Emotional Status by Self-Assessment Manikin Scale (SAM)* [122]: SAM is a straightforward and efficient technique used to assess natural emotions in three dimensions: pleasure, arousal, and dominance [123]. It is an imagery-based measure easily understood and widely applied as a language-free tool [124]. The valence dimension of SAM represents a range of emotions from negative to positive, the arousal dimension reflects values from calm to excited, and the dominance dimension encompasses values from submissive to in-control.
- Worker Perception about Safely Working with Drones:
 - *Safety Risk Perception Scale* [125,126]: Safety risk is fundamentally defined as the product of frequency and severity of safety incidents [127]: $\text{Safety Risk} = \text{Incident Frequency} \times \text{Incident Severity}$. This concept has been widely used in a large number of studies to assess the relative risk of construction activities [128]. Pandit et al. [126] developed the Safety Risk Perception Scale by adapting the incident severity score proposed by Hallowell [125], and the Safety Risk Perception Scale was scored by multiplying the incident severity score with the expected frequency of the incident.

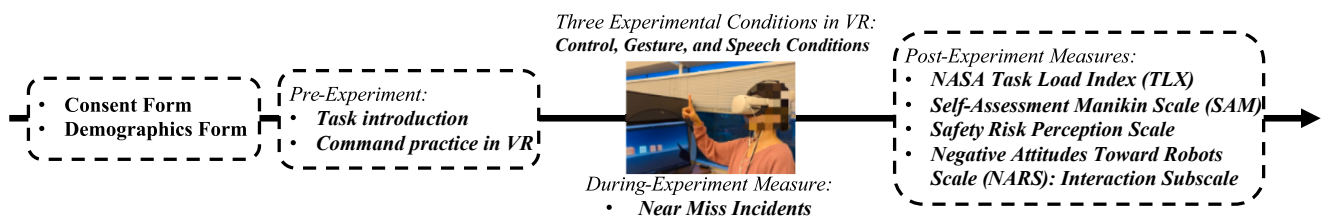


Fig. 3. Experiment procedures.

- o *Negative Attitudes Toward Robots Scale (NARS) Interaction Subscale* [129]: NARS is a validated tool widely used in HRI studies, which was designed to determine human attitudes toward robots when interacting with them. In this study, the subscale of NARS specifically focusing on “negative attitude toward interaction with robots,” was employed. This subscale includes six items, and each item is scored on a five-point Likert scale.

9. Results and discussion

A total of 100 participants (as shown in Table 2) were recruited for this study and randomly assigned to one of three conditions: the Control condition (33 subjects), the Gesture condition (34 subjects), and the Speech condition (33 subjects). The safe communication protocol is designed for non-operators working on site, including anyone who might be present on a construction site where drones are used. The target population for the experiment included personnel who are currently working in the construction industry or students from AEC (architecture engineering and construction) background who have acquired construction knowledge through practical activities such as site visits and will soon become construction professionals. The insights gained from these participants could offer initial insights into how communication protocols might affect construction practitioners' safety and perceptions. The majority of participants were male (65 %), aged between 20 and 30 (68 %), graduate-level education background (71 %), and majoring in construction, civil engineering, or architecture (80 %). Furthermore, a significant portion of participants had previous work experience on construction sites (81 %) and possessed some to fair degrees of familiarity with VR (75 %) and drones (81 %). Importantly, none of the participants reported experiencing severe dizziness or side effects from the VR device that could impede their ability to perform the experimental tasks, and all participants were in good physical and mental condition.

9.1. Near-Miss incidents

Analysis result of the total number of near-miss incidents during the

Table 2
Demographics and Background Information.

Variable	Category	Number (out of 100 subjects)
Gender	Male	65
	Female	34
	Non-binary	1
Age	≤ 20	13
	> 20 and ≤ 25	41
	> 25 and ≤ 30	27
	> 30	19
Educational Status	Undergraduate	29
	Master	35
	PhD	36
Educational Background	Construction	45
	Management	
	Civil Engineering	26
	Architecture	9
	Other (from AEC field)	20
Work Experience on Construction Site	None	19
	Less than 1 year	41
	1 to 2 years	15
	More than 2 years	25
Understanding of VR	None	7
	Some Knowledge of	46
	Fair	29
Understanding of Drone	Competent	18
	None	10
	Some Knowledge of	55
	Fair	26
	Competent	9

experiment (Table 3) revealed a lower number of incidents for the Gesture condition (8.18 ± 5.73) and Speech condition (11.67 ± 7.09) in comparison to the Control condition (12.45 ± 6.48). This suggests that both communication protocols may have contributed to a reduction in safety incidents when participants interacted with the drone on the construction site. The normality assumption of the near-miss incident data was rejected (p -value < 0.001) using the Shapiro-Wilk test [130]. Consequently, a nonparametric Kruskal-Wallis test [131] was utilized to evaluate differences among the conditions, resulting in a p -value of 0.004, indicating statistical significance. Subsequently, a post-hoc Dunn-Bonferroni test [132] was conducted to discern specific condition differences (Table 4). The outcomes indicated significant differences in Gesture vs. Control (p -value = 0.005) and Gesture vs. Speech (p -value = 0.033) means, while no significant difference between Speech vs. Control means (p -value = 1.000).

The results did not provide enough evidence that subjects utilizing the speech modality demonstrated enhanced safety performance compared to the Control condition, where no specific communication modality was available. Interestingly, the findings highlight that the utilization of the gesture modality for human-drone interaction significantly reduced near-miss incidents in comparison to the Control condition (no communication) and the Speech condition. The results suggested that gesture communication showed an advancement over speech communication in preventing safety incidents on construction sites.

This gap might come from various reasons. First, in the construction context, the loud noise of background activities and the sound from fast-spinning propellers can mitigate the accurate recognition of voice commands [52,58,71]. The immersive VR environment in this study used realistic audio and spatial sound effects to mimic the real construction environment, which could cause the speech recognition system to be disrupted by various noises. In addition to technical factors, the perception of speech commands by the subjects could also be influenced by the noisy environment, making it challenging for them to hear their own voices clearly and adjust the speech commands accordingly. This noise disturbance particularly affected individuals who speak softly, as mentioned in subject feedback: “... I spoke too softly, but after working in virtual reality, I can see that I have to speak louder and more confidently.” At the same time, gestures can remain effective in noisy environments and are already observed as a popular communication mode among workers [133]. Furthermore, existing studies have proved that gesture is the more intuitive communication modality [134], which enables precise adjustments and continuous control throughout the interaction compared to speech [71,135]. The gesture modality does not depend on the user's language [24], while the speech accent changes from person to person, impacting the recognition result [72]. During the experiment, 6 out of the 33 subjects spontaneously incorporated gestures into their speech commands despite not receiving any explicit instructions regarding gesture-based communication. Notably, these gestures were aligned with the intended meaning of their speech commands, for instance, extending their palm toward the drone while uttering “Back” commands. This observation indicated that a significant 18 % of the subjects exhibited a preference for employing gesture-based communication, even when they were in the Speech condition.

Table 3
Near-miss incidents analysis results.

	Control (Mean ± SD)	Gesture (Mean ± SD)	Speech (Mean ± SD)	Kruskal-Wallis Test p-value
Near-miss incidents	12.45 ± 6.48	8.18 ± 5.73	11.67 ± 7.09	0.004*

* p -value < 0.05 .

Table 4

Near-miss incidents post-hoc analysis results.

Conditions	Mean Difference	Dunn-Bonferroni Test p-value
Gesture vs. Control	3.15	0.005*
Speech vs. Control	0.60	1.000
Gesture vs. Speech	2.54	0.033*

* p-value < 0.05.

9.2. Cognitive workload by NASA-TLX

Table 5 displays the results for NASA-TLX, including subscales of mental demand, physical demand, temporal demand, performance, effort, and frustration. Overall, the subjects in the Control condition had the lowest workload, except for physical demand and performance success (reversed score). The subjects in the Control condition had no means to communicate with drones while performing construction tasks on site. When they felt unsafe or uncomfortable, the only option was to adjust their body postures or move around to avoid any negative influence from the drone. However, without any communication protocols to utilize, they tended to have a lower sense of success regarding the performing task.

In terms of the overall NASA-TLX score for each experimental condition (See Table 6), the Speech condition exhibited the highest score (3.75 ± 0.79), followed by the Gesture condition (3.59 ± 0.81), and lastly, the Control condition (3.11 ± 0.92). Subjects who need to use communication protocols during the experiment must memorize the newly learned instructions for the protocols and utilize them precisely when they feel unsafe or uncomfortable while interacting with drones. As a result, they processed more information simultaneously, without being sure about the potential results, e.g., *"It was definitely demanding a lot of effort especially that it is my first time communicating with a drone while there are a lot going on, on the jobsite"*; *"..., Remembering which one I wanted to use was hard when the drones started going on a dangerous path."* This also led to a higher demand for mental and temporal effort and tended to make them more frustrated, even though they had less physical demand and better task performance. Furthermore, subjects who utilized communication protocols mentioned that they would perform better if they had more practice time, e.g., *"Learning the sign commands was a little bit challenging. Perhaps more time to memorize the sign commands is needed."*; *"I think if I had more time to observe them and practice the gestures, then I would have been much better."* or they can perform the task with less effort, e.g., *"I think I was nervous I didn't remember the signals properly, but with more time it would become easier."*

Table 5

NASA-TLX descriptive statistics results.

NASA-TLX Questions*	Control (Mean $\pm$ SD)	Gesture (Mean $\pm$ SD)	Speech (Mean $\pm$ SD)
1: Mental demand: How mentally demanding was the task?	3.52 $\pm$ 1.37	3.97 $\pm$ 1.57	4.33 $\pm$ 1.47
2: Physical demand: How physically demanding was the task?	2.85 $\pm$ 1.25	2.76 $\pm$ 1.28	2.70 $\pm$ 1.31
3: Temporal: How hurried or rushed was the pace of the task?	3.15 $\pm$ 1.42	4.24 $\pm$ 1.37	3.76 $\pm$ 1.48
4: Performance: How successful were you in accomplishing what you were asked to do? **	5.03 $\pm$ 1.36	4.65 $\pm$ 1.12	4.00 $\pm$ 1.46
5: Effort: How hard did you have to work to accomplish your level of performance?	3.12 $\pm$ 1.29	3.91 $\pm$ 1.60	3.94 $\pm$ 1.39
6: Frustration: How insecure, discouraged, irritated, stressed, and annoyed were you?	2.91 $\pm$ 1.63	3.18 $\pm$ 1.57	3.88 $\pm$ 1.69

* Likert Scale: Very Low (1) to (7) Very High.

** Statement worded reversely.

Table 6

NASA-TLX One-way ANOVA test analysis results.

	Control (Mean $\pm$ SD)	Gesture (Mean $\pm$ SD)	Speech (Mean $\pm$ SD)	One-way ANOVA Test p-value
Overall NASA-TLX score	3.11 $\pm$ 0.93	3.59 $\pm$ 0.81	3.75 $\pm$ 0.79	0.007*

* p-value < 0.05.

The Shapiro-Wilk test confirmed the normality assumption for the NASA-TLX scores (p-value > 0.05) [130]. Subsequently, a one-way ANOVA test [136] was conducted to evaluate differences among the conditions, yielding a statistically significant p-value of 0.007. A post-hoc Tukey HSD test [137] was conducted to identify specific differences among conditions (Table 7). The outcomes indicated significant differences in the Speech vs. Control means (p-value = 0.007). However, no significant differences were observed between the Gesture vs. Control (p-value = 0.056) and the Gesture vs. Speech (p-value = 0.721). The data suggests that, although subjects who utilized gesture communication protocols had a higher cognitive load compared to those who did not have any communication methods, the difference was not statistically significant. On the other hand, utilizing speech communication could result in a significant cognitive load increase for subjects interacting with drones on a construction site. As discussed in the previous section, gesture modalities are more natural and effortless for subjects to adapt to during tasks, while speech communication can be influenced by environmental noise and may be challenging to adjust for improved performance, leading to a higher cognitive load compared to gesture communication.

9.3. Emotional status by Self-Assessment Manikin Scale (SAM)

The results from the SAM Scale, which measures emotional status across dimensions of pleasure, arousal, and dominance, are presented in Table 8. As shown in the figures of visual Likert scales, the scores range from low to high in each dimension, indicating a transition from positive to negative emotion, from excited to calm, and from being submissive to being in control. In all conditions, the average pleasure scores were similar (Control: 1.94 ± 0.86 ; Gesture: 1.94 ± 0.74 , Speech: 1.94 ± 0.90). This suggests that a short period of interaction with drones, regardless of whether subjects use any communication method, may not impact their overall emotional state in terms of the pleasure dimension. Regarding the arousal dimension, the Control condition (2.97 ± 0.98) had a slightly higher average score than the Gesture (2.91 ± 0.87) and the Speech (2.82 ± 0.95) conditions, indicating that subjects in the control condition were slightly calmer than those in the other two conditions. This suggests that subjects became more excited when using communication protocols to interact with drones compared to those without communication methods. Subjects were required to effectively apply their newly acquired knowledge of protocols as they noticed the drone approaching. This, in turn, led them to react more intensively. For example, one subject provided feedback, stating, *"For most of the time, it was fairly calm, but when the drones started getting closer, I would get a little nervous"*. Regarding the dominance dimension, the Gesture condition had the highest average score (3.32 ± 0.84), followed by the Speech

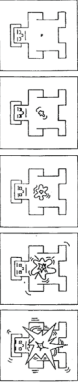
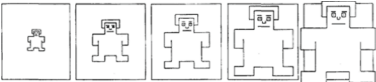
Table 7

NASA-TLX post-hoc analysis results.

Conditions	Difference	Tukey HSD Test p-value
Gesture vs. Control	0.48	0.056
Speech vs. Control	0.64	0.007*
Gesture vs. Speech	-0.16	0.721

* p-value < 0.05.

Table 8
SAM descriptive statistics and Kruskal-Wallis test results.

SAM Dimensions (Visual Likert Scale)	Control (Mean $\pm$ SD)	Gesture (Mean $\pm$ SD)	Speech (Mean $\pm$ SD)	Kruskal-Wallis Test p-value
Pleasure (From positive to negative emotion)	1.94 $\pm$ 0.86	1.94 $\pm$ 0.74	1.94 $\pm$ 0.90	0.970
				
Arousal (From excited to calm)	2.97 $\pm$ 0.98	2.91 $\pm$ 0.87	2.82 $\pm$ 0.95	0.804
				
Dominance (From being submissive to being in control)	3.06 $\pm$ 1.00	3.32 $\pm$ 0.84	3.12 $\pm$ 0.78	0.464
				

(3.12 $\pm$ 0.78) and the Control (3.06 $\pm$ 1.00) conditions. This suggests that subjects utilizing gesture- and speech-based communication modalities tended to perceive themselves as more in control while interacting with drones on-site because they feel safer and more comfortable by keeping drones out of high-risk zones that could influence them. For example, subjects from the Gesture condition provided feedback that the gesture communication protocol made it easy to control drone movements when needed, e.g., “I felt in control of the drone because I was sure that if it makes a mistake, I can change its direction or action.” ()

The normality assumption for all SAM dimensions, including pleasure, arousal, and dominance, was rejected (p-value < 0.001) using the Shapiro-Wilk test [130]. Therefore, a nonparametric Kruskal-Wallis test [131] was conducted to assess differences among conditions, resulting in a p-value higher than 0.05. This indicates no statistical significance for any SAM dimensions. These results did not provide enough statistical evidence to support that the communication protocols employing gestures or speech had an impact on the emotional status of subjects while interacting with drones on the construction site. The data suggests that participants utilizing communication protocols tended to experience a slightly higher level of arousal and a heightened sense of dominance when compared to the Control condition. However, overall, emotional states remained relatively stable throughout the short duration of the experiment.

9.4. Safety risk perception

Table 9 illustrates the subjects’ responses across all three conditions, revealing distinct perceptions regarding the frequency of injury

incidents across various severity levels during their interactions with drones at a construction site. Subjects most commonly perceived Discomfort/Pain (58 %-47 %-52 % for control-gesture-speech) and First Aid incidents (58 %-62 %-55 % for control-gesture-speech) as “Very Likely” to occur. For the Media Case incident, subjects in the Control and Speech conditions mostly perceived it as “Unlikely but Possible” (33 %-39 % for control-speech), while subjects in the Gesture condition mostly perceived it as “Very Likely” (29 %). Regarding the Lost Work Time incident, subjects in the Control condition mostly perceived it as “Very Likely” (33 %), while subjects in the Gesture condition mostly perceived it as “Unlikely but Possible” (38 %), and subjects in the Speech condition were divided between perceiving it as “Unlikely But Possible” (30 %) or “Very Likely” (30 %). For the Permanent Disablement or Fatality incident, subjects in the Control and Speech conditions mostly perceive it as “Not Possible” (36 %-30 % for control-speech) or “Unlikely but Possible” (36 %-30 % for control-speech). Subjects in the Gesture condition most perceived it as “Unlikely But Possible” (38 %).

To compute the perceived safety score, we adapted scores developed by Hallowell [125] and Pandit et al. [126], as presented in Table 10.

The safety risk perception score results for all conditions were analyzed and presented in Table 11. The average safety risk perception scores of conditions that use communication modalities to interact with drones (Gesture condition: 3.89 $\pm$ 7.28, Speech condition: 2.35 $\pm$ 4.44) were higher than the condition without any communication modality (Control condition: 1.79 $\pm$ 3.26), but with higher standard deviations. The results indicate that subjects using communication modalities tended to perceive higher risks of safety accidents resulting in injuries. Several factors may contribute to this observation. Firstly, subjects may

Table 9
Percentage response results for safety risk perception scale (control-gesture-speech).

Injury Frequency Severity	Not Possible	Unlikely But Possible	Likely	Very Likely	Almost Certain	Total
Discomfort/Pain	6 %-3%-3%	6 %-15 %-15 %	9 %-9%-12 %	58 %-47 %-52 %	21 %-26 %-18 %	100 %-100 %-100 %
First Aid	0 %-6%-3%	24 %-6%-12 %	9 %-9%-18 %	58 %-62 %-55 %	9 %-18 %-12 %	100 %-100 %-100 %
Media Case	9 %-12 %-3%	33 %-26 %-39 %	27 %-26 %-24 %	27 %-29 %-27 %	3 %-6%-6%	100 %-100 %-100 %
Lost Work Time	12 %-9%-6%	30 %-38 %-30 %	21 %-15 %-27 %	33 %-29 %-30 %	3 %-9%-6%	100 %-100 %-100 %
Permanent Disablement or Fatality	36 %-26 %-30 %	36 %-38 %-30 %	12 %-9%-12 %	15 %-18 %-27 %	0 %-9%-0%	100 %-100 %-100 %

Table 10
Scores for Safety Risk Perception Scale.

Injury Frequency Severity	Not Possible	Unlikely But Possible	Likely	Very Likely	Almost Certain
Discomfort/Pain	1.25×10^{-4}	1.25×10^{-3}	0.01	0.06	2.5
First Aid	2.75×10^{-4}	2.75×10^{-3}	0.03	0.14	5.5
Media Case	3.50×10^{-4}	3.50×10^{-3}	0.04	0.18	7.0
Lost Work Time	4.00×10^{-4}	4.00×10^{-3}	0.05	0.20	8.0
Permanent Disablement or Fatality	4.75×10^{-4}	4.75×10^{-3}	0.06	0.24	9.5

Table 11
Safety risk perception Kruskal-Wallis test analysis.

	Control (Mean $\pm$ SD)	Gesture (Mean $\pm$ SD)	Speech (Mean $\pm$ SD)	p-value
Safety risk perception score	1.79 $\pm$ 3.26	3.89 $\pm$ 7.28	2.35 $\pm$ 4.44	0.248

have perceived drones as more uncertain and distracting when utilizing communication modalities due to the extended reaction time required to spot the drones, make distance judgments and communication decisions, compared to subjects in the Control condition who intuitively changed their postures or body positions in a shorter time to avoid drones, e.g., “locating the drones was a bit difficult so I was always looking to spot it and that made it distracting”. Secondly, the lack of sufficient feedback information following communication may have hindered their ability to confirm that the drones were no longer present in potentially high-risk areas. “... I was skeptical about drone’s movements and kept on giving orders.”; “The gesture controls can be very precise after practice, but the resultant motions of the drones would be a little bit unpredictable”. Furthermore, subjects would perceive providing communication commands based on personal judgment as unsafe because it was difficult to determine the timing for executing the commands and preventing potential incidents, e.g., “sometimes felt a bit dangerous to work with drones. Especially if it couldn’t automatically avoid workers but depends on human commands”; “it was difficult to determine what is considered safe or not safe.”.

The Shapiro-Wilk normality test [130] was adapted to assess the normality of the safety risk perception score for 100 subjects (2.69 ± 5.32). The obtained p-value was < 0.001 , suggesting the normality assumption is rejected. Therefore, a nonparametric Kruskal-Wallis test [131] was conducted to examine the condition differences in safety risk perception scores. The p-value was 0.248, which is higher than 0.05, indicating that while subjects using communication protocols generally perceived higher safety risks, there was no statistically significant difference in safety risk perception scores between the subjects who utilized gestures or speech and those who could not use any communication modalities to interact with the drones.

9.5. Negative attitudes toward robots scale (NARS): Interaction subscale

The data results for the NARS interaction subscale are presented in Table 12. The results show that all the subjects in the Control condition rated the lowest score on the statement: “I felt uneasy when I worked on site and drones came close to me (3.33 ± 1.22), followed by a slightly higher score (indicating more agreeing on the statement) in the Gesture condition (3.53 ± 1.05) and Speech condition (3.58 ± 1.17). These scores, while slightly higher in the conditions with communication capabilities to drones, still fall within the range of 3.5, which implies a sentiment between “neutral” and “agree.” Additionally, subjects from all

Table 12
NARS: Interaction descriptive statistics results.

NARS: Interaction Subscale Questions*	Control (Mean $\pm$ SD)	Gesture (Mean $\pm$ SD)	Speech (Mean $\pm$ SD)
1: I felt uneasy when I worked on site and drones came close to me.	3.33 ± 1.22	3.53 ± 1.05	3.58 ± 1.17
2: Drones meant nothing to me when I performed the task on site.	2.33 ± 1.11	2.06 ± 1.01	1.94 ± 1.00
3: I felt nervous working with drones in front other people on site.	2.91 ± 1.07	2.74 ± 1.33	3.27 ± 1.38
4: I hate drones performing tasks automatically and making decisions on site.	2.33 ± 1.22	2.26 ± 1.08	2.30 ± 1.16
5: I felt nervous when working around drones on site.	3.21 ± 1.11	3.24 ± 1.07	3.21 ± 1.19
6: I felt paranoid when I tried to communicate with drones on site.	2.52 ± 0.97	2.59 ± 1.26	2.69 ± 1.24

* Likert Scale: Strongly Disagree (1) to (5) Strongly Agree.

three conditions have a similar rate of around 3 (indicating “neutral” in the original scale) for the following statements: “I felt nervous working with drones in front of other people on site,” “I felt nervous when working around drones on site,” and “I felt paranoid when I tried to communicate with drones on site.” These findings indicate that subjects generally held neutral opinions regarding their emotions during interactions with drones. Additionally, the subjects in all conditions scored around 2 (indicating “disagree” in the original scale) for the following items: “Drones meant nothing to me when I performed the task on site” and “I hate drones performing tasks automatically and making decisions on site.” This suggests that the presence of drones did not negatively impact subjects’ perceptions of drones and their roles in on-site tasks in any of the conditions.

As presented in Table 13, the average negative score of the Speech condition (2.83 ± 0.74) was slightly more than the score of the Control condition (2.77 ± 0.63) and the Gesture condition (2.74 ± 0.62). This suggests that communication protocols did not contribute to an improvement in attitudes toward drones when subjects interacted with them on construction sites.

The Shapiro-Wilk normality test [130] was adapted to test the normality of the data results to evaluate the normality of the NARS scores for 100 subjects (2.78 ± 0.66). The obtained p-value was 0.31, which is higher than 0.05, suggesting the normality assumption is true. Therefore, a one-way ANOVA test [136] was conducted to examine the condition differences in NARS scores. The p-value was 0.826, indicating there was no significant difference in negative attitudes between conditions. The results suggest that the attitude toward interaction with drones did not significantly differ between subjects who used gesture or speech communication modalities to interact with drones on the virtual construction site and those who interacted with drones naturally, without any communication methods, while working on the same site. However, it should be noted that the negative attitude of subjects using communication protocols could be partly attributed to the higher cognitive load discussed in the previous session. The lack of information cannot assure subjects that the drone is no longer within an unsafe or uncomfortable zone and could still pose a threat, even though communication protocols have helped reduce safety incidents. Additionally, the qualitative feedback from subjects who utilized communication protocols also indicated that they hesitated to use the commands even

Table 13
NARS One-way ANOVA test analysis.

	Control (Mean $\pm$ SD)	Gesture (Mean $\pm$ SD)	Speech (Mean $\pm$ SD)	p-value
Overall NARS score	2.77 ± 0.63	2.74 ± 0.62	2.83 ± 0.74	0.826

though they felt unsafe or uncomfortable because they perceive productivity as a higher priority than safety, e.g., *“I did not use the go away gesture because I did not want to stop its work.”*; or reduce productivity, *“Using the gesture commands would decrease productivity, but they can keep workers safe.”* This conservative strategy of utilizing communication modalities could also impact the attitude towards drones for subjects who lost the opportunities to improve when they felt unsafe or uncomfortable.

10. Research limitation and future work

While this study provides valuable insights, certain limitations must be acknowledged. Firstly, the latency and accuracy of both the gesture and speech recognition systems can vary in real-world settings compared to our virtual environment. Most participants, whether in the Gesture or Speech condition, reported that the communication protocols were reliable and user-friendly during the VR experiment. For instance, comments included: *“The gesture controls can be very precise after practice”* and *“The drones are easy to control by voice.”* However, in real-world scenarios, these recognition systems might not be as consistent, and there could be discrepancies between the systems integrated into our VR simulation and those in an actual setting. Furthermore, speech recognition systems might exhibit greater latency and reduced accuracy in real-world applications due to the inherent intricacies of natural languages [138,139]. To enhance recognition accuracy when integrating the Windows Speech Recognition system into Unity3D®, we deliberately set the speech recognizer’s confidence level lower, aiming to account for the wide variety of nationalities and accents among participants. Nonetheless, latency remained a challenge due to system constraints, as echoed by participant feedback. During the experiment, several participants observed significant latency in the Speech condition. For example, they mentioned: *“The audio commands work but are not that accurate. There is a delay which may confuse the user”* and *“The drones seemed to have a lag time with commands.”* Interestingly, those using the gesture communication protocol did not highlight any latency-related concerns. Another concern regarding speech command recognition is the inherent noise present in the construction site environment. Although the scenario in this study already included various sources of environmental noises and drone sounds, the real site could pose more disturbances and instability for speech recognition compared to the VR environment, thereby reducing the usability of speech commands. The limited scope of scenario design only covers general situations where drone capabilities for data capturing, including both image and speech, work effectively. It does not account for adverse conditions such as heavy rain or foggy weather, where visual and audio cues may be obscured.

Moreover, as detailed in the Results and Discussion section, while subjects claimed familiarity with the communication protocols before experiencing either the Gesture or Speech conditions, they might require additional effort to accurately employ these newly learned protocols when interacting with drones, particularly in safety-critical situations. As a result, an extended and more intensive training program could significantly enhance subjects’ understanding of these protocols, boosting their usability and effectiveness. In subsequent studies or applications using the proposed communication protocols, it’s crucial to offer more detailed and user-centric instructions. It would also be beneficial to evaluate the frequency of command usage and user preferences for each communication command. This analysis could help determine if modifications or refinements to essential commands are required, ensuring that users receive only pertinent information. Such measures will guarantee that users can adeptly apply the communication protocols in the least amount of time. There are limitations related to individual differences resulting from the between-subject experimental design. As a trade-off to avoid participant fatigue and VR sickness, as well as to mitigate carry-on effects from the three conditions, individual differences such as participants’ knowledge and experience

may also have affected the results, including how they utilized communication or related safety impacts. Moreover, the participant group in this study has varying industry work experience, including AEC background students who are not full-time employed and lack industry work experience. This group may not fully represent construction practitioners. Statistical analysis showed that these individual characteristics, as reported in surveys, including industry experience, had no significant effect on any of the experimental metrics (near-miss, NASA TLX, SAM, Safety Risk Perception Scale, and NARS: interaction sub-scale). Nevertheless, future studies should consider individual differences in participant demographics more carefully, given the trade-offs in sampling methodology, including balancing research goals, costs, representativeness, and different dimensions of generalizability [140,141]. Therefore, a better recruiting strategy should be adopted to acquire a more representative sample of construction practitioners, enhancing the generalizability of future study results.

Furthermore, while subjects using the gesture communication protocol showed enhanced safety performance, effectively reducing near-miss incidents without added cognitive strain, they did not necessarily feel safer or more at ease when working alongside drones. This underscores the need for future studies to refine human-drone communication. It is essential to present drones not merely as autonomous robots but as dependable, predictable collaborators. This requires a robust drone-to-human communication system that clearly communicates critical drone flight statuses, such as readiness to approach a work zone or adherence to safe distance guidelines. In addition to the proposed human-to-drone communication protocols, an improved drone-to-human communication system should offer real-time feedback on human commands and subsequent drone actions, like flight path changes or task completion updates. By ensuring workers receive immediate confirmations regarding drone safety measures, such a system could significantly reduce cognitive demands on workers and address their safety concerns.

Finally, future research should also consider construction environments with varied working conditions, as these can pose challenges for communication protocols, especially those reliant on gestures or other specific modalities. The inspection at heights scenario designed in this study aimed to represent workers performing general construction activities in hazardous environments and facing additional safety risks related to drones. However, this specific scenario or task content is limited and cannot fully replicate the numerous construction tasks in the real world. Although the training requirements for the communication commands were minimal during the experiment, all participants confirmed they became familiar with the communication protocol and were ready to utilize it within three minutes. Differences in construction activities or tasks could lead to varied safety impacts and affect which communication modalities are more suitable for specific scenarios, including potential workload burdens on workers such as mental, physical, and effort demands. This study focused on evaluating fundamental communication protocols within a VR-based construction environment to understand their safety and psychological impacts on non-operator construction workers. While the scope was limited to basic instructions, the findings provide a foundational understanding that can inform the development of more complex communication methods. Future research should explore the application of these protocols in comprehensive construction tasks to address the challenges and costs associated with more intricate communication methods that offer users a range of modality options. For instance, workers engaged in intricate tasks, where their hands are occupied with tools, may find gesture-based communication impractical. Moreover, situations where workers and drones collaborate closely demand an enriched information exchange. Communication protocols in such contexts must be finely tuned to the intricacies of the task at hand. For example, in scenarios where workers and drones collaborate on safety inspections, there is a pressing need for communication tools that address risk levels, pinpoint risk locations, and update the status of risk mitigation efforts.

11. Conclusion

In this study, gesture-based and speech-based communication protocols were developed and assessed to enhance the safety of human-drone interactions on construction sites. The study particularly focused on non-operator workers who have no control over drones and limited information about their mission. Gesture and speech modalities, which are the most intuitive and commonly used methods for communicating with drones, were employed in designing the safe communication protocols. Critical commands “Stop Task,” “Keep Distance,” “Change Path,” and “Resume Task” were identified to assist construction workers in maintaining safety while working around drones. An immersive VR environment, replicating construction site dynamics and integrating gesture and speech recognition systems via the Unity3D® game engine, served as the foundation for our user-centric experiment.

The impact of these protocols on safety, covering physical risks, psychological effects, and worker perceptions during human-drone interactions, was investigated using a between-subject research design. The results showed that effective communication reduced the likelihood of accidents (as indicated by near-miss incident numbers in the control condition vs other conditions). The results also revealed that the gesture communication protocol was particularly effective in minimizing the risk of physical contact during human-drone interactions on construction sites. It demonstrated no substantial adverse effects on participants’ psychological well-being or perceptions. In contrast, while the speech protocol added cognitive load, indicating potential psychological strain, it did not significantly reduce physical contact risks. Overall, gesture-based protocols outperformed speech-based ones in promoting safe communication on construction sites.

This research deepens the understanding of how various human-drone interaction (HDI) communication modalities can enhance the safety and well-being of construction workers. Given the unique challenges posed by construction environments—marked by their complexity and dynamism—it is essential to address the needs of general workers, especially those not part of drone operating teams with limited drone-related knowledge. As drones become more prevalent in construction, potential risks arising from increased human-drone interactions will intensify. Our proposed protocols offer an innovative strategy to ensure safety in these interactions, emphasizing the importance of HDI considerations for all stakeholders. The proposed protocol can be implemented as an innovative intervention strategy for drones employed in construction sites while bringing up the safety considerations in human-drone interaction for all the stakeholders. The assessment results from the user-centered experiment can guide drone manufacturers and tech firms in developing functions tailored to the construction industry, prioritizing worker safety and well-being. This study also introduced a unique and novel framework for assessing the impact of human-drone interactions on construction worker safety using immersive virtual reality. This framework can be employed for broader human-robot interaction studies in the construction industry. The immersive VR environment with integrated communication protocols could also serve as a valuable tool for providing accessible opportunities for construction workers to learn about the applications of drones and the innovative future of construction sites.

CRedit authorship contribution statement

Zixian Zhu: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jiun-Yao Cheng:** Writing – review & editing, Visualization, Validation, Data curation. **Idris Jeelani:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Masoud Gheisari:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: [Zixian Zhu reports financial support was provided by National Science Foundation. Jiun-Yao Cheng reports financial support was provided by National Science Foundation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper].

Data availability

Data will be made available on request.

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