Understanding and Mitigating Drone-Induced Distraction: Behavioral Experiments and Distraction-Aware Path Planning for Construction Safety

by

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“Together we go far. Together the world is different because we have been here.”

ABSTRACT

Drones are increasingly adopted in construction for applications such as site mapping, inspection, progress monitoring, and safety management. Their ability to capture high-resolution data and automate repetitive tasks such as surveying, visual inspection, and material tracking. These improve operational efficiency by reducing manual labor, shortening data collection time, and increasing measurement accuracy. The timely and precise information collected by drones enables managers to identify deviations, assess risks, and adjust construction schedules based on real-time site conditions. This supports data-driven decision making in project planning and safety management. These capabilities allow construction teams to monitor progress more effectively and maintain tighter control over quality and safety. However, integrating drones into construction practices also introduces new safety concerns. While previous research has largely focused on physical hazards such as collisions and mechanical failures, little is known about whether and how drones' presence distracts workers on construction sites. These distractions may affect workers' cognitive focus and situational awareness, further impair their ability to recognize hazards, and increase the likelihood of accidents in demanding construction environments.

To fill that gap in the body of knowledge, this research investigates drone-induced distraction and its implications for construction safety. Specifically, the objectives are to evaluate workers' visual attention to hazards with drones flying at different heights and directions, and to assess tower crane operators' visual attention and performance when drones fly at different heights and distances. Two virtual reality experiments were conducted. In the first experiment, participants performed material-moving tasks at height while drones flew at different heights and directions to examine how drone motion affects workers' fixation time and count on hazard areas. In the second experiment, participants operated a virtual tower crane to complete a material-moving task while

drones flew at varying heights and horizontal distances to assess their influence on operators' visual attention and performance metrics, including collisions, payload deviation, and task completion time. The results show that drones significantly reduced workers' fixation time on hazard areas by up to 60 % when flying at 16 ft and 48 ft in front of the worker, while tower crane operators experienced more collisions when drones flew below the operator at 16 ft compared with above or no-drone conditions. Based on these findings, drones are not recommended to operate at low altitudes between 16 and 48 ft around workers performing tasks at height, as these flight configurations produce substantial visual distraction and may compromise hazard awareness. For tower crane operations, the results indicate that drones flying above the operator at approximately 35 ft did not cause measurable distraction effects, suggesting that maintaining a sufficient vertical clearance is a safer operating practice for aerial monitoring near cranes.

Building upon the behavioral findings from both experiments, this research further proposed a drone path planning method that integrates physical collision avoidance with a distraction-aware soft cost. This method allows drones to complete assigned traveling points missions efficiently while minimizing the amount of distraction to construction workers and tower crane operators. Quantitative comparisons demonstrated that while the distraction-aware path increased total flight distance by approximately 3% to 50%, it reduced worker exposure time by around 10% to 25%, potential to achieve a balance between operation efficiency and cognitive safety.

Overall, this research contributes a comprehensive understanding of indirect cognitive risks posed by drones on construction sites, provides empirical evidence of distraction effects on attention and performance. Also, it introduces a novel distraction-aware path planning strategy for drone deployment. The outcomes offer valuable insights for policymakers, safety engineers, and system developers seeking to integrate drones safely and effectively into future construction workflows.

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CHAPTER ONE: INTRODUCTION

Drone usage in construction projects is gaining significant traction due to its potential to enhance project efficiency, safety, and decision making. Drones are equipped with advanced sensors such as RGB, multispectral, thermal, and LiDAR. Which can rapidly collect extensive aerial data [1]. This data can be transmitted and processed through specialized software to enable efficient analysis and interpretation. These capabilities contribute to streamlined workflows, improved site management, and more thorough inspections. For instance, drones can survey large areas in a fraction of time required by traditional methods, providing planning hoisting operations [2]. Moreover, drone can monitor machinery locations to detect operational issues and assess construction quality [3]. Drones can be employed in a wide range of construction applications, including topographic mapping, equipment tracking, progress monitoring, and site inspections. Statistic shows that the global construction drone market was valued at $4,800 million in 2019 and expected to reach 7.1 billion by 2030 [4]. Thus, the advanced capabilities of drones, along with promising market forecasts, support their growing integration into construction practices.

However, introducing drone to construction project may cause new safety risks and hazards to construction workers on sites. These risks can be broadly categorized into direct and indirect hazards. Direct risks include the potential for physical collision between drones and workers or equipment, which can result in severe injuries given that drones are machines carrying mass and velocity. For example, a practical risk-assessment model has identified unsafe work environments created by over-flying drone as a core causal factor in on-site hazards [5]. Technical failures such as rotor malfunctions or loss of control may also cause drones or their parts to fall, striking personnel or property. Furthermore, insufficient pilot training and operational errors amplify the likelihood of accidents involving both workers and bystanders [6]. On the other hand, drone-induced risks and hazards are not confined to potential physical collisions or contacts with onsite workers, equipment, or permanent and temporary facilities within the drone operating zones [7]. The indirect risks are equally significant, as drones can compromise workers' cognitive focus and situational awareness [8]. The presence or intrusion of drones can divert workers' attention and cause visual, auditory, or even cognitive distractions [9]. For example, Union Pacific Corp railroad workers reported that drones flying over rail yards were distracting, leading them to look up instead of focusing on their tasks, even when 200-ton locomotives and railcars were moving along the tracks [10]. A study investigated the reactions of workers after they were disrupted by external interruptions in office environments [11]. Some workers took up to 25 minutes to regain full concentration on their tasks. Similar interruptions can also happen to construction workers. For example, a study found that drones interrupt workers while they are doing their jobs [12]. These kinds of distraction could reduce the workers' capacity to identify hazards and assess safety risks [13], [14].

Existing research on drone safety in construction has made substantial progress in addressing direct risks. For example, [15] conducted VR-based 4D simulations focusing on high-risk work zones such as roofs, ladders, and scaffolds, and identified specific physical risk scenarios like drone collisions in those contexts, paving the way for targeted mitigation strategies. Similarly, [16] highlighted the role of drones in providing impact protection, where these systems can assess and preemptively reduce collision risk near moving equipment, boom vehicles, and cranes by supplying real-time hazard awareness. These contributions demonstrated that direct physical risks are beginning to be systematically identified and mitigated through both simulation-based studies and applied technological interventions. In contrast, research addressing indirect risks such as distraction, cognitive load, and situational awareness remains at an early stage. Zhu et al. explored construction students' safety perceptions in VR environments and found that drone presence raised mild safety concerns and cognitive load, which signals the beginning of systematic investigation into cognitive effects [17]. In addition, Albeaino et al. conducted empirical investigations into workers' physiological, attentional, and emotional responses to drone presence, but the findings remain preliminary and have yet to be translated into actionable mitigation strategies [18]. These studies show that while direct risks are being actively explored, the indirect risks associated with drone use on construction sites are only beginning to be systematically explored.

Since drones often operate above buildings on construction sites, workers positioned at high elevations such as those on rooftops or in tower cranes may be particularly exposed to drone-induced indirect risks. Such indirect hazards can impair situational awareness, delay hazard recognition, and disrupt normal work routines, thereby elevating the likelihood of accidents. For example, rooftops workers can overreach and lose their balance on platforms that are cluttered with idle tools and equipment, or have inadequate edge protection, unguarded floor openings, etc. As a result, they may fall and potentially die or sustain injuries that require time away from work. In Figure 1, the Bureau of Labor Statistics (BLS) reported that falls, slips, and trips accounted for 38.4% of all fatalities and 47.4% of nonfatal injuries in the construction industry in 2022; and most fatal falls, slips, and trips happened to those workers at heights who fell to a lower level [19]. When drones have the potential to divert the workers' attention through their sight or sound, the risk of falls, slips, and trips increases. A survey of over 1,200 safety professionals found that distraction was the leading cause of such incidents [20]. Similarly, tower crane operators, who must maintain continuous focus on load movement and site coordination, may experience reduced attention when distracted by drone noise or movement in their line of sight. This loss of attention is critical, as inattention has been reported to account for 19% of tower crane incidents, including both near misses and actual accidents [21]. Crane operators are already exposed to various sources of distraction that can impair concentration [22], and fatigue may further exacerbate this issue, as 65 out of 100 operators reported being easily distracted after working overtime [23]. However, the quantitative impacts of drone distraction on tower crane operators and workers at heights remains unclear.

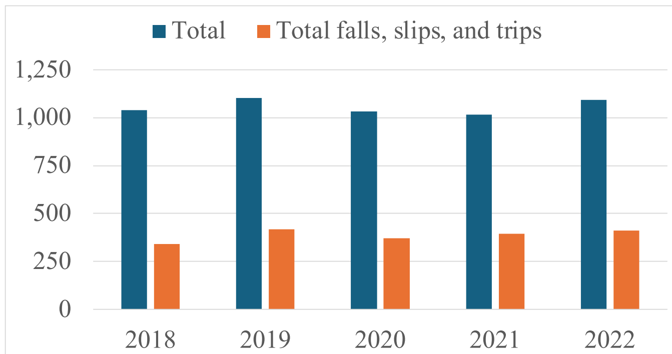

Figure 1. Number of Fatal work injuries in the construction industry from 2018 to 2022.

Thus, to safely introduce drones into construction projects, it is important to understand how specific drone behaviors, such as flight height, distance from workers, movement patterns, and noise, affect workers' attention. This thesis addresses this need by conducting two controlled experiments in a virtual reality environment that replicates realistic construction conditions. To enable the potential applications of our VR experiment results to real-world scenarios, our industrial partner, Mortenson, has been actively involved in this research, including experiment design, setup, and data collection. They tested our virtual environment and experiment settings and provided us with feedback to ensure that our experiment setups capture essential construction site conditions. The first experiment focuses on rooftop workers and evaluates their visual attention and situational awareness while performing a material moving task, which is one of the most common activities on construction sites. The second experiment examines tower crane operators and evaluates their performance by requiring them to complete the one of the tasks in Certified

Crane Operator practical task, where maintaining continuous focus on load movement and site coordination is essential. By systematically analyzing workers' responses across these two scenarios, this research provides insights into how different drone flight configurations influence safety-critical attention and task performance in high-risk construction environments. Building on these findings, the final step of this study is to apply the behavioral insights to develop safe drone path planning strategies, ensuring that aerial monitoring can be conducted effectively while minimizing distraction-related safety risks.

CHAPTER TWO: RELATED WORKS

Drone Application in Construction

In recent years, unmanned aerial vehicles (UAVs), commonly referred to as drones, become emerging technology in construction projects that are redefining conventional practices in project planning, execution, and maintenance. Through the integration of advanced sensors, high-resolution imaging systems, and global positioning system (GPS) technology, drones enable the systematic collection of real-time data, the generation of highly accurate three-dimensional models, and the execution of remote inspection tasks [24]. This section reviews the drone applications in different phases of construction project: design, construction and maintenance phases.

Design Phase

One of the most widely adopted applications of drones in design phase is surveying and mapping. Traditional land surveying and mapping methods, which often require extensive manual measurements and ground-based equipment, are labor-intensive and time-consuming. Drone-based surveying captures high-resolution aerial imagery that offers a comprehensive view of construction sites. By collecting data from sensors such as LiDAR [25], [26], [27], [28] and thermal [26] cameras, drones enable precise evaluation of site topography, existing structures, and boundary conditions. These support the development of detailed 3D models and precise calculations. Furthermore, drones help establish survey control points for georeferencing, thereby enhancing the precision and dependability of subsequent mapping processes.

Drone-based mapping leverages photogrammetry algorithms to process high-resolution aerial images that cover large areas [29], [30]. These algorithms generate precise 2D and 3D maps of construction sites [25], [31], [32], [33]. For example, the algorithms stitch near-by aerial images together to create orthomosaic maps for measuring and visual information. Since the maps also include existing structures, utilities and vegetation information, which combines the information for construction projects during design phase [34], [35].

In general, there are three steps for surveying and mapping using drones in construction projects. The first step is to acquire the required permits and safety measures as well as plan the flying paths based on survey areas [36], [37], [38]. Second, by following the planned paths, drone captures required data by equipped sensors. The final step is post-process the collected data to produce 2D and/or 3D maps [35], [39], [40], [41].

Construction Phase

During construction phase, drone applications can provide benefits in different aspects which include earthwork and grading, quality control, progress tracking, safety monitoring, and the management of material logistics and delivery [42]. In earthwork and grading, traditional methods depend on manual measurements, which are both time-consuming and prone to human error. In contrast, drones provide enhanced accuracy and precision by capturing high-resolution imagery and site data that support reliable volumetric calculations [43], [44], [45], [46], cutting and filling analysis [47], [48], and slope measuring [49], [50], [51].

Leveraging drones can also help in quality control and progress monitoring. For example, drone captures high-quality data for the inspector to identify overlooked defects during ground inspections [52], [53]. The data collected by drones can be compared with construction plans or 3D models to identify discrepancies between the design and the as-built conditions. This comparison enables inspectors to implement corrective measures promptly, thereby minimizing potential losses and preventing project delays. Moreover, by comparing collected data with project timeline, the managers can track the progress and identify if there is any delays or bottlenecks [54],

[55], [56]. These data not only can be used inside the team for communication, but also can be visualized to stakeholders to understand the progress [57], [58].

In addition to enhancing efficiency, drones also contribute to safety monitoring by supporting the identification of hazards and strengthening on-site safety measures. For example, Drones are capable of detecting unsafe site conditions, including unstable structures, accumulated debris, equipment failures, and improper use of personal protective equipment [59], [60], [61], [62]. The safety inspectors can gather more comprehensive information in aerial perspective by flying drone in the sky [63], [64].

Maintenance Phase

Drones can help in the maintenance of structure by using high-resolution cameras, LiDAR technology, and thermal cameras. These sensors detect defects and damages in structures that are difficult to detect by naked human eye. High-resolution cameras are used to capture RGB images and videos for inspections. For example, drones can access locations that are difficult to reach or pose significant safety risks to workers. Thus, using drone in bridge inspections not only provide more detailed analysis of damages and defects but also provide a safer way to collect required data [65], [66], [67], [68], [69], [70], [71], [72]. Traditional bridge inspections required workers to climb or move to specific locations to capture data. In contrast, drones can quickly fly around the bridge to efficiently complete the data collection process. High-resolution images and videos captured by drones can provide details that may be overlooked during visual inspections, such as fine cracks or subtle signs that are not obvious to the human eye [73], [74], [75]. As for LiDAR sensors, they capture 3D information of structures. This information requires special software, technologies, expertise to transform it to understandable information for analysis[76], [77]. The analysis can help to identify damage such as cracks, deformations, and corrosion [78]. As for thermal cameras, they can capture infrared radiation emitted by structures, provide their temperature information [79], [80], [81]. This temperature information can help inspectors to identify insulation problems, moisture infiltration, electrical defects, and thermal bridges.

Safety Risks Associated with Drone Usage

The safety risks of drone usage in construction projects can be broadly divided into direct physical risks and indirect cognitive risks. Direct risks include incidents such as drone crashes, falling debris, or collisions with structures and equipment, all of which pose immediate threats of injury or fatality to workers on site. In contrast, indirect risks do not involve physical contact but stem from the way drones influence workers' cognitive states. These include the invasion of personal space, distraction caused by the noise and motion of drones, and the resulting increase in cognitive load that can impair hazard recognition and situational awareness. Both categories are critical for ensuring safety on construction sites, as direct risks can cause immediate harm while indirect risks can subtly compromise workers' focus and decision-making, thereby elevating the likelihood of accidents over time.

Direct Physical Risks

Direct physical risks refer to the hazards that drones pose to workers, equipment, and property on construction sites. These risks involve direct physical contact or mechanical failure that potentially result in direct worker injury or property damage. One of the primary contributing factors is the lack of trained pilots [9], which increases the likelihood of operational mishandling and accidents. In such cases, the high-speed rotating blades may strike nearby workers, or the drone may fall unexpectedly, both of which pose serious risks of injuries such as blunt head trauma or contusions [82]. Human errors can also lead to drone malfunctions, which may result from defects in hardware (e.g., loose connections, defective electronic components) or software (e.g., programming flaws, algorithmic errors, or signal disruptions) [83]. Such malfunctions can generate hazardous situations, including loss of stopping capability, unintentional deviations from designated flight paths, uncontrolled velocity, or abrupt and unpredictable maneuvers. Moreover, insufficient flight planning and preparation can also cause accidents [9]. For example, if the flight team fails to consider boom cranes within the drone's flight path, the drone may collide with the crane structure, leading to equipment damage, work interruptions, or even severe injuries to nearby workers. Besides human errors, congested construction environment and weather conditions (e.g., snow, rain, wind, and sunlight) increasing the safety risk of applying drone in construction [5].

The above are the leading cause to drone-related accidents which includes struck-by accidents, property damage, and fire hazards. Struck-by accidents are one of the leading causes of fatalities and serious injuries in construction. During drone operations, pilot errors such as misjudging distances, losing control, or failing to maintain safe separation can result in drones striking workers or equipment [84]. These incidents increase worker safety risks and can also cause delays or equipment damage. Small-sized UASs pose inherent dangers due to their mass and velocity. They generally operate at or near the height of the structures under inspection, typically within an altitude of less than 400 feet [85]. Such close distance significantly increases the risk to workers' safety, particularly in the event of operational mistakes or mechanical failures. In these scenarios, an out-of-control or falling UAS could strike individuals on site, resulting in severe injuries or even fatalities. The combination of drone speed and weight amplifies this hazard, as the resulting momentum and blade force can produce serious consequences. In construction, small drones typically weigh between 250 g (0.55 lb) and 1.38 kg (3 lb) [86], while capable of reaching speeds of up to 70 km/hour (43 mile/hour), with some models achieving speeds as high as 100 km/hour [87].

Uncontrolled or falling UASs pose risks not only to workers but also to surrounding objects and structures on the construction site. Collisions with temporary or permanent structures can result in significant property damage and disrupt ongoing operations. In some cases, such impacts may generate secondary hazards, including flying debris or partial structural collapse, which could injure or even kill nearby workers [88]. Furthermore, if a malfunctioning drone or even sparks generated by its components come into contact with flammable materials commonly present on construction sites, such as fuel, oil, or gas, they could ignite fires that result in catastrophic property damage and place both the project site and surrounding areas at serious risk [89].

Indirect Cognitive Risks

The use of drones in construction introduces potential distraction hazards, as their presence can trigger workers' curiosity or draw attention through noise and motion. Such distractions may compromise focus and situational awareness, thereby increasing the likelihood of workplace accidents. According to [90], personal space in this context is represented by a cylindrical zone with a radius of 1.2 m (4 ft) and a height of 3 m (10 ft), within which workers perceive their privacy to be maintained. When drones intrude into this space, workers may experience discomfort, irritation, and stress, which can negatively influence their performance, behavior and actions. For example, construction workers may experience concerns related to midair collisions, mechanical failures of UASs, and potential operator errors [12], all of which increase their stress and mental load.

Moreover, curiosity, as a basic human instinct, is a key factor contributing to distraction. Survey shows that 58% of the US population feels curious and 45% feels interested when seeing a drone [91]. Thus, drones on construction sites can create distractions that may affect worker safety and performance [90]. Prior research has shown that distractions often contribute to unsafe behaviors [92] and unsafe worker behavior is one of the primary contributors to construction site accidents [93]. Distractions have been shown to contribute to errors, miscommunication, and diminished awareness of workplace hazards [13]. For example, if a heavy equipment (e.g., tower crane) operator momentarily shifts focus to observe a drone overhead, the lapse in attention could trigger a serious accident [94].

The noise and movement of drone operations can pose distractions and reduce workers' concentration [90]. According to distraction theory [95], inattentive workers face an increased likelihood of accidents and injuries. Hazard recognition, which is essential for identifying potential risks, requires continuous alertness and focus [96]. When workers are distracted, basic cognitive functions such as observation, reasoning, attention, and situational awareness are disrupted, which in turn raises the probability of errors and accidents [12].

Situation Awareness and Distraction in Construction

Situation Awareness

Human error accounts for a considerable proportion of accidents, with deficiencies in situation awareness recognized as a primary factor. Situation awareness is the perception of environmental elements within a given spatial and temporal context, the understanding of their meaning, and the prediction of their future status [97]. According to Endsley's model of situation awareness, situation awareness is structured into three levels: Level 1 involves the perception of environmental elements; Level 2 refers to the comprehension of the current situation; Level 3 concerns the projection of the future status of those elements.

To study situation awareness, there are many techniques for measuring situation awareness in the construction domain. Table 1 organizes and explain the measurements used in the literatures. Among these, the Situation Awareness Global Assessment Technique (SAGAT) is the most common across industries. It evaluates situation awareness by pausing tasks and asking structured questions based on Goal-Directed Task Analysis (GDTA), addressing perception (Level 1), comprehension (Level 2), and projection (Level 3). For example, Level 1 questions include whether the participant noticed a safety sign or piece of equipment [98]. Level 2 questions assess whether the distance between a robot and a structural element is sufficient for safe operation [99]. Level 3 questions ask participants to anticipate the consequences of continuing a task, such as predicting interactions between a forklift and a coworker [100]. While SAGAT is considered a direct and objective method, its intrusiveness and questionable ecological validity are recognized limitations.

The Situational Awareness Rating Technique (SART) is another widely used method, applied in several construction studies [101], [102], [103]. It is a post-task, self-rating approach where participants evaluate the accuracy and comprehensiveness of their situational understanding. SART is valued for being inexpensive, non-intrusive, and easy to administer, although it is subjective in nature.

The Situation Present Assessment Method (SPAM) has also been adapted in construction. Originally developed for air traffic controllers, it measures situation awareness dynamically through real-time probes during task performance. Fang et al., for example, applied SPAM to mobile crane operations[104], noting that it is less intrusive than SAGAT and capable of capturing real-time, dynamic aspects of situation awareness.

Eye-tracking techniques represent another approach, capturing gaze behavior and attention distribution toward safety-related objects. This method has been applied to study hazard detection and visual attention in construction environments [105], [106]. While eye-tracking provides objective and non-intrusive data, it primarily assesses Level 1 situation awareness (perception), has practical limitations for users with eyeglasses, and is difficult to scale to real-world applications. In one notable study, Hasanzadeh et al. combined mobile eye-tracking with SART to validate attentional data against subjective self-ratings [107]. Other direct measures include questionnaires and self-scale items, which have been used to assess comprehension, risk perception, or situational understanding. For example, Gurevich and Sacks applied questionnaires in VR environments [108], and Whiteoak and Mohamed employed self-scale items [109]. However, these methods are less structured, and their validity for capturing situation awareness remains debatable.

In addition to direct methods, several indirect measures have been used to examine components that influence situation awareness. The NASA Task Load Index (NASA-TLX) is the most common, applied in four construction studies [101], [102], [103], [104]. NASA-TLX evaluates workload across six factors: mental demand, temporal demand, physical demand, performance, effort, and frustration. Although it does not directly measure situation awareness, it provides valuable insights into cognitive load and task performance. Physiological measures have also been explored, including heart rate (HR), heart rate variability (HRV), electroencephalography (EEG), and electrodermal activity (EDA). Ibrahim et al. used wearable sensors to assess how physical fatigue impacts hazard recognition performance and safety risk assessment [110]. Kim et al. examined the relationship between workers' situation awareness, workload, and heart rate data [98]. These studies highlight the potential of physiological data to complement direct situation awareness measures, though challenges remain in establishing theoretical connections between physiology and situation awareness. Other indices include key performance indicators (KPIs) were used to assess load control accuracy and efficiency in crane operations [104], [111]. Although informative, the validity of these indicators remains uncertain.

Table 1. Measurement methods for situation awareness

Situation Awareness Method	Explanation
Eye-tracking (Level 1)	Tracks workers' gaze and attention on safety-related objects [105], [106].
Projected view analysis (Level 1)	Tracking crane operator visibility and blind spot [112]
Situation Awareness Global Assessment Technique (SAGAT) (Level 1, 2, and 3)	Examples questions of SAGAT for level 1, 2, and 3: • Level 1: "Did you see the safety sign (or equipment)?" [98] • Level 2: "Is the distance between the robot and the element to be demolished sufficient for a proper operation" [99]

	• Level 3: "What will happen to the forklift and the coworker if I continue moving on my direction?" [100]
Situational Awareness Rating Technique (SART) (Composition of level 1 and 2)	Post-task self-rating method where participants evaluate their situation awareness [101], [102], [103].
Situation Present Assessment Method (SPAM) (Level 2 and 3)	Real-time probing method where participants answer questions during tasks; response accuracy and time indicate situation awareness. Captures dynamic situation awareness and is less intrusive than SAGAT, but still interrupts performance [104].
Questionnaires & self-scale items (Level 1 and/or 2)	Used in VR/AR or psychological studies to assess comprehension, risk perception, or situational understanding [108], [109].
NASA-TLX (Task Load Index) (Indirect measurement)	Measures perceived workload (mental, temporal, physical, performance, effort, frustration). Not a direct situation awareness tool but often used to evaluate factors influencing situation awareness [101], [102], [103], [104].
Physiological measures (HR, HRV, EEG, EDA) (Indirect measurement)	Capture mental workload, fatigue, and stress affecting situation awareness [98], [110].
Performance (KPI)	Task-specific metrics (e.g., accuracy, efficiency) used to indirectly assess situation awareness [104], [111].

<u>Distraction</u>

The Oxford Dictionary defines distraction as “something that distracts the attention and prevents concentration [113].” In construction, workplaces are dynamic and rapidly changing environments where distracting stimuli are constantly present. When individuals are distracted, their performance in primary tasks, such as hazard recognition, often declines. Distractions divert and consume part of the limited attentional resources available to workers to carry out cognitive activities [114]. As a result, distraction has been shown to be associated with slower reaction times, higher error rates, and reduced work quality [115]. The relation between distraction and situation awareness is that distraction interrupts attention and initiates a sequence of cognitive breakdowns that weaken overall awareness. When workers are distracted, their ability to perceive critical cues in the environment is reduced, leading to deficiencies in Level 1 situation awareness. This incomplete perception undermines comprehension (Level 2), as the worker struggles to interpret the meaning and significance of the observed elements. The impairment continues to projection (Level 3), limiting the capacity to anticipate how the situation may develop in the near future. Together, these effects reduce overall situation awareness and heighten the risk of accidents by compromising hazard recognition, decision-making, and timely responses.

Thus, studying distraction and its consequences is to study situation awareness, since distraction directly disrupts the processes that sustain awareness in dynamic environments. The details of the primary methods for assessing situation awareness are presented in Table 1 in Section Situation Awareness. These methods have been widely applied to examine distraction across domains such as construction, transportation, aviation, and healthcare. To apply these methods, a platform is needed for executing these methods. Experimental platforms provide the environments in which distraction can be studied, and they vary in terms of control, realism, and applicability.

The platforms used to study distraction can be broadly categorized into three groups: laboratory or simulator experiments, virtual reality (VR) and augmented reality (AR) environments, and field or naturalistic settings. Laboratory and simulator experiments are among the most common. These platforms allow researchers to systematically introduce distractors and examine their effects on performance metrics such as reaction time, error rates, lane deviation, or hazard detection. Their strength lies in high internal validity and the ability to establish causal relationships between distraction and performance outcomes. For example, in construction, laboratory experiments have been used to examine how distraction impairs hazard recognition. Participants were asked to identify hazards in construction site images under distraction conditions, finding reduced recognition accuracy [13], [114]. In aviation, simulator studies demonstrate how interruptions degrade flight performance. Study showed that aural and visual interruptions during flight-deck simulations increased workload and reduced accuracy [116]. In transportation, driving simulators have established the risks of secondary tasks. Strayer and Johnston showed that cell-phone conversations slowed reaction times and impaired braking performance[117]. Follow-up studies confirmed that conversation itself, not manual handling, was the main cause of attention failures [118], [119].

Virtual and augmented reality (VR/AR) experiments provide immersive, controlled environments that allow researchers to safely replicate distractions and measure their impact on attention, performance, and situation awareness. Jeelani et al. used virtual reality to simulate construction sites and assess the impact of drone presence on workers' attention and stress, finding that drones distracted workers at distances of 12 and 25 ft but did not significantly affect psychological distress [120]. Similarly, Albeaino et al. applied VR to examine attentional impacts at varying distances, showing that drones at greater distances elicited longer and more frequent fixations [121]. In transportation, Barlow et al. used a VR driving simulator to show that drones near the roadside distract drivers, recommending a minimum 25 ft buffer [122]. A VR study by the Oregon Department of Transportation found increased glance frequency and unsafe glances (>2 s) at lateral offsets of 0, 25, and 50 ft [123]. Ryan et al. further demonstrated with a simulator using a real vehicle seat that drones caused critically long glances in 11% of cases [124]. Collectively, these studies confirm that VR and simulators are effective tools for assessing drone-induced driver distraction. In healthcare, VR surgical simulators have been applied to study how interruptions compromise performance. Feuerbacher et al. reported that realistic auditory and procedural distractions increased major errors in laparoscopic tasks [125]. In a VR simulator study with 86 medical students, distraction was introduced by asking clinical case questions during a cystoscopy task, which led to significantly more errors and longer completion times compared to controls [126].

Field and naturalistic studies capture distraction in real-world settings, offering high ecological validity and revealing how interruptions unfold under authentic working conditions. In construction, mobile eye-tracking has been used on active jobsites to capture real worker behavior. These studies showed that uncontrolled site stimuli diverted gaze away from hazards, reducing recognition accuracy, and highlighted the role of natural distractions in safety performance [105], [107], [127]. In transportation, large-scale naturalistic driving projects such as the 100-Car Study and SHRP2 continuously recorded driver behavior with in-vehicle video and sensors. Analyses revealed that secondary tasks, especially mobile phone use and long glances away from the road, sharply increased crash and near-crash risk[128], [129].

In healthcare, operating room observations have shown that distractions occur roughly every few minutes, often disrupting surgical flow. These interruptions have been linked to increased workload, technical errors, and patient safety risks, while similar findings have been reported in ward-based studies [130], [131].

Drone Path Planning

Path Planning Algorithm

Drone path planning algorithms can be examined in terms of two main aspects: the type of input information and the type of output. Input information defines whether algorithms use static maps or adapt to real-time environmental data. Output type indicates whether algorithms produce a single optimal path or a set of candidate paths. These two dimensions provide a structured basis for comparing approaches in prior studies.

Path planning algorithms can be broadly categorized according to the type of input information they utilize. Two principal forms are identified in the literature: static and dynamic [132], [133]. Static approaches determine drone paths based on fixed spatial data (e.g., maps of terrain, buildings, trees, and defined no-fly zone) [134]. In contrast, dynamic approaches adjst routes in response to real-time spatial information (e.g., temporary restrictions, weather variations, or the moving people, animals, and vehicles) [135], [136], [137]. To enable such adaptability, studies adopted technologies including LiDAR, GPS, cameras, radar, thermal imaging, and ultrasonic sensors [138], [139], [140]. For example, LiDAR and thermal data can support trajectory adjustments in response to unforeseen obstacles or environmental changes [141], [142], [143]. GPS signals provide dynamic input to mitigate inter-drone collision risks [144], [145]. Overall static approaches are suitable in stable, predictable environments and for long-distance operations dure to their efficiency and accuracy. On the other hand, although dynamic approaches require higher computation, they are more suitable in complex or unpredictable settings, where they reduce collision risks and enhance responsiveness in emergency situation.

Path planning algorithms can also be classified based on their outputs, single-solution and multiple-solution algorithms. Single solution algorithms iteratively refine and initial candidate path until they converge on one optimal or near-optimal trajectory. Examples include mixed-integer programming [146], gradient-based search [147], greedy algorithms [148], [149], Dubin curves [139], least-cost path models [150], and classic graph search techniques (e.g., Dijkstra [151], [152], [153] and A* [154]). Other heuristic approaches have also been employed to optimize discrete choices such as sequencing of stops and path allocation [155], [156]. As for multiple-solution algorithms, they generate a population of candidate paths and refine them over successive iterations. These include evolutionary algorithms such as genetic algorithms [157], [158], [159], [160], differential evolution [161], and evolutionary strategies [162], and physics-based algorithms [163], [164], [165], [166]. Physics-inspired algorithms, such as firefly optimization [167], swarm intelligence [168], and ant colony optimization[169], have also been widely applied. Hybrid algorithms, such as the genetic algorithm with simulated annealing, further extend these algorithms [170]. Multiple-solution approaches are particularly effective at identifying near-optimal routes within reasonable computation times by leveraging diverse search operators and, in some cases, integrating prior knowledge [171].

Path Planning in Construction

Recent research has increasingly explored drone path planning algorithms to construction applications, aiming to enhance safety, inspection efficiency and automated monitoring as mentioned in section Drone Application in Construction.

For inspection, Xu et al. focused on drone path planning for bridge construction safety inspection by proposing an enhanced Snake optimization algorithm (CSGLSO). This algorithm considered energy efficiency collision avoidance, trajectory smoothness, rapid convergence, and the avoidance of local optima in 3D environments [172]. Zheng et al. proposed a drone-based building facade visual inspection through coverage path planning. Their two-stage framework combined normal vector segmentation, k-means clustering, and greedy optimization for viewpoint generation with a hybrid Ant Colony Optimization and Differential Evolution (DACO-DE) for path planning. The study emphasized complete surface coverage, minimizing redundancy, reducing path length, collision avoidance, smoothness in flight trajectories, and energy efficiency [173].

Moreover, Liu et al. developed a drone-based construction site refinement inspection method integrating BIM and 3D reconstruction. Waypoints were selected using an improved Artificial Potential Field combined with a greedy algorithm, while global path optimization relied on A* and Simulated Annealing. Their method considered obstacle avoidance, low-altitude flight safety, efficient waypoint distribution, image coverage, and energy consumption reduction [174]. Freimuth and König explored drones for construction inspection and structural health monitoring (SHM) within a BIM-integrated workflow. They generated collision-free flight paths using a discretized graph from BIM data and validated navigation strategies with Software-In-The-Loop simulation. The framework considered collision avoidance, battery usage, weather and lighting effects, camera parameters, and overall safety of autonomous drone operations [175].

For monitoring, Huang and Hammad focused on unmanned aerial vehicle-based automated video collection of dynamic construction activities to support progress and safety monitoring. Path optimization was achieved using a Non-Dominated Sorting Genetic Algorithm II, while routing relied on the A-star algorithm and a random-key genetic algorithm. The approach incorporated visual coverage, occlusion avoidance, travel time minimization, collision risk management, integration with four-dimensional Building Information Modeling micro-schedules, and data quality for computer vision processes [176].

CHAPTER THREE: OBJECTIVE, RESEARCH GAP, AND METHEDOLOGY OVERVIEW

Existing studies on drone safety in construction have primarily concentrated on direct physical risks, such as collisions, equipment interference, and operational malfunctions. Prior work has largely addressed these hazards through simulation-based analyses and sensor-driven safety frameworks that enhance drone's obstacle detection and situational awareness in high-risk areas [15], [16]. While such efforts have advanced the technical reliability of drone operations, much less attention has been given to indirect cognitive risks, including distraction, elevated mental workload, and reduced situational awareness among workers. Qualitative investigations have shown that drone can cause distraction to workers, compromising their cognitive focus and situation awareness [8], [9]. Quantitative studies using virtual reality and eye-tracking further verified that drones flying at low altitudes or close distances significantly alter fixation behavior, but the findings remain preliminary and have yet to be translated into actionable mitigation strategies [18]. Although these studies provide initial evidence of cognitive disruption, the impacts of drone distraction to the workers in construction sites still needs to be systematically explored.

Existing studies on drone safety in construction have made progress in identifying direct physical hazards but have several limitations regarding indirect cognitive risks. First, few studies have provided systematic quantitative evidence on how flight configurations influence workers' visual attention and performance. The findings of safe drone flight configurations can help establish practical operational guidelines for minimizing cognitive interference and enhancing worker safety during drone-assisted construction activities. Second, existing research has not investigated how drone-induced distraction affects tower crane operators, despite tower crane operation being recognized as one of the most hazardous and attention-critical tasks in construction practice. Third, current guidelines for safe drone operation lack consideration of human attention and cognitive load, leaving an important gap between technology design and worker safety. Finally, despite growing advances in drone path planning for collision avoidance and inspection coverage, there remains no studies that integrates behavioral findings on distraction into drone flying planning. Addressing these gaps requires an interdisciplinary approach that combines behavioral experimentation, human factors analysis, and algorithmic modeling.

The overarching objective of this dissertation is to quantitatively evaluate drone-induced distraction and develop a distraction-aware path planning method to enhance cognitive safety in construction environments. This research is structured into three main components. The first objective is to investigate how drone flight height and direction influence workers' visual attention to hazard areas during material-handling tasks at height. The second objective is to examine how drone flight height and horizontal distance affect tower crane operators' visual attention and task performance, including collisions, payload deviation, and completion time. The third objective is to develop a distraction-aware path planning algorithm that integrates worker attention data with physical collision avoidance, enabling drones to complete missions efficiently while minimizing their interference with worker focus.

To achieve these objectives, a two-phase research methodology was adopted. In the first phase, a virtual reality experiment was conducted to simulate construction tasks at height. Participants performed material-moving activities in immersive 3D environments while drones flew at different heights and directions. Eye-tracking technology was used to capture fixation time and count on hazard areas, allowing quantitative analysis of distraction effects under various flight conditions. Moreover, another virtual reality experiment was designed to evaluate tower crane operators' performance under different drone configurations. The experiment replicated the Certified Crane Operator (CCO) zigzag corridor test, with operators controlling a virtual crane to move payloads while drones flew above or below operator at varying distances. Visual attention and performance data were analyzed using repeated-measures mixed models to determine the influence of drone proximity and position. The second phase of this research involved developing a distraction-aware drone path planning method. Based on findings from the first phase, a soft cost function representing distraction risk was incorporated into a three-dimensional path planner. The algorithm integrates physical constraints, such as obstacles and worker locations, with cognitive safety considerations, allowing drones to generate safer and more efficient routes.

The outcomes of this research provide both empirical and practical contributions to the field of construction safety and automation. The experimental findings establish quantitative relationships between drone flight parameters and worker attention/performance, offering evidence-based recommendations for safe flight configurations. The distraction-aware path planning algorithm extends this knowledge into practical application by demonstrating how cognitive safety metrics can be integrated into autonomous drone navigation. Collectively, these contributions bridge the gap between behavioral safety studies and technological innovation, advancing the development of human-centered and safety-aware drone operation in construction.

CHAPTER FOUR: IMPACT OF DRONE DISTRACTION ON CONSTRUCTION WORKERS WORKING AT HEIGHT

The purpose of this chapter is to evaluate the workers' visual attention to hazards with drones flying at different heights and directions. The basic research question is, "How does the time workers spend observing hazard areas vary with drone flight at different heights and directions?"

Problem Statement, Objectives, and Research Questions

Existing research has identified the risks of drone-related distractions for construction workers, primarily focusing on their visual attention toward drones. While drones can be a source of distraction, they may also require workers to assess their size, position, speed, and direction as a necessary safety behavior. Thus, the best practice is to observe the drone with enough attention while not reducing the time observing other hazards. However, a comprehensive analysis of how drones influence workers' attention and the time they spend observing surrounding hazards in construction environments remains unexplored. The main objective of this paper is to evaluate the workers' visual attention to hazards with drones flying at different heights and directions. The basic research question is, "How does the time workers spend observing hazard areas vary with drone flight at different heights and directions?"

Experiment Design and Implementation

Variables

We employed three kinds of variables in our experiment, namely, control variables, independent variables, and dependent variables. Control variables were held constant, including drone flying speed and sound. Drone flying speed was set at 11.2 mph (~5 m/s) [177]. To enhance the realism of virtual construction environments, real background construction noise and real drone flying sounds were incorporated to provide a more immersive and authentic auditory experience.

The independent variables were drone presence or absence, flying height, and flying direction. Morgenthal and Hallermann investigated the effectiveness of drone applications in visual inspections and found that clear images can be taken when the drone height is between 16 ft and 82 ft [178]. Therefore, 16ft, 48ft, and 82 ft were chosen for our experiment. The height of 48 ft was selected because it is between 16 ft and 82 ft. All the heights were measured relative to the elevation of the test participants. To ensure that all test participants had the same experience in the experiment, only two flying directions were used. One was the drone appearing from the far front of the participants and disappearing from behind. The other was the opposite: the drone appeared from behind and disappeared from the front. As for the dependent variables, we selected eye gaze fixation time on danger areas and sky as well as fixation count on danger areas. Since the drone may or may not appear in the view of the participant, fixation time on the sky was measured to capture participants' visual attention behaviors when they searched for the source of the drone sound or looked directly at the drone. The fixation time and count on danger areas were chosen to capture their visual attention to danger areas. Here, the danger areas were openings, edges, and fences in the virtual construction environments.

Metrics

Visual observation is a critical component of hazard awareness, enabling individuals to identify and respond to potential risks effectively. To measure visual observation, eye fixation time and count are commonly used in eye-tracking studies to assess visual attention and cognitive processing [179]. The variable eye gaze fixation time refers to the duration for which a person's gaze remains focused on a specific point. Fixation count means the number of times the fixation occurred [180]. Fixations occur when the eyes temporarily stop moving for at least 100 milliseconds to process visual information [179]. In research settings, these metrics are often used to evaluate how individuals interact with visual stimuli [18], such as identifying hazards in a construction environment or distractions caused by external factors like drones.

Participants

24 test participants (16 males and 8 females) were recruited. They were interns, professionals, managers, and workers, all of whom with work experience in construction. Their average age was 27 and their average years of work experience was 2.8. The research protocol was approved by the University of Wisconsin-Madison's Institutional Review Board (IRB).

Instruments

The virtual environments were run on a computer with an Intel® Core™ i7-9800X CPU (Central Processing Unit) @ 2.90 GHz, an NVIDIA GeForce RTX 2080Ti SUPER GPU (Graphic Processing Unit), and 64 GB memory. As shown in Figure 2, the test participants wore the Meta Quest Pro VR headset and walked on the KAT Walk C2+ omnidirectional treadmill (ODT). Meta Quest Pro software was used to capture fixation data because it had eye-tracking capabilities. KAT Walk C2+ allowed participants to physically walk within the virtual environments. The device was used to replicate similar physical demands to those encountered in real-world construction tasks. In the experiment, seven virtual construction environments were developed in Unity, a game engine used to create interactive 3D and VR experiences and applications popular for game development and real-time simulations. To enhance the realism, Unity allows the participants to experience spatially accurate drone sounds, with the participants hearing the drone's flying noise in stereo based on its distance and location. The virtual environments had three different buildings and the same number of openings and edges with similar lengths of walking routes. This ensured that all the virtual environments had the same difficulty for the test participants to complete their tasks. All test participants trialed all these virtual environments. Figure 3 shows a sample of the virtual construction environment and drone used in this paper. The virtual drone model used in this study was a Mavic 3 Pro with a real-world recording of its flying sound.

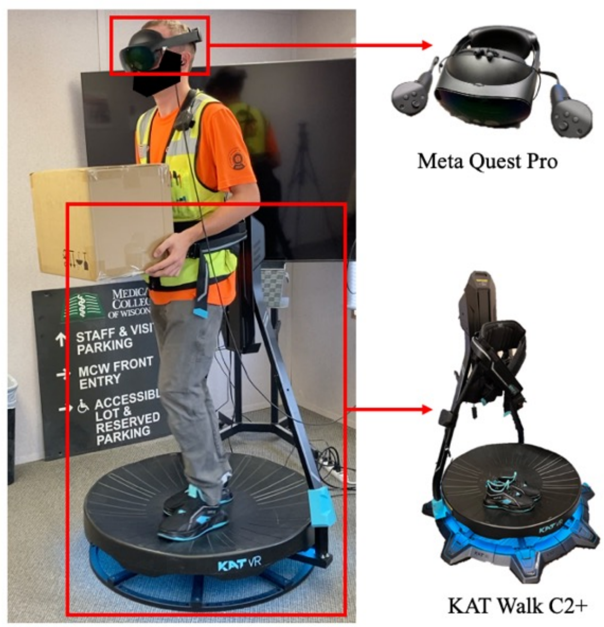

Figure 2. Test participant wearing a Meta Quest Pro VR headset on KAT Walk C2+

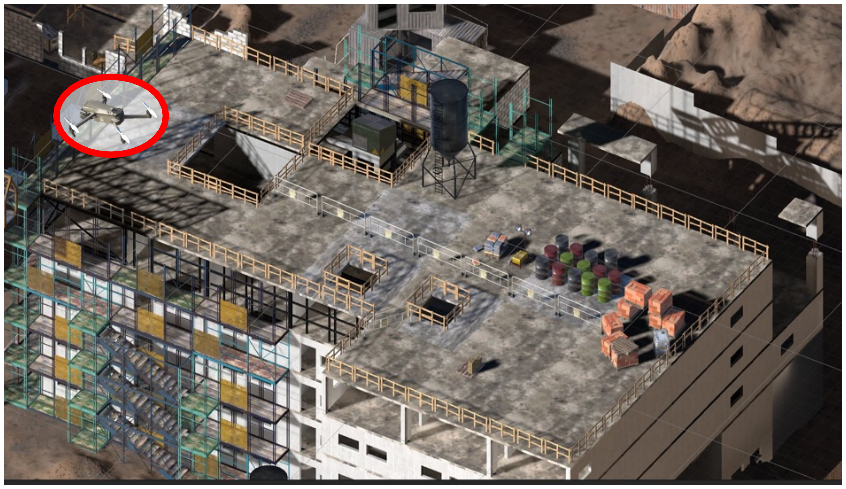

Figure 3. Virtual construction environment and drone.

Procedure

Upon arrival, the test participants were asked to read and sign the IRB-approved consent form, which informed them that they were doing an experiment related to drone safety in construction sites and the experiment is related to drone. Before collecting data from the test participants, eye height calibration was carried out to ensure data accuracy. Each test participant was asked to stand on the ODT, put on the VR headset, and hold the VR headset's hand controller. The position of the controller relative to the VR headset was automatically calibrated by the device. This ensured that the distance between the participant's hand and eyes was the same as the distance between the virtual hand and eyes. Then, the test participants were asked to touch the ground with their hands while holding the controller in the virtual environment. Eye height calibration was completed when they touched the virtual ground and the surface of the ODT at the same time.

Our experiment adopted a repeated measures design, where every participant was tested on all virtual scenes, to remove between-participant variation [181]. Seven virtual construction scenes with different drone flight configurations (i.e., heights and directions) were used, as shown in Table 2. To control order or sequence effects, the test participants were randomly divided into seven groups using a Latin Square design to approximately balance those effects. Table 3 shows the scene sequences for the groups. The drone flight configurations in each scene number are given in Table 2.

Table 2. Drone intervention settings of scenes.

Scene Number	Drone Presence	Drone Direction	Drone Heights
1	No	N/A	N/A
2	Yes	Front to back	82 ft
3	Yes	Front to back	16 ft
4	Yes	Back to front	48 ft
5	Yes	Back to front	82 ft
6	Yes	Back to front	16 ft
7	Yes	Front to back	48 ft

Table 3. Scene sequences of different groups

Group	Sequence of Scenes
A	1 → 2 → 3 → 4 → 5 → 6 → 7
B	3 → 1 → 2 → 7 → 6 → 5 → 4
C	5 → 4 → 7 → 2 → 1 → 3 → 6
D	2 → 3 → 1 → 6 → 4 → 7 → 5
E	6 → 7 → 4 → 5 → 3 → 1 → 2
F	7 → 5 → 6 → 3 → 2 → 4 → 1
G	4 → 6 → 5 → 1 → 7 → 2 → 3

The test participants performed the same task in each scene, which was to carry a 16.5” x 12” x 14” box from a start to an end location twice. The drone randomly appeared during one of the two times. During the experiment, the participants’ gaze fixation points were recorded at a frequency of 100 times per second. Figure 4 shows a virtual construction scene. The yellow (dashed and solid) line is the route taken by the test participants. To ensure the drone appeared from the front or behind the test participants, each of the virtual construction sites was designed to have one straight part of the route as indicated by the yellow solid line. The red dashed line is the drone flying route.

Figure 4. A sample of the virtual construction site.

The experiment included 24 test participants and 3 experimental factors, namely, sequence order (1-7), height of drone (16, 48, and 82 ft.), and direction of drone (back and front). Each participant was tested on each of the 6 combinations of height and direction, as well as a 7th condition in which there was no drone. We use the name "Condition" to refer to this combination variable, with levels indexed from 0 - 6, as shown in Table 4.

Table 4. Condition level indices (k) and definitions

k	Direction and Height	k	Direction and Height
0	No drone	4	Front, 48 ft
1	Back, 16 ft	5	Back, 82 ft
2	Front, 16 ft	6	Front, 82 ft
3	Back, 48 ft		

To ensure that the virtual environments we developed with sufficient rigor, this paper adopted a participatory and iterative design approach. we not only collaborated closely with our industry partner, who provided critical input on construction site layouts, typical activities, and operator workflows. Also, we conducted pilot tests and iterative feedback sessions with practitioners to validate the realism, task relevance, and visual fidelity of the environments. Subsequent refinements were made based on the expert feedback to improve construction object placement, drone flight behavior, and background until consensus was reached on the environment's authenticity and suitability for the study objectives. For example, we used spatialized drone sound recordings and accurate drone motion paths. The drone flight heights (16, 48, and 82 ft) were selected based on documented industry practices for visual inspections. Scene complexity and layout were controlled to maintain consistency across all test scenarios. A Latin Square design was adopted to counterbalance sequence effects across participants. Through this participatory and iterative design approach, the virtual environments were carefully calibrated to balance experimental control with real-world realism, enabling us to investigate distraction-related safety risks under conditions representative of actual construction sites.

Data Processing

The raw data were gaze fixation points in time sequence. A total of 57600 gaze fixation points were collected. For each scene, the fixation time and count were calculated by adding the values that occurred within the sky and predefined danger areas. This let us calculate the total fixation time and count on the sky and on the danger areas for each scene.

Statistical Analysis

To analyze the effects of drone flight factors on distraction, we employed a repeated measures linear mixed model. Owing to the presence of zero fixation times and counts, the model was fitted to the natural logarithms of fixation time plus 1 (*ln*(TP1)) and fixation count plus 1 (*ln*CP1)) to improve the normality of the residuals. The notation TP1 stands for "time plus 1"; and CP1 stands for "count plus 1." The model had a random effect on the test participants to account for individual variability and fixed effects for order sequence, drone flight configuration, and their interaction. A Type III ANOVA was used to evaluate the statistical significance of each fixed effect, specifically focusing on the effects of the drone flight factors. All computations were done using the lme4 and lmerTest packages in R [182], [183].

Results

Our experimental design included dividing participants into seven groups, each of which experienced the conditions in a different sequence order. This approach was intended to equalize any potential order effects. That is, the possibility that the order in which participants encountered the drone conditions may affect their responses. Importantly, the results showed no statistically significant effect of sequence order, meaning that the order of the conditions did not have a measurable impact on the results. Additionally, there was no significant interaction between sequence order and drone flight condition, further confirming that the sequence of conditions did not significantly affect how participants responded to the drone's presence. To determine the adequacy of the sample size for our experiment, we calculated the p-values of the dependent variables, namely TP1 and CP1. The p-values for TP1s (in danger areas and sky) and CP1 (in danger areas) under different conditions were 7.5×10^{-9}, 1.2×10^{-7}, and 4.7×10^{-7}, respectively, all substantially smaller than the 0.05 threshold. This indicates that the sample size was sufficient to support the validity of our findings.

The results report the participants' fixation time and count on danger areas as well as their fixation time on the sky. In this study, a variable is defined as statistically significant when its p-value is smaller than 0.05. Tables 5, 6, and 7 show that sequence order was not statistically significant on fixation time and count (p-values equal to 0.08, 0.073, and 0.707), indicating that the order in which participants encountered the scenes and drone conditions did not significantly influence gaze fixation time. The main effect of condition was highly statistically significant on fixation time and count (p-values equal to 7.52×10^{-9}, 4.69×10^{-7}, and 1.19×10^{-7}) but the interaction between sequence order and condition was not (p-values equal to 0.233, 0.268, 0.174).

Table 5. Type III ANOVA for *ln*(TP1) in danger areas vs Period and Condition

	P-value
Sequence order	0.080
Condition	7.52×10^{-9}
Sequence order-Condition Interaction	0.233

Table 6. Type III ANOVA for *ln*(CP1) in danger areas vs Period and Condition

	P-value
Sequence order	0.073
Condition	4.69×10^{-7}
Sequence order-Condition Interaction	0.268

Table 7. Type III ANOVA for *ln*(CP1) in sky vs Period and Condition

	P-value
Sequence order	0.707
Condition	1.19×10^{-7}
Sequence order-Condition Interaction	0.174

Table 8 shows the estimated fixation time-plus-one (TP1) in danger areas of the 6 conditions where a drone was present, as a fraction of the TP1 for the "No drone" condition. The estimated fractions were all statistically significant, ranging from 0.41 to 0.70. This shows that the presence of a drone can distract a worker and reduce their visual attention on danger areas by as much as 60 %. When the drone direction was “Back”, the TP1 was fairly constant at 0.63 - 0.69 of the TP1 for “No drone”. But when the direction was “Front” and height was 16 ft or 48 ft, the reduction in the TP1 was greater (0.41 - 0.42 of the TP1 for “No drone”). On the other hand, when height was 82 ft, the reduction was less, being about 0.70 of the TP1 for “No drone” for both flying directions. Thus, drone distraction was greatest when the height was 16 or 48 feet, and the direction was “Front.”

Table 8. Estimated TP1 in danger areas as a fraction of the TP1 for “No drone”, with 95% confidence intervals

	16ft	48ft	82ft
Back	0.63 (0.49, 0.82)	0.69 (0.53, 0.90)	0.67 (0.52, 0.87)
Front	0.42 (0.32, 0.55)	0.41 (0.31, 0.53)	0.70 (0.54, 0.91)

Analysis of fixation count-plus-one (CP1) in danger areas showed similar results. Table 9 gives the estimated CP1 on danger areas as a fraction of the CP1 for the “No drone” condition. Mean fixation count was reduced by 53 ~ 60% when the direction was “Front” and the height was 16 or 48 ft, and about 30% when the direction was “Back” and the height was 16 ft, or the direction was “Front” and height 82 ft. Reduction in mean fixation count was not statistically significant when the direction was “Back” and height was 48 or 82 ft. Overall, the results indicate that participants experienced greater distraction when the drone approached from the front, especially if the drone was flying at 16ft or 48ft.

Table 8. Estimated CP1 in danger areas as a fraction of the CP1 for “No drone”, with 95% confidence intervals

	16ft	48ft	82ft
Back	0.72 (0.52, 0.98)	0.87 (0.63, 1.20)	0.87 (0.63, 1.19)
Front	0.47 (0.34, 0.64)	0.40 (0.29, 0.55)	0.70 (0.51, 0.96)

Table 9 shows the increase of TP1 on the sky for the 6 conditions with drone presence minus TP1 in the condition without drone. For all conditions where the drone approached from behind the participants, the TP1 exhibited the greatest increase when the drone was flying at 16 feet. Conversely, when the drone approached from the front, the TP1 showed the highest increase at 48 feet.

Table 9. Estimated increase of TP1 in the sky as a fraction of the TP1 for "No drone"

	16ft	48ft	82ft
Back	0.288	0.043	0.098
Front	0.190	0.576	0.170

CHAPTER FIVE: IMPACT OF DRONE DISTRACTION ON TOWER CRANE OPERATOR

The purpose of this chapter is to evaluate tower crane operators' visual attention and performance when drones fly at different heights and directions. The central research question is: "How do different drone flight configurations affect the performance and visual attention of a tower crane operator?"

Problem Statement, Objectives, and Research Questions

Prior studies have identified risks of drone-related distraction for construction workers, with most focusing on workers' visual attention to drones. Drones can distract workers, but they may also require workers to assess drone size, position, speed, and direction as part of maintaining safety. The challenge is to determine how workers can allocate sufficient attention to drones without reducing their performance on primary tasks. A comprehensive analysis of how drones influence tower crane operators' attention and performance has not yet been conducted. The objective of this study is to evaluate operators' visual attention to the payload and their operating performance when drones fly at different heights and distances. The research question is, "How different drone flight configuration impact on the performance and visual attention of a tower crane operator?"

Experiment Design and Implementation

Variables

We employed three kinds of variables in our experiment, namely, control variables, independent variables, and dependent variables. Control variables were held constant, including drone flying speed and sound. Drone flying speed was set at 11.2 mph (~5 m/s) [177]. To enhance the realism of virtual construction environments, real background construction noise and real drone flying sounds were incorporated to provide a more immersive and authentic auditory experience.

Moreover, because the tower crane cabin is located at a high elevation, operators are typically exposed to the sound of wind striking the windshield. To replicate this condition, the noise of wind hitting the glass was included in the experimental environment.

The independent variables were drone presence, flying height, and flying distance, as shown in Figure 5. Flying heights were set at 16 ft below the operator and 35 ft above the operator to examine whether vertical positioning influences operators' attention and performance. Flying distances were set at 50 ft and 111 ft. Distance was measured horizontally from the position of the tower crane cabin. The distance of 50 ft is to place the drone outside the immediate operating area of the assigned task but within the swing range of the crane boom. The 111 ft is to place the drone outside the crane boom range. Including distance as an independent variable allowed assessment of whether proximity affects operators' allocation of attention between the drone and the payload. The dependent variables include visual attention and task performance. For the visual attention, fixation time and fixation count on both the payload and the drone are used for capturing participants' visual attention behaviors. For performance evaluation, collision, payload deviation, and task completion time are used.

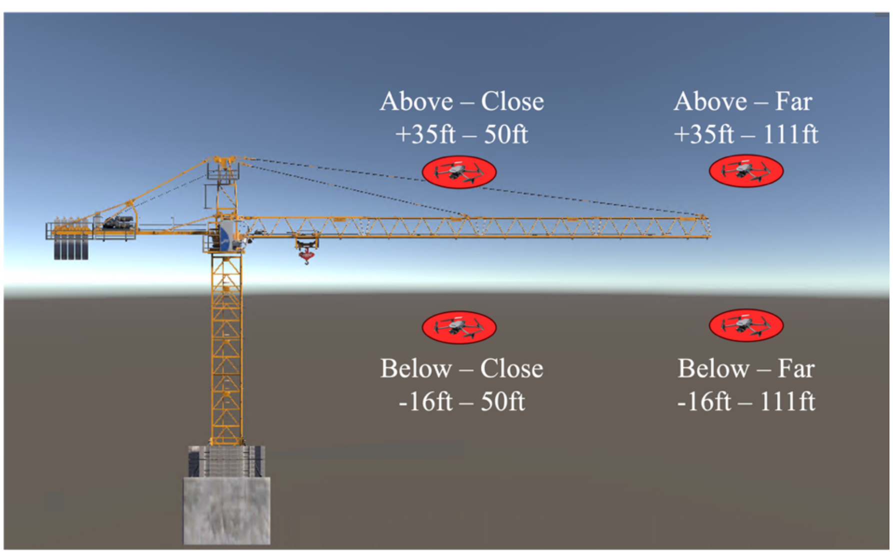

Figure 5. Independent Variables for Tower Crane Experiment

Metrics

Visual attention is a critical component of crane operation because operators must focus on the payload to ensure its stability during movement and to prevent collisions with surroundings. To measure visual observation, eye fixation time and count are commonly used in eye-tracking studies to assess visual attention and cognitive processing [179]. The variable eye gaze fixation time refers to the duration for which a person's gaze remains focused on a specific point. Fixation count means the number of times the fixation occurred [180]. Fixations occur when the eyes temporarily stop moving for at least 100 milliseconds to process visual information [179]. In research settings, these metrics are often used to evaluate how individuals interact with visual stimuli [18], such as monitoring a payload in a crane operation or distractions caused by external factors like drones.

Task performance metrics included collision, payload deviation, and completion time. In the experiment, participants were required to move the payload along a designated path within a range defined by poles. This task is designed by referencing zigzag corridor test in Certification of Crane Operation (CCO) from National Commission for the Certification of Crane Operators (NCCCO). In the zigzag corridor test, collision and completion time are used to evaluate the performance of operator. Thus, these two metrics were selected to be the performance metrics in this experiment. In detailed, collision was measured as the number of poles knocked down during the task. Completion time was measured as the total duration required to complete the task. Furthermore, payload deviation was added to evaluate the displacement of the payload trajectory from the center line of the designated path. The displacement is calculated by following Symmetrized Segment-Path Distance (SSPD) as shown in Eq. (1) and (2) [184].

$$D_{SPD}(T^a, T^b) = \frac{1}{n_a} \sum_{i_a=1}^{n_a} D_{pt}\left(p_{i_a}, T^b\right) \quad (1)$$

$$D_{SSPD}(T^p, T^r) = \frac{D_{SPD}(T^p, T^r) + D_{SPD}(T^r, T^p)}{2} \tag{2}$$

where T^p and T^r is payload and designated route trajectory, p is a sampled point from trajectory, $D_{pt}(p, T)$ is the minimum Hausdorff distance [185] from point p to trajectory T, and n is the number of points sampled from the trajectory T. SSPD is the symmetric segment-path distance, defined as the average of the distances from T^p to T^r and T^r to T^p.

Instruments

The virtual environments were run on a computer with an Intel® Core™ i7-9800X CPU (Central Processing Unit) @ 2.90 GHz, an NVIDIA GeForce RTX 2080Ti SUPER GPU (Graphic Processing Unit), and 64 GB memory. As shown in Figure 6, the test participants wore the Meta Quest Pro VR headset and use Thrustmaster T 16000M Space Sim Duo Stick. Meta Quest Pro was used to capture fixation data because it had eye-tracking capabilities. Thrustmaster T 16000M Space Sim Duo Stick is a pair of joysticks, mimicking tower crane control mechanism in real life. The left-handed joystick is to control the boom to swing left and right. The right-handed joystick is to lower and raising the hook. In the experiment, five virtual construction environments were developed in Unity, a game engine used to create interactive 3D and VR experiences and applications popular for game development and real-time simulations. To enhance the realism, Unity allows the participants to experience spatially accurate drone sounds, with the participants hearing the drone's flying noise in stereo based on its distance and location.

Figure 6. Test participant wearing a Meta Quest Pro VR headset and using Thrustmaster T 16000M Space Sim Duo Stick

The design of the virtual environments referenced zigzag corridor test in CCO from NCCCO as shown in Figure 7. The width is 1.5 times wider than the original zigzag corridor test and so the number of poles increase accordingly. Although these five virtual environments have same layout settings for the task, the surrounding environments are different. This is to increase the randomness of environments and minimizing the carrying over effect of participants. All test participants trialed all these virtual environments. Figure 8 shows a sample of the virtual construction environment. The virtual drone model used in this study was a Mavic 3 Pro with a real-world recording of its flying sound.

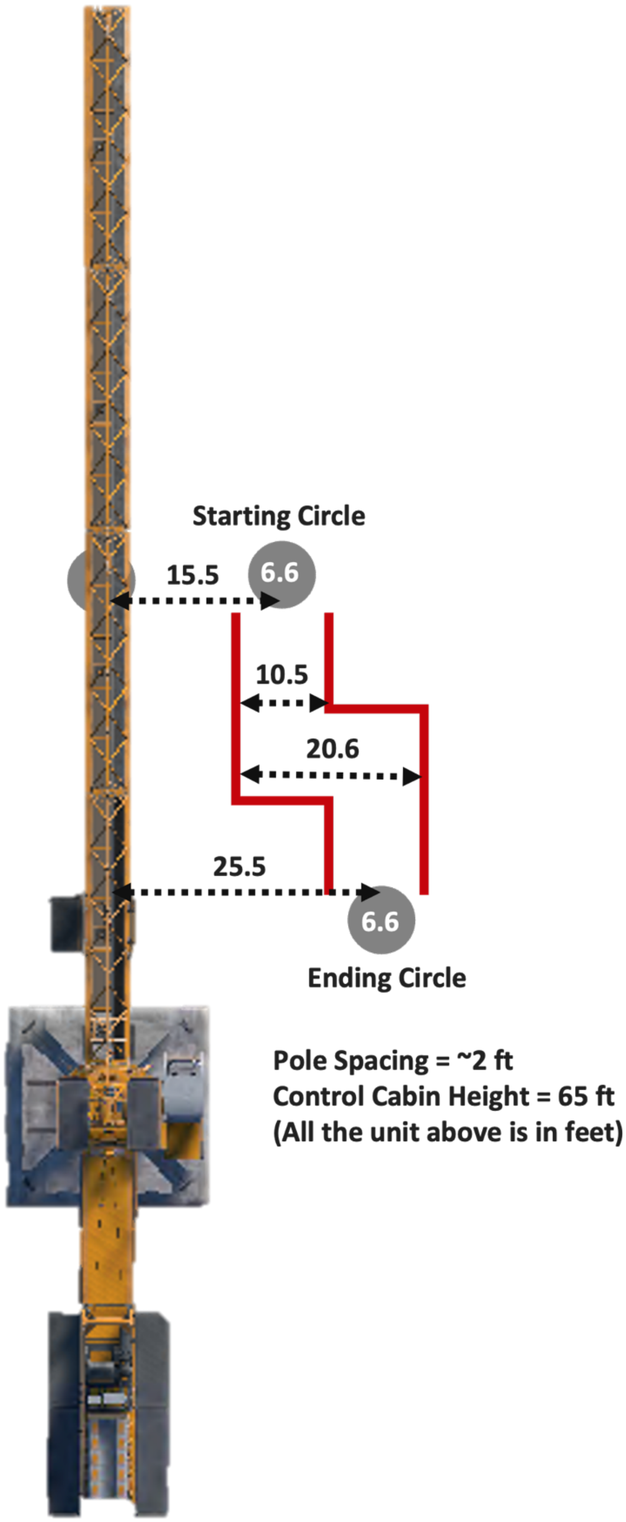

Figure 7. Virtual Environment Design Referencing the Zigzag Corridor Test from NCCCO's CCO Practical Exam

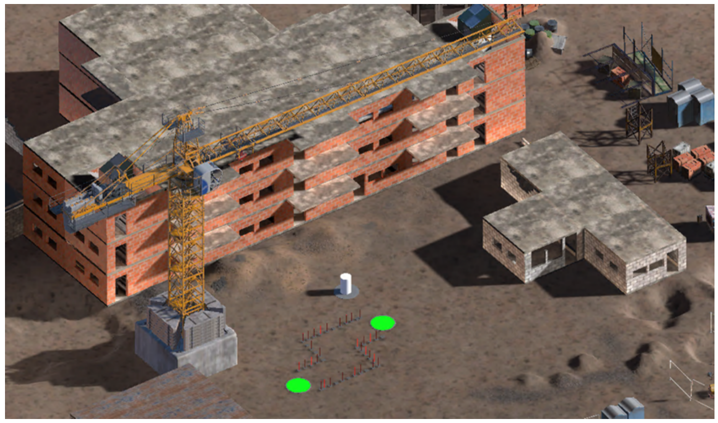

Figure 8. Virtual construction environment and drone.

Procedure

Upon arrival, participants were informed that the experiment involved operating a tower crane to complete a construction-related task and the experiment is related to drone. The experiment consisted of two stages: training and testing. The training stage was designed to familiarize participants with crane operation. During training, participants practiced the zigzag corridor task until they could complete it within 120 seconds while knocking down fewer than ten boundary poles. Once these criteria were met, participants proceeded to the testing stage. This procedure ensured consistent performance during the actual test and minimized sequence effects across scenes. The task itself was identical in both the training and testing stages.

The task was to operate a tower crane to move a cylindrical payload. It began by picking up the payload located outside the zigzag corridor and placing it in the starting circle of the corridor. When the payload was lifted, the starting circle turned green to indicate the next destination. Participants then lowered the payload until it fully touched the ground inside the starting circle. Once the payload touched the ground, the starting circle turned grey and the circle at the end of the corridor turned green. Participants were instructed to raise the payload slightly, so it no longer touched the ground but remained below the height of the poles. They then moved the payload along the zigzag corridor while avoiding collisions with the boundary poles. Upon reaching the end circle, participants lowered the payload until it touched the ground completely inside the circle. At that point, the end circle turned grey, and the starting circle turned green again. Participants then moved the payload backward through the corridor to the starting circle and lowered it until it fully touched the ground. This sequence completed one trial.

This experiment adopted a repeated measures design, where every participant was tested on all virtual scenes, to remove between-participant variation [181]. Five virtual construction scenes with different drone flight configurations (i.e., heights and distances) were used, as shown in Table 10. To control order or sequence effects, the test participants were randomly divided into five groups using a Latin Square design to approximately balance those effects. Table 11 shows the scene sequences for the groups. The drone flight configurations in each scene number are given in Table 10.

Table 10. Drone intervention settings of scenes.

Scene Number	Drone Presence	Drone Distance	Drone Heights
1	No	N/A	N/A
2	Yes	50 ft	-16 ft (below)
3	Yes	50 ft	+35 ft (above)
4	Yes	111 ft	-16 ft (below)
5	Yes	111 ft	+35 ft (above)

Table 11. Scene sequences of different groups

Group	Sequence of Scenes
A	1 → 2 → 3 → 4 → 5
B	4 → 1 → 2 → 5 → 3
C	3 → 5 → 1 → 2 → 4
D	2 → 4 → 5 → 3 → 1
E	5 → 3 → 4 → 1 → 2

The experiment included 23 test participants and 3 experimental factors, namely, sequence order (1-5), height of drone (-16 ft and +35 ft.), and distance of drone (50 ft and 111 ft). Each participant was tested on first condition in which there was no drone, as well as each of the 4 combinations of height and distance.

To ensure that the virtual environments we developed with sufficient rigor, this paper adopted a participatory and iterative design approach. we not only collaborated closely with our industry partner, who provided critical input on construction site layouts, control realism, and operator workflows. Also, we conducted pilot tests and iterative feedback sessions with practitioners to validate the realism, training process, and visual fidelity of the environments. Subsequent refinements were made based on the expert feedback to improve construction object placement, drone flight behavior, and background until consensus was reached on the environment's authenticity and suitability for the study objectives. For example, we used spatialized drone sound recordings and accurate drone motion paths.

Data Processing

The raw data were gaze fixation points in time sequence. A total of 11,213,200 gaze fixation points were collected. For each scene, the fixation time and count were calculated by adding the values that occurred on the drone and payload. This let us calculate the total fixation time and count on the drone and on the payload for each scene.

Statistical Analysis

To analyze the effects of drone flight factors on distraction, we employed a repeated measures linear mixed model. Due to the presence of zero fixation times and counts on the drone, the model was fitted using the natural logarithm of fixation time plus one and fixation count plus one to improve the normality of residuals. The results obtained from these log-transformed values were then back-transformed to the original scales of seconds and counts for interpretation. This preprocessing only applied on dependent variables of fixation times and counts on drone, while others were analyzed using their raw values. The model had a random effect on the test participants to account for individual variability and fixed effects for order sequence, drone flight configuration, and their interaction. A Type III ANOVA was used to evaluate the statistical significance of each fixed effect, specifically focusing on the effects of the drone flight factors. All computations were done using the lme4 and lmerTest packages in R [182], [183].

Results

This research investigated the effects of a drone's presence, height, and distance on tower crane operator's performance and visual attention behaviors. A key finding from our analysis is that the drone's height was the only factor to have a statistically significant impact on the collision performance metric. The drone's presence and its horizontal distance did not produce statistically significant effects on any of the measured outcomes.

In Table 12, the analysis of participants experiencing sequence showed no significant sequence effects across any of the dependent variables, with all p-values being greater than 0.05, suggesting that the order in which participants experienced the scenes did not systematically influence the results.

Table 12. Type III ANOVA of Period vs Scene

Metrics	**P-value**	
	Period	Period - Scene Interaction
Fixation time on payload	0.1281	0.7157
Fixation count on payload	0.9858	0.9176
Fixation time on drone	0.4709	0.4733

Fixation count on drone	0.9225	0.4733
Collision	0.6772	0.9851
Completion time	0.5458	0.7248
Deviation	0.2772	0.8316

This experiment contains five scenes: No Drone, Far (111 ft) -Above (+35 ft), Far - Below (-16 ft), Close (50 ft) - Above, and Close - Below. Far and close indicates the drone flying distance to the participants. Above and below indicates the drone flying height. Following figures use these names to represent different scenes. Followings are the results of the visual attention metrics. Analysis of variance for fixation time percentage on payload and fixation time on drone showed no statistically significant main effects for the experimental factors of interest: Scene ($p = 0.4677$ and $p = 0.4065$, respectively), Height ($p = 0.8049$ and $p = 0.3709$, respectively), or Distance ($p = 0.8491$ and $p = 0.2862$, respectively). Figures 9 and 10 show the 95% confidence interval of fixation time on payload's percentage and fixation time on drone in five scenes. Similarly, the analysis of fixation count on payload and drone revealed no significant effects for Scene ($p = 0.4901$ and $p = 0.4065$, respectively), Height ($p = 0.9761$ and $p = 0.3709$, respectively), or Distance ($p = 0.3079$ and $p = 0.2862$, respectively). Figure 11 and 12 shows the 95% confidence interval of fixation count on payload and drone for five Scenes. Table 13 summarizes the p-value of all the variables in different visual attention metrics

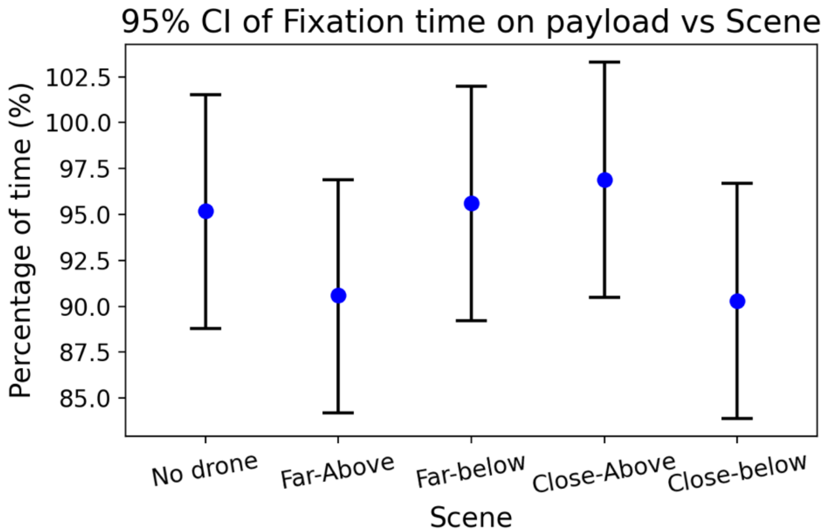

Figure 9. 95% Confidence Interval of the fixation time on payload's percentage in different scenes

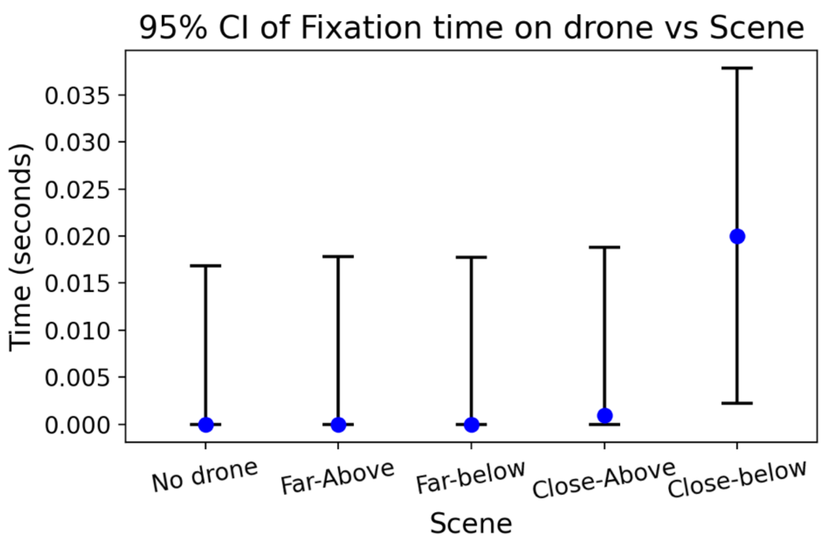

Figure 10. 95% Confidence Interval of the fixation time on drone in different scenes

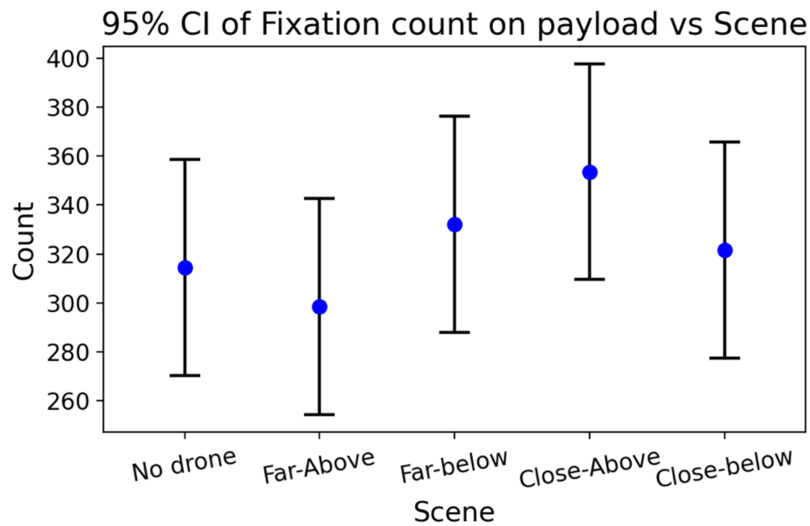

Figure 11. 95% Confidence Interval of fixation count on payload in different scenes

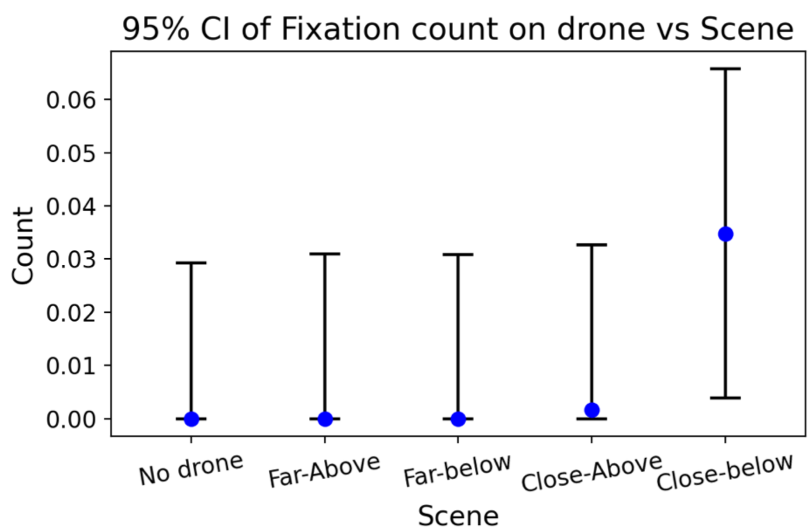

Figure 12. 95% Confidence Interval of fixation count on drone in different scenes

Table 13. Type III ANOVA of performance metrics vs Scene, Height, and Distance

Metrics	**P-value**		
	Scene	Height	Distance
Fixation time on payload	0.4677	0.8049	0.8491
Fixation count on payload	0.4901	0.9761	0.3079
Fixation time on drone	0.4065	0.3709	0.2862
Fixation count on drone	0.4065	0.3709	0.2862

Followings are the performance metrics. Analysis of the deviation metric indicated that neither Scene ($p = 0.1717$), Height ($p = 0.1035$), nor Distance ($p = 0.2237$) had a statistically significant impact on path deviation. Figure 13 shows the 95% confidence interval of deviation in five scenes. For completion time, no main effects were found for Scene ($p = 0.2873$) or Distance ($p = 0.8053$), or Height ($p = 0.0697$). Figure 14 shows the 95% confidence interval of completion time for five scenes.

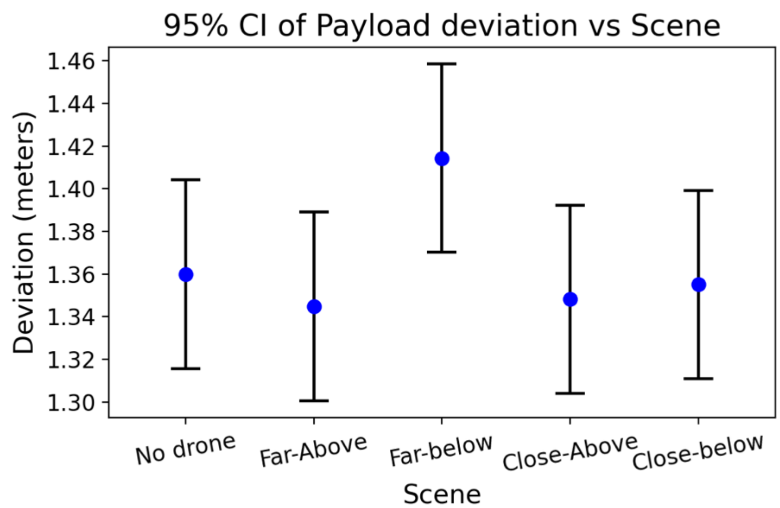

Figure 13. 95% Confidence Interval of payload deviation in different scenes

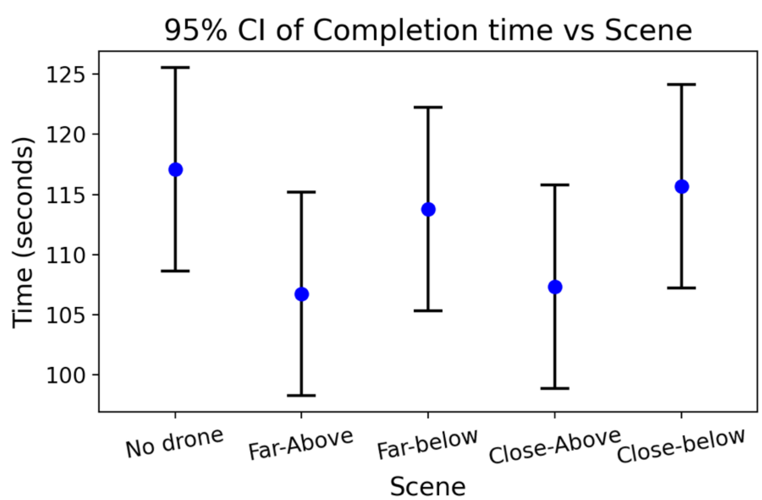

Figure 14. 95% Confidence Interval of task completion time in different scenes

However, the collisions showed significant effects across multiple factors. There was a significant main effect of Scene on collisions (p = 0.0468). Collisions were highest in Close-Below (7.999) and Far-Below (7.898) scenes, and lowest in No-drone (5.096), Close-Above (5.432), and Far-Above (5.475) scenes as shown in Figure 15. Thus, Height significantly influenced collision number (p = 0.0116). As shown in Figure 16, collisions averaged 7.947 with the drone 16 ft below the operator versus 5.468 when drone 35 ft above, a difference of 2.479. Furthermore, the presence of a drone flying below resulted in a significant difference in collisions (p = 0.0179). Specifically, the mean collision number was higher when the drone was present and below (7.976) versus when there was no drone (5.092) as shown in Figure 17. The factor of Distance was non-significant (p = 0.9975). Table 14 summarizes the p-values of all the variables in different performance metrics.

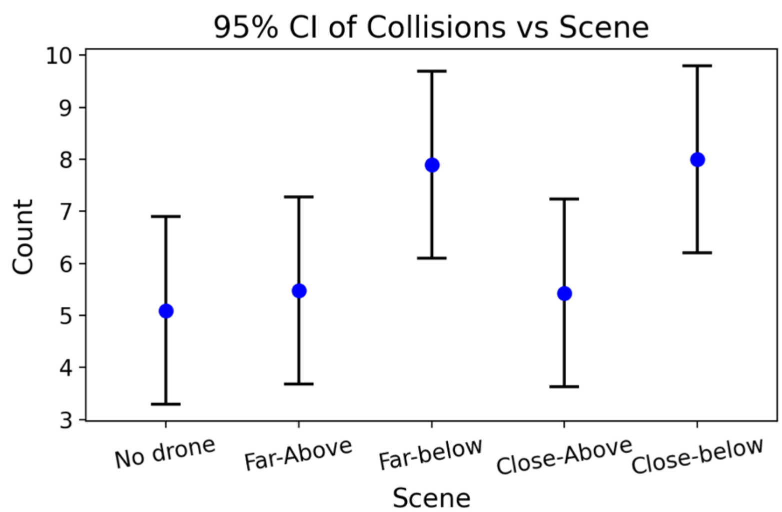

Figure 15. 95% Confidence Interval of collisions in different scenes

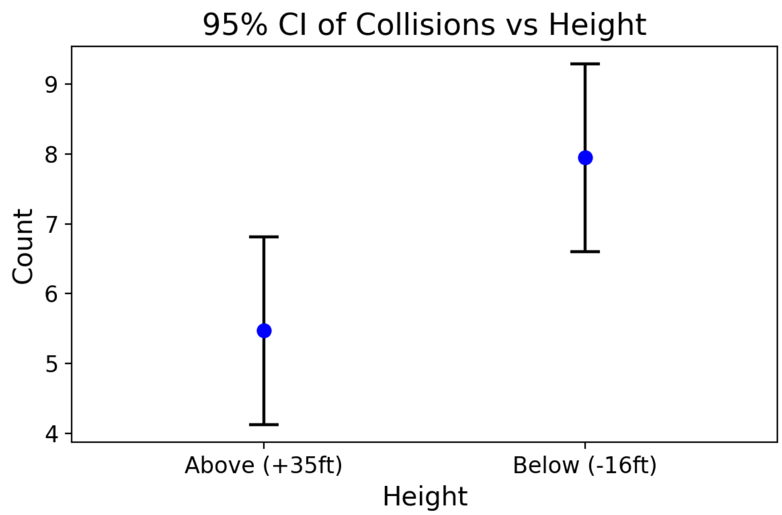

Figure 16. 95% Confidence Interval of collision on payload in different heights

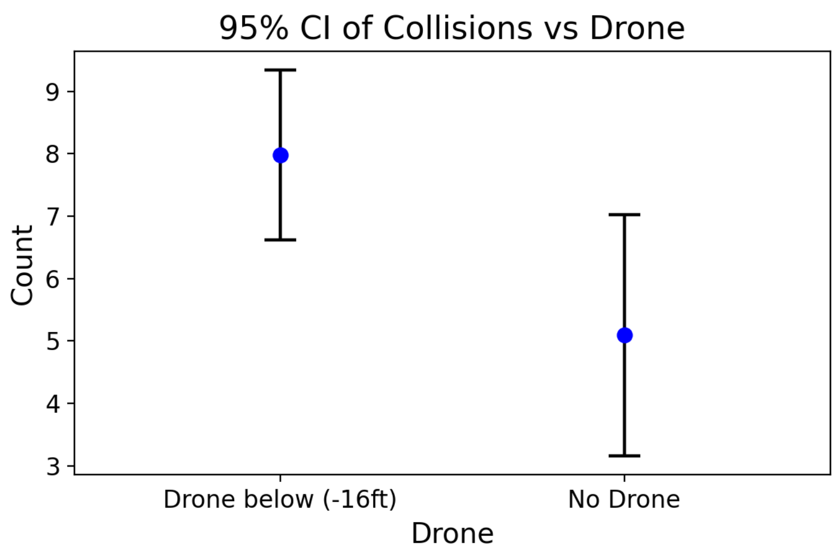

Figure 17. 95% Confidence Interval of collisions in no drone and drone at low height scenes

Table 14. Type III ANOVA of performance metrics vs Scene, Height, and Distance

Metrics	P-value		
	Scene	Height	Distance
Collisions	0. 0468	0.0116	0.9975
Completion Time	0.2873	0.0697	0.8053
Payload Deviation	0.1717	0.1035	0.2237

The above results are based on data from 20 of the 23 test participants. Three participants were identified as outliers and removed during the data analysis process. The outlier criterion was defined as having more than 10 collisions in the no-drone scenario, which is consistent with the same performance threshold used during the training phase to determine eligibility to proceed to the actual experiment. Completion time was not used as a criterion for outlier removal because participants who knocked down multiple boundary poles sometimes deviated from the intended path. This unintended shortcut can artificially reduce their completion time, which does not reflect genuine task proficiency. Therefore, collision number is a more reliable indicator of whether a participant was performing the task correctly and consistently.

However, the analysis of full data is still important. Thus, followings are the analysis of all 23 participants. Table 15 shows that the analysis of participants' exposure sequence revealed no significant order effects across the dependent variables, as all p-values were greater than 0.05 except for fixation time on payload. The only significant sequencing effect occurred for fixation time on payload, indicating that participants' attention to the payload changed slightly as they progressed through the experiment, likely due to increasing task familiarity or adaptation over time.

Table 15. Type III ANOVA of Period vs Scene

Metrics	**P-value**	
	Period	Period - Scene Interaction
Fixation time on payload	0.0289	0.5327
Fixation count on payload	0.9994	0.9998
Fixation time on drone	0.4757	0.4891
Fixation count on drone	0.4338	0.4891
Collision	0.9056	0.8628
Completion time	0.3948	0.4792
Deviation	0.4769	0.5560

Following are the results of the visual attention metrics, including fixation time/count on payload/drone. Figure 18 shows the 95% confidence interval if fixation time on payload in five different scenes. Analysis of variance for fixation time percentage on payload and fixation time on drone showed no statistically significant main effects for the experimental factors of interest: Scene ($p = 0.4569$ and $p = 0.4338$, respectively), Height ($p = 0.8569$ and $p = 0.9539$, respectively), or Distance ($p = 0.6804$ and $p = 0.3546$, respectively). Figures 18 and 19 show the 95% confidence interval of fixation time on payload's percentage and fixation time on drone in five scenes. Similarly, the analysis of fixation count on payload and drone revealed no significant effects for Scene ($p = 0.4196$ and $p = 0.4338$, respectively), Height ($p = 0.9539$ and $p = 0.3205$, respectively), or Distance ($p = 0.3546$ and $p = 0.3189$, respectively). Figure 19 and 20 shows the 95% confidence interval of fixation count on payload and drone for five Scenes. Table 16 summarizes the p-value of all the variables in different visual attention metrics.

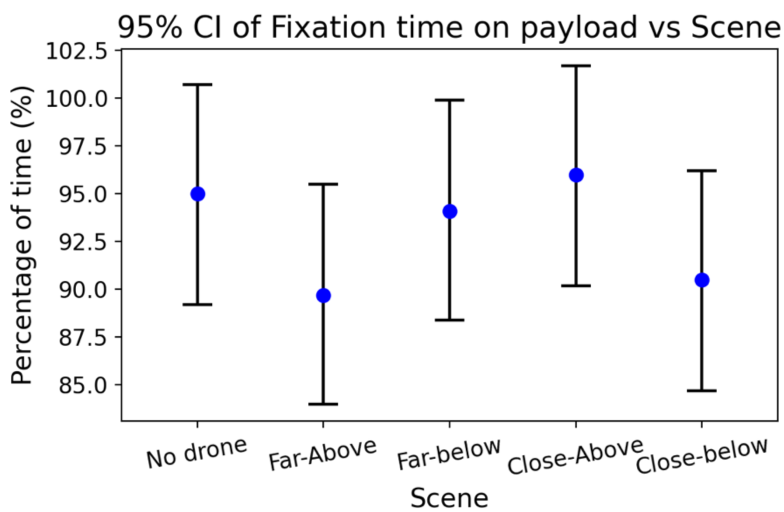

Figure 18. 95% Confidence Interval of fixation time on payload in different scenes

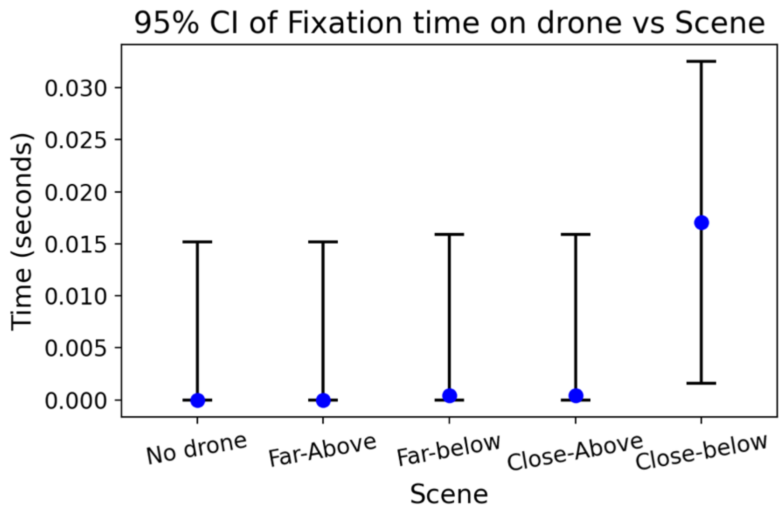

Figure 19. 95% Confidence Interval of fixation time on drone in different scenes

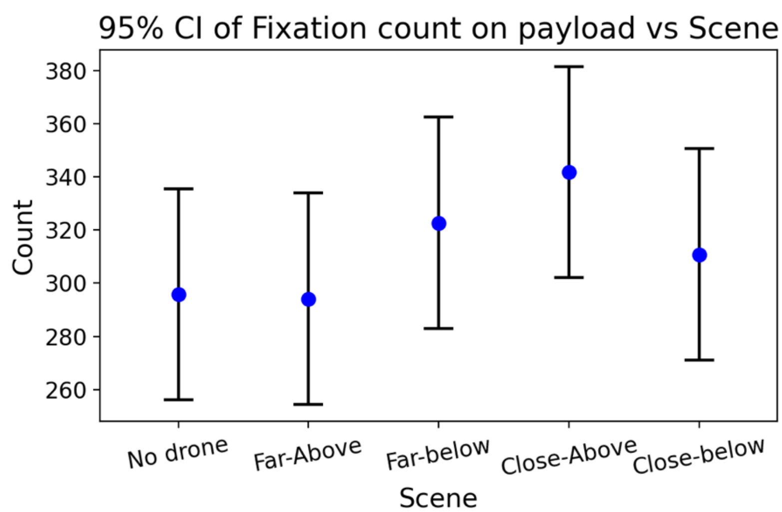

Figure 20. 95% Confidence Interval of fixation count on payload in different scenes

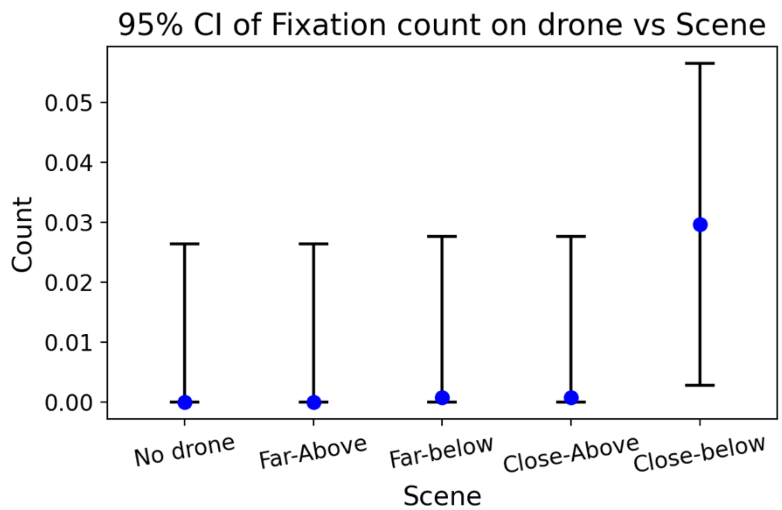

Figure 21. 95% Confidence Interval of fixation count drone in different scenes

Table 16. Type III ANOVA of performance metrics vs Scene, Height, and Distance

Metrics	**P-value**		
	Scene	Height	Distance
Fixation time on payload	0.4569	0.8569	0.6804
Fixation count on payload	0.4196	0.9539	0.3546
Fixation time on drone	0.4338	0.3205	0.3189
Fixation count on drone	0.4338	0.3205	0.3189

Followings are the performance metrics. Analysis of the deviation metric indicated that neither Scene (p = 0.2486), Height (p = 0.3033), nor Distance (p = 0.2694) had a statistically significant impact on path deviation. Figure 22 shows the 95% confidence interval of deviation in five scenes. For collisions, no main effects were found for Scene (p = 0.1107) or Distance (p = 0.4789. Figure 23 shows the 95% confidence interval of collisions for five scenes. For completion time, no main effects were for Scene (p = 0.2175) or Distance (p = 0.7611). Figure 24 shows the 95% confidence interval of completion time for five scenes.

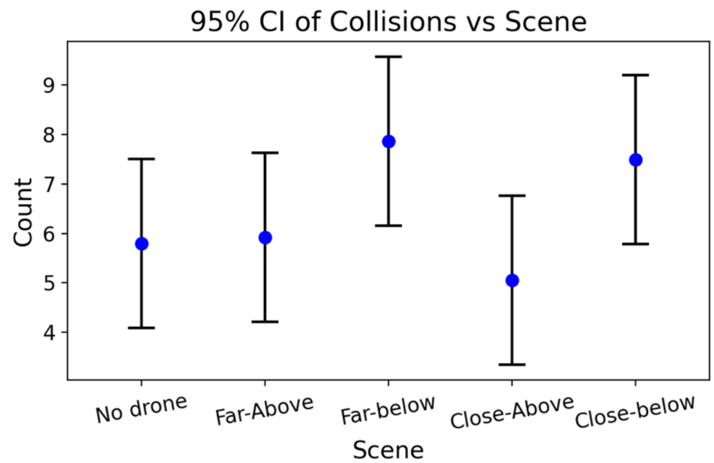

Figure 22. 95% Confidence Interval of collisions in different scenes

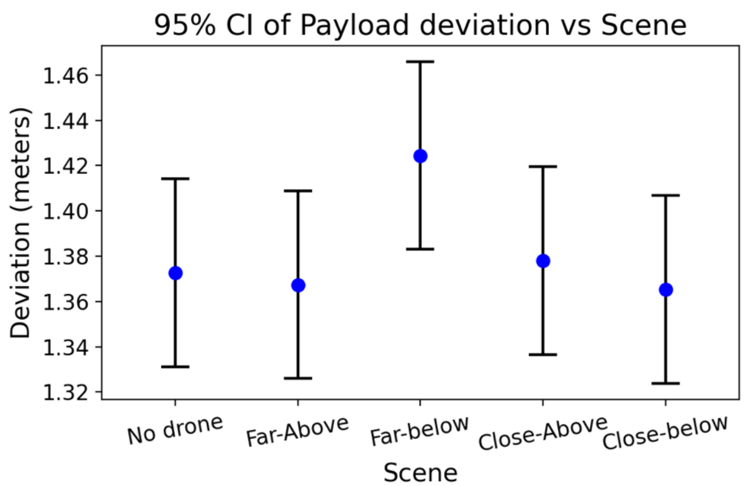

Figure 23. 95% Confidence Interval of payload deviation in different scenes

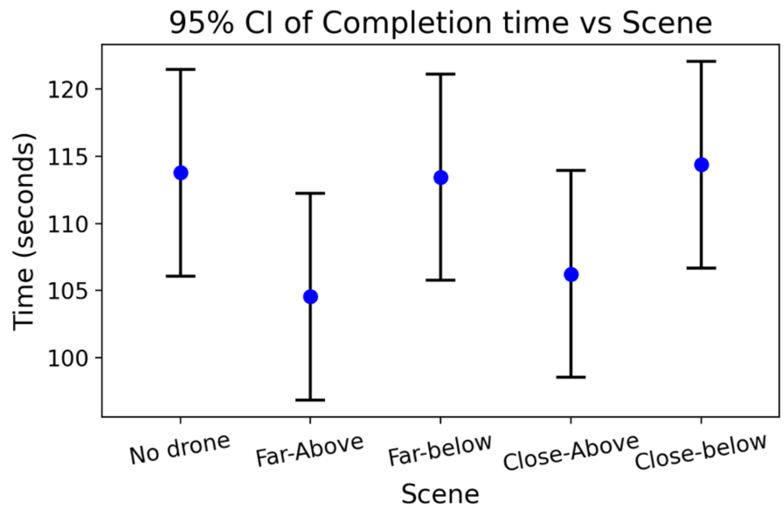

Figure 24. 95% Confidence Interval of completion time in different scenes

However, both collision and completion time show significant differences on the factor of Height (p = 0.0147 and p = 0.0260, respectively). Collisions were highest in Close-Below (7.867) and Far-Below (7.488) scenes, and lowest in No-drone (5.801), Close-Above (5.056), and Far-Above (5.918) scenes as shown in Figure 22. But there is no significant (p = 0.2654) when comparing No-drone and drone flying below the operator. Completion time were highest in Close-Below (114.371 seconds), Far-Below (113.430 seconds) and No-drone (113.767 seconds) scenes, and lowest in Close-Above (106.248 seconds) and Far-Above (104.553 seconds) scenes as shown in Figure 24. But there is no significant (p = 0.3392) when comparing No-drone scene and drone flying below the operator. Table 15 summarizes the p-values of all the variables in different performance metrics.

Table 15. Type III ANOVA of performance metrics vs Scene, Height, and Distance

Metrics	**P-value**		
	Scene	Height	Distance
Collisions	0.1107	0.0147	0.4789
Completion Time	0.2175	0.0260	0.7611
Payload Deviation	0.2486	0.3033	0.2694

CHAPTER SIX: DISTRACTION-AWARE DRONE PATH PLANNING

This chapter explain the development and evaluation of the proposed path-planning method that enables drones to navigate construction sites safely and efficiently while minimizing distraction risk to workers and crane operators identified in earlier chapters. We formalize the research question as "How can a drone travels a set of predefined waypoints while (1) avoiding physical collisions and (2) minimizing distraction risk to workers and crane operator."

Problem Statement, Objectives, and Research Questions

Existing studies on drone path planning in construction have primarily focused on optimizing parameters such as energy efficiency, trajectory smoothness, path length, image coverage, occlusion avoidance, and travel time. While these objectives contribute to operational efficiency, they overlook an equally critical aspect: the potential distraction of drones to on-site workers and crane operators. In dynamic and visually demanding construction environments, drones operating in close proximity to personnel may unintentionally divert attention or interfere with task performance, creating indirect safety risks. Addressing this gap, the present research reformulates the drone navigation problem to jointly consider physical safety, operating efficiency, and human-factor impacts. The core research question is: How can a drone travel a set of predefined waypoints while (1) avoiding physical collisions and (2) minimizing distraction risk to workers and crane operators? To answer this, the study developed a navigation method that integrates collision-free path planning with a soft safety penalty, enabling the drone to balance spatial efficiency with cognitive safety considerations on active construction sites.

Methodology

The proposed drone navigation method is composed of four modules: (1) a 3D cost grid, (2) a local path planning module, (3) a traveling points ordering module, and (4) a soft cost weight estimation module. The 3D cost grid serves as the spatial foundation of the method by representing the construction environment in a discretized three-dimensional structure. Each grid cell encodes two types of information, hard costs and soft costs. Hard costs are defined as non-traversable areas corresponding to physical obstacles. Soft costs represent the distraction risks. The distraction risks are derived from the "distraction areas" identified in Chapters Four and Five, where drone proximity has been shown to cause potential distraction to workers and crane operators. Using this grid-based environment model, the local path planning module computes feasible flight paths between any two traveling points. The module evaluates both spatial efficiency and safety by integrating geometric distance, obstacle avoidance, and distraction risk. A weight factor is introduced to balance efficiency and safety within the soft-cost function. Higher weights place greater emphasis on safety over efficiency. The soft-cost weight estimation module determines the appropriate weight based on the spatial relationships between travel points and distraction areas. These computed costs are then passed to the travel point ordering module, which identifies the optimal visiting sequence to minimize the overall travel cost. Finally, the routes between consecutive points are combined to generate a complete navigation path that enables the drone to visit all target locations efficiently while avoiding obstacles and minimizing exposure to high-risk distraction zones.

<u>3D Cost Grid</u>

The 3D Cost Grid Module provides the spatial foundation for the drone navigation method by discretizing the construction site into a structured three-dimensional grid. Each grid cell $G(i, j, k)$ represents a voxel of the environment with dimensions defined by the grid resolution R. Within this grid, environmental objects such as workers, cranes, and static structures are projected according to their physical boundaries. The cost of each cell is composed of two primary components: hard cost and soft cost.

The hard cost defines whether a cell is traversable or not. Cells that intersect with physical objects or lie within a predefined safety buffer around these objects, are marked as non-traversable, ensuring that the drone avoids any potential collisions. The hard cost $H(i, j, k)$ can be represented as a binary occupancy function as shown in Eq. (3). If the cell is occupied or within the safety margin of obstacles, it will be marked as infinity. Which means it cannot be included in path planning.

$$H(i, j, k) = \begin{cases} \infty, & if\ the\ cell\ is\ occupied\ or\ within\ safety\ margin. \\ 0, & otherwise. \end{cases} \tag{3}$$

The soft cost represents the distraction potential or cognitive safety risk associated with drone proximity to human workers or crane operations. These "distraction areas," identified in Chapters Four and Five, are modeled as unified fields with same penalty to the entire areas. Figure 25 shows the definition of distraction areas. The worker distraction area is modeled as the entire construction volume below a height of 82 ft above the highest worker position. Based on the findings presented in Chapter Five, no significant distraction effects were observed when the drone operated more than 35 ft above the operator cabin. Therefore, the tower crane distraction area is modeled as the entire construction volume below a height of 35 ft above the highest tower crane control cabin position. Any grid cell located inside the distraction areas is defined as part of the tower crane operator distraction area. The soft cost $S(i,j,k)$ is defined as Eq. (4). Based on above, the hard cost and the soft cost of the grid cell can be formulated as Eq. (5).

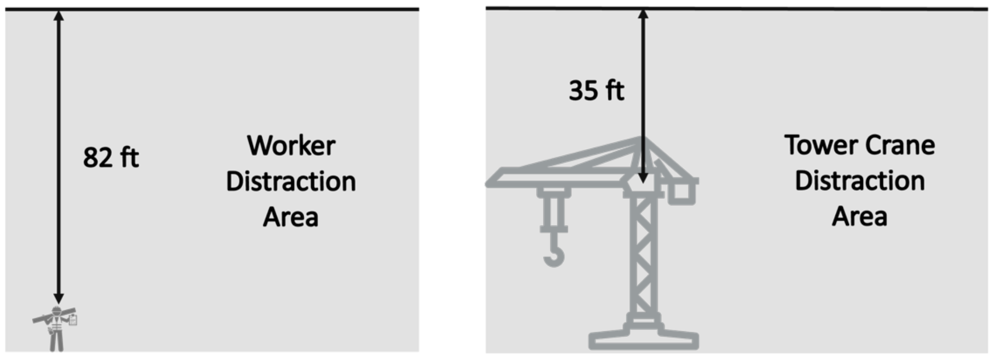

Figure 25. Definition of worker (left) and tower crane operator (right) distraction areas.

$$S(i,j,k) = \begin{cases} 1 & if\ cell\ in\ crane\ or\ worker\ distraction\ areas. \\ 0, & otherwise. \end{cases} \tag{4}$$

$$G(i,j,k) = (H(i,j,k) + \lambda * S(i,j,k)) \tag{5}$$

where λ is a weighting coefficient that controls the relative importance of distraction-related soft costs compared to the hard occupancy cost, allowing the planner to balance between path length efficiency and minimizing distraction risks. Based on the definitions of these two distraction areas, they overlap vertically but have different ceiling heights. To simplify two distraction areas, these two areas can be combined into a joint distraction area defined by the higher ceiling of the two. Consequently, the joint distraction area can be represented by a single boundary height.

Local Path Planning Module

The Local Path Planning Module computes feasible flight routes between any two travel points within the 3D cost grid. This module employs a greedy search process that explores neighboring grid cells to find a continuous route minimizing the total accumulated cost. In each iteration of the greedy search process, the current grid cell considers 26 neighboring directions in three-dimensional space as potential candidates for the next movement step. These neighboring cells represent all possible moves along the principal axes, face diagonals, and space diagonals. The objective is to minimize the sum of motion and Gird (hard and soft) costs across all points, which is to minimize the objective function of Eq. (6). In short, this module provides a sequence of continuous 3D points $P = \{p_0, p_1, \dots, p_n\}$ based on given pair of two traveling points.

$$\min_{p_0, \dots p_n} A(P) = \sum_{k=0}^{n-1} (t_{dist}(p_k, p_{k+1}) + t_{soft}(p_k, p_{k+1})) \tag{6}$$

$$t_{dist}(p_k, p_{k+1}) = \sqrt{\left(\frac{\Delta x}{v_h}\right)^2 + \left(\frac{\Delta y}{v_v}\right)^2 + \left(\frac{\Delta z}{v_h}\right)^2} \tag{7}$$

$$t_{soft}(p_k, p_{k+1}) = G(p_{k+1}) \times t_{dist}(p_k, p_{k+1}) \tag{8}$$

where v_h and v_v represent the horizontal and vertical flying speeds, respectively.

<u>Traveling Point Ordering Module</u>

The Traveling Point Ordering Module determines the optimal visiting sequence of all predefined traveling points that the drone must travel with a starting point. This process is formulated as a Traveling Salesman Problem (TSP), the goal is to find the shortest possible route that visits all traveling points once and returns to the starting position. To construct the TSP cost matrix, the pairwise distances between all traveling points are calculated using the Local Path Planning Module described in the previous section. For each pair of points, the local path planner provides not only the feasible route but also the total accumulated cost $A(P)$, which already incorporates both the motion cost and the distraction-related soft cost from Eq. (6). Consequently, the resulting distance matrix inherently reflects obstacle avoidance and distraction-aware constraints within the environment.

Once the distance matrix is constructed, a Nearest-Neighbor heuristic is applied to generate a traveling sequence that minimizes the overall travel cost. The heuristic begins from the starting point and iteratively selects the next point that yields the lowest travel cost among the remaining unvisited points. This process continues until all points are visited, forming a complete closed loop that defines the drone's global navigation route.

The final flight route of the drone is obtained by concatenating the locally planned paths between consecutive traveling points according to the optimized visiting order. This hierarchical approach, which integrates local path optimization with global route ordering, enables the drone to achieve efficient, collision-free, and distraction-aware navigation across the construction site.

Soft Cost Weight Estimation Module

The Soft Cost Weight Estimation module is designed to estimate λ within the 3D cost grid module for use in the local path planning module. The local path planning module serves as the core of the proposed method, incorporating distraction time as a soft cost term to balance path efficiency with distraction avoidance. To achieve this, the soft cost weight estimation module evaluates all possible spatial relationships between the traveling points and the ceiling of the combined distraction area. Since the local path planning module processes two points at a time, three primary conditions are defined:

1. Both points are above the ceiling.
2. One point is above the ceiling while another is below it.
3. Both points are below the ceiling.

Figure 26 illustrates the first condition, where both points are located above the ceiling of the distraction area. In this case, the optimal route between points p_1 and p_2 is a direct straight line. The presence or consideration of the distraction area does not affect the path, as the entire route remains outside the distraction area. Thus, the value of soft cost weight (λ) will not affect the path planning in such condition.

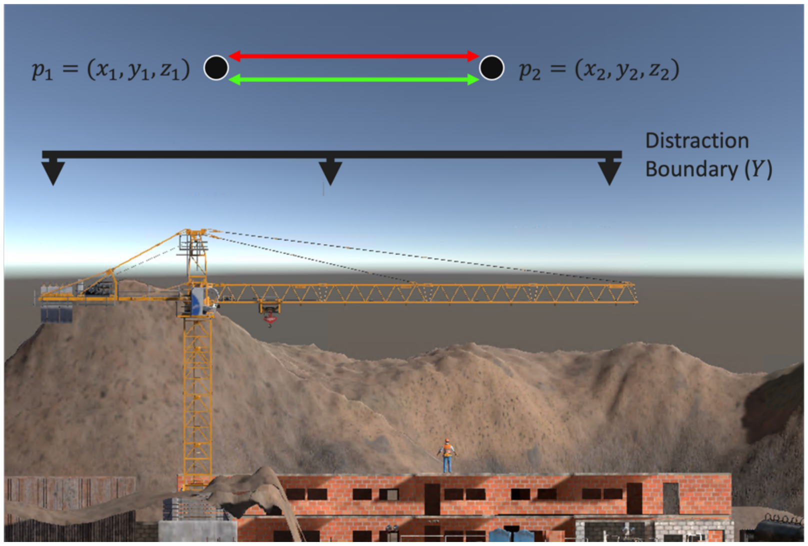

Figure 26. The condition of both points outside the distraction area.

Figure 27 presents the second condition, where one point is outside and the other is inside the distraction area. The red line represents the optimal route without considering distraction, while the green line shows the optimal route when distraction is taken into account. To enable the proposed method to select the green route, the minimum value of λ can be derived as shown in Eq. (9), ensuring that the cost of the red route is higher than that of the green route. Eq. (10) provides the simplified form of this relationship.

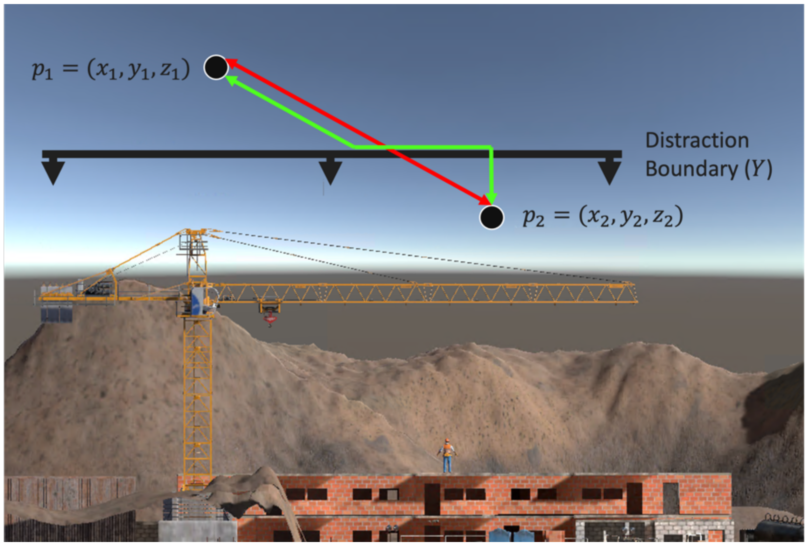

Figure 27. The condition of one point outside and another point inside the distraction area.

$$pdt\left(1+\lambda\left(\frac{y_{p2}}{y_{p1}+y_{p2}}\right)\right) > pdt\left(\frac{y_{p1}}{y_{p1}+y_{p2}}\right) + pdt_h\left(\frac{y_{p2}}{y_{p1}+y_{p2}}\right) + \frac{y_{p2}}{v_v}(\lambda+1) \tag{9}$$

$$\lambda > \frac{-pdt\left(\frac{y_{p2}}{y_{p1}+y_{p2}}\right)+pdt_h\left(\frac{y_{p2}}{y_{p1}+y_{p2}}\right)+\frac{y_{p2}}{v_v}}{pdt\left(\frac{y_{p2}}{y_{p1}+y_{p2}}\right)-\left(\frac{y_{p2}}{v_v}\right)} \tag{10}$$

$$y_{p1} = |y_1 - Y|, y_{p2} = |y_2 - Y| \tag{11}$$

$$pdt_h = \frac{\sqrt{(x_1-x_2)^2+(z_1-z_2)^2}}{v_h} \tag{12}$$

$$pdt = \sqrt{\left(\frac{x_1-x_2}{v_h}\right)^2 + \left(\frac{y_1-y_2}{v_v}\right)^2 + \left(\frac{z_1-z_2}{v_h}\right)^2} \tag{13}$$

where v_h and v_v represent the horizontal and vertical flying speeds, respectively.

Figure 28 shows the third condition, where both traveling points are located inside the distraction area. Similar to the previous case, the red line represents the route without considering distraction, and the green line represents the distraction-aware route. To ensure that the proposed method identifies the green route as optimal, the minimum value of λ can be derived as shown in Eq.14, where the cost of the red route exceeds that of the green route. Eq.15 provides the simplified form of Eq.14.

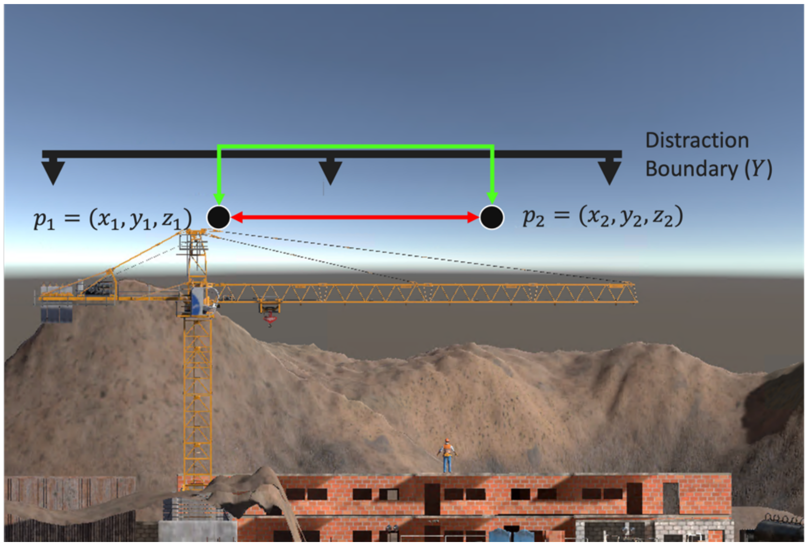

Figure 28. The condition of both points inside the distraction area.

$$pdt(\lambda + 1) > (y_{p1} + y_{p2})(\lambda + 1) + pdt_h \quad (14)$$

$$\lambda > \frac{pdt_h - pdt + y_{p1} + y_{p2}}{pdt - y_{p1} - y_{p2}}, pdt - y_{p1} - y_{p2} > 0 \quad (15)$$

Since multiple spatial relationships may occur among the same set of traveling points, the final estimation of λ is determined as the maximum value calculated from all point pairs using Eq.10 and Eq.15. In other words, λ is selected as the largest value among all possible two-point combinations within the set of traveling points, since each of the three equations gives the smallest λ for its respective pair.

Implementation and Results

The proposed drone path-planning method was implemented and tested in a three-dimensional physics-based simulator developed in Unity. The simulator reproduces a realistic virtual construction environment that includes static structures, a tower crane, and a human worker. This virtual tested allows the evaluation of both physical feasibility and distraction-related behavior within a controlled setting. Figure 29 shows the simulated construction site used in this research.

Figure 29. Simulated virtual construction site in Unity.

The drone was programmed to travel between predefined waypoints that represent inspection or monitoring targets. During each experiment, the proposed method computed a complete flight route. The drone's horizontal flight speed was set to 4.5 miles per hour (mph), while the vertical speed was limited to 2.25 mph to emulate realistic maneuvering performance, where moving vertically usually is slower than moving horizontally. The grid resolution R for the 3D cost grid was set to 3.28 ft (1 m), determining the spatial precision of occupancy and cost calculations. To ensure accurate enforcement of safety margins at this resolution, the effective thresholds were adjusted accordingly. The worker distraction safety height was set to 82 ft + 3.28 ft from the worker, the tower-crane distraction threshold was set to 35 ft + 3.28 ft from the control cabin, and the hard-cost collision margin was also set to 3.28 ft. These parameters ensure that the simulated soft- and hard-constraint regions in the grid accurately reflect the intended safe-distance area of workers, equipment, and structures.

Based on three conditions mentioned in section Soft Cost Weight Estimation Module, three experiments were designed to evaluate the proposed method. Moreover, another additional condition is designed and added when the Eq. (15) is invalid, meaning $pdt - y_{p1} - y_{p2}$ is not greater than 0. This extreme condition was introduced to tests the robustness of the proposed method under more challenging flight conditions. Thus, four experimental scenarios (Scene A to Scene D) in total were designed to evaluate the performance of the proposed path planning method. All scenarios share the same starting location and include six traveling points that must be visited before returning to the start point. While the horizontal coordinates of these six points remain identical across scenarios, their heights differ, creating varying levels of exposure to the distraction area generated by workers and the tower crane.

- Scene A places all traveling points above the distraction area at a height of 144.36 ft (44 m), meaning the route remains fully in distraction-free space.
- Scene B positions half of the traveling points within the distraction area at 128 ft (39 m), while the remaining half are above it at 95.14 ft (29 m), requiring the planner to balance travel efficiency against exposure to distraction.
- Scene C places all traveling points inside the distraction area at a uniform height of 88.58 ft (27 m), so every leg of the tour incurs penalty time.
- Scene D is similar to Scene C but uses an even lower height of 75.46 ft (23 m), representing deeper persistence within the distraction area.

As illustrated in Figure 30, the traveling points in Scene A (blue), Scene B (red), Scene C (yellow), and Scene D (orange) have identical horizontal coordinates but differ in elevation. The green marker indicates the shared starting point. The black horizontal line represents the distraction boundary line, where all space below the line belongs to the distraction area and all space above it is free space. The line is at the height of 111.55 (34 m).

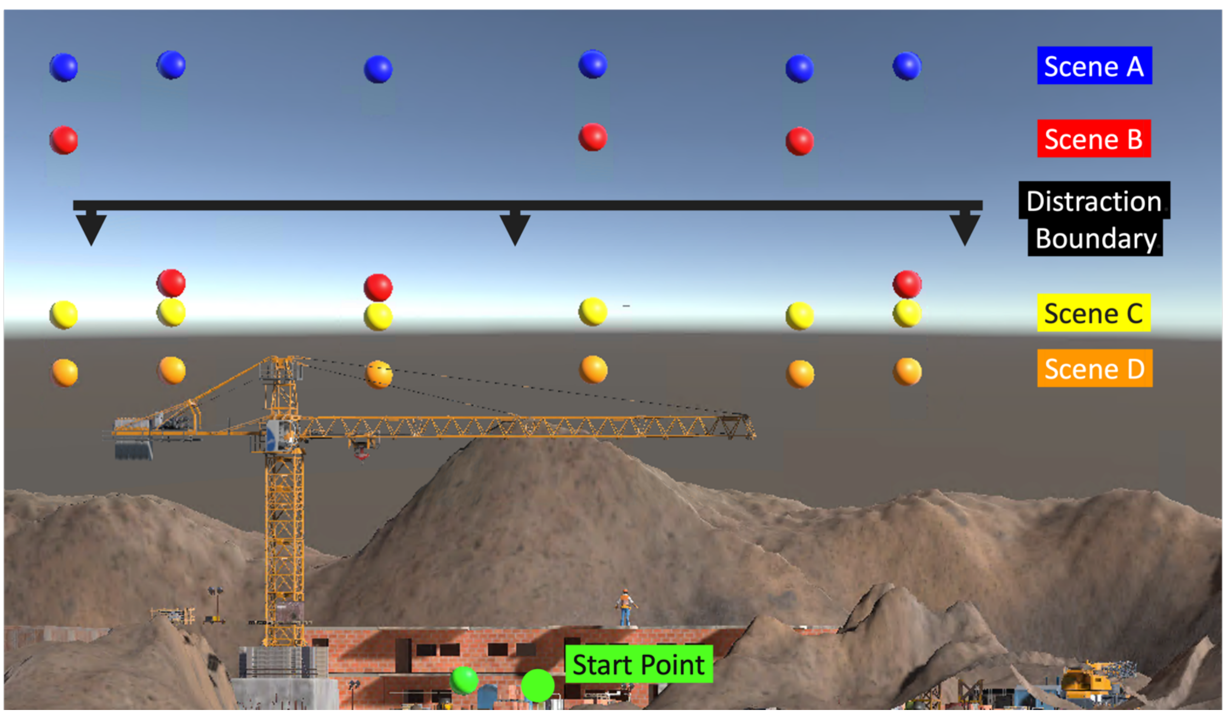

Figure 30. The top view (upper) and the side view (lower) of Scene A and Scene B.

The method was tested under two configurations: one that considered both Euclidean distance and distraction-related soft costs, referred to as “With Soft Cost”, and another that considered only Euclidean distance without distraction penalties, referred to as “Without Soft Cost”. To evaluate the effectiveness of incorporating soft costs in reducing potential distractions to workers and tower crane operators, this study employed three performance metrics: total path length, completion time, time spent within the tower crane and/or worker distraction area (distraction time). The distraction time metric was defined jointly because the distraction areas of the worker and the tower crane overlap vertically. The overlap boundary varies depending on which source of distraction has the higher ceiling, and therefore the measured time represents the duration during which the drone entered either or both distraction areas.

The quantitative results are summarized in Table 16. When the distraction-aware soft cost was included (With Soft Cost), the drone exhibited a tendency to take longer routes and completion time, as indicated by increases in total path length and total flight time. However, this behavior substantially reduced the time spent in proximity to workers and crane operators.

Table 16. Comparison of path-planning performance with and without soft cost in Scene A and B.

Configuration	λ	Scene	Path length (ft)	Completion time (sec.)	Distraction time
w/o soft cost	0	A	804	158	61
w/ soft cost	6.4	A	830 (+3.3%)	163 (+3.2%)	55 (-9.8%)
w/o soft cost	0	B	801	166	86
w/ soft cost	23.4	B	928 (+ 16%)	195 (+17.5%)	69 (-19.8%)
w/o soft cost	0	C	705	127	127
w/ soft cost	14	C	912 (+33.5%)	190 (+49.6 %)	96 (-24.4%)
w/o soft cost	0	D	682	120	120
w/ soft cost	20	D	682 (+0%)	120 (+0%)	120 (-0%)

In Scene A, the total path length and completion time increased by approximately 26 ft (3.3%), and 5 seconds (3.2%), respectively, yet the distraction time decreased by 6 seconds (9.8%). The λ for the soft cost weight was computed as 6.4 in Scene A. Figure 31 illustrates the route differences between two algorithm configurations in Scene A. From Figure 31 to Figure 34, the red line represents the route generated by the method without considering distraction, while the green line shows the route generated by the method with distraction awareness. As highlighted in the lower-left part of the figure, the main difference is that the green route ascends vertically when the drone inside the distraction area. This behavior helps minimize the duration that the drone remains within the distraction area, thereby reducing potential exposure to worker and crane distractions.

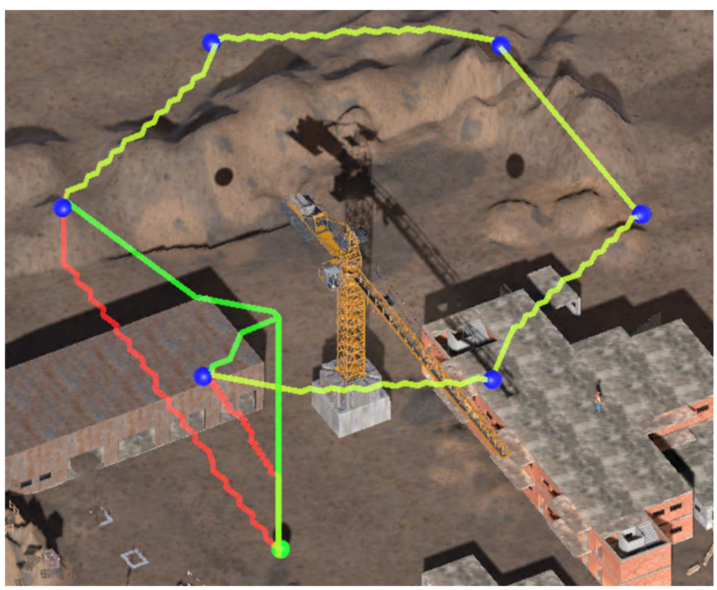

Figure 31. Visualization of planned drone paths with (green) and without (red) soft cost consideration in Scene A. (Yellow line is two lines overlapping)

In Scene B, although the path length and completion time increased by 127 ft (16%) and 29 seconds (17.5%), respectively, the time spent in the distraction area was reduced by 17 seconds (9.8%). The λ was computed as 23.4 in Scene B. Figure 32 illustrates the route differences between two configurations in Scene B. Similar to Scene A, the lower-left portion of the figure shows that the distraction-aware method plans a route that moves vertically within the distraction area to minimize the drone's distraction time. In addition, the upper-right, lower-right, and middle-left sections demonstrate that the green route remains above the distraction zone until reaching the vertical position directly above a target point located within the distraction area. The drone then descends straight down to reach the point and ascends vertically afterward to continue to the next destination. This behavior represents the optimal strategy for reducing the drone's total distraction exposure time.

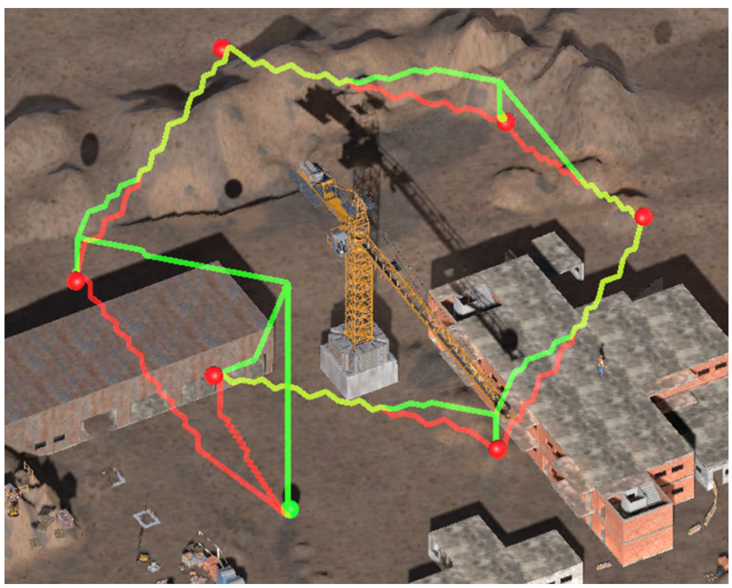

Figure 32. Visualization of planned drone paths with (green) and without (red) soft cost consideration in Scene B. (Yellow line is two lines overlapping)

In Scene C, the path length and completion time increased by 207 ft (33.5%) and 63 seconds (49.6%), respectively, while the distraction time decreased by 31 seconds (24.4%). The weight factor λ was computed as 14 in this case. Figure 33 illustrates the route differences between the two configurations in Scene C, showing two major distinctions similar to those in Scene B. First, the lower-left portion of the figure shows that the green route moves vertically within the distraction area, unlike the red route. Second, all the traveling points in Scene C are inside the distraction area. Thus, the green route directs the drone to hover directly above each target point, descend straight down to reach it, and then ascend vertically back to the distraction-free area. These behaviors demonstrate the effectiveness of the proposed method in finding an optimal route that minimizes distraction time while maintaining the shortest possible completion time under the given objective.

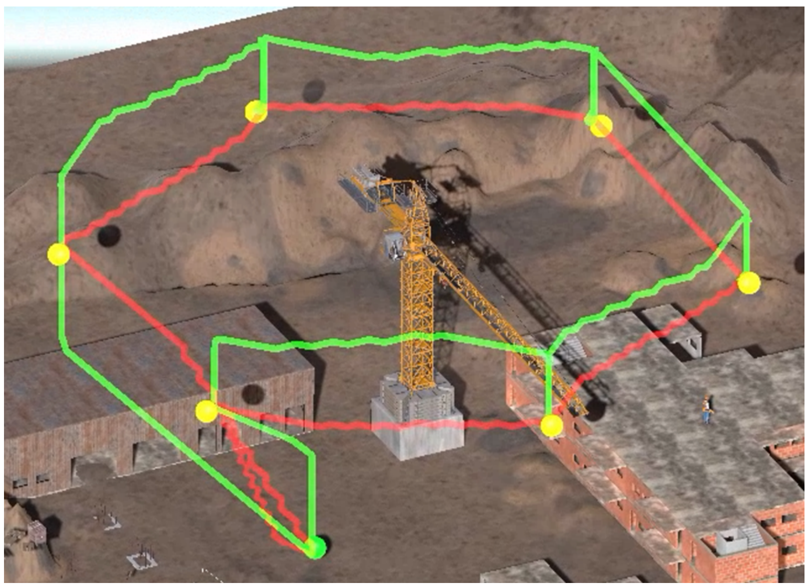

Figure 33. Visualization of planned drone paths with (green) and without (red) soft cost consideration in Scene C. (Yellow line is two lines overlapping)

In Scene D, the path length, completion time, and distraction time were identical across both configurations of the proposed method. Since Eq. (15) was invalid in Scene D, there is no meaningful value of λ that influences or alters the path planning outcome. Here, λ was set as 20 for demonstration. As shown in Figure 34, the green and red routes completely overlap, appearing as a single yellow line. This outcome occurs because all target points are positioned at low elevations, making it inefficient for the drone to ascend to the distraction-free area above each point and descend again. Such unnecessary vertical movements would increase overall distraction time rather than reduce it, resulting in identical optimal routes for both configurations.

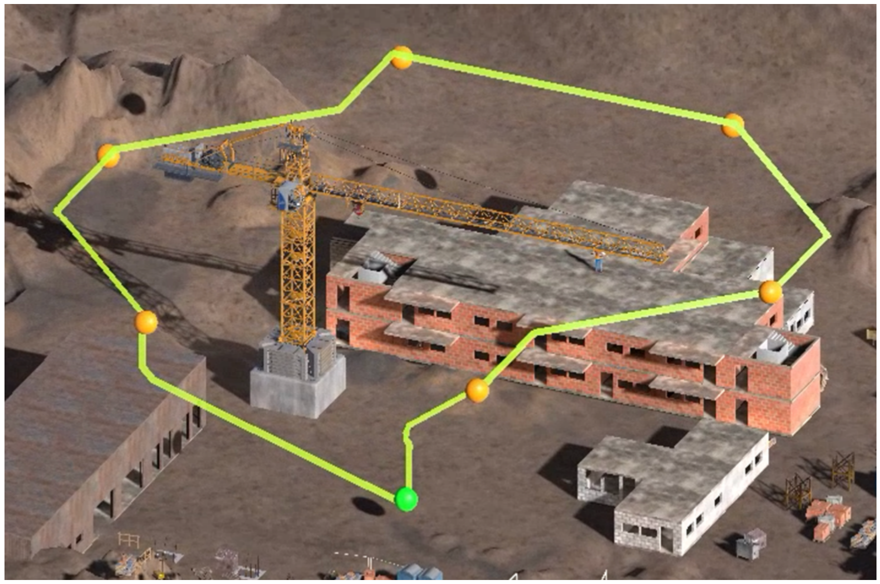

Figure 34. Visualization of planned drone paths with (green) and without (red) soft cost consideration in Scene D. (Yellow line is two lines overlapping)

Moreover, an additional soft-cost (λ) analysis was performed using two representative scenarios. Scenario 1 included one worker at height and one tower crane with an operator, while Scenario 2 included three workers at height and two tower cranes with operators. Both scenarios incorporated 20 randomly distributed traveling points. Figure 35 presents the corresponding completion time, travel distance, and drone dwell time within distraction areas (DT) under varying λ values. The results illustrate how λ governs the trade-off between operational efficiency and distraction mitigation. Higher λ values place greater emphasis on reducing DT, leading to flight paths that are less efficient but expose workers to shorter distraction durations. Conversely, lower λ values prioritize efficient routing at the expense of increased DT. Across both scenarios, the proposed path-planning method demonstrated the ability to reduce DT by up to 54%, with a corresponding increase in completion time of approximately 30%.

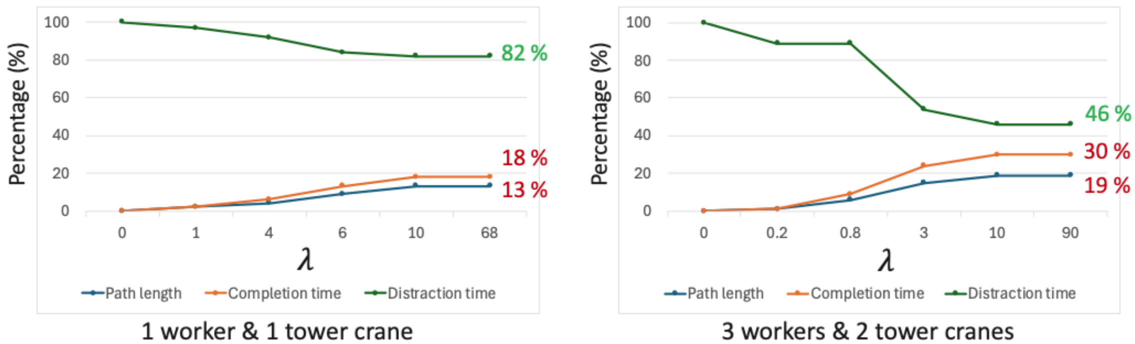

Figure 35. Analysis of the impacts of different soft costs (λ) on drone path length, completion time, and drone dwell in distraction area time (distraction time)

CHAPTER SEVEN: DISCUSSION

This research addresses the existing knowledge gap regarding the indirect risks of drone operation in construction, specifically focusing on cognitive distraction. It examines how drone presence influences workers' attention and proposes a method to minimize these impacts, particularly for workers at heights and tower crane operators. The study first conducted two human-subject experiments in a virtual environment to quantify how drone flight configurations affect visual attention and performance. Based on these empirical findings, a distraction-aware path planning method was then developed to integrate the observed distraction patterns and reduce the likelihood of the drone interfering with workers' situational awareness.

In the first experiment, the results of this experiment provide insights into how drone flying height and direction affect workers' visual attention to hazards. Our findings show that participants spent less time observing the surrounding hazards when the drone approached from the front, particularly at lower heights. Specifically, we found that when a drone flew at 16 and 48 ft from the front, the fixation time and count on danger areas were significantly reduced, potentially compromising a worker's ability to focus on danger areas. These results are important for construction safety, as reduced attention to danger zones can increase the likelihood of accidents such as slips, falls, and trips. When drones came from behind the workers, their distraction effect was less pronounced, suggesting that visibility and proximity to the worker's line of sight play a crucial role in distraction. Moreover, the results of fixation time on the sky show that test participants typically took less than one second to locate the drone in the sky when it was approaching from the front or back (Figure 5). However, even such a brief glance significantly reduced the time they spent monitoring openings and edges on the site, particularly when the drone was flying at heights of 16 ft and 48 ft above the participants. These findings align with previous research, which suggests that distracted workers may take up to 25 minutes to fully regain focus on their tasks; and during this period, their ability to recognize surrounding hazards diminishes, increasing the likelihood of errors and the risk of accidents [11]. After the experiment, we discussed with participants to gather their feedback and asked them whether the drone distracted them during the task. Half of them reported experiencing distraction.

In the second experiment, the findings show that drones flying below the operator at 16 ft produced noticeable distraction, while drones flying above the operator at 35 ft did not interfere with attention or performance. This indicates that maintaining a sufficient vertical clearance above the operator's eye line can effectively reduce distraction during lifting operations. However, this experiment could not determine the exact minimum safe height at which distraction is no longer triggered. It only confirms that 35 ft above the operator is safe, but does not clarify whether lower heights such as 20 ft, 25 ft, or 30 ft would also be non-distracting. Establishing that threshold would require additional testing at incremental height levels. In terms of operational impact, operators showed an increase in collisions when the drone was positioned at the lower elevation, demonstrating that distraction can translate directly into declined control precision. Although the horizontal distance of the drone did not show a statistically significant effect on the performance of tower crane operators in this study, this finding may be influenced by the limited range of distances tested. In the post-experiment feedback, 16 out of 20 participants reported feeling more distracted when the drone was closer and around half of them report the drone noise affect their focus. It is possible that greater horizontal separations could lead to reduced perceptual salience of the drone or diminished auditory interference, thereby further mitigating distraction. Future research should therefore examine a wider range of drone distances to determine whether there are threshold effects or nonlinear relationships between drone proximity and operator performance.

The path planning component of this research demonstrates that distraction can be reduced not only through flight altitude but also through intentional routing strategies that prevent the drone from entering the worker's attentional zone. The inputs of this method include the geometry and context information of the construction site as well as the distraction parameters. Geometry information including the positions and sizes of the obstacles and workers. Context information includes the traveling point locations of drone. For distraction parameters, the distraction-aware soft cost integrates the findings from both experiments by using location and proximity rules derived from observed visual attention patterns. In the first experiment, workers were most distracted when the drone appeared in front of them at lower heights, and in the second experiment, crane operators were most distracted when the drone flew below the cabin and within their primary field of view. By incorporating a distraction-aware soft cost into the planning process, the drone selects routes that maintain visual and cognitive distance from operators even if doing so slightly increases total flight length. From a practical standpoint, this tradeoff is favorable because construction safety is much more sensitive to distraction-induced errors than to marginal increases in travel time. The results show that the distraction-aware routes substantially reduce the duration of exposure within the operator's distraction area, which directly lowers the likelihood of attentional interference during precision operations. More importantly, this method converts the behavioral insights from the human-subject experiments into a rule that can be embedded into autonomous navigation logic, ensuring safer operation without depending on the pilot's judgment alone. For industry adoption, this provides a scalable framework that can support proactive safety management, where distraction avoidance becomes an automated default behavior rather than a discretionary choice, making drone deployment more compatible with crane operations and high-risk construction workflows.

Beyond its immediate findings, this research also introduces an effective and repeatable experimental protocol that integrates immersive VR, eye-tracking, spatialized audio, and realistic task simulation to understand the safety implications of drone operations in construction environments. This protocol enabled the study to quantify how drone flight height, direction, and distance affect workers' visual attention to hazards and crane operation performance. The empirical findings derived from this protocol provide actionable insights into safer drone deployment strategies by linking specific flight configurations to distraction outcomes. In addition, the protocol offers a scalable framework that can be readily extended to investigate other drone-related factors such as noise level, proximity dynamics, flight stability, hover duration, or maneuver patterns. More broadly, the methodology is not limited to drones and can be adapted to study distraction from other autonomous systems on construction sites, including ground robots, teleoperated equipment, or wearable safety devices. As for the proposed path planning method, new kind of workforce and drone flight factors identified through future experiments can be incorporated into the soft cost function by adding additional terms, enabling the system to evolve as more behavioral data becomes available. Therefore, this research should be viewed as a starting point, establishing both a measurement framework and a control strategy that future studies can expand upon to support increasingly complex human-robot interaction scenarios in construction.

While this study provides important insights into how drone flight configurations influence worker distraction, several limitations should be acknowledged. First, in both human study experiments, we examined limited factors. For example, in the first experiment, it examined two factors, flight height (with three conditions) and approach direction (with two conditions), resulting in seven combinations (3×2 + no drone). The process, from experiment design and setup to data collection, took approximately 10 months. Introducing additional factors would significantly increase the number of combinations due to combinatorial explosion. Given these constraints, it is impractical to analyze all these factors within two experiments. Thus, the limitation is that only one type of virtual drone were used and during the experiment. In practice, drones differ in their acoustic properties, physical dimensions, and operational functions, all of which may influence the extent of distraction experienced by tower crane operators or workers at heights. For instance, larger drones that generate higher noise levels may attract greater visual and auditory attention, whereas smaller and quieter models may cause minimal interference. Future research should investigate how variations in drone type, size, and noise characteristics affect worker distraction to better inform safe and effective drone operations in construction environments. Second, although drones can distract construction workers and tower crane operator, the drones themselves may also be considered potential hazard factors. Therefore, a drone's size, position, speed, and direction can be safety factors. The safest behavior might be for the worker to have enough time to see the drone without reducing their attention on observing other surrounding hazards. This study, however, did not consider looking at a drone as hazardous behavior. Future studies could explore optimal gaze duration across multiple hazards. Third, the study focused on a specific task context: material handling at height and tower crane operation. Construction sites involve a wide range of tasks, and distraction may manifest differently for workers operating earthmoving equipment, driving haul trucks, performing welding at elevation, or coordinating rigging tasks. Future work should evaluate whether similar distraction patterns emerge in other operational roles. Forth, the experiment tested a limited set of flight behaviors and did not vary other influential drone factors such as flight speed, hover duration, or maneuver aggressiveness, even though real-world drone missions often involve more dynamic movement patterns. Fifth, the experiments only include the sunny day as weather. Further study with rainy, snowy, and overcast conditions should be included to examine whether reduced visibility, ambient noise, or altered lighting conditions modify distraction patterns or affect workers' ability to detect both drones and surrounding hazards.

In addition, the proposed path planning method was designed to balance routing efficiency and distraction-related safety but did not incorporate other mission-level objectives commonly considered in drone path planning, such as battery constraints, sensor coverage, required dwell time over targets, payload limitations, or airspace priority rules. Integrating these additional operational factors will be needed to extend the framework into a fully deployable system for real-world construction monitoring. Expanding the model to jointly optimize between distraction avoidance and mission performance would allow for more comprehensive and context-aware flight decisions. Taken together, these limitations indicate that while this study establishes important behavioral thresholds and introduces a distraction-aware routing framework, there remains substantial opportunity for future research to generalize, refine, and operationalize these findings across a broader range of drone technologies, construction tasks, and deployment scenarios.

CHAPTER EIGHT: RESEARCH CONTRIBUTION

In summary, this dissertation makes the following technical contributions: (1) quantitatively assessed the impact of drone-induced distraction on construction workers' visual attention and situation awareness at heights, (2) provided quantitative evidence of drone-induce distraction on tower crane operators' visual attention and performance, (3) proposed an experimental framework that integrates virtual reality and eye-tracking to safely and systematically study cognitive distraction in construction tasks, (4) provide practical guidelines for safe drone operation near workers at heights and tower crane operators based on the empirical findings, (5) developed a distraction-aware drone path planning method that incorporates distraction areas of workers at heights and tower crane operator, and (6) proposed a flexible path planning method that not only accounts for the distraction areas of workers at height and tower crane operators but can also be extended to incorporate additional distraction findings from other construction tasks or workforce groups.

The first contribution is important because it provides the first quantitative understanding of how drone flight configurations influence workers' attention and situational awareness at height. Prior studies mainly relied on qualitative observations and did not measure impacts of distraction directly. The quantitative evidence generated in this study provides a scientific basis for assessing the cognitive safety of drones in elevated work environments. Academically, it adds new data to the field of human factors in construction, while practically, it helps safety managers and drone operators recognize how flight altitude and direction can unintentionally divert workers' focus away from hazards.

The second contribution holds both academic and practical significance by extending distraction research to complex and precision-based operations such as tower crane control. This is important because crane operation requires constant focus and coordination, and even minor visual interruptions can result in severe safety consequences. The findings establish the first quantitative link between drone flight configurations and operator performance degradation, expanding existing human factors research to include machine-induced distraction during equipment operation. In practical terms, the outcomes can guide policymakers, site supervisors, and drone service providers to define safe distance and visibility thresholds for drones operating near cranes.

The third contribution is significant because it offers a rigorous experimental framework that future researchers can adopt to investigate cognitive distraction in construction tasks. By combining virtual reality and eye-tracking technologies, this framework allows safe, repeatable, and data-rich testing of human responses to different environmental and technological factors. Academically, this method enhances experimental control and data accuracy, supporting more reliable behavioral research in construction safety. Practically, it provides a research tool that can be adapted by industry or academia to evaluate new technologies such as wearable sensors, autonomous robots, or assistive systems before they are deployed in the field.

The fourth contribution provides practical value by translating the experimental findings into clear and evidence-based guidelines for safe drone operation near workers and operators. These guidelines identify safe flight altitudes to reduce distraction risk without limiting the operational benefits of drones. Academically, this contribution bridges experimental research and applied safety policy. Practically, it helps standardize drone operation procedures, informs training and certification practices, and assists construction firms in implementing site-specific drone safety protocols that protect both workers and operators.

The fifth contribution advances both automation theory and construction practice by developing a distraction-aware path planning method that integrates cognitive safety considerations into drone navigation. Unlike traditional algorithms that optimize only for spatial efficiency or obstacle avoidance, this method incorporates real human distraction zones into flight planning. Academically, this represents a new direction in human-centered automation, where behavioral data directly inform control algorithms. Practically, it enables drones to plan safer paths that minimize exposure to human attention zones, reducing potential interference with active workers or operators while maintaining operational efficiency.

The sixth contribution enhances the long-term applicability and scalability of safety-aware path planning. The proposed flexible method allows additional distraction-related data from future studies or other construction tasks to be integrated into the same model. Academically, this contribution lays the groundwork for a continually evolving research platform that can incorporate new behavioral insights as they emerge. In practice, it provides a dynamic decision-support system that can adapt to changing site conditions, different worker roles, or new safety requirements, ensuring that drone operations remain responsive to human factors and environmental variability.

Collectively, these six contributions strengthen the academic foundation of human-drone interaction research and offer practical strategies for improving safety and efficiency in construction. The findings provide a foundation for identifying and mitigating cognitive risks in construction, a validated framework for studying distraction in a controlled and systematic manner, and a method that enable drones to operate safely with awareness of human attention and behavior. Together, they form a coherent methodology that bridges scientific understanding and real-world application, enabling safer, smarter, and more human-aware drone deployment in construction environments.

CHAPTER NINE: CONCLUSION AND FUTURE WORK

The increasing use of drones in construction has brought significant benefits for site monitoring, inspection, and data collection. However, their presence also introduces new safety concerns related to cognitive distraction among workers and equipment operators. Existing studies have primarily focused on addressing direct physical hazards such as collisions, equipment interference, and mechanical reliability. In contrast, limited research has examined indirect risks such as the cognitive and attentional impacts of drones on human performance. To address this gap, this dissertation aimed to investigate how drone flight configurations influence construction workers' visual attention and performance, develop a framework to measure distraction systematically, and propose a distraction-aware flight planning method to enhance operational safety.

To achieve these objectives, two virtual reality experiments were designed to simulate realistic construction tasks under controlled conditions. The first experiment examined workers performing material-moving tasks at height, while the second focused on tower crane operators conducting OCC zigzag task. Both studies employed integrated eye-tracking technology to quantify fixation behavior, attention allocation, and performance metrics. Statistical analyses, including repeated-measures ANOVA and mixed-effects modeling, were used to identify the effects of flight height, distance, and direction on cognitive and operational outcomes. The results showed that drones flying at lower altitudes (16 ft and 48 ft) or within the worker's forward field of view caused longer fixation times and reduced attention to hazard areas. Similarly, drone presence below the crane cabin for 16 ft significantly affected task performance, increasing collision number. These findings provide quantitative evidence that drone proximity and movement patterns can impose measurable distraction effects on construction workers and equipment operators.

Building on the experimental findings, the research developed a distraction-aware drone path planning method that integrates cognitive safety considerations into autonomous flight control. By incorporating distraction areas derived from the empirical findings of the two experiments, the proposed algorithm enables drones to select flight paths that minimize worker exposure while maintaining efficiency. Simulation results demonstrated that while the distraction-aware method increased total flight distance by approximately 18% to 54%, it reduced worker exposure time from 18% to 30%. This finding highlights that cognitive safety and operational efficiency can be balanced through data-driven flight planning. In addition, practical guidelines were proposed for drone operation near workers at height and tower crane operators, recommending appropriate altitudes, safe approach angles, and visibility boundaries for minimizing distraction risks.

In practical construction workflows, drones are primarily intended to enhance jobsite efficiency by supporting tasks such as progress monitoring, inspection, surveying, material tracking, and site documentation. Their value lies in enabling rapid data collection, improving situational awareness for project managers, and reducing the need for workers to physically access hazardous areas. However, these benefits can only be fully realized when drone operations do not introduce new sources of cognitive distraction that interfere with workers' ability to recognize hazards or perform precision tasks. The findings of this research directly support this industry need by identifying flight configurations that minimize distraction and by providing evidence-based guidelines for safe drone deployment near workers at height and tower crane operators. Furthermore, the distraction-aware path planning method offers a practical mechanism for integrating human factors into autonomous flight control, allowing drones to adjust their routes to avoid workers' attentional zones without requiring additional effort or judgment from the pilot. Together, these outcomes help ensure that drones function as supportive technologies that enhance productivity and safety simultaneously, making their adoption more compatible with modern construction operations.

The key contributions of this dissertation include providing the first quantitative evidence of the impacts of drone-induced distraction on construction workers and tower crane operators, establishing an experimental framework combining virtual reality and eye-tracking, proposing evidence-based safety guidelines, and developing a distraction-aware path planning method that integrates human factors into automation. Together, these contributions advance the understanding of human-drone interaction, introduce a new methodological approach for studying cognitive safety, and deliver practical solutions that support safer and more intelligent drone operations in construction environments.

Although this research provides important insights, several opportunities remain for future work. Future studies could examine how other drone-related factors, such as sound intensity, color contrast, flight speed, and payload size, influence distraction and worker perception. The experimental framework could be extended to multi-worker environments to capture group-level distraction dynamics and communication effects. Incorporating physiological signals such as heart rate, skin conductance, or brainwave activity could deepen understanding of cognitive load and emotional response under drone exposure. The proposed path planning method could be further enhanced through including other workforce and construction tasks. Finally, collaboration with construction companies could enable large-scale field validation of the findings, facilitating the translation of this research into industry practices and standards.

In conclusion, this dissertation bridges the gap between behavioral safety research and autonomous system design. It establishes a comprehensive foundation for studying cognitive distraction, quantifies its impact on worker performance and visual attention, and applies these insights to develop intelligent drone operation strategies. The outcomes of this research contribute to both academic knowledge and practical safety management by promoting human-centered automation that prioritizes worker attention and well-being. As the construction industry continues to adopt drone technologies, the principles and methods presented in this work can help ensure that innovation and safety progress together.

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