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INVESTIGATING THE RELATIONSHIP BETWEEN SITUATIONAL AWARENESS AND COGNITIVE LOAD IN A MIXED REALITY LEARNING ENVIRONMENT FOR CONSTRUCTION EDUCATION

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SUMMARY: *The recent rise in the adoption of sensing technologies, such as laser scanners and drones for improving efficiency, safety, and productivity, has driven the need for a technically skilled workforce prepared to implement these technologies. Academia is also inclined to meet this need, but is often impaired by the high cost of sensing technologies and the need for hands-on experiences. Mixed Reality (MR) has been explored as an alternative learning environment to equip construction students with the needed technical skills due to its potential to provide experiential learning. However, to advance the adoption of MR as an alternative learning environment, concerns persist regarding the safety risks and potential distractions posed by reduced situational awareness (SA) during interactions. While studies have explored SA in various domains, its assessment within MR environments for construction education remains unexplored. This study addresses that gap by evaluating participants' SA and cognitive load while interacting with sensing technologies in an MR learning environment. Nineteen undergraduate students participated in MR-based tasks. Their SA and cognitive load were assessed using the Situational Awareness Rating Technique (SART), NASA Task Load Index (NASA-TLX), and eye-tracking metrics. Results showed that participants generally had a strong awareness of their surroundings, reflected in high familiarity and the ability to process relevant information during MR tasks. The findings also indicate that participants with lower SA exhibited longer fixation durations, while those with higher SA showed shorter fixation durations. Additionally, individuals with lower SA experienced greater cognitive load and demonstrated more extensive visual scanning (e.g., higher fixation count). These findings not only align with cognitive load theory and prior eye-tracking research but also offer practical recommendations for MR instructional design. This study contributes to the development of virtual learning environments cognizant of users' SA, which often culminates in reduced cognitive overload, enhanced student learning, improved attention, and engagement.*

KEYWORDS: *Situation Awareness, Mixed Reality Environment, Construction Education, Cognitive load, Eye tracking data.*

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1. INTRODUCTION

Construction education has long been challenged by the barriers to exposing students to construction sites for hands-on experiences (Tomori & Ogunseiju, 2025d). These barriers often arise from the dynamic nature of construction sites, weather challenges on the selected day for site visits, safety concerns, and challenges from incompatible class and site visit schedules. To address this challenge, Mixed Reality (MR) has emerged as a transformative learning environment, offering construction students and professionals experiential learning opportunities (Brunzini et al., 2022; Tomori et al., 2025b). MR's potential to simulate real-world environments offers a unique opportunity for users to interact virtually and acquire knowledge and skills. For example, several studies have utilized MR for knowledge and skills acquisition in construction education. Studies by Wu et al. (2018) simulated a wood framing lab in MR for training undergraduate students. Sebastian et al. (2018) designed a building information modeling (BIM) in MR for easy as-built analysis for construction professionals. Similarly, Ogunseiju et al. (2023) implemented a Mixed Reality Learning Environment (MRLE) for learning sensing technologies in construction education.

Despite its potential, MR environments can lead to cognitive overload due to high informational load (Brunzini et al., 2022; Wu et al., 2013) and potentially reduce situational awareness. This can result in heightened safety risks for students during learning. Situational awareness (SA) is a critical measure of how well individuals understand their environment, often used to evaluate the safety and effectiveness of systems that depend on human behavior (Bolton et al., 2021). Endsley and Garland (2000) defines SA as knowing what is happening around you while engaged in a task. Similarly, Taylor (skybrary) defines SA as the knowledge, cognition, and anticipation of events affecting the safe, expedient, and effective conduct of tasks (Taylor, 1995). While there is extensive research on SA in various domains such as aviation, power plants, medical, and advanced manufacturing systems (Endsley, 2021; Endsley & Garland, 2000), its application in MR for construction education remains underexplored. Studies such as Aromaa et al. (2020) have revealed the risk of reduced SA in virtual environments, and emphasized the importance of considering attention, awareness, and cognitive load when using an MR System, as these factors impact safety. Cognitive load can be defined as the amount of mental effort required to process information in working memory during learning or task performance (IxDF, 2016). According to Cognitive Load Theory (CLT), human working memory has limited capacity, and when instructional materials or tasks exceed this capacity, learning can be impaired (De Jong, 2010; Sweller et al., 1998). Endsley and Garland (2000) identified two levels of SA, highlighting Level 2 SA as closely related to cognition. Endsley and Garland (2000) stated that awareness goes beyond mere perception (Level 1 SA), encompassing how individuals interpret, process, and focus on their surroundings (Endsley, 2015), which involves cognitive workload. Endsley and Garland (2000) further underscores that SA is essential for effective task performance, highlighting the need to assess the relationship between SA and cognitive load.

Given the widespread use of MR for construction workforce development, it is crucial to evaluate user awareness of their surroundings to ensure a safe and effective learning environment free from distractions, especially because SA is a widely adopted cognitive construct in human factors and often associated as a causal factor for performance (Bakdash et al., 2022). This study aims to assess the relationship between SA and cognitive load in MR environments during interactions with sensing technologies on a virtual construction site. Furthermore, owing to the potential of eye tracking data for gauging attentional focus and cognitive load during immersive learning experiences (Dong et al., 2024; Huang et al., 2025; Jiang et al., 2024; Li et al., 2023). This study further leveraged eye-tracking metrics, such as fixations, to investigate cognition during learning interactions in the MR environment and identify patterns associated with higher or lower awareness levels of SA. The study recruited nineteen undergraduate students, who were engaged in hands-on learning activities with five sensing technologies in the MR environment. During the learning interactions, students' eye tracking data were procured, while their SA and cognitive load after the learning interactions, through the Situational Awareness Rating Technique (SART), the NASA Task Load Index (TLX) questionnaires. This study uniquely contributes to the field by integrating eye-tracking into MR-based construction tasks to explore the relationship between cognitive load and situational awareness. The findings from this study provide foundational insights for designing adaptive MR systems that can facilitate timely interventions, ensuring that learners maintain optimal SA throughout the training process. For instance, eye-tracking could be integrated into MR platforms as a diagnostic tool to monitor learner attention and SA in real time.

2. BACKGROUND

2.1 Situational Awareness (SA) in Virtual Learning Environments

Situational awareness (SA), defined as an individual's perception and understanding of their environment, is a critical factor in ensuring safety and supporting effective decision-making (Endsley, 1995). A comprehensive understanding of SA is pivotal for executing efficient and safe operations, particularly in high-risk environments like construction sites. Construction workers depend on SA to identify potential hazards, assess risks, and make timely decisions to prevent accidents (Gheisari et al., 2010). Theories surrounding SA, especially Endsley's widely recognized model (Endsley, 1995; Endsley & Garland, 2000), provides a structured framework to analyze how individuals perceive, comprehend, and anticipate outcomes based on their situational context. This framework is especially vital for users of MR environments, where virtual elements are overlaid onto real-world settings during interaction. MR devices are increasingly utilized on construction sites; however, given the dynamic and hazard-filled nature of these environments, it is essential for MR users to effectively perceive, comprehend, and project what is happening around them to maintain situational awareness and enhance safety. Research highlights the intricate relationship between SA and cognitive load, with some studies indicating that increased cognitive load can negatively impact situational awareness (Endsley et al., 2024; Hendy, 1995; Li et al., 2023). While numerous studies have examined situational awareness in virtual environments, the majority have concentrated on virtual reality and a few on augmented reality, such as Wallmyr et al. (2019). Despite these studies, there remains a gap in examining how cognitive load interacts to influence SA, particularly during hands-on interactions in construction education.

2.2 Eye-Tracking Data for Understanding Situational Awareness

Eye-tracking metrics, such as gaze fixation duration, fixation count, and scan path, allow researchers to capture real-time data regarding where a learner directs their visual focus, which can serve as an indicator of SA within virtual environments (Dong et al., 2024; Huang et al., 2025; Jiang et al., 2024; Li et al., 2023; Tomori & Ogunseiju, 2025e). Studies indicate that gaze patterns can significantly correlate with SA levels, as the duration and frequency of gaze on specific elements often correlate with the emphasis placed on them in the decision-making process (Arias-Portela et al., 2024; Mahanama et al., 2022). For instance, Mahanama et al. (2022) observed that distracted drivers had higher fixation durations. Similarly, Arias-Portela et al. (2024) mentioned that prolonged gaze fixations are essential cues that can suggest the rate of comprehension and attention allocation. Other studies (Kummetha et al., 2020; Wallmyr et al., 2019) have investigated how work zone complexity and different attention allocation strategies impact SA under varying mental workloads. These studies analyzed eye-tracking metrics such as fixation count and duration, pupil diameter and position, and gaze direction, and their findings revealed that higher work zone complexity increases mental workload while diminishing SA. Furthermore, attention diversion from critical elements may signal cognitive overload, compromising SA (Endsley, 1995; Endsley & Garland, 2000). Such insights become vital when designing MR learning environments aimed at enhancing educational efficacy and fostering deeper comprehension of complex construction scenarios. Despite these insights, limited research exists examining how eye-tracking metrics provide insights into SA, particularly in MR-based learning environments. This study seeks to address this gap by exploring the relationships between SA, cognitive load, and eye-tracking data, ultimately informing the design of MR systems that better support user perception, comprehension, and decision-making.

2.3 Theoretical Framework

This study is rooted in the Cognitive Load Theory (CLT), which emphasizes the importance of managing cognitive processing capabilities (Paas et al., 2016; Paas et al., 1994; Sweller et al., 1998). As Endsley and Garland (2000) notes, attention, memory, and workload significantly influence situational awareness (SA). Several researchers have adopted CLT to understand workload and design in virtual learning environments. Moreover, cognitive theories provide frameworks for assessing and addressing individual differences in learning, guiding the design of virtual learning experiences. Researchers (Kirschner, 2002) have adopted CLT to design learning environments where information is presented in a manner that stimulates learning and promotes intellectual performance (Oviatt, 2006). The theory posits that the working memory is limited while the long-term memory is unlimited. However, CLT further explains that the limitations of working memory can be mitigated by developing several elements of information as one element in cognitive schemata by automating rules and presenting information with different modalities (Kirschner, 2002). In these environments, how attention is distributed affects SA, and design changes that alter attention distribution can impact SA (Endsley, 1995; Endsley & Garland, 2000). Memory also plays a crucial role in SA, as information about the environment is stored in both working and long-term memory (Endsley, 1995; Endsley & Garland, 2000). Therefore, maintaining SA requires careful consideration of how learning environments are designed to manage attention and memory effectively.

2.4 Research Gap

Despite growing interest in the use of MR for construction education, limited research has explored how learners cognitively respond to complex task environments, such as those involving the implementation of sensing technologies. In particular, the interaction between situational awareness (SA) and cognitive load remains underexamined in MR contexts. While prior studies have examined SA and cognitive load independently, few have investigated their interdependent effects on learners' mental processing in dynamic MR learning environments. Additionally, although eye-tracking technology offers a promising, objective method for assessing attention, visual behavior, and cognitive effort, there is a lack of empirical research connecting eye-tracking metrics to understand the levels of SA and perceived cognitive load. Most existing work focuses on eye-tracking as a standalone tool for SA or cognitive load. This gap is particularly significant in the context of construction education, where effective implementation of sensing technologies requires learners to navigate complex, simulated scenarios. By addressing the identified research gaps, the research aims to explore how SA impacts cognitive load, and how eye-tracking data can be used to distinguish between high- and low-SA learners, thereby advancing both theory and practice in MR-based construction education. This study seeks to provide answers to the following research questions:

i. *R1: How does situational awareness (SA) relate to cognitive load in a mixed reality learning environment for implementing sensing technologies?*
ii. *R2: How do eye-tracking metrics and mental demand differ between learners with high and low situational awareness in a mixed reality learning environment?*
iii. *R3: What is the relationship between situational awareness, cognitive load, and eye-tracking measures in a mixed reality learning environment?*

Based on the stated research questions, the following hypotheses are proposed:

i. *H1. Higher situational awareness is associated with lower mental demand of cognitive load.*
ii. *H2. Learners with lower situational awareness in an MR learning environment will exhibit higher fixation counts and longer fixation durations.*
iii. *H3. Cognitive load (mental demand) and eye-tracking measures (Fixation count, fixation duration) are negatively associated with situational awareness.*

3. RESEARCH METHODOLOGY

3.1 Research Design

This study evaluates situational awareness (SA) and cognitive load while interacting with the MR learning environment. Students completed a semester project using the MR environment, and their SA was assessed using two subjective measures (NASA TLX and SART questionnaire). The NASA TLX questionnaire gauged six cognitive load factors: physical demand, effort, frustration, mental demand, temporal demand, and performance. The data was tested for normality, which informed the use of non-parametric tests such as Spearman correlation and Wilcoxon signed-rank tests. Figure 1 shows the methodology overview. The study also procured students' eye-tracking data for understanding its relationship to situational awareness.

3.1.1 Participant Demographics

Nineteen students from a Construction Technology course at Georgia Tech participated in the study. The demographic breakdown was 70% male, 25% female, and 5% transgender, with ages ranging from 18-24 years. The racial and ethnic composition included 70% non-Hispanic, 10% Hispanic, 20% preferred not to answer, 65% White, 20% Black/African American, and 5% Asian, revealing a diverse set of participants. Over half (58%) reported having prior experience in the construction industry, with most of that experience gained through internships (82%), while a smaller portion had hands-on trade experience (18%). Among those with construction experience, durations varied from less than a year to up to four years. Most interns had less than one year of experience. A large majority of participants (89%) were familiar with immersive technologies such as Virtual Reality (VR), Augmented Reality (AR), or Mixed Reality (MR). Self-reported experience levels with these technologies varied: for AR, most rated themselves at moderate or low experience; for MR, nearly half reported low experience, and only one participant rated themselves highly. In contrast, participants had a broader range of experience with VR, including a small subset (16%) who rated their experience as very high. Table 1 highlighted the participants' demographics.

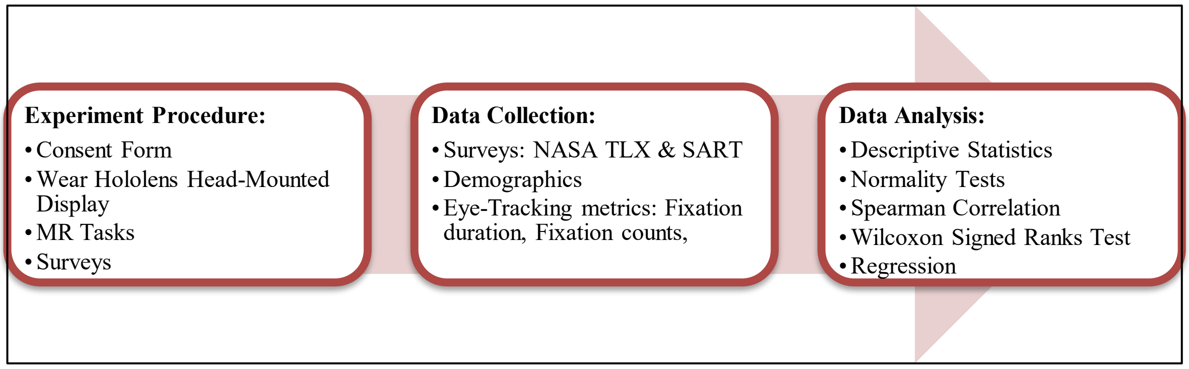

Figure 1: Methodology Overview.

Participants reported varying levels of knowledge across five key sensing technologies. For laser scanners, 42% reported moderate knowledge, while 47% indicated either a great deal (42%) or extensive (5%) knowledge. Regarding drones, 32% had moderate knowledge, and 68% reported a great deal (47%) or extensive (21%) knowledge. In contrast, RFID had lower familiarity, with 74% of participants indicating no (47%) or little (26%) knowledge. Similarly, IMU knowledge was limited, with 63% reporting no (37%) or little (26%) knowledge. In comparison, GPS was more familiar to participants, with 63% reporting a great deal (37%) or extensive (26%) knowledge. These findings suggest that students were generally more familiar with laser scanners, drones, and GPS, while RFID and IMU technologies were less well understood.

Table 1: Participant Demographics (n = 19).

Demographic Item	**Category/Response**	**n**	**%**
Experience in the construction industry	Yes	11	58%
	No	8	42%
Type of construction experience	Intern	9	82%
(Among those with experience, n = 11)	Construction trade worker	2	18%
Extent of construction experience	3–4 years	1	50%
(n = 2)	Less than 1 year	1	50%
Internship experience	< 6 months	4	44%
(n = 9)	6 months – 1 year	3	33%
	1 – 2 years	2	22%
Familiarity with VR/AR/MR	Yes	17	89%
	No	2	11%
Experience Level with AR	1 (Very Low)	2	11%
	2 (Low)	6	32%
	3 (Moderate)	7	37%
	4 (High)	2	11%
	5 (Very High)	2	11%
Experience Level with MR	1 (Very Low)	3	16%
	2 (Low)	9	47%
	3 (Moderate)	6	32%
	4 (High)	1	5%
	5 (Very High)	0	0%
Experience Level with VR	1 (Very Low)	2	11%
	2 (Low)	5	26%
	3 (Moderate)	5	26%
	4 (High)	4	21%
	5 (Very High)	3	16%

3.1.2 Experimental Setup

The Microsoft HoloLens 2, an MR Head-Mounted Display (HMD), was used to facilitate interaction with the MR learning environment, which was developed using Unity3D. This environment consisted of three scenes: Explore Jobsite, Sensor Tutorial, and Sensor Implementation scenes.

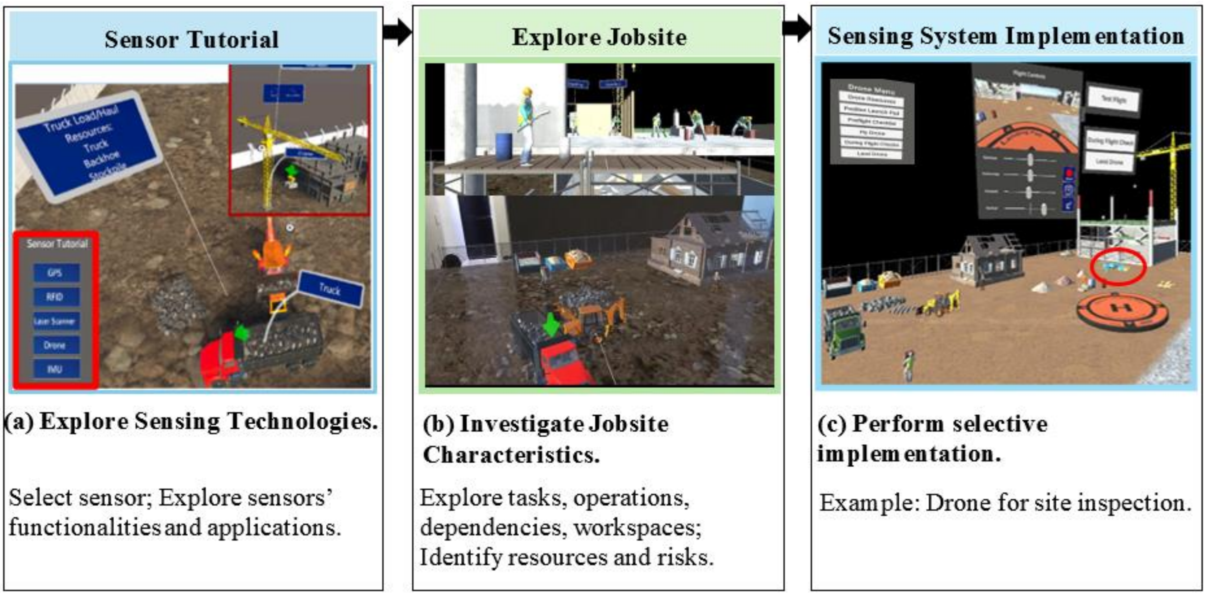

Figure 2: MR environment for learning sensing technologies.

3.1.3 Eye-tracking calibration

Participants wore the HoloLens headset, which was equipped with integrated eye-gaze tracking sensors (Microsoft, 2022). Prior to engaging in the main study tasks, each participant underwent an eye-gaze calibration procedure to enable precise tracking of their visual focus and cognitive engagement during the interaction. Eye-gaze calibration is the procedure by which the Hololens adjusts to the unique eye movements of each participant, allowing for precise tracking of where the participant is looking within the MRLE (Microsoft, 2022). This calibration process involved participants focusing on a series of predefined visual targets that appeared on the screen within the HoloLens display (Microsoft, 2022). These targets were placed in different areas of the visual field, and the participant was asked to look at each point for a brief moment, allowing the HoloLens to capture the eye's position relative to the display (Microsoft, 2022). The HoloLens system used these targets to calibrate the eye-tracking sensors by detecting each participant's gaze as they fixated on the points. The system automatically adjusted to the unique characteristics of each individual's eyes, including gaze vectors and orientation (Microsoft, 2022), to optimize gaze detection accuracy as they accessed the simulated construction job site within the MRLE.

This eye-gaze calibration is a critical part of the study, as it enables precise measurement of participants' visual focus during their interactions with the MRLE. Accurate eye-gaze tracking provides valuable data on cognitive engagement and decision-making processes, allowing us to analyze how students engage with different construction-related tasks in the MRLE. By ensuring that the eye-tracking system is finely tuned to each participant, the study minimizes errors and maximizes the reliability of cognitive engagement data, which is essential for understanding the differences between professional and novice behaviors. During this task, the HoloLens' built-in eye-tracking device continuously recorded data to capture where and how participants directed their gaze, providing insight into their interaction patterns, attentional focus, and cognitive processes.
Microsoft provides official documentation that explains how to request eye-tracking permissions, invoke calibration routines programmatically, and integrate user prompts to ensure data reliability in Unity. They also provided a Unity sample script and example scenes that demonstrate extended eye tracking features for HoloLens 2, including calibration support. Here is the link to the script adapted in Unity: https://github.com/microsoft/MixedReality-EyeTracking-Sample; https://learn.microsoft.com/en-us/windows/mixed-reality/develop/advanced-concepts/eye-tracking-calibration, https://learn.microsoft.com/en-

us/windows/mixed-reality/develop/unity/extended-eye-tracking-unity. This was directly utilized and edited during our Unity game development.

3.2 Data Collection

3.2.1 Questionnaires

The participants completed the SART and NASA TLX questionnaires immediately after interaction with the MR environment. The 3-D version of SART was used, and it contained ten basic dimensions of situation awareness. The main advantage of SART is that it is easy to use and has been administered in a wide range of task types (Bolton et al., 2021; Endsley et al., 1998), does not require customization for different domains, and can be used in real-world tasks as well as simulations (Endsley et al., 1998). The SART questionnaire assessed user awareness of the surrounding situation during the MR experiment. The SART questionnaire is scaled from 1 (very low) to 10 (very high) across three dimensions: understanding, attentional supply, and attentional demand. These dimensions encompass other awareness factors such as familiarity, information quality, attention, alertness, and variability of the surrounding environment. These scales are then combined to provide an overall SART score for a given system. The study analyzed the SART dimensions and calculated an overall situational awareness score. The SART score is calculated by SA = (Understanding – (Supply-Demand)) (Mazur et al., 2020). The NASA TLX Questionnaire was employed for procuring data on the cognitive load of the learning environment. NASA TLX provides subjective cognitive load evaluations based on six factors (Makarov et al., 2021) and has been adopted in the evaluation of construction-related systems (Abbas et al., 2020). The NASA TLX questionnaire, scaled from 1 (very low) – to 10 (very high) and assessed mental demand, physical demand, temporal demand, performance, effort, and frustration.

3.2.2 Eye-Tracking Data

Eye-tracking data are obtained from the HoloLens device to understand user behavior and interactions within virtual environments (Ogunseiju et al., 2022). Eye-tracking data has been extensively used to study SA in various domains, including aviation, driving, and construction. . This real-time eye tracking provides valuable information on where users are looking, such as users' eye movements, head direction, focus eye gaze duration, eye origins, eye hit positions, head origins, Target names, and positions at 30 frames per second. Fixation durations, saccade frequencies, and areas of interest (AOIs) are common eye-tracking metrics used to infer levels of SA in real time (Arias-Portela et al., 2024; Li et al., 2023). Previous studies have demonstrated the effectiveness of eye-tracking data for SA measurement (Arias-Portela et al., 2024). For example, research in air traffic control has shown that eye-tracking metrics, such as fixation duration and count, are significantly correlated with SART scores and NASA-TLX ratings (Li et al., 2023). During the experimental procedure, eye-tracking data were collected to investigate the visual attention of the participants, which is a critical component of SA.

3.3 Data Analysis

3.3.1 Descriptives and Inferential Statistics of SA Measures

The NASA-TLX and SART scores and the eye-tracking data were analyzed using descriptive statistics, and both Microsoft Excel and SPSS were used for this analysis. Correlation and regression analysis were conducted on the eye-tracking metrics, NASA-TLX, and SART scores. First, the SART dimensions were correlated with the NASA-TLX dimensions. Second, the eye-tracking data were correlated with the SART score and the mental demand dimension of the NASA-TLX. Lastly, inferential statistics were conducted using the Mann-Whitney rank test because the data deviated from normality (from the Shapiro Wilk test).

3.3.2 Data Preprocessing and Eye-tracking Metrics

In this study, eye-tracking data collected from HoloLens was used to predict and assess situational awareness (SA) in a virtual construction site within a MRLE. The eye-tracking data was filtered and cleaned. Key eye-tracking metrics used include fixation duration and fixation counts (Table 2). Fixation Duration is the length of time a participant's gaze remains on a single point. For this study, fixation durations were extracted from the eye-tracking data to analyze instances where the eyes remain relatively still and focused on a specific point in the visual field (Keskin et al., 2023). Studies suggest that fixation duration can range from 150 to 650 ms (Sekhri et al., 2022). However, studies by Ogunseiju et al. (2022); Olsen (2012); and Negi and Mitra (2020) stated a minimum fixation duration between 50 -150 ms can be adopted for tasks such as reading and visual search (Hooge et al., 2022). For this study, a minimum fixation of 70 ms, and a maximum fixation duration of 650 ms were utilized. Additionally, fixation count measures the number of times a participant's gaze fixes on a specific area of interest (Hooge et al., 2022). 1 outlines the key fixation metrics utilized in our analysis in Table 1, including fixation duration and fixation count (Hooge et al. 2022). The eye-tracking data was analyzed and filtered using Microsoft Excel and Statistical Software (SPSS).

Table 2: Eye tracking metrics.

Data Inputs	Description	References
Fixation Duration	Fixation time measured in milliseconds (ms)	(Sekhri et al., 2022)
Fixation Count	The number of times eyes focus on a particular spot	(Zhou et al., 2023)

4. RESULTS

4.1 R1: How does situational awareness (SA) relate to cognitive load in a mixed reality learning environment used for implementing sensing technologies?

4.1.1 Descriptive Statistics and Normality Tests

Descriptive statistics and correlation analyses were conducted using SPSS to examine the impact and relationship between SA and cognitive load. Descriptive statistics were used to measure the central tendencies and normality of the data. The data suggests a moderate degree of mental demand, physical demand, and temporal demand, with performance identified as the highest cognitive load. Similarly, the SART results imply that the situation awareness is moderate, as reflected by the SART score (SART = 29). Situation awareness score has a SART score ranging from 0 – 46, where 0 means low situation awareness and 46 means high situation awareness (Mazur et al., 2020). The Shapiro-Wilk test was adopted to understand the data distribution. Tables 3 and 4 revealed that both the situation awareness and cognitive load data were not normally distributed for most dimensions, as evidenced by significant Shapiro-Wilk tests ($p < 0.05$ for most dimensions). The mean rating of the dimensions of all data implied that the cognitive load and situation awareness imposed by the MR environment are moderate.

Table 3: The Descriptive Statistics and Normality Test for Situation Awareness.

Dimension	Descriptive Statistics				Shapiro-Wilk Tests	
	Mean	Sd Dev	Kurtosis	Skewness	Statistic	Sig.
Familiarity of situation	7.58	2.36	0.21	-0.90	0.86	0.01
Information quantity	7.58	1.83	-0.22	-0.50	0.87	0.01
Information quality	7.68	1.67	-0.17	-0.32	0.87	0.01
Alertness	7.79	1.75	0.79	-0.89	0.81	0.001
Concentration of attention	5.26	2.23	0.53	0.84	0.87	0.013
Division of attention	4.1	1.69	1.60	1.11	0.757	0.000
Spare mental capacity	4.84	1.92	-0.69	0.25	0.883	0.024
Instability of situation	5.47	2.09	-0.90	-0.38	0.871	0.015
Complexity of situation	4.74	1.79	-0.45	0.18	0.887	0.028
Variability of situation	5.58	2.63	-0.83	-0.06	0.875	0.017
SART Score	29.05	8.31	-0.53	-0.06	0.975	0.870

4.1.2 SART Dimensions

Familiarity with the surroundings situation had a mean score of 7.58, suggesting participants generally felt familiar with their surroundings. However, the negative skewness (-0.90) indicates that a small number of participants were not familiar with the situation, which could impact their situation awareness. Information quantity and quality had mean values of 7.58 and 7.68, respectively, indicating high levels of understanding (Figure 3).

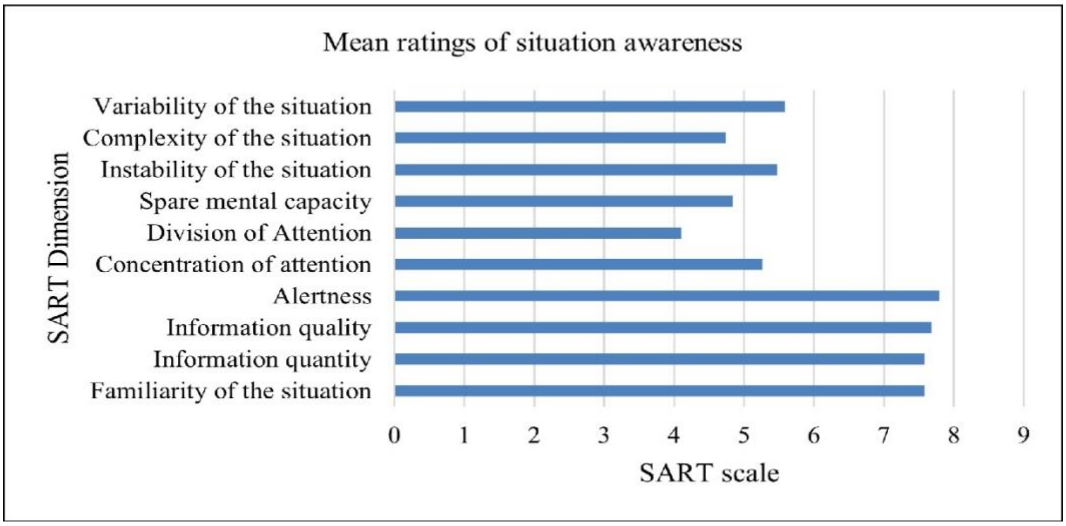

Figure 3: Participants' mean ratings of the findings on situational awareness.

However, information quantity had a skewness closer to zero, indicating that most participants rated these aspects positively, which is conducive to maintaining situation awareness. Alertness had the highest mean score (7.79), suggesting that participants were highly alert during the task. However, attention-related dimensions showed varied results, with concentration of attention (mean = 5.26) and division of attention (mean = 4.1) varied more significantly, suggesting challenges in maintaining focus on the surroundings while engaged in the MR learning environment (Table 3 and Figure 3). The study evaluated the participants' spare mental capacity during the simulation to determine their ability to manage additional cognitive demands, the result indicates limited mental resources available. A moderate mean score for "the instability, complexity, and variability of the surrounding situation" indicates that participants perceived the surroundings as somewhat unstable, complex, and variable, but not to an extreme extent. This is likely manageable for most participants with some effort and attention to maintain situational awareness.

4.1.3 Cognitive Load Factors

Mental, physical, and temporal demands had moderate mean scores, suggesting these factors contribute significantly to the overall cognitive load (Table 4 & Figure 4). Performance had a relatively high mean score (6.63) but also a high kurtosis (1.66), indicating participants generally felt successful in their tasks. Effort (mean = 5.37) and frustration (mean = 5.68, SD = 2.93) scores were also notable, highlighting significant cognitive and emotional strain.

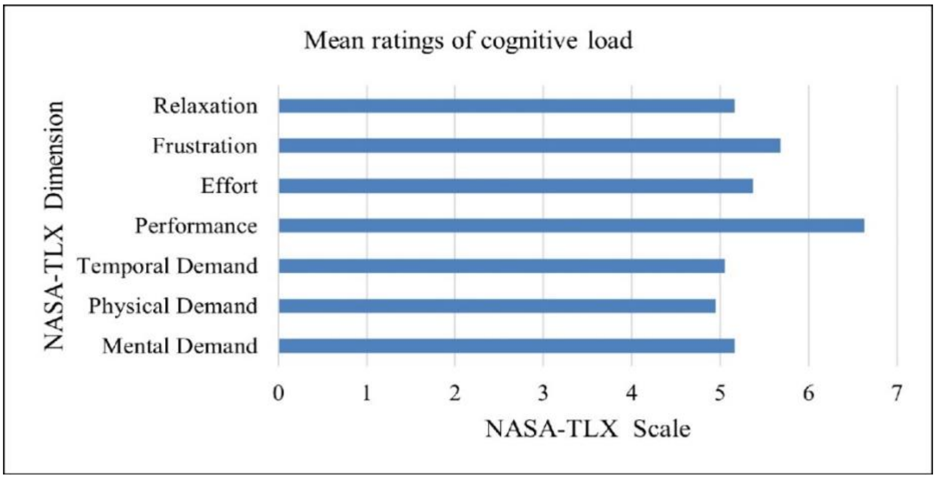

Figure 4: Participants' mean ratings of the findings on cognitive load.

Table 4 Descriptive Statistics and Normality Test for Cognitive Load.

	Descriptive Statistics				Shapiro-Wilk Test	
Dimension	**Mean**	**St. Dev**	**Kurtosis**	**Skewness**	**Statistic**	**Sig.**
Mental Demand	5.16	2.14	-1.10	-0.23	0.87	0.02
Physical Demand	4.95	1.81	-0.50	0.34	0.87	0.01
Temporal Demand	5.05	2.15	0.17	0.53	0.91	0.07
Performance	6.63	1.77	1.66	-0.71	0.86	0.01
Effort	5.37	2.01	-1.07	-0.02	0.87	0.02
Frustration	5.68	2.93	-1.35	0.07	0.89	0.03
Relaxation	5.16	2.52	-0.43	0.54	0.90	0.05

4.2 R2: How do eye-tracking metrics and mental demand differ between learners with high and low situational awareness in a mixed reality learning environment?

4.2.1 Relationship of eye-tracking metrics, mental demand, and overall SA

This section specifically focuses on Mental Demand, as it is considered the core dimension of workload in the NASA-TLX framework and directly reflects the cognitive effort involved in task performance (Chakraborty et al., 2023; Tolvanen et al., 2022). While other NASA-TLX dimensions address aspects such as task complexity, physical effort, or temporal demands, Mental Demand captures the internal cognitive processes, such as looking, thinking, and remembering that are most relevant to learning and interaction within mixed reality environments (Chakraborty et al., 2023; Hart & Staveland, 1988). According to Chakraborty et al. (2023), *"Cognitive load refers to the amount of mental effort and resources required to complete a task or solve a problem,"* and Mental Demand serves as a proxy for assessing this load. Mental Demand was selected for this study because it offers insight into how much mental effort participants exerted during the learning task, which is critical for evaluating how MR tools affect user performance, safety, and satisfaction. Therefore, this section examines Mental Demand in relation to the two eye-tracking metrics focused on in this study, alongside SART score to explore how perceived cognitive workload aligns with visual attention, cognitive processing behaviors, and SA.

Table 5: Participant grouping with respective variables.

Participants	SA Groups	Fixation duration	Fixation count	SART Score	Mental Demand
P1	HIGH SA	117.81	1941	44	6
P2	HIGH SA	101.96	3212	30	2
P3	HIGH SA	101.77	2578	38	2
P4	HIGH SA	108.88	1193	36	2
P5	LOW SA	105.26	3213	22	4
P6	HIGH SA	87.21	3561	40	4
P7	LOW SA	132.98	3845	24	6
P8	LOW SA	111.58	3069	22	6
P9	HIGH SA	113.72	2435	34	4
P10	HIGH SA	108.85	3341	30	8
P11	LOW SA	113.94	1657	20	2
P12	HIGH SA	98.11	3308	38	8
P13	LOW SA	142.43	2889	28	8
P14	LOW SA	113.44	3829	26	6
P15	LOW SA	108.91	7870	24	8
P16	LOW SA	96.64	5211	12	6
P17	LOW SA	115.34	4672	28	6
P18	LOW SA	125.82	7403	20	4
P19	HIGH SA	109.45	6292	36	6

The nineteen participants were classified into High SA and Low SA groups based on their SART Score (High SA > Mean SART Score and Low SA < Mean SART Score). Figure 8 and Table 5 show the participants' grouping with respective variables. Descriptive statistics were used to compare eye-tracking metrics (fixation duration and fixation count), SART scores, and NASA-TLX mental demand ratings between participants categorized as high or low SA (Figures 5, 6, and 7). Participants with High SA (n = 9) had a mean fixation duration of 105.31 ms (SD

= 9.17), while the Low SA group exhibited a higher mean fixation duration of 116.64 ms (SD = 13.54). Similarly, the Low SA group recorded a higher mean fixation count (4365.80, SD = 1983.28) compared to the High SA group (3095.67, SD = 1423.45). Regarding perceived mental demand, the Low SA group reported a slightly higher mean (5.60, SD = 1.84) than the High SA group (4.67, SD = 2.45), suggesting that participants with lower SA experienced greater cognitive workload during the tasks (Table 6).

Table 6: Descriptive Statistics.

	High SA Fixation duration	**Low SA Fixation duration**	**High SA Fixation count**	**Low SA Fixation count**	**High Sart Score**	**Low SART Score**	**High SA Mental Demand**	**Low SA Mental Demand**
Mean	105.31	116.64	3095.67	4365.80	36.22	22.60	4.67	5.60
Median	108.85	113.69	3212.00	3837.00	36.00	23.00	4.00	6.00
Std D	9.17	13.54	1423.45	1983.28	4.52	4.72	2.45	1.84

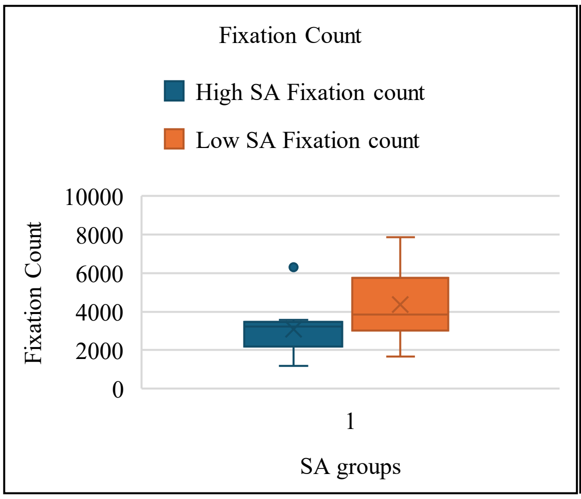

Figure 5: Fixation count based on SA level.

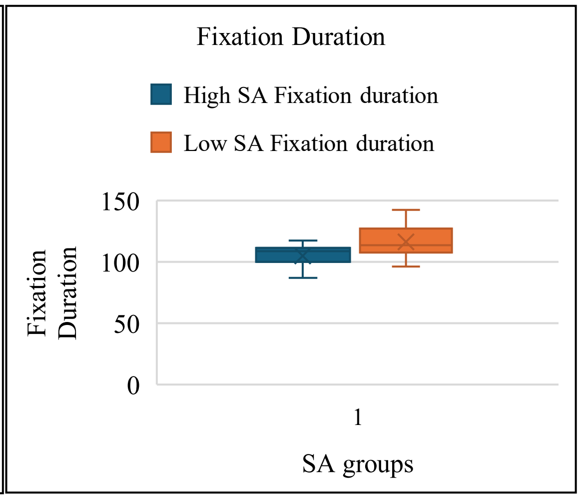

Figure 6: Fixation duration based on SA level.

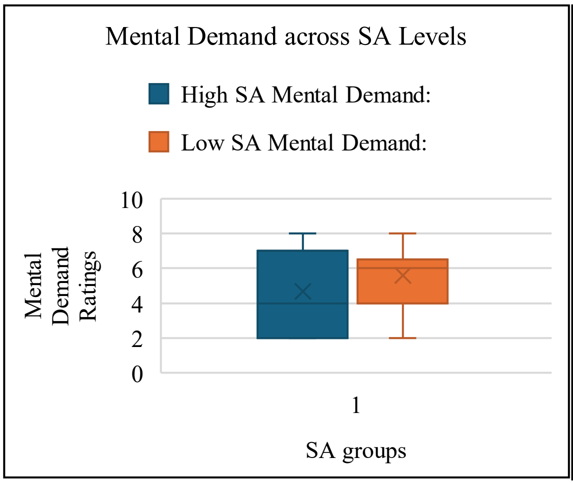

Figure 7: Mental demand based on SA levels.

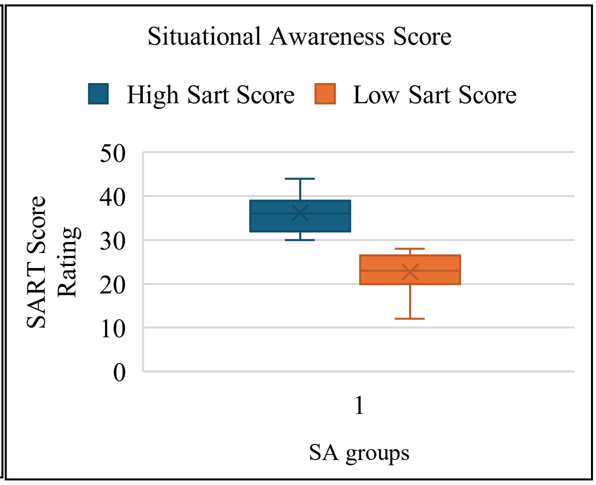

Figure 8: SA level classification based on SART Score.

4.2.2 Test of Normality and Significance

The Shapiro-Wilk test indicated that fixation duration (p = .416), fixation count (p = .055), and SART_score (p = .870) were normally distributed, while Mental Demand deviated from normality (p = .016). Given these findings, the Wilcoxon signed-rank test was used for all pairwise comparisons to ensure consistency and robustness, as the dataset included both normally and non-normally distributed variables. This approach aligns with recommendations in the literature (Field, 2017), where nonparametric methods are preferred when data include mixed distributions or when the assumption of normality is not uniformly met. The Wilcoxon Signed Ranks test revealed significant differences across all comparisons, with Z-values of -3.823 or -3.829 and p-values less than .001 (Table 7). The effect size (r) for the Wilcoxon Signed-Rank Test was calculated using the formula (r=Z/SqrN), and an approximate r value of 0.88 was obtained, showing a very large effect size, which suggests there is a strong difference between the paired variables.

Table 7: Normality and Wilcoxon Signed Ranks Test.

Shapiro-Wilk			**Wilcoxon Signed Ranks**			
Variable	**Statistic**	**Sig.**	**Pairwise Comparison**	**Z**	**Sig.**	**r**
Fixation_Duration	.951	.416	Fixation_Count – Fixation_Duration	-3.823	< .001	0.876
Fixation_Count	.903	.055	SART_Score – Fixation_Duration	-3.823	< .001	0.876
SART_Score	.975	.870	Mental_Demand – Fixation_Duration	-3.823	< .001	0.876
Mental_Demand	.873	.016	SART_Score – Fixation_Count	-3.823	< .001	0.876
			Mental_Demand – Fixation_Count	-3.823	< .001	0.876
			Mental_Demand – SA_Score	-3.829	< .001	0.878

4.3 R3: What is the relationship between situational awareness, cognitive load, and eye-tracking measures in a mixed reality learning environment?

4.3.1 Spearman's rho correlation

The correlation results (Table 8) reveal nuanced interactions between situational awareness (SA) factors and cognitive load dimensions. Familiarity with the surrounding situation generally reduces mental and temporal demands and frustration while enhancing relaxation and performance. Information quantity and quality tend to decrease frustration and effort. Alertness is moderately associated with improved performance. Higher spare mental capacity correlates with increased physical demand but potentially better performance. The instability and complexity of the situation increase mental demands but may reduce physical and temporal demands. Lastly, greater variability in the situation negatively impacts performance. These findings suggest that enhancing specific SA aspects can effectively manage cognitive load and improve performance in MR learning environments.

Table 8: SA and Cognitive load measures for correlation.

Situational awareness dimensions	**Cognitive load dimensions**						
	Mental	Physical	Temporal	Performance	Effort	Frustration	Relaxation
F	-0.31	0.04	-0.28	0.28	-0.26	-0.09	0.39
I qty	0.03	0.29	0.19	0.11	-0.23	-0.36	0.19
I qty	0.08	0.28	0.27	0.14	-0.23	-0.39	0.15
A	0.14	0.22	-0.08	0.39	0.16	-0.23	0.15
C	0.23	-0.04	-0.14	0.05	0.17	0.10	-0.09
D	0.10	-0.01	-0.40	0.07	-0.21	-0.28	0.28
S	-0.06	0.56*	-0.15	0.29	0.2	-0.18	-0.02
I	0.44	-0.14	-0.28	0.16	-0.12	-0.19	0.10
C	0.07	-0.41	-0.44	0.05	-0.21	-0.07	0.15
V	-0.2	0.04	-0.13	-0.42	0.03	-0.31	-0.16

Note: SA Dimension: F-Familiarity of the surrounding situation; I qty- Information quantity of the surrounding; I qlty- Information quality; A- Alertness; C- Concentration of attention; D- Division of Attention; S-Spare mental capacity; I- Instability of the situation; C- Complexity of the situation; V-Variability of the situation. The color ranges from green (low), yellow (medium) to red color (highest correlation coefficient).

The correlation analyses of eye-tracking metrics, mental demand, or overall SA revealed that fixation duration had a weak negative correlation with SART score (rho = -0.253, p = .295) and a weak positive correlation with mental demand (rho = 0.166, p = .497), neither of which was statistically significant. Fixation count showed a stronger positive correlation with mental demand (rho = 0.446, p = .056), approaching significance, and a negative correlation with SART score (rho = -0.338, p = .157), which was not significant. SART score had virtually no correlations with both fixation duration (rho = -0.253, p = .295) and mental demand (rho = -0.027, p = .914). None of the correlations reached statistical significance (Table 9).

Table 9: Correlations of eye-tracking metrics, mental demand, and SART Score.

Metric Pair	ρ (rho) = r	p-value	Effect Size (η^2)
Fixation Duration – Fixation Count	-0.049	.842	-0.049
Fixation Duration – SART Score	-0.253	.295	-0.253
Fixation Duration – Mental Demand	0.166	.497	0.166
Fixation Count – SART Score	-0.338	.157	-0.338
Fixation Count – Mental Demand	0.446	**.056**	0.446
SART Score – Mental Demand	-0.027	.914	-0.027

Effect Size Interpretation for Spearman's rho: $\rho < 0.1$ is Negligible, $\rho \approx 0.1$–0.29 is a small effect, $\rho \approx 0.3$–0.49 is medium effect, and $\rho \geq 0.5$ is Large effect.

4.3.2 Regression Analysis

Regression analyses were conducted to determine whether Mental Demand, Fixation Duration, and Fixation Count individually predicted Situational Awareness using SART Score (Table 10). The result shows that none of the predictors showed a statistically significant effect on SART scores. The regression with Mental Demand yielded an R^2 of 0.005, indicating that only 0.5% of the variance in SART Score was explained by Mental Demand. The relationship was not statistically significant (F = 0.089, p = .769), with a weak negative beta coefficient (β = -0.72), suggesting no meaningful predictive value. For Fixation Duration, the model explained just 5% of the variance (R^2 = .05) and was also not statistically significant (F = 0.8, p = .384). The beta coefficient was small and negative (β = -0.212), indicating a negligible impact on SART Score. The Fixation Count model accounted for 14% of the variance (R^2 = .14) in SART Score, with a slightly stronger beta coefficient (β = -0.38). Although the F-value was higher (F = 2.9), the relationship still did not reach statistical significance (p = .110). This suggests a trend toward a negative relationship between Fixation Count and situational awareness that may warrant further investigation with a larger sample size. Fixation Count exhibited a potentially meaningful trend, indicating that higher fixation count may be linked to lower situational awareness.

Table 10: Regression Analysis Predicting Situational Awareness using SART Score with other variables.

Variables	R	R^2	Adjusted R^2	Beta Coeff	t-values	F	Sig.	η^2 (Eta Squared)
SART Score – Mental Demand	0.72	0.005	-0.053	-0.72	-0.3	0.089	0.769	0.005
SART Score – Fixation Duration	0.21	0.05	-0.011	-0.212	0.894	0.8	0.384	0.05
SART Score – Fixation Count	0.38	0.14	0.094	-0.38	-1.69	2.9	0.110	0.14

Dependent Variable: SART Score; Predictors: (Constant), Mental_Demand, Fixation duration, Fixation count.

5. DISCUSSION

This study investigated the relationship between situational awareness (SA), cognitive load, and eye-tracking metrics within an MRLE designed for implementing sensing technologies on a virtual construction site. The discussion is structured around the three research questions and supported by descriptive and inferential findings from SART, NASA-TLX, and eye-tracking data.

5.1.1 Situational Awareness and Cognitive Load in MR Environments (R1)

The first research question aimed to explore how SA relates to cognitive load in an MR environment. Results revealed that participants in the MR learning environment experienced moderate levels of both SA (Mean SART

Score = 29.05) and cognitive load across most NASA-TLX dimensions. Findings from descriptive analyses partially support hypothesis H1, because moderate cognitive load components and higher situational awareness of the environment were, on average, experienced by learners. For example, the NASA-TLX scores indicated moderate mental, physical, and temporal demand, with performance scores highest among cognitive load dimensions. High levels of alertness, information quality, and familiarity indicate that students can effectively process and interact with the MR content with a high level of understanding of the surroundings. However, moderate levels of concentration and spare mental capacity suggest that while students are engaged, there are limitations to their attentional supply to the surroundings. This is also evidenced by the high performance exhibited by the participants. Similar studies by Bayounis and Basahel (2020) identified high-performance scores, but low SART results occurred because the individuals cautiously applied the required safety requirements. Whereas, low performance scores but high SART were individuals with "high awareness level but careless when applying the safety requirements" (Bayounis & Basahel, 2020). This is consistent with literature indicating that moderate cognitive load can support SA by promoting engagement without overwhelming cognitive resources (Arias-Portela et al., 2024; Endsley, 1995; Endsley & Garland, 2000).

Similarly, to better understand the relationship between situational awareness (SA) and cognitive load, Table 8 presents correlation values across several dimensions. For example, a negative correlation between familiarity and mental demand ($r = -0.31$) suggests that when participants feel more familiar with the environment, they experience lower cognitive effort, which aligns with the theory that familiarity reduces the mental resources required for task performance (Endsley, 1995). Also, instability of the situation (I) shows a moderate positive correlation with mental demand ($r = 0.44$), indicating that greater instability increases mental effort. Similarly, division of attention (D) is moderately negatively correlated with temporal demand ($r = -0.40$), implying that those who struggle to divide attention may perceive higher time pressure. Spare mental capacity (S) is positively associated with physical demand. These patterns support prior findings that increased task complexity or situational instability tends to raise cognitive load, impacting learning and performance (Sweller et al., 1998).

5.1.2 Differences between Eye-Tracking Metrics and Mental Demand of High and Low SA Learners (R2)

The second research question focused on the differences in eye-tracking metrics (fixation duration and fixation counts) and mental demand between learners with high and low SA. Participants with higher SA had shorter fixation durations (Mean = 105.31 ms) and lower fixation counts (Mean = 3095.67) compared to those with lower SA (Mean fixation duration = 116.64 ms; fixation count = 4365.80). Additionally, the high SA group reported lower mental demand (Mean = 4.67) than the low SA group (Mean = 5.60). These differences indicate that learners with lower situational awareness were associated with longer and more frequent fixations, as well as higher perceived cognitive effort. Hypothesis H2 is hereby supported because findings from the analysis show that learners categorised under the Low SA group experienced higher Fixation Duration (116.64 ms) than the High SA group, with a fixation duration of 105.31 ms. Similarly, for Fixation Count, the Low SA group has a higher count (4365.80) than the High SA group (3095.67). This pattern may indicate that Low SA participants spent more time searching for or processing information, or navigating the MR environment. These findings are consistent with eye-tracking research, which emphasizes that a higher frequency of fixations and lower fixation counts could indicate a lower level of SA (Arias-Portela et al., 2024; Mahanama et al., 2022), and also linking longer fixations to increased cognitive effort or uncertainty (Kummetha et al., 2020; Wallmyr et al., 2019). Conversely, High SA participants spent less time fixating and engaged in fewer fixations overall. This supports Endsley's model (Endsley, 1995; Endsley & Garland, 2000), where SA relies on effective perception and comprehension of environmental cues potentially observable through visual attention patterns. These findings indicate that learners who can better filter and prioritize relevant cues without becoming overwhelmed by environmental complexity are better able to maintain situational awareness.

5.1.3 Relationships between Situational Awareness, Cognitive Load, and Eye-Tracking Metrics (R3)

In addressing the third research question, the study explored potential relationships among SA, cognitive load, and eye-tracking behavior. Participants with lower SA not only experienced higher cognitive load, particularly in mental demand and effort, but also exhibited more visual scanning behavior (e.g., higher fixation count). This triadic relationship supports the notion that reduced SA in MR environments may be a consequence of visual and cognitive overload. This relationship aligns with studies highlighting cognitive load as a critical constraint on SA in dynamic environments (Kummetha et al., 2020; Wallmyr et al., 2019). The findings indicate that the dimensions of cognitive load and SA are not significantly correlated. Notably, alertness and concentration dimensions of SA were more affected than familiarity or information quality. Similarly, spare mental capacities have a positive correlation with physical demand and attention dimensions, suggesting that students who manage their cognitive load effectively can better maintain situational awareness. Furthermore, the negative correlation between relaxation and frustration in this study underscores the need for stress management interventions to improve cognitive performance and overall well-being during learning. Although most correlations were not statistically significant, a pattern emerged that may be meaningful for future research. In particular, fixation count showed a stronger positive correlation with mental demand approaching significance, and a negative correlation with SART score, which was not significant. SART score had virtually no correlation with both fixation duration and mental demand. This means that a higher fixation count being associated with increased mental demand suggests that visual scanning intensity could reflect perceived task complexity or mental effort. These preliminary associations indicate that eye-tracking metrics such as fixation count may have latent predictive value for cognitive load under certain task conditions. These trends suggest potentially meaningful associations that should be further explored with larger samples. Future studies with larger samples or more complex MR tasks might be necessary to justify the generalization of these trends. Therefore, Hypothesis H3 is partially supported, although a trend is observed, but not statistically significant, which means that fixation count and duration are weak predictors of situational awareness.

5.2 Implications for Mixed Reality Learning Environments

The study's findings have practical implications for designing tasks in an MR environment that optimizes cognitive load to enhance situation awareness. For instance, ensuring that individuals are familiar with their environment and providing high-quality information can help maintain situation awareness. Additionally, managing the division of attention and mental capacity is crucial in high-demand situations to prevent cognitive overload. Based on the findings, effective training, information management, and stress reduction strategies are critical for enhancing cognitive efficiency and overall situational awareness. As Endsley and Garland (2000) highlighted "having good situation awareness was largely a matter of training and experience". Similarly, effort should be made to reduce frustration and enhance relaxation during learning in an MR environment, as these factors significantly impact overall cognitive load. Eye-tracking could be integrated into MR platforms as a diagnostic tool to monitor learner attention and SA in real time. Eye-tracking integration could allow for adaptive instruction based on learner engagement and gaze behavior. For example, eye-tracking data such as fixation duration and fixation count could be analyzed continuously during MR use to identify moments when learners become cognitively overloaded (e.g., short fixation times) or disengaged (e.g., prolonged gaze away from task-relevant areas). The system could then respond adaptively by slowing down task complexity, highlighting critical information, providing audio or visual cues, or pausing to offer additional prompts. This kind of real-time adaptation would create a feedback loop in which the MR system personalizes content delivery based on moment-to-moment cognitive and attentional states. Such integration aligns with adaptive learning principles and can improve instructional efficiency, especially in complex environments like construction sensing technologies learning tasks, where maintaining situational awareness is critical.

5.3 Study Limitations and Future Research

While participants interacted with the MR learning environment for one hour, it may be beneficial to assess the long-term effect of MR environments on cognitive load and situational awareness. Key limitations may also exist in potential individual differences (e.g., prior MR experience) that were not analyzed. Future studies could use a larger sample size and deepen insights into the impact of prior experience with MR on SA, cognitive load, and visual attention in MR environments. Future longitudinal studies could provide deeper insights into how these factors evolve with prolonged MR exposure and training. Additionally, this research assessed situational awareness in a controlled laboratory, and future studies should explore the application of MR learning environments for upskilling the current construction workforce on the actual construction sites, which are often dynamic and unpredictable. Future studies with larger samples or more complex MR tasks might further clarify or validate the correlation between fixation count and mental demand.

6. CONCLUSION

This study provides valuable insights into the relationship between situational awareness, cognitive load, and eye-tracking metrics within an MR learning environment for construction education. The study shows that integrating subjective cognitive load assessments with objective eye-tracking data analysis, using fixation count, fixation duration, and mental demand, are strong behavioral indicator of situational awareness. The study reveals high levels of familiarity, along with the quality and quantity of information, indicating that participants generally had a good understanding of their surroundings during the MR tasks. Similarly, the negative correlation between relaxation and frustration indicates that reducing frustration could improve relaxation and overall performance. Implementing effective strategies to enhance spare mental capacity can lead to better attention management and lower cognitive load. The study further revealed that participants with lower SA not only experienced prolonged fixation durations and higher cognitive load but also exhibited more visual scanning behavior (e.g., higher fixation count). Similarly, fixation count showed a stronger positive correlation with mental demand approaching significance, and a strong negative correlation with SART score, although statistically insignificant. This means that a higher fixation count being associated with increased mental demand suggests that visual scanning intensity could reflect perceived task complexity or mental effort. This indicates that eye-tracking data can be adopted as behavioral indicators for learners' situational awareness within the MR system. These findings not only align with cognitive load theory and prior eye-tracking research but also offer practical recommendations for MR instructional design. Eye-tracking could be integrated into MR platforms to predict SA in real time. For example, eye-tracking data such as fixation duration and fixation count could be analyzed continuously during MR use to identify moments when learners become cognitively overloaded (e.g., short fixation times) or disengaged (e.g., prolonged gaze away from task-relevant areas). The system could then respond adaptively by slowing down task complexity, highlighting critical information, providing audio or visual cues, or pausing to offer additional prompts. This kind of real-time adaptation would create a feedback loop in which the MR system personalizes content delivery based on moment-to-moment cognitive and attentional states. Such integration aligns with adaptive learning principles and can improve instructional efficiency, especially in complex environments like construction sensing technologies learning tasks, where maintaining situational awareness is critical. By understanding the relationship between cognitive load, situational awareness, and eye tracking metrics, educators and developers can design more effective MR learning environments that enhance student learning, mitigate cognitive overload, guide attention, and enhance engagement.

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DISCLOSURE OF INTERESTS

The authors have no competing interests to declare that are relevant to the content of this article.

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