Developing a Digital Twin-based Framework for Construction Fire Hazard Recognition Training

Kexin Liu[1], Mohamed Sabek[1], Gaang Lee[1], Max Kinateder[2], Vicente A. Gonzalez[1]

[1]Department of Civil & Environmental Engineering, University of Alberta, Canada
[2]Construction Research Centre, National Research Council Canada, Canada
kexin10@ualberta.ca, sabek@ualberta.ca, gaang@ualberta.ca, Max.Kinateder@nrc-cnrc.gc.ca, vagonzal@ualberta.ca

Abstract –

Construction sites are dynamic environments where fire hazards pose significant safety risks. Effective hazard recognition is the key step to prevent such hazards. While existing research has developed various training methods, limited studies focus on fire hazards in construction. Moreover, most approaches fail to adapt to evolving site conditions. To address these gaps, this study proposes a digital twin (DT)-based framework for dynamic fire hazard recognition training, with current validation progress presented. This framework integrates 360° imagery, 3D Gaussian Splatting, and Immersive Virtual Reality (IVR) to create an adaptive and interactive training environment. A user-centered training approach is designed to enhance personalized learning by incorporating individual trainee profiles and situation awareness (SA) assessments. Additionally, a cloud-based data system enables long-term tracking and scenario updates based on historical hazard data and trainee performance. This modular conceptual framework provides a foundation and guideline for future research on dynamic fire hazard recognition training. Further work will focus on framework validation through pilot studies in real construction settings to assess training effectiveness and usability.

Keywords –

Construction Fire; Hazard Recognition; Safety Training; Digital Twin; Situation Awareness

1 Introduction

Construction sites face continuous challenges in hazard prevention due to dynamic changing environments, diverse stakeholders, and complex interactions between people, equipment, and materials. Fire hazards, though less frequently than the “fatal four” hazards (i.e., falls, electrocutions, struck-by, and caught-in/between), often result in severe consequences, including risks to human life, significant property damage, and project delays. From 2016 to 2020, an annual average of 4,300 fires on construction sites were reported in the United States, causing five deaths, 62 injuries, and USD 376 million in property damage [1].

Fires can spread rapidly in construction sites with lots of combustibles, making early-stage hazard recognition critical [2]. With advancements in sensors and vision-based systems, such as computer vision and machine learning, automated detection systems are increasingly being developed to monitor, identify, and predict construction hazards [3]. While these systems provide valuable support, SA and human judgment remain indispensable [4]. SA involves three levels: perception (Level 1), perceiving the current state of the environment; comprehension (Level 2), understanding the meaning of the situation; and projection, anticipating potential future developments[5]. These abilities allow experts to make timely and accurate decisions and adapt to unexpected states [5]. Construction personnel (e.g., construction workers and managers) equipped with well-developed SA can adapt to unexpected situations, interpret subtle contextual signals, and make informed decisions that automated systems may not be able to address [6]. Unfortunately, individuals often struggle to identify hazards in dynamic and complex environments due to high cognitive demands and a lack of SA, stemming from the complexity of fully recognizing and predicting fire, a complicated process involving many factors, and the absence of structured training approaches [2]. Traditional training methods, such as classroom-based presentations, often adopt a one-size-fits-all approach, failing to engage workers and overlooking individual learning needs and weaknesses [7][8].

Immersive technologies, such as virtual reality (VR) and augmented reality (AR), have proven to be effective safety training tools, providing immersive and engaging learning experiences without exposing individuals to risks [9]. Despite their potential, existing studies on construction hazard training tend to focus on either broad categories of construction hazards or high-frequency hazards, such as slips and falls [10]. Research suggests that workers often recall familiar hazards while overlooking less obvious but equally critical hazards, such as fire hazards [11]. Moreover, since each construction project is unique and evolves through different phases, the fire hazards workers encounter can vary significantly. For instance, the foundation phase involves fire hazards from flammable fuels for machinery, while the structure phase faces hazards from welding, cutting, and improper material storage. Additionally, tailoring training to the unique hazards of each construction site has proven to be more effective, as varying hazards impose different cognitive demands [12].

Collectively, there are gaps in (1) the lack of training systems specifically designed to improve SA in construction fire hazard recognition and (2) the absence of systems capable of dynamically adapting training focus to specific construction site conditions and evolving stages. To bridge these gaps and guide future research in this direction, this paper proposes a DT-based framework for fire hazard recognition training and presents the current progress in its validation.

2 Literature Review

2.1 Construction Hazard Recognition Training

The proposed training framework aims to improve construction personnel's SA ability to recognize and prevent fire hazards, a process influenced by various factors. Understanding these factors is vital for developing effective training programs. Environmental conditions, such as low visibility due to darkness or dust during construction, are one of the key factors [13], along with distractions prevalent in construction settings, which can hinder workers' focus [14]. Workers' physical or mental state (e.g., fatigue) also affects hazard recognition performance [6][15]. Furthermore, individual characteristics, such as age [16], personality traits [17], safety knowledge [18], and experience [19], affect how workers perceive, comprehend, and project potential risks. Additionally, cues provided during training, such as visual and question cues, affect trainees' performance [19]. Therefore, it is extremely important to consider the environmental variations trainees will encounter in the field, strategy, and trainees' individual features and needs when developing training programs.

Albert et al. [2] developed the first high-fidelity Building Information Modeling (BIM)-based augmented virtual environment. They categorized construction hazards into ten energy sources and incorporated cognitive retrieval mnemonics to improve long-term cue retention. Building on this work, Jeelani et al. [8] developed a personalized training strategy using eye-tracking data for individualized performance feedback and self-diagnosis correction. However, 3D BIM models face challenges in presenting real-world environments, as they offer an artificial, computer-generated representation of construction sites, potentially reducing training effectiveness [20]. Eiris et al. [21] observed that participants identified more hazards in BIM-based virtual environments than in 360 images of real construction sites due to clearer visuals. However, 360 images better reflected real-site conditions, raising concerns about the applicability of training methods that do not closely align with real-world environments. To address these limitations, researchers have adopted augmented 360 images, enhanced with cues (e.g., visual, audio) or instructions, as training environments, known as augmented virtuality, delivered by screen-based or VR head-mounted devices (HMDs) [22][23]. Given the page limitation, Table 1 summarizes key research in this field, detailing hazard type, training material and environment, cues, interaction, and assessment metrics. The literature review highlights a lack of focus on less frequent hazards, such as fire, as discussed in the Introduction section, as well as the insufficient integration of SA as training objectives to further improve hazard recognition abilities.

Table 1. Key studies on construction hazard recognition training

	Hazard Type	Training Material and Environment	Cues	Interaction	Assessment Metrics
[2]	Various types	BIM models augmented by experts and with construction images	Visual	Screen-based Devices	Hazard recognition index
[8]	Various types	Static real-world images annotated by experts	Visual	Screen-based Devices	Hazard-Recognition Level
[22]	Various types	Augmented stereo-panoramic videos and virtual models	Visual	Screen-based Devices	Hazard Recognition Score
[24]	Various types	BIM models enriched with avatars	Question	VR HMDs	The time used; the number of hazards identified
[23]	Fall hazard	Augmented 360-degree Panorama	Visual and audio	VR HMDs	Hazard Identification Index (HII)

[25]	Various types	construction site simulations with hazards	Visual and audio	VR HMDs	Eye-tracking metrics; hazard recognition accuracy
[26]	Fatal four	BIM model supplemented with regulations	Visual	VR HMDs	HII; Eye-tracking metrics

2.2 DT Frameworks for Construction Safety

In the architecture, engineering, and construction (AEC) industry, a digital twin is typically defined as a dynamic, real-time digital replica of physical assets, processes, and systems to enhance the management and optimization of construction and facility operations [27]. A DT system should include three key components: the physical artifact, the digital counterpart, and the bidirectional data exchange between them [28]. Unlike static models such as BIM, digital models, or digital shadows, which may only offer one-way updates, a true DT is characterized by its ability to synchronize with real-world changes in real time or near real time [27].

In the context of construction safety, DT applications are emerging but remain underdeveloped. In the area of hazard detection, DTs have been used to dynamically track workers' locations and detect risk events, such as falls, in real time [29]. For training, Vahdatikhaki et al. [30] developed a DT-based system for excavator training, allowing instructors to review trainee performance and provide targeted feedback dynamically. Harichandran et al. [32] further proposed a DT-based framework for dynamically updating VR safety training scenarios based on construction progress, enabling trainees to perceive and familiarize themselves with potential safety risks before entering the actual site.

A major advantage of DT-based training lies in its potential to improve SA [31]. In manufacturing, for instance, DT-enhanced training has been shown to improve operators' responsiveness and anticipation of risks by aligning VE with live system conditions [33]. DT can deliver higher-fidelity contextual information by dynamically reflecting environmental and operational changes, which is particularly valuable in fast-changing construction sites. Applying this concept in construction safety training, especially hazard recognition training, allows for site-specific interventions to support continuous hazard awareness and safer decision-making under realistic conditions. Despite its potential, research on integrating DT into construction safety training for enhancing SA remains limited and fragmented [31]. Furthermore, the application of DT in construction hazard recognition training has been largely unexplored.

3 System Architecture

To address the identified gaps, a conceptual framework was developed following a structured methodology for system architectures [34]. The primary objective of this framework is to provide context-specific training for construction personnel, aiming to improve their SA while strengthening their ability to effectively recognize and respond to fire hazards. Based on a comprehensive review of the literature, the system's key objectives and functions are outlined below, with detailed explanations in the following subsections.

- Objective 1: Enable trainees to perceive training environments realistically, ensuring their reactions and decisions reflect actual site conditions. Function 1: Capture real construction site environments with detailed representations of site objects and spatial arrangements.
- Objective 2: Provide context-specific training scenarios that adapt to evolving project phases. Function 2: Dynamically update virtual environments from real construction site data based on project checkpoints.
- Objective 3: Deliver personalized feedback and reinforcement training to foster targeted skill improvement. Function 3: Provide pre- and post-training assessments and a dynamic feedback mechanism to adapt training content (e.g., scenarios and strategies).
- Objective 4: Record identified construction site conditions for fire hazards and trainee performance metrics to support continuous improvement. Function 4: Provide an accessible database to store and manage historical data.

Accordingly, a system architecture has been proposed. As illustrated in Figure 1, it consists of four major components: (1) data acquisition and (2) data processing and integration, which together address objective 1, (3) user-centric training, which addresses objective 3, and (4) dynamic updating with cloud storage, which address objective 2 and 4. These components form a continuous loop, enabling the system to deliver effective and adaptive fire hazard recognition training. As this framework is based on existing DT frameworks, it can be integrated as a detailed subcomponent within broader DT-based construction safety frameworks. The following sections provide a detailed explanation of each function and current validation progress.

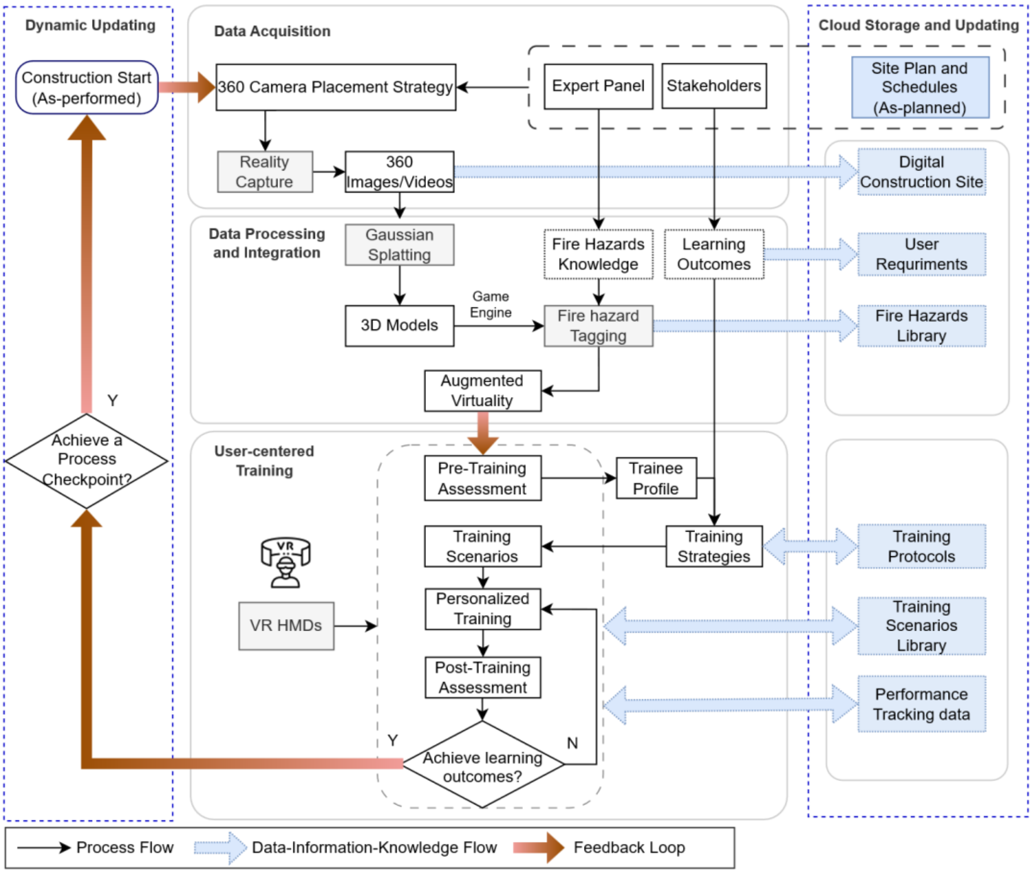

Figure 1. The system architecture of DT-based construction fire hazard recognition training system

3.1 Data Acquisition

Given the limited historical data (e.g., incident reports) and guidelines on construction fire hazards, obtaining input from stakeholders, such as safety managers and construction workers, and fire hazard experts, is the critical first step in building a reliable system (as shown in the dashed box in Figure 1). However, as more data becomes available, Artificial Intelligence-driven methods can be integrated to enhance autonomy over time. Regular with stakeholders, combined with analysis of site plans and schedules, help identify high fire risk zones, where fire hazards are likely to occur and relevant to training (e.g., areas requiring identification of hidden hazards such as electrical wiring). This guides the development of comprehensive camera placement plans, ensuring effective data collection aligned with real-world safety requirements and training needs. Additionally, fire hazards category and learning outcomes can be identified to further tailor training to specific objectives.

This paper proposes the use of 360° cameras to capture construction environments for training. Compared to synthetic, BIM model-based training scenarios, those captured from real construction site data, such as 360° imagery, are more effective in achieving training outcomes, as highlighted in the literature review section. However, recognizing the limitations of 360° images/videos in navigation and interactivity, this paper introduces 3D Gaussian Splatting (3DGS) [35] as a method to convert these images/videos into 3D models (detailed in Section 3.2). In a recent study, Rüter et al.[36] demonstrated the potential of 3DGS for construction site visualization, highlighting that it enables fast, high-quality 3D model generation while eliminating the need for time-consuming methods such as laser scanning. Given its efficiency, cost-effectiveness, and ease of deployment, the process of converting 360° images/videos into 3DGS was selected for this research.

To maximize environmental representation while avoiding obstructions and distortions caused by low ceilings or personnel, 360° cameras are proposed to be strategically placed across the construction site. Medium-height placements are prioritized to achieve optimal results. To ensure consistency in subsequent cube map conversions, the camera can be maintained in a vertical position. Frames can be extracted from recorded videos at regular intervals, producing a uniform and structured visual dataset. Using a dual-lens 360° camera, this method can generate equirectangular images, and rectangular projections of spherical data in a 2:1 aspect ratio, ensuring full site coverage with minimal effort [37]. This approach reduces the need for precise camera framing while providing detailed, comprehensive captures of construction environments. Figure 2 shows an example of the generated data.

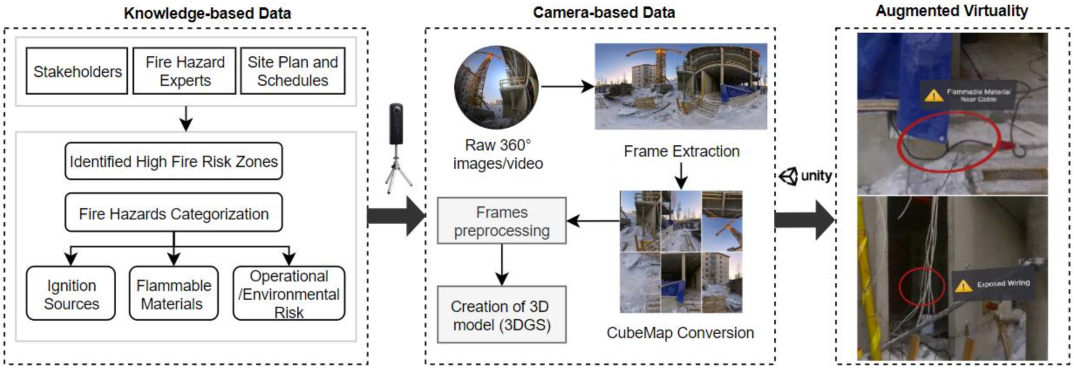

Figure 2. Illustration of data acquisition, processing and integration flow for the proposed system

3.2 Data Processing and Integration

In this phase, the collected raw 360 images or videos can be converted into 3D models, while input gathered from fire hazard experts is used to augment the generated 3D model in game engines (e.g., Unity 3D), to generate training scenarios. Figure 2 illustrates the data processing and integration process of knowledge-based and camera-based data, with an example provided to demonstrate current progress in the development effort. The acquired equirectangular images are processed for 3D model generation and training applications. First, to address the distortion inherent in spherical images captured with fisheye lenses, equirectangular images are converted into cube maps. This process projects the spherical data onto six cube faces, straightening perspective lines and removing distortions [35]. These cube maps, compatible with 3D modelling tools, enable further processing [35]. To optimize dataset quality and efficiency, only the left, right, and front views, which are central to the camera and environment, are retained [37]. Less relevant views, such as the top and bottom faces, are excluded to streamline the data and focus on critical environmental details. Furthermore, to ensure the usability of the curated cube map images, frames with poor lighting or obstructions are removed. Additional angles can be extracted using software (e.g., Insta360 Studio) that allows for frame extraction, stitching, and refinement of 360° images, ensuring dataset completeness and quality [37]. These processed images are then put into tools supporting gaussian splatting, such as Jawset Postshot and Polycam, to generate high-fidelity 3D point clouds.

To augment the generated 3D virtual environments for creating training scenarios, game engines are commonly used to enable interactivity and functionality [23]. In the development progress of this paper, Unity 3D, a widely used game engine known for its flexibility, was used for tagging fire hazards and enhancing interactivity. By using knowledge obtained from fire hazard experts and fire safety regulations, fire hazards in specific scenes can be identified and annotated. For instance, as shown on the right of Figure 2, exposed wiring and flammable materials near the cable that could potentially cause a fire are annotated with a red circle. The augmented scenarios form the foundation for further training scenario design. This structured and refined data acquisition, processing, and integration pipeline enables the system to deliver tailored, context-specific fire hazard recognition training.

3.3 User-centered Training System

The proposed system emphasizes a customizable and user-centered VR training framework, guided by four essential dimensions, learner specifics, context, representation, and pedagogy, adapted from established frameworks for immersive virtual training [38]. Learner specifics serve as the foundation, including trainees' roles and baseline SA. As shown in Figure 3(a), users can select their role, such as safety manager or construction worker, to tailor the training content based on their responsibilities. Baseline testing is typically conducted as a pre-training assessment, using a combination of questionnaires and virtual environments exploration [2]. During these explorations, trainees navigate scenarios with hazards but without any cues, allowing the system to evaluate their baseline hazard recognition abilities [2] [24]. Metrics such as the hazard recognition index and hazard identification index, summarized in Table 1, are commonly used to assess perception (Level 1 SA) by counting the number of hazards recognized. However, these metrics provide limited evaluations of comprehension (Level 2 SA) and projection (Level 3 SA). Given the visual nature of fire hazard recognition, data such as eye-tracking metrics could be incorporated to assess different levels of SA [4].

Context-specific scenarios developed in the data processing and integration phase form the foundation for interactive design guided by pedagogical strategies. Representation of the training content is achieved through immersive VR simulations delivered via HMDs, recreating realistic and interactive construction site environments, ensuring that trainees exhibit behaviors and reactions approximately similar to those they would have in real-world scenarios [23]. For pedagogical strategies, the system incorporates scenario-based learning and interactive learning approaches widely adopted in existing research [22-26]. For example, as shown in Figure 3(d), hazards such as exposed wiring are annotated within the virtual environment. When the trainee points and clicks on the hotspot using a VR controller, the corresponding fire hazard label is displayed, as shown in Figure 3(e). This interaction helps develop fire hazard perception (Level 1 SA), which involves identifying fire hazard elements in the workplace. To further develop comprehension (Level 2), understanding that exposed wiring poses a fire hazard, and projection (Level 3), predicting the consequences of such a hazard and proposing interventions, detailed instructions are provided when the trainee clicks the "Instruction" button, as shown in Figure 3(f). However, more specific training strategies need to be developed to align with specific training objectives, and evaluating the effectiveness of different training strategies requires further well-designed experiments. Currently, there is limited research exploring how different training protocols affect trainees' performance [24]. Following each training session, a post-training assessment will be conducted using metrics in pre-training assessment, evaluating the trainee's performance on SA across all three levels. If it does not meet the learning outcomes, tailored reinforcement training will be conducted.

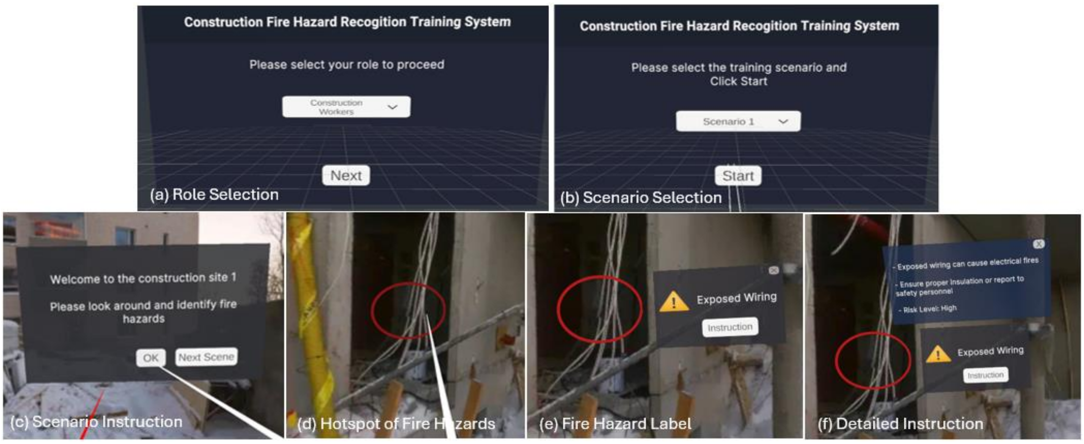

Figure 3. An Example of a VR Training Scenario in the Proposed System

3.4 Dynamic Training Scenarios Updating and Data Storage

The key role of DT in this system is to (1) dynamically update training scenarios, (2) track training performance over time, and (3) store historical data for continuous improvement. For scenario updating, the frequency depends on the specific project needs, as real-time data input is not required for training based on recognition site objects [32]. Instead, new training scenarios are updated when obvious changes occur in the construction layout or activities, such as the introduction of new materials or equipment. Milestones are typically a point when significant changes occur at the construction site. At each milestone, the system initiates the data acquisition phase to capture updated site environments. The triggering process can be initiated manually by construction managers who identify such changes or automatically through sensors integrated into the project that detect alterations in site conditions. Consequently, this data enters the data processing and integration procedure, identifying new fire hazards and ensuring training scenarios remain relevant and aligned with real-world requirements. The updating mechanism uses both the as-planned construction schedule and real-site conditions to determine when a milestone is reached. Regarding training performance, most existing construction training programs focus only on short-term learning without assessing how well trainees retain and apply knowledge over time [22]. By integrating DT, the proposed system stores trainees' performance data after every session. Over time, this data can be analyzed alongside construction phases and training frequencies to support skill development and reinforcement [23]. For historical data storage, the system uses a cloud storage platform (e.g., Amazon S3) to securely store identified fire hazards, established training scenarios, and training performance. Stored digital representations of construction sites can support not only fire but broader hazards, while also serving as training data for AI-based automated hazard detection to assist human detection. Notably, for smaller projects with limited data requirements, local or hybrid storage can be used as an alternative to cloud storage based on specific needs.

4 Conclusions and Future Work

This study presents a DT-based framework for construction fire hazard recognition training, designed to develop and improve trainees' SA. This framework contributes to the body of knowledge in construction fire safety by introducing a rapid workflow for creating augmented virtual construction environments, integrating SA into user-centered fire hazard recognition training, and integrating DT technology for dynamic training scenarios updating and long-term performance tracking. The proposed system has the potential to help trainees to better adapt to dynamic construction sites, develop and improve the SA of construction fire hazards, and ultimately reduce the risk of construction fires. Additionally, the modular structure of the framework allows for gradual adoption, reducing the need for a full-scale investment upfront. While the proposed system shows significant promise, several areas require further development. First, stakeholder engagement is needed to validate system requirements. Second, the framework's performance and scalability need to be validated through real-world implementation across various construction scenarios. Future work will focus on conducting pilot studies to evaluate training effectiveness, user experience, and SA improvements.

Acknowledgement

This research has been supported by the Natural Sciences and Engineering Research Council of Canada (NSERC) via the Discovery Grant program (Grant No. RGPIN-2023-04239). The authors gratefully acknowledge NSERC's support for this research.

References

[1] Richard Campbell, Fires in structures under construction, 2022. Accessed: Nov. 21, 2023. [Online]. Available: www.nfpa.org/education-and-research/building-and-life-safety/construction-safety

[2] A. Albert, M. R. Hallowell, B. Kleiner, A. Chen, and M. Golparvar-Fard, Enhancing construction hazard recognition with high-fidelity augmented virtuality, *J Constr Eng Manag*, vol. 140, no. 7, Jul. 2014.

[3] S. Chen, F. Dong, and K. Demachi, Hybrid visual information analysis for on-site occupational hazards identification: a case study on stairway safety, *Saf Sci*, vol. 159, Mar. 2023.

[4] Y. Luo, Q. Yang, J. Seo, and S. Ahn, Theoretical framework for utilizing eye-tracking data to understand the cognitive mechanism of situational awareness in construction hazard recognition, *J Constr Eng Manag*, vol. 40. 2024.

[5] M. R. Endsley, Toward a theory of situation awareness in dynamic systems, *Human Factor*, 1995.

[6] A. Ibrahim, C. Nnaji, M. Namian, A. Koh, and U. Techera, Investigating the impact of physical fatigue on construction workers' situational awareness, *Saf Sci*, vol. 163, Jul. 2023.

[7] M. Wolf, J. Teizer, B. Wolf, S. Bükrü, and A. Solberg, Investigating hazard recognition in augmented virtuality for personalized feedback in construction safety education and training, *Advanced Engineering Informatics*, vol. 51. 2022.

[8] I. Jeelani, S. M. Asce, A. Albert, A. M. Asce; Roger Azevedo, and E. J. Jaselskis, Development and testing of a personalized hazard-recognition training intervention, *J Constr Eng Manag*, 2016.

[9] L. I. Domgue K *et al.*, Video see-through augmented reality fire safety training: a comparison with virtual reality and video training, *Saf Sci*, vol. 184, Apr. 2025.

[10] S. Hasanzadeh, B. Esmaeili, and M. D. Dodd, Examining the relationship between construction workers' visual attention and situation awareness under fall and tripping hazard conditions: using mobile eye tracking, *J Constr Eng Manag*, vol. 144, no. 7, Jul. 2018,

[11] A. Albert, M. R. Hallowell, B. Kleiner, A. Chen, and M. Golparvar-Fard, Enhancing construction hazard recognition with high-fidelity augmented virtuality, *J Constr Eng Manag*, vol. 140, no. 7, Jul. 2014.

[12] P. C. Liao, X. Sun, and D. Zhang, A multimodal study to measure the cognitive demands of hazard recognition in construction workplaces, *Saf Sci*, vol. 133, Jan. 2021.

[13] J. Hong, S. Song, H. Kang, J. Choi, T. Hong, and D. E. Lee, Influence of visual environments on struck-by hazards for construction equipment operators through virtual eye-tracking, *Autom Constr*, vol. 161, May 2024.

[14] M. Namian, A. Albert, and J. Feng, Effect of distraction on hazard recognition and safety risk perception, *J Constr Eng Manag*, vol. 144, no. 4, Apr. 2018.

[15] J. Li, H. Li, H. Wang, W. Umer, H. Fu, and X. Xing, Evaluating the impact of mental fatigue on construction equipment operators' ability to detect hazards using wearable eye-tracking technology, *Autom Constr*, vol. 105, Sep. 2019.

[16] J. Li, Y. Ouyang, and X. Luo, Impact of age on construction workers' preattentive and attentive visual processing for hazard detection, *Journal of Management in Engineering*, vol. 40, no. 3, 2024,

[17] S. Hasanzadeh, B. Dao, B. Esmaeili, and M. D. Dodd, Role of personality in construction safety: investigating the relationships between personality, attentional failure, and hazard identification under fall-hazard conditions, *J Constr Eng Manag*, vol. 145, no. 9, Sep. 2019,

[18] H. Fu, Y. Tan, Z. Xia, K. Feng, and X. Guo, Effects of construction workers' safety knowledge on hazard-identification performance via eye-movement modeling examples training, *Saf Sci*, vol. 180, Dec. 2024.

[19] H. Fu, Z. Xia, Y. Tan, and X. Guo, Influence of cues on the safety hazard recognition of construction workers during safety training: evidence from an eye-tracking experiment, *Journal of Civil Engineering Education*, vol. 150, no. 1, Jan. 2024.

[20] R. Eiris, M. Gheisari, and B. Esmaeili, Pars: using augmented 360-degree panoramas of reality for construction safety training, *Int J Environ Res Public Health*, vol. 15, no. 11. 2018.

[21] R. Eiris, M. Gheisari, and B. Esmaeili, Desktop-based safety training using 360-degree panorama and static virtual reality techniques: a comparative experimental study, *Autom Constr*, vol. 109, Jan. 2020.

[22] I. Jeelani, K. Han, and A. Albert, Development of virtual reality and stereo-panoramic environments for construction safety training, *Engineering, Construction and Architectural Management*, vol. 27, no. 8. 2020.

[23] R. Eiris, A. Jain, M. Gheisari, and A. Wehle, Safety immersive storytelling using narrated 360-degree panoramas: a fall hazard training within the electrical trade context, *Saf Sci*, vol. 127, Jul. 2020.

[24] A. F. E. Lucena and F. A. Saffaro, Guidelines for exploring construction sites in virtual reality environments for hazard identification, *International Journal of Occupational Safety and Ergonomics*, vol. 28, no. 1, pp. 86–95, 2022.

[25] M. Wolf, J. Teizer, B. Wolf, S. Bükrü, and A. Solberg, Investigating hazard recognition in augmented virtuality for personalized feedback in construction safety education and training, *Advanced Engineering Informatics*, vol. 51. 2022.

[26] D. Liu and C. Li, Construction hazard-recognition training for generation z students: a comparison study based on eye-movement data, *Engineering, Construction and Architectural Management*, 2024.

[27] Z. Fang, Q. Lu, X. Xie, A. K. Parlikad, J. Schooling, and M. Pitt, Definitions and principles of digital twins, in *Digital Twins in the Built Environment*, ch. Chapter 2, pp. 5–27.

[28] R. Sacks, I. Brilakis, E. Pikas, H. S. Xie, and M. Girolami, Construction with digital twin information systems, *Data-Centric Engineering*, vol. 1, no. 6, Nov. 2020.

[29] L. Messi, A. Corneli, M. Vaccarini, and A. Carbonari, Development of a twin model for real-time detection of fall hazards. In *Proceedings of the 37th International Symposium on Automation and Robotics in Construction*， 2020, 256–263.

[30] F. Vahdatikhaki, L. Olde Scholtenhuis, and A. Doree, Digital twin-based instructor support system for excavator training. In *Proceedings of the 41st International Symposium on Automation and Robotics in Construction*， 2024, 521–528.

[31] Z. Zhang *et al.*, Digital technology enhanced situation awareness for construction safety: systematic review and future research directions, *Saf Sci*, vol. 167, Nov. 2023.

[32] A. Harichandran, K. W. Johansen, E. L. Jacobsen, and J. Teizer, A conceptual framework for construction safety training using dynamic virtual reality games and digital twins, in *38th International Symposium on Automation and Robotics in Construction (ISARC 2021)*, 2021, pp. 621–628.

[33] G. P. Agnusdei, V. Elia, and M. G. Gnoni, Is digital twin technology supporting safety management? A bibliometric and systematic review, Mar. 02, 2021, *MDPI AG*.

[34] NASA, Systems engineering handbook, Rev 1. Washington, DC: National Aeronautics and Space Administration (NASA), 2007.

[35] B. Kerbl, G. Kopanas, T. Leimkuehler, and G. Drettakis, 3D gaussian splatting for real-time radiance field rendering, *ACM Trans Graph*, vol. 42, no. 4, Aug. 2023.

[36] S. Rüter, K. Waldow, N. Bartels, and A. Fuhrmann, 3D gaussian splatting for construction sites, in *24 th International Conference on Construction Applications of Virtual Reality (CONVR 2024)*, 2024.

[37] L. Barazzetti, M. Previtali, and F. Roncoroni, 3D modelling with the samsung gear 360, in *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, International Society for Photogrammetry and Remote Sensing, Feb. 2017, pp. 85–90.

[38] Z. Feng *et al.*, Towards a customizable immersive virtual reality serious game for earthquake emergency training, *Advanced Engineering Informatics*, vol. 46, Oct. 2020.