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Perception-Responsive Adaptive Virtual Reality for Construction Hazard Recognition: A Feasibility Study

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Abstract: Hazard recognition deficiencies remain a primary factor contributing to accidents in the construction industry, where workers often fail to visually detect critical safety cues due to perceptual and attentional limitations. Although virtual reality (VR) has emerged as an effective tool for immersive safety training, most current systems do not account for individual differences in visual attention or perceptual capability. This study investigates the feasibility of a gaze-driven adaptive VR training framework that dynamically modifies instructional support and scenario complexity in response to trainees' real-time perceptual performance. The system continuously captures eye-tracking metrics across predefined hazard Areas of Interest, including Time-to-First Fixation, fixation count, normalized dwell time, and scanpath dispersion. These metrics are synthesised into discrete perceptual performance states using a Support Vector Machine (SVM) classifier, which subsequently guides adaptive adjustments to hazard salience, visual guidance, and task difficulty within the VR environment. A pilot study involving 17 participants was conducted across baseline (n=7) and adaptive VR (n=10) conditions to evaluate system feasibility, real-time operation, and user experience. Results indicate that the framework effectively distinguished variability in participants' perceptual patterns and successfully triggered adaptive modifications during training. The classifier achieved an overall accuracy of 88.3% with a ROC–AUC of 0.92, while usability evaluation using the System Usability Scale (SUS) produced a mean score of 84.25 for the adaptive condition, indicating strong perceived usability at the prototype stage. Overall, the findings demonstrate the feasibility of integrating gaze-based perceptual monitoring with adaptive VR safety training and highlight the potential of perception-responsive training systems for supporting construction hazard recognition.

Keywords: Construction safety; Virtual reality; Adaptive training; Situational awareness; Hazard recognition

1 INTRODUCTION

The construction industry continues to experience disproportionately high rates of occupational injuries and fatalities worldwide (Dodoo & Al-Samarraie, 2023). Globally, it is estimated that around 60,000 fatal accidents occur annually within the construction sector (O'Neill et al., 2022). A significant proportion of incidents are associated with failures in hazard recognition and unsafe behaviours on dynamic construction sites (Jeelani et al., 2017). Effective hazard identification is widely recognized as a foundational element of construction safety management , and safety training has long been implemented as the primary strategy for mitigating unsafe acts and enhancing workers' capacity to detect risks before accidents occur (Namian et al., 2016). Hazard recognition performance is strongly influenced by workers' visual attention and perceptual awareness when scanning complex environments (Jeelani et al., 2019). Workers frequently overlook critical safety cues not due to a lack of procedural knowledge, but because of perceptual and attentional limitations that prevent initial detection of hazards (Lee, Shinde, et al., 2022). Impairments in perceptual proccessing can contribute to hazard recognition failures and elevated injury risk (Kim et al., 2022).

Virtual Reality (VR) has emerged as a promising tool for construction hazard identification training, offering immersive and experiential learning environments in which trainees can interact with realistic hazard scenarios under controlled and repeatable conditions (Nykänen et al., 2020; Rokooei et al., 2023; Sacks et al., 2013). VR-based training has increasingly attracted attention due to its ability to support immersive and experiential “learning-by-doing” approaches, enabling trainees to interact with realistic hazard scenarios in safe and controlled environments (Englund et al., 2017). Yet despite its growing, many VR-based safety training systems remain one-size-fits-all and do not account for individual differences in perceptual attention or hazard recognition behavior (Jeelani et al., 2017; Lee, Hasanzadeh, et al., 2022). This uniformity limits training effectiveness as workers vary considerably in their visual search strategies and hazard recognition performance within construction environments (Cheng et al., 2022).

In parallel, Eye-tracking technology has increasingly been used to objectively assess trainees visual attention and perceptual behaviour during construction hazard recognition tasks (Hasanzadeh et al., 2017; Luo et al., 2024). Different eye-tracking metrics provide measurable indicators of how workers detect and perceptually process hazards within complex environments (Luo et al., 2024). However, existing applications of eye-tracking in construction VR safety research have remained largely confined to post-hoc performance evaluation rather than real-time adaptive use (Cheng et al., 2022). This limitation is increasingly recognized in recent literature, which identifies real-time adaptive intervention systems as important future directions for improving hazard recognition training and supporting proactive safety assistance (Liu et al., 2025).

This gap constitutes the central motivation of the present study. Specifically, there is a need for VR training frameworks capable of monitoring trainees' perceptual states continuously and modifying training conditions in real time when hazard recognition failures are detected. To address this, the study investigates the feasibility of a perception-responsive adaptive VR training system that integrates real-time gaze-based perceptual monitoring with dynamic hazard salience modulation. A Support Vector Machine (SVM) classifier is trained on eye-tracking features extracted from predefined hazard Areas of Interest to distinguish between high and low perceptual awareness states. When sustained low awareness is detected, the system triggers adaptive adjustments to hazard visibility, guiding trainees' attention toward overlooked hazards without interrupting the training experience. The study makes three principal contributions: (1) it demonstrates the technical feasibility of real-time gaze-based perceptual state classification within a live VR environment; (2) it establishes that adaptive hazard salience modulation can be implemented without compromising user experience; and (3) it provides a methodological foundation for perception-responsive safety training systems in the construction domain.

2 LITERATURE REVIEW

2.1 Hazard Recognition and Situational Awareness

Hazard identification is a fundamental prerequisite for effective safety management within construction environments (Albert et al., 2014). Construction sites are among the most cognitively demanding work environments, characterised by dynamic conditions, concurrent activities, and complex interactions between workers, equipment, and materials (Almaskati et al., 2024). Workers are expected to identify unsafe conditions and potential risks before accidents occur, yet this process often depends heavily on their perceptual awareness and situational understanding of the work environment (Mitropoulos et al., 2005). Within this context, both novice and experienced workers frequently fail to identify critical hazards during inspection tasks, not due to deficits in procedural knowledge, but because perceptual and attentional limitations prevent hazards from entering conscious awareness (Bahn, 2013; Lee, Shinde, et al., 2022).

Situational Awareness (SA) theory explains this failure through a sequential cognitive model comprising three stages: perception, comprehension, and projection (Endsley, 1988). Because this sequence is irreversible, failure at the perceptual stage severs the entire downstream chain, so workers cannot assess, decide, or act on a hazard they have not seen. This positions perceptual awareness as the foundational target for safety training intervention and raises a direct design requirement: training systems must be capable of detecting perceptual failures as they occur and responding to them in real time.

2.2 Eye-Tracking as a Diagnostic Instrument

Eye-tracking technology has increasingly been used to investigate visual attention behaviour during hazard recognition tasks (Hasanzadeh et al., 2017). Key metrics in perception stage include Time-to-First Fixation (TTFF), fixation count, dwell time on Areas of Interest (AOIs), and scanpath dispersion. These measures collectively characterise the speed, depth, and spatial scope of a worker's perceptual engagement with safety-relevant stimuli providing objective indicators of hazard recognition performance and situational awareness (Luo et al., 2024). Previous research has demonstrated that fixation-related metrics can be used to evaluate during safety training tasks (Jeelani et al., 2019). Importantly, studies also show workers differ substantially in visual search strategies, attention allocation, and hazard recognition performance, highlighting the need for more personalized safety training interventions that account for individual perceptual differences (Luo et al., 2024). Despite the potential of eye-tracking to reveal such perceptual deficiencies, existing eye-tracking applications in construction safety training remain predominantly focused on offline analysis and post-training evaluation of visual attention and hazard recognition performance, while the development of real-time intelligent systems capable of dynamically monitoring attention allocation and responding to unsafe perceptual behaviors during training remains comparatively limited (Cheng et al., 2022).

2.3 Adaptive VR Training: Capability and Current Limitation

Construction safety training has traditionally relied on classroom instruction, toolbox meetings, and document-based training materials. While these approaches are widely used, they often provide limited interaction and fail to replicate the complexity of real construction environments. (Han et al., 2022; Ojha et al., 2020). Virtual reality provides a training platform capable of addressing this gap. It offers experiential learning, behavioural engagement, skill development, and long-term retention in recognizing and evaluating dangers compared to traditional approaches (Man et al., 2024; Nykänen et al., 2020). Immersive simulations also enable repeated practice and safe exposure to hazardous situations that would otherwise be difficult to reproduce in real training environments (Dzeng et al., 2015).

However, many VR training systems continue to follow a one-size-fits-all approach, presenting identical scenarios regardless of trainees' individual performance or attentional behaviour (Jeelani et al., 2017). This limitation reduces training effectiveness because workers differ significantly in their visual attention behavior and hazard recognition capabilities. Effective immersive safety training systems therefore require the incorporation of real-time biometric feedback and AI-driven personalization to support responsive and user-centered learning environments (Cordeiro et al., 2025). Recent literature suggests that personalized and adaptive safety training is becoming increasingly important in construction due to substantial differences among workers in hazard recognition performance, perceptual behavior, cognitive responses, and individual learning needs (Lin et al., 2023). The review further highlighted that existing universal training methods may not adequately address variations in worker characteristics including safety awareness.

Adaptive VR training systems attempt to address this challenge by modifying simulation conditions based on trainee input. Adaptive systems typically consist of three components: performance assessment, adaptive variables, and adaptive logic (Zahabi & Abdul Razak, 2020). By continuously monitoring trainee states, adaptive systems can dynamically adjust training parameters such as task difficulty, instructional feedback, and environmental cues (Zhang & Jebelli, 2025). However, existing adaptive systems in construction such as Jacobsen et al. (2022) and Li et al. (2022) have relied predominantly on task-level outcome indicators including error rates, completion times, and behavioural logs. These limitations indicate a growing need for adaptive VR safety training systems that combine real-time gaze-based monitoring with AI-driven personalization to dynamically respond to individual differences in workers' perceptual attention and hazard recognition behaviour during training (Cheng et al., 2022; Cordeiro et al., 2025; Lin et al., 2023).

2.4 REFLECTIONS ON RISKS

Despite the advantages of immersive training technologies, several potential risks must be acknowledged. First, VR systems equipped with sensors such as eye-tracking collect detailed behavioral and biometric data, which may raise privacy and data-governance concerns if not properly managed (Adhanom et al., 2023). Appropriate consent procedures and responsible data handling are therefore necessary when using biometric monitoring technologies in training environments. Second, prolonged exposure to immersive VR environments may lead to symptoms commonly referred to as *cybersickness*, including nausea, dizziness, and visual fatigue, which may affect user comfort and effectiveness of training (Biswas et al., 2024). Additionally, highly realistic simulations may increase cognitive load or psychological stress if training scenarios are not carefully designed (Radianti et al., 2020). Therefore, VR-based adaptive systems should be applied primarily as training support tools, accompanied by careful ethical considerations, balanced instructional design, and appropriate safeguards to ensure safe and responsible implementation.

3 METHOD/METHODOLOGY

3.1 System Overview

The proposed framework was designed to operationalise the real-time perceptual monitoring and adaptive response capability identified as absent in the existing literature. Specifically, the system translates continuous gaze behaviour into discrete perceptual awareness states and uses these states to modulate training conditions dynamically, shifting the role of eye-tracking from post-hoc assessment tool to active component of the instructional loop. Figure 1 illustrates the overall system architecture, which comprises four integrated stages: (1) VR hazard scenario design with predefined inspection viewpoints; (2) eye-tracking data acquisition and hazard-episode segmentation; (3) gaze feature extraction and SVM classifier training using baseline participant data; and (4) real-time perceptual state inference to trigger adaptive hazard salience modulation during training.

3.2 Virtual Environment and Hazard Design

The immersive VR environment was developed in Unity 6 and deployed using the HTC Vive Pro Eye headset, which provides integrated high-precision eye-tracking in immersive settings (Schuetz & Fiehler, 2022). The training scenario embedded 19 predefined hazards across fall, slip, and electrocution categories. Fall hazards were prioritised because falls remain the leading cause of fatalities in construction and present elevated perceptual demands in hazard identification tasks (Nafe Assafi et al., 2025). Electrical hazards were included due to their severe consequences and the necessity of detecting less visually salient cues in cluttered environments.

Hazard placement followed SafeWork Australia Codes of Practice for managing fall and electrical risks and was reviewed by construction safety professionals to ensure realism and face validity. To enhance internal validity and ensure consistent perceptual exposure, the environment was structured around six predefined inspection viewpoints. Participants navigated using teleport-based movement between fixed observation nodes strategically positioned to provide controlled visibility of specific hazards. This structured inspection workflow reduces variability in viewing distance, occlusion, and field-of-view exposure, thereby strengthening comparability of gaze metrics across participants. The fundamental analytical unit for machine-learning modelling was the hazard episode. A hazard episode was defined as the temporal interval during which a specific hazard Area of Interest (AOI) was visible and perceptually available to the participant. Episode onset occurred when the hazard entered the participant's view frustum without occlusion, and termination occurred when the hazard was successfully tagged or permanently exited the field of view.

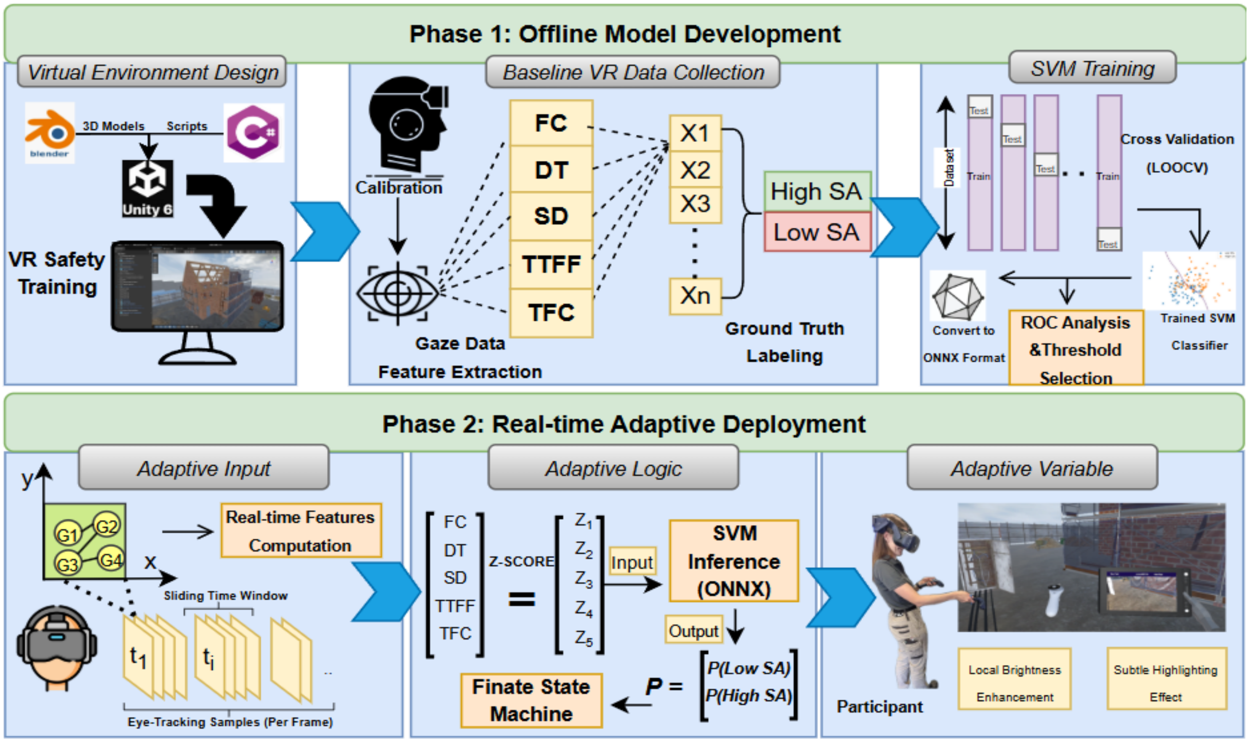

Figure 1: Architecture of the gaze-driven adaptive VR training framework, illustrating gaze data acquisition, feature extraction, SVM-based perceptual state classification, and real-time hazard salience adaptation.

3.3 Baseline Gaze Data and Feature Extraction

Eye-tracking data used for machine-learning model development were collected during the non-adaptive baseline phase. Seven participants completed the hazard inspection task without adaptive support, and their gaze behaviour and tagging performance were recorded for classifier training. Gaze data were recorded continuously at 120 Hz using the SRanipal SDK. Fixations were identified using a dispersion-based algorithm with a minimum duration threshold of 120 ms (Harezlak et al., 2014). Five gaze features were extracted for each hazard episode: Time-to-First Fixation (TTFF), Fixation Count (FC) within the hazard AOI, Normalized Dwell Time (DT_norm), Scanpath Dispersion (SD) computed from fixation coordinates, and Total Fixation Count (TFC) within the viewpoint. These features formed the episode-level feature vector X = [TTFF, FC, DT_norm, SD, TFC] for machine-learning analysis.

3.4 Support Vector Machine Model Development

The machine-learning task was formulated as a binary hazard-episode–level classification problem distinguishing high and low Level 1 Situational Awareness (SA_1). To preserve construct validity and avoid circular inference, ground-truth labels were derived from observable behavioral tagging performance rather than from subjective self-report measures. An episode was labelled High SA_1 when the hazard was successfully identified and tagged within the VR environment and at least one valid fixation (≥120 ms) occurred on the hazard AOI during the episode. Fixation features represent perceptual behavior prior to tagging and are therefore treated as predictors rather than labels. Episodes were labelled Low SA_1 when the hazard was not successfully tagged. This category includes both perceptual omission (no fixation) and incomplete perceptual awareness (fixation without tagging). In applied construction safety contexts, perceptual awareness is operationalized as successful detection sufficient to support hazard identification; therefore, fixation without behavioral confirmation was classified as Low SA_1.

A Support Vector Machine (SVM) classifier with radial basis function (RBF) kernel was employed due to its robustness in moderate-sized datasets and its suitability for high-dimensional eye tracking feature spaces

(Nafe Assafi et al., 2025). Data partitioning was performed at the participant level to prevent overfitting individual gaze patterns. Data partitioning was performed at the participant level and given the limited baseline sample (n = 7), Leave-One-Out-Cross-Validation (LOOCV) cross-validation was used for model evaluation. Feature standardization was conducted using z-score normalization computed exclusively from the training cohort. Class imbalance was addressed using balanced class weighting. The trained model outputs probabilistic estimates of High SA_1 and was frozen prior to deployment.

3.5 Adaptive VR Deployment Phase

Following model training, the classifier was exported to ONNX format and embedded in the Unity runtime using ONNX Runtime to enable real-time inference. During adaptive sessions, gaze features were computed continuously using a sliding temporal window and standardized using stored training statistics. The normalized feature vector was passed to the embedded SVM model to estimate the probability of High SA_1. A decision threshold determined through ROC-based validation, combined with a temporal persistence constraint, was used to classify perceptual state. When sustained low awareness was detected, a finite-state perceptual controller triggered subtle hazard salience modulation through brightness and contrast adjustments.

Seventeen participants took part in the study, with seven assigned to the non-adaptive baseline condition and ten to the adaptive condition. User experience was assessed using the System Usability Scale (SUS) and the short-form User Engagement Scale. Independent sample comparisons were conducted to explore differences between conditions, and effect sizes were reported given the pilot-scale design.

4 RESULTS

The SVM-based perceptual state classification model demonstrated strong performance in distinguishing between High and Low SA_1 at the hazard-episode level. Using LOOCV (n = 7), the model achieved an overall accuracy of 88.3%.

Performance metrics are summarized in Table 1. The classifier achieved a precision of 0.90, recall of 0.86, and F1-score of 0.88 for the High SA_1 class. The ROC–AUC of 0.92 indicates strong separability between perceptual states. The confusion matrix (Figure 2) shows the distribution of correctly and incorrectly classified hazard episodes between High and Low SA_1 states.

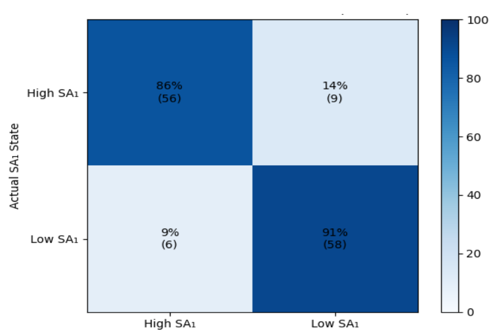

Figure 2: Confusion matrix of the SVM perceptual awareness classifier

Table 1: Performance metrics for SA_1classification

Class	Precision	Recall	F1-Score
High SA_1	0.9	0.86	0.88
Low SA_1	0.87	0.91	0.89

Misclassifications were primarily observed in borderline cases involving brief fixations without successful hazard tagging. Overall, results confirm that gaze-derived features provide sufficient discriminative capacity to support real-time perceptual state estimation.

4.1 Adaptive System Operation

Eye-tracking data were captured at 120 Hz using the integrated tracking system of the HTC Vive Pro Eye. Gaze-derived features were computed within a 5-second sliding temporal window and continuously passed to the inference module to estimate perceptual awareness states during interaction. When the predicted probability of High SA_1 remained below the defined threshold for 10 seconds, the system triggered adaptive hazard salience modulation to guide visual attention toward unattended hazards. The perceptual state inference and adaptation loop operated with an average latency below 80 ms, enabling seamless real-time interaction within the VR environment.

4.2 Training Evaluation

User experience was evaluated using the System Usability Scale (SUS), a widely used ten-item questionnaire designed to assess perceived usability of interactive systems. Participants rated each item on a five-point Likert scale ranging from *1 (strongly disagree)* to *5 (strongly agree)*. Following the standard SUS scoring procedure, responses were converted to a normalized usability score ranging from 0 to 100, where higher values indicate better perceived usability. The baseline VR condition (n = 7) achieved a mean SUS score of 78.57 (SD = 4.97), indicating good usability according to established SUS benchmarks. The adaptive VR condition (n = 10) achieved a higher mean score of 84.25 (SD = 3.81), corresponding to excellent usability (Figure 3).

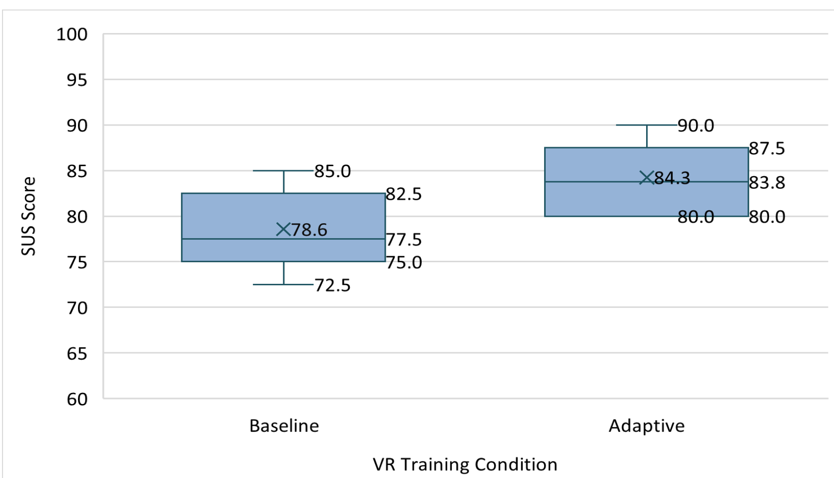

Figure 3: Comparison of System Usability Scale (SUS) scores between baseline and adaptive VR training conditions

To examine potential differences in perceived usability between the two conditions, an independent samples t-test was conducted. Results indicated a preliminary indication of usability improvement in SUS scores between the baseline and adaptive conditions ($t = -2.56$, $p = 0.021$). A Mann–Whitney U test, used as a non-parametric alternative due to the small sample size, produced consistent results ($U = 13$, $p \approx 0.018$). The difference corresponds to a large effect size (Cohen's $d = 1.31$), suggesting a substantial usability improvement. These findings suggest that the adaptive VR system maintained high usability while providing slightly improved user experience compared with the non-adaptive baseline condition.

5 DISCUSSION AND CONCLUSIONS

The results of this feasibility study support the central proposition that gaze-derived perceptual features can be classified in real time with sufficient reliability to drive adaptive instructional responses within a VR construction safety training environment. The SVM classifier achieved 88.3% accuracy and a ROC-AUC of 0.92, but more analytically significant is the Low SA_1 recall of 0.91, which represents the safety-consequential class. In applied hazard recognition training, failing to detect a genuine perceptual failure carries substantially higher cost than a spurious adaptation trigger; the classifier's asymmetric performance therefore reflects a functionally appropriate characteristic for deployment in safety-critical training contexts. In addition, the classification performance achieved by the SVM model supports previous findings that visual attention patterns are closely associated with hazard recognition performance in construction environments (Hasanzadeh et al., 2017; Luo et al., 2024).

The architecture's operation can be understood as a closed perceptual loop. When a trainee's gaze behaviour signals sustained inattention toward a hazard AOI, characterised by absent or insufficient fixation within the defined temporal window, the classifier transitions the episode to a Low SA_1 state. Once this state persists beyond the temporal threshold, the adaptive module responds by modulating hazard salience through brightness and contrast adjustment, drawing visual attention toward the overlooked hazard without interrupting the inspection workflow. When fixation is subsequently re-established and the classifier transitions back to High SA_1, modulation deactivates. This loop completed within 80 ms average latency, preserving immersion throughout. Critically, adaptation is triggered at the perceptual stage before task failure occurs, which represents a meaningful departure from existing adaptive VR systems in construction that intervene only after observable outcome errors such as missed tags or incorrect completions.

The usability findings further support practical viability. The adaptive condition achieved a mean SUS score of 84.25 versus 78.57 in the baseline, with a large effect size (Cohen's $d = 1.31$). This indicates that subtle environmental modulation, rather than explicit instructional interruption, is perceived as enhancing rather than disrupting the training experience,

These findings should be interpreted within the study's limitations. The classifier was trained on seven participants and evaluated on ten, making generalisation claims premature. The evaluation focused on system operation and usability rather than learning outcomes; whether gaze-driven adaptive training produces superior hazard recognition performance and retention relative to non-adaptive VR remains an open empirical question requiring longitudinal study designs with larger and more diverse participant cohorts.

This study demonstrated the feasibility of integrating real-time gaze-based perceptual monitoring with adaptive VR safety training for construction hazard recognition. The SVM classifier reliably distinguished perceptual awareness states at the hazard-episode level, adaptive salience modulation was successfully triggered in response to detected perceptual failures, and the system maintained strong usability across both conditions. These findings establish a methodological foundation for perception-responsive training systems in construction and identify personalised, biometric-driven VR training as a viable direction for addressing the individual perceptual differences that uniform safety training approaches cannot accommodate.

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