

Article

Impacts of Real and Virtual Environments on Construction Safety Knowledge Learning in Virtual Reality Classrooms

Xinyang Guo, Chendi Wang *  and Xiaojian Fang 

Department of Construction Management and Real Estate, School of Economics and Management, Nanjing Tech University, No. 30 Puzhu South Road, Nanjing 211816, China; 202321053056@njtech.edu.cn (X.G.); fangxiaojian@njtech.edu.cn (X.F.)

* Correspondence: chendiwang@njtech.edu.cn

Abstract

Background: As construction safety training increasingly shifts toward virtual reality (VR)-based learning platforms, concerns have emerged regarding whether real ambient and virtual visual conditions may affect safety knowledge learning and cognitive responses; **Methods:** This study examined how real ambient factors (temperature and sound) and virtual visual factors (window view and visual complexity) influenced perceived environmental distraction, subjective workload, learning experience, and EEG-based cognitive responses in a VR classroom. Forty-eight university students completed a construction safety knowledge learning task and were categorized into high- and low-performing groups based on learning gains. Subjective responses were measured using post-experimental questionnaires, while EEG indicators included mental workload, attention, and mental fatigue. **Results:** Based on independent-samples t-tests, group-specific Spearman correlations, descriptive analyses, and two-way interaction regression, the results revealed: (1) Low-performing students reported greater disturbance from temperature and sound, and higher mental demand and effort. (2) Nominal associations between environmental factors and subjective outcomes were broader in the low-performing group. (3) The EEG results served mainly as supplementary descriptive evidence, showing individual variability in cognitive responses. (4) Learning scores varied across environmental combinations, with Temperature $\times$ Sound emerging as the only significant interaction. **Conclusions:** These findings guide cognitively supportive VR-based construction safety learning environments.

Keywords: cognitive response; construction safety; learning experience; real environment; subjective workload; virtual environment; virtual reality



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1. Introduction

Virtual reality (VR) is increasingly used as a learning platform for construction safety training because it can deliver safety knowledge in a controlled, repeatable, and risk-free environment [1]. Evidence from VR safety training implementation suggests that such training may contribute to accident prevention by improving safety-related knowledge, responses, and behavior [2]. For example, recent meta-analytic evidence shows that VR-based construction safety training is more effective than traditional training in improving safety-related behaviors, skills, and learning experiences, suggesting its potential contribution to accident prevention in construction safety education [3]. These findings indicate that improving the quality of VR-based safety knowledge learning is practically important. However, VR learning outcomes are not shaped by instructional content alone. In VR

classrooms, trainees are exposed to real ambient factors, such as temperature and sound, while also processing virtual visual factors, such as window view and visual complexity [4]. Since thermal, acoustic, and visual conditions can influence comfort, attention, learning quality, and cognitive functioning, these environmental conditions may affect how trainees acquire construction safety knowledge during immersive learning tasks [5,6].

Existing VR construction safety studies have mainly focused on training effectiveness, simulation design, and safety-learning outcomes [3], while less attention has been paid to how the real and virtual environmental conditions of VR classrooms affect learners' subjective and cognitive responses. Related studies have already shown that VR can be combined with controlled physical environments to examine human responses under specific environmental conditions [7–9]. However, these studies were not centered on construction safety knowledge learning in VR classrooms, and they did not examine real ambient factors and virtual visual factors together within the same safety-learning task. In addition, limited evidence is available on whether students with different learning performance levels experience the same VR classroom conditions differently, or on how these environmental factors are associated with immediate learning gains. Therefore, this study investigates how temperature, sound, virtual window view, and visual complexity influence construction safety knowledge learning in a VR classroom. Specifically, this study compares high-performing (HP) and low-performing (LP) students in perceived environmental distraction, subjective workload, and learning experience, examines group-specific associations between environmental factors and subjective outcomes, evaluates EEG-based cognitive responses during the learning task, and analyzes how different combinations of real ambient factors and virtual visual factors are associated with immediate learning gains. The contributions of this study are fourfold: (1) it identifies differences between HP and LP students in perceived environmental distraction, subjective workload, and learning experience during VR-based construction safety knowledge learning; (2) it examines whether real ambient factors and virtual visual factors show different subjective associations in HP and LP students; (3) it evaluates EEG-based cognitive responses, including mental workload, attention, and mental fatigue, under different environmental conditions; and (4) it evaluates learning-gain differences across four-factor environmental combinations and tests the main and two-way interaction effects of temperature, sound, virtual window view, and visual complexity using individual-level regression analysis.

2. Literature Review

2.1. Environmental Conditions and Construction Safety Knowledge Learning

Environmental conditions play an important role in VR-based construction safety knowledge learning because trainees experience not only instructional content but also the physical and virtual conditions under which the learning task occurs. These conditions include real ambient factors and virtual visual factors, such as real temperature and sound, and virtual window view and visual complexity [10]. Temperature affects comfort, attention, and cognitive functioning, and classroom studies have linked thermal conditions with learning performance and cognitive efficiency [5,6]. Sound can interfere with concentration, working memory, and learning, particularly when learners process information under limited attentional capacity [11,12]. Recent EEG-based evidence further suggests that noise exposure is related to attention, stress, and mental workload [13]. Window view may influence attention, satisfaction, and cognitive performance because access to outdoor views is associated with improved cognitive outcomes and reduced eyestrain [14–16]. Visual complexity affects cognitive load, attention allocation, and engagement in immersive learning environments; both overly simple and overly complex visual scenes can hinder performance depending on task demands [17–19].

Moreover, evidence suggests that learning-related outcomes are often influenced by combined environmental exposures rather than single factors alone. Thermal, acoustic, and visual conditions can interact to shape comfort, attention, and cognitive performance, indicating that the effect of one factor may depend on the presence of others [6,20]. This is especially relevant for VR classrooms, where learners are physically exposed to real ambient factors while cognitively immersed in virtual visual factors. VR and immersive learning research further highlight that cognitive load, engagement, and instructional design interact with environmental characteristics to influence learning outcomes [18,21]. In the context of construction safety knowledge learning, such combined exposure may affect perceived environmental distraction, subjective workload, learning experience, cognitive responses, and learning scores, emphasizing the importance of considering both physical and virtual classroom design for effective immersive safety training.

2.2. Virtual Reality for Construction Safety Knowledge Learning

VR has developed from an emerging instructional technology into a widely used platform for safety learning and immersive educational simulation. In educational research, studies across different countries and disciplines have reported the usefulness of VR for improving knowledge acquisition, engagement, motivation, spatial understanding, and skill development (see Table 1). Immersive VR is also recognized as a context-rich and embodied medium that allows learners to engage with complex scenarios under controlled and repeatable conditions, while recent theoretical work suggests that VR learning outcomes are shaped by presence, agency, engagement, cognitive load, and self-regulation rather than by exposure alone [20]. In construction safety specifically, VR has been used for general safety training, hazard-recognition learning, unsafe-behavior identification, and exposure to high-risk scenarios without physical danger [21,22]. VR-based construction safety training effectiveness has been examined through factors such as telepresence, risk perception, and training satisfaction, while VR construction teaching has also been shown to improve students' learning enthusiasm and satisfaction in undergraduate construction education [23,24]. Recent synthesis studies further provide quantitative support for its effectiveness, showing that VR-based construction safety training outperforms traditional methods in behavioral, skill-related, and experiential outcomes [7].

Beyond training content itself, recent studies suggest that VR learning and simulation outcomes may also be influenced by the relationship between the real physical environment and the virtual scene. In construction-related research, VR has been combined with controlled physical environments to examine how real sensory exposure affects task performance; for example, VR and a climate chamber were used to evaluate construction noise exposure, showing that masonry productivity increased by 1.05% at 60 dBA but decreased by 2.33% at 100 dBA, with psychological and physiological responses also related to productivity [25]. Built-environment VR studies further show that virtual visual context can influence users' perception of real environmental conditions. For instance, exposure to visually pleasing outdoor virtual environments increased subjective thermal comfort even when the physical environment remained unchanged [26]. Comparative studies of physical and immersive virtual environments also indicate that virtual classrooms can evoke psychological and neurophysiological responses comparable to real spaces, supporting their use for studying attention and memory-related processes [27]. These findings suggest that VR-based learning should be understood as an experience shaped by both real ambient factors and virtual visual factors, rather than by virtual instructional content alone. Therefore, in construction safety knowledge learning, the surrounding physical conditions and embedded virtual visual design may jointly influence learners' performance, subjective workload, learning experience, and cognitive responses.

Table 1. Empirical studies using VR in education and training.

Year	Learning Domain	Participants	Country	Main Educational Finding	Reference
2018	Science education (biology)	55–57 undergraduates	United States	VR increased motivation and engagement, while summary prompts improved learning in the immersive condition.	[28]
2019	Social studies/virtual field trips	24 elementary school students	Chinese Mainland	The VR field trip enhanced motivation, especially by reducing test anxiety, and improved teacher–student interaction patterns.	[29]
2020	Science education	90 sixth-grade students	Chinese Mainland	The VR group showed significantly higher academic achievement and stronger engagement than the control group.	[30]
2020	Physics education	65 female eighth-grade students (32 VR, 33 control)	Oman	The VR group demonstrated higher achievement and stronger motivation toward physics learning.	[31]
2023	Dental education	69 first-year dental students	Saudi Arabia	The VR approach increased engagement and provided an interactive method for radiographic anatomy training, although lecture-based students performed better on some anatomy items.	[32]
2024	Entrepreneurship education	150 university students	Iran	The VR-based course produced the strongest improvement in entrepreneurial intention compared with traditional teaching.	[33]
2024	Nursing education (maternity care)	59 junior nursing students (30 VR, 29 control)	South Korea	The VR group achieved higher knowledge, satisfaction, self-efficacy, and confidence in maternity nursing care.	[34]
2025	Chemistry education	86 Grade 11 students (43 VR, 43 control)	Indonesia	The VR group showed significantly higher creative-thinking disposition and academic achievement.	[35]
2025	Mental health nursing education	Qualitative learning-activity study with nursing students in mental health practice	Norway	Students reported stronger confidence, self-reflection, and a sense of mastery, indicating that VR was a relevant supplement to clinical preparation.	[36]
2026	Nursing education	60 undergraduate nursing students	Taiwan Region (China)	The progressive prompting approach significantly improved learning motivation, communication, EPA competence, and learning satisfaction.	[37]
2026	Mathematics education (learning disabilities)	10 elementary students with learning disabilities (5 VR, 5 control)	Turkey	The VR group outperformed the control group on post-test and retention, with higher enjoyment, engagement, and confidence in learning fractions.	[38]

2.3. Performance-Related Differences in Construction Safety Knowledge Learning

Differences in learning performance are important in construction safety knowledge learning because students may acquire and retain safety-related information to different degrees even when they receive the same instructional content. Previous construction safety research has shown that learners with different levels of safety-related performance may differ in how effectively they process and respond to safety information, including differences in attention to safety-relevant content [37]. In VR-based construction safety

training, such performance differences are particularly relevant because immersive learning requires students to process instructional information while responding to the demands of the virtual learning environment. Empirical studies have indicated that individual learning performance in VR-based construction safety training can be explained or predicted through learners' physiological responses and their responses to interactive learning elements [38,39]. More broadly, immersive learning research suggests that learning gains in VR are shaped by cognitive load, engagement, self-regulation, and prior knowledge, meaning that students may not benefit equally from the same VR learning task [21,40]. Accordingly, students with higher and lower learning gains may also differ in their responses to environmental conditions during VR-based construction safety knowledge learning. Higher-performing students may maintain more stable learning experiences under changing conditions, whereas lower-performing students may be more sensitive to distraction or additional cognitive demands. Examining HP and LP students separately therefore provides a performance-oriented perspective for understanding differences in perceived environmental distraction, subjective workload, learning experience, and cognitive responses during immersive construction safety knowledge learning.

3. Materials and Methods

3.1. Research Design

The research was conducted in four sequential stages using VR-based experiments with key factor identification, experiment design, formal experiment, and data analysis. In the first stage, a literature review was undertaken to identify the key ambient and virtual factors that were most relevant to subjective workload, learning experience, and cognitive responses in learning environments and to establish the theoretical and methodological basis for the study. In the second stage, the experimental platform and materials were developed. A VR-based virtual classroom was constructed as the core learning environment, and the corresponding learning tasks, assessment materials, and subjective evaluation instruments were prepared in alignment with the research objectives. The learning task required participants to watch a construction safety education video presented in the VR classroom and to learn and remember as much construction safety-related knowledge as possible. This task was designed to simulate a classroom-based safety knowledge learning process and to assess participants' short-term acquisition of construction safety information after immersive video-based instruction. This stage ensured that the environmental manipulations, learning activities, and measurement tools could be implemented consistently within a controlled experimental setting. In the third stage, participant screening and data collection were carried out.

Participants completed the learning task in the VR-simulated classroom under different combinations of real ambient factors and virtual visual factors. The real ambient factors included temperature and sound conditions, while the virtual visual factors included virtual window view and visual complexity. EEG signals were recorded continuously throughout the session to capture participants' cognitive responses under each environmental condition. After the task, participants completed the questionnaire survey, and their learning outcomes were used to categorize them into different performance groups for subsequent comparison. In the fourth stage, the collected data were processed and analyzed. EEG signals were preprocessed and transformed into relevant cognitive indicators, and the subjective and objective data were then statistically analyzed to examine both group differences and the relationships between environmental variables and cognitive responses (see Figure 1). Overall, this four-stage design provided an integrated framework linking environmental manipulation, immersive learning experience, measurement of participants' subjective and objective responses, and comparative analysis, thereby allowing the study to investigate

how real ambient factors and virtual visual factors shape subjective workload, learning experience, and cognitive responses in a VR-based safety knowledge learning context.

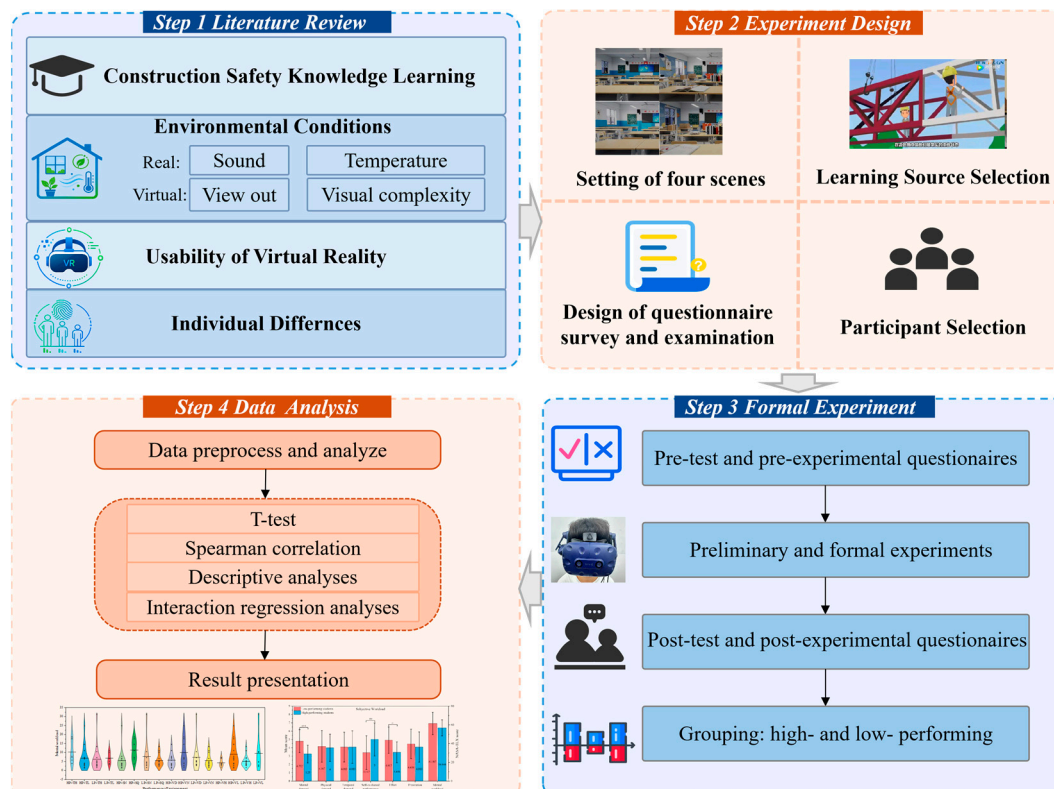


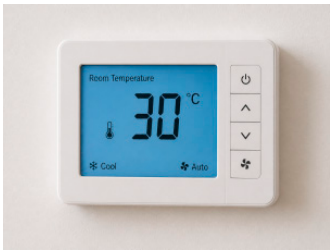
Figure 1. Research design flowchart.

3.2. Generation of 3D Learning Environment Scenes

A virtual classroom was developed as the experimental platform to provide a realistic but controlled indoor safety knowledge learning environment and to examine how environmental conditions may influence subjective workload, learning experience, and cognitive responses (see Table 2). The experiment adopted a $2 \times 2 \times 2 \times 2$ factorial design, including two real ambient factors and two virtual visual factors. The real ambient factors were temperature and sound, while the virtual visual factors were window view and visual complexity. The classroom scene was designed to resemble a typical indoor learning space, including seating arrangement, desks, teaching perspective, wall finishes, windows, and general lighting style. To reduce confounding effects, room geometry, camera viewpoint, baseline illumination, major furniture layout, teaching screen position, and the overall viewing perspective were kept constant across all conditions. Within this standardized virtual classroom, two virtual visual factors were manipulated: window view and visual complexity. The window-view factor referred specifically to the virtual outdoor scene presented through the classroom window, with two levels: daytime and nighttime. The indoor classroom lighting and interior layout were kept constant, while the image outside the window was changed to represent either a daytime or nighttime scene. Therefore, differences in brightness, color tone, contrast, and visual salience outside the window were treated as part of the overall daytime–nighttime window-view manipulation, rather than as separate variables examined independently. To avoid excessive visual artifacts, glare and strong reflections were reduced in both window-view conditions. Visual complexity was manipulated by changing the amount and diversity of visual information in the classroom scene. The high-complexity condition included more classroom objects, learning materials, desk items, wall details, and textured surfaces, whereas the low-complexity condition used

fewer objects, simpler surface finishes, and less decorative information. The manipulation was therefore operationalized as a difference in the richness and density of non-instructional visual elements in the virtual classroom. As a design-stage manipulation check, the two visual-complexity conditions were compared to ensure that the main instructional elements, viewing angle, furniture arrangement, and classroom function remained consistent, while the number and variety of peripheral visual elements clearly differed. This manipulation was designed to examine whether different levels of virtual visual richness would influence learners’ attention, workload, and learning experience during safety knowledge learning.

Table 2. Overview of design attributes in classroom models.

Design Attributes		Type-A	Type-B
Virtual Visual Factors	Visual Complexity	High	Low
	View Out	Daytime	Night
Real Ambient Factors	Temperature	22 °C	30 °C
	Sound	60–65 dB	30–35 dB

Note: The virtual classroom conditions were developed according to a 2 × 2 × 2 × 2 factorial design.

In parallel, two real ambient factors, including temperature and sound conditions, were manipulated in the physical experimental room. Temperature was controlled using the indoor air-conditioning system and was set at either 22 °C or 30 °C. The 22 °C condition represented a thermally neutral indoor environment, whereas the 30 °C condition represented a warm but realistic indoor condition that may induce thermal discomfort and cognitive burden, consistent with previous indoor-environment research on thermal effects on workload and cognitive performance [41]. Before each session, the room temperature

was stabilized at the assigned level. Temperature was measured at the participant's seated position, approximately at head height, to reflect the thermal condition actually experienced during the VR learning task. The temperature was checked before the experiment and monitored during the session to ensure that it remained within the target range. Sound condition was implemented through standardized audio playback. The noisy condition was maintained within approximately 60–65 dB(A), representing a noticeable but realistic indoor noise exposure level, while the quiet condition was maintained within approximately 30–35 dB(A) without the additional noise track. These sound levels were selected to create a clear contrast between quiet and noise-exposed learning conditions, as previous research has shown that indoor noise can affect cognitive performance and perceived disturbance [42]. The same playback device, sound source, gain setting, and participant-to-speaker distance were used across sessions to maintain consistency. Sound level was measured near the participant's seated position before the learning task and checked during the session to ensure that each condition remained within its intended range. By combining controlled real ambient factors with manipulated virtual visual factors, this experimental setup enabled the study to examine how physical and virtual environmental conditions jointly shape learning performance, subjective experience, and cognitive responses in a VR-based construction safety knowledge learning context.

3.3. Experimental Procedure

At the beginning of the experiment, the researcher introduced the overall procedure and explained the task requirements to each participant. Participants first completed a pre-test consisting of the same safety-related questions that were later used in the post-test. Both the pre-test and post-test contained 30 construction safety-related questions, with a total score of 100 points. The item order was kept the same in the pre-test and post-test to ensure that the two tests were directly comparable in content and structure. After completing the pre-test, participants did not receive any feedback on their answers, including correctness, scores, or explanations, in order to avoid additional learning effects before the VR-based instructional task. The use of identical items before and after the intervention was intended to provide a direct measure of immediate learning gain on the specific safety concepts addressed in the instructional video. In short-duration educational interventions, pre-test/post-test comparisons using the same question set are commonly adopted to evaluate immediate knowledge acquisition, although the resulting score difference should be interpreted as short-term learning change rather than long-term retention [43,44].

After the pre-test, each participant was seated comfortably in front of the display under the researcher's guidance. The VR headset and EEG device were then fitted and adjusted to ensure both participant comfort and stable signal recording. During this stage, participants were instructed to remain relaxed and to avoid unnecessary movements before the formal task began. EEG recording was conducted from the beginning to the end of the instructional video, corresponding to the formal learning period of the experiment. Next, a short narrative script was presented in the virtual environment to create a classroom-based situational context. Immediately afterward, the instructional video on construction safety knowledge was played for approximately 10 min. The video was designed as a structured construction safety training material and covered several basic safety topics commonly involved in construction-site education. In the first part, approximately 0 to 2 min, the video introduced the general importance of construction safety and the main sources of safety risks on construction sites. From approximately 2 to 4 min, it explained the correct use of personal protective equipment, including safety helmets, reflective vests, protective gloves, and safety shoes. From approximately 4 to 6 min, the video focused on fall prevention and safe work at height, including the use of guardrails, safety

belts, scaffolding precautions, and safe access routes. From approximately 6 to 8 min, it introduced safety requirements related to construction machinery, temporary electricity, and material storage, emphasizing the need to follow operating procedures and maintain safe distances from equipment and hazardous areas. In the final part, approximately 8 to 10 min, the video summarized emergency response principles, including reporting hazards, responding to accidents, and following evacuation instructions. The content was presented in a classroom-style instructional format and was intended to provide participants with standardized construction safety knowledge before the post-test. EEG signals were recorded continuously during video viewing in order to capture participants' real-time neurophysiological responses throughout the learning process. To reduce motion-related contamination of the EEG signals, participants were required to maintain a stable sitting posture and minimize head movements, speaking, and excessive blinking during the recording session, as eye blinks and body motion are major sources of EEG artifacts [45]. After the video ended, participants completed the same set of questions again as a post-test and then filled out the post-experimental questionnaire. This procedure allowed the study to compare knowledge performance before and after the VR-based learning task while also capturing participants' immediate subjective evaluations of the simulated environment, workload, and learning experience (see Figure 2).

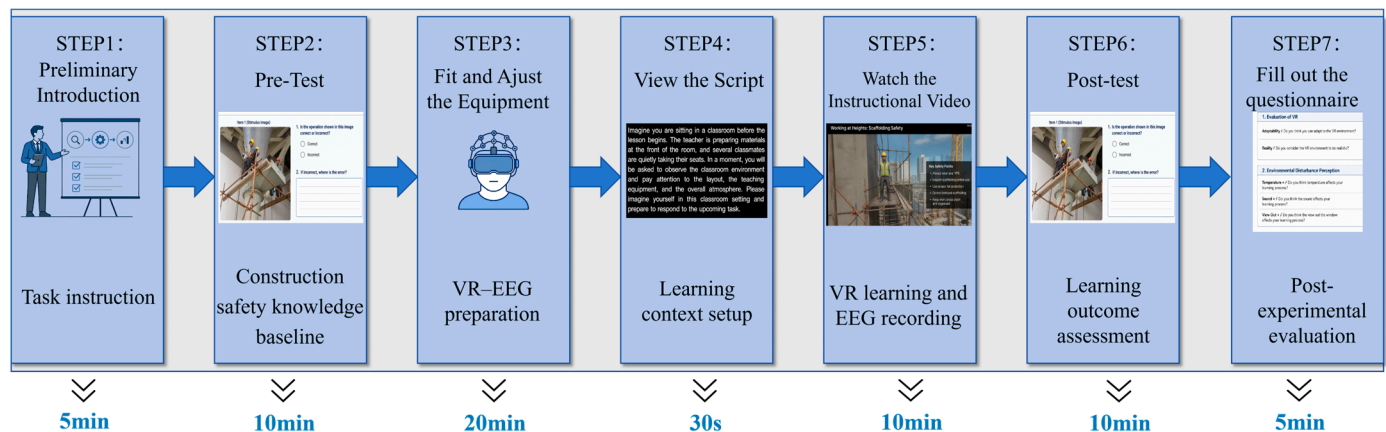


Figure 2. Experimental procedure diagram.

3.4. Post-Experiment Questionnaire Design

A post-task questionnaire was administered immediately after the VR learning session to collect participants' subjective evaluations of the simulated learning environment. As shown in Table 3, the questionnaire covered four parts: VR adaptability and perceived realism, perceived environmental distraction, subjective workload, and learning experience. The first part was used to verify whether participants could adapt to the VR environment and whether the virtual classroom was perceived as realistic. The second part assessed participants' perceived disturbance from the manipulated real ambient factors and virtual visual factors. Subjective workload was measured using the NASA Task Load Index (NASA-TLX), and the overall workload score was calculated using the raw NASA-TLX approach [46,47]. Learning experience was assessed using selected items adapted from the Course Experience Questionnaire (CEQ), focusing on instructional helpfulness and perceived skill development [48–50]. All items were completed after the learning task to avoid interrupting the VR learning process.

Table 3. Items to evaluate students' perceived environmental responses, workload, and learning-related evaluations.

Dimensions	Type	Nature	Items	Scales	Reference
Evaluation of VR Scenes	Adaptability	/	Do you think you can adapt to the VR environment?	/	[21]
	Reality	/	Do you consider the VR environment to be realistic?		
Perceived Environmental Distraction	Temperature	+	Do you think temperature affects your learning process?	/	[51]
	Sound	+	Do you think the sound affects your learning process?		
	View Out	+	Do you think the view out the window affects your learning process?		
	Visual Complexity	+	Do you think the complex environment affects your learning process?		
Subjective Workload	Mental demand	+	How much mental and perceptual activity was required?	NASA Task Load Index (NASA-TLX)	[47]
	Physical demand	+	How much physical activity was required?		
	Temporal demand	+	How much time pressure did you feel due to the pace of the task?		
	Self-evaluated Performance	-	How successful were you in achieving your learning goals?		
	Effort	+	How hard did you have to work to accomplish your level of performance?		
	Frustration	+	How irritated, stressed, and annoyed, rather than content, relaxed, and comfortable, did you feel?		
Learning Experience	Good Teaching	Helpful	Do you think the course was helpful to you?	Course Experience Questionnaire (CEQ)	[48]
		Motivated	Do you think the course motivated you to do your best work?		
		Interested	Do you think the course stimulated your interest in the topic?		
	Generic Skills	Problem-solving skills	Do you think the course developed your problem-solving skills?		
		Analytic skills	Do you think the course developed your analytic skills?		
		Unfamiliar problem-tackling skills	Do you think that after completing this course, you will be able to independently tackle unfamiliar challenges?		

3.5. Experimental Equipment

EEG data were collected using the Emotiv EPOC (EPOC X; EMOTIV Inc., San Francisco, CA, USA) system. The EEG cap included 14 electrode sites arranged according to the international 10–20 electrode placement system, covering frontal, central, temporal, parietal, and occipital regions. The electrode layout used in this study included AF3, AF4, F7, F3, F4, F8, FC5, FC6, T7, T8, P7, P8, O1, and O2. Due to differences in headset architecture across EEG devices, the exact positions of some electrodes may deviate slightly from the theoretical locations defined in the standard 10–20 system. This is common in portable EEG devices, which are designed to balance signal acquisition, portability, setup efficiency, and participant comfort in immersive experimental settings. EEG signals were recorded at a sampling rate of 128 Hz. During acquisition, electrode contact quality was checked before the formal task began, and the headset was adjusted until stable signals were obtained. The

reference was set as the device-default CMS/DRL reference during acquisition and then re-referenced to the average reference during preprocessing.

The VR presentation was delivered through the HTC VIVE Pro Eye (HTC Corporation, New Taipei City, Taiwan, China), a head-mounted display with integrated eye-tracking capability, dual OLED displays, a combined resolution of 2880×1600 pixels, a 90 Hz refresh rate, and an approximately 110° field of view. These specifications allowed the system to provide a stable and immersive visual presentation for the controlled VR-based learning experiment.

3.6. EEG Data Collection and Analysis

EEG data were collected during the instructional video period to capture participants' cognitive responses while learning construction safety knowledge in the VR classroom. Because the task required participants to continuously attend to the video, process safety-related information, and remember as much knowledge as possible, EEG indicators were selected to reflect three cognitive states that were most relevant to the learning process: mental workload, attention, and mental fatigue. These indicators allowed the study to examine whether different real ambient factors and virtual visual factors influenced not only participants' subjective evaluations but also their neurophysiological responses during immersive safety knowledge learning. Raw EEG data were exported and processed in Python using MNE-Python (version 1.6.1). The continuous EEG signals were first visually inspected to identify segments with severe noise or signal loss. Data were then filtered using a zero-phase FIR band-pass filter from 1 Hz to 45 Hz. A notch filter at 50 Hz was applied to reduce power-line interference. The frequency bands used for subsequent EEG analysis were defined as follows: theta, 4–8 Hz; alpha, 8–13 Hz; and beta, 13–30 Hz. These bands were selected because they are commonly used to characterize workload-, attention-, and fatigue-related cognitive states in learning and task-performance studies. After filtering, independent component analysis (ICA) was applied to reduce non-neural artifacts [45]. ICA components were inspected based on their time courses, scalp distributions, and spectral characteristics. Components showing typical eye-blink, eye-movement, muscle activity, or motion-related patterns were removed before signal reconstruction. In particular, components with large frontal activity and blink-like temporal patterns were treated as ocular artifacts, while components dominated by high-frequency activity or irregular bursts were treated as muscle or movement artifacts. After preprocessing, all participants were retained for EEG analysis. The average usable EEG duration was 538.6 ± 32.4 s, corresponding to $89.8 \pm 5.4\%$ of the original instructional-video recording period. The retained data duration was considered sufficient for subsequent frequency-domain analysis because the EEG indicators were calculated from continuous video-viewing periods after artifact correction. Power spectral density (PSD) was then estimated from the cleaned EEG signals using Welch's method in MNE-Python (version 1.6.1), with a sliding Hamming window of 2.0 s and 50% overlap. Welch's method was used because it provides stable frequency-domain estimates by averaging power spectra across successive time windows, and MNE-Python (version 1.6.1) provides a reproducible framework for EEG preprocessing and spectral analysis [52,53].

Three EEG-derived indicators were calculated to reflect participants' cognitive states during video-based learning. First, an EEG-based mental workload index was computed from frontal theta and parietal alpha relative power, following prior studies showing that frontal theta increases and parietal alpha changes are sensitive to workload demands. In thermal-environment research, this combination has been used to reflect workload-related

changes under different indoor conditions [41,54]. In the present study, the workload index was calculated as:

$$\text{Mental workload indicator} = \frac{F3\theta(\text{RP}) + F4\theta(\text{RP}) + F7\theta(\text{RP}) + F8\theta(\text{RP})}{P3\alpha(\text{RP}) + P4\alpha(\text{RP})} \quad (1)$$

$$\text{Relative power (RP)} = \frac{\text{power of certain frequency band}}{\sum \text{all frequency bands power}} \quad (2)$$

Second, attention was indexed using the frontal beta/theta ratio. Previous EEG studies have shown that the frontal theta/beta ratio is negatively associated with attentional control and executive control, such that lower theta/beta values indicate better attention regulation [55–58]. For ease of interpretation, the present study used the reciprocal form, beta/theta, so that higher values directly represent better attentional control. This indicator was calculated from frontal channels AF3, AF4, F7, F3, F4, F8, FC5, and FC6:

$$\text{Attention Index} = \frac{\beta(\text{RP}_{\text{frontal}})}{\theta(\text{RP}_{\text{frontal}})} \quad (3)$$

Third, mental fatigue was quantified using the whole-brain $(\theta + \alpha)/\beta$ ratio. Prior EEG studies have reported that mental fatigue is typically accompanied by increased alpha activity and reduced beta activity, making combined band-ratio measures useful for fatigue detection [59]. Similar ratio-based indicators have also been used in construction-related fatigue studies [60,61]. The fatigue index was calculated as:

$$\text{Mental Fatigue Index} = \frac{\theta(\text{RP}_{\text{whole brain}}) + \alpha(\text{RP}_{\text{whole brain}})}{\beta(\text{RP}_{\text{whole brain}})} \quad (4)$$

3.7. Sample Selection

A total of 50 participants were recruited from the host university. University students were selected because the present study examined safety learning in an educational context, and a relatively homogeneous higher-education sample helps reduce between-subject variability in age, educational background, and prior learning experience, thereby improving the comparability of cognitive and environmental responses under controlled experimental conditions [62,63]. To ensure the feasibility and reliability of the VR-based experiment, participants were required to meet the following inclusion criteria: (1) no history of psychiatric disorders or cognitive impairment; (2) normal or corrected-to-normal vision (binocular visual acuity ≥ 1.0); (3) no color vision deficiency; (4) no severe motion sickness or contraindications to VR use; and (5) residence in on-campus dormitories rather than off-campus housing or their family home. The exclusion of participants with severe motion sickness or VR-related contraindications was necessary because immersive VR exposure may induce cybersickness symptoms such as nausea, dizziness, disorientation, and visual fatigue, which may interfere with task completion and data quality [64,65].

Before the formal experiment, all participants completed a screening form that collected demographic and background information, including gender, age, educational level, and prior familiarity with VR. In addition, several attention-related items adapted from the Swanson, Nolan, and Pelham Rating Scale (SNAP-IV) were included to assess baseline attentional characteristics, such as distractibility and difficulty sustaining attention. The SNAP-IV has been widely used as a screening instrument for inattentive and related behavioral symptoms; however, in the present study, it was used only as a non-clinical baseline screening tool rather than for diagnostic purposes [66]. After screening, 48 valid participants remained and were assigned to 16 experimental groups (see Table 4), defined by the four manipulated binary variables (window view, temperature, sound condition,

and visual complexity), with three participants in each complete four-factor combination. Since each manipulated factor had two levels, each level of a single environmental factor included 24 participants. Therefore, the main analyses were conducted at the participant level by comparing the two levels of each environmental factor and examining their associations with subjective responses, EEG indicators, and learning gains. Similar VR-based environmental studies have also used participant-level samples of a comparable or smaller scale. For example, one study on the influence of virtual environments on thermal perception used 43 participants divided into three groups, while another study comparing immersive virtual and real indoor environments used 18 participants to examine thermal sensation and physiological responses [8,67]. These studies provide methodological references for conducting controlled VR and environmental-response experiments with moderate participant-level samples. This screening and grouping procedure was intended to reduce the influence of pre-existing attentional difficulties, visual limitations, and VR intolerance, while improving the comparability of participants under the simulated learning conditions.

Table 4. Experimental groups and participants.

Group	View Out	Visual Complexity	Temperature	Sound	Participants
1	Daytime	High	22 °C	Noisy	P1, P2, P3
2	Daytime	High	22 °C	Quiet	P4, P5, P6
3	Daytime	High	30 °C	Noisy	P7, P8, P9
4	Daytime	High	30 °C	Quiet	P10, P11, P12
5	Night	Low	22 °C	Noisy	P13, P14, P15
6	Night	Low	22 °C	Quiet	P16, P17, P18
7	Night	Low	30 °C	Noisy	P19, P20, P21
8	Night	Low	30 °C	Quiet	P22, P23, P24
9	Daytime	Low	22 °C	Noisy	P25, P26, P27
10	Daytime	Low	22 °C	Quiet	P28, P29, P30
11	Daytime	Low	30 °C	Noisy	P31, P32, P33
12	Daytime	Low	30 °C	Quiet	P34, P35, P36
13	Night	High	22 °C	Noisy	P37, P38, P39
14	Night	High	22 °C	Quiet	P40, P41, P42
15	Night	High	30 °C	Noisy	P43, P44, P45
16	Night	High	30 °C	Quiet	P46, P47, P48

4. Results

4.1. Participant Characteristics and Performance Grouping

Following screening, participants with clearly abnormal responses on the Swanson, Nolan, and Pelham Rating Scale (SNAP-IV) were excluded from further analysis. Of the 50 students initially recruited, 2 were excluded, resulting in a final sample of 48 valid participants and 48 valid questionnaires. The final sample was balanced by gender (24 males, 50.0%; 24 females, 50.0%). Most participants were aged 18–25 years (46/48, 95.8%), and all were enrolled in undergraduate or higher education programs (100%). In terms of prior VR familiarity, 27 participants (56.3%) reported being familiar with VR, 14 (29.2%) reported being unfamiliar, and 7 (14.6%) reported being very unfamiliar. Post-task evaluation further indicated that participants were generally able to adapt to the VR environment (47/48, 97.92%) and regarded the virtual classroom as realistic (45/48, 93.75%), supporting the usability and face validity of the simulated setting. To examine whether environmental responses differed according to learning performance, participants were divided into HP and LP groups based on learning gain, calculated as the difference between post-test and pre-test scores. A median-split approach was applied using a median value of 13.33, such

that participants scoring above the median were classified as the HP group and those scoring below the median were classified as the LP group, resulting in two equally sized groups of 24 participants each. This grouping strategy was adopted to facilitate direct comparison of subjective evaluations and EEG indicators between learners with relatively higher and lower levels of short-term learning improvement, while acknowledging that dichotomizing a continuous variable may reduce statistical power and obscure within-group variability.

4.2. Perceived Environmental Distraction, Subjective Workload, and Learning Experience Between HP and LP Students

To examine whether students with different levels of learning improvement responded differently to the experimental environment, independent-samples *t*-tests were conducted to compare the HP and LP groups across subjective measures, including perceived environmental distraction, subjective workload, and learning experience. To address multiple comparisons, Benjamini–Hochberg FDR correction was applied across the *t*-tests, and Cohen's *d* with 95% confidence intervals was calculated to indicate effect size. Exact *p*-values, FDR-adjusted *q*-values, and effect sizes are reported in the note to Figure 3. The results showed clear group differences in several subjective dimensions. In terms of Perceived Environmental Distraction, compared with HP students, LP students perceived real ambient factors as significantly more disruptive to their learning process, whereas virtual visual factors did not show significant group differences (see Figure 3a). Differences were also evident in participants' perceptions of subjective workload (see Figure 3b). The LP group reported significantly higher mental demand and effort, whereas the HP group reported significantly better self-evaluated performance. By contrast, no significant differences were observed in physical demand, temporal demand, frustration, or the overall NASA-TLX score. This pattern suggests that the distinction between the two groups was reflected more strongly in selected dimensions of subjective workload than in the overall workload measure. A similar pattern emerged in the learning experience (see Figure 3c). HP students gave more positive ratings for the helpfulness of the learning activity, reported stronger motivation, and perceived greater improvement in problem-solving skills. However, no statistically significant differences were found for interest, analytic skills, or unfamiliar problem-tackling skills.

4.3. Group-Specific Spearman Correlations Between Environmental Factors and Perceived Environmental Distraction, Subjective Workload, and Learning Experience

Spearman's correlations were calculated separately for HP and LP students to examine whether the relationships between environmental factors and subjective outcomes differed by learning performance (see Table 5). Spearman's ρ was reported as the effect size, and FDR-adjusted *q*-values were reported for all correlations. Exact *p*-values with approximate 95% confidence intervals were added for the associations that reached the uncorrected $p < 0.05$ level. Overall, correlations were selective rather than pervasive, with LP students showing a broader pattern of environment-related associations than HP students. Within perceived environmental distraction, LP students reported higher view-out disturbance under the real low-temperature condition and lower perceived sound disturbance under virtual daytime window view, suggesting that lower-performing learners showed more environment-related variation in distraction appraisal. HP students showed no significant correlations for perceived environmental distraction. In Subjective Workload, LP students showed specific associations: the virtual daytime window view was linked to lower self-evaluated performance and higher frustration, while low visual complexity corresponded to reduced effort. HP students exhibited no significant correlations across subjective workload dimensions. In learning experience, HP students showed associations primarily for specific evaluation measures: helpfulness ratings were higher under virtual daytime

window view, while perceived problem-solving skills were lower under real ambient quiet sound conditions. LP students displayed selective correlations as well, with analytic skills higher under real low temperature, whereas other learning-related measures showed no consistent associations.

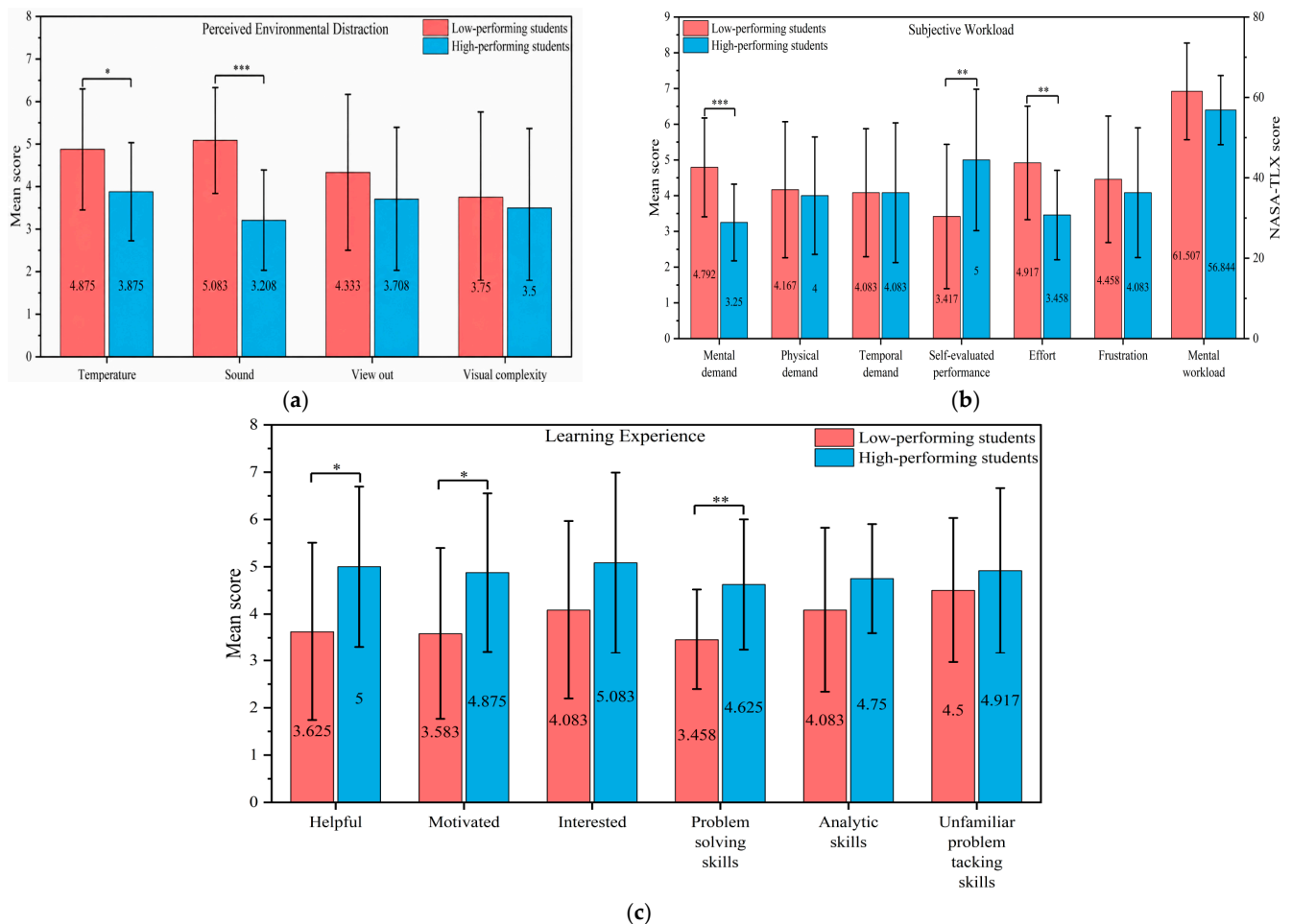


Figure 3. (a) Comparison of perceived environmental distraction between HP and LP groups; (b) subjective workload between HP and LP groups; (c) learning experience between HP and LP groups. Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Temperature disturbance: $p = 0.010$, $q = 0.026$, $d = -0.77$, 95% CI $[-1.36, -0.18]$; sound disturbance: $p < 0.001$, $q < 0.001$, $d = -1.54$, 95% CI $[-2.19, -0.90]$; mental demand: $p < 0.001$, $q < 0.001$, $d = -1.25$, 95% CI $[-1.87, -0.63]$; self-evaluated performance: $p = 0.009$, $q = 0.026$, $d = 0.79$, 95% CI $[0.20, 1.38]$; effort: $p < 0.001$, $q = 0.005$, $d = -1.02$, 95% CI $[-1.62, -0.42]$; helpfulness: $p = 0.014$, $q = 0.029$, $d = 0.74$, 95% CI $[0.15, 1.32]$; motivated: $p = 0.011$, $q = 0.026$, $d = 0.77$, 95% CI $[0.18, 1.35]$; problem-solving skills: $p = 0.002$, $q = 0.008$, $d = 0.95$, 95% CI $[0.35, 1.55]$. Other comparisons were not significant after FDR correction.

Table 5. Correlation analysis between environmental factors and subjective outcomes.

Factor		Groups	Temperature	FDR q	Sound	FDR q	View Out	FDR q	Visual Complexity	FDR q
Perceived Environmental Distraction	Temperature	HP	−0.245	0.773	−0.226	0.773	0.107	0.860	0.048	0.912
		LP	−0.032	0.784	0.274	0.966	−0.088	0.888	−0.206	0.872
	Sound	HP	0.187	0.789	0.077	0.900	0.169	0.789	0.021	0.931
		LP	−0.129	0.884	0.108	0.884	−0.513	0.585	−0.185	0.884
	View out	HP	−0.085	0.912	−0.102	0.773	−0.062	0.789	−0.223	0.789
		LP	0.405	0.784	0.333	0.784	0.111	0.969	−0.115	0.884
	Visual Complexity	HP	−0.050	0.888	0.223	0.866	−0.179	0.912	0.169	0.773
		LP	0.291	0.776	0.304	0.585	0.012	0.884	−0.094	0.884
Subjective Workload	Mental demand	HP	−0.132	0.852	0.125	0.857	0.293	0.773	0.237	0.912
		LP	0.285	0.784	0.146	0.884	−0.408	0.585	0.237	0.795
	Physical demand	HP	0.071	0.900	−0.108	0.860	0.161	0.803	−0.209	0.590
		LP	−0.354	0.761	−0.266	0.784	−0.018	0.969	−0.209	0.872
	Temporal demand	HP	−0.207	0.789	−0.242	0.773	0.428	0.599	−0.095	0.773
		LP	0.050	0.945	−0.146	0.884	0.142	0.884	−0.095	0.884
	Self-evaluated Performance	HP	−0.036	0.912	0.280	0.773	0.198	0.789	0.108	0.789
		LP	0.149	0.884	0.139	0.884	−0.490	0.945	0.108	0.884
	Effort	HP	−0.036	0.912	0.212	0.789	−0.019	0.931	−0.453	0.773
		LP	−0.256	0.784	0.133	0.884	−0.074	0.888	−0.453	0.585
	Frustration	HP	−0.283	0.773	−0.380	0.653	−0.197	0.789	−0.095	0.773
		LP	−0.085	0.888	−0.184	0.884	0.407	0.585	−0.095	0.884
	Mental workload (NASA-TLX score)	HP	−0.231	0.773	0.044	0.912	0.334	0.773	−0.073	0.900
		LP	−0.154	0.884	−0.094	0.884	−0.006	0.978	−0.186	0.884
Learning experience	Helpful	HP	0.172	0.789	0.154	0.803	0.449	0.599	0.123	0.857
		LP	0.227	0.784	0.254	0.809	0.160	0.884	0.235	0.795
	Motivated	HP	−0.270	0.773	0.299	0.773	0.041	0.599	0.108	0.860
		LP	−0.013	0.884	0.122	0.969	0.181	0.884	0.177	0.884
	Interested	HP	−0.171	0.789	0.115	0.860	0.366	0.670	0.156	0.803
		LP	0.013	0.969	−0.014	0.969	0.271	0.784	0.270	0.784
	Problem-solving skills	HP	0.252	0.773	−0.515	0.590	−0.056	0.912	−0.144	0.813
		LP	0.078	0.966	0.036	0.888	0.108	0.884	−0.167	0.884
	Analytic skills	HP	0.398	0.614	−0.323	0.773	−0.025	0.931	−0.227	0.773
		LP	0.404	0.888	0.078	0.585	0.062	0.607	0.235	0.795
	Unfamiliar problem-tacking skills	HP	0.035	0.912	−0.146	0.813	0.093	0.888	0.088	0.888
		LP	0.331	0.944	0.057	0.776	−0.278	0.784	−0.034	0.966

Note: Coding scheme: temperature was coded as 30 °C = 0 and 22 °C = 1, sound condition as noisy = 0 and quiet = 1, window view as nighttime = 0 and daytime = 1, visual complexity as high = 0 and low = 1; No association survived the FDR-corrected threshold of $q < 0.05$; therefore, no coefficients are marked as statistically significant in the table. For transparency, exact p -values, approximate 95% confidence intervals for the associations that reached the uncorrected $p < 0.05$ level were as follows: LP sound disturbance $\times$ window view, $p = 0.010$, 95% CI [−0.759, −0.138]; LP view-out disturbance $\times$ temperature, $p = 0.050$, 95% CI [0.002, 0.695]; LP self-evaluated performance $\times$ window view, $p = 0.015$, 95% CI [−0.746, −0.108]; LP effort $\times$ visual complexity, $p = 0.026$, 95% CI [−0.724, −0.061]; LP frustration $\times$ window view, $p = 0.048$, 95% CI [0.004, 0.696]; HP helpful $\times$ window view, $p = 0.028$, 95% CI [0.056, 0.722]; HP problem-solving skills $\times$ sound, $p = 0.010$, 95% CI [−0.760, −0.141]; LP analytic skills $\times$ temperature, $p = 0.050$, 95% CI [0.001, 0.694].

4.4. EEG Results Under Different Environmental Conditions

After calculating the three EEG indicators, the four environmental factors showed no significant effects on EEG-based mental workload, attention, or mental fatigue in either the HP or LP group. The violin plots were therefore used to present the distribution of EEG indicators across environmental conditions and performance groups. As shown in Figure 4, LP students generally exhibited wider distributions in mental workload and mental fatigue than HP students, with more pronounced upper ranges under several environmental conditions. HP students showed relatively more compact distributions, suggesting smaller variation in EEG-based cognitive responses during the learning task. Among the three indicators, mental workload showed the most visible between-group dispersion, whereas attention remained within a comparatively narrow range in both groups. Across the four environmental contrasts, visual complexity showed a relatively clear descriptive pattern. Compared with the high-complexity condition, the low-complexity condition appeared to be accompanied by higher mental workload, lower attention, and greater fatigue in both groups. The other environmental factors, including window view, sound, and temperature, showed less consistent distributional changes across HP and LP students. Overall, the EEG results indicate that the environmental manipulations did not produce statistically significant changes in EEG-based cognitive responses, although the distributional patterns provide descriptive information about individual variability during VR-based construction safety knowledge learning.

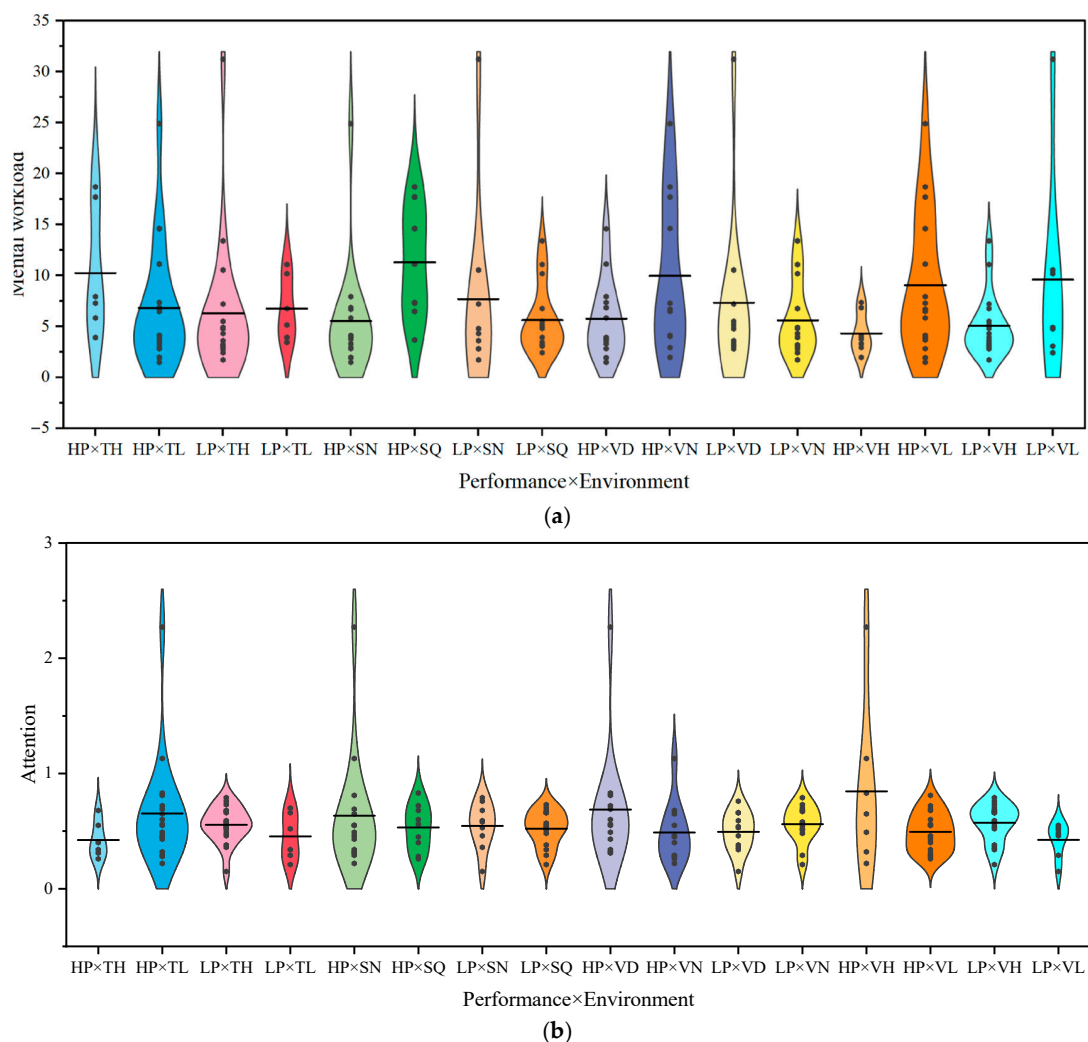


Figure 4. Cont.

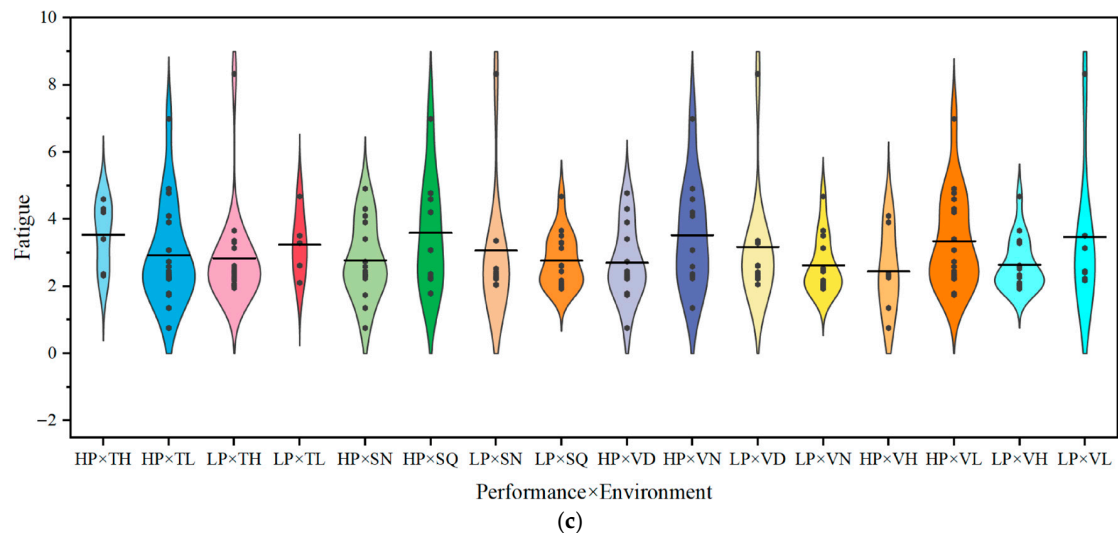


Figure 4. Violin plots of EEG-based cognitive responses between HP and LP groups under different environmental conditions: (a) mental workload; (b) attention; (c) mental fatigue. Note: VH = visual complexity is high; VL = visual complexity is low; VD = view out is daytime; VN = view out is night; SN = sound is noisy; SQ = sound is quiet; TH = temperature is high; TL = temperature is low; Different colors represent different performance $\times$ environment combinations; The black dots indicate the distribution of individual data points; The horizontal lines denote the median values.

4.5. Interactive Effects Analysis of Real and Virtual Environmental Factors on Student Performance

A post hoc sensitivity power analysis was conducted to clarify the detectable effect size under the present sample size. The experiment used a 2^4 factorial design with sixteen environmental combinations and 48 participants in total, resulting in three participants per combination. For single-degree-of-freedom effects in the factorial model, with $\alpha = 0.05$ and $N = 48$, the present design had sufficient power to detect relatively large effects. Specifically, the sensitivity analysis indicated that approximately 80% power would require an effect size of about $f = 0.42$ for an individual main or interaction effect. For a medium effect size of $f = 0.25$, the estimated power was approximately 0.39, indicating limited power for detecting moderate interaction effects. Therefore, the factorial analysis was considered appropriate for exploratory analysis and for identifying relatively large environment-related associations, particularly for interaction effects. This analytical approach is also supported by comparable controlled-environment research with a similar participant-level sample size. For example, interaction effects among multiple environmental factors have been examined in a controlled indoor-environment experiment with 52 young adults, where temperature, lighting, and noise were analyzed in relation to cognitive performance and perceived comfort [20]. This provides methodological support for applying interaction analysis in controlled environmental experiments with a comparable overall sample size.

To examine how different combinations of real ambient factors and virtual visual factors were related to student learning performance, descriptive statistics were first calculated for each four-factor condition using learning gain scores, which were defined as the difference between the post-test score and the pre-test score (see Table 6). For each condition, the mean score, standard deviation, and sample size were computed. Since each environmental combination contained three participants, these descriptive statistics were used to show the observed distribution of learning gains across the sixteen experimental conditions. The descriptive results showed that relatively higher scores were generally observed under low-temperature conditions (22°C). Several combinations with low temperature and noisy sound produced higher mean learning gains, including low

temperature with noisy sound combined with high visual complexity and daytime window view, low visual complexity and nighttime window view, or low visual complexity and daytime window view. The lower mean score was observed under the combination of high temperature, noisy sound, high visual complexity, and nighttime window view. A two-way interaction regression model was conducted using individual-level learning gain scores from all 48 participants to further examine the main and combined effects of environmental factors on raw learning scores (see Table 7). The model included the four main effects of temperature, sound, window view, and visual complexity, as well as all six two-way interaction terms. The overall model was statistically significant, $R^2 = 0.673$, adjusted $R^2 = 0.585$, $F(10, 37) = 7.622$, $p < 0.001$. Among the main effects, temperature, visual complexity, and window view were significant predictors, indicating that low temperature, low visual complexity, and daytime window view were associated with higher learning scores. The main effect of sound was not significant. For the interaction effects, only the Temperature $\times$ Sound interaction reached statistical significance, indicating that these two real ambient factors jointly influenced learning performance. The other two-way interactions involving virtual visual factors were not statistically significant, although the Visual Complexity $\times$ Temperature interaction approached significance. Residual diagnostics were conducted to examine the regression assumptions. The Breusch–Pagan test showed no evidence of heteroscedasticity, $LM = 14.835$, $p = 0.138$, suggesting that the variance of residuals was acceptable. The Shapiro–Wilk test indicated a deviation from residual normality, $W = 0.708$, $p < 0.001$. Therefore, the regression results were interpreted as exploratory evidence of associations between environmental factors and learning gain scores.

Table 6. Mean student scores across four-factor combinations.

Temperature	Sound	View Out	Visual Complexity	Mean Score	S.D.
30 °C	Noisy	Night	High	−3.33	20.28
30 °C	Noisy	Daytime	High	11.11	1.92
30 °C	Noisy	Night	Low	13.33	0.00
30 °C	Noisy	Daytime	Low	18.89	1.92
30 °C	Quiet	Night	High	6.67	0.00
30 °C	Quiet	Daytime	High	10.00	3.33
30 °C	Quiet	Night	Low	10.00	3.33
30 °C	Quiet	Daytime	Low	18.89	1.92
22 °C	Noisy	Night	High	18.89	1.92
22 °C	Noisy	Daytime	High	24.44	3.85
22 °C	Noisy	Night	Low	24.44	1.92
22 °C	Noisy	Daytime	Low	24.44	1.92
22 °C	Quiet	Night	High	11.11	1.92
22 °C	Quiet	Daytime	High	15.56	3.85
22 °C	Quiet	Night	Low	15.56	1.92
22 °C	Quiet	Daytime	Low	16.67	0.00

Table 7. Two-way Interaction Regression Results.

Type	Term	B	SE	t	p	95% CI	Partial η^2
Main Effect	Temperature	18.889	3.163	5.972	<0.001	[12.481, 25.298]	0.288
Main Effect	Sound	3.889	3.163	1.229	0.227	[−2.520, 10.297]	0.231
Main Effect	View out	10.555	3.163	3.337	0.002	[4.147, 16.964]	0.491
Main Effect	Visual complexity	12.222	3.163	3.864	<0.001	[5.813, 18.630]	0.039
Interaction	Temperature $\times$ Sound	−9.723	3.163	−3.074	0.004	[−16.131, −3.314]	0.025
Interaction	Temperature $\times$ View out	−5.278	3.163	−1.669	0.104	[−11.687, 1.130]	0.099

Table 7. Cont.

Type	Term	B	SE	t	p	95% CI	Partial η^2
Interaction	Temperature $\times$ Visual Complexity	−6.389	3.163	−2.02	0.051	[−12.798, 0.019]	0.025
Interaction	Sound $\times$ View out	−1.944	3.163	−0.615	0.543	[−8.353, 4.464]	0.070
Interaction	Sound $\times$ Visual Complexity	−3.055	3.163	−0.966	0.34	[−9.464, 3.353]	0.010
Interaction	View out $\times$ Visual Complexity	−3.055	3.163	−0.966	0.34	[−9.464, 3.353]	0.203

5. Discussion

5.1. Differences in Perceived Environmental Distraction, Subjective Workload, and Learning Experience Between HP and LP Students

The significant differences in perceived environmental distraction, subjective workload, and learning experience between HP and LP students indicate that VR-based construction safety knowledge learning is not only affected by instructional content but also by how learners perceive and regulate environmental demands. LP students reported higher mental demand and effort, as well as greater significance to real ambient disturbances such as temperature and sound. This suggests that these students may have allocated more cognitive resources to coping with the learning environment itself, leaving fewer resources available for understanding and retaining construction safety knowledge. This interpretation is consistent with immersive learning theory, which emphasizes that VR learning outcomes are shaped by cognitive load, motivation, self-efficacy, self-regulation, and affective engagement, rather than by immersion alone [21]. It also agrees with recent VR safety training reviews, which indicate that VR can support engagement and training effectiveness, but its effects depend on learner characteristics, training design, and implementation context [2,3]. Evidence from classroom and environmental conditions research further suggests that thermal, acoustic, lighting, and visual conditions can influence learning quality, short-term academic performance, and cognitive functioning [5,6]. Therefore, the present results extend previous research by showing that subjective responses to VR-based construction safety knowledge learning are performance-dependent. For learners with lower learning gains, environmental discomfort may increase perceived workload and reduce the perceived quality of the learning experience, which is especially relevant for safety education because trainees need to understand, remember, and apply procedural safety knowledge accurately.

5.2. Associations Between Environmental Factors and Perceived Environmental Distraction, Subjective Workload, and Learning Experience

The group-specific Spearman correlation results suggested possible associations between environmental conditions and perceived environmental distraction, subjective workload, and learning experience in HP and LP students during VR-based construction safety knowledge learning. For LP students, the daytime window view was nominally associated with lower self-evaluated performance and higher frustration, although it was also associated with lower perceived sound disturbance. This result differs from studies in conventional indoor environments, where daytime window views have generally been associated with improved comfort, satisfaction, and cognitive performance [14,15]. One possible explanation is that, during a video-based VR learning task, the daytime virtual view provided additional visual information that was not directly relevant to the safety content. For students with lower learning gains, this additional virtual visual information may have been experienced as less helpful for performance evaluation, even though it

reduced perceived sound disturbance. In contrast, HP students showed a nominal positive association between daytime window view and helpfulness, suggesting that the subjective role of virtual visual information may differ according to learning performance. LP students also reported lower effort under the low visual-complexity condition, which is consistent with research indicating that reducing non-essential visual information can decrease unnecessary cognitive processing during learning tasks [18]. Regarding real ambient factors, low temperature showed a nominal association with higher perceived analytic skills among LP students, suggesting that a more comfortable thermal condition may support students' evaluation of learning-related thinking skills. However, the finding that quiet sound was associated with lower perceived problem-solving improvement among HP students should be interpreted cautiously, as it reflects subjective evaluation rather than objective learning performance. Overall, these findings suggest that real ambient factors and virtual visual factors may be related to selected aspects of learners' subjective evaluation, and that these associations may differ between students with higher and lower construction safety knowledge learning gains.

5.3. EEG-Based Cognitive Response Under Different Environmental Conditions

The EEG-based results showed that the manipulated real ambient factors and virtual visual factors did not produce significant differences in mental workload, attention, or mental fatigue in either performance group during VR-based construction safety knowledge learning. Although the EEG effects were not statistically significant, the distributional results still provide useful descriptive information. LP students showed broader distributions in mental workload and fatigue than HP students, suggesting greater individual variation in cognitive responses during the same learning task. This pattern is consistent with the idea that biometric responses in VR-based construction safety training may reflect individual differences in learning performance [27]. In addition, the violin plots showed a descriptive tendency in which low visual complexity was accompanied by relatively higher workload, lower attention, and greater fatigue, although this pattern was not statistically significant. These findings should be understood together with the broader results of the study. The subjective and learning-performance analyses provided stronger evidence that environmental conditions were related to learners' perceived distraction, workload, learning experience, and learning gains, whereas EEG indicators mainly showed descriptive variation. Therefore, the role of virtual visual complexity in VR-based construction safety learning should not be evaluated only by assuming that simpler scenes are always better. Instead, visual design should be considered together with subjective experience and learning performance, while the EEG findings in this study serve as supplementary descriptive evidence rather than the main basis for practical recommendations.

5.4. Combined Effects of Real Ambient and Virtual Visual Factors on Construction Safety Knowledge Learning Performance

The descriptive and two-way interaction regression results provide complementary evidence on how environmental conditions were related to construction safety knowledge learning performance in the VR classroom. In the descriptive results, several higher-scoring combinations shared the same real ambient configuration of low temperature and noisy sound, whereas their virtual visual configurations differed. This pattern suggests that the real ambient environment was an important feature of the observed learning gains, but it does not indicate that noisy sound alone improved performance or that one virtual visual configuration was consistently optimal. The regression results provide further evidence for this pattern. Temperature, visual complexity, and window view were significantly associated with learning gain scores, while sound alone was not significant. The significant Temperature $\times$ Sound interaction indicates that the two real ambient factors

acted jointly in relation to learning performance. This result is consistent with previous evidence that thermal and acoustic conditions can produce combined effects on cognitive performance and perceived comfort, rather than functioning as completely independent influences [19]. The importance of temperature in the present results also agrees with evidence from learning environments that thermal conditions are related to short-term learning quality and cognitive functioning [5,6]. The sound-related results need to be interpreted together with both the learning-gain results and the subjective results. In the descriptive learning-gain results, several combinations with relatively higher scores included noisy sound. However, the subjective results showed that LP students perceived sound as more disturbing. This means that the noisy sound was not experienced as comfortable by these students, even though some higher learning gains were observed under conditions that included noise. Importantly, sound was not a significant main effect in the regression model, so the results do not show that noise itself improved learning performance. Instead, the significant Temperature $\times$ Sound interaction suggests that the role of sound was related to the temperature condition. In other words, sound should be understood as part of the thermal-acoustic setting rather than as an independent beneficial factor. One possible explanation is that subjective disturbance and immediate learning gain reflect different aspects of the learning process. LP students may have felt that noise disturbed their learning, but this feeling did not always lead to lower immediate test scores. A moderate level of background sound may also have increased alertness during the short video-based learning task for some students, while still being perceived as disturbing. Therefore, the present findings should not be interpreted as evidence that noisy sound is helpful for VR safety learning. They only suggest that the relationship between sound, temperature, subjective disturbance, and short-term learning gain is more complex than a simple “quiet is always better” assumption.

In contrast, no significant interaction was identified between real ambient factors and virtual visual factors. Therefore, the significant terms for visual complexity and window view indicate that virtual scene characteristics were related to learning scores, but not that their effects were strengthened or weakened by the real ambient conditions in this experiment. For VR-based construction safety knowledge learning, these findings suggest that the physical conditions surrounding the learner, particularly the thermal-acoustic configuration, should be carefully considered alongside virtual scene design when creating environments that support the acquisition of safety knowledge.

6. Research Limitations and Future Study

Several limitations should be considered when interpreting the findings of this study. The sample was drawn from a single university and consisted mainly of young adults on-campus students with undergraduate or higher educational backgrounds. This may limit the generalizability of the findings to broader learner populations, such as vocational trainees, older adults, or workers with practical construction experience. Although the study included 48 participants, the $2 \times 2 \times 2 \times 2$ factorial design produced sixteen environmental combinations, with three participants in each condition. The experimental design involved four binary environmental factors, namely temperature, sound, window view, and visual complexity. Therefore, the sample size should not be interpreted only as sixteen separate environmental scenes with three participants in each scene. For each single environmental factor, the two levels each included 24 participants, and the main analyses were conducted at the participant level using the four manipulated factors and their corresponding levels. Nevertheless, when all four factors were considered simultaneously as complete environmental combinations, each combination contained only three participants. Therefore, the descriptive results for the sixteen environmental combinations should be

interpreted as observed learning-gain patterns, while higher-order interaction effects would still require larger samples in future studies. The study mainly focused on main effects and two-way interactions because its purpose was to examine how real ambient factors and virtual visual factors were related to VR-based construction safety knowledge learning. Model fit, adjusted R^2 , degrees of freedom, and residual diagnostics were also reported to improve the transparency of the regression results. Previous controlled-environment studies with comparable participant-level samples have also used interaction analysis to examine combined environmental effects, which provides methodological support for this analytical approach. Future studies could include more diverse participant groups, increase the number of participants in each condition and further examine the full factorial structure, including higher-order interactions among temperature, sound, window view, and visual complexity.

The grouping and subjective-response analyses also have some limitations. HP and LP groups were created using a median split of learning gain, which helped compare students with different levels of learning improvement, but learning gain itself is a continuous measure. Therefore, the HP/LP comparison should be viewed as a way to describe performance-related response patterns rather than the only way to analyze learning performance. In this study, learning gain was also analyzed as an individual-level outcome in the interaction regression, which partly reduced the reliance on group comparison. In addition, the group-specific Spearman correlation analysis was used to explore possible associations between environmental factors and subjective outcomes. After multiple-comparison correction, the correlation results were interpreted mainly as preliminary evidence of possible response patterns rather than strong confirmatory findings. Future research could retain learning gain as a continuous variable and use larger samples to examine the relationships among environmental conditions, subjective responses, and learning outcomes in greater depth. Some subjective measures also need further improvement. In this study, perceived environmental distraction was measured separately for temperature, sound, window view, and visual complexity using one item for each environmental factor. This design allowed participants to directly report which environmental factor disturbed their learning process, but it also limited the assessment of internal reliability and construct validity. In addition, although NASA-TLX and the adapted CEQ items were used to collect broader subjective responses, reliability indices were not further analyzed in the present study. Therefore, the interpretation of subjective results should consider this measurement limitation. Future studies could develop multi-item scales for perceived environmental distraction in VR learning environments and report reliability indices, such as Cronbach's alpha, for all multi-item subjective constructs to provide stronger evidence of measurement validity.

This study focused on immediate learning gains. The pre-test and post-test used the same set of construction safety questions, and no feedback was provided after the pre-test to reduce additional learning before the VR task. This design was suitable for measuring short-term knowledge change after the instructional video, but it cannot show whether the learned knowledge was retained over time. Future studies could use delayed post-tests, equivalent question sets, or transfer tasks to examine longer-term learning effects. EEG was also used as a complementary measure of cognitive responses, but the environmental conditions did not produce significant EEG differences in mental workload, attention, or mental fatigue. This may be because the environmental manipulations were realistic and moderate, and their effects were more visible in subjective evaluation and immediate learning gain than in EEG indicators. Future studies could combine EEG with eye tracking, heart-rate variability, skin conductance, or behavioral attention measures to provide a fuller understanding of how real ambient factors and virtual visual factors affect construction safety learning in VR classrooms.

7. Conclusions

This study examined how real ambient factors and virtual visual factors are related to construction safety knowledge learning in VR classrooms by considering perceived environmental distraction, subjective workload, learning experience, cognitive response, and immediate learning gain. The findings indicate that students with different levels of learning improvement responded differently to the experimental environment. LP students reported significantly greater disturbance from temperature and sound, as well as higher mental demand and effort, whereas HP students reported significantly better self-evaluated performance and more favorable ratings of helpfulness, motivation, and perceived improvement in problem-solving skills. The group-specific correlation results further showed that environmental manipulations had a nominal association with perceived environmental distraction, subjective workload, and learning experience in LP students, whereas nominal associations in HP students were confined to selected learning experience measures. Although no significant condition effects were identified for EEG-based mental workload, attention, or mental fatigue in either group, the descriptive patterns showed greater variability in cognitive responses among LP students and suggested possible attention–fatigue differences across visual complexity conditions.

The learning-performance results provide specific implications for the design of VR-based construction safety knowledge learning environments. Descriptively, several higher-gain environmental combinations shared the same real ambient configuration of 22 °C and noisy sound, while their virtual visual configurations differed, indicating that the present results do not support prescribing one optimal combination of window view and visual complexity. The regression analysis further identified significant condition-specific terms for temperature, visual complexity, and window view, together with a significant Temperature $\times$ Sound interaction, showing that temperature and sound were jointly associated with immediate learning gain. Accordingly, under the conditions tested in this study, the thermal-acoustic setting should be configured and evaluated as a combined learning condition rather than assuming that a quieter environment alone will necessarily produce better safety knowledge learning outcomes. In addition, virtual visual factors were related to learning gains, although their effects should be interpreted together with the broader subjective and performance results rather than based on EEG patterns alone. The EEG results did not show significant condition effects, but the descriptive results suggested that a visually simplified setting may be accompanied by reduced attention and greater fatigue. Therefore, the design of VR-based construction safety classrooms may need to maintain sufficient visual context to support engagement with safety-learning content while avoiding unnecessary visual distraction. These findings demonstrate that the effectiveness of immersive construction safety knowledge learning is related not only to the instructional content presented in VR, but also to the specific real ambient and virtual visual conditions under which short-term learning takes place.

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Abbreviations

The following abbreviations are used in this manuscript:

HP	High-performing
LP	Low-performing
NASA-TLX	NASA task load index
CEQ	Course experience questionnaire
ICA	Independent component analysis
PSD	Power spectral density
VH	High visual complexity
VL	Low visual complexity
VD	View out for daytime
VN	View out for night
SN	Sound is noisy
SQ	Quiet sound
TH	High temperature
TL	Low temperature

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