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Integrating AI-Based Instruction into Immersive Site Visit in Construction Education: A Pilot Study

Mahzerin Sultana[1], Aushmeet Singh[1], Farshad Askari[1], Gilles Albeaino[1], and Wei Yan[1]
[1]Texas A&M University

Site visits are significant in Architecture, Engineering and Construction (AEC) education as they provide hands-on knowledge that bridges theory with practice. However, logistical, safety, and instructional constraints often limit their accessibility and effectiveness. While interactive virtual learning environments offer a promising alternative, most existing AEC virtual site visits rely on rigid, non-adaptive content with limited responsiveness to diverse learner needs. AI-based adaptive instructional support has the potential to address these limitations, yet its integration into AEC virtual site visits remains underexplored, leaving its feasibility and influence on learner experience insufficiently understood. This study presents the development and pilot evaluation of an AI-assisted virtual electrical systems site visit delivered through a desktop-based immersive virtual environment. By integrating AI models trained on domain-specific knowledge, the virtual environment provides context-aware and personalized instruction through real-time guidance, animations, and interaction via voice and text. The pilot study evaluated workload, motivation, usability, sense of presence, and engagement. Results indicated low workload, moderate motivation, acceptable usability, a moderate-to-high sense of presence, and active engagement among participants during the site visit. Overall, the findings demonstrate the feasibility of AI-assisted virtual environments for supporting practical AEC learning while highlighting the need for further refinement and investigation.

Keywords: AI-Assisted Virtual Environment, Adaptive Learning, AEC, Education, Site Visits

Introduction

Site visits play a key role in AEC education by connecting theoretical learning with practical, real-world experience through direct engagement in active jobsite environments (Sun et al., 2022). This active learning approach enhances students’ attention, sense of relevance, and motivation to engage in learning activities as well as critical thinking (Jusoh & Hadibarata, 2024), while encouraging peer and professional collaboration and expanding students’ understanding of career pathways (Adedokun et al., 2012). Yet, physical site visits encounter several challenges, including safety risks, restricted access, scheduling difficulties, financial and logistic constraints, and limited capacity for student participation, all of which can hamper their effective implementation (Eiris Pereira & Gheisari, 2019). To address this issue, alternative approaches are needed to overcome these challenges while preserving the educational and professional benefits of site visits and enhancing their accessibility and effectiveness within AEC education.

Among different solutions, virtual site visits have been developed to address the limitations of traditional in-person visits, primarily using Virtual Reality (VR) technology to recreate realistic construction site experiences (Wen & Gheisari, 2020). For example, Huang et al. (2020) found that students in a VR-assisted welding course achieved significantly higher final test scores and reported greater accuracy, efficiency and satisfaction compared to traditional training methods. Shiradkar et al. (2021) developed a VR-based site visit experience that enhanced student engagement and enjoyment while incorporating both text and visual-based training materials to accommodate diverse cognitive learning styles and improve knowledge retention. Some researchers have further increased the realism of their VR environments by incorporating Building Information Modeling (BIM) data and interactive 3D models. For instance, Cheng et al. (2021) utilized BIM-based 3D models of construction sites to create task-oriented safety training scenarios, allowing users to experience and learn to navigate fall hazards safely in a virtual environment. VR-based site visits offer key advantages over traditional methods by enabling realistic simulations in a controlled, risk-free setting, removing spatial, temporal, and logistical barriers, and providing flexible learning opportunities without the need for physical attendance (Wen & Gheisari, 2020). However, most existing virtual environments are static and pre-scripted, offering limited flexibility and requiring significant time and cost to modify, enhance, or adapt to changing learning goals. As a result, they lack adaptability to different learning contexts (Ogunseiju et al., 2023). Additionally, learners also vary in their cognitive capacities, prior experience, psychological characteristics, and preferred learning approaches. As a result, static or non-adaptive virtual content can overwhelm some learners with excessive cognitive loads while offering overly simple experiences to others, resulting in unequal learning outcomes (Zahabi & Abdul Razak, 2020). This lack of adaptability leads to monotonous, uniform learning experiences that fail to address individual learner needs (Moon et al., 2022), reducing engagement and failing to meet different and personalized learning needs.

The use of artificial intelligence (AI), including conversational and generative AI, has the potential to enhance AEC teaching and learning through the development of intelligent virtual training systems that enhance user interaction via virtual agents and dynamic content delivery. For example, Sabir et al. (2025) developed an AI-driven training system, featuring a virtual instructor that personalizes construction safety education by adapting content to the learner's trade and expertise level, thereby overcoming the static nature of traditional VR training. However, the feasibility and educational implications of embedding AI-driven instructional models specifically for virtual site visit environments remain underexplored. AI has the potential to address limitations of both in-person and virtual site visits by enabling more adaptive, interactive, and personalized learning experiences within digital immersive environments. Therefore, this study addresses this gap by developing and testing the AI-integrated virtual, intelligent, and scalable immersive environment designed to replicate site visit experiences in AEC education. The developed environment integrates AI-assisted instruction and dynamic content adaptation to enhance engagement, personalization, and learning retention. The study objectives are: (1) Development of AI assisted virtual site-visit training environment: to create a virtual training platform that allows AEC students to explore, interact, and learn in a way comparable to physical site visits ; (2) Integration of AI Assistant Models into the developed environment: to incorporate a domain-trained AI assistant that provides real-time instruction and contextual feedback within the virtual environment, enabling personalized learning experiences similar to a real instructor; and (3) Pilot Study of the developed environment: to conduct a pilot study evaluating the environment's usability, functionality, and preliminary educational feasibility and user experience with a sample group of users. This paper contributes to the body of knowledge by developing and pilot-testing an AI-embedded virtual site visit for AEC education and demonstrating its feasibility, thereby motivating future studies for further refinement and evaluation.

Methodology

A three-step procedure was adopted to accomplish the study objectives. While the developed system is designed to support virtual reality headset use, the pilot study described below was conducted exclusively using a desktop-based interface to increase accessibility and focus the evaluation on usability. The first step involved developing an interactive virtual site environment to simulate an electrical systems site visit. The second step consisted of developing an AI instructional model and integrating it into the developed environment. The third and final step included conducting a user centered pilot study where participants were asked to complete an electrical systems site visit in the developed environment and evaluated their cognitive workload, sense of presence, and the usability of the system. The following sections describe each step in detail.

Site Visit Selection

An electrical systems site visit was selected as the case study since Mechanical, Electrical and Plumbing (MEP) systems are known to be complex topics for AEC students and have been found to be associated with the highest number of site visits (Eiris Pereira & Gheisari, 2019). In this study, the virtual site visit within the virtual interactive environment replicated that of an in-person electrical system tour described in (Xu et al., 2025), conducted as a part of the *Course: COSC 325: Mechanical, Electrical, and Plumbing Systems* in the *Department of Construction Science at Texas A&M University*. The original tour followed the flow of electrical power through Francis Hall at the university, from the outdoor transformer and crawl space to the electrical rooms on each floor while the instructor described systems operations, safety, and equipment specifications.

Virtual Environment Development

There were two steps in the development of the virtual environment: (1) 3D Model Preparation and (2) Integration in Unity©. During the 3D model preparation stage, the electrical rooms targeted for the virtual site visit were first captured using an Insta360© camera. The captured data were converted into point cloud and imported into the existing 3D model of Francis Hall at their corresponding locations using Autodesk® Revit. The building's electrical system was then modeled against the imported point cloud data. This point-cloud-based modeling approach ensured accurate alignment between the digital model and real-world conditions, thereby enhancing the realism of the virtual environment. Major electrical components, including conduit ducts, outdoor transformers, and power distribution elements, were modeled using manufacturer-provided Revit families when available, while custom families were created as needed. Finally, the updated BIM assets were exported as FBX files and imported into Unity©, where textures, materials, lighting, and scene settings were optimized to support real-time interaction.

AI Assistant Development

This phase focused on developing an AI assistant capable of delivering personalized, context-aware guidance within the virtual environment (see Figure 1). Text-based data were extracted from electrical manuals, system codes, and site documentation, then organized into a structured JSON format to enable efficient querying and retrieval. Additionally, the instructor responsible for these site visits was recorded conducting a real-world walkthrough to capture authentic instructional context and dialogue. The raw text was cleaned, segmented into smaller sections, and semantically organized into a visual graph representing electrical system connection within the Francis Hall. A Retrieval-Augmented

Generation (RAG) model pipeline was implemented by indexing ~5,000 pages of construction related documents in a FAISS vector store and providing retrieved context to GPT-4o-mini for response generation. The data included the national electrical code, equipment manuals, Francis Hall floor plans, course notes, and the tour script. The assistant was validated via expert review (research team and course instructor) using >200 domain-specific questions. The fine-tuned conversational AI was integrated into Unity©, establishing a two-way communication link that maintained conversational context and supported real-time responses through either local inference or API calls.

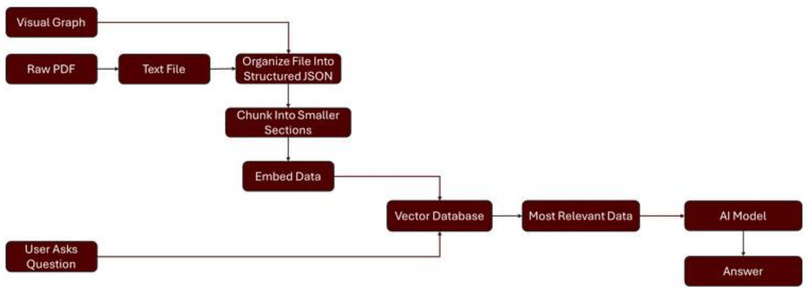

Figure 1. Workflow of AI Assistant model development

The developed AI Assistant model was then integrated into the interactive virtual environment (see Figure 2) enabling two-way communication through both text and voice. This integration allowed users to engage naturally with the system, while the personalized AI responded to user queries, creating a more immersive and realistic experience that closely replicated an actual, instructor-led site visit. A glowing highlight feature was applied to the electrical system components (e.g., conduits, ducts, equipment) to capture users' attention during the AI-guided narrations in the environment. The environment and AI model were iteratively enhanced with feedback from the course instructor to ensure technical accuracy and alignment with the learning objectives of the in-person site tour.

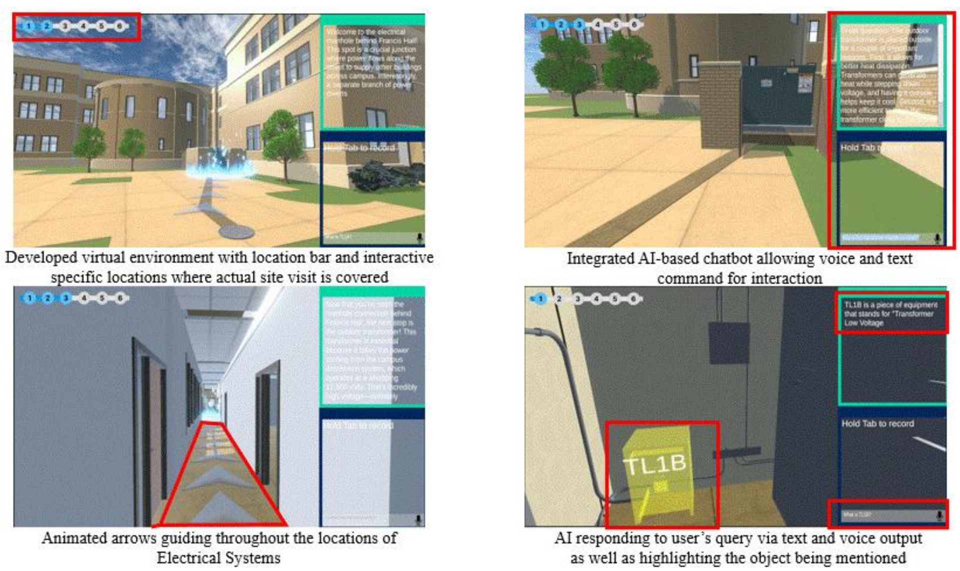

Figure 2. Developed environment and interactive UI

Pilot Study

The pilot study aimed to assess the preliminary educational feasibility of the developed platform. Participants were first provided with an online link via Qualtrics© to complete a demographic questionnaire. Upon completion, they were then invited to go through the virtual electrical site visit. The virtual electrical systems tour mirrored the structure of the real-world visit to the Francis Hall, leading participants from the outdoor transformer and crawl space to the top floor electrical room. During the session, the AI assistant delivered context-aware guidance and explanations by synchronized animations, graphical cues, and text-based instructions that highlighted key components and processes related to electrical systems throughout the environment. The AI model was also programmed to ask relevant questions after covering a specific electrical system topic and to answer participants' questions throughout the visit. This approach was designed to replicate the instructional flow of the original in-person site visit while leveraging the interactive capabilities of the virtual platform to enhance engagement and comprehension.

Each participant completed the virtual tour individually, exploring the building's electrical systems under the guidance of the integrated AI assistant. Immediately after the visit, students completed a post-visit quiz designed to assess their understanding of the electrical systems discussed during the tour. However, these test scores were not analyzed or reported because this feasibility pilot study prioritized system reliability and user experience measures; learning gains will be evaluated in a follow-up comparative study. Following the activity, participants completed six validated and widely used questionnaires to assess their experiential responses within the developed environment. These included the iGroup Presence Questionnaire (IPQ) for sense of presence (Schubert et al., 2001); the NASA Task Load Index (NASA-TLX) for perceived workload (Hart & Staveland, 1988); System Usability Scale (SUS) for overall system usability (Brooke, 1996); Chatbot Usability Questionnaire (CUQ) for AI assistance performance (Holmes et al., 2019a); Situational Motivation Scale (SIMS) for learner's motivation (Guay et al., 2000); and Engagement Questionnaire (EQ) for perceived engagement (Hannum & Simons, 2020). Statistical analyses were conducted to compute mean and standard deviation for each measure, and results were compared against established benchmark values.

Results and Discussion

Demographics

A total of 15 participants completed the experiment. Participants were split between males (N = 10, 67%) and females (N = 5, 33%). Most participants were under the age of 25 (N = 10, 66.7%), while the remaining participants were between 26 and 35 years old (N = 5, 33.33%). In terms of educational level, the sample consisted of eight (53.3%) undergraduate and seven (46.67%) graduate students. Participants had diverse educational backgrounds, ranging from Construction (N = 6, 40%) and Civil Engineering (N = 4, 26.67%), to Computer science (N = 2, 13.33%), Architecture (N = 1, 6.67%), Industrial Engineering (N = 1, 6.67%), and Mechanical Engineering (N = 1, 6.67%). Most participants reported having prior experience in AEC related work, with 10 participants (66.7%) having over two years of experience, while the remaining reported experience ranging from less than six months (N = 3, 20%) to two years (N = 2, 13.33%). In terms of familiarity with electrical systems, (N = 12) 80% of the participants indicated being either not familiar at all or slightly familiar, while (N = 3) 20%

reported being moderately familiar. Finally, participants reported moderate to high familiarity with digital platforms. Specifically, 53.3% (N = 8) indicated similar levels of familiarity with digital environments and the rest (N = 7, 46.67%) indicated slight familiarity.

Sense of Presence

The average score (M: mean; SD: Standard Deviation) of participants on a 7-point Likert scale (ranging from -3 to +3, where higher values indicate stronger presence and lower values indicate weaker presence; 0 indicates a neutral midpoint) are summarized on the four factors: Presence, Spatial Presence, Involvement, and Experienced realism. The overall mean score on the IPQ (M = 0.21, SD = 0.74) indicates that participants experienced a generally high level of presence during the pilot study when compared to established benchmarks for 3D monoscopic displays (Tran et al., 2024). This suggests that the virtual environment successfully conveyed a credible and engaging sense of being in the simulated space, even within the constraints of a desktop-based format. Examining the subscales provides further insight into the nature of this experience. Participants reported a modest but notable sense of 'being there' *(Presence*; M = 1.00, SD = 1.65) and a moderate level of *spatial presence* (M = 0.75, SD = 1.04), reflecting a satisfactory level of immersion and spatial awareness in the virtual environment. In contrast, *Involvement* was relatively low (M = -0.22, SD = 0.89), suggesting that participants' attention may have fluctuated between the virtual and real world, likely due to the use of a desktop interface rather than a head-mounted display. Meanwhile, *Experienced Realism* (M = -0.23, SD = 1.23) fell within the moderate-to-high range, indicating that the visual and contextual elements of the developed environment were perceived as believable and aligned with real-world expectations.

Perceived Workload

Table 1 summarizes participants' raw NASA-TLX scores (range: 0-20) for the six workload aspects (Mental, Physical, Temporal, Performance, Effort and Frustration). Overall, participants reported a minimal perceived workload throughout the virtual electrical systems site visit using the developed environment. While analyzing the six workload aspects individually, participants reported low mental load (M = 6.93, SD = 4.88), indicating the activity required cognitive involvement but was not mentally taxing. The physical demand was minimal (M =2.53, SD = 2.07), as anticipated in a virtual environment where physical engagement is restricted to basic navigation or viewpoint manipulation. The temporal demand was also low (M= 5.80, SD = 6.09), indicating that participants did not perceive time constraints and were able to proceed at their own pace, which is consistent with the study design, as no time pressure was imposed during the task. Regarding self-perceived performance, participants rated themselves relatively well (M = 7.20, SD = 6.85), demonstrating that they felt successful in completing the assigned task. Effort was also relatively minimal (M = 5.20, SD = 4.93) indicating participants did not have to work hard mentally or physically to accomplish their performance level. In terms of Frustration, the score was found to be extremely low (M = 2.20, SD = 3.63), which suggests participants felt secure and content, avoiding feelings of irritation, or stress during the task. The calculated overall NASA-TLX score (M = 24.89, SD = 12.37; range: 0-100) supports the interpretation that the perceived workload was below established benchmarks for desktop-based applications (Hertzum, 2021) but similar to other studies comparing VR, AR, and traditional methods Abdullah et. al (2024). While these findings suggest that students experienced no major difficulties using the system, additional studies are needed to examine the relationship between cognitive load and performance, especially since research suggests that maintaining an optimal level of cognitive workload can enhance learning and performance, whereas excessively low or high load may lead to under-engagement or cognitive overload.

Table 1. NASA-TLX Questionnaire

Workload Dimensions	**Mean ± SD**
Mental Demand (0 = Low, 20 = High)	6.93 ± 4.88
Physical Demand (0 = Low, 20 = High)	2.53 ± 5.18
Temporal Demand (0 = Low, 20 = High)	5.80 ± 6.09
Performance (0 = Good, 20 = Poor)	7.20 ± 6.85
Effort (0 = Low, 20 = High)	5.20 ± 4.93
Frustration Level (0 = Low, 20 = High)	2.20 ± 3.63
Overall Average NASA-TLX Score (0 = Low – 100 = High)	24.89 ± 12.37

System Usability

The SUS was used to measure the usability of the system, consisting of 10 questions rated on 5-point Likert scale (1 = strongly agree, 5 = strongly disagree). Participants' SUS responses reflected a positive perception of system usability. They indicated moderate interest in using the system frequently (M = 3.47, SD = 0.74) and strongly disagree that it was unnecessarily complex (M = 1.67, SD = 0.72). Most participants agreed that the system was easy to use (M = 4.40, SD = 0.51) and reported that they would not require technical support to operate it (M = 1.73, SD = 0.96). They also felt the system's functions to be well integrated (M = 4.0, SD = 0.92) and found little inconsistency in its operation (M = 1.67, SD = 0.91). Participants believed that most users would learn to use the system quickly (M = 4.33, SD = 0.72) and did not find it awkward to use (M = 2.07, SD = 0.96). Confidence while interacting with the system was high (M= 4.07, SD = 1.22), and participants disagreed that extensive learning or preparation was needed prior to use (M = 1.33, SD = 0.49). The overall SUS score was 79.50 ± 10.95, placing the system between the 'Good' and just below 'Excellent' usability range (Bangor et al., 2009). This indicates that participants found the system intuitive, efficient, and easy to learn, with minimal usability barriers that could interfere with task completion to overall experience.

Chatbot Usability Questionnaire

The CUQ was used to evaluate the usability of the chatbot integrated in the system, comprising 16 balanced questions rated on 5-point Likert scale (1 = strongly agree, 5 = strongly disagree). The overall CUQ score was 73.13 ± 13.97, which was above the benchmark value of 68 (Holmes et al., 2019b), indicating good usability and positive user experience comparable to other well performing chatbot systems. Participants moderately agreed that the chatbot's personality was realistic and engaging (M = 3.4, SD = 0.63) and were neutral about it seeming robotic (M = 3.0, SD = 0.85). They found the chatbot welcoming during the initial setup (M = 4.07, SD = 0.46) and strongly disagreed that it appeared unfriendly (M = 1.53, SD = 0.64). Participants also found the chatbot to be able to effectively explain its scope and purpose (M = 4.13, SD = 1.06), and they also disagreed that it failed to do so (M = 1.93, SD = 1.10). Navigation and ease of use were among the system's strongest aspects, with participants agreeing that the chatbot was easy to navigate (M = 4.20, SD = 0.77). Participants disagreed that it would be easy to get confused when using the chatbot (M = 1.80, SD = 1.08), suggesting that the interface was intuitive. They moderately agreed that the chatbot understood them well (M = 3.40, SD = 1.12) and disagreed that it failed to recognize many inputs (M = 2.20, SD = 1.26). Responses were viewed positively, with participants agreeing that the chatbot's replies were useful, appropriate, and informative (M = 4.07, SD = 0.96) and disagreeing that they were irrelevant

(M = 1.80, SD = 1.08). Error handling was rated moderately well, with participants agreeing that the chatbot coped well with mistakes (M = 3.40, SD = 0.83) and disagreeing that it was unable to handle errors (M = 2.33, SD = 0.98). They also found the chatbot very easy to use (M = 4.13, SD = 0.83) and strongly disagreed that it was complex (M = 1.40, SD = 0.51). Overall, these results indicate that the chatbot demonstrated strong usability, particularly in terms of ease of use, navigation, and friendliness. Moderate scores on understanding and naturalness suggest that while the system was effective overall, improvements could enhance the chatbot's conversational accuracy and responsiveness.

Situational Motivation Scale

The SIMS score was analyzed using four subscales: Amotivation (AM), External Regulation (ER), Identified Regulation (IR), and Intrinsic motivation (IM); each rated on a 7-point Likert scale (1 = corresponds not at all, 7 = corresponds exactly). The results reveal an increase from Amotivation to Intrinsic Motivation. Participants reported low *Amotivation* (M = 2.48, SD = 1.10), indicating that most participants saw relevance in the activity and did not feel disconnected from its purpose. *External Regulation* was also relatively low (M = 2.53, SD = 1.28), suggesting that engagement was not primarily driven by external pressures, grades, or rewards. In contrast, both *Identified Regulation* (M = 4.20, SD = 1.22) and *Intrinsic Motivation* (M = 4.40, SD = 1.46) were substantially higher. This pattern shows moderate overall response that aligns with Cluster 5 in the benchmark "blah" typology proposed by Stolk et al. (2021). This indicates that participants felt a little bit of everything, but nothing is particularly high or low.

Engagement Questionnaire

Participants' engagement during the virtual electrical systems site visit was measured using the Engagement Questionnaire (EQ), a validated 10-item scale comprising three factors: Active Involvement, Purposeful Intent, and Affective Value. Each item was rated on a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree). The scores were compared with the benchmarks of high engagement, defined as an average item score above 4.00 on a 7-point Likert scale, as established in the EQ validation (Hannum et al., 2021). Overall participants reported high levels of engagement. *Active Involvement* received the highest rating (M = 5.24, SD = 1.17), suggesting participants maintained strong focus and attention throughout the task. *Purposeful Intent* followed (M = 5, SD = 1.03), indicating that participants found the activity meaningful and were motivated to complete it. *Affective Value* was moderate compared to other factors (M = 4.76, SD = 1.72), reflecting general enjoyment and positive attitudes toward the experience. These results indicate that participants were attentive and positively engaged during the virtual activity.

Conclusion

The goal of this study was to develop and evaluate the feasibility of an AI-assisted, scalable environment for electrical systems site visit training. The conducted pilot study involved an AI-assisted virtual site visit within the developed environment, where participants examined their sense of presence, perceived workload, system usability, chatbot usability, motivation, and engagement. The results indicate that participants experienced high levels of presence, suggesting that the developed intelligent, interactive immersive environment effectively simulated aspects of a physical site visit.

Perceived workload scores were low, reflecting that participants could navigate and complete tasks without excessive cognitive or physical demand. Both system and chatbot usability were rated favorably, and participants demonstrated strong engagement and self-determined motivation throughout the activity. However, the overall sense of presence requires further improvement to enhance immersion and user experience in future development. Additionally, although the results indicate feasibility, the study's small sample size and single-domain focus (electrical systems) limit the generalizability of the findings. Moreover, the absence of direct comparisons with traditional physical site visits or other VR-based training platforms constrains the evaluation of the proposed system's relative educational effectiveness. Future research is warranted to address these limitations by improving the developed platform based on participant feedback, integrating the developed environment into a headset for MR applications to increase the sense of presence, expanding the sample size, introducing diverse AEC disciplines, enhancing the chatbot with more detailed data, and conducting comparative studies for comprehensive learning effectiveness evaluation. These efforts seek to strengthen the validation of the developed intelligent immersive environment as a scalable, accessible, and effective substitute for conventional site visits in AEC education.

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