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BEYOND SURVEYS: OBJECTIVE EEG-BASED ACCEPTANCE OF AR-HMDS FOR CONSTRUCTION TRAINING

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Xiaoying Yang, graduate student
Myers-Lawson School of Construction, Virginia Polytechnic Institute and State University
ORCID: https://orcid.org/0009-0001-9900-0451
xiaoyingy@vt.edu

Hanwen Ju, graduate student (Corresponding author)
Myers-Lawson School of Construction, Virginia Polytechnic Institute and State University
ORCID: https://orcid.org/0000-0003-1680-4698
hanwen@vt.edu

Jeremy Withers, Assistant Professor of Practice
Myers-Lawson School of Construction, Virginia Polytechnic Institute and State University
ORCID: https://orcid.org/0009-0002-9376-3922
jeremyw7@vt.edu

Tanyel Bulbul, Associate Professor
Myers-Lawson School of Construction, Virginia Polytechnic Institute and State University
ORCID: https://orcid.org/0000-0002-3015-5412
tanyel@vt.edu

SUMMARY: *Augmented Reality Head-mounted Displays (AR-HMD) hold great promise in improving construction workers' performance and safety through immersive training. However, their adoption in high-risk construction environments remains limited due to insufficient understanding of user acceptance. This study advances the measurement of technology adoption by integrating an extended Technology Acceptance Model (TAM) with Electroencephalogram (EEG) signals, creating a dual assessment framework that combines survey responses with objective neurophysiological indicators. The extended TAM incorporates motivational and experiential factors, while EEG captures mental workload and engagement to support the model's constructs. Both Partial Lease Square Structural Equation Modeling (PLS-SEM) and Bayesian Structural Equation Modeling (Bayesian SEM) confirmed perceived usefulness is a central predictor of user acceptance, with enjoyment, motivational support, and perceived system quality emerging as key drivers. EEG-derived measures, validated via correlation and multiple regressions, provided converging evidence that higher motivation and stronger adoption intentions were associated with reduced cognitive workload, and that EEG ratios independently predict perceptions of usefulness, ease of use, and enjoyment. These results highlight the value of combining subjective and objective measures to inform the design of cognitively supportive, user-centered AR training systems in safety-critical construction scenarios.*

KEYWORDS: *AR-HMD, EEG, work at height, technology acceptance model, PLS-SEM, Bayesian SEM.*

REFERENCE: *Xiaoying Yang, Hanwen Ju, Jeremy Withers & Tanyel Bulbul (2025). Beyond surveys: objective EEG-based acceptance of AR-HMDS for construction training. Journal of Information Technology in Construction (ITcon), Vol. 30, pg. 1912-1928, DOI: 10.36680/j.itcon.2025.078*

1. INTRODUCTION

Working at height is one of the most hazardous scenarios in construction. Tasks like welding, assembly, and installation require precise tool handling and balance on narrow surfaces, creating a cognitively demanding environment that compromises safety and efficiency. Inadequate training under such conditions can lead to hesitation, errors, and severe accidents.

Augmented Reality Head-mounted Displays (AR-HMDs), which overlay digital information onto real-world environments hands-free, have emerged as a promising tool to address these challenges by providing immersive, interactive training without exposing workers to physical risk (Li et al., 2018). By simulating hazardous scenarios, AR-HMD enables users to learn skills and familiarize themselves with work environments in safe settings. However, the realistic application of AR-HMD in safety-critical construction training remains limited, partly due to an incomplete understanding of users' perceptions. Prior studies have applied the Extended Technology Acceptance Model (TAM), a widely accepted framework for evaluating technology adoption, to VR/AR-based construction training. However, these studies typically rely on self-reported surveys without incorporating objective measures (Elshafey et al., 2020; Lee et al., 2022). Cognitive neuroscience offers an innovative, objective perspective for understanding user preferences beyond self-reported measures.

Electroencephalogram (EEG) is an electrical device that records brain signals in real time with high temporal resolution, reflecting users' cognitive states across different scenarios. With increasing portability, EEG has been used to examine workers' mental workload and engagement in construction tasks such as frame assembly and working on scaffolding (Qin et al., 2023; Jeon and Cai, 2023). Prior studies suggest that under high mental demand, users may perceive a system as less usable regardless of its actual utility (Wei and Lee, 2022). This indicates that cognitive states can affect user preference toward technical applications, yet no previous research has explored technology acceptance in construction from a neuroscientific perspective. Integrating EEG with TAM provides an opportunity to validate subjective acceptance constructs with physiological evidence and reveal the cognitive mechanisms driving technology adoption.

To address this gap, this study aims to understand users' perceptions towards AR-HMD-based training in an objective, neuroscientific manner. A work-at-height AR-HMD training system was developed to provide both safety and task-oriented instructions. The system is designed for novice construction trainees with no prior work-at-height experience and includes interactive guidance on safe movement, positioning, and measurement tasks fundamental to elevated work scenarios. To our knowledge, this study is among the first to combine an extended TAM with EEG measurements to evaluate user acceptance in high-risk construction contexts. The extended TAM includes motivational and experiential factors, while EEG measures cognitive workload and engagement during task performance. The objectives are to (1) assess user acceptance of the AR-HMD training system, (2) examine how EEG-based cognitive metrics affect user's subjective perceptions to provide an integrated understanding of AR-HMD technology acceptance in construction training.

2. LITERATURE REVIEW

2.1 XR in construction training

Extended Reality (XR) is an umbrella term for all real-and-virtual blended environments and human-machine interactions created through computing technology and wearable devices. It includes Virtual Reality (VR), Augmented Reality (AR) and Mixed Reality (MR), all of which have shown great potential in construction applications.

Virtual Reality (VR) uses computer software to generate realistic sounds, images, and other sensory inputs that create immersive environments simulating a user's physical presence. In construction, VR has been applied in project schedule control (Fu and Liu, 2018), site layout optimization (Muhammad et al., 2019) and enhancing collaboration among stakeholders and designers (Alizadehsalehi et al., 2019; Sutcliffe et al., 2019). Research shows that VR is effective for construction skills and safety training. For example, Pooladvand et al. (2021) developed a VR crane simulator integrated with databases to teach lift studies and crane path planning, while Teharni et al. (2022) created a VR scaffold training system. VR has also been used for hazard detection, where Jeon and Cai (2023) showed its feasibility in identifying construction hazards in immersive environments. However, the fully virtual nature of VR can limit physical realism and contextual awareness, which are critical in high-risk construction tasks (Li et al., 2018).

AR overlays virtual content onto the real world so users can interact with both virtual and real objects. It can be delivered through desktop-based systems and wearable devices. Wearables are widely used in construction applications as they allow hands-free operation, enabling workers to access digital information without interrupting tasks, despite limitations in field of vision and resolution (Alizadehsalehi et al., 2019). Interest in AR for construction is growing due to its ability to provide intuitive visual information and enhance environmental interaction (Fazel and Izadi, 2018; Chiang et al., 2022), and such trend has been further expedited by the COVID-19 epidemic where remote training is more favorable (Patel et al., 2025; Yang et al., 2025). Studies show AR supports frame assembly, timber fastening, and safety management (Huang, 2020; Qin and Bulbul, 2023).

Compared to VR, AR has advantages in construction training by integrating with real tools, providing users with greater on-site mobility, and helping users maintain awareness of their physical environment (Gong et al., 2024). This makes AR suitable for training in high-risk settings with real construction elements. For example, Qin and Bulbul (2023) reported lower cognitive workload with AR-based instruction for frame assembly compared to paper-based methods. Tan et al. (2024) found that AR increased engagement during collaborative steel reinforcement training. AR was also applied in hazard identification in safety training: Kim et al. (2017) delivered hazard information to help workers develop preliminary awareness and take proactive safety actions through AR system, while Liu et al. (2024) argued that AR's effect on hazard identification varied in terms of the complexity and safety of the work environment. Therefore, AR has shown promise in improving task efficiency, enhancing user engagement, and reducing cognitive workload, which are crucial to ensure worker safety and effective training. However, there is still a debate about high customization costs in various usage scenarios and the limited exploration of its technological acceptance among trainees and workers (Paoletti, 2017; Merhar et al., 2019).

Mixed Reality (MR), a concept between VR and AR, is also applied in construction training, where Wu et al. (2022) developed real-time hazard information system with wearable mixed reality device, showing high alignment accuracy and improved feasibility in high-risk environments. However, it is less used as it's loosely defined and has few devices on the market (Alizadehsalehi et al., 2019).

2.2 Technology acceptance in AR

User acceptance is a key concern when introducing new technologies in safety-critical environments, where the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) are among the most widely used frameworks to investigate adoption (Williams et al., 2015). Derived from the theory of human reasonability (Ajzen, 1980), TAM explains the technology acceptance through Perceived Usefulness and Perceived Ease of Use (Davis et al., 1989). To address the complexity of modern technologies, additional constructs can be incorporated to form extended TAM.

Extended TAM is commonly used to assess the adoption of AR systems for learning. Through extended TAM, Iqbal and Sidhu (2022) found that complexity, enjoyment, and self-efficacy significantly influenced the usability of a dance learning system. From the teaching perspective, similarly, Jang et al. (2021) assessed teachers' readiness to integrate VR/AR in classrooms, highlighting the role of motivational support in shaping ease of use and subsequent adoption. Common external constructs in extended TAM of AR include enjoyment, motivational support, and social norms (Jang et al., 2021; Iqbal and Sidhu, 2022; Graser and Böhm, 2024).

In the construction domain, extended TAM has proven effective in evaluating emerging technologies. Through the TAM model, Liu et al. (2018) identified usefulness and user-friendliness as key factors in smart construction system adoption, while Sorce and Issa (2021) found that usefulness, culture, and industry influence affect the intention to use information and communication technologies among U.S. construction professionals. When AR/VR is introduced in construction, Elshafey et al. (2020) showed that user control and ease of use significantly influence the perceived usefulness of AR-BIM systems, while both Yan et al. (2021) and Zhang et al. (2022) used TAM to show that enjoyment affects users' perceived usefulness and ease of use while evaluating VR applications in safety-related construction training. However, existing research rarely addresses high-risk construction scenarios in AR. Since Liu et al. (2024) found that effectiveness of AR system varied depending on the safety level and complexity of construction tasks, such variability suggests in high-risk scenarios with restricted movement, limited visibility, and elevated cognitive load, adoption of AR may face distinct challenges. This underscores the need to investigate user acceptance of AR training systems in high-risk contexts. While with broad applications in all fields, evaluate TAM subject to overestimation and reduced reliability due to its survey-based nature (Goodhue, 2007; Venkatesh et al., 2012). There is a growing need to complement self-reported data with objective methods to improve the validity of TAM-based estimates.

2.3 EEG for measuring cognitive workload and user experience

EEG is a non-invasive neuroimaging technique that measures brain activity through electrodes on the scalp. Its portability, high temporal resolution, and ability to provide real-time feedback make it well-suited for dynamic and safety-critical environments like construction. For instance, Tehrani et al. (2022) assessed workers' mental fatigue during VR-based work-at-height simulations using EEG, showing that height exposure induced higher mental fatigue levels. Similarly, Qin et al. (2023) evaluated users' mental workload during assembly tasks with instructions and demonstrate that EEG effectively captured changes in cognitive demand.

Beyond performance monitoring, EEG has also been linked to user perceptions. Moridis et al. (2018) revealed that frontal EEG asymmetry could predict users' perceptions of key elements in the TAM framework such as playfulness, usefulness and ease of use. Likewise, Ding et al. (2020) found a positive correlation between subjective experience with smartphones and gamma band power, suggesting neural patterns can be used as indicators of perceived system quality. These findings underscore EEG's potential to capture user states which are not easily accessible through self-report methods. However, in most construction scenarios, the integration of EEG and subjective surveys remain largely unexplored.

2.4 Structural equation modeling approaches in TAM evaluation

Structural Equation Modeling (SEM) is statistical technique that examines the relationships between multiple independent and dependent variables (Ullman and Bentler, 2012). Among SEM techniques, Partial Least Squares Structural Equation Modeling (PLS-SEM) is flexible with respect to sample size and data distribution, making it suitable for exploratory research and small-sample contexts (Hair et al., 2021). Therefore, it has been widely applied to evaluating technology adoption in both construction and AR studies (Chong et al., 2023; Saqib et al., 2023; Cheng et al., 2024). In terms of the measurement model, Hair et al. (2021) suggest that averaged variance extracted (AVE) ensures the convergent validity. Cross-loading and Fornell-Larcker criterion are commonly used to assess discriminant validity (Henseler et al., 2015). Nevertheless, PLS-SEM has been criticized for potential bias in indicator weights, AVE and Composite Reliability (Rönkkö et al., 2023). Therefore, alternative metrics such as the Heterotrait - Monotrait ratios of correlations (HTMT) need to be considered (Henseler et al., 2015).

While PLS-SEM is well-suited for exploratory analysis in small-sample contexts (Al-Maroof and Al-Emran, 2018), Bayesian Structural Equation Modeling (Bayesian SEM) can be employed to validate findings and assess the robustness of results under a Bayesian estimation framework (Rahman et al., 2025). As another effective SEM tool to evaluate small-sample studies (McNeish, 2016), Bayesian SEM combined the SEM framework with Bayesian estimation, enabling the incorporation of prior knowledge into the model and producing full posterior distributions for parameters (Smid et al., 2020). However, the performance of Bayesian estimation depends heavily on the choice of prior distributions, where inappropriate priors may lead to unstable results and high uncertainty in posterior estimates (McNeish, 2016). Given the respective advantages and limitations of both SEM techniques, the choice for evaluating technology acceptance should be based on the study goals, data characteristics and availability of prior information.

3. METHODOLOGY

To evaluate user acceptance of AR-based training systems in high-risk construction scenarios, this study proposes an extended TAM augmented with EEG-based cognitive measures shown in Figure 1. A multi-layered analytical framework was employed, integrating subjective user-perception data with objective neurophysiological measures. First, structural modeling methods including PLS-SEM and Bayesian SEM were used to test the extended TAM and validate theoretical pathways among latent constructs. Next, Pearson correlation analysis examined the linear relationship between EEG-derived cognitive features and TAM latent variable scores. Finally, multiple linear regression identified EEG features that independently predict user perceptions while controlling for shared variance among EEG bands. By combining survey data, structural modeling, and EEG metrics, the study provides a triangulated neurophysiological assessment of user acceptance of AR training in high-risk construction tasks.

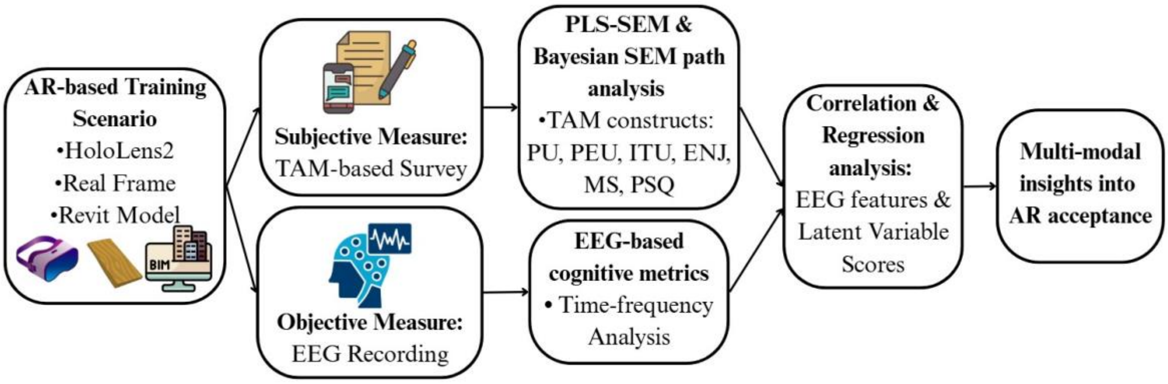

Figure 1: Methodological Framework of the TAM and EEG-Enhanced User Acceptance Study.

3.1 Experimental design

40 participants, including 28 male and 12 female construction students without cybersickness in the virtual environment, were recruited for the experiment. Most participants had limited or no prior experience working at height, making this simulation a valuable opportunity to engage in tasks that are difficult to replicate in conventional classroom settings. Demographic data, construction knowledge, and prior exposure to AR technologies were collected to characterize the participant pool.

To simulate a work-at-height training environment, an AR-HMD was applied to overlay a virtual 3D model onto a real-scale wooden frame laid flat on the ground. As shown in Figure 2(a), the virtual model created by Revit represents a two-story, 3,000-square-foot hybrid wood residential building and was deployed on HoloLens 2, the AR device used in this study. The experimental area is highlighted in Figure 2(b), where participants were instructed to move between point A and point B four times, performing tasks including standing, walking, lifting, and measuring according to the training instructions in each round. Figure 2(c) illustrates a participant measuring on the frame using laser from the index finger, while Figure 2(d) provides the view of the AR interface from the user's perspective. The simulation offered high visual fidelity and immersive user experience. To enhance the sense of presence, passive haptic feedback was incorporated through the wooden frame placed on the ground. As shown in Figure 2(e), users can see the virtual model while performing the experimental tasks on the frame, creating a mixed-reality training environment.

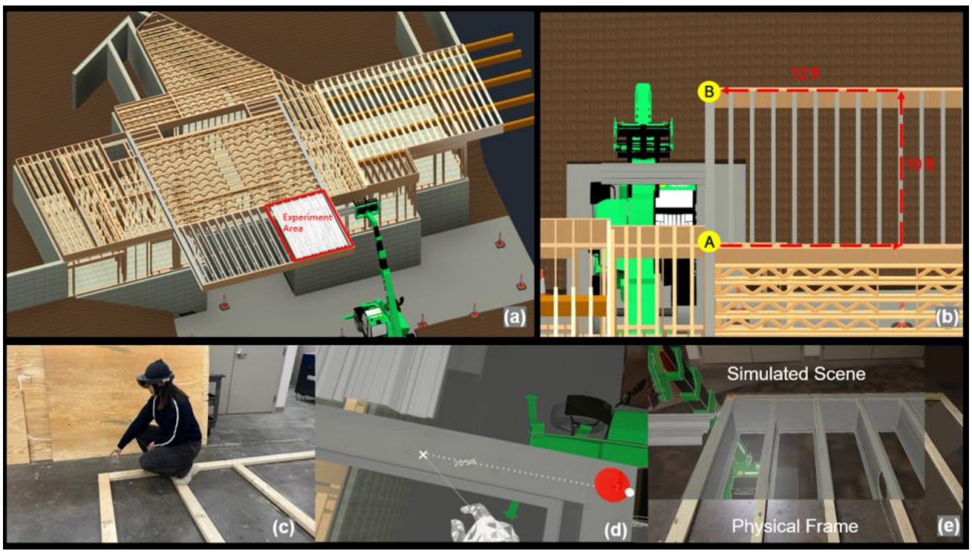

Figure 2: AR-based work-at-height training setup. (a) Revit model of the building with experiment area. (b) Task zone and movement path. (c) Participant measuring on the physical frame. (d) User's AR view with virtual overlay. (e) Passive haptic feedback via real-scale frame.

3.2 TAM constructs and hypotheses

The core TAM construct, including Perceived Usefulness (PU), Perceived Ease of Use (PEU), and Intention to Use (ITU), were retained while three external commonly used in AR acceptance studies were incorporated: Perceived Enjoyment (ENJ), Motivational Support (MS), Perceived System Quality (PSQ).

(1) Intention to Use (ITU)

ITA refers to a user's willingness to use technology in the future (Davis, 1989). In this context, it captures the extent to which participants are willing to use similar AR applications for future construction training or real-world applications.

(2) Perceived Usefulness (PU)

PU is the degree to which an individual believes that using technology will improve their job performance (Davis, 1989). In this study, it reflects how participants perceived the AR system as improving their ability to understand, perform, and practice work-at-height construction tasks effectively and safely. PU is a critical factor of ITU in the TAM framework (Saqib et al., 2023).

(3) Perceived Ease of Use (PEU)

PEU is the extent that an individual believes that using a new technology requires minimal effort (Davis, 1989). Here, PEU reflects how intuitive and user-friendly that participants found the AR training experience. Prior studies indicate that PEU can affect PU, ITU, and external factors such as enjoyment (Choi et al., 2017; Saqib et al., 2023).

(4) Perceived Enjoyment (ENJ)

ENJ refers to the degree to which using a system is perceived to be enjoyable, independent of any performance outcomes (Davis, 1992). In this case, ENJ captures how engaging and satisfying the participants found the AR training. Similar studies have shown that ENJ can influence acceptance of mixed reality in museums (Hammady et al., 2020). Zhou and Feng (2017) showed that it is a key determinant of users' perceptions of usefulness of video calling system.

(5) Motivational Support (MS)

MS refers to the encouragement, guidance, and resources provided by supervisors and peers that create a collaborative and supportive culture for technology use (Ertmer and Ottenbreit-Leftwich, 2010). In this study, MS is used as an external factor reflecting the level of support participants felt during the AR training. It represents the AR system's ability to make users encouraged and capable in a novel learning environment. In Jang's study (2021), MS significantly influences PEU and may also impact PU.

(6) Perceived System Quality (PSQ)

PSQ refers to a user's perception of the consistency between real haptic feedback and virtual elements in an AR system that reflects the accuracy and reliability of the system. Previous studies have shown that perceived system quality significantly effects user satisfaction in e-learning system (Islam, 2012). Calisir et al. (2014) also demonstrated that perceived ease of use can be explained by perceived system quality. Haptic-virtual consistency is critical in evaluating AR training systems, as it enables users to interact seamlessly and trust the system's guidance. Inconsistencies such as misaligned virtual instructions, have been found to significantly impact performance (Lee et al., 2015), which may reduce the system's perceived reliability (lowering PU), and increase interaction difficulty (lowering PEU).

Based on literature and contextual characteristics of the AR application, the hypotheses for this study were established as listed below. To ensure the validity and reliability of the extended TAM model, latent variables were assigned to each construct, and its theorical framework is presented in Figure 3.

H1: PEU positively influences PU.

H2: PEU positively influences ITU.

H3: PU positively influences ITU.

H4: PEU positively influences ENJ.

H5: ENJ positively influences PU.

H6: MS positively influences PU.

H7: MS positively influences PEU.

H8: MS positively influences ITU.

H9: PSQ positively influences PEU.

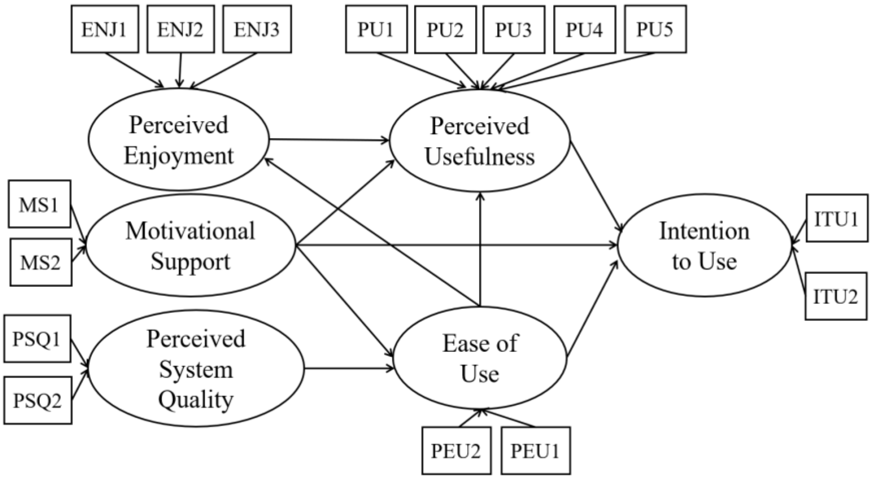

Figure 3: Theoretical framework of extended TAM model.

3.3 Structural equation modeling: PLS-SEM and Bayesian SEM

To test the proposed model and hypotheses, both PLS-SEM and Bayesian SEM were conducted using WrapPLS 8.0 software and python. Considering the small sample size in this exploratory study (n=40) and the lack of prior knowledge regarding AR application in high-risk construction tasks, PLS-SEM was selected as the primary method to examine the relationships among extended TAM constructs, while Bayesian SEM with default prior distributions was applied to validate the PLS-SEM results.

In PLS-SEM, measurement model is first assessed to ensure the reliability and validity of the latent constructs. Cronbach's alpha (α) and Composite Reliability (CR) no less than 0.7 indicated acceptable internal consistency. Then, convergent validity was examined using the Average Variance Extracted (AVE), with a minimum value of 0.5 indicating adequate convergence. Discriminant validity was confirmed using the Fornell-Larcker criterion (FL criterion) through AVE and HTMT (> 0.9), ensuring that each construct was distinct from the others. All indicators were retained if they showed strong factor loadings (≥ 0.7) and contributed meaningfully to the construct measurement.

Once the measurement model was validated, the structural model was examined to test the proposed hypotheses. Path coefficients (β) were estimated to determine the strength and direction of relationships between constructs. Bootstrapping with 5,000 resamples was used to assess the statistical significance of each path by calculating p-values. In addition, the coefficient of determination (R^2) values was reported to reflect the proportion of variance explained in each endogenous variable. The structural model results provided evidence on which hypotheses were supported and clarified how latent constructs affect users' intention to adopt the AR training system.

To validate the PLS-SEM results, Bayesian SEM was conducted using Python. Default normal priors were assigned to all regression coefficients, and half-normal priors to residual standard deviations. Posterior distributions were estimated using Markov Chain Monte Carlo sampling with 2,000 draws and 1,000 tuning steps. The Bayesian SEM results were evaluated using posterior mean, standard deviation, and 95% highest density interval for each parameter to determine the strength and credibility of the relationships. Convergence was assessed using the R-hat statistics and effective sample size. This approach provided a robustness check of the relationships among extended TAM constructs and confirmed whether the patterns observed in PLS-SEM were supported under a Bayesian framework. The consistent results in both models will be accepted in this study.

3.4 EEG acquisition, preprocessing and feature extraction

To complement subjective data with objective metrics, EEG was used to capture users' cognitive states. EEG was recorded using Emotive FLEX with 32 channels (Figure 4(b)) throughout the AR training session, covering all tasks including walking, measuring, and placing boards. As shown in Figure 4(c), electrodes were placed in terms of the international 10-20 system (Homan et al. 1987). The sampling rate was set to 128 Hz to ensure high-resolution capture of brain activity during the AR session.

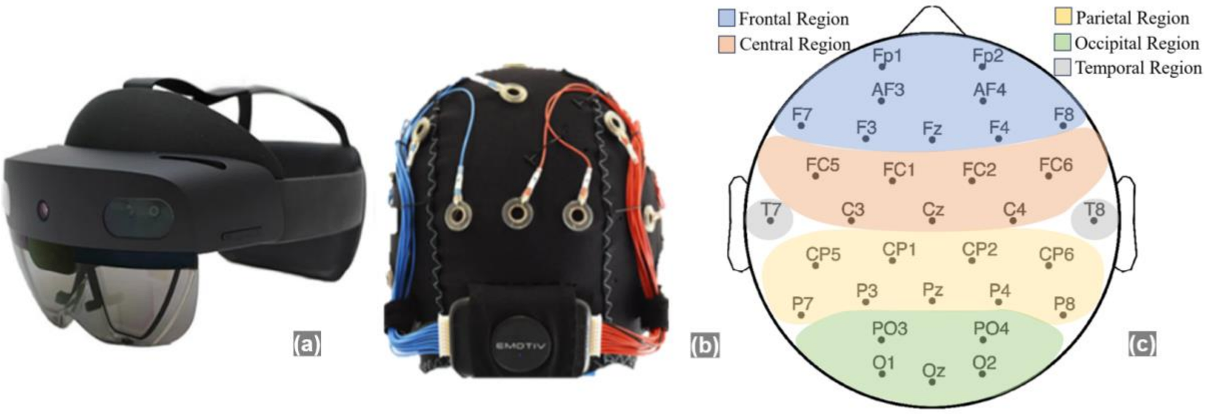

Figure 4 : Experimental devices and EEG electrodes layout.
(a) HoloLens2; (b) Emotive FLEX (32 channels); (c) EEG electrodes and regions layout.

As the experiment involved body movement during part of AR-HMD use, several procedures were implemented to minimize motion-related EEG artifacts. First, participants were instructed to keep head movements smooth and avoid abrupt motions. The EEG cap was secured with additional straps to reduce displacement during movement. In preprocessing, EEG signals were filtered using a 0.5-60 Hz band-pass filter to remove frequency components outside the range of interest. Bad channels were removed, and Independent Component Analysis (ICA) was applied to remove eye blinks, muscle artifacts, and movement-related components. Epochs exceeding amplitude or variance thresholds were automatically rejected. These combined hardware- and software-based steps are consistent with prior research for EEG acquisition in mobile AR/VR environments and ensure that the retained segments reflect reliable neural activity. Then, the cleaned time-series signals were segmented into non-overlapping 2-second epochs. For each epoch, power spectral density was calculated using Discrete Wavelet Transform (DWT), which preserves temporal structure for non-stationary signals (Asaduzzaman et al., 2010). The signals were decomposed into standard EEG frequency bands: delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-50 Hz). EEG features were extracted from frontal electrodes (Fz, Afz, AF3, AF4, F3, F4, F1, F2), which are associated with attention, emotion, and other higher-order cognitive functions (Wascher et al., 2014; So et al., 2017; Allen et al., 2018).

Table 1: Cognitive states and corresponding EEG frequency-based metrics.

Cognitive State	**EEG Metric**	**Formula**	**Reference**
Cognitive Workload	Theta/Alpha	θ/α	Gruzelier, 2009; Qin et al. 2023
Attention	Theta/Beta	θ/β	Morillas-Romero et al. 2015
Engagement	(Alpha + Theta)/Beta	$(\theta + \alpha) / \beta$	Zhang et al. 2019
Engagement	Beta/ (Theta + Alpha)	$\beta / (\theta + \alpha)$	Zhang et al. 2019
Vigilance	(Theta + Beta) / (Alpha + Gamma)	$(\theta + \beta) / (\alpha + \gamma)$	Wang et al. 2017
Emotional Valence	Frontal Alpha Asymmetry (FAA)	$\log(\alpha\_right) - \log(\alpha\_left)$	Allen et al. 2018

To quantify cognitive states, frequency band ratios were computed using frontal lobe activity. These ratios are frequently used in EEG-based cognitive neuroscience to evaluate mental workload, engagement, vigilance, attention, and emotions, which are listed in Table 1. EEG features were calculated as the average power across the entire AR session and across all participants to capture participants' general neurophysiological responses during system use, allowing correlation analyses with their responses to the extended TAM questionnaire.

3.5 Correlation and regression analysis between EEG and TAM constructs

To complement the structural modeling results and integrate objective cognitive indicators into the evaluation of user acceptance, EEG-derived features were statistically associated with TAM latent constructs. Each participant's latent variable scores were calculated as the means of their corresponding indicators for equal latent construct representation (Anggorowati, 2014; Rönkkö et al., 2023).

The analysis consisted of two steps. First, Pearson's correlation coefficient was computed between each TAM construct (PU, PEU, ITU) and the EEG features including both frequency-band power and cognitive-state ratios. Statistical significance was evaluated using $p < 0.05$. These correlations provided an initial overview of linear associations between subjective technology acceptance measures and neurophysiological responses during AR-HMD use. Second, multiple regression analyses were conducted to determine whether specific EEG features independently predicted individual TAM construct. This step was necessary as EEG features are often intercorrelated, and regression allows unique predictors that contribute to explaining variance in each TAM outcome. The regression was evaluated using standardized coefficients, p values, and R^2 values to quantify the proportion of variance in each TAM construct explained by the EEG metrics.

Together, the correlation and regression analysis provided a comprehensive understanding of the correlations between neural activity and technology acceptance. By linking subjective perceptions with brain-based indicators, the study offers a richer, neurophysiological interpretation on user experience and acceptance in AR-based construction training environments.

4. RESULTS

This section presents the descriptive results of the survey, followed by the validity and reliability analysis of the TAM model, the structural model results of the extended TAM, and finally the correlations between EEG metrics and latent variable scores of the TAM constructs.

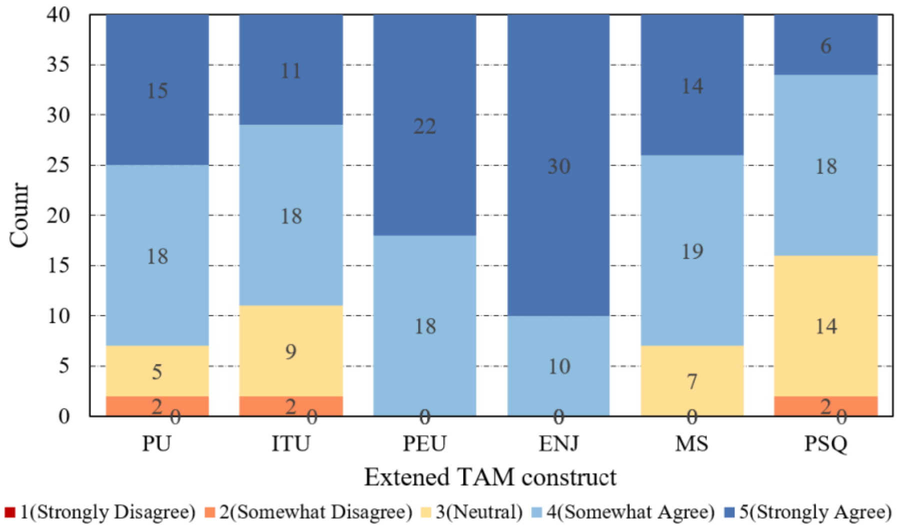

Figure 5: Descriptive Results of extended TAM constructs.

Figure 5 presents the distribution of participants' responses to the extended TAM constructs. The survey data collected from 40 participants is shown as stacked bar plots reflecting Likert-scale responses (1 = strongly disagree to 5 = strongly agree). Overall, the responses skewed positively across most constructs. Notably, ENJ received the strongest agreement, with 30 participants selecting "strongly agree," indicating high satisfaction with the AR training system. PEU and PU also showed favorable responses, with 22 and 15 participants selecting "strongly agree," respectively. For PSQ and MS, a greater variation in responses was observed, including a higher number of neutral responses, suggesting more diverse perceptions in these domains.

Table 2 presents the results of construct reliability and convergent validity assessments. All constructs demonstrated acceptable internal consistency, with Composite Reliability (CR) values ranging from 0.825 to

0.904, exceeding the recommended threshold of 0.70 (Hair et al., 2021). Cronbach's alpha values were also satisfactory ($\alpha > 0.70$) for most constructs, except for ITU ($\alpha = 0.575$), which is marginal but acceptable considering its strong performance in CR and AVE (Venkatesh and Davis, 2000). In terms of convergent validity, all Average Variance Extracted (AVE) values exceeded the 0.50 threshold, indicating that each construct explains more than half of the variance in its respective indicators (Fornell and Larcker, 1981).

Table 2: Construct reliability and convergent validity results.

Factors	PU	ITU	PEU	ENJ	PSQ	MS
Composite Reliability (CR)	0.834	0.825	0.837	0.859	0.890	0.904
Cronbach's alpha	0.752	0.575	0.704	0.749	0.753	0.788
Averaged Variance Extracted (AVE)	0.502	0.702	0.633	0.674	0.802	0.825

Table 3 reports AVEs to evaluate inter-construct correlations. Based on FL criterion, discriminant validity is confirmed when the square root of each construct's AVE (shown on the diagonal in parentheses) is greater than its correlations with other constructs, which is true for all cases. Meanwhile, HTMT results in Table 4 are all below 0.9, further supporting discriminant validity. Overall, the measurement model shows strong reliability, convergent validity, and discriminant validity, providing a solid foundation for evaluating the structural model.

Table 3: Discriminant Validity Assessment by Fornell-Larcker Criterion.

	PU	ITU	PEU	ENJ	PSQ	MS
PU	(0.709)					
ITU	0.465**	(0.838)				
PEU	0.479**	0.113	(0.795)			
ENJ	0.705***	0.327*	0.611***	(0.821)		
PSQ	0.182	0.250	0.025	0.064	(0.896)	0.279
MS	0.821***	0.421**	0.356*	0.628***	0.279	(0.909)

*(Note: Diagonal values are square roots of AVEs. $p < .05$ = *, $p < .01$ = **, $p < .001$ = ***.)*

Table 4: Discriminant Validity Assessment by HTMT (good if <0.90).

	PU	ITU	PEU	ENJ	PSQ	MS
PU						
ITU	0.717					
PEU	0.672	0.326				
ENJ	0.890	0.499	0.836			
PSQ	0.296	0.379	0.173	0.193		
MS	0.895	0.625	0.476	0.822	0.362	

Figure 6 (a) and (b) present structural model comparable results from both PLS-SEM and BSEM respectively. As PLS-SEM uses frequentist statistics relying on p-values while BSEM uses Bayesian inference generating probabilistic intervals, their results look different while comparable. PLS-SEM represents standardized coefficients (β) with p-values from bootstrapping, while BSEM reports the posterior mean with its 95% credible interval (CI). Effects are considered credible when zero is not included in the CI (Zyphur and Oswald, 2015), serving a role similar to significance testing.

The PLS-SEM model explains 79% of the variance in PU, 34% in PEU, and 32% in ITU. In both approaches, the results show consistent patterns: Motivational Support (MS) is a strong determinant of PEU, PU, and ITU; Perceived Enjoyment (ENJ) contributes positively to PU; Perceived System Quality (PSQ) predicts PEU; and PU consistently derives ITU. These stable effects in both statistical methods indicate that motivation, enjoyment, system quality, and perceived usefulness are robust factors in shaping user acceptance of the AR system.

The main inconsistencies appear around PEU. In PLS-SEM, PEU significantly predicts PU ($\beta = 0.36$, $p = 0.01$) but shows no predict effect on ITU ($\beta = 0.15$, $p = 0.15$). In contrast, BSEM finds no credible link from PEU to PU (-0.04 [-0.37, 0.32]) but identifies a credible positive influence of PEU on ITU (0.43 [0.04, 0.82]). Taken together, the findings consistently support the roles of MS, ENJ, PSQ, and PU, while revealing that PEU's influence depends on the estimation method This divergence highlights further studies of PEU in AR training system are needed. Among the proposed hypotheses, all hypotheses were supported except for H1 and H2.

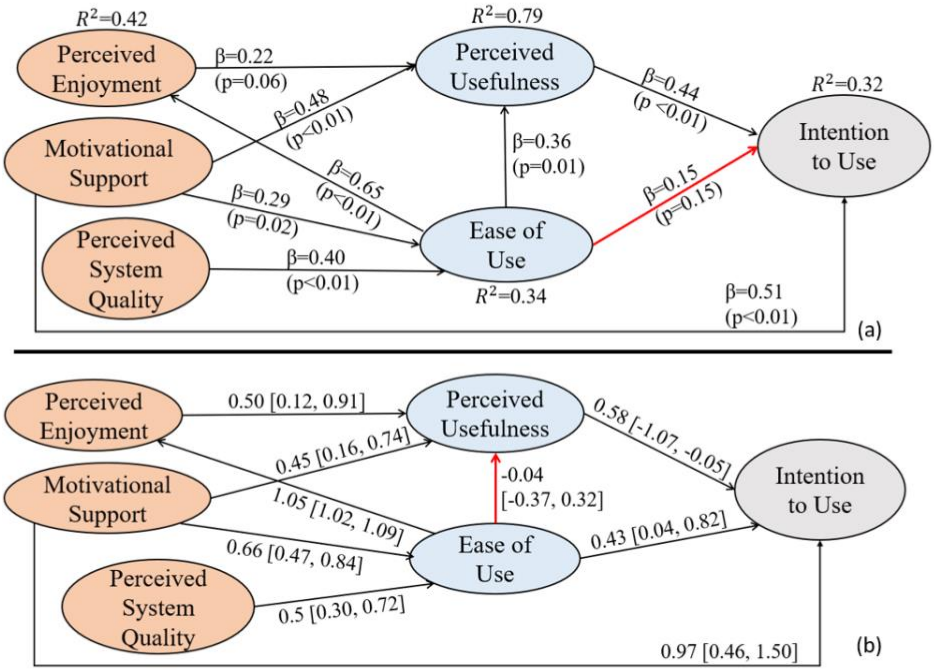

Figure 6: Results of Structural Path Model using (a) PLS-SEM and (b) BSEM.

Table 6 reveals correlations between EEG-derived cognitive metrics and participants' self-reported TAM constructs. MS was negatively correlated with the Theta/Alpha ratio (r = -0.35, p = 0.028), suggesting that lower Theta/Alpha, a marker of reduced cognitive workload, was observed in participants reporting higher motivational support. Similarly, ITU was negatively correlated with Theta/Alpha (r = -0.33, p = 0.041), indicating an association between behavioral intentions and EEG-based cognitive workload. Additional trends included negative correlations between MS and composite vigilance ratio ((Theta + Beta) / (Alpha + Gamma), r = -0.31, p = 0.053) and between PU and Theta/Alpha (r = -0.29, p = 0.066). Gamma power showed a positive trend with PSQ (r = 0.29, p = 0.069), reflecting increased cognitive processing or arousal during analytical engagement with the AR system.

Table 6: Correlation results between TAM constructs and EEG features.

TAM construct	EEG features	Correlation (R)	Probability (p value)
MS	Theta / Alpha	-0.347	0.028
ITU	Theta /Alpha	-0.325	0.041
MS	(Theta + Beta) / (Alpha + Gamma)	-0.308	0.053
PU	Theta / Alpha	-0.293	0.060
PSQ	Gamma	0.290	0.069

Moreover, Table 7 presents the results of multiple linear regression examining the predictive relationships between EEG-derived cognitive metrics and TAM constructs. For PU, both the Theta/Alpha ratio (β = 10.712, p = 0.049) and Theta/Beta ratio (β = -39.575, p = 0.044) significantly predicted participants' perceptions of usefulness, with the model explaining 52.6% of the variance (R^2 = 0.526). PEU was significantly predicted by the Theta/Beta ratio (β = -27.661, p = 0.049), accounting for 36.0% of its variance. Perceived enjoyment (ENJ) was influenced by multiple EEG metrics, including Theta/Beta (β = -37.665, p = 0.006), Theta/Alpha (β = 8.887, p = 0.027), and (Alpha + Theta)/Beta ratio (β = 26.732, p = 0.013), with the regression model explaining 53.7% of the variance. These results indicate that specific EEG features independently contribute to predicting participants' cognitive and affective perceptions of the AR system.

Table 7: Multiple linear regression results between TAM constructs and EEG features.

TAM construct	EEG feature	Regression β	Regression p	R^2
PU	Theta/Alpha	10.712	0.0492	0.526
PU	Theta/Beta	-39.575	0.0441	0.526
PEU	Theta/Beta	-27.661	0.0487	0.360
Enjoy	Theta/Beta	-37.665	0.0059	0.537
Enjoy	Theta/Alpha	8.887	0.0271	0.537
Enjoy	(Alpha + Theta)/Beta	26.732	0.0128	0.537

5. DISCUSSION

This research developed an AR-HMD acceptance model to examine usage intention for work-at-height training in construction. Survey results indicated strong user acceptance, where 72.5% of participants expressed intent to use the system, and all reported it as enjoyable, highlighting both engagement and practical relevance. Structural TAM analysis using PLS-SEM and Bayesian SEM consistently showed that perceived usefulness has a significant positive effect on user acceptance of AR-HMD, confirming prior studies that identify usefulness as the core determinant to AR adoption (Schuster et al. 2021; Iqbal and Sidhu, 2022).

Both approaches also proved the influence of external factors, including motivation, enjoyment, and perceived system quality (PSQ). Enjoyment significantly influences usefulness and was affected by perceived ease of use, which aligns with previous work highlighting the effect of pleasure on intentions to use the AR systems (Rasimah et al., 2011; Sugara and Mustika, 2016). Motivational support influenced PU, PEU, and ITU, reinforcing evidence that motivation-aligned systems enhance adoption (Jang et al., 2021). PSQ positively affected PEU, suggesting that well-aligned physical and virtual elements improve usability perceptions (Calisir et al., 2014). Notably, our study emphasized the effect of PEU on enjoyment ($\beta = 0.65$, $p<0.01$; mean = 1.05, [1.02, 1.09]), and the influence of motivation on adoption ($\beta = 0.51$, $p<0.01$; mean = 0.97, [0.46, 1.05]), whose path coefficients and posterior means outperform those of all TAM paths.

A key limitation lies in the inconsistent results for PEU-related paths (H1: PEU to PU; H2: PEU to ITU), indicating failing to demonstrate PEU's effect on PU and ITU. Multiple factors can contribute: users prioritize usefulness over device complexity (Chen and Zou, 2024), limited variance in PEU and ITU, reflected in positively skewed distributions, reduce explanatory power, and small sample sizes can produce unstable estimates (Imbens and Kolesar, 2016). The low R^2 for PEU (0.34) further suggests that motivation and PSQ partially explain PEU, with other relevant factors unmeasured. Methodological differences may also contribute, as PLS-SEM emphasizes prediction, while Bayesian SEM priors produce more conservative intervals, amplifying discrepancies in borderline effects (Anggorowati, 2014). Despite these limitations, most paths in the extended TAM model showed consistent results across both SEM models, supporting significant positive effects on AR-HMD acceptance and proving the value of dual SEM validation.

The combination of EEG-derived cognitive metrics with TAM results provides additional insight. Regression analyses identified frontal EEG ratios, including Theta/Alpha and Theta/Beta, as significant predictors of PU, PEU, and ENJ, controlling for shared variance across frequency bands. These results indicate that EEG metrics not only correlate with but also independently explain variability in user perceptions. For example, lower Theta/Alpha ratios, associated with reduced cognitive workload, predicted higher motivational support and ITU, while perceived system quality showed a positive association with Gamma power, reflecting increased vigilance during sensory misalignment. Taken together, the correlation and regression analyses consistently highlight relationships between EEG-derived cognitive metrics and key TAM constructs, providing converging evidence that neurophysiological measures can complement subjective survey data. This combined approach highlights the value of integrating behavioral and neural metrics in evaluating immersive training systems, informing both system design and strategies for enhancing user engagement and performance.

6. CONCLUSION

This study evaluates the acceptance of AR-HMD training in high-risk construction tasks through the extended TAM using two statistical approaches suited for small samples: PLS-SEM and Bayesian SEM. Findings confirmed perceived usefulness as the core determinant of users' acceptance, while external factors such as enjoyment, motivation, and perceived system quality also played critical roles.

Beyond behavioral modeling, the study integrated EEG-derived cognitive measures with behavioral data, offering an objective, neurophysiological perspective on user experience. Both correlation and regression analyses consistently highlighted relationships between frontal EEG measures and key TAM constructs: lower Theta/Alpha ratios were associated with higher motivational support and intention to use, while regression results showed that specific EEG metrics independently predict perceived usefulness, ease of use, and enjoyment that are critical to predict user perceptions. These findings demonstrate that cognitive workload and engagement, as measure by EEG, can complement subjective survey data to provide a more nuanced understanding of acceptance and inform system design.

Limitations include limited explaining power for perceived ease of use and adoption. Practical deployment challenges, such as PPE compatibility and restricted field of view also remain. Future work should focus on refining TAM constructs measurement items for immersive AR environments, exploring adaptive AR systems responsive to physiological states, and validating findings in larger, real-world applications.

Overall, the study contributes to the design of user-centered, neuro-ergonomically informed AR training platforms that enhance engagement, reduce cognitive workload, and support adoption in high-risk construction domains and beyond.

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