

Factors Influencing Readiness for Integrating AR and VR in Distance Learning: An Application of the eTAM Model

Anusorn Koedsri[✉] and Thanyasinee Laosum^{*}

Office of Registration Records and Evaluation, Sukhothai Thammathirat Open University, Nonthaburi 11120, Thailand

*Corresponding author: thanyasinee.lao@stou.ac.th

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Abstract

The objectives were 1) to validate an extended Technology Acceptance Model (eTAM) measurement model for augmented reality (AR)/virtual reality (VR) readiness of undergraduate distance-learning students and 2) to estimate the direct and indirect effects of institutional, social, and psychological factors on the students' behavioral intention (BI). Data were collected from 384 undergraduate distance-learning students. A three-step sampling procedure was used: (1) the population was divided into 12 fields of study; (2) 384 participants were proportionally allocated across the fields; and (3) students were selected by simple random sampling within each field. An initial 36-item instrument was reduced to 22 indicators through confirmatory factor analysis (CFA). The measurement model was evaluated using CFA with robust maximum likelihood estimation. The construct validity was examined using composite reliability, average variance, the Fornell-Larcker, and HTMT criteria. Structural equation modeling (SEM) was used to test the proposed eTAM relationships. The model showed acceptable fit with CFI = .93, TLI = .92, robust CFI = .95, robust TLI = .94, SRMR = .048, and robust RMSEA = .066, satisfying the recommended criteria (CFI/TLI > .90, SRMR < .08, and RMSEA close to .06). It was found that self-efficacy (SE) strongly predicted perceived ease of use (PEOU; $\beta = .899$). Social interaction and sense of belonging (SI) was a strong predictor of SE ($\beta = .837$). Institutional technology and infrastructure support (TI_{in}; $\beta = .099$) contributed modestly. Behavioral intention (BI) was most strongly predicted by PU ($\beta = .339$), whereas TI_{in} influenced BI indirectly through PU rather than through a direct path. The model explained substantial variance in SE ($R^2 = .75$), PEOU ($R^2 = .71$), PU ($R^2 = .96$), and BI ($R^2 = .81$).

Keywords: AR, VR, eTAM, distance learning, factors influencing readiness

Introduction

In the digital era, universities worldwide increasingly use immersive technologies in teaching and learning. The augmented reality (AR) and virtual reality (VR) are the immersive learning technologies that gain popularity among distance learning students. These tools enhance students' learning experiences. They transform how learners interact with learning content. Learning becomes more active and engaging. AR and VR can create realistic and interactive learning environments. These environments can promote learners participation as well as their understanding of the subject content by facilitating direct audiovisual engagement and immersion within simulated objects, locations, or scenarios.

AR adds digital information to the real world. Users can interact with virtual objects and at the same time feeling their real surroundings (Liberati, 2016). AR is not fully immersive. AR keeps users aware of the physical environment. This supports continued engagement. Abad-Segura et al. (2020) and Liarokapis (2007) claims that AR does not transport users to a separate virtual space. AR adds digital layers to the real world. This experience deepens learners on spatial perception.

VR creates stimulating environments. Users can interact with these virtual worlds as if they are real. Slater and Sanchez-Vives (2016) described that VR used multiple senses. VR can use dynamic 3D scenes and interactive simulations. This design helps users feel present

in the virtual environment. VR also increases supports perceptual, cognitive engagement, and enjoyment. Gonzalez Cordova and Solis Garza (2025) claimed that VR game design in higher education could increase motivation. It could also improve learning experiences and teaching quality. Li et al. (2022) found that VR in distance learning could enhance instructor-learner interaction.

In distance learning, AR can improve learning and teaching. It adds interactiveness and authenticity to lessons. Students can view and manipulate 3D content, which can enrich memory and understanding (Akçayır & Akçayır, 2017). Bacca et al. (2014) found that AR facilitated mobile learning. Students could have access to materials anywhere at anytime, which was useful for online learning. Integrating with specific instructional methodologies, such as inquiry-based or problem-based learning, AR could promote critical-thinking and problem-solving skills (Wu et al., 2013). It could also boost learner engagement and motivation. Through self-directed instructional designs, AR can enhance individualized learning, allowing students to learn at their own pace and choose activities that fit their interests (Cheng & Tsai, 2013). Billingham and Duenser (2012) also found that AR could enhance learning experiences and modernize instructional design in the digital-era distance learning.

Although AR and VR have been extensively beneficial to educational services, their perceived usefulness and

acceptance in distance learning remain insufficiently examined. To address this gap, this study adopts the Extended Technology Acceptance Model (eTAM), an extension of Davis's (1989) Technology Acceptance Model (TAM), as its theoretical framework. eTAM incorporating external, psychological, and contextual factors, such as social influence and self-efficacy, making the model more suitable for examining technology acceptance in complex learning environments. However, empirical evidence on AR and VR adoption in distance learning remains limited, particularly in university settings. Existing studies have focused largely on system design and short-term outcomes rather than on acceptance models that capture broader influences on learners' readiness, behavioral intention, and sustained engagement with AR and VR in distance learning.

In addition, this study will provide empirical evidences through the eTAM framework, on the factors shaping learners' readiness and behavioral intention to use these technologies.

Since the examination of factors that shape learners' readiness to adopt AR and VR are important, this study employed the eTAM framework to investigate learners' acceptance and readiness in distance-learning contexts. Although AR and VR can make online learning more interactive and participatory and can improve distance-learning effectiveness, successful adoption depends on learners' technological capabilities, the availability of infrastructure, and the perceived value of AR and VR. A clear understanding of these factors can explain differences in readiness and intention to use AR and VR in distance learning. This study therefore addresses this shortfall by empirically testing key institutional, social, psychological, and perceptual factors that influence readiness for AR/VR integration.

■ Research Objectives

1. To validate the extended Technology Acceptance Model (eTAM), a measurement model for augmented reality and virtual reality readiness, of STOU (Sukhothai Thammathirat Open University) undergraduate distance-learning students.

2. To estimate the direct and indirect effects of institutional, social, and psychological factors on the STOU students' behavioral intention.

■ Literature Review

The conceptual basis for the study of factors influencing readiness for integrating AR and VR in distance learning is the eTAM, which extends TAM by linking perceived ease of use (PEOU) and perceived usefulness (PU) to behavioral intention (BI) and technology use (Davis, 1989). The review therefore emphasized key external factors—institutional technology and infrastructure support (TI_{in}), social interaction and sense of belonging (SI),

and self-efficacy (SE) with the explanation of how these factors shape readiness to adopt AR and VR in distance learning (Venkatesh et al., 2003; Al-Adwan et al., 2023).

The extended Technology Acceptance Model (eTAM) is the extended model of TAM which is the key original framework for technology adoption, positing that PEOU and PU shape BI, which predicts actual use (Davis, 1989). Venkatesh et al. (2003) and Al-Adwan et al. (2023) later worked on TAM and incorporated contextual and psychological factors, yielding eTAM and related models such as the Unified Theory of Acceptance and Use of Technology (UTAUT). Compared with the original TAM and broader models such as UTAUT, eTAM retains the core constructs of perceived ease of use (PEOU), perceived usefulness (PU), and behavioral intention (BI) while incorporating context-specific external factors, making it more suitable for explaining AR/VR adoption in distance-learning environments. In more recent works, Al-Adwan et al. (2023), Ichsan et al. (2025), Jung et al. (2015), Radianti et al. (2020), and Fan et al. (2022) found that immersive learning, AR/VR offer spatial immersion, embodied interaction, and rich sensory feedback, yet outcomes depend on learners' perceptions, skills, infrastructure, and learning environment. This study adapts eTAM to AR/VR in distance learning to examine how TI_{in}, SI, and SE influence PEOU, PU, and BI, which consequently will help improve readiness and acceptance of AR/VR of the distance-learners. Consistent with prior eTAM applications in VR, safety, and metaverse education (Al-Adwan et al., 2023; Ichsan et al., 2025; Fan et al., 2022), these external factors are modeled as key antecedents of beliefs, intentions, and readiness for AR/VR integration.

Technology and Infrastructure Support (TI). In this study, it refers to the availability of personal (TI_p) and institutional (TI_{in}) resources that allow learners to use AR/VR in distance learning, including reliable connectivity, capable devices, access to platforms, and basic technical help. This construct aligns with facilitating conditions in the UTAUT, where organizational and technical support lower barriers to technology use (Venkatesh et al., 2003). TI_p reflects learners' own digital environment and capacity to incorporate AR/VR into everyday study, whereas TI_{in} captures the infrastructure and services provided by the university. Empirical work on VR-based distance learning shows that institutional support, technical assistance, and system quality predict PEOU, PU, and BI (Ichsan et al., 2025; Fan et al., 2022; Venkatesh et al., 2003). The model hypothesizes that TI_{in} positively influences SE, PEOU, PU, and BI.

Social Interaction and Sense of Belonging (SI). SI describes the extent to which learners perceive social presence, collaboration, and the influence of important others within AR/VR-supported distance learning. Social presence theory suggests that higher perceived social

presence in computer mediated environments enhances learners' engagement, satisfaction, and sense of community (Gunawardena & Zittle, 1997; Biocca et al., 2003). In UTAUT, social influence captures the perceived pressure or encouragement from significant others to use a technology (Venkatesh et al., 2003).

AR/VR can support synchronous collaboration, embodied interaction, and avatar based communication that simulate face to face classroom dynamics (Jung et al., 2015; Noble et al., 2022). Empirical work in metaverse and VR-based education shown that interaction and social presence contribute to learners' perceived value of the platform and their intention to use it (Al-Adwan et al., 2023; Wang & Shin, 2022). Socially rich learning environments can also reduce anxiety and encourage experimentation, as learners receive support and encouragement from peers and instructors (Akour et al., 2022).

SI is expected to operate in two ways. First, social interaction and support can strengthen learners' confidence in using AR/VR by providing vicarious experiences and verbal persuasion, consistent with social cognitive theory. Second, feeling connected and supported in AR/VR environments should enhance learners' perception that AR/VR is useful for sustaining engagement in distance learning. The eTAM hypothesizes that SI positively influences PU and SE.

Self-Efficacy (SE). SE refers to an individual's belief in their capability to perform activities required to use AR/VR. Grounded in social cognitive theory (Bandura, 1997) and the notion of computer self-efficacy (Compeau & Higgins, 1995), this construct believes that learners' confidence in performing technical operations, solving problems, and persisting when they encounter difficulties.

Al Adwan et al. (2023) found that SE significantly influenced both PU and PEOU of metaverse based learning platforms. Luo and Du (2022) and Xie et al. (2022) found that, in VR and online learning contexts, higher SE associated with greater perceived usability, reduced perceived complexity, and stronger perceptions of learning benefits.

Learners must manage multisensory input, 3D interfaces, and unfamiliar interaction modes. Those with higher SE are more likely to approach these challenges as manageable and persevere, which lead them to perceive AR/VR as easier to use and beneficial for learning. The eTAM hypothesizes that SE positively influences PU and PEOU.

Perceived Ease of Use (PEOU). Davis (1989) defines PEOU as the degree to which a person believes using a particular system requires little effort. PEOU reflects learners' perceptions that AR/VR platforms are easy to use, stable, intuitive, and require minimal mental or technical effort to operate.

According to Davis (1989) and Venkatesh et al. (2003), PEOU is a core determinant of both PU and BI.

Radianti et al. (2020) claim that immersive learning, responsive systems, intuitive interfaces, and clear guidance help to lower cognitive load and reduce frustration, allowing learners to focus on content rather than on how to operate the technology. Huang and Liaw (2018) and Fan et al. (2022) found that PEOU positively affected BI and PU in virtual reality learning systems and related to immersive applications.

PEOU is determined by SE, TI_{in}, and prior AR/VR experience. Liaw and Huang (2013) found that prior experience could reduce uncertainty and lower familiarity barriers, making interaction with immersive systems feel more intuitive and less effortful. These factors collectively shape learners' perceptions of usefulness and their readiness to adopt AR/VR. The eTAM hypothesizes that PEOU positively influences BI and PU, and that prior AR/VR experience positively influences PEOU.

Perceived Usefulness (PU). Davis (1989) defines PU as the extent to which learners believe that using AR/VR will improve their learning performance, understanding, and engagement. PU encompasses perceived benefits such as improved visualization of complex content, more authentic learning experiences, and increased motivation.

Davis (1989) and Venkatesh et al. (2003) found that PU was widely recognized as a primary determinant of technology acceptance. A few researchers such as Al Adwan et al. (2023), Ichsan et al. (2025), Jung et al. (2015), and Fan et al. (2022) confirmed that PU significantly predicted attitudes toward use of BI.

PU is conceptualized as the result of PEOU and external enabling factors TI_{in}, SI, and SE. Learners who perceive AR/VR beneficial are expected to show greater readiness to integrate these technologies in distance learning. The eTAM hypothesizes that PU positively influences BI.

Behavioral Intention (BI). Davis (1989) and Venkatesh et al. (2003) define BI as an individual's plan to perform a behavior—to adopt and continue using AR/VR in distance learning. TAM, eTAM, and UTAUT (Unified Theory of Acceptance and Use of Technology). These frameworks conceptualize BI as the proximal antecedent of actual system use. BI is used as an operational indicator of readiness for AR/VR integration in distance learning.

Al-Adwan et al. (2023), Ichsan et al. (2025), and Fan et al. (2022) have shown that BI is strongly influenced by PEOU and PU, and in some cases by institutional support or facilitating conditions. Learners who perceive AR/VR as both useful and easy to use in their learning context are more likely to demonstrate a strong intention to integrate these technologies into their study routines. Ichsan et al. (2025) found that user support and infrastructure could directly encourage continued use by reducing technical difficulties.

This study positions behavioral intention (BI) as the outcome variable representing learners' readiness to adopt and integrate AR/VR in distance learning. Consistent with the eTAM, perceived usefulness (PU) and perceived ease of use (PEOU) are conceptualized as the central beliefs that directly influence BI. It is believed that learners are more likely to use AR/VR when they perceive AR/VR as useful and easy to use. In addition, TI_in is hypothesized to influence BI both directly and indirectly through PU and PEOU, indicating that students' intention could be shaped by both technology-related perceptions and learners' technological readiness. The model further identifies TI_in, SI, and SE as external antecedents of learners' perceptions of AR/VR. Specifically, TI_in is expected to enhance SE, PEOU, and PU, whereas SI is hypothesized to strengthen SE and PU. In turn, SE is

therefore consequently hypothesized to improve both PEOU and PU, suggesting that learners with greater confidence in using technology are more likely to perceive AR/VR as manageable and beneficial.

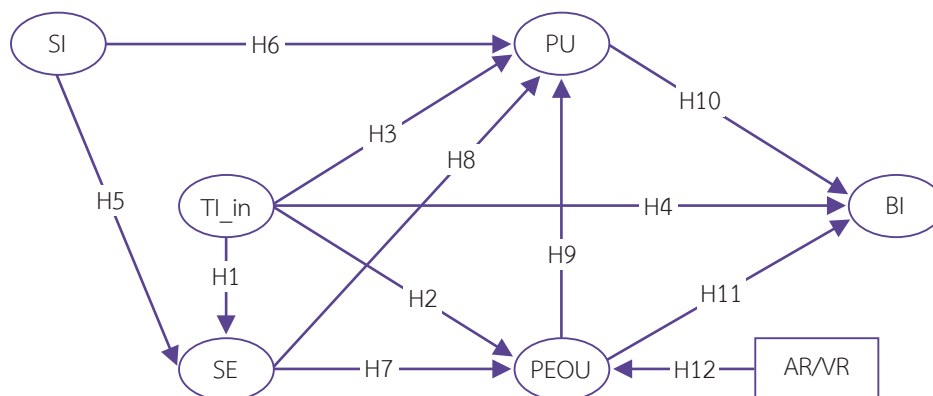
The model also proposes that PEOU positively influences PU, as technologies that are easier to use are more likely to be viewed as useful for learning tasks. In addition, the AR/VR variable is expected to influence PEOU, reflecting the idea that AR/VR-related characteristics or prior exposure may shape perceived ease of use. Taken together, these relationships explain the causal logic of the proposed framework: external factors shape learners' efficacy and perceptions, which in turn influence intention, with BI ultimately representing readiness for AR/VR integration in distance learning. The hypothesized paths are summarized in Table 1 and presented in Figure 1.

Table 1
Summary of Hypothesized Relationships

Hypothesis	Path	Expected Effect
H1	TI_in -> SE	Institutional support and resources enhance learners' confidence in using AR/VR. (Bandura, 1997; Venkatesh et al., 2003)
H2	TI_in -> PEOU	Access to reliable infrastructure enhances perceived ease of system use. (Venkatesh et al., 2003; Ichsan et al., 2025)
H3	TI_in -> PU	Robust infrastructure increases perceived educational value of AR/VR. (Ichsan et al., 2025; Radianti et al., 2020)
H4	TI_in -> BI	Institutional support directly strengthens intention to use AR/VR. (Venkatesh et al., 2003; Ichsan et al., 2025)
H5	SI -> SE	Social support and peer influence build confidence in using AR/VR. (Bandura, 1997; Venkatesh et al., 2003)
H6	SI -> PU	Greater social connectedness enhances perceived learning value and usefulness. (Gunawardena & Zittle, 1997; Biocca et al., 2003)
H7	SE -> PEOU	Confidence in using AR/VR promotes ease of use perception. (Bandura, 1997; Compeau & Higgins, 1995)
H8	SE -> PU	Higher self-efficacy increases perceived learning benefits of AR/VR. (Al-Adwan et al., 2023; Xie et al., 2022)
H9	PEOU -> PU	Systems perceived as easy to use are also perceived as more useful. (Davis, 1989; Venkatesh et al., 2003; Ichsan et al., 2025)
H10	PU -> BI	Learners who find AR/VR useful intend to continue using it. (Davis, 1989; Radianti et al., 2020; Al-Adwan et al., 2023)
H11	PEOU -> BI	Ease of operation enhances intention to use AR/VR systems. (Ichsan et al., 2025)
H12	AR/VR -> PEOU	AR/VR experience positively influences PEOU of AR/VR systems. (Davis, 1989; Venkatesh et al., 2003; Liaw & Huang, 2013; Radianti et al., 2020)

Figure 1

Hypothesized Research Model



■ Research Methodology

Research Design

This study adopted a quantitative, survey-based research design grounded in the eTAM.

Participants

A total of 384 undergraduate students from Sukhothai Thammathirat Open University (STOU), Thailand's only open distance-learning university, participated in the study through multistage random sampling. STOU emphasizes self-directed learning through multimedia and digital delivery to expand educational opportunities for learners who face time limitations and barriers to attending in-person classes, thereby enabling students access to learning anytime and anywhere. The sampling procedure consisted of three steps: 1) the population was divided into 12 fields of study; 2) the sample size for each field was determined using proportional stratified sampling, yielding a total sample of 384 participants; and 3) students in each field were then selected using simple random sampling. Data were collected through the use of questionnaire administered via the Google Form platform.

Materials and Tools

Following the review of relevant literature, the five-point Likert scale questionnaire was developed and employed. It was developed based on Al-Adwan et al. (2023). In-depth interviews with five students to explore their acceptance of and adaptation to AR and VR in distance learning were summarized and concluded. The questionnaire comprised seven constructs (36 items): 1) TI_p (5 items); 2) TI_in (4 items); 3) SI (4 items); 4) SE (6 items); 5) PU (8 items); 6) PEOU (5 items); and 7) BI (4 items). The Item-Objective Congruence (IOC) method by three experts to evaluate the relevance of individual items was used to assess content validity of the tools. The IOC values for all items ranged from .67–1.00, which met the accepted criterion (>.50) (Rovinelli & Hambleton, 1977). The Cronbach's alpha which yielded a coefficient of .90 demonstrating high internal consistency (George &

Mallery, 2010) thus confirmed the reliability of the tools.

During the CFA process, indicators with low standardized factor loadings were removed. Two item parcels were created for the PU construct by averaging correlated items reflecting 1) usefulness for learning activities and 2) learning accessibility. These modifications reduced multicollinearity, improved model parsimony, and produced a more stable measurement model for subsequent structural equation modeling (SEM).

Data Analysis

The in-depth interview data were analyzed by using content analysis. Responses to the student questionnaire were analyzed using descriptive statistics, and data-screening procedures were conducted to examine missing data, outliers, and item distributional properties. Multivariate normality was assessed using Mardia's test, which indicated a violation of the assumption of multivariate normality, and a robust maximum likelihood estimator (MLR) was employed for CFA and SEM estimation using the lavaan package in R. Following measurement model refinements, including the removal of indicators with low factor loadings or substantial cross-loadings and the use of item parceling for selected indicators, the final SEM was estimated to examine direct and indirect effects among TI_in, SI, SE, PEOU, PU, and BI within the eTAM framework.

The measurement and structural models were evaluated using CFI, TLI, SRMR, and robust RMSEA. CFI and TLI values of .90 or higher, RMSEA values close to .06, and SRMR values below .08 were considered acceptance of model fit (Hu & Bentler, 1999; Kline, 2024). Standardized factor loadings of .50 or higher were considered acceptable, with values of .70 or higher regarded as desirable (Cheung et al., 2024). Construct reliability (CR) values of .70 or higher indicated acceptable internal consistency, where as average variance extracted (AVE) values of .50 or higher supported convergent validity (Fornell & Larcker, 1981; Cheung et al., 2024).

Findings and Discussion

Findings

1. Descriptive Statistics of Participants

The participants comprised 384 undergraduate students from STOU (54.90% female and 45.10% male). Most were in their fourth year (31.80%), followed by first-year students (27.90%), with a smaller proportion in their fifth year or above (9.90%). The largest group was enrolled in Management Science (26.00%), followed by Agriculture and Cooperatives (19.50%), Education (16.70%), and Law (14.30%). Regarding technological experience, the majority (74.70%) had never used AR/VR technology, 21.40% had used it once or twice, and 3.90% used it regularly. Smartphones were the most commonly used devices for distance learning, either alone or in combination with laptops or computers. In terms of awareness, 43.20% had heard of AR/VR but never used it, 21.60% had both heard of and used it. Additionally, 28.90% of students were aware that STOU had implemented AR/VR but had not yet had the opportunity to use it.

2. eTAM Measurement Model for AR/VR Readiness

2.1 Instrument Development and Item Refinement.

The initial eTAM instrument included 36 items representing seven constructs: personal technology and infrastructure (TI_p: TI1p–TI5p), institutional technology and infrastructure (TI_{in}: TI6–TI9), social interaction and belonging (SI: SI1–SI4), self-efficacy (SE: SE1–SE6 plus one behavioral item), perceived ease of use (PEOU: PEOU1–PEOU5), perceived usefulness (PU: PU1–PU8), and behavioral intention (BI: BI1–BI4). Following recommended scale-development steps, descriptive item analysis and CFA to screen items (Brown, 2015; Worthington & Whittaker, 2006). Items with standardized factor loadings (λ) below .60, clear cross-loadings, redundant content, or large modification indices without substantive justification were removed. For perceived usefulness, four very similar items were averaged into two composite indicators (PU_U and PU_A) to improve model estimation when items were highly correlated (Little et al., 2002). The latent correlation matrix showed that the personal technology and infrastructure factor (TI_p) correlated very strongly with self-efficacy and perceived ease of use and also had high correlations with perceived usefulness, social interaction, and behavioral intention (above .90). These values exceed common cutoffs for discriminant validity and indicate serious multicollinearity among predictors (Fornell & Larcker, 1981;

Henseler et al., 2015). In this dataset, TI_p thus behaved more like a broad personal readiness index than a distinct infrastructure factor.

The final measurement model retained 22 indicators across six constructs—TI_{in}, SI, SE, PEOU, PU, and BI—as summarized in Table 2.

2.2 Factor Structure and Global Model Fit. The refined six-factor eTAM measurement model was tested with CFA using MLR. The model included TI_{in}, SI, SE, PEOU, PU, and BI. Overall fit was acceptable: $\chi^2(191) = 605.14$, $p < .001$; scaled $\chi^2(191) = 407.50$, $p < .001$ (scaling factor = 1.49). The comparative fit indices were CFI = .93 and TLI = .92; scaled CFI = .94 and scaled TLI = .93; robust CFI = .95 and robust TLI = .94. The RMSEA was .075, 90% CI [.068, .082]; scaled RMSEA = .054, 90% CI [.048, .060]; and robust RMSEA = .066, 90% CI [.057, .075]. The SRMR was .048. Following common guidelines, CFI/TLI above .90, SRMR below .08, and robust RMSEA close to .06 support an acceptable measurement model, even if some misfit remains (Hu & Bentler, 1999; Kline, 2024). All standardized factor loadings were significant ($p < .001$) and mostly fell between .65 and .89, with most item R^2 values above .40. A small number of within-factor residual covariances were freely estimated to account for local dependence due to similar wording or response processes, in line with practical CFA recommendations (Hair et al., 2019).

2.3 Reliability and Convergent Validity. Model-based composite reliability (CR) from the standardized CFA solution indicated good internal consistency for all six factors: CR = .84 for TI_{in}, .86 for SI, .89 for SE, .84 for PEOU, .86 for PU, and .85 for BI. All coefficients were higher than the .70 benchmark, suggesting that the constructs were measured with sufficient precision under a congeneric model (Fornell & Larcker, 1981; Hair et al., 2019). Convergent validity was examined using Average Variance Extracted (AVE). AVE values were .64 for TI_{in}, .66 for SI, .59 for SE, .60 for PEOU, .62 for PU, and .67 for BI, all above the .50 threshold. Thus, each construct explained more than half of the variance in its indicators. Combined with the moderate to high factor loadings and item R^2 values, these CR and AVE results indicate that the eTAM measurement model has adequate internal consistency and convergent validity for AR/VR readiness in distance-learning (Fornell & Larcker, 1981), as shown in Table 2.

Table 2
CFA Results for the eTAM Measurement Model

Construct	Indicator	λ	R^2	CR	AVE
TI_in	TI6	.85	.72	.84	.64
	TI7	.71	.50		
	TI8	.89	.79		
SI	SI1	.80	.64	.86	.66
	SI2	.83	.69		
	SI4	.82	.67		
SE	SE1	.65	.43	.89	.59
	SE3	.77	.60		
	SE4	.76	.58		
	SE5	.80	.65		
	SE6	.81	.65		
PEOU	PEOU1	.69	.47	.84	.60
	PEOU2	.77	.59		
	PEOU4	.83	.68		
	PEOU5	.80	.64		
PU	PU1	.78	.61	.86	.62
	PU5	.72	.52		
	PU_U	.82	.66		
	PU_A	.85	.72		
BI	BI1	.85	.72	.85	.67
	BI2	.83	.69		
	BI4	.78	.61		

2.4 Discriminant Validity. Evidence for discriminant validity was less clear-cut than for reliability and convergent validity. The square roots of AVE ($\sqrt{\text{AVE}}$) were ranged from .78 to .82 and exceeded the corresponding inter-construct correlations, in line with the Fornell–Larcker criterion (Fornell & Larcker, 1981). However, several correlations among the belief constructs were very large, especially SI–PU ($r = .96$), SE–PEOU ($r = .90$), SE–PU ($r = .92$), and PU–BI ($r = .86$); SI was also highly correlated with PEOU ($r = .80$) and SE ($r = .89$). These coefficients approached

or exceeded the $\sqrt{\text{AVE}}$ of one or both constructs, which suggests limited discriminant separation among SI, SE, PEOU, PU, and BI. Heterotrait–monotrait ratios exceeded common cutoff values for key construct pairs such as SI–PU and SE–PEOU (Henseler et al., 2015). Therefore, these belief constructs were treated as conceptually distinct but empirically intertwined dimensions of AR/VR acceptance, and structural paths were interpreted with caution due to their potential overlap. The Fornell–Larcker discriminant validity matrix is shown in Table 3.

Table 3

Fornell–Larcker Discriminant Validity Matrix of the eTAM Constructs

Construct	TI_in	SI	SE	PEOU	PU	BI
TI_in	.80					
SI	.53	.82				
SE	.54	.89	.78			
PEOU	.49	.80	.90	.78		
PU	.63	.96	.92	.82	.79	
BI	.74	.80	.80	.74	.86	.82

Note. Values on the diagonal (in bold) are $\sqrt{\text{AVE}}$. Off-diagonal entries are latent factor correlations.

3. Structural Model (eTAM)

3.1 Model Fit and Explained Variance. The overall model fit was acceptable, $\chi^2(218) = 777.29, p < .001$, with a robust scaled $\chi^2(218) = 532.68, p < .001$ (scaling factor = 1.46). The robust incremental fit indices exceeded the conventional .90 benchmark, with robust CFI = .93 and robust TLI = .91, and the robust RMSEA indicated a reasonable degree of approximation error, RMSEA = .074, 90% CI [.066, .082]. The SRMR was .066. These indices indicate an acceptable level of fit for a SEM in applied research (Hair et al., 2019; Kline, 2024).

The proposed model demonstrated strong explanatory power across all endogenous constructs. PU exhibited the highest explained variance ($R^2 = .96$), indicating that PU was strongly explained by PEOU, TI_in, SI, and SE. This was followed by BI, which showed substantial explained variance ($R^2 = .81$), suggesting that PU, PEOU, and TI_in jointly accounted for a large proportion of students' intention to adopt AR/VR. SE also demonstrated a high level of explained variance ($R^2 = .75$) based on TI_in and SI. Finally, PEOU was well explained by AR/VR, SE, and TI_in ($R^2 = .71$). The overall R^2 values suggest that the model explains a substantial proportion of variance in AR/VR adoption in distance learning. However, these

values should be interpreted cautiously, as the strong explanatory power may partly reflect the conceptual closeness of TAM/eTAM constructs and the complexity of the extended model.

3.2 Hypothesis Testing. The hypothesized structural relationships among the constructs were evaluated using standardized path coefficients (β), p values and confidence intervals, as shown in Table 4.

The results indicate that H4, H5, H7, H10, and H12 were statistically significant. Specifically, H4, H5, H7, and H12 had positive effects ($\beta = .339, .837, .899$, and $.099$, respectively; $p < .05$). H10 was also supported, with a moderate positive effect ($\beta = .534, p < .05$). These results indicate that only selected predictors retained unique direct effects within the structural model.

In contrast, H1, H2, H3, H6, H8, H9, and H11 were not statistically significant ($p > .05$). These non-significant paths may reflect overlapping variance among conceptually related TAM/eTAM constructs and possibly that some relationships operated indirectly rather than through direct effects. Perceived usefulness acted as a partial mediator in the model, indicating that some antecedents influenced behavioral intention both directly and indirectly through PU.

Table 4

Hypothesis Testing

Hypothesis	β	est_mean	se	z	p	ci.lower	ci.upper	Assumption
H1	.099	.219	.166	1.317	.188	-.079	.579	No
H2	.005	.012	.142	.084	.933	-.283	.287	No
H3	.139	.723	1.576	.459	.646	.225	2.495	No
H4	.339	.776	.190	4.089	.000	.437	1.168	Yes
H5	.837	1.862	.514	3.623	.000	1.228	3.162	Yes

Table 4
(continued)

Hypothesis	β	est_mean	se	z	p	ci.lower	ci.upper	Assumption
H6	.649	3.375	7.373	.458	.647	1.453	12.737	No
H7	.899	.959	.226	4.247	.000	.605	1.516	Yes
H8	.328	.766	1.941	.395	.693	-.293	3.859	No
H9	-.063	-.137	.891	-.154	.877	-1.758	.514	No
H10	.534	.235	.093	2.537	.011	.079	.466	Yes
H11	.134	.129	.112	1.150	.250	-.102	.354	No
H12	.099	.542	.189	2.862	.004	.161	.896	Yes

Note. Standardized path coefficients (β) are reported as the primary basis for interpretation. Supported hypotheses are indicated in the Assumption column.

3.3 Indirect Effect Assessment. The significance of the indirect effects in the eTAM model was shown in Table 5. Overall, the results indicated that only a limited number of indirect paths were statistically significant, whereas most indirect effects did not reach statistical significance.

Indirect effects through PU. SI demonstrated a statistically significant indirect effect on BI via PU ($\beta = .347, p = .005$). This finding suggests that AR/VR learning environments that promote interaction and collaboration enhance students' perceptions of usefulness, and consequently strengthen their intention to continue using AR/VR in distance learning.

TI_{in} showed a significant indirect effect on BI through PU ($\beta = .074, p = .022$). Although TI_{in} did not exert a significant direct effect on BI, the significant indirect pathway indicated that institutional support contributed to students' behavioral intention primarily by

increasing their perceived usefulness of AR/VR systems.

In contrast, indirect effects involving PEOU were not statistically significant. Neither SE, SI, nor TI_{in} exerted significant indirect effects on BI through PEOU. PEOU itself did not show a significant indirect effect on BI through PU, indicating that ease-of-use perceptions alone were insufficient to translate into stronger behavioral intention unless accompanied by higher usefulness beliefs.

These findings highlight the central mediating role of PU in the model. While institutional support and social interaction indirectly influence students' intention to adopt AR/VR, their effects operate primarily through PU rather than through PEOU. This pattern underscores the importance of designing AR/VR learning environments and institutional support systems that clearly demonstrate practical value and learning benefits to students in distance learning.

Table 5
Indirect Effects in the eTAM Structural Model of Distance-learning Students

Path	mean_est	se	β	βse	ci_lb_ β	ci_up_ β	z	p
PEOU -> PU -> BI	-.025	.071	-.027	.074	-.175	.120	-.446	.656
arvr -> PEOU -> BI	.065	.067	.012	.012	-.012	.037	1.018	.309
arvr -> PEOU -> PU -> BI	-.012	.042	-.002	.008	-.017	.015	-.411	.681
SE -> PEOU -> BI	.124	.114	.115	.105	-.098	.316	1.068	.285
SE -> PU -> BI	.186	.133	.174	.125	-.047	.437	1.326	.185
SE -> PEOU -> PU -> BI	-.029	.071	-.025	.067	-.160	.106	-.419	.676
SI -> PU -> BI	.816	.281	.347	.114	.142	.585	2.787	.005
SI -> SE -> PEOU -> BI	.225	.213	.095	.088	-.082	.264	1.060	.289

Table 5
(continued)

Path	mean_est	se	β	βse	ci_lb_ β	ci_up_ β	z	p
SI -> SE -> PU -> BI	.345	.265	.144	.107	-.039	.376	1.284	.199
SI -> SE -> PEOU -> PU -> BI	-.051	.136	-.021	.057	-.136	.092	-.414	.679
TI_in -> PU -> BI	.175	.074	.074	.031	.023	.141	2.298	.022
TI_in -> PEOU -> BI	.003	.024	.001	.010	-.019	.025	.063	.950
TI_in -> PEOU -> PU -> BI	.000	.012	.000	.005	-.010	.010	-.034	.973
TI_in -> SE -> PEOU -> BI	.026	.034	.011	.014	-.012	.045	.769	.442
TI_in -> SE -> PU -> BI	.043	.050	.018	.020	-.007	.069	.798	.425
TI_in -> SE -> PEOU -> PU -> BI	-.006	.020	-.003	.008	-.023	.012	-.326	.744

Discussion

Support for TAM/eTAM and Extensions in AR/VR-Based Distance Learning. Consistent with the classic TAM pathway (Davis, 1989; Venkatesh & Davis, 2000), PU was a significant predictor of BI to continue using AR/VR ($\beta = .534, p < .05$). Learners who judged AR/VR as more useful reported stronger intentions to adopt AR/VR in distance-learning activities. The structural model explained variance in the core endogenous constructs— $R^2(\text{PEOU}) = .71, R^2(\text{PU}) = .96, R^2(\text{SE}) = .75$ and $R^2(\text{BI}) = .81$ —indicating that eTAM explained a substantial proportion of the variation in AR/VR-related beliefs and intentions. However, these high R^2 values should be interpreted cautiously, as they may partly reflect the close conceptual relatedness among TAM/eTAM constructs and the complexity of the extended model.

The findings both confirmed and modified canonical TAM. The central PU BI pathway remained significant, there by confirming the core TAM proposition that perceived usefulness is a proximal determinant of intention. The model also extended TAM by showing that contextual antecedents, particularly SE and TI_in, contributed meaningfully to AR/VR acceptance in distance-learning settings. SE showed a strong positive link with PEOU ($\beta = .899, p < .05$) and TI_in predicted BI directly ($\beta = .339, p < .05$). These findings suggest that the extension beyond TAM was only partially supported, because the added contextual variables were influenced through selected pathways rather than uniformly across the model. These patterns align with recent eTAM work showing that immersive-learning adoption depends on a broader set of social and institutional conditions, rather than usability alone (Al-Adwan et al., 2023; Radianti et al., 2020; Puiu & Udriștioiu, 2024).

Deviations from Canonical TAM Relationships. Several expected TAM/eTAM paths were not supported. The path PEOU -> PU was small and non-significant ($\beta = -.063, p = .877$).

Unlike the classic TAM pattern in which easier systems are judged more useful (Davis, 1989). In this model, PU was less strongly associated with ease-of-use perceptions and more closely related to broader psychosocial and contextual considerations once all predictors were included simultaneously. This may indicate that, in AR/VR-based distance learning, students evaluate usefulness primarily in terms of instructional value, learning relevance, and institutional support rather than interface simplicity alone. This supports the argument that, for AR/VR, usefulness depends more on pedagogical fit, immersion, and social presence than on interface simplicity (Radianti et al., 2020; Puiu & Udriștioiu, 2024).

The direct path PEOU -> BI was also non-significant ($\beta = .134, p = .250$) after PU and TI_in were controlled, suggesting that PEOU may function as a background condition rather than a proximal driver of intention. A possible explanation is that once students have already formed judgments about usefulness and institutional support, ease of use no longer retained a distinct direct contribution to intention. This pattern is theoretically defensible in extended TAM contexts, where conceptually adjacent constructs share substantial variance and some effects may operate indirectly rather than through direct pathways.

External variables showed inconsistent links to PU and PEOU: SE was a non-significant predictor of PU ($\beta = .328, p = .693$), TI_in was non-significant in predicting PU ($\beta = .139, p = .646$), and TI_in was also non-significant for PEOU ($\beta = .005, p = .933$). These non-significant institutional paths suggest that infrastructure and technical support may not directly shape students' beliefs regarding usefulness or ease of use. Instead, institutional conditions may matter more as enabling factors that support adoption readiness and behavioral intention, particularly in contexts where many students have limited direct AR/VR experience.

Likewise, the non-significant SE $\rightarrow$ PU path may indicate confidence in handling technology is more immediately translated into perceptions of ease of use than into judgments of usefulness. Overall, these results suggest that AR/VR adoption in this sample did not fully follow the reciprocal pattern typically assumed in canonical TAM. The findings point to a context in which usefulness remained central, whereas ease of use and several institutional antecedents did not retain unique direct effects once other related predictors were considered. These deviations may reflect the conceptual proximity of TAM/eTAM constructs, the possibility of indirect effects, and the specific conditions of AR/VR-based distance learning, and therefore warrant cautious interpretation, and further model testing should be interpreted cautiously and examined further in future studies.

Roles of Self-efficacy, Social Interaction, and Infrastructure in Acceptance. Both prior AR/VR experience and self-efficacy contributed to perceived ease of use. Prior AR/VR experience had a significant positive effect on PEOU ($\beta = .099, p < .05$), indicating that even limited familiarity with AR/VR may help students perceive the technology as easier to use. SE was a central antecedent of PEOU ($\beta = .899, p < .05$). Students who felt able to handle technical problems, manage frustration when systems failed, and persist with new tools tended to view AR/VR as easier to use, consistent with work showing that computer SE lowers perceived task difficulty and supports technology adoption (Compeau & Higgins, 1995; Xie et al., 2022). SI operated primarily through SE, as SI strongly predicted SE ($\beta = .837, p < .05$). Learners who experienced AR/VR as socially engaging and inclusive reported higher confidence and judged it more useful, in line with social-presence research emphasizing community, interaction, and shared experience (Gunawardena & Zittle, 1997; Noble et al., 2022). TI_in contributed significantly to behavioral intention. Specifically, TI_in had a strong direct effect on BI ($\beta = .339, p = .01$), although its relationship with PU was non-significant ($\beta = .139, p = .646$). However, the pattern echoes the facilitating conditions construct in UTAUT and VR-in-education studies that highlight connectivity, equipment access, and technical support as key enablers of AR/VR integration (Puiu & Udriștioiu, 2024; Sumardani & Lin, 2024).

Practical and Policy Implications for Distance-learning Universities. The structural results pointed to three main levers for AR/VR integration in distance-learning: 1) strengthening institutional technology and infrastructure support (TI_in), 2) developing students' self-efficacy (SE), and 3) designing AR/VR learning activities that promote meaningful social interaction (SI). These implications are grounded primarily in the supported structural paths, especially TI_in $\rightarrow$ BI, SI $\rightarrow$ SE, SE $\rightarrow$ PEOU, and PU $\rightarrow$ BI.

The strong effect of SE on PEOU suggesting that structured orientations, guided practice, and other

low-stakes introductory activities that allow students to use AR/VR in a supported setting can strengthen technological SE and improve ease-of-use perceptions. The role of SI in explaining SE indicates that AR/VR activities should foster interaction and belonging to build learner confidence. For example, through collaborative simulations, small-group tasks in virtual spaces, and tutorials with visible co-presence, may help strengthen students' self-efficacy. Since TI_in also showed a direct positive effect on BI, universities should prioritize stable connectivity, access to suitable devices, responsive technical support, and reliable AR/VR platforms. Faculty development is likewise needed so instructors can design interaction-rich AR/VR activities and embed them meaningfully in the curriculum. By contrast, recommendations that extend beyond these supported paths should be treated as future-oriented rather than as direct implications from the present model.

■ Conclusion and Future Research

This study developed and evaluated an eTAM for AR/VR-based distance learning using a six-factor SEM measurement model (TI_in, SI, SE, PEOU, PU, BI) with 22 indicators that showed acceptable fit, reliability, and convergent validity. TI_p was excluded during model refinement because of its high latent correlations with SE and PEOU indicated poor discriminant validity, and its removal improved construct distinctiveness and parsimony. The structural model showed that behavioral intention was predicted by perceived usefulness and institutional technology support, perceived ease of use by self-efficacy and prior AR/VR experience, and self-efficacy through social interaction, with substantial explained variance across the endogenous constructs. These patterns suggest that, in distance-learning settings, institutional infrastructure, social interaction, self-efficacy, and basic AR/VR experience are important conditions for AR/VR readiness, whereas ease-of-use perceptions function more as an enabling or background condition, given their non-significant direct effect on behavioral intention, rather than as an independent driver of intention. For practice, distance-learning universities that plan to integrate AR/VR should prioritize infrastructure and support services, design AR/VR activities that social interaction and sense of belonging, and provide structured introductory AR/VR sessions that build self-efficacy and experience, rather than focusing on interface simplicity alone. The study is limited to a single open-university context using a cross-sectional survey design, includes many students with little or no direct AR/VR use, and relies on adapted TAM/eTAM instruments in which several construct perceptions are highly correlated, which constrains generalizability and discriminant separation, while limited AR/VR experience may have restricted response precision

and contributed to greater uncertainty in model validity and parameter estimation.

Future research should use multi-institutional or cross-national samples and adopt longitudinal or repeated-measures designs to address the limitations of the present cross-sectional approach. It should also examine AR/VR acceptance in contexts of actual use rather than relying primarily on self-reported intentions, incorporate experiential constructs such as enjoyment, flow, and presence, and refine the adapted scales to sharpen distinctions among usefulness, ease-of-use, self-efficacy, social interaction, and intention.

■ Ethics

Ethical approval was waived under the Thailand Science Research and Innovation (TSRI) guidelines. This study was exempt from institutional review because it exclusively utilized strictly anonymous questionnaires, involved no physical or psychological interventions, and collected no personally identifiable information.

■ Declaration of Generative AI

The authors did not use any generative artificial intelligence tools in the preparation of this article.

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■ Declaration of Competing Interest

There is no conflict of interest.

■ Author Contributions

Anusorn Koedsri: Writing – original draft, Writing – review & editing, Conceptualization, Methodology, Investigation, Formal analysis, Visualization, Project administration. **Thanyasinee Laosum:** Writing – original draft, Writing – review & editing, Conceptualization, Methodology, Investigation, Data curation, Validation, Supervision.

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■ References

- Abad-Segura, E., González-Zamar, M.-D., Luque-de la Rosa, A., & Morales-Cevallos, M. B. (2020). Sustainability of educational technologies: An approach to augmented reality research. *Sustainability*, 12(9), Article 4091. <https://doi.org/10.3390/su12104091>
- Akçayır, M., & Akçayır, G. (2017). Advantages and challenges associated with augmented reality for education: A systematic review of the literature. *Educational Research Review*, 20, 1–11. <https://doi.org/10.1016/j.edurev.2016.11.002>
- Akour, I., Al-Marouf, R., Alfaisal, R., & Salloum, S. (2022). A conceptual framework for determining metaverse adoption in higher institutions of the Gulf area: An empirical study using a hybrid SEM–ANN approach. *Computers and Education: Artificial Intelligence*, 3, Article 100052. <https://doi.org/10.1016/j.caeai.2022.100052>
- Al-Adwan, A. S., Li, N., Al-Adwan, A., Abbasi, G. A., Albelbisi, N. A., & Habibi, A. (2023). Extending the Technology Acceptance Model (TAM) to predict university students' intentions to use metaverse-based learning platforms. *Education and Information Technologies*, 28, 15381–15413. <https://doi.org/10.1007/s10639-023-11816-3>
- Bacca, J., Baldiris, S., Fabregat, R., Graf, S., & Kinshuk. (2014). Augmented reality trends in education: A systematic review of research and applications. *Educational Technology & Society*, 17(4), 133–149. <http://www.jstor.org/stable/jeductechsoci.17.4.133>
- Bandura, A. (1997). *Self-efficacy: The exercise of control*. W. H. Freeman.
- Billingshurst, M., & Duenser, A. (2012). Augmented reality in the classroom. *Computer*, 45(7), 56–63. <https://doi.org/10.1109/MC.2012.111>
- Biocca, F., Harms, C., & Burgoon, J. K. (2003). Toward a more robust theory and measure of social presence: Review and suggested criteria. *Presence: Teleoperators and Virtual Environments*, 12(5), 456–480. <https://doi.org/10.1162/105474603322761270>
- Brown, T. A. (2015). *Confirmatory factor analysis for applied research* (2nd ed.). The Guilford Press.
- Cheng, K. H., & Tsai, C. C. (2013). Affordances of augmented reality in science learning: Suggestions for future research. *Journal of Science Education and Technology*, 22(4), 449–462. <https://doi.org/10.1007/s10956-012-9405-9>
- Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2024). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management*, 41, 745–783. <https://doi.org/10.1007/s10490-023-09871-y>
- Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly*, 19(2), 189–211. <https://doi.org/10.2307/249688>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- Fan, X., Jiang, X., & Deng, N. (2022). Immersive technology: A meta analysis of augmented/virtual reality applications and their impacts on tourism experience. *Tourism Management*, 91, Article 104534. <https://doi.org/10.1016/j.tourman.2022.104534>
- Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research*, 18(3), 382–388. <https://doi.org/10.1177/002224378101800313>
- George, D., & Mallery, P. (2010). *SPSS for Windows step by step: A simple guide and reference* (10th ed., 17.0 update). Allyn & Bacon.
- Gonzalez Cordova, C. V., & Solis Garza, C. M. (2025). Enhancing learning through VR game design in higher education. *The 19th European Conference on Games Based Learning, Levanger, Norway*, 19(1), 329–338. <https://doi.org/10.34190/ecgb1.19.1.3985>
- Gunawardena, C. N., & Zittle, F. J. (1997). Social presence as a predictor of satisfaction within a computer-mediated conferencing environment. *American Journal of Distance Education*, 11(3), 8–26. <https://doi.org/10.1080/08923649709526970>
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage.
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Hu, L.-T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1–55. <https://doi.org/10.1080/10705519909540118>

- Huang, H., & Liaw, S. (2018). An analysis of learners' intentions toward virtual reality learning based on constructivist and technology acceptance approaches. *The International Review of Research in Open and Distributed Learning*, 19(1), 91–115. <https://doi.org/10.19173/irrodl.v19i1.2503>
- Ichsan, M., Sik-Lanyi, C., & Guzsvinecz, T. (2025). Virtual reality in skill development through user experience and technology advancements. *Discover Computing*, 28, Article 171. <https://doi.org/10.1007/s10791-025-09703-1>
- Jung, T., Chung, N., & Leue, M. C. (2015). The determinants of recommendations to use augmented reality technologies: The case of a Korean theme park. *Tourism Management*, 49, 75–86. <https://doi.org/10.1016/j.tourman.2015.02.013>
- Kline, R. B. (2024). *Principles and practice of structural equation modeling* (5th ed.). Guilford Press.
- Li, P., Fang, Z., & Jiang, T. (2022). Research into improved distance learning using VR technology. *Frontiers in Education*, 7, Article 757874. <https://doi.org/10.3389/educ.2022.757874>
- Liarokapis, F. (2007). An augmented reality interface for visualizing and interacting with virtual content. *Virtual Reality*, 11, 23–43. <https://doi.org/10.1007/s10055-006-0055-1>
- Liaw, S. S., & Huang, H. M. (2013). Perceived satisfaction, perceived usefulness and interactive learning environments as predictors to self regulation in e learning environments. *Computers & Education*, 60(1), 14–24. <https://doi.org/10.1016/j.compedu.2012.07.015>
- Liberati, N. (2016). Augmented reality and ubiquitous computing: The hidden potentialities of augmented reality. *AI & Society*, 31(1), 17–28. <https://doi.org/10.1007/s00146-014-0543-x>
- Little, T. D., Cunningham, W. A., Shahar, G., & Widaman, K. F. (2002). To parcel or not to parcel: Exploring the question, weighing the merits. *Structural Equation Modeling: A Multidisciplinary Journal*, 9(2), 151–173. https://doi.org/10.1207/S15328007SEM0902_1
- Luo, Y., & Du, H. (2022). Learning with desktop virtual reality: Changes and interrelationship of self-efficacy, goal orientation, technology acceptance and learning behavior. *Smart Learning Environments*, 9, Article 22. <https://doi.org/10.1186/s40561-022-00203-z>
- Noble, S. M., Saville, J. D., & Foster, L. L. (2022). VR as a choice: What drives learners' technology acceptance? *International Journal of Educational Technology in Higher Education*, 19, Article 6. <https://doi.org/10.1186/s41239-021-00310-w>
- Puiu, S., & Udriști-oiu, M. T. (2024). The behavioural intention to use virtual reality in schools: A technology acceptance model. *Behavioural Sciences*, 14(7), Article 615. <https://doi.org/10.3390/bs14070615>
- Radianti, J., Majchrzak, T. A., Fromm, J., & Wohlgenannt, I. (2020). A systematic review of immersive virtual reality applications for higher education: Design elements, lessons learned, and research agenda. *Computers & Education*, 147, Article 103778. <https://doi.org/10.1016/j.compedu.2019.103778>
- Rovinelli, R. J., & Hambleton, R. K. (1977). On the use of content specialists in the assessment of criterion-referenced test item validity. *Tijdschrift voor Onderwijsresearch*, 2(2), 49–60. <https://files.eric.ed.gov/fulltext/ED121845.pdf>
- Slater, M., & Sanchez-Vives, M. V. (2016). Enhancing our lives with immersive virtual reality. *Frontiers in Robotics and AI*, 3, Article 74. <https://doi.org/10.3389/frobt.2016.00074>
- Sumardani, D., & Lin, C. H. (2024). Investigating the factors that influence the implementation of virtual reality in science learning. *Journal Pendidikan IPA Indonesia*, 13(1), 76–89. <https://doi.org/10.15294/jpii.v13i1.44018>
- Venkatesh, V., & Davis, F. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186–204. <https://doi.org/10.1287/mnsc.46.2.186.11926>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://ssrn.com/abstract=3375136>
- Wang, G., & Shin, C. (2022). Influencing factors of usage intention of metaverse education application platform: Empirical evidence based on PPM and TAM models. *Sustainability*, 14(24), Article 17037. <https://doi.org/10.3390/su142417037>
- Worthington, R. L., & Whittaker, T. A. (2006). Scale development research: A content analysis and recommendations for best practices. *The Counseling Psychologist*, 34(6), 806–838. <https://doi.org/10.1177/0011000006288127>
- Wu, H. K., Lee, S. W. Y., Chang, H. Y., & Liang, J. C. (2013). Current status, opportunities and challenges of augmented reality in education. *Computers & Education*, 62, 41–49. <https://doi.org/10.1016/j.compedu.2012.10.024>
- Xie, T., Zheng, L., Liu, G., & Liu, L. (2022). Exploring structural relations among computer self-efficacy, perceived immersion, and intention to use virtual reality training systems. *Virtual Reality*, 26, 1725–1744. <https://doi.org/10.1007/s10055-022-00656-0>