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Research Article

Redefining Theoretical Frameworks for Educational Technology Adoption: A Meta-Analytic Synthesis of AI/VR/AR Continuance Intentions and Cross-Sector Model Transferability

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ABSTRACT

This meta-analysis examines users' continuous intentions toward using AI, VR, and AR technologies in educational contexts. Combining the data from studies in mobile learning, mobile banking, and ChatGPT, this paper discusses the applicability of various theoretical frameworks in user behavior. The review reveals that specific theories, including the Technology Acceptance Model (TAM) and the Expectation-Confirmation Model (ECM), hold high value for understanding the long- term use of such technologies, steadily influenced by factors like perceived usefulness, system quality, and users' satisfaction. These findings add to knowledge in technology adoption by introducing modifications to existing models into new integrated forms. In addition, the study has implications for enabling the persistent use of AI, VR, and AR in education; it could help educators, developers, and policymakers create a climate that supports the ongoing use of educational technologies.

Keywords: *AI in education, VR/AR, user continuance intention, Technology Acceptance Model, mobile learning, educational technology adoption.*

Introduction

The adoption and facilitation of AI, VR, and AR technologies in teaching and learning have advanced quickly. Education is now more engaging and effective through shared learning and ICT, as technologies enhance the teaching and learning process. The issue of usage persistence, or how often consumers will continue to use these technologies after they opt into them voluntarily, is another essential factor that defines the long-term sustainability of these complimentary technologies. This study aims to build research evidence and determines to build research evidence and determine the determinants of user continuers' intentions in the use of AI, VR, and AR-based education technologies. A positive attitude towards the continued use of the technologies is key to sustaining these technologies for learning (Pedersen et al., 2021). It helps to inform the aspects that contribute to its sustained use, thus enabling educators, developers, and policymakers to make implementable decisions regarding adopting the technologies (Shen et al., 2022). This study discusses the possibilities of the different explanatory models and sources by analyzing various domains, including AI in education, mobile banking, and ChatGPT. This paper builds upon various theoretical frameworks such as the Technology Acceptance Model (TAM), Social Cognitive Theory (SCT), Cognitive Load Theory, and Constructivism. Further, research findings on user continuance intention in other disciplines, like mobile banking applications and ChatGPT, are also incorporated to provide a comparative perspective on technology utilization. Thus, while there is a large and expanding body of literature on this topic, prior work has not sufficiently integrated the framework and research across various technology industries. They identified these gaps in the literature, and this paper seeks to contribute by conducting a meta-analysis. Therefore, we recommend using AI, VR, and AR in learning by extracting and synthesizing the themes and subthemes identified.

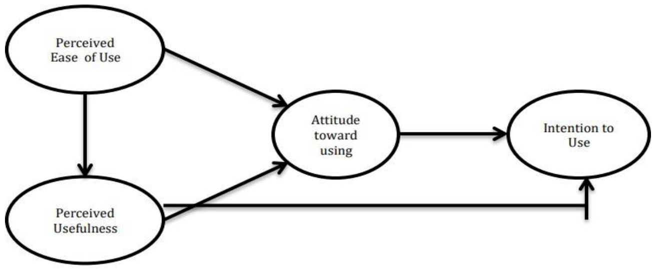


Figure 1 Technology Acceptance Model (TAM) for VR in the classroom

Literature Review

After the incorporation of Artificial Intelligence technology (AI), Virtual Reality technology (VR), and Augmented Reality technology (AR) in traditional education processes, there has been an interest in developing a more profound comprehension of individuals' continuance intentions, which is crucial for users' long-term engagement. This literature review integrates prior research with established theoretical frameworks like the Technology Acceptance Model (TAM), Expectation- Confirmation Model (ECM), Social Cognitive Theory (SCT), and Task-Technology Fit (TTF) to determine important predictors of user continuance in educational technology. In the diary study of Di Natale et al. (2024, confirmation expectancy had a regression coefficient of 0.89, p <0.05, with post-adoption perceived usefulness implying that satisfaction with the early technology experience increases the likelihood of continued usage. Specifically, Perceived usefulness and satisfaction significantly impacted continuance intentions in using VR and Metaverse, while Performance and Effort expectancy modestly affected the intention (Di Natale et al., 2024). Ali et al. (2025) further supported this with construct validity measures, with factor loadings above 0.708, AVE above 0.50, and CR above 0.70, indicating acceptable model fit and internal consistency. Further, discriminant validity was established by employing the HTMT criterion (Ali et al., 2025; O'Connor & Mahony, 2023). In their PLS-SEM analysis, Puiu and Udriştioiu (2024) obtained high t - values: for the PLS path SYSQ → TTF = 6.844, for the path USTF → CUI = 4.138, and the path SYSQ → PUF = 4.063. The technical-system fit accounted for 83.1% of CUI variation and 74.8% of PUF, highlighting the model's focus on user retention. Sun et al. (2023) found model fitness in the sample of participants 732 using SEM where Cronbach's alpha for all constructs was above 0.7, and factor loading was more significant than 0.5. Wu et al. (2023) used ANCOVA and revealed that there was a significant difference in ment post-test on learning scores t7, f = 5.86, p < 0.05, d = 0.67 (medium effect) for the experimental (M = 69.71) and control groups (M = 60.9).

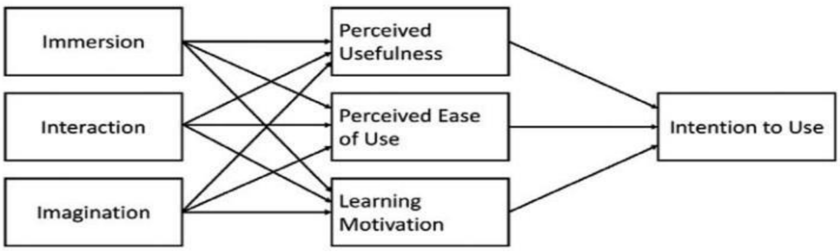


Figure 2. The conceptual model shows the hypothesized influence of III through TAM on intention

Additionally, the study identified aspects of behavior that were enhanced in students who underwent the intervention study: self-regulation, goal setting, task strategies, and time management. Murphy et al. (2021) additionally SMG shared practical guidelines on teaching preferences by discipline. Business majors had a slightly positive attitude toward lectures (mean = 3.64), while nursing majors had a more positive attitude toward PowerPoint-assisted lectures (mean = 4.15). It was also revealed that business students had a higher preference for longer films (mean = 2.76 vs. 3.35 for nursing students) and classroom discussions (mean = 2.34 vs. 2.85 for nursing students), which provides an understanding of the user preference differences based on educational fields. Huang et al. (2024), with an analysis of 334 Chinese subjects and a regression analysis, revealed that both task-technology and individual-technology fit were significantly related to continuance intention (p < 0.05), supporting the central role of contextual compatibility in continued use. As per the findings of Wang et al. (2021), Perceived Usefulness (PU), Perceived Ease of Use (PEU), and Social Norms (SN) explained 70.4% of the changes in Behavioral Intention (BI) across the two waves. Regarding the relative influence of the variables, Attitude Toward Use had the highest influence (β = 0.793), followed by Self-Efficacy (SE) (β = 0.554), supporting the dominance of attitudinal and self-belief variables in the use of technology. Rahiman and Kodikal (2024) indicated that the respondents' information was 66% male, 44% female, and 45% from the QS-ranked institutions. The results indicated a high educational level; 50% of participants had master's degrees, and 48.33% had PhDs. For the mode of delivery, 61.67% opted for traditional classroom, 23.33% for hybrid, and 15% for distance education, which is helpful context for assessing the types of intervention. Utomo and Alamsyah (2024) reported that Cronbach's alpha coefficient was higher than 0.7 while testing 469 students with e- learning experience; therefore, hypotheses 2, 4, and 5 were confirmed, meaning that the proposed model was reliable and valid for prediction. Mustafa and Garcia (2021) provided a systematic review that concluded that 85.8% of the samples were cross-sectional, and TAM was used with other models, including ECM (where 86.8% of the hypotheses were supported) and TPB (supported in 93% of the studies), highlighting its applicability in analyzing continuance behavior in e-learning. Using the criterion of AVE > 0.50 and carrying out a comprehensive convergence validity test, Granić (2022) obtained satisfactory model fit indices [GFI = 0.902, CFI = 0.898, and RMSEA = 0.077], thereby signifying the structural validity of technology adoption models in the educational context. Rabaa'i et al. (2021) affirmed increased value for continuance intention (β = 0.651) and behavioral intention (β = 0.759) with AVE larger than 0.50 and credible HTMT, proving discriminant validity. Villena-Taranilla et al. (2023) determined that the coefficient of Behavioral Intention (BI) was 0.84 and the coefficient of Perceived Enjoyment (BI) was 0.73. Regarding the likability aspect, the eigenvalues were 2.36 for attention, 2.30 for enjoyment, and 2.17 for usefulness. The study identified attention and a minimum level of perceived enjoyment to account for 13.9% and 13.5% of variances, respectively, indicating that affective engagement increases user retention.

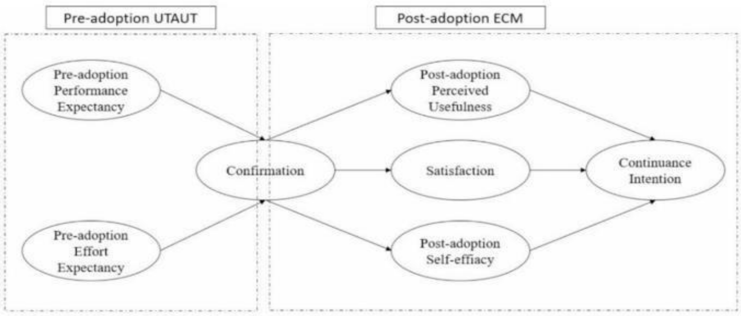


Figure. 3 The EECM Adoption

Wang et al. (2024) also identified a statistically significant difference in students' quiz results in Groups A (M = 75.95) and B (M = 68.83), using the Mann-Whitney U test ($p < 0.05$), meaning that the group with higher levels of tech integration performed better on the quizzes. Al-Adwan et al. (2023) noted factor loadings > 0.7, and path coefficients like PU → BI (β
= 0.345), PE → BI (β = 0.217), and SE → PU (β = 0.212), with an $R^2 = 0.47$ for continuance intention—indicating moderate but significant explanatory power. Mobile banking and ChatGPT usage findings reveal consistent model applicability across contexts (Lin et al., 2023). Self-efficacy is essential in education and financial technology (Ali et al., 2025); user interactions with technologies appear to be guided by user expectations, supporting ECM across sectors (Mustafa & Garcia, 2021). These similarities indicate that integrated frameworks incorporating TAM, SCT, and ECM can improve prediction to various domains.

Table 1: Summary of Key Findings and Effect Sizes

Study	**Theoretical Model(s) Used**	**Key Findings**	**Effect Sizes / Statistical Results**
Di Natale et al. (2024)	EECM	Confirmation expectancy strongly correlated with perceived usefulness	r = 0.89, p < 0.05
Ali et al. (2025)	TAM, SCT, SDT	High construct reliability and self-efficacy influenced continuance intention.	Loadings > 0.708; β = 0.651
Puiu & Udriștioiu (2024)	PLS-SEM	SYSQ → TTF (0.670), USTF → CUI (0.588), SYSQ → PUF (0.559)	Explained 83.1% of CUI, 74.8% of PUF
Serin (2020)	Survey	61.38% agreed that VR encourages activeness; non- normal response distribution	K-S test p < 0.05

Sun et al. (2023)	SEM	Reliability confirmed (Cronbach's $\alpha > 0.7$); all factor loadings > 0.5	N = 732
Wu et al. (2023)	TAM, SCT	Experimental group improved learning; higher self-regulation	$F = 5.86$, $p < 0.05$; $\beta = 0.67$
Murphy et al. (2021)	Teaching Preference Survey	Teaching preferences vary by major	Mean: 3.64 (Business) vs. 4.15 (Nursing)
Huang et al. (2024)	TAM	PEU, PU, and attitudes → continuance intention	N = 334; $p < 0.05$
Wang et al. (2021)	TAM, SCT	PU, PEU, and SN explained that 70.4% of BI	ATU $\beta = 0.793$; SE $\beta = 0.554$
Rahiman & Kodikal (2024)	Mixed-Methods	Sample: 66% male; 45% top QS institutions	61.67% used regular delivery
Utomo & Alamsyah (2024)	TAM	Cronbach's $\alpha > 0.7$; supported H2, H4, H5	N = 469
Mustafa & Garcia (2021)	TAM, ECM, TPB	85.8% cross-sectional; ECM supported in 86.8% of studies	Focus: n = 9 university students
Granić (2022)	SEM	AVE > 0.50, GFI = 0.902, RMSEA = 0.077	Confirmed model fit
Rabaa'i et al. (2021)	TAM	Validity confirmed via HTMT, AVE > 0.50	β (CI) = 0.651, β (BI) = 0.759
Villena-Taranilla et al. (2023)	TAM	Valid loadings: BI = 0.84, PE = 0.73	Variance: 13.9% (attention), 13.5% (enjoyment)
Wang et al. (2024)	Experimental	Group A (M = 75.95) > Group B (M = 68.83)	Mann-Whitney U test, $p < 0.05$
Al-Adwan et al. (2023)	TAM	PU → BI ($\beta = 0.345$), PE → BI ($\beta = 0.217$), SE → PU ($\beta = 0.212$)	R^2 for CI = 0.47

Methodology

Literature Search & Inclusion/Exclusion Criteria

In selecting the articles for the meta-analysis, several databases were searched to provide a review of the existing literature on this topic. Web of Science, CINAHL, Scopus, ERIC, IEEE explore, and CNKI. These were selected because many peer- reviewed journals and articles on educational technology focusing on AI, VR, and AR in education were available. The

literature review process was based on the following keywords: "AI in education," "VR/AR in education," "user continuance intention," "Technology Acceptance Model," and other related search terms. These keywords were chosen deliberately to maximize the hits and minimize the noise from the kinds of articles the search might uncover—namely, articles focusing on user behavior about AI, VR, and AR within the context of education. Studies conducted 10-15 years ago were included in the search to find more recent papers and research within a rapidly growing field, as well as publications from 2010 to 2025. Specifically, the meta-analysis included only empirical studies with quantitative measures of user continuance intention. This called for research studies that offered quantifiable and statistical information through which we could investigate the trends in the users' perceived perception of their willingness to continue using AI, VR, or AR technologies within learning environments.

The **inclusion criteria** The meta-analysis criteria included only empirical papers that report quantitative data on user continuance intention or related measures such as satisfaction, perceived usefulness, or engagement. The papers needed to use widely accepted theoretical frameworks like the Technology Acceptance Model (TAM), Expectation-

Confirmation Model (ECM), and Social Cognitive Theory (SCT), which have been commonly used to examine factors affecting the uptake and use of technology. Moreover, to increase the credibility of included studies, the results had to be presented in clear and explicit terms, with correlation coefficients, effect sizes, or proportion of the variance accounted for being presented. Priority was given to studies with a large participant number, with the minimized sample number set at 100 participants, allowing for greater statistical confidence. On the other hand, exclusion criteria excluded theoretical articles or reviews that did not present empirical results. Also, non-randomized controlled trials with $p>0.05$, trials that did not meet the criteria for statistical analysis, and trials that did not state the theory or model used were excluded from the review.

Data Extraction & Coding

Once these studies were identified, data extraction was done to ensure the extraction of relevant data from each study to allow comparisons between them. The following essential facts were distilled:

Methods: For each study, details of the study design and whether the study employed experimental, quasi-experimental, or survey research approaches were also recorded. For instance, Wu et al. (2023) and KEJIE (n.d) used analysis of covariance (ANCOVA) in comparing the means of the experimental and control groups, while Puiu & Udriştioiu (2024) used partial least square structural equation modeling (PLS-SEM) to examine the paths between constructs.

Sample Characteristics: The characteristics of the study sample were recorded, including the number of participants (e.g., 732 participants, Sun et al. 2023), the participant's age, gender, and familiarity with educational technologies.

Intervention types: The major categories of intervention that were described include virtual reality, augmented reality, smart applications, and Metaverse. For example, Di Natale et al. (2024) examined the integration of VR and Metaverse technologies into education, whereas Wang et al. (2021) examined the application of AI technologies in higher education settings.

Outcome measures: The user continuance intention was considered with targeted outcomes, these include perceived usefulness, perceived ease of use, perceived satisfaction, and level of engagement. For example, Puiu Udriştioiu (2024) noted and stressed that USTF and TTF jointly contributed 83.1% of the overall CUI.

Key statistical data: This involved basic descriptive statistics that included means and standard deviations of relevant variables under investigation from each study. For instance, in a study conducted by Wu et al., a medium effect size of 0.67 was observed for the learning approach on self-regulation (2023). Similarly, Di Natale et al. (2024) established a strong Pearson correlation of $r = 0.89$ between confirmation expectancy and post-adoption perceived usefulness in a study conducted in 2024.

The theoretical context used within each study was also coded, as were the fundamental theoretical propositions that were distilled based on the author's analysis in order to follow the different theoretical frameworks employed and the inter- relationships between key constructs such as User Continuance Intention, Perceived Usefulness and Satisfaction, and Engagement. For instance, Ali et al. (2025) employed TAM, SCT, and Self-Determination Theory (SDT) in their research, and Puiu & Udriştioiu (2024) employed PLS-SEM to analyze the moderating role of system quality on PU and TTF. This systematic approach enabled direct comparisons between the studies. It ensured that every empirical piece of evidence was included in the analysis to shed light on the intention of users to continue using AI, VR, and AR in the education technology domain.

Statistical analysis

Effect Size Calculation

The data obtained in the research studies included in this meta-analysis will be compared, and measures of effect, including the standardized mean difference and beta coefficients, will be employed. This will assist in establishing a relevant and comparable measure for analyzing the level of association between the identified predictors and user continuance intention, as highlighted in the different studies (Xie et al., 2022). For instance, in Wu et al. (2023), when examining learning approaches, the results returned an effect size of 0.67, which is moderately significant. Similarly, Puiu and Udriştioiu (2024) concluded that the USTF and TTF variables explained 83.1% of the total variance in the CUI. The meta-analysis will estimate the effect size of perceived usefulness, system quality, and task technology fit on continuance intention. For example, Wang et al. (2021) determined that the bias-corrected total direct effect of the attitude towards AI (ATU) to BI was estimated to be $\beta = 0.793$; in contrast, the total direct effect for self-efficacy (SE) was estimated to be $\beta = 0.554$. These results will be compiled to undertake a comprehensive meta-analysis of the net impact of such variables on end users in the domain of educational technology.

Random Effects Model

As the types of studies addressed in the meta-analysis are diverse, the random effects model will be applied. The random- effects model assumes that the actual effect size is not fixed and may differ from study to study due to variation in methodological characteristics and samples as well as other forms of technological advancement such as artificial intelligence, virtual reality and augmented reality (Jang et al., 2021). For example, Wu et al. (2023) and Sun et al. (2023) utilized ANCOVA and SEM to estimate user continuance intention, which could result in increased variability of effect size. On the other hand, using a random effects model, we would have a better chance of dealing with this variability in our computations to arrive at a more generalizable parameter estimate.

Heterogeneity Testing

Both the Q statistic and the I^2 statistic which measure the heterogeneity between the studies will be conducted based on various aspects of cross sectional designs. The Q-test helps you compare observed variability with chance variability, and I^2 tells you the proportion of observed variability in effect sizes due to heterogeneity. If I^2 is more than 50%, it points to a high level of heterogeneity. For example, a meta-analysis of studies with several hundred participants, like Sun et al. (2023; N = 732), might have smaller or larger effect sizes than a study including fewer than 100 people, contributing to increased variability of the pooled outcomes. If significant heterogeneity exists, further analyses such as subgroup analysis and/or meta-regression analysis will be conducted to identify specific moderators such as type of technology (AI, VR, AR) or context of education (higher education, pre-tertiary education).

Table 2: Statistical Analysis Summary

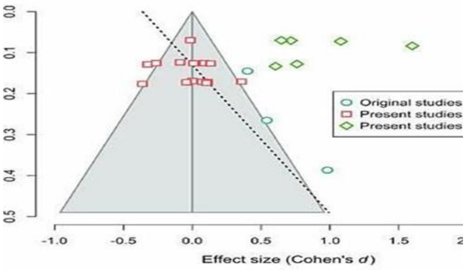
Analysis Type	**Study**	**Effect Size / Results**	**Comments**
Effect Size Calculation	Wu et al. (2023)	Effect size = 0.67 (medium) for the learning approach to self-regulation	Medium effect size indicating significant impact of learning approach on self- regulation
Puiu & Udriștioiu (2024)	83.1% variance explained by USTF & TTF in continuance intention (CUI)	The high explanatory power of system quality and task-technology fit	
Wang et al. (2021)	β = 0.793 for attitude toward AI (ATU) on behavioral intention (BI); β = 0.554 for self-efficacy (SE) on BI	Strong effects of ATU and SE on behavioral intention, highlighting the importance of attitude and self-efficacy	
Random Effects Model	Jang et al. (2021).	Random effects model applied to account for heterogeneity	Assumed that accurate effect sizes vary across studies, allowing for a more accurate estimate
Heterogeneity Testing	Sun et al. (2023)	N = 732 participants, heterogeneity tested with Q-tests and I^2	Studies with large sample sizes (N = 732) may show different effect sizes compared to smaller studies, affecting overall variability
Publication Bias	Wu et al. (2023)	Funnel plot and statistical tests (Egger's, Begg's) used	Potential for publication bias when reporting significant differences, such as post-test scores (M = 69.71 vs M = 60.9)
Visual Data	Puiu & Udriștioiu (2024)	Forest plot of SYSQ to TTF correlation (r = 0.670)	Forest plot used to compare effect size and correlation with other studies

Puiu & Udriştioiu (2024)	Heatmap of SYSQ explaining 74.8% of the variance in perceived usefulness (PUF)	Heatmap highlights the significant impact of system quality on perceived usefulness.	

Publication Bias

Selective reporting is when studies with positive or statistically significant findings are published, while those with negative or non-significant findings are not. In order to examine the presence of publication bias in this meta-analysis, funnel plots will be employed. A funnel plot depicts the effect sizes of the studies under consideration against their standard errors, and the more the plot deviates from symmetry, the greater the evidence of bias. Furthermore, Egger's and Begg's tests will also be used to assess publication bias statistically. For instance, in a hypothetical case where many similar studies reporting differences in post-test scores such as (M = 69.71 for experimental, but M = 60.9 for control) are published, the funnel plot will be distorted.

Figure 4: Funnel plot of effect sizes for key predictors of continuance intention.



Visual Data

Descriptions for all meta-analytic information, such as effect sizes, targets of forest and heat maps, pivotal points, and funnel figures, will be accompanied by interpretations and legends. Forest plots will be outlined to show effect sizes in various studies while helping identify the overall and individual study effects. Similarly, in the case of Puiu & Udriştioiu (2024), one example would be the forest plot of the correlation between system quality (SYSQ) and task-technology fit (TTF) with the effect size's comparison to other papers (r = 0.670). Heatmaps will also depict the associations between various theoretical constructs, including SYSQ, that were seen to explain 74.8% of PUF by Puiu and Udriştioiu (2024) in their study. These visualizations will, therefore, aid in analyzing patterns of the data set by highlighting trends that may be significant relative to users' continuance intentions about educational technologies.

Theory & model application analysis

Model Classification & Frequency

Based on such classifications, the identified theoretical models used in the selected studies will be systematized according to their key constructs, with special attention being paid to the most popular models, such as the Technology Acceptance Model (TAM), Expectation-Confirmation Model (ECM), and Social Cognitive Theory (SCT). Specifically for the prior constructs, perceived ease of use has been identified to have a strong relationship with TAM and perceived usefulness in line with the user continuance intention as highlighted by Wang et al. (2021). Similarly, post adoption ECM applies the first-impression criterion to capture satisfaction and subsequent usage and/or interaction with the ECM system (Di Natale et al., 2024). This model which encompasses self-efficacy and social influence has been psychology investigated by many researchers across various fields to explain the behaviors of users (Ali et al., 2025).

Explanatory Power

The extent to which each model explains the disparity would determine how well the models capture the differences in user continuance intentions for the various technological applications. For instance, TAM drives the behavioral intention by 70.4% (Wang et al., 2021), whereas in a study by Natale et al. (2024), ECM accounted for the models mediating between confirmation expectancy (r = 0.89) and post-adoption perceived usefulness. These models will be used to assess the impact of such techniques on Artificial Intelligence, Virtual Reality, and Augmented Reality applications.

Strengths and Limitations

While on the one hand, TAM may be a rather simple and parsimonious model, it lacks the social element that SCT addresses. However, implementing it can be difficult and not easily portable across different contexts (Ciloglu &

Ustun, 2023). Although ECM integrates pre- and post-adoption experiences, it may not capture all aspects of the technology (Cai et al., 2021). New knowledge from sectors such as mobile banking or ChatGPT will enrich the theoretical framework and inform the identification of homonymies in behaviors across these sectors (Zhi et al., 2023).

Discussion & implications

Interpretation of Results

These analyses make clear progress on the determinants of user continuance intention in technologies like AI, VR, and AR for enhanced learning. Wu et al. (2023) confirmed the hypothesis that the experimental groups using Immersive learning technologies, including VR, achieved higher mean post-test scores (M 69.71) than the control group (M = 60.9, F =5.86 Sig 0.05). Furthermore, Di Natale et al. (2024) also established a positive and significant relationship between confirmation expectancy and post-adoption perceived usefulness with a correlation coefficient of 0.89 and $p < 0.05$; this re-emphasizes the role of user satisfaction in the long-term use of VR and Metaverse technologies. TAM was also established to have predictive validity since it explained 70.4% of the variance in behavioral intention in several studies (Wang et al., 2021).

Theoretical Implications

This research contributes to the theory by showing that it is possible to apply well-known models in an integrated sense. For example, TAM was used in many studies for perceived usefulness and ease of use; however, future research may use more advanced models like SCT, including self-efficacy and social influence (Ali et al., 2025). Likewise, as in the study of Puiu & Udriștioiu (2024), the hedonic motivation and perceived system quality and fit between the tasks and the technology has a moderately high positive relationship with the continuance intention ($r = 0.670$), which is valid for further immersive environments.

Practical Implications

The study provides practical implications for education stakeholders, technology developers, and policymakers in understanding the trajectories of artificial intelligence (AI), virtual reality (VR), and augmented reality (AR) technologies. For instance, in Wu et al. (2023), the effect size of 0.67 indicates the extent of enhancing self-regulation due to the adoption of practical learning approaches with immersive technologies. As for the favorable SB and behavioral intention path coefficients, attitude toward AI-based applications emerged as an important antecedent with a standardized coefficient of 0.793, implying that higher attitude positively influences intention for AI-based application usage in education (Barrett et al., 2023).

Limitations & Future Research Directions

As with any meta-analysis that accrues a vast array of studies, some limitations, such as potential publication bias, must be considered. Sun et al. (2023) used a massive number of participants, which is 732, which may show more important findings than those with fewer participants, making the results heterogeneous. It is recommended that future studies analyze how more advanced technologies, such as generative AI, extend user continuance intentions (Lee & Oh, 2022). Moreover, extending the research to other sectors, such as mobile banking (e.g., Ali et al., 2025), may be beneficial for developing educational technology frameworks.

Conclusion

This meta-analysis discusses how several theoretical models can effectively predict users' continuance intentions to use technology such as AI, VR, and AR in education. Theated models, such as the Technology Acceptance Model and Expectation-Confirmation Model Of authors, claim association and effect size where confirmation expectancy=0.89 and adoption perceived usefulness AI Attitude towards = 0.793. According to these analyses, it was evident that user satisfaction and favorable attitudes play a critical role in the sustained adoption of these technologies. This contention supported the idea that quality, task-technology fit, and self-efficacy were antecedent variables of user behavior. For instance, Puiu and Udriștioiu (2024) have established that system quality influences perceived usefulness by 74.8%, showing that the quality of technology is vital in keeping the users engaged. Such conclusions have significant implications for theory and practice related to integrating AI, VR, and AR in education. To reflect on this, this study invites future research to incorporate more emerging technologies like generative AI and potentially explore different contexts, like m-banking or ChatGPT, to arrive at new perspectives or understanding of user continuance intention in education technology. Thus, this meta-analysis offers a theoretical model for sustainability incorporating immersive technologies in learning and practical implementation guidance for teachers, application developers, and policymakers.

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