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Understanding factors influencing AI adoption in education: Insights from a Meta-Analytic Structural Equation Modelling study

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Abstract

The rapid integration of Artificial Intelligence in Education (AIED) transformed teaching and learning processes. The study employed the Technology Acceptance Model (TAM) to analyse factors influencing the acceptance of AI tools in educational settings. By utilising One-step Meta-analytic Structural Equation Modelling (OSMASEM), findings from 17 empirical studies were synthesised to explore the relationships among TAM constructs—Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude Towards Use (ATU), and Intention to Use (ITU)—in the context of AIED. The analysis revealed significant direct and indirect effects, with PEOU strongly influencing PU and both PEOU and PU positively affecting ATU and ITU. The results highlighted TAM's robustness and applicability in predicting technology acceptance behaviours in education, highlighting the critical roles of usability and perceived benefits in driving AI adoption. The findings provided valuable insights for educators, policymakers, and developers aiming to enhance AI integration in education, emphasising the importance of designing user-friendly and beneficial AI tools to foster positive attitudes and increased usage intentions among educators and students.

Introduction

The rapid evolution of artificial intelligence (AI) technologies has significantly impacted various sectors, including education, where AI can enhance teaching strategies, offer personalised learning experiences, and streamline administrative tasks (Holmes et al., 2019; Luckin et al., 2016; Tan, 2020). As educational institutions increasingly adopt AI tools, it is crucial to understand the factors influencing the acceptance and use of these technologies. The Technology Acceptance Model (TAM), developed by Davis (1989), provides a robust framework for exploring how users accept new technologies, focusing on perceived usefulness and perceived ease of use. This study aims to utilise TAM to examine the acceptance of Artificial Intelligence in Education (AIED), offering insights into educators' and students' perceptions of AI tools and identifying factors that either facilitate or hinder their adoption.

Davis and Granić (2024) have comprehensively reviewed the origins and impact of TAM, tracing its development from Davis' doctoral research at MIT in the 1980s (Davis, 1986). Originally designed to predict technology acceptance, TAM introduced perceived usefulness (PU) and perceived ease of use (PEOU) as key determinants, thereby linking system design with user experience. This foundational model has since been central to understanding technology acceptance across diverse fields, evolving from an innovative concept to a cornerstone of information systems and human-computer interaction (Davis & Granić, 2024).

Its applicability spans various contexts, including educational technology (Aldraiweesh & Alturki, 2023), healthcare settings such as telemedicine and electronic health records (Taufiq-Hail et al., 2023), and business environments for ERP system adoption (Virani et al., 2023). Over time, TAM has been utilised to examine the evolving landscape of educational technology (Al-Azawei et al., 2017; Mayer & Girwidz, 2019; Venter et al., 2012).

AIED offers numerous benefits, including personalised learning, efficient administration, and improved student engagement (Chen et al., 2020; Zawacki-Richter et al., 2019). However, the adoption of AIED tools largely depends on users' willingness to engage with these technologies. This research applied TAM to identify key factors affecting AI acceptance in educational contexts, aiming to enhance the theoretical and practical understanding of technology acceptance in AI settings. Previous studies have validated TAM's broad applicability across various technologies (Davis, 1989; Venkatesh & Bala, 2008). For example, King and He (2006) conducted a meta-analysis that confirmed TAM's robustness across different technologies and user groups. Additionally, Zawacki-Richter et al. (2019) conducted a systematic review of AI in higher education, emphasising the need for further research into educators' perspectives, while Chen et al. (2020) explored AI's impact on student engagement, highlighting the importance of understanding user acceptance.

This study synthesised findings from previous research to deepen our understanding of TAM's application to AIED. By employing One-step Meta-analytic Structural Equation Modelling (OSMASEM), as developed by Jarek and Cheng (2022), this research analysed TAM literature specific to AIED, uncovering trends and key determinants of technology acceptance within this field. The study also assessed the robustness and consistency of TAM's relationships when applied to AIED, aiming to bridge gaps in TAM research through a meta-analytic approach and providing an updated perspective on the factors influencing technology acceptance in educational settings.

Literature review

Artificial intelligence in education (AIED)

AI is increasingly recognised as a change catalyst in education, promising to revolutionise traditional teaching methods and enhance the overall learning experience (Holmes et al., 2019). The field of AIED explores how intelligent technologies can be integrated into educational settings to support and improve learning and teaching (Luckin & Holmes, 2016). AIED involves a broad range of applications, including intelligent tutoring systems, adaptive learning platforms, administrative tools, and predictive analytics (Holmes et al., 2019; Luckin et al., 2016; Chen et al., 2020; Zawacki-Richter et al., 2019). According to Holmes et al. (2019), AIED combines machine learning, natural language processing, and data analytics to personalise learning experiences, optimise educational outcomes, and automate administrative tasks. These technologies emulate human cognitive functions such as inference, analysis, and decision-making, providing personalised guidance and feedback to students while also assisting educators and policymakers in making informed decisions. Recent research has particularly focused on AIED's potential to deliver tailored educational experiences that meet individual student needs (Chen et al., 2020; Zawacki-Richter et al., 2019). These technologies are not merely theoretical but are increasingly being implemented in classrooms worldwide, demonstrating their practical utility and transformative potential (Luckin et al., 2016).

Baker (2000) discussed the evolution of models in AIED research, advocating for a shift from individual cognition models to more collaborative learning scenarios. This era marked the early integration of AI in educational technologies, with a focus on intelligent tutoring systems (ITS) and adaptive learning environments. These systems have shown significant improvements in learning outcomes by providing personalised feedback and guidance, particularly in STEM disciplines (Chen et al., 2020; Ezzaim et al., 2022; Hamal et al., 2022; Hwang et al., 2020; Roll & Wylie, 2016; Zhai et al., 2021). Among the most notable AI applications in education are intelligent tutoring systems (ITS) and adaptive learning technologies. ITS was designed to offer immediate, personalised feedback to learners, closely resembling one-on-one tutoring (Nkambou et al., 2010). Research by VanLehn (2011) and Graesser et al. (2014) demonstrated ITS's effectiveness in enhancing student learning outcomes, especially in subjects like mathematics and science. These systems employed AI algorithms to evaluate student responses and modify instruction as needed, thus enhancing both efficiency and effectiveness in learning. Adaptive learning platforms use AI to create dynamic and personalised learning paths for students, adjusting content delivery based on real-time analysis of student performance and engagement (Khosravi et al., 2020). Studies by Walkington (2013) and Pane et al. (2017) indicated that adaptive learning could lead to substantial gains in student achievement by ensuring instructional material is appropriately challenging and relevant.

Roll and Wylie (2016) noted that research efforts had focused on developing systems as effective as human one-on-one tutoring, addressing the problem by achieving similar learning gains more efficiently. This focus led to the creation of various interactive learning environments that improved learning efficiency by reducing the time needed to achieve similar outcomes. Traditionally, AIED research has concentrated on empirical studies evaluating system performance and student interactions within specific domains, primarily in STEM (VanLehn, 2011; Koedinger et al., 2012). These studies have consistently shown that ITS and adaptive learning environments significantly enhance learning outcomes by providing personalised, immediate feedback (Graesser et al., 2014; Aleven et al., 2013). However, the traditional emphasis on domain-specific, step-based problem-solving has often overlooked broader educational goals, such as metacognition, critical thinking, and collaboration, which are increasingly valued in modern educational theories (Luckin et al., 2016).

Beyond classroom instruction, AI has demonstrated the potential to improve administrative efficiency within educational institutions. AI-powered systems can automate routine tasks like grading, scheduling, and attendance tracking, allowing educators to focus more on teaching and mentoring (Luckin et al., 2016). Moreover, predictive analytics can help identify at-risk students and tailor interventions to improve retention and success rates (Sclater, 2017). Research by Siemens and Baker (2012) and Arnold and Pistilli (2012) highlighted the potential of learning analytics to provide actionable insights for educators and administrators.

Hwang et al. (2020) discussed the vision, challenges, roles, and research issues of AIED, emphasising the need for interdisciplinary collaboration to tackle the complexities of integrating AI technologies into educational practices. They stressed the importance of aligning AI applications with educational theories and pedagogical practices to ensure AIED systems' effectiveness and relevance. The study also highlighted the potential of advanced AI techniques, such as deep learning and natural language processing, to further personalise and enhance educational experiences. Chen et al. (2020) expanded the traditional focus by highlighting the development of adaptive systems that support general learning skills and competencies. They noted that recent shifts in educational priorities have led to the creation of more complex and authentic learning environments that incorporate collaborative structures and real-world problem-solving activities. These environments aim to provide students with meaningful, context-rich learning experiences that promote deeper understanding and skill development. Chen et al. (2023) also emphasised the importance of future research focusing on embedding AI technologies within students' everyday lives, supporting their cultural practices, goals, and communities.

Hamal et al. (2022) noted that over the past 30 years, AIED had effectively combined AI with learning sciences to create adaptive learning environments that addressed challenges brought by emerging technologies such as smartphones, tablets, cloud computing, and big data. This interdisciplinary approach led to the development of AIED systems, including ITS, adaptive learning technologies, and AI-driven feedback mechanisms. These significantly enhanced learning outcomes by providing personalised educational experiences tailored to individual learner needs. Ezzaim et al. (2022) highlighted the diverse and impactful applications of AIED across various educational contexts, including adaptive learning systems, ITS, conversational agents, recommendation systems, virtual learning environments, and expert systems. These applications aimed to personalise content, increase learner engagement, and offer real-time feedback and support. Meanwhile, Chen et al. (2022) conducted a comprehensive review of AIED, identifying key areas of progress and ongoing challenges, emphasising the importance of integrating AI technologies with educational theories and practices and the need for interdisciplinary collaboration to effectively address the complexities of implementing AI in educational settings.

Crompton and Burke (2023) examined the use of AI in higher education, noting a rapid increase in publications and emerging trends in researcher affiliations and study focuses. They identified five primary usage codes for AI in education: assessment/evaluation, predicting, AI assistants, ITS, and managing student learning, highlighting AI's potential to make higher education more personalised, engaging, and effective. Hwang et al. (2024) defined AIED as the application of AI technologies to enhance educational processes through personalised learning experiences, support for teachers in administrative tasks, and decision-making assistance (Ifelebuegu et al., 2023). These technologies used advanced machine learning, natural language processing, and data analytics to simulate cognitive functions, thus improving educational outcomes and operational efficiency. Significant advancements in AIED included personalised learning, adaptive assessment, and real-time feedback mechanisms that used AI-driven learning analytics to monitor student performance and tailor instructional strategies. AI-powered tools enhanced interactive learning environments by fostering collaborative learning and peer interactions, adapting to individual learning styles. Additionally, the use of conversational agents and AI tutors improved student engagement and academic performance.

Luckin et al. (2024) highlighted the importance of integrating artificial intelligence (AI) into education in a way that is both learner-centred and ethically responsible. She advocated for balancing the roles of AI and human educators, highlighting AI's potential to personalise learning and streamline educational processes. However, Luckin warned of ethical challenges, particularly concerning data privacy, transparency, and the risk of over-reliance on AI systems for decision-making and critical thinking. She stressed the need for interdisciplinary collaboration among educators, researchers, and developers to design AI tools that are trustworthy and promote equitable learning outcomes.

Technology acceptance model (TAM)

The development of AM was driven by the need for a comprehensive and user-centric framework to understand the adoption and acceptance of new technologies. Over the past three decades, TAM has become one of the most influential theories in technology adoption research. Before the emergence of TAM, researchers had explored various models and theories, including Rogers's (1962) Diffusion of Innovations theory, Fishbein and Ajzen's (1975) Theory of Reasoned Action, and Ajzen's (1985) Theory of Planned Behaviour. However, these models did not specifically target technology acceptance. TAM originated from Davis's (1986) doctoral dissertation, which laid the groundwork for the model. Davis drew on concepts from cognitive psychology, such as Festinger's (1957) Theory of Cognitive Dissonance. He incorporated the Perceived Usefulness construct from Delone and McLean (1992) to develop a model explaining how individuals decide to accept and use technology.

Davis introduced the Technology Acceptance Model (TAM) in 1989, suggesting that a user's intention to use technology is primarily influenced by perceived usefulness (PU) and perceived ease of use (PEOU) (Figure 1). PU refers to the belief that using a particular technology will enhance one's performance or effectiveness, highlighting the utilitarian aspect of technology acceptance. PEOU, on the other hand, pertains to how easily the user finds the technology to learn and operate; a system perceived as user-friendly is more likely to be adopted. Intention to Use (ITU) acts as a mediator between PU, PEOU, and actual use (AU) in TAM, reflecting the user's intention to utilise the technology, which is a strong predictor of their subsequent behaviour. AU represents the real usage of the technology, driven by behavioural intention. Attitude towards Using (ATU) encapsulates the user's overall emotional and evaluative response to technology, including their feelings, predispositions, and subjective assessment of its value and utility.

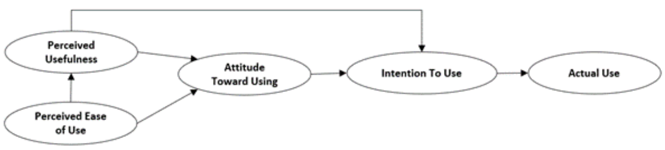

Figure 1. Technology Acceptance Model. *Note*. Adapted from "Technology Acceptance Model" by D. Marikyan & S. Papagiannidis, in S. Papagiannidis (Ed.), *Theory Hub Book*, 2023 (https://open.ncl.ac.uk/theories/1/technology-acceptance-model/). CC BY-NC-ND 4.0.

One of the reasons why TAM is a useful framework for studying and understanding technology adoption and acceptance is its simplicity and clarity. The model only has a few key constructs, mainly PU and PEOU, which are not difficult to measure and analyse. This makes TAM user-friendly and practical for various purposes. Another reason is TAM's strong predictive power in explaining and forecasting technology adoption and usage behaviour. Research has consistently shown that PU and PEOU are reliable predictors of users' behavioural intentions and technology use. This predictive accuracy is essential for organisations and policymakers seeking to understand and influence technology adoption. A third reason is that TAM's core constructs are generic and broad, making the model applicable to various technologies and contexts.

Researchers in education have applied TAM to examine how educators adopt different educational technologies, such as online learning platforms, digital teaching tools, and collaborative software (Camilleri & Camilleri, 2022; Fearnley & Amora, 2020; Davis & Granić, 2024). TAM has enabled researchers to compare how different technologies are accepted in the same educational context. By using TAM to evaluate various tools or platforms, researchers can better identify which ones match users' needs and preferences. Researchers in education have also used TAM to investigate the factors that affect technology acceptance among educators and students. They have explored how training, support, attitudes, and external pressures shape users' perceptions of technology (Hamutoglu, 2021; Saleh et al., 2022). Educational institutions have relied on TAM to inform their technology integration strategies. By knowing teachers' and students' perceptions, institutions can make better decisions about which technologies to invest in and how to support their effective implementation (Almulla, 2021; Chugh et al., 2023; Hamutoglu, 2021). TAM has also helped educators design educational content and instruction that aligns with students' needs and preferences (Etemi et al., 2024; De Vega et al., 2023; Tawafak et al., 2023). By focusing on technologies that are perceived as useful and easy to use, educators can create more engaging and effective learning experiences. With the increase of online and remote learning, TAM has been used to evaluate the acceptance of digital tools and platforms in virtual learning environments (Almulla, 2022; Alqahtani & Al-Rahmi, 2022; Camilleri & Camilleri, 2022). This research informs the design of online courses and the selection of appropriate technologies.

One-stage meta-analytic structural equation modelling (OSMASEM)

OSMASEM is a statistical technique that integrates meta-analysis and structural equation modelling (SEM) elements. This technique offers several advantages, such as estimating construct relationships more precisely by pooling data across studies, addressing complex questions involving indirect effects and mediation, accounting for measurement error and modelling latent variables, and reducing bias and improving the accuracy of parameter estimates (Cheung, 2015; Cheung & Chan, 2005; Eisenberg et al., 2019; Jak, 2015). OSMASEM provides a comprehensive framework for synthesising research findings, especially in fields where constructs are complex and interrelated (Cheung, 2019). As such, OSMASEM can benefit TAM research in educational contexts in several ways. It can integrate diverse datasets from various educational institutions, settings, and populations, facilitating the generalisation of findings about technology acceptance in education (Or, 2023). It can also enhance statistical power, allowing researchers to detect smaller effects and relationships that may be missed in individual studies due to sample size limitations. This is valuable for identifying nuances in the associations between PEOU, PU, ITU, and AU. Within OSMASEM, SEM quantitatively synthesises relationships between TAM constructs, calculating summary effect sizes that provide a clearer understanding of the strength and direction of associations between PU, PEOU, ITU, and AU in educational settings.

The current study using one-stage meta-analytic structural equation modelling (OSMASEM)

The current study utilised the correlation-based OSMASEM technique (Jak et al., 2021) to synthesise existing empirical research on the Technology Acceptance Model (TAM) in the context of AI in Education (AIED). TAM is widely used to explore the factors influencing the acceptance and adoption of AIED systems by both learners and educators (Gros, 2016; Looi et al., 2011). While previous studies on TAM have employed various methods, such as traditional meta-analysis (King & He, 2006), structural equation modelling (SEM) (Lee et al., 2003), and longitudinal studies, to investigate the relationships between TAM constructs, these approaches have limitations in integrating diverse findings and adapting to the specific characteristics of AIED contexts (Marangunić & Granić, 2015). To address these gaps, this meta-analysis aimed to answer the following research questions:

1) How stable are the relationships between key factors in TAM, based on a synthesis of past studies using meta-analytic techniques?

2) To what extent does TAM provide a good explanation of how educators and students accept AIED based on a combined analysis of data from multiple studies?

3) What role does ATU play in shaping the acceptance of AIED, and how does including this factor impact the relationships among other key factors in TAM?

The need for this study is driven by the rapid adoption of AI in educational settings and the growing necessity to understand how educators and students interact with these technologies. While TAM has been widely used to assess technology adoption, its application to AIED remains underexplored, particularly in terms of synthesising existing empirical evidence through meta-analytic techniques. Given the increasing integration of AI-powered tools in classrooms, universities, and administrative processes, understanding the stability of relationships among TAM constructs is crucial for designing AI systems that are not only effective but also widely accepted by users. This study provides valuable insights for educators, policymakers, and developers by identifying key determinants of AI acceptance and addressing gaps in existing research. By doing so, it offers a comprehensive perspective on how usability, perceived benefits, and attitudes shape AI adoption, ultimately contributing to more informed decision-making in AI-driven educational innovation.

The other important mention is the theoretical framework for this meta-analysis study. Despite AU being the endogenous construct in the original TAM, it was not included in this study's model because only four out of the 17 studies in the analysis included AU as a variable. The limited representation of AU across the datasets raised concerns about consistency and completeness, which could have impacted the reliability and validity of the model. As a result, the study prioritised constructs that were more consistently measured across the available studies, as shown in Figure 2. This approach ensured that the model accurately reflected the most reported relationships while acknowledging the constraints of the existing data.

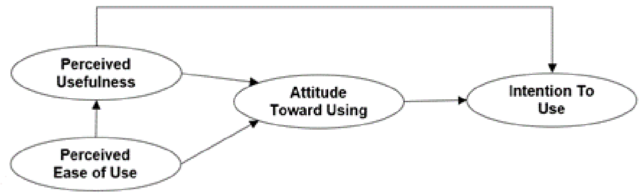

Figure 2. Adapted theoretical framework for meta-analysis.

Methodology

Literature search and screening procedures

The literature search for relevant studies on TAM in education covered the period from 1989 to 2024. Using Primo by Ex Libris, the following search string was applied across multiple databases: "technology" AND "acceptance" AND "model" AND "education" AND "artificial intelligence". The databases included the DOAJ, IngentaConnect Journals, Springer Ejournals, Journals@Ovid Ovid Autoload, Springer Nature OA/Free Journals, ScienceDirect Ejournals, CINAHL Complete, Wiley Online Library - AutoHoldings Journals, Public Library of Science, Taylor & Francis Online, Business Source Complete, IOP Publishing Free Content, BMJ Journals, Taylor & Francis Open Access, Wiley Online Library Open Access, SAGE Journals PREM24 Premier 2024, and Oxford Journals Online. The search filters were English language, article document type, open access, peer-reviewed, and the specified years. The initial screening of the 3440 identified studies was based on the following criteria: (1) the studies examined technology acceptance in school or university settings; (2) the studies reported quantitative data and correlations of TAM constructs; (3) the studies were written in English. This resulted in 29 eligible empirical studies. Further exclusion criteria were: (1) the studies did not target teachers, lecturers, educators, or students in K-12, college, or university education; (2) TAM was examined outside of educational contexts; (3) the studies were not based on the TAM models; (4) the studies had insufficient statistical reporting of the correlations between TAM constructs; (5) correlations between variables were negative, which the R package "metaSEM" (Cheung, 2014) could not compute (R Core Team, 2024); (6) the studies did not include original TAM endogenous constructs, ITU. Finally, 17 studies with sample sizes greater than 100 were included in the meta-analysis using correlation matrices. Figure 3 shows PRISMA, which describes the literature search and selection process. Table 1 lists the studies that provided the data for this OSMASEM study.

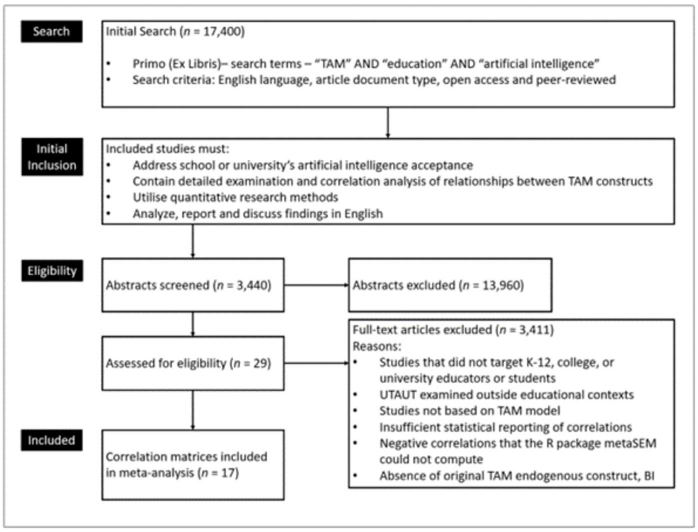

Figure 3. PRISMA diagram depicting the literature search and selection process for eligible studies in the meta-analysis.

Table 1. TAM studies from which data are used.

S/N	Sample Size	Study
1	314	Li, K. (2023). Determinants of College Students' Actual Use of AI-Based Systems: An Extension of the Technology Acceptance Model. *Sustainability, 15*(6), 5221.
2	311	Wang, Y., Liu, C., & Tu, Y. F. (2021). Factors affecting the adoption of AI-based applications in higher education. *Educational Technology & Society, 24*(3), 116-129.
3	147	Musyaffi, A. M., Baxtishodovich, B. S., Afriadi, B., Hafeez, M., Adha, M. A., & Wibowo, S. N. (2024). New Challenges of Learning Accounting With Artificial Intelligence: The Role of Innovation and Trust in Technology. *European Journal of Educational Research, 13*(1).
4	215	Choi, S., Jang, Y., & Kim, H. (2023). Influence of pedagogical beliefs and perceived trust on teachers' acceptance of educational artificial intelligence tools. *International Journal of Human–Computer Interaction, 39*(4), 910-922.
5	665	Chen, S., Qiu, S., Li, H., Zhang, J., Wu, X., Zeng, W., & Huang, F. (2023). An integrated model for predicting pupils' acceptance of artificially intelligent robots as teachers. *Education and Information Technologies, 28*(9), 11631-11654.
6	528	Ni, A., & Cheung, A. (2023). Understanding secondary students' continuance intention to adopt AI-powered intelligent tutoring system for English learning. *Education and Information Technologies, 28*(3), 3191-3216.
7	303	Pan, Z., Xie, Z., Liu, T., & Xia, T. (2024). Exploring the Key Factors Influencing College Students' Willingness to Use AI Coding Assistant Tools: An Expanded Technology Acceptance Model. *Systems, 12*(5), 176.
8	372	Malik, R., Shrama, A., Trivedi, S., & Mishra, R. (2021). Adoption of chatbots for learning among university students: Role of perceived convenience and enhanced performance. *International Journal of Emerging Technologies in Learning (iJET), 16*(18), 200-212.
9	413	Awal, M. R., & Haque, M. E. (2024). Revisiting university students' intention to accept AI-Powered chatbot with an integration between TAM and SCT: a south Asian perspective. *Journal of Applied Research in Higher Education.*
10	458	Almogren, A. S., Al-Rahmi, W. M., & Dahri, N. A. (2024). Exploring Factors Influencing the Acceptance of ChatGPT in Higher Education: A Smart Education Perspective. *Heliyon.*
11	315	Molefi, R. R., Ayanwale, M. A., Kurata, L., & Chere-Masopha, J. (2024). Do in-service teachers accept artificial intelligence-driven technology? The mediating role of school support and resources. *Computers and Education Open, 100191.*
12	375	Tiwari, C. K., Bhat, M. A., Khan, S. T., Subramaniam, R., & Khan, M. A. I. (2023). What drives students toward ChatGPT? An investigation of the factors influencing adoption and usage of ChatGPT. *Interactive Technology and Smart Education.*
13	156	Saif, N., Khan, S. U., Shaheen, I., ALotaibi, F. A., Alnfiai, M. M., & Arif, M. (2024). Chat-GPT; validating Technology Acceptance Model (TAM) in education sector via ubiquitous learning mechanism. *Computers in Human Behavior, 154*, 108097.
14	274	Guo, S., Shi, L., & Zhai, X. (2024). Validating an Instrument for Teachers' Acceptance of Artificial Intelligence in Education. *arXiv preprint arXiv:2406.10506.*
15	140	Gayashan, S. P., & Samarasinghe, S. (2024, April). Factors Affecting the Intention to Use AI-Based Chatbots in Learning. In 2024 International Research *Conference on Smart Computing and Systems Engineering (SCSE) (Vol. 7, pp. 1-9). IEEE.*
16	207	Bilquise, G., Ibrahim, S., & Salhieh, S. E. M. (2024). Investigating student acceptance of an academic advising chatbot in higher education institutions. *Education and Information Technologies, 29*(5), 6357-6382.
17	637	Albayati, H. (2024). Investigating undergraduate students' perceptions and awareness of using ChatGPT as a regular assistance tool: A user acceptance perspective study. *Computers and Education: Artificial Intelligence, 6*, 100203.

Analysis using metaSEM for one-stage meta-analytic structural equation modelling (OSMASEM)

The R package 'metaSEM' (Cheung, 2015; version 1.3.1) was used to analyse the correlation matrices derived from the TAM studies, utilising R software (R Core Team, 2024; version 4.3.1). This package implements the OSMASEM method, which integrates meta-analysis and SEM using the 'OpenMx' package in R. Meta-analysis is a statistical technique that combines the findings from independent studies to estimate the overall effect size and trend (Borenstein et al., 2009). It involves systematically collecting and synthesising data from multiple research studies to reach a comprehensive conclusion with greater statistical power and reliability than individual studies. The metaSEM package extends this technique by allowing for the evaluation of complex relationships between observed and latent variables using SEM. OSMASEM is especially relevant for this study because it can process past study data and map the evolution of relationships between variables over continuous time points (Cheung, 2014). OSMASEM combines all the data from multiple studies into a single analysis, treating the pooled data as if it were from one large study. This approach retains the complexity and richness of the original data while enhancing the statistical power to detect significant effects.

The correlation matrices from the included studies were inspected for completeness and consistency before analysis. Any discrepancies or missing data points were addressed through imputation or exclusion as appropriate. The matrices were then standardised to ensure comparability across studies. The meta-analytic technique in the 'metaSEM' package was used to combine the individual correlation matrices. Specifically, the OSMASEM method was employed to aggregate the data across studies. This process involves pooling the correlation matrices using a maximum likelihood estimation approach, which summed the sample sizes from each study rather than averaging them. This approach allowed for a more accurate computation of standard errors for the path coefficients in the SEM. Mediation analyses were conducted within the OSMASEM framework to examine the indirect effects between variables. These analyses were moved from the results section to provide a more coherent and comprehensive description of the methodological process.

Results

Internal structure

The metaSEM package (Cheung, 2014; version 1.3.0) in R (version 4.3.3) and R Studio (version 2023.12.1, Build 402) was used to analyse the TAM model 1 using data from 17 TAM studies, encompassing a total sample size of 5,830 participants, to analyse the determinants of AI-based system adoption in educational settings. This analysis tested the model's theoretical framework by comparing the observed correlations with the proposed measurement model to assess the fit and loadings of the factors (Albright & Park, 2009; Bollen, 1989; Hair et al., 2006; Kline, 2015). Five fit indices were used to evaluate the model: (a) chi-square to degrees of freedom ratio ($\chi2$/df), (b) root mean square error of approximation (RMSEA; Steiger, 1990), (c) standardised root mean square residual (SRMR), (d) comparative fit index (CFI; Bentler, 1990), and (e) Tucker-Lewis index (TLI; Bentler & Bonett, 1980) as shown in Table 2. The $\chi2$ statistic is sensitive to sample size, so the $\chi2$/df ratio was used, with values below 3 indicating acceptable fit (Kline, 2015). For RMSEA, values below .050 indicate a close fit, between .050 and .080 a good fit, between .080 and .100 a mediocre fit, and above .100 an unacceptable fit (Browne & Cudeck, 1992). Recent guidelines have confirmed these ranges, emphasising the importance of a lower RMSEA for a better model fit (Byrne, 2016; Kenny et al., 2015; Kline, 2015; Schreiber et al., 2006). The CFI and TLI, which compare the model with a baseline null model while adjusting for complexity, suggest an acceptable fit for values above .950. The TAM model's fit indices ($\chi2$/df = 2.395; RMSEA = .016; SRMR = .028; CFI = .994; TLI = .962) indicated that it fit the data well (Table 2). Reliability analysis conducted with IBM SPSS (version 28.0.1.1) showed high-scale reliability, as indicated by Cronbach's alpha (N = 17; α = .886).

Table 2. Goodness-of-fit indices of model.

Measure	Threshold	Value
χ^2	--	2.395
df	--	1.000
χ^2/df	< 3.000	2.395
p-value	> .050	.122
RMSEA	< .050	.016
SRMR	<.080	.028
CFI	> .950	.994
TLI	> .950	.962

The effect of PEOU on PU was significant (β = .619, p < .001), indicating that easier technology use is strongly linked to higher perceived usefulness (Figure 4). Additionally, PU directly influenced ATU (β = .340, p < .001), indicating that as users perceived the technology to be more useful, their attitude toward using it became more favourable. PEOU also had a direct effect on ATU (β =.425, p < .001). This suggested that PEOU not only contributed to PU but also independently enhanced users' attitudes toward the technology. ATU significantly predicted ITU (β =.488, p < .001), while PU also had a direct effect on ITU (β =.324, p < .001).

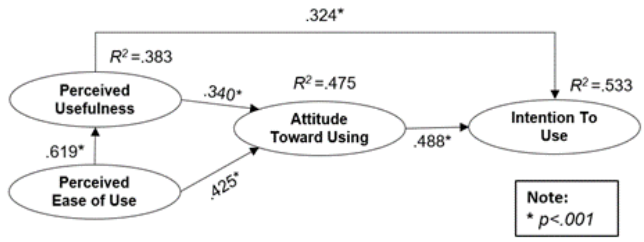

Figure 4: Paths analysis of meta-analysis.

The variance explained by the model was substantial across constructs. PU had an R^2 value of .383, indicating that PEOU explained 38.3% of its variance. ATU had an R^2 value of .475, showing that PU and PEOU explained 47.5% of its variance. Lastly, ITU had an R^2 value of .533, meaning that ATU and PU together explained 53.3% of the variance in users' intention to use the technology.

Table 3: Direct, indirect and total effects.

Path	Direct Effect	Indirect Effect	Total Effect
PEOU → PU	.619*	-	-
PU → ATU	.340*	-	-
ATU → ITU	.488*	-	-
PEOU → ATU	.425*	.309*	.365*
PU → ITU	.324*	.166*	.490*
PEOU → ITU	-	.511*	.511*

*Note: *p<.001*

The current study examined the relationships between the TAM constructs in a structural equation model. The results indicated several significant direct and indirect effects, highlighting the pathways through which these constructs interacted to influence ITU (Table 3). The analysis revealed several significant indirect effects. The indirect effect of PEOU on ATU, mediated through PU, was significant (β = .309, p < .001), suggesting that the influence of PEOU on ATU occurred not only directly but also through its impact on PU. Similarly, the indirect effect of PU on ITU, mediated by ATU, was also significant (β = .166, p < .001). Notably, the total indirect effect of PEOU on ITU, incorporating multiple pathways (PEOU → PU → ITU, and PEOU → PU → ATU → ITU), was significant (β = .511, p < .001).

The total effect of PEOU on ATU, combining both direct and indirect pathways, was significant (β = .635, p < .001), demonstrating that PEOU substantially influenced ATU. The total effect of PU on ITU was significant as well (β = .490,

p < .001), highlighting the combined impact of direct and mediated pathways through which PU contributed to the ITU. The overall effect of PEOU on ITU was also significant (β = .511, p < .001), affirming the importance of PEOU as a foundational determinant of technology acceptance through various mediated pathways.

Table 4: Estimated missing studies, heterogeneity statistics, and effect size estimates for each path.

Path	Estimated Missing Studies	Effect Size (95% CI)	τ^2 (SE)	I^2 (%)
PEOU → PU	1 (SE = 2.701)	.628 [.561, .695]	.019 (.007)	91.56
PEOU → ATU	0 (SE = 1.535)	.611 [.514, .707]	.019 (.011)	91.41
PU → ATU	0 (SE = 2.046)	.619 [.522, .715]	.019 (.011)	91.8
PU → BIU	0 (SE = 2.427)	.611 [.542, .680]	.019 (.007)	91.65
ATU → BIU	0 (SE = 1.753)	.638 [.503, .772]	.040 (.021)	96.42

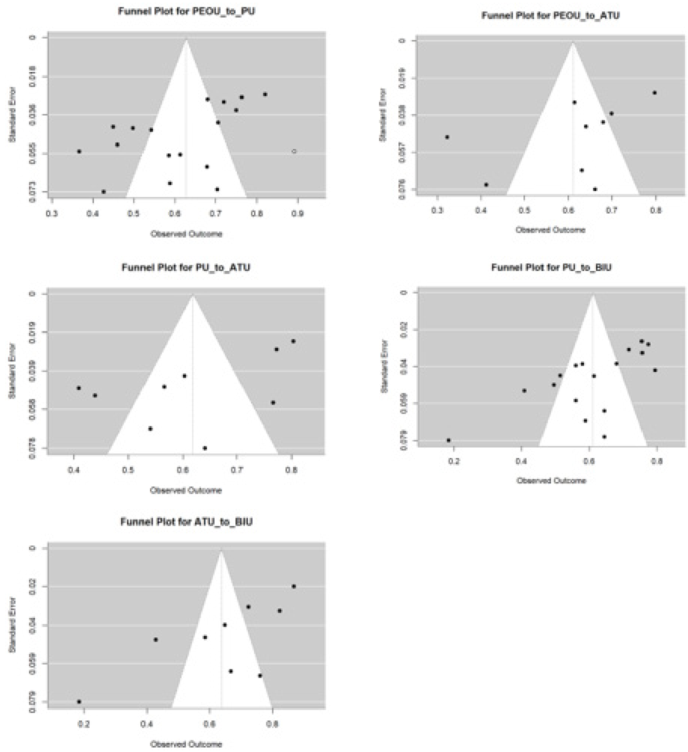

Figure 5: Funnel plots with Trim-And-Fill method for each path.

Publication bias was assessed using the Trim-and-Fill method in a funnel plot, focusing on key relationships within the Technology Acceptance Model (TAM). The analysis was conducted using R software (R Core Team, 2024; version 4.3.1) and the 'metafor' package (Viechtbauer, 2010; version 3.8-1). Table 1 presents the estimated number of missing studies, heterogeneity statistics, and effect size estimates for each relationship. For the PEOU → PU path, the Trim-and-Fill analysis suggested one potentially missing study on the right side, indicating possible publication bias, with the random-effects model estimating an effect size of .628, 95% CI [.561, .695], and substantial heterogeneity (τ^2 = .019, I^2 = 91.560%). In contrast, the PEOU → ATU path showed no missing studies, suggesting minimal publication bias, with an effect size estimate of .611, 95% CI [.514, .707], and high heterogeneity (τ^2 = .019, I^2 = 91.410%). Similarly, no missing studies were identified for the PU → ATU path, resulting in an effect size of .619, 95% CI [.522, .715], and considerable heterogeneity (τ^2 = .019, I^2 = 91.800%). For the PU → BIU path, the analysis found no missing studies, with an effect size of .611, 95% CI [.542, .680], and high heterogeneity (τ^2 = .019, I^2 = 91.650%). The ATU → BIU path showed no missing studies, with an effect size of .638, 95% CI [.503, .772], and the highest heterogeneity observed among the paths (τ^2 = .040, I^2 = 96.420%). Overall, the results indicated some potential publication bias for the PEOU → PU path due to the estimated missing study. Nevertheless, the effect sizes across all paths remained statistically significant after adjustment, demonstrating robust relationships within the TAM.

Discussion

The results of the TAM model in this study confirmed the significant roles of its construct in predicting acceptance of AEID. The significant paths between these constructs, all statistically significant at p < 0.001, reinforced the foundational premises of TAM proposed by Davis (1989). Notably, the path from PEOU was strong (β = .635, p < .001), suggesting that greater ease of use was significantly associated with increased perceived usefulness. This finding aligned with the core TAM assumption that usability is a critical determinant of perceived usefulness, as demonstrated in previous studies (Davis, 1989; Venkatesh & Davis, 2000). It iterated the importance of designing user-friendly interfaces to enhance the perceived value of the technology, thereby increasing the likelihood of adoption.

Furthermore, PU directly influenced ATU (β = .340, p < .001), indicating that as users perceived the technology to be more useful, their attitude toward using it became more favourable. It is interesting to note that Davis (1989) had removed ATU from the TAM while many researchers have reintroduced it to their studies. The original TAM, proposed by Davis in 1986, included ATU as a central construct, reflecting the user's overall affective response to the technology (Davis, 1986). ATU was initially considered an important mediator between PU, PEOU, and ITU. However, in the 1989 revision of TAM, ATU was excluded after empirical studies revealed that its mediating role was redundant; PU directly and strongly influenced ITU, rendering ATU unnecessary (Davis, 1989).

The direct effect of PEOU on ATU (β =.425, p < .001) further emphasised the role of usability in shaping users' attitudes. This finding supported previous meta-analytic results, such as those by King and He (2006), which found that PEOU not only contributed to PU but also independently enhanced users' attitudes toward the technology. The significant impact of ATU on ITU (β =.488, p < .001) reaffirmed the mediating role of ATU in the TAM framework. This relationship suggested that a positive attitude toward using the technology strongly drove users' intentions to use it, a finding that aligned with prior studies that have established attitude as a critical mediator between PU, PEOU, and ITU (Wu & Chen, 2017). Additionally, the direct effect of PU on ITU (β =.324, p < .001) emphasised the pivotal role of PU in technology acceptance. This direct link suggested that highlighting the practical benefits and usefulness of the technology could directly influence users' behavioural intentions, reinforcing findings from previous studies (Venkatesh & Davis, 2000; Schepers & Wetzels, 2007).

The R^2 values further illustrated the robustness of the TAM. PU explained 38.3% of its variance through PEOU, while PU and PEOU explained ATU with a combined variance of 47.5%. ITU had the highest explained variance at 53.3%, influenced by both ATU and PU. These findings were consistent with previous TAM studies, which reported similar levels of explained variance, affirming the model's predictive power (Venkatesh & Bala, 2008). However, compared to some studies that reported higher R^2 values for ITU, the slightly lower explained variance in this study could have been attributed to contextual differences or the specific technology that was evaluated (King & He, 2006; Schepers & Wetzels, 2007; Chin et al., 2008). King and He (2006) conducted a meta-analysis of TAM and found that PEOU and PU consistently influenced ITU across various studies. Moreover, Chin et al. (2008) highlighted that interaction effects and specific contextual variables could significantly influence the variance explained in ITU, further emphasising the importance of considering the specific context and technology being evaluated.

OSMASEM has emerged as a powerful analytical approach in synthesising research findings across multiple studies, particularly within the context of TAM applications in AIED. In the context of AIED, OSMASEM is particularly useful because it can handle diverse datasets from studies that apply TAM to understand the acceptance of AI technologies in the educational context. For example, the technique allows researchers to examine whether the relationships between TAM constructs remain consistent when applied to different AI applications, such as intelligent tutoring systems, adaptive learning platforms, or AI-powered administrative tools (Jarek & Cheng, 2022). This approach not only provides a robust framework for understanding the determinants of AI acceptance in education but also addresses potential heterogeneity among studies by modelling latent variables and accounting for measurement errors, which is crucial given the varied nature of AI technologies and their implementation contexts (Eisenberg et al., 2019). OSMASEM is advantageous in educational settings where data may be incomplete or where constructs like AU are not consistently reported across studies. OSMASEM's ability to synthesise complex relationships offers a more accurate and comprehensive view of how educators and students perceive and engage with AI technologies, providing valuable insights for policymakers, educators, and technology developers aiming to enhance AI adoption in education (Jak et al., 2021). The findings of this study offered insights for educators navigating the integration of AEID. Given that PEOU and PU significantly influence ATU, educators should prioritise selecting AI tools that are user-friendly and demonstrate clear pedagogical benefits. For instance, AI-powered tutoring systems and personalised learning platforms that reduce cognitive load while enhancing learning outcomes are more likely to gain acceptance among both educators and students (Tapalova & Tapalova, 2023). Understanding these factors allows educators to advocate for professional development programmes that equip them with the necessary skills to integrate AI seamlessly into their teaching practices (Zawacki-Richter et al., 2019). Additionally, institutions can leverage these insights to design policies that promote meaningful AI use while mitigating concerns about workload and digital literacy barriers (Popenici & Kerr, 2017; Holmes et al., 2019).

Limitations

The study identified two primary limitations: the availability of primary studies and the complexity of OSMASEM. These limitations may impact the reliability and applicability of the findings and pose challenges for researchers, especially those less experienced with OSMASEM. The availability and quality of primary studies are crucial for the scope and validity of OSMASEM, as the method relies on comprehensive datasets to accurately estimate relationships among constructs (Cheung, 2015). However, many studies lack sufficient and consistent data, such as correlation matrices and omission of constructs, which are essential for data extraction and synthesis in OSMASEM. This deficiency restricts the inclusion of potentially valuable research, thereby reducing the robustness of the meta-analytic structural equation model. A notable issue within the scope of TAM studies is the frequent omission of the AU construct, which significantly narrows the comprehension of technology acceptance behaviours. Out of 17 TAM studies analysed in this research, only four included AU. Chen This assumption might prove slightly flawed in educational settings, wherein factors such as access, training, or institutional support can impede the conversion of intention into genuine use, thus compromising the practical relevance of the findings and the credibility of OSMASEM when evaluating AI adoption in education.

Additionally, OSMASEM's complexity combines the intricacies of SEM and meta-analysis, necessitating a high level of proficiency in both techniques. This study utilised the metaSEM package within the R software environment—a powerful tool for conducting MASEM analysis, but one that also has its own set of complexities and limitations. Users must be adept with both the metaSEM package and R software, highlighting the need for researchers to master SEM and meta-analysis fundamentals before attempting OSMASEM.

Conclusions

This study's findings corroborated and extended the existing body of TAM research, reinforcing the critical roles of PEOU and PU in shaping ITU. The significant paths and robust R^2 values provided strong empirical support for TAM, confirming its applicability in understanding technology acceptance across various contexts. These insights are valuable for higher education practitioners aiming to enhance technology adoption by emphasising usability and perceived benefits, and they contribute to the ongoing refinement of TAM in predicting technology-related behaviours.

Future studies should further examine the interplay between PU, PEOU, ITU and even ATU to ensure that technology acceptance models remain robust and relevant in evolving contexts. As AI continues to advance and its applications in education become more complex, understanding the role of ATU will likely become increasingly important (Hwang et al., 2024). This understanding can guide the design of AI tools that not only meet functional needs but also resonate positively with users, fostering greater acceptance and more effective integration into educational environments.

With the continuous evolution of AI technologies, interdisciplinary collaboration will be essential to address the complex challenges and opportunities they present. Researchers, educators, policymakers, and technologists must work together to ensure that AIED is developed and implemented ethically, equitably, and effectively (Holmes et al., 2019). This collaborative approach will help maximise the benefits of AIED while mitigating potential risks. The integration of AI in education offers significant potential to enhance teaching and learning experiences, improve administrative efficiency, and personalise education. However, realising this potential requires careful consideration of ethical, practical, and pedagogical challenges. By leveraging insights from existing research and fostering collaborative efforts across disciplines, the educational community can harness AI to create more inclusive and effective learning environments.

Looking ahead, the future of AIED appears promising with ongoing advancements in technology and pedagogy. Emerging research areas include developing AI systems that can understand and respond to students' emotional and motivational states (D'Mello & Graesser, 2012; Bosch et al., 2020). There is also increasing interest in using AI to support collaborative learning and peer interactions (Rosé et al., 2019). These areas represent the next frontier in AI-enhanced education, focusing on the social and emotional aspects of learning. Zhai et al. (2021) emphasised the importance of developing adaptive systems that support general learning skills and competencies, incorporating collaborative learning structures and real-world problem-solving activities to provide students with meaningful, context-rich learning experiences. Integrating AI technologies with educational theories is crucial to achieving these goals. They identified emerging trends in AIED research, such as the integration of the Internet of Things (IoT), swarm intelligence, deep learning, and neuroscience, which are expected to further transform educational practices. However, significant challenges remain, including the inappropriate use of AI techniques, the evolving roles of teachers and students, and various social and ethical concerns. Addressing these challenges will be crucial for the effective implementation of AI in educational settings, as highlighted by Zhai et al. (2021).

References

Ajzen, I. (1985). From intentions to actions: A theory of planned behaviour. In J. Kuhl & J. Beckmann (Eds.), *Action control: From cognition to behavior* (pp. 11-39). Springer. https://doi.org/10.1007/978-3-642-69746-3_2.

Al-Azawei, A., Parslow, P., & Lundqvist, K. (2017). Investigating the effect of learning styles in a blended e-learning system: An extension of the Technology Acceptance Model (TAM). *Australasian Journal of Educational Technology, 33*(2), 1-23. https://doi.org/10.14742/ajet.2741

Albayati, H. (2024). Investigating undergraduate students' perceptions and awareness of using ChatGPT as a regular assistance tool: A user acceptance perspective study. *Computers and Education: Artificial Intelligence, 6*, 100203. https:// 10.1016/j.caeai.2024.100203

Albright, J. J., & Park, H. M. (2009). *Confirmatory factor analysis using AMOS, LISREL, Mplus, SAS/STAT CALIS*. Indiana University. https://hdl.handle.net/2022/19736

Aldraiweesh, A., & Alturki, U. (2023). The effectiveness of TAM in educational technology. *Journal of Educational Technology Research and Development, 71*(1), 58-75. https://doi.org/10.1007/s11423-023-10038-2

Aleven, V., Roll, I., McLaren, B. M., & Koedinger, K. R. (2013). Help helps, but only so much: Research on help seeking with intelligent tutoring systems. *International Journal of Artificial Intelligence in Education, 26*(1), 205-218. https://doi.org/10.1007/s40593-015-0089-1

Almogren, A. S., Al-Rahmi, W. M., & Dahri, N. A. (2024). Exploring factors influencing the acceptance of ChatGPT in higher education: A smart education perspective. *Heliyon*. https://doi.org/10.1016/j.heliyon.2024.e29317

Almulla, M. (2021). Technology Acceptance Model (TAM) and e-learning system use for education sustainability. *Academy of Strategic Management Journal*. https://www.abacademies.org/abstract/technology-acceptance-model-tam-and-elearning-system-use-for-education-sustainability-11056.html

Alqahtani, M., & Al-Rahmi, W. (2022). A systematic review of the Technology Acceptance Model for the sustainability of higher education during the COVID-19 pandemic. *Sustainability, 14*(18), 11389. https://doi.org/10.3390/su141811389

Alraimi, K. M., Zo, H., & Ciganek, A. P. (2015). Understanding the MOOCs continuance: The role of openness and reputation. *Computers & Education, 80*, 28-38. https://doi.org/10.1016/j.compedu.2014.08.006

Arnold, K. E., & Pistilli, M. D. (2012). Course signals at Purdue: Using learning analytics to increase student success. *Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 267-270). https://doi.org/10.1145/2330601.2330666

Awal, M. R., & Haque, M. E. (2024). Revisiting university students' intention to accept AI-Powered chatbot with an integration between TAM and SCT: A south Asian perspective. *Journal of Applied Research in Higher Education*. https://doi.org/10.1108/JARHE-11-2023-0514

Baker, M. (2000). The roles of models in artificial intelligence and education research: A prospectus. *Journal of Artificial Intelligence in Education, 11*(1), 122-141. https://hal.science/hal-00190395/en/.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin, 107*(2), 238-246. https://doi.

org/10.1037/0033-2909.107.2.238

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin, 88*(3), 588-606. https://doi.org/10.1037/0033-2909.88.3.588

Bilquise, G., Ibrahim, S., & Salhieh, S. E. M. (2024). Investigating student acceptance of an academic advising chatbot in higher education institutions. *Education and Information Technologies, 29*(5), 6357-6382. https://doi.org/10.1007/s10639-023-12076-x

Bollen, K. A. (1989). *Structural equations with latent variables*. Wiley. https://doi.org/10.1002/9781118619179

Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein, H. R. (2009). *Introduction to meta-analysis*. Wiley. https://doi.org/10.1002/9780470743386

Bosch, N., D'Mello, S., Baker, R. S., Shute, V., Ventura, M., Wang, L., & Zhao, W. (2020). Automatic detection of learning-centered affective states in the wild. *Proceedings of the National Academy of Sciences, 117*(2), 755-762. https://doi.org/10.1073/pnas.1910402117

Browne, M. W., & Cudeck, R. (1992). Alternative ways of assessing model fit. *Sociological Methods & Research, 21*(2), 230-258. https://doi.org/10.1177/0049124192021002005

Byrne, B. M. (2016). *Structural equation modeling with AMOS: Basic concepts, applications, and programming* (3rd ed.). Routledge.

Camilleri, M. A., & Camilleri, A. C. (2022). Technology-enhanced learning: The role of social media in online education. *Educational Technology & Society, 25*(2), 143-156.

Chen, C.-M., Chen, C.-M., & Lin, M.-H. (2020). Artificial intelligence in education: A review. *IEEE Access, 8*, 75264-75278. https://doi.org/10.1109/ACCESS.2020.2988510

Chen, G., Wang, C., & Liang, L. (2022). A comprehensive review of artificial intelligence in education: Progress and challenges. *Educational Technology & Society, 25*(1), 112-125. https://doi.org/10.1016/j.eswa.2024.124167

Chen, S., Qiu, S., Li, H., Zhang, J., Wu, X., Zeng, W., & Huang, F. (2023). An integrated model for predicting pupils' acceptance of artificially intelligent robots as teachers. *Education and Information Technologies, 28*(9), 11631-11654. https://doi.org/10.1007/s10639-023-11601-2

Cheung, M. W. L. (2014). metaSEM: An R package for meta-analysis using structural equation modeling. *Frontiers in Psychology, 5*, 1521. https://doi.org/10.3389/fpsyg.2014.01521

Cheung, M. W.-L. (2015). Meta-analytic structural equation modeling: A primer. *Prevention Science, 16*(6), 843-851. https://doi.org/10.1007/s11121-014-0480-5

Cheung, M. W.-L. (2019). A guide to conducting a meta-analysis with non-independent effect sizes using the metaSEM package. *Behavior Research Methods, 51*(5), 1971-1980. https://doi.org/10.3758/s13428-018-1118-2.

Cheung, M. W.-L., & Chan, W. (2005). Meta-analytic structural equation modeling: A two-stage approach. *Psychological Methods, 10*(1), 40-64. https://doi.org/10.1037/1082-989X.10.1.40.

Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2008). A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research, 14*(2), 189–217. https://doi.org/10.1287/isre.14.2.189.16018

Choi, S., Jang, Y., & Kim, H. (2023). Influence of pedagogical beliefs and perceived trust on teachers' acceptance of educational artificial intelligence tools. *International Journal of Human–Computer Interaction, 39*(4), 910-922. https://doi.org/10.1080/10447318.2022.2049145

Chugh, R., Ruhi, U., & Brzozowski, M. (2023). Extending Technology Acceptance Model to higher-education students' use of digital academic reading tools on computers. *International Journal of Educational Technology in Higher Education*. https://educationaltechnologyjournal.springeropen.com/counter/pdf/10.1186/s41239-023-00403-8.pdf

Crompton, H., & Burke, D. (2023). The rise of artificial intelligence in higher education: A review of research and trends. *Computers & Education, 175,* 104328. https://doi.org/10.1016/j.compedu.2023.104328

Davis, F. D. (1986). *A technology acceptance model for empirically testing new end-user information systems: Theory and results*. Massachusetts Institute of Technology. https://dspace.mit.edu/handle/1721.1/15192.

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

Davis, F. D., & Granić, A. (2024). The evolution and impact of the Technology Acceptance Model. *Information Systems Research, 35*(2), 123-138. https://doi.org/10.1287/isre.2024.1110

Delone, W. H., & McLean, E. R. (1992). Information systems success: The quest for the dependent variable. *Information Systems Research, 3*(1), 60-95. https://doi.org/10.1287/isre.3.1.60.

De Vega, R., Bustamante, M. S., & García, M. (2023). Extending the Technology Acceptance Model (TAM) to predict university students' intentions to use metaverse-based learning platforms. *Education and Information Technologies*. https://doi.org/10.1007/s10639-023-10950-7

D'Mello, S., & Graesser, A. (2012). Dynamics of affective states during complex learning. *Learning and Instruction, 22*(2), 145-157. https://doi.org/10.1016/j.learninstruc.2011.10.001

Eisenberg, D., Post, C., & DiTomaso, N. (2019). Meta-analytic structural equation modeling in management research: A guide for using metaSEM in R. *Organizational Research Methods, 22*(4), 969-1000. https://doi.org/10.1177/1094428118772670

Etemi, F., Basholli, A., & Bytyqi, A. (2024). Extending the Technology Acceptance Model (TAM) for AI-powered ChatGPT in education: A mixed-methods study. *Heliyon, 10*(8), e29317. https://doi.org/10.1016/j.heliyon.2024.e29317

Ezzaim, F., Alarifi, I. M., & Al-Mutairi, S. (2022). AIED applications in diverse educational contexts. *Journal of Educational Technology Systems, 50*(4), 403-423. https://doi.org/10.1177/00472395221043914

Fearnley, M. R., & Amora, J. T. (2020). Learning management system adoption in higher education using the Extended Technology Acceptance Model. *IAFOR Journal of Education: Technology in Education, 8*(2), 89-106. https://doi.org/10.22492/ije.8.2.05.

Festinger, L. (1957). *A theory of cognitive dissonance*. Stanford University Press.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research.* Addison-Wesley.

Gayashan, S. P., & Samarasinghe, S. (2024, April). Factors affecting the intention to use AI-based chatbots in learning. In *2024 International Research Conference on Smart Computing and Systems Engineering (SCSE)* (Vol. 7, pp. 1-9). IEEE. https://doi.org/10.1109/SCSE61872.2024.10550537

Graesser, A. C., Conley, M. W., & Olney, A. (2014). Intelligent tutoring systems. In M. J. Furlong, R. Gilman, & E. S. Huebner (Eds.), *Handbook of positive psychology in schools* (pp. 311-321). Routledge.

Gros, B. (2016). The design of smart educational environments. *Smart Learning Environments, 3*(1), 15. https://doi.org/10.1186/s40561-016-0039-x

Guo, S., Shi, L., & Zhai, X. (2024). *Validating an instrument for teachers' acceptance of artificial intelligence in education.* arXiv preprint, arXiv:2406.10506. https://doi.org/10.48550/arXiv.2406.10506

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate data analysis* (6th ed.). Prentice Hall.

Hamal, O., El Faddouli, N.-E., Alaoui Harouni, M. H., & Lu, J. (2022). Artificial intelligent in education. *Sustainability (Switzerland), 14*(5), 2862. https://doi.org/10.3390/su14052862

Hamutoglu, N. B. (2021). Testing the effects of technological barriers on high school teachers' role in technology integration. *Asian Journal of Distance Education, 16*(1), 74-89. https://eric.ed.gov/?id=EJ1303725

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign. https://circls.org/primers/artificial-intelligence-in-education-promises-and-implications-for-teaching-and-learning

Hwang, G.-J., Sung, H.-Y., & Chang, S.-C. (2024). Artificial intelligence in education: Theories, applications, and challenges. *Journal of Educational Technology & Society, 27*(1), 1-14.

Hwang, G.-J., Xie, H., & Yuan, C. (2020). The vision, challenges, roles, and research issues of artificial intelligence in education. *Computers & Education: Artificial Intelligence, 1*, 100001. https://doi.org/10.1016/j.caeai.2020.100001

Ifelebuegu, A. O., Kulume, P., & Cherukut, P. (2023). Chatbots and AI in Education (AIEd) tools: The good, the bad, and the ugly. *Journal of Applied Learning and Teaching, 6*(2), 332-345. https://doi.org/10.37074/jalt.2023.6.2.29

Jak, S. (2015). *Meta-analytic structural equation modeling*. Springer. https://doi.org/10.1007/978-3-319-27174-3.

Jak, S., Cheung, M. W.-L., & Mak, T. M. (2021). Meta-analytic structural equation modeling with multiple mediators: A comparison of three methods. *Research Synthesis Methods, 12*(5), 590-606. https://doi.org/10.1002/jrsm.1478

Jarek, P., & Cheng, L. (2022). One-step meta-analytic structural equation modelling (OSMASEM) in educational research. *Journal of Structural Equation Modelling, 29*(3), 201-215. https://doi.org/10.1080/10705511.2022.2074236

Kenny, D. A., Kaniskan, B., & McCoach, D. B. (2015). The performance of RMSEA in models with small degrees of freedom. *Sociological Methods & Research, 44*(3), 486-507. https://doi.org/10.1177/0049124114543236

Khosravi, H., Cooper, K., & Kitto, K. (2020). Towards adaptive feedback for student learning improvement. *Journal of Learning Analytics, 7*(1), 33-46. https://doi.org/10.18608/jla.2020.71.3

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management, 43*(6), 740-755. https://doi.org/10.1016/j.im.2006.05.003

Kline, R. B. (2015). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.

Koedinger, K. R., Anderson, J. R., Hadley, W. H., & Mark, M. A. (2012). Intelligent tutoring goes to school in the big city. *International Journal of Artificial Intelligence in Education, 8*(1), 30-43. https://kilthub.cmu.edu/articles/journal_contribution/Intelligent_Tutoring_Goes_To_School_in_the_Big_City/6470153

Lee, Y., Kozar, K. A., & Larsen, K. R. T. (2003). The Technology Acceptance Model: Past, present, and future. *Communications of the Association for Information Systems, 12*, 752-780. https://doi.org/10.17705/1CAIS.01250

Li, K. (2023). Determinants of college students' actual use of AI-based systems: An extension of the Technology Acceptance Model. *Sustainability, 15*(6), 5221. https://doi.org/10.3390/su15065221

Looi, C. K., Seow, P., Zhang, B., So, H.-J., Chen, W., & Wong, L. H. (2011). Leveraging mobile technology for sustainable seamless learning: A research agenda. *British Journal of Educational Technology, 42*(1), 154-169. https://doi.org/10.1111/j.1467-8535.2009.01016.x.

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education.* Pearson Education. https://discovery.ucl.ac.uk/id/eprint/1475756/

Luckin, R., Rudolph, J., Grünert, M., & Tan, S. (2024). Exploring the future of learning and the relationship between human intelligence and AI. An interview with Professor Rose Luckin. *Journal of Applied Learning and Teaching, 7*(1), 346-363. https://doi.org/10.37074/jalt.2024.7.1.27

Malik, R., Shrama, A., Trivedi, S., & Mishra, R. (2021). Adoption of chatbots for learning among university students: Role of perceived convenience and enhanced performance. *International Journal of Emerging Technologies in Learning iJET, 16*(18), 200-212. https://doi.org/10.3991/ijet.v16i18.24315

Marangunić, N., & Granić, A. (2015). Technology acceptance model: A literature review from 1986 to 2013. *Universal Access in the Information Society, 14*(1), 81-95. https://doi.org/10.1007/s10209-014-0348-1.

Marikyan, D., & Papagiannidis, S. (2023). Technology acceptance model. In S. Papagiannidis (Ed.), *Theory hub book*. Newcastle University. https://open.ncl.ac.uk/theories/1/technology-acceptance-model/ (CC BY-NC-ND 4.0).

Mayer, R. E., & Girwidz, R. (2019). Educational technology in a digital age: Promise and pitfalls. *Educational Psychologist, 54*(3), 170-183. https://doi.org/10.1080/00461520.2019.1630068

Molefi, R. R., Ayanwale, M. A., Kurata, L., & Chere-Masopha, J. (2024). Do in-service teachers accept artificial intelligence-driven technology? The mediating role of school support and resources. *Computers and Education Open, 6*, 100191. https://doi.org/10.1016/j.caeo.2024.100191

Musyaffi, A. M., Baxtishodovich, B. S., Afriadi, B., Hafeez, M., Adha, M. A., & Wibowo, S. N. (2024). New challenges of learning accounting with artificial intelligence: The role of innovation and trust in technology. *European Journal of Educational Research, 13*(1), 183-195. https://doi.org/10.12973/eu-jer.13.1.183

Ni, A., & Cheung, A. (2023). Understanding secondary students' continuance intention to adopt AI-powered intelligent tutoring system for English learning. *Education and Information Technologies, 28*(3), 3191-3216. https://doi.org/10.1007/s10639-022-11305-z

Nkambou, R., Bourdeau, J., & Mizoguchi, R. (Eds.). (2010). *Advances in intelligent tutoring systems*. Springer. https://doi.org/10.1007/978-3-642-14363-2

Or, C. C. P. (2023). Examining unified theory of acceptance and use of Technology 2 through Meta-analytic Structural Equation Modelling. *Journal of Applied Learning and Teaching, 6*(2), 283-293. https://doi.org/10.37074/jalt.2023.6.2.7

Pan, Z., Xie, Z., Liu, T., & Xia, T. (2024). Exploring the key factors influencing college students' willingness to use AI coding assistant tools: An expanded technology acceptance model. *Systems, 12*(5), 176. https://doi.org/10.3390/systems12050176

Pane, J. F., Griffin, B. A., McCaffrey, D. F., & Karam, R. (2017). Effectiveness of cognitive tutor Algebra I at scale. *Educational Evaluation and Policy Analysis, 36*(2), 127-144. https://doi.org/10.3102/0162373713507480

Popenici, S. A. D., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning, 12*(1), 22. https://doi.org/10.1186/s41039-017-0062-8

R Core Team (2024). *_R: A language and environment for statistical computing_*. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org

Rogers, E. M. (1962). *Diffusion of innovations.* Free Press.

Roll, I., & Wylie, R. (2016). Evolution and revolution in artificial intelligence in education. *International Journal of Artificial Intelligence in Education, 26*(2), 582-599. https://doi.org/10.1007/s40593-016-0110-3

Rosé, C. P., Wang, Y. C., Cui, Y., Arguello, J., Stegmann, K., Weinberger, A., & Fischer, F. (2019). Analysing collaborative learning processes automatically: Exploiting the advances of computational linguistics in computer-supported collaborative learning. *International Journal of Computer-Supported Collaborative Learning, 3*(3), 237-271. https://doi.org/10.1007/s11412-008-9057-6

Saif, N., Khan, S. U., Shaheen, I., ALotaibi, F. A., Alnfiai, M. M., & Arif, M. (2024). Chat-GPT; validating Technology Acceptance Model (TAM) in education sector via ubiquitous learning mechanism. *Computers in Human Behavior, 154,* 108097. https://doi.org/10.1016/j.chb.2023.108097

Saleh, M., Alqahtani, M., & Al-Rahmi, W. (2022). Challenges and barriers for effective integration of technologies into teaching and learning. *Education and Information Technologies.* https://doi.org/10.1007/s10639-022-10951-7

Schepers, J., & Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. *Information & Management, 44*(1), 90-103. https://doi.org/10.1016/j.im.2006.10.007

Schreiber, J. B., Stage, F. K., King, J., Nora, A., & Barlow, E. A. (2006). Reporting structural equation modeling and confirmatory factor analysis results: A review. *The Journal of Educational Research, 99*(6), 323-338. https://doi.org/10.3200/JOER.99.6.323-338

Sclater, N. (2017). Learning analytics explained. Routledge.

Siemens, G., & Baker, R. S. (2012). Learning analytics and educational data mining: Towards communication and collaboration. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 252-254). https://doi.org/10.1145/2330601.2330661

Steiger, J. H. (1990). Structural model evaluation and modification: An interval estimation approach. *Multivariate Behavioral Research, 25*(2), 173-180. http://www.statpower.net/Steiger%20Biblio/Steiger90b.pdf

Tan, S. (2020). Artificial Intelligence in education: Rise of the machines. *Journal of Applied Learning and Teaching, 3*(1), 129-133. https://doi.org/10.37074/jalt.2020.3.1.17

Tapalova, O., & Tapalova, O. (2023). Artificial Intelligence in education: AIEd for personalised learning systems. *International Journal of Emerging Technologies in Learning, 18*(2), 45–60. https://10.34190/ejel.20.5.2597

Taufiq-Hail, S., Ahmad, S., & Malik, F. (2023). Relevance of TAM in healthcare: The case of telemedicine and electronic health records. *Journal of Medical Systems, 47*(4), 23. https://doi.org/10.1007/s10916-023-00510-8

Tawafak, R. M., Romli, A., & Alfarsi, G. (2023). *Extending the Technology Acceptance Model for e-learning platforms in higher education: Factors influencing student engagement*. Education and Information Technologies. https://doi.org/10.1007/s10639-023-11816-3

Tiwari, C. K., Bhat, M. A., Khan, S. T., Subramaniam, R., & Khan, M. A. I. (2023). What drives students toward ChatGPT? An investigation of the factors influencing adoption and usage of ChatGPT. *Interactive Technology and Smart Education, 21*(3), 333-355. https://doi.org/10.1108/ITSE-04-2023-0061

VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational Psychologist, 46*(4), 197-221. https://doi.org/10.1080/00461520.2011.611369

Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a research agenda on interventions. *Decision Sciences, 39*(2), 273-315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. D. (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

Venter, I. M., Blignaut, A. S., & Stoltz, A. (2012). Exploring the Technology Acceptance Model in explaining student intentions to use e-learning: The role of subjective norm and perceived behavioural control. *South African Journal of Higher Education, 26*(3), 352-370. https://doi.org/10.20853/26-3-1665

Viechtbauer, W. (2010). Conducting Meta-Analyses in R with the Metafor package. *Journal of Statistical Software, 36*(3), 1–48. https://doi.org/10.18637/jss.v036.i03

Virani, R., Khanna, K., & Desai, P. (2023). TAM and business: Adoption of ERP systems. *Journal of Business Research, 148,* 112-124. https://doi.org/10.1016/j.jbusres.2023.02.015

Walkington, C. (2013). Using adaptive learning technologies to personalise instruction to student interests: The impact of relevant contexts on performance and learning outcomes. *Journal of Educational Psychology, 105*(4), 932-945. https://doi.org/10.1037/a0031882

Wang, Y., Liu, C., & Tu, Y. F. (2021). Factors affecting the adoption of AI-based applications in higher education. *Educational Technology & Society, 24*(3), 116-129. https://doaj.org/article/e2fe5622b1fa4f88a3f1f90285a4126a

Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior, 67*, 221-232. https://doi.org/10.1016/j.chb.2016.10.028

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education, 16*(1), 39. https://doi.org/10.1186/s41239-019-0171-0

Zhai, X., Chu, X., & Wang, Z. (2021). The role of artificial intelligence in education: A review and outlook. *Journal of Educational Computing Research, 59*(2), 303-327. https://doi.org/10.1177/07356331211006728