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Thirty-Five Years of the Technology Acceptance Model: Insights From Meta-Analytic Structural Equation Modelling

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Abstract
This study uses one-step meta-analytic structural equation modelling to delve into the technology acceptance model's (TAM) application within education, assessing perceived usefulness, ease of use, intentions to use, and actual technology use. It synthesises previous findings to validate the TAM's effectiveness and uncover the model's predictive power in educational settings. Significant insights include the direct influence of perceived ease of use on actual technology use, bypassing intentions—a novel finding contrasting with the TAM's traditional formulation. The research confirms the TAM's enduring relevance, offering valuable guidance for educational technology integration.

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Keywords: technology acceptance model, TAM, meta-analytic structural equation modelling, one-step meta-analytic structural equation modelling, OSMASEM

Introduction

In a thoughtful retrospective, Davis and Granić (2024) delved into the genesis and far-reaching impact of the technology acceptance model (TAM), a framework that emerged from Davis' doctoral research at the Massachusetts Institute of Technology in the 1980s (Davis, 1986). Confronting the then scepticism around the predictability of technology acceptance, the TAM introduced the concepts of perceived usefulness and perceived ease of use as the essential determinants of technology adoption. These principles provided insights into the interplay between system design and user interaction and laid the groundwork for the TAM's extensive application and evolution across varied domains. Through his reflections, Davis highlighted the TAM's transition from a groundbreaking theory to a foundational element within information systems and human-computer interaction, emphasising its sustained significance and impact (Davis & Granić, 2024).

Since its establishment, the TAM has played a crucial role in explaining the elements that influence individuals' acceptance and use of novel technologies, securing its position as an important reference in both scholarly and practical domains. A study by Aldraiweesh and Alturki (2023) showed its effectiveness in educational technology, while Taufiq-Hail et al. (2023) demonstrated its role in healthcare for telemedicine and electronic health records. Virani et al. (2023) applied the TAM to business, particularly in adopting Enterprise Resource Planning systems. Over time, the model has been subject to numerous enhancements and expansions to more accurately reflect educational technology developments (Al-Azawei et al., 2017; Mayer & Girwidz, 2019; Venter et al., 2012). In today's digital age, where educational technologies are integral to learning environments across schools, colleges, and universities, the imperative to grasp technology acceptance dynamics remains as relevant as ever.

This study examined and synthesised past findings to shed new light on the insights offered by the TAM. Employing the advanced methodology of one-step meta-analytic structural equation modelling (OSMASEM) developed by Jarek and Cheung (2022), this study delved into the literature on the TAM to identify trends and determinants of technology acceptance in educational contexts and evaluate the strength and consistency of relationships posited by the model. This research aimed to bridge the gap between the body of TAM studies by applying a meta-analytic approach. By synthesising the findings from many studies, this study provides an updated understanding of the factors influencing technology acceptance in educational contexts. This study also contributes to refining and validating the TAM as a robust theoretical framework, offering insights for academics, practitioners, and policymakers alike.

Literature Review

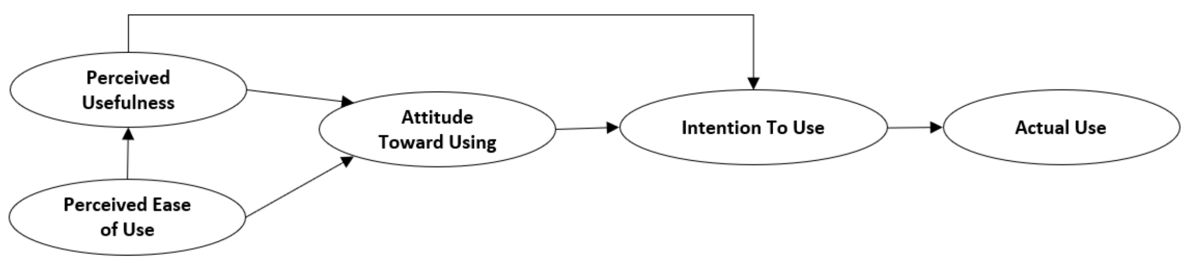
The TAM

The TAM has played a pivotal role in shaping information systems research (Hsiao & Yang, 2011). The model was developed to address the need for a comprehensive and user-centred framework to understand the adoption and acceptance of new technologies. Over the last three decades, the TAM has garnered widespread attention and has become one of the most influential theories in technology adoption and acceptance. Before the inception of the TAM, researchers explored various models and theories to explain technology adoption, such as the diffusion of innovations theory by Rogers (1962), the theory of reasoned action (TRA) by Fishbein and Ajzen (1975), and the theory of planned behaviour (TPB) by Ajzen (1985). These models emphasised different aspects of behaviour and cognition but did not specifically focus on technology acceptance. The roots of the TAM can be traced back to Davis's (1986) doctoral dissertation, which laid the theoretical foundation for TAM. Davis drew on concepts from cognitive psychology, specifically the theory of cognitive dissonance by Festinger (1957) and the perceived usefulness construct from DeLone and McLean (1992), to propose a model that could explain how individuals make decisions regarding the acceptance and use of technology.

In 1989, Davis formally introduced the TAM model in his groundbreaking paper "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology" (Davis, 1989). The TAM posits that a user's intention to use a technology is primarily determined by two key factors: perceived usefulness (PU) and perceived ease of use (PEOU). PU represents the degree to which a person believes using a particular technology will enhance their job performance or overall effectiveness. It captures the practical aspect of technology acceptance. PEOU reflects the user's perception of how easy it is to learn and use the technology. A system perceived as easy to use is more likely to be accepted and adopted. Intention to use (ITU) in TAM mediates between PU, PEOU, and actual use (AU). It represents the user's intention to use the technology, strongly predicting their behaviour. AU represents the user's actual use of the technology and is influenced by their behavioural intention. Attitude towards technology (ATT) is the individual's overall emotional and evaluative response to using a specific technology, encompassing their feelings, predispositions, and subjective assessment of its value and utility.

Figure 1

Technology Acceptance Model

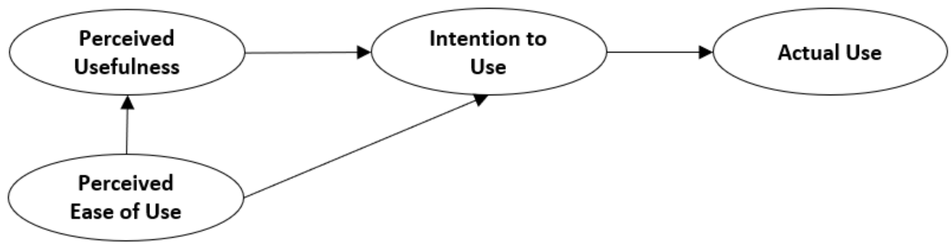


Note. Adapted from "Technology Acceptance Model," by D. Marikyan & S. Papagiannidis, in S. Papagiannidis (Ed.), *Theory Hub Book*, 2023 (https://open.ncl.ac.uk/theories/1/technology-acceptance-model/). CC BY-NC-ND 4.0.

As the TAM has been subject to scrutiny and evolution, one significant change has been excluding ATT as a construct. While the original model posited that PU and PEOU influenced ITU indirectly through attitudes towards usage, subsequent empirical studies have challenged the necessity of this mediating variable. These studies suggested that PU and PEOU had sufficiently strong direct effects on behavioural intention (BI), thereby questioning the mediating role of ATT (Venkatesh & Davis, 2000). It led to the development of streamlined models, such as the TAM2 and the unified theory of acceptance and use of technology (UTAUT), where the direct relationship between PU, PEOU, and BI was highlighted, and the construct of attitude was removed (Venkatesh et al., 2003). See Figure 2.

Figure 2

Streamlined 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.

The TAM offers several advantages, making it a valuable framework for studying and understanding technology adoption and acceptance. These advantages have contributed to the TAM's widespread use and relevance in various fields and industries. Firstly, TAM is known for its simplicity and straightforwardness. It consists of only a few core constructs, primarily PU and PEOU, which are relatively easy to measure and analyse. This simplicity makes the TAM accessible to researchers, practitioners, and even non-experts, making it a practical choice for various applications. Secondly, the TAM has demonstrated strong predictive power in explaining and forecasting technology adoption and usage behaviour. Research has consistently shown that PU and PEOU are robust predictors of users' behavioural intentions and technology use. This predictive accuracy is crucial for organisations and policymakers seeking to understand and influence technology adoption. Thirdly, the TAM's core constructs are broad and generic, making the model applicable to various technologies and contexts. Researchers have successfully applied the TAM to study the adoption of various technologies, including software, hardware, mobile apps, and websites. This generalizability enhances the model's versatility.

Educational researchers have employed the TAM to investigate educators' acceptance of various educational technologies, such as learning management systems, digital teaching aids, and online collaboration tools (Camilleri & Camilleri, 2022; Fearnley & Amora, 2020; Granić, 2023). The TAM has been used to compare the acceptance of different educational technologies within the same context. Researchers can assess which technologies align better with users' preferences and needs by applying the TAM to various tools or platforms. Educational researchers have used the TAM to explore the factors influencing technology acceptance among educators and students. It includes investigating the role of training, support, attitudes, and external pressures in shaping perceptions of technology (Hamutoglu, 2021; Saleh et al., 2022).

Educational institutions use the TAM to guide their technology integration strategies. By understanding teachers' and students' perceptions, institutions can make informed decisions about which technologies to invest in and how to support their implementation effectively (Almulla, 2021; Chugh et al., 2023; Hamutoglu, 2021). The TAM assists in tailoring educational content and instructional design to better align with students' preferences and needs (De Vega et al., 2023; Etemi et al., 2024; Tawafak et al., 2023). By focusing on technology perceived as valuable and easy to use, educators can create more engaging and effective learning experiences. With the rise of remote and online learning, the TAM has been applied to assess the acceptance of digital tools and platforms in virtual educational environments (Almulla, 2021 Alqahtani & Al-Rahmi, 2022; Camilleri & Camilleri, 2022). This research informs the design of online courses and the selection of suitable technologies.

The TAM is a foundational framework for understanding how users accept and use new technologies. Starting with assessing technology's PEOU, the model progresses to evaluate its PU and ITU and culminates in AU, illustrating a logical flow from initial perception to tangible action. The sequential relationship among these constructs highlights the complexity of technology acceptance and the importance of addressing technology use's functional and psychological aspects.

PEOU as a Predictor of PU

The relationship between PEOU and PU is a cornerstone of the TAM model, positing that the ease with which an individual can use a technology directly influences their perception of its usefulness. This dynamic suggests that if users find a technology straightforward and effortless to learn and use, they are more likely to perceive it as beneficial and effective in enhancing their job performance or task completion (Davis, 1989). The premise is that ease of use reduces the effort required to engage with the technology, thereby increasing the likelihood of its acceptance and adoption. This relationship highlights the importance of designing user-friendly technologies that minimise complexity and learning curves, as these factors significantly impact users' perceptions of technology's utility. By prioritising PEOU, developers and implementers can enhance PU, leading to higher acceptance rates and more effective integration of new technologies into everyday practices, particularly in contexts requiring innovative tools and systems (Dimulescu, 2023; Shal et al., 2024).

PU as a Mediator of PEOU and ITU

PU serves as a mediator between PEOU and ITU within the framework of the TAM (Davis, 1989; Venkatesh & Davis, 2000). This mediating role implies that the ease of using technology directly influences its PU and indirectly affects the users' ITU through the mediation of PEOU (Davis, 1989; Venkatesh & Davis, 2000). In essence, when users find technology easy to use (PEOU), they are more likely to perceive it as beneficial (PU), which, in turn, strengthens their intention to use the technology (ITU; Davis, 1989). The mediation by PU highlights the interconnectedness of these constructs. It highlights the importance of ease of use and perceived benefits in shaping the willingness to adopt and use new technologies. It suggests that for a technology to be widely accepted and integrated into daily tasks, it must be user-friendly and perceived as providing tangible benefits that justify its use. This interplay is particularly vital when deciding to adopt a technology, which involves weighing its practical advantages against the effort required to learn and use it (King & He, 2006).

ITU as a Mediator of PU, PEOU, and AU

ITU is a mediator in the TAM, bridging the gap between PU, PEOU, and AU (Venkatesh & Davis, 2000). This mediating role of ITU highlights the process by which positive perceptions of technology translate into tangible user engagement and adoption (Davis, 1989; Szajna, 1996). Specifically, when users perceive technology as useful (PU) and easy to use (PEOU), these perceptions foster a stronger intention to use the technology (ITU), which, in turn, significantly increases the likelihood of its actual use (AU; Venkatesh & Davis, 2000). This mediation illustrates the sequential decision-making process users undergo, starting from their initial evaluation of the technology, moving through their intentionality towards its use, and culminating in the actual adoption and utilisation of the technology. The centrality of ITU in this model highlights the importance of addressing both the cognitive assessments of technology's benefits and usability, as well as the motivational factors that drive users towards integrating the technology into their practices, thereby affecting the outcome of technology adoption and integration efforts (Dimulescu, 2023).

ITU as a Predictor of AU

In the TAM, ITU is posited as a predictor of AU, encapsulating a fundamental premise that the stronger an individual's intention to engage with a technology, the higher the likelihood of its adoption and usage (Venkatesh & Davis, 2000; Davis, 1989). This relationship explains the role of user intentions in the technology acceptance process, suggesting that understanding and influencing these intentions can significantly impact the successful integration of new technologies. ITU encapsulates a user's commitment towards using a technology, which is influenced by their perceptions of its usefulness and ease of use (Davis, 1989; Legris et al., 2003). The predictive power of ITU on AU shows the importance of designing and promoting technologies that meet users' performance expectations and are also perceived as accessible and manageable. By focusing on strategies that enhance both PU and PEOU, developers and implementers can foster stronger intentions to use among potential users, thereby facilitating higher rates of actual technology use (Dimulescu, 2023; Fink et al., 2023; Hsu et al., 2009; Venkatesh & Davis, 2000). This relationship between ITU and AU emphasises the necessity of addressing the psychological and behavioural components of technology acceptance, offering a roadmap for increasing technology adoption rates through targeted interventions that reinforce user intentions (Dimulescu, 2023).

Past research has explored the potential direct relationships between key constructs in TAM, specifically the direct paths from PEOU to AU and from PU to AU. This exploration is crucial for understanding the dynamics of technology adoption without relying solely on intermediary constructs like ITU. Empirical research supports the premise that PEOU directly influences AU. For instance, King and He (2006) conducted a meta-analysis demonstrating that users who found a technology easy to use were more likely to adopt it directly. Similarly, research on digital libraries corroborates that PEOU has a substantial direct effect on AU, emphasising that ease of use alone can drive technology adoption (Ali & Warraich, 2024). This direct path is particularly relevant in contexts where user experience and ease of use are critical for the rapid adoption of technology. In educational settings, for example, user-friendly technologies are adopted more quickly by educators and students, directly impacting their AU (Scherer et al., 2019).

While the direct relationship between PU and AU is less emphasised in traditional TAM literature, substantial evidence supports this link as well. Users who perceive a technology as highly useful are likely to integrate it into their daily activities, even if some initial learning effort is required. Studies have shown that PU can directly influence AU, especially where the perceived benefits of the technology motivate users to overcome potential usability barriers (Marangunić & Granić, 2015). This direct relationship is also evident in domains such as mobile banking and educational technologies, where the utility of the technology significantly drives actual usage behaviours (Lee et al., 2003).

OSMASEM

OSMASEM is a powerful statistical technique that seamlessly integrates meta-analysis and structural equation modelling (SEM) elements. Combining SEM with meta-analysis offers several distinct advantages, such as allowing researchers to estimate the relationships between constructs more precisely by leveraging the increased statistical power and robustness from pooling data across multiple studies. This integrated approach can address complex research questions involving indirect effects and mediation, which traditional meta-analytic techniques alone might not feasibly resolve (Cheung, 2015). Moreover, SEM's ability to account for measurement error and model latent variables adds rigour and clarity to meta-analytic findings, providing more insights into the relationships among variables (Cheung & Chan, 2005). This combination facilitates a more comprehensive understanding of theoretical models, enhancing the generalizability and reliability of conclusions drawn from meta-analytic research. Furthermore, OSMASEM has shown significant methodological benefits over traditional meta-analysis or SEM used in isolation. It integrates the strengths of both methods by simultaneously estimating effect sizes and modelling structural relationships, reducing bias, and improving the accuracy of parameter estimates (Jak, 2015). Recent studies demonstrate that OSMASEM provides a holistic framework for synthesising research findings, particularly in fields where theoretical constructs are complex and interrelated (Cheung, 2019).

Applying OSMASEM to study the TAM in educational contexts offers several notable benefits. OSMASEM enables researchers to synthesise findings from multiple studies conducted in educational contexts, facilitating the integration of diverse datasets from various educational institutions, settings, and populations. By aggregating results from numerous studies, researchers can draw more generalizable conclusions about the factors influencing technology acceptance in education. Additionally, OSMASEM enhances statistical power, allowing researchers to detect smaller effects and relationships that may be missed in individual studies due to sample size limitations. This increased statistical power is particularly valuable in TAM research for identifying subtle nuances in the relationships between PEOU, PU, ITU, and AU. Within the OSMASEM framework, SEM quantitatively synthesises relationships between TAM constructs. It enables researchers to calculate 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 TAM Study Using OSMASEM

The current study synthesised existing empirical research on the TAM in educational contexts, leveraging the potential of correlation-based OSMASEM (Jak et al., 2021). Over the years, TAM studies have employed various methodologies, including traditional meta-analysis (King & He, 2006), SEM (Lee et al., 2003), and longitudinal studies, to understand technology acceptance. Each method has contributed unique insights but also faced limitations in integrating diverse findings and adapting to educational contexts (Marangunić & Granić, 2015). This meta-analysis aims to address the following research questions:

1. To what extent do pooled correlation matrix relationships among the TAM constructs show significant variations from past empirical studies when analysed using the OSMASEM approach?

2. How well does the TAM fit the data from a pooled correlation matrix using the OSMASEM method?

3. Can AU of a technology be directly influenced by PEOU and PU without mediating through ITU?

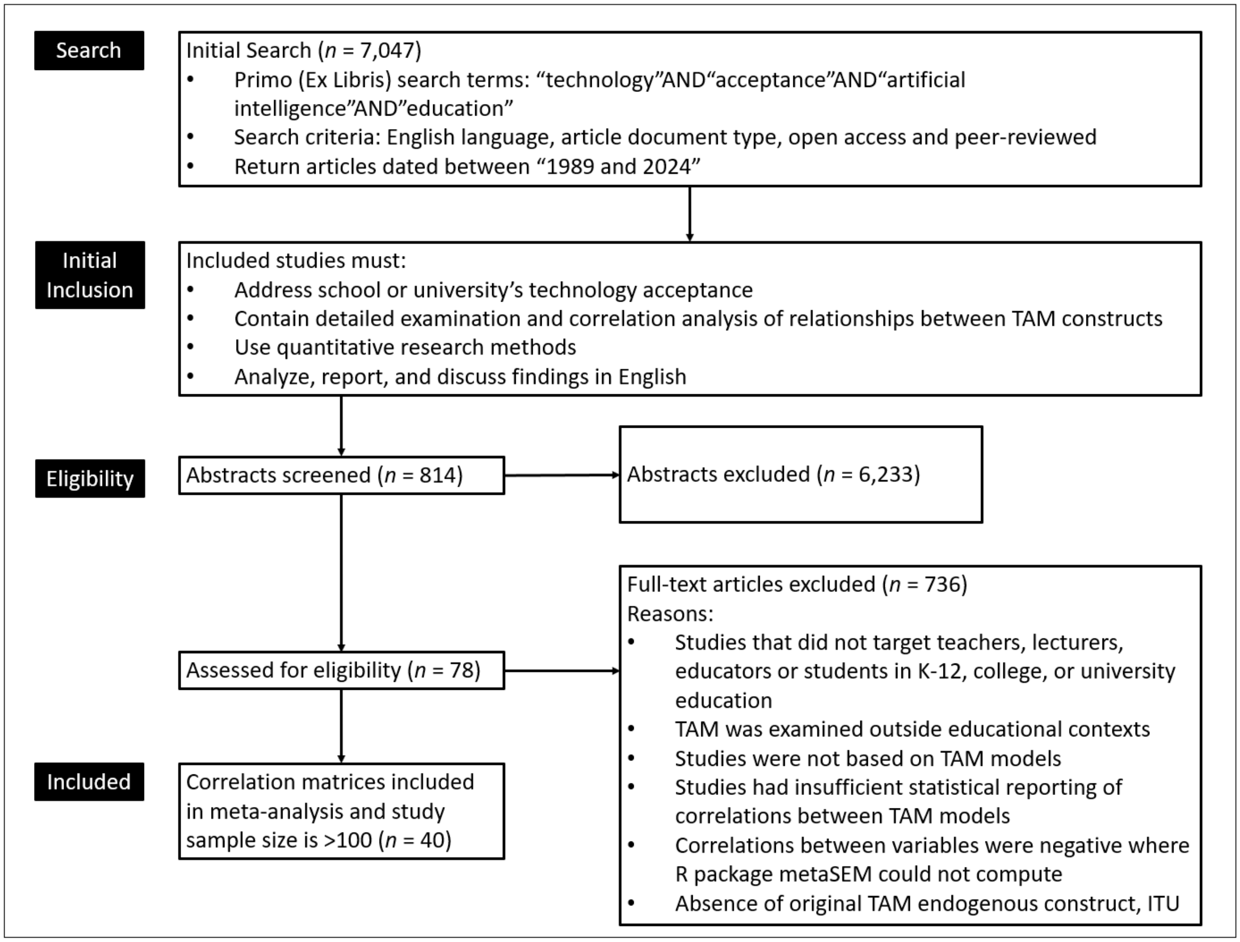
Method

Literature Search and Screening Procedures

The search for relevant studies on the acceptance of technology models in education covered a period from 1989 to 2024, using a formulated search string on Primo by Ex Libris: "technology" AND "acceptance" AND "model" AND "education" across multiple databases to ensure a comprehensive literature capture. These databases included the DOAJ (Directory of Open Access Journals), 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 (PLoS), 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—English language, article document type, open access, peer-reviewed, and the specified years—ensured that the results were within the scope of the study. The selection of databases and search criteria yielded a pool of literature to be further reviewed and analysed for the meta-analysis. After the search, an initial abstract screening of the identified 7,047 studies was performed according to the following criteria: (a) must address the school or university's technology acceptance; (b) detailed examination and correlation analysis of the relationships between the TAM constructs; (c) use of quantitative research methods; and (d) must analyse, report, and discuss the findings in English. The initial screening resulted in 814 eligible empirical studies. Some studies were then excluded by applying the following criteria: (a) did not target teachers, lecturers, educators, or students in K–12, college, or university education; (b) the TAM was examined outside of educational contexts; (c) not based on the TAM; (d) insufficient statistical reporting of the correlations between TAM constructs; (e) correlations between variables were negative where R package, metaSEM (Cheung, 2015), is unable to compute (R Core Team, 2024); (f) absence of both original TAM endogenous constructs in the measured model, specifically ITU and AU. Forty studies with sample sizes greater than 100 were included in the meta-analysis using correlation matrices. Figure 3 summarises the results of the literature search and screening procedures. Table 1 lists the various research from which the data was drawn in this OSMASEM study.

Figure 3

Flowchart of the Literature Search and the Selection of Eligible Studies for Meta-Analysis



Note: TAM = technology acceptance model; ITU = intention to use

Table 1

TAM Studies From Which Data Were Drawn and Their Sample Sizes

Study	Sample Size
Al-Adwan, A. S. (2020). “Investigating the Drivers and Barriers to MOOCs Adoption: The Perspective of TAM.” *Education and Information Technologies*, *25*(6), 5771–5795.	403
Al-Okaily, M., Alqudah, H., Matar, A., Lutfi, A., & Taamneh, A. (2020). “Dataset on the Acceptance of E-Learning System Among Universities Students' Under the COVID-19 Pandemic Conditions.” *Data in Brief*, 32, Article 106176.	587
Almulla, M. (2021). “Technology Acceptance Model (TAM) and E-Learning System Use for Education Sustainability.” *Academy of Strategic Management Journal*, *20*(4), 1–13.	174
Alshurideh, M., Abuanzeh, A., Kurdi, B., Akour, I., & AlHamad, A. (2023). “The Effect of Teaching Methods on University Students’ Intention to Use Online Learning: Technology Acceptance Model (TAM) Validation and Testing.” *International Journal of Data and Network Science*, *7*(1), 235–250.	146

Alyoussef, I. Y. (2022). “Acceptance of a Flipped Classroom to Improve University Students’ Learning: An Empirical Study on the TAM Model and the Unified Theory of Acceptance and Use of Technology (UTAUT).” *Heliyon, 8*(12), Article e12529.	213
Ayele, A. A., & Birhanie, W. K. (2018, December). Acceptance and Use of E-Learning Systems: The Case of Teachers in Technology Institutes of Ethiopian Universities. *Applied Informatics*, *5*, Article 1.	400
Bag, S., Aich, P., & Islam, M. A. (2022). “Behavioral Intention of ‘Digital Natives’ Toward Adapting the Online Education System in Higher Education.” *Journal of Applied Research in Higher Education, 14*(1), 16–40.	430
Balog, A., & Pribeanu, C. (2010). “The Role of Perceived Enjoyment in the Students’ Acceptance of an Augmented Reality Teaching Platform: A Structural Equation Modelling Approach.” *Studies in Informatics and Control, 19*(3), 319–330.	139
Bazelais, P., Doleck, T., & Lemay, D. J. (2018). “Investigating the Predictive Power of TAM: A Case Study of CEGEP Students’ Intentions to Use Online Learning Technologies.” *Education and Information Technologies, 23*(1), 93–111.	213
Bhatiasevi, V., & Naglis, M. (2016). “Investigating the Structural Relationship for the Determinants of Cloud Computing Adoption in Education.” *Education and Information Technologies, 21*(5), 1197–1223.	390
Chang, C.-C., Yan, C.-F., & Tseng, J.-S. (2012). “Perceived Convenience in an Extended Technology Acceptance Model: Mobile Technology and English Learning for College Students.” *Australasian Journal of Educational Technology, 28*(5).	158
Chang, C.-C., Liang, C., Yan, C.-F., & Tseng, J.-S. (2013). “The Impact of College Students’ Intrinsic and Extrinsic Motivation on Continuance Intention to Use English Mobile Learning Systems.” *The Asia-Pacific Education Researcher, 22*, 181–192.	158
Chang, C.-T., Hajiyev, J., & Su, C.-R. (2017). “Examining the Students’ Behavioral Intention to Use E-Learning in Azerbaijan: The General Extended Technology Acceptance Model for E-Learning Approach.” *Computers & Education, 111*, 128–143.	714
Elkaseh, A. M., Wong, K. W., & Fung, C. C. (2016). “Perceived Ease of Use and Perceived Usefulness of Social Media for E-Learning in Libyan Higher Education: A Structural Equation Modeling Analysis.” *International Journal of Information and Education Technology, 6*(3), 192–199.	227
Farooq, A., Ahmad, F., Khadam, N., Lorenz, B., & Isoaho, J. (2020). “The Impact of Perceived Security on Intention to Use E-Learning Among Students”. In M. Chang, D. G. Sampson, R. Huang, D. Hooshyar, N.-S. Chen, Kinshuk, & M. Pedaste (Eds.), *2020 IEEE 20th International Conference on Advanced Learning Technologies* (ICALT) (pp. 360–364). IEEE.	313
Gill, A. A., Malik, S., Iqbal, S., Haseeb, H., & Akhtar, N. (2020). “An Empirical Study of Higher Education Students’ Intentions to Use E-Learning: Developing Country Perspective.” *PalArch’s Journal of Archaeology of Egypt/Egyptology, 17*(8), 1046–1058.	220
Gong, M., Xu, Y., & Yu, Y. (2004). “An Enhanced Technology Acceptance Model for Web-Based Learning.” *Journal of Information Systems Education, 15*(4), 365–374.	152
Gumbi, N. M., Sibaya, D., & Chibisa, A. (2024). “Exploring Pre-Service Teachers’ Perspectives on the Integration of Digital Game-Based Learning for Sustainable STEM Education.” *Sustainability, 16*(3), Article 1314.	255
Habes, M., Pasha, S. A., Ali, S., Elareshi, M., Ziani, A., & Bashir, B. A. (2022). “Technology-Enhanced Learning Acceptance in Pakistani Primary Education.” In A. M. A. M. Al-Sartawi, A. Razzaque, & M. M. Kamal (Eds.), *From the Internet of Things to the Internet of Ideas: The Role of Artificial Intelligence: Proceedings of European, Asian, Middle Eastern, North African Conference on Management & Information Systems 2022* (pp. 53–61). Springer International Publishing.	310

Habibi, A., Riady, Y., Alqahtani, T. M., Muhaimin, M., Albelbisi, N. A., Jaya, A., & Yaqin, L. N. (2023). “Drivers Affecting Indonesian Pre-Service Teachers’ Intention to Use M-Learning: Structural Equation Modeling at Three Universities.” *E-Learning and Digital Media, 20*(6), 519–538.	772
Ibili, E., Resnyansky, D., & Billinghurst, M. (2019). “Applying the Technology Acceptance Model to Understand Maths Teachers’ Perceptions Towards an Augmented Reality Tutoring System.” *Education and Information Technologies, 24*, 2653–2675.	148
Kalsi, P. S., & Kaur, R. (2024). “Structural Equation Modelling (SEM) Based Assessment of Students’ M-Learning Behavioural Adoption Using an Extended-Simplified TAM.” *Migration Letters, 21*(S2), 1333–1344.	392
Kusumadewi, A. N., Lubis, N. A., Prastiyo, R., & Tamara, D. (2021). “Technology Acceptance Model (TAM) in the Use of Online Learning Applications During the Covid-19 Pandemic for Parents of Elementary School Students.” *Edunesia: Jurnal Ilmiah Pendidikan, 2*(1), 272–292.	155
Li, C., He, L., & Wong, I. A. (2021). “Determinants Predicting Undergraduates’ Intention to Adopt E-Learning for Studying English in Chinese Higher Education Context: A Structural Equation Modelling Approach.” *Education and Information Technologies, 26*, 4221–4239.	199
Mailizar, M., Almanthari, A., & Maulina, S. (2021). “Examining Teachers’ Behavioral Intention to Use E-Learning in Teaching of Mathematics: An Extended TAM Model.” *Contemporary Educational Technology, 13*(2), Article ep298.	161
Martínez-Torres, M. D. R., Toral Marín, S. L., García, F. B., Vázquez, S. G., Oliva, M. A., & Torres, T. (2008). “A Technological Acceptance of E-Learning Tools Used in Practical and Laboratory Teaching, According to the European Higher Education Area.” *Behaviour & Information Technology, 27*(6), 495–505.	220
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.	147
Pal, D., & Patra, S. (2021). “University Students’ Perception of Video-Based Learning in Times of COVID-19: A TAM/TTF Perspective.” *International Journal of Human–Computer Interaction*, *37*(10), 903–921.	232
Şahin, F., Doğan, E., & İlic, U. (2024). “Instructors’ Continuance Intention to Use Technology in Online and Hybrid Settings: Integrating Psychological Needs and Emotions.” *International Journal of Human–Computer Interaction*, 1–14.	308
Şahin, F., & Şahin, Y. L. (2021). “Examining the Acceptance of E-Learning Systems During the Pandemic: The Role of Compatibility, Enjoyment and Anxiety.” *International Technology and Education Journal, 5*(1), 1–10.	1,709
Sánchez-Mena, A., Martí-Parreño, J., & Aldás-Manzano, J. (2017). “The Effect of Age on Teachers’ Intention to Use Educational Video Games: A TAM Approach.” *Electronic Journal of E-Learning, 15*(4), 355–366.	312
Sánchez-Prieto, J. C., Huang, F., Olmos-Migueláñez, S., García-Peñalvo, F. J., & Teo, T. (2019). “Exploring the Unknown: The Effect of Resistance to Change and Attachment on Mobile Adoption Among Secondary Pre-Service Teachers.” *British Journal of Educational Technology, 50*(5), 2433–2449.	222
Sharma, B. K., Kumar, V. V. R., & Bhatt, V. K. K. (2023). “Factors Influencing E-Learning Technology Among Youth in India: An Extended TAM Model.” *Management and Labour Studies*, *49*(3), 504–526.	348
Teo, T. (2010). “Examining the Influence of Subjective Norm and Facilitating Conditions on the Intention to Use Technology Among Pre-Service Teachers: A Structural Equation Modeling of an Extended Technology Acceptance Model.” *Asia Pacific Education Review, 11*, 253–262.	314

Thohir, M. A., Ahdhianto, E., Mas'ula, S., Yanti, F. A., & Sukarelawan, M. I. (2023). "The Effects of TPACK and Facility Condition on Preservice Teachers' Acceptance of Virtual Reality in Science Education Course." *Contemporary Educational Technology, 15*(2), Article ep407.	406
Tran, H. T. T., Nguyen, N. T., & Tang, T. T. (2023). "Influences of Subjective Norms on Teachers' Intention to Use Social Media in Working." *Contemporary Educational Technology, 15*(1), Article ep400.	1,105
Unal, E., & Uzun, A. M. (2021). "Understanding University Students' Behavioral Intention to Use Edmodo Through the Lens of an Extended Technology Acceptance Model." *British Journal of Educational Technology, 52*(2), 619–637.	218
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Analysis Using metaSEM for OSMASEM

The correlation matrices derived from the TAM studies were analysed using the R package metaSEM (Version 1.3.1), which facilitates the implementation of the OSMASEM method. The metaSEM package integrates several functions for meta-analysis, including univariate and multivariate techniques, three-level meta-analysis, two-stage SEM, and OSMASEM, employing structural equation modelling through the OpenMx package in R. Meta-analysis is a statistical technique for combining the findings from independent studies to determine the overall trend or effect size. It involves systematically collecting and synthesising data from multiple research studies to arrive at a comprehensive conclusion that has greater statistical power and reliability than individual studies. The metaSEM package enhances this process by allowing for the integration of SEM, a method used to evaluate complex relationships between measured and latent variables. OSMASEM is particularly pertinent for this study due to its efficacy in processing past study data and mapping the evolution of relationships between variables over continuous time points (Cheung, 2014). OSMASEM integrates all the data from multiple studies into a single analysis, treating the pooled data as if it were derived from one large study. This approach is advantageous because it retains the complexity and richness of the original data while enhancing the statistical power to detect significant effects.

Prior to analysis, the correlation matrices from the included studies were inspected for completeness and consistency. 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 individual correlation matrices were combined using the meta-analytic technique implemented in the metaSEM package. Specifically, the OSMASEM method was employed to aggregate the data across studies. This process involved pooling the correlation matrices using a maximum likelihood estimation approach, which involved summing the sample sizes from each study rather than averaging them, allowing for a more accurate computation of standard errors for the path coefficients in the structural equation model. 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 analysis of the TAM model 1 using historical data was conducted in R Studio (Version 2023.12.1, Build 402) and R (Version 4.3.3), using the metaSEM package (Version 1.3.0). This examination aimed to validate the model's theoretical framework by statistically comparing correlations against the proposed measurement model to ascertain the congruence of actual factor structure and loadings (Albright & Park, 2009; Bollen, 1989; Hair et al., 2006; Kline, 2005). Five indices were employed to assess the model's data fit: (a) chi-square to degrees of freedom ratio ($\chi 2/df$), (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. Due to the $\chi 2$ statistic's sensitivity to sample size, the $\chi 2/df$ ratio was used, considering values below 3 to indicate acceptable fit (Kline, 2005). For RMSEA, values under .050 signify a close fit, between .050 and .080 a good fit, between .080 and .100 a mediocre fit, and over .100 an unacceptable fit (Browne & Cudeck, 1992). More 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 assess the model against a baseline "null" model while accounting for complexity, suggest an acceptable fit for values over .950. The TAM model's indices ($\chi 2/df$ = 1.674; RMSEA = .007; SRMR = .049; CFI = .996; TLI = .989) indicated its fit within acceptable thresholds (Table 2). Reliability assessment conducted with IBM SPSS (Version 28.0.1.1) demonstrated high-scale reliability, as indicated by coefficient alpha (N = 40; α = 886).

Table 2

Goodness-of-Fit Indices of Model 1

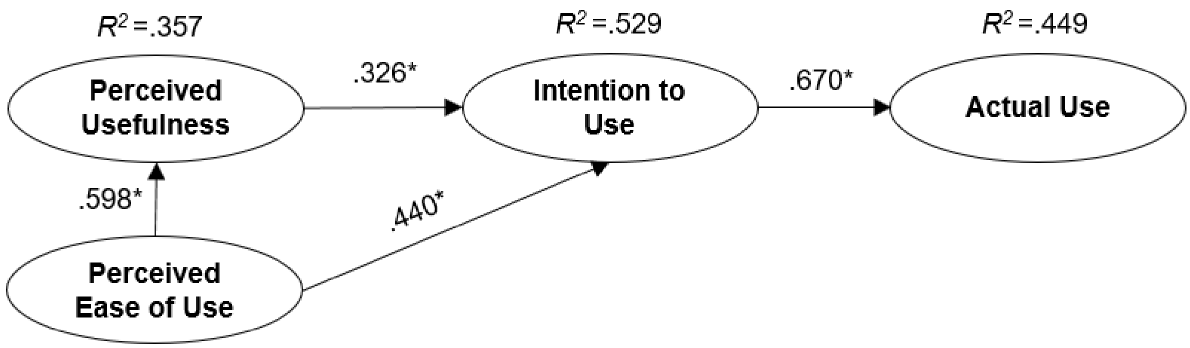
Measure	Threshold	Value
χ^2	--	3.348
df	--	2.000
χ^2/df	< 3.000	1.674
p-value	> .050	.188
RMSEA	< .050	.007
SRMR	< .080	.049
CFI	> .950	.996
TLI	> .950	.989

Note. RMSEA = root mean square error of approximation; SRMR = standardised root mean square residual; CFI = comparative fit index; TLI = Tucker-Lewis index.

In model 1, PU significantly influenced ITU (β = .326), confirming its role as a predictor of technology acceptance, in line with the original TAM principles. PEOU also had a significant impact on ITU (β = .440), emphasising that ease of system operation contributed to user intention. This model omitted ATT from the original TAM, showing a more direct relationship between perceived system attributes and usage intentions. ITU strongly predicted AU (β = .670), highlighting the importance of intentionality in user behaviour. These insights from model 1 explained the direct pathways from perceived system characteristics to actual usage. See Figure 4.

Figure 4

Path Diagram of TAM Model 1



* p < .001.

One additional model (model 2) tested in this OSMASEM study was to include a possible relationship between PEOU and AU (Figure 5). It was modelled and tested in model 2 that PEOU had a possible and significant effect on AU. The goodness-of-fit indices for model 2 fell within the recommended thresholds for acceptable model fit ($\chi2/df$ = 1.155; RMSEA = .003; SRMR = .029; CFI = .999; TLI = .997) See Table 3. However, when it was tested whether PU influenced AU, the model became overfitted. This overfitting suggested that adding the direct path from PU to AU introduced unnecessary complexity. In the context of SEM, overfitting occurs when a model is too closely aligned to the sample data, capturing noise rather than underlying patterns. This reduces the model's parsimony, meaning it is less efficient in explaining the variance with fewer parameters, and it undermines the model's predictive accuracy and generalizability to other data sets.

Table 3

Goodness-of-Fit Indices of Model 2

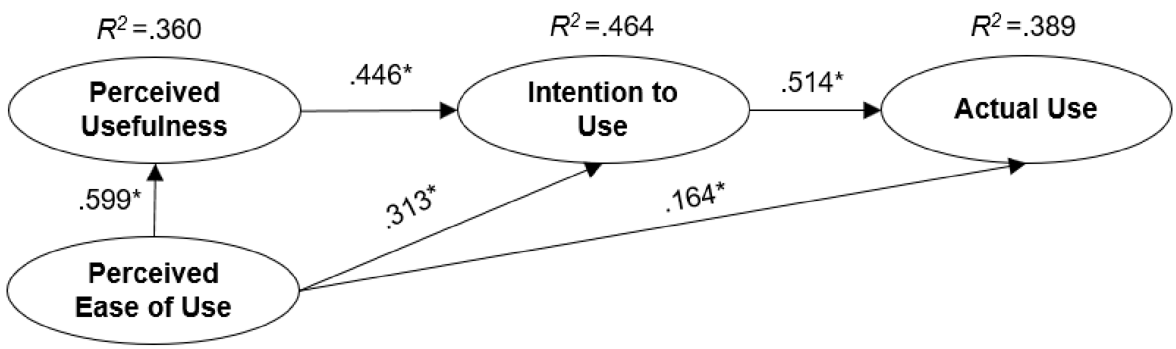
Measure	Threshold	Value
χ^2		1.155
df		1.000
χ^2/df	< 3.000	1.155
p-value	> .050	.283
RMSEA	< .050	.003
SRMR	< .080	.029
CFI	> .950	.999
TLI	> .950	.997

Note. RMSEA = root mean square error of approximation; SRMR = standardised root mean square residual; CFI = comparative fit index; TLI = Tucker-Lewis index.

In model 2, the path analysis revealed that PU had a positive and significant effect on ITU (β = .446), and PEOU not only significantly affected ITU (β = .313) but also exerted a positive and significant effect on AU (β = .163). See Figure 5. This addition of a direct path from PEOU to AU marked a divergence from the original TAM, suggesting that users' ease with a system could directly lead to increased usage without the mediation of ITU. Furthermore, ITU positively and significantly affected AU (β = .514), reinforcing its centrality in the user adoption process. Model 2 offered a revised perspective on the TAM by highlighting the immediate effect of usability on usage behaviours alongside the established route through user intention.

Figure 5

Path Diagram of TAM Model 2



* p < .001.

This study assessed the extent to which each independent variable impacts the dependent variables by examining their direct, indirect, total indirect, and cumulative effects. The direct impact of one factor on another within the models is captured by a coefficient that connects them. An indirect impact reflects how a factor affects a target variable via its influence on other variables within the model. The total indirect impact for a variable is calculated by multiplying its indirect impacts, whereas the total impact combines both direct and indirect effects. As noted by Cohen (1988), effect sizes of .200 are small, .500 represent a moderate effect, and values of .800 or higher are large. These effects are summarised in Table 4.

In model 1, PEOU did not have a direct effect on AU; however, there was a significant indirect effect (β = .425) through the mediating variables PU and ITU, resulting in a total effect of .425. This highlighted the importance of PU and ITU as intermediary factors in translating PEOU into AU. The indirect effect indicated that while PEOU did not directly influence AU, it significantly impacted AU when mediated by PU and ITU. Specifically, PEOU enhanced PU (β = .598), which subsequently influenced ITU (β = .326), and ITU, in turn, drove AU (β =.670). This sequential mediation highlighted the critical roles that PU and ITU play in the adoption and actual usage of technology.

In model 2, there was a significant indirect effect (β = .298) for PEOU on AU, mediated by PU and ITU. Additionally, there was a direct effect of PEOU on AU (β = .164), resulting in a stronger overall impact of PEOU on AU with a total effect of .462. This higher total effect in model 2 indicated that the combined influence of direct and indirect paths from PEOU to AU was more substantial than in model 1, emphasising the multifaceted ways through which PEOU could drive AU. While the direct path from PEOU to AU is significant in model 2 (β = .164), its coefficient is considerably smaller than that of the indirect path (β = .298). As such, the direct effect in model 2 suggested that users' perception of PEOU could directly influence their AU, bypassing the mediating variables PU and ITU to some extent. However, the indirect pathway remained significant, reinforcing the importance of PU and ITU in the adoption process. The other question addressed by the study is whether ITU is always necessary for AU or if AU can be directly influenced by PEOU and PU. The findings indicated that model 2 fit the data better than model 1, demonstrating a direct effect from PEOU to AU. This suggested that AU could be initiated directly by perceiving a tool as easy to use or useful without the need for forming explicit intentions first.

These results illustrated the consistent and differential impacts of PEOU, PU, and ITU on AU across the two models within the TAM framework. In both models, PEOU significantly affected PU, which in turn influenced ITU and, ultimately, AU. The significance of these effects showed the robustness of the relationships. Model 2 provided additional insights by highlighting a direct path from PEOU to AU, which was not found in model 1.

Table 4

Direct, Indirect and Total Effects Implied in Model 1 & Model 2

Pathway	Effects on model 1			Effects on model 2		
	Direct	Indirect	Total	Direct	Indirect	Total
PEOU → PU	0.598			0.599		
PEOU → ITU	0.440			0.313		
PEOU → AU		0.425	0.425	0.164	0.298	0.462
PU → ITU	0.326			0.446		
ITU → AU	0.670			0.514		

Note: PEOU = perceived ease of use; PU = perceived usefulness; ITU = intention to use; AU = actual use.

* p < .001.

Discussion

The analysis of the TAM in this study featured the utility of employing OSMASEM to explain the relationships involved in technology adoption. By applying OSMASEM via the metaSEM package in R, this research validated the theoretical constructs of the TAM. It enhanced the understanding of how PEOU and PU interact to influence ITU and AU. The findings revealed that both model 1 and model 2 exhibited significant direct effects of PEOU on PU and ITU, confirming the foundational assertions of TAM that a system's usability and perceived utility significantly impacted users' adoption decisions. The introduction of a direct path from PEOU to AU in model 2 suggested that users' perceptions of ease of use could directly lead to higher technology usage, bypassing the mediating role of ITU. In fact, past studies have demonstrated that PEOU had a significant effect on AU. For instance, a meta-analysis conducted by King and He (2006) found that PEOU significantly influenced AU. This finding is further supported by a meta-analysis of technology acceptance in mobile and digital libraries, which confirmed the effect of PEOU on AU (Ali & Warraich, 2024). Similarly, research on tool use in computer-based learning environments found significant effects of PEOU on AU, highlighting the direct impact of ease of use on technology adoption (Juarez Collazo et al., 2014). While PEOU's impact on BI is well-documented, its direct effect on AU is less emphasised in TAM, leading to gaps in understanding how ease of use translates directly into usage behaviour without the mediation of perceived usefulness. Technological changes and usage trends since the introduction of the TAM in 1986 have further highlighted these gaps. The rapid evolution of technology, including the proliferation of mobile devices, social media platforms, and cloud-based applications, has transformed user expectations and interaction patterns. Model 2 offered a new relationship within TAM, highlighting the role of PEOU in driving technology adoption directly, a departure from traditional TAM formulations that prioritise intention as the primary mediator. These findings are important because they offer a new perspective in the literature, demonstrating that PEOU can have a direct impact on actual use, potentially reshaping how future studies conceptualise and measure technology adoption processes.

The differences between model 1 and model 2 were illuminated by distinct paths and the varying influence of PEOU, PU, ITU, and AU on technology adoption. A stronger direct effect of PU on ITU (.446) was shown in model 2 compared to model 1 (.326), indicating that PU played a more crucial role in forming the intention to use in this model. Similarly, the direct effect of ITU on AU was slightly lower in model 2 (.514) than in model 1 (.670), which might suggest a redistributed influence where PEOU had a more balanced direct and indirect effect on AU. The complexity of technology adoption processes and the importance of considering multiple pathways and their respective strengths in influencing user behaviour were highlighted by the distinctions between these models.

The analysis through OSMASEM provided evidence supporting the TAM in explaining technology adoption behaviours. The evidence highlighted the TAM's robustness in the educational context and with varying technological tools. The findings from OSMASEM validated the TAM's core constructs of PEOU and PU, demonstrating their continued relevance in predicting technology adoption. Understanding the dual pathways from PEOU to AU can help tailor interventions and training programs to enhance user engagement and satisfaction. These constructs continue to demonstrate relevance in predicting technology adoption, as confirmed by various meta-analyses and empirical studies. For instance, research has highlighted the TAM's robustness in the educational context with varying technological tools. Scherer et al. (2019) used a MASEM approach to explain teachers' adoption of digital technology, affirming the significant influence of PEOU and PU on technology acceptance. Similarly, a comprehensive review by Marangunić and Granić (2015) from 1986 to 2013 indicated that the TAM effectively predicts user behaviour across different settings and technologies, reinforcing its applicability and adaptability.

Limitations

While the OSMASEM approach offers numerous benefits for exploring TAM within educational settings, it is crucial to consider its constraints. A significant challenge is the dependency on the availability and quality of relevant primary studies that provide sufficient and consistent data. Not all studies offer detailed information or present it uniformly, complicating the data extraction and synthesis processes. The integrity and thoroughness of the studies selected for analysis profoundly influence the reliability and applicability of the OSMASEM findings. Some studies might omit essential statistics or details required for OSMASEM, such as correlation matrices, path coefficients, or standard errors, limiting the inclusion of potentially insightful research in the analysis.

Additionally, the process of OSMASEM incorporates complex SEM techniques. Researchers embarking on one-step MASEM must be proficient in SEM and meta-analysis to accurately formulate, compute, and interpret the model. This intricacy may deter those with less experience from using this method. This investigation used the metaSEM package within the R software environment for the OSMASEM analysis. Although the metaSEM package is a robust tool for MASEM analysis, users must navigate its complexities and limitations. Given that OSMASEM is a sophisticated statistical method that merges SEM with meta-analysis, the metaSEM package introduces an additional layer of complexity. It could mean facing a steep learning curve for individuals not well-versed in meta-analysis. Therefore, researchers should dedicate time to mastering the basics of SEM and meta-analysis before attempting OSMASEM, ensuring a solid foundation for effectively leveraging this advanced analytical technique.

Conclusions

In summary, exploring the TAM within educational settings through the lens of OSMASEM has yielded significant insights into the dynamics of technology adoption and acceptance among educators, students, and administrators. This approach has enabled a holistic analysis of numerous studies, providing a detailed overview of the determinants affecting technology acceptance in education. The advantages of this method are evident in its ability to integrate relationships within the TAM framework quantitatively, adapt to the heterogeneity of educational environments, and support data-driven policy and practice decisions in educational institutions. This research offers an examination of their interconnectedness in educational settings by delving into key constructs such as PU, PEOU, ITU, and AU through OSMASEM. Future research should enhance the TAM framework by incorporating new variables affecting technology acceptance and evaluating the model’s relevance in modern educational formats such as online, blended learning, and artificial intelligence tools. This investigation also marks a significant step towards a refined, evidence-based comprehension of technology integration in education. It contributes to a broader knowledge base, aiding educators, administrators, policymakers, and researchers in improving technology adoption and educational quality amidst the rapidly changing educational environment.

Future studies should consider expanding the TAM model within the OSMASEM framework to include constructs related to technological readiness, societal impacts, and external influences, crafting a more comprehensive understanding of technology acceptance in education. The importance of meta-analysis is also highlighted to track changes in technology acceptance over time, offering insights into how initial perceptions may or may not align with long-term engagement and outcomes. Given the swift progress in educational technologies such as virtual reality, artificial intelligence, and augmented reality, focused investigations into these areas are essential.

Additionally, the role of cultural and contextual factors in shaping technology acceptance within educational realms warrants further exploration. Comparative studies across different cultural and educational landscapes can shed light on the influence of cultural norms and policies on technology acceptance patterns. An important avenue for future research is investigating how technology acceptance impacts learning outcomes. By using the OSMASEM approach, studies can quantify the effects of technology acceptance on student performance, engagement, and retention, informing educational policy and practice. This would include validating extended TAM models through OSMASEM, which can offer insights into the applicability and relevance of these models in diverse educational contexts.

Looking forward, the study of the TAM in educational settings using OSMASEM promises to deepen the understanding of technology acceptance, foster evidence-based educational practices, and adapt to the continuous evolution of educational technology. This research trajectory is pivotal for enhancing educational experiences in a digital age, guiding the development of technology integration strategies, teacher training, and curriculum design to meet the challenges and opportunities of digital learning environments.

Author's Contributions

As sole author, my work encompassed all aspects of the research process, including conceptualization, data collection, analysis, and drafting of the manuscript.

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Ethics Statement

Ethical approval was not required for the work described in this article as it constitutes a meta-analysis study. As such, no formal ethics review process was applicable.

Conflict of Interest

The author does not declare any conflict of interest.

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