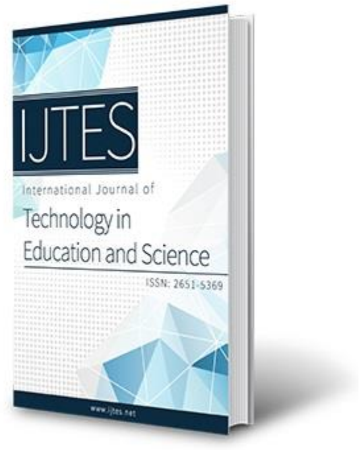

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Watch That Attitude! Examining the Role of Attitude in the Technology Acceptance Model through Meta-Analytic Structural Equation Modelling

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Watch That Attitude! Examining the Role of Attitude in the Technology Acceptance Model through Meta-Analytic Structural Equation Modelling

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Abstract

The Technology Acceptance Model (TAM), proposed by Fred Davis in 1986, is a foundational framework for understanding technology adoption, emphasizing Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) as key determinants of Intention to Use (ITU). While Attitude Toward Using (ATU) was initially central to TAM, it was later omitted in iterations like TAM2 and UTAUT. This paper revisits the role of ATU within TAM, employing One-Step Meta-Analytic Structural Equation Modelling (OSMASEM) to analyze educational technology acceptance. The findings reveal that ATU significantly mediates the relationship between PEOU, PU, and ITU, enhancing the explanatory power of TAM. By comparing models with and without ATU (TAM-O and TAM-R), the findings demonstrate that incorporating ATU provides a more comprehensive understanding of user behavior, particularly in voluntary use contexts. The study underscores the importance of attitudes in technology adoption and suggests that future TAM iterations should consider ATU to improve predictive accuracy. This research contributes to theoretical advancements in TAM and offers practical insights for enhancing technology acceptance in educational settings.

Introduction

Since Fred Davis proposed it in 1986, the Technology Acceptance Model (TAM) has been a critical framework for studying how users adopt and use new technologies (Davis, 1986). At its core, TAM posits that two key factors—Perceived Ease of Use (PEOU) and Perceived Usefulness (PU)—determine an individual's intention to use a technology, which subsequently influences their actual use of that technology. Central to this framework was the construct of Attitude Toward Using (ATU) technology, which was initially included to mediate the effects of PEOU and PU on the Intention to Use technology (ITU). Over time, however, ATU has been excluded in later iterations of TAM, TAM2, and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Bagozzi, 2007; Turner et al., 2010; Venkatesh & Davis, 2000; Venkatesh et al., 2003; Venkatesh et al., 2012).

ATU, as posited by TAM, encompasses users' positive or negative evaluations of technology use, shaping their propensity to engage with technological innovations (Davis, 1986). Over the years, numerous studies have investigated the determinants and effects of ATU, highlighting its critical importance in predicting technology adoption (Mahardika, 2019; Mardiana et al., 2015; Turner et al., 2010; Venkatesh et al., 2003). However, the complex nature of attitude and its interactions with other variables, such as PEOU, PU, self-efficacy, and social influences, remains underexplored in a holistic manner (Holden & Karsh, 2010; Ifenthaler & Schweinbenz, 2013; Sánchez-Mena & Martí-Parreño, 2017; Teo, 2011; Venkatesh et al., 2003; Zhang & Lin, 2020). This gap in the literature highlights the necessity for a more integrative and comprehensive analysis of attitudes within the TAM framework.

The significance of understanding ATU in TAM is further amplified by the rapid advancements in technology and the increasing reliance on digital tools across various sectors, including education, healthcare, and business (AlQudah et al., 2021; Holden & Karsh, 2010; Turner et al., 2010; Venkatesh et al., 2016). In the educational context, the COVID-19 pandemic, for instance, has accelerated the adoption of remote learning technologies and e-learning platforms, making it imperative to understand the factors that influence users' acceptance and sustained use of these technologies (Al-Adwan et al., 2021; Nadlifatin et al., 2021; Shahzad et al., 2021; Tandon, 2021). Positive ATU is crucial for ensuring successful adoption, user satisfaction, and ultimately, the effective integration of technology into daily practices (Cheung & Vogel, 2013; Holden & Karsh, 2010; Lee et al., 2003; Venkatesh et al., 2012).

This paper aims to address the gap in understanding the role of ATU within TAM by employing one-stage meta-analytic structural equation modeling (OSMASEM) (Cheung, 2015; Cheung, 2021; Jak & Cheung, 2020). Through this comprehensive meta-analytic review, the paper aims to provide detailed insights into how attitudes shape educational technology acceptance behaviors. This research enhances the theoretical basis of TAM. It provides valuable suggestions for applying educational technology, thereby adding to the broader discussion on technology acceptance and its relevance for academic and educational fields.

Literature Review

Technology Acceptance Model (TAM)

TAM is a widely adopted model for understanding how users accept and utilize new technologies (Al-Emran et al., 2018; Davis, 1989; Saleh et al., 2022). At the heart of TAM are the constructs of PU and PEOU, which collectively influence an individual's ITU and, subsequently, their Actual System Use (ASU) of a technology (Davis, 1986) (see Figure 1).

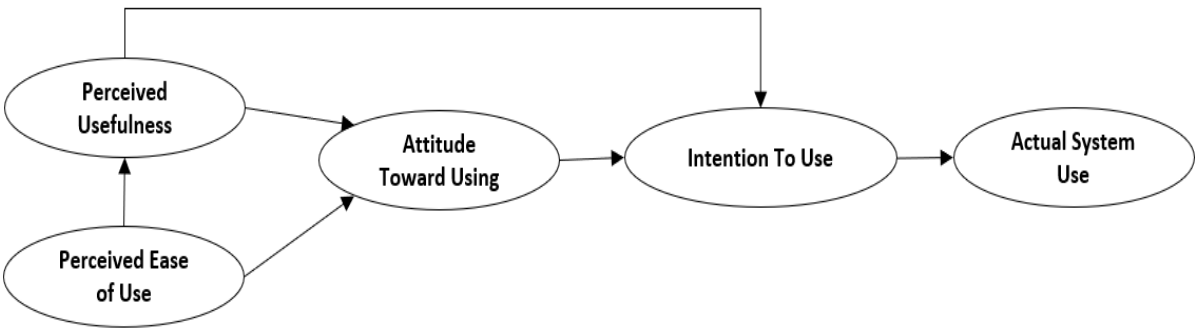

Figure 1. Technology Acceptance Model (Davis et al., 1989)

This model is apt to explain the relationship between user perceptions and technological engagement, offering an approach to analyzing technology adoption (Davis, 1989; Marangunić & Granić, 2015; Venkatesh & Davis, 2000). TAM commences by assessing the user's perception of how easy a technology is to use (PEOU) and then evaluates its perceived usefulness (PU). These evaluations are essential as they lead to ITU, culminating to ASU. ATU, excluded from later versions of TAM and TAM2, was first posited to affect ITU significantly.

TAM has evolved significantly since its introduction, refining its approach to better capture the determinants of technology adoption. Initially rooted in Davis's doctoral dissertation in the mid-1980s, TAM was formally presented in 1989 in Davis's seminal paper, which argued that PU and PEOU primarily influence ITU. This model has since been simplified in subsequent TAM iterations, such as TAM2 and the Unified Theory of Acceptance and Use of Technology (UTAUT), to emphasize the direct impacts of PU and PEOU on behavioral intentions, moving away from earlier versions that included ATU as a mediating variable (see Figure 2).

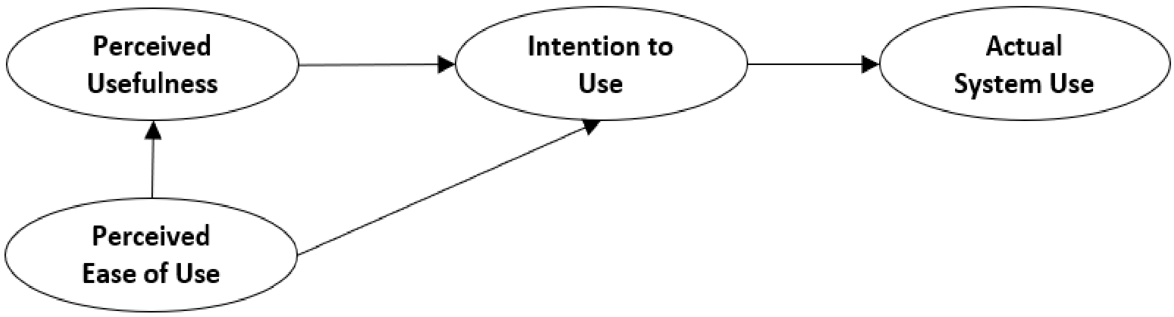

Figure 2. Technology Acceptance Model, Davis and Venkatesh (1996)

The following sections will explore how each TAM construct contributes to the model.

Perceived Ease of Use (PEOU)

According to the initial version of TAM, PEOU of a technology significantly predicts PU and influences ATU (Davis, 1986). If a technology is easy to learn and use, users are more likely to view it as beneficial and effective in improving their job performance or task completion. This is because user-friendly technologies with low learning curves reduce the effort required to engage with them, increasing their likelihood of acceptance and adoption. Moreover, in this earlier version of TAM, PEOU not only impacts PU but also positively affects ATU.

Perceived Usefulness (PU)

Within TAM, PU is a crucial mediator between PEOU and ITU (Davis, 1986). This mediating role indicates that the straightforwardness of a technology directly enhances its perceived usefulness, which, in turn, indirectly influences the user's intention to use the technology. Specifically, when users find technology easy to operate (PEOU), they are more likely to view it as beneficial (PU), thereby strengthening their intention to use it (ITU).

The mediation by PU illustrates the interconnectedness of these constructs and highlights the significance of user-friendliness and perceived benefits in fostering the willingness to adopt and utilize new technologies. Furthermore, in the initial version of TAM, PU is also a predictor of ATU. Users who perceive technology as useful will likely develop a positive attitude toward its adoption and continued use.

Attitude Towards Use (ATU)

In the first version of TAM, ATU is pivotal, serving dual roles as both a mediator and a predictor in the technology adoption process (Davis, 1986). This complex function significantly impacts how technologies are embraced and utilized in practical settings. ATU acts as a mediator between PEOU and ITU, illustrating a critical relationship where PU directly enhances the user's perception of the technology's utility, subsequently shaping a positive attitude toward its use.

The favorable attitude is crucial here as it strengthens the user's intention to adopt the technology. Similarly, ATU mediates the relationship between PU and ITU. Beyond its mediating roles, ATU also serves as a predictor of ITU.

Intention to Use (ITU)

In TAM, ITU plays a mediating role in integrating PU, PEOU, and ASU (Davis, 1986). The mediating position highlights how users' favorable evaluations of a technology's usefulness and ease of use contribute significantly to their intention to adopt and use it. The pathway begins with users' assessments of the technology's utility (PU) and user-friendliness (PEOU). When a technology is perceived as useful, it addresses the user's needs and is likely to enhance performance or productivity, increasing its attractiveness. Similarly, when the technology is easy to use, it lowers barriers to entry, reducing the efforts needed to learn and operate it, further encouraging its adoption.

Removal of Attitude Toward Use as a Construct

TAM has evolved significantly since its inception, particularly with removing ATU as a construct. Originally, ATU was integral, serving as a mediator between PU, PEOU, and ITU. However, subsequent research and empirical studies began to question the necessity of ATU. Findings indicated that PU and PEOU could directly influence ITU without needing ATU as an intermediary (Cai et al., 2021; Chen et al., 2013; Szajna, 1996). It led to a significant paradigm shift in the model's structure where he revised version of TAM, known as TAM2, and later iterations like UTAUT streamlined the model by removing ATU altogether (Venkatesh & Davis, 2000; Venkatesh et al., 2003; Venkatesh et al., 2016)

This simplification was based on a growing consensus that the direct effects of PU and PEOU on ITU were sufficiently robust and that the additional layer of attitude was not only redundant but could complicate the model without adding substantial explanatory power (Blucky & Ghasemzadeh, 2019; Echeng et al., 2022; Hussain & Mir, 2019). It was especially evident in contexts where technology use is mandatory, such as in specific organizational settings, where individual attitudes may have less sway over the decision to use technology (Tarhini et al., 2014; Teo, 2012; Yousafzai et al., 2007).

Studies on Attitude in TAM

Although ATU was omitted in later versions of TAM, many other past studies have consistently examined the role of attitude within the TAM, highlighting its significant influence on ITU and ASU (Cheung & Vogel, 2013; King & He, 2006; Schepers & Wetzels, 2007). Researchers have explored various attitude dimensions, revealing their multifaceted impact on technology acceptance (Celik & Yesilyurt, 2013; Davis et al., 1989). Furthermore, research has also demonstrated that social influences, such as peer interactions and organizational support, could significantly enhance users' attitudes toward technology, promoting adoption (Kelman, 1953; Lu et al., 2005). Additionally, the strength and confidence of users' attitudes have been identified as critical predictors of technology acceptance, with more robust and more confident attitudes leading to higher likelihoods of adoption (Kim et al., 2009). The complex nature of attitude has also been highlighted, with user satisfaction and dissatisfaction playing pivotal roles in shaping attitudes and influencing technology acceptance behaviors (Guo & Zhou, 2016). These studies emphasized the importance of understanding and incorporating attitude-related constructs in TAM to develop more effective strategies for promoting technology adoption across diverse contexts.

In their study, López-Bonilla and López-Bonilla (2017) examined the role of attitude and its influence on TAM's efficacy. The research investigated whether the inclusion or exclusion of the attitude construct (referred to as "TAM-O" for inclusion and "TAM-R" for exclusion) affected the predictive power and applicability of TAM in different contexts. The researchers employed two statistical methodologies to analyze the data: Covariance-Based Structural Equation Modeling (CB-SEM) and Partial Least Squares Structural Equation Modeling (PLS-SEM). The dual approach was crucial in addressing the main research question regarding the model's performance under different analytic conditions. The findings revealed that the choice of statistical method significantly impacted which model variant (TAM-O vs. TAM-R) provided better fit and predictive accuracy. Specifically, the study found that when using PLS-SEM, TAM with the attitude construct (TAM-O) yielded better results, while CB-SEM favored the model without the attitude construct (TAM-R). The research was significant as it highlighted the methodological considerations that could affect the interpretation and application of TAM in educational technology research. It suggested that researchers must carefully consider their methodological approach when evaluating models that include subjective measures such as attitude.

Several studies have explored the role of attitude in TAM in educational contexts. For example, Cheung and Vogel (2013) extended TAM by incorporating social influences, demonstrating how peer interactions could foster positive attitudes towards collaborative e-learning technologies. The insights were vital for developing strategies that promoted technology adoption in educational settings. Similarly, Teo et al. (2015) delved into how the attitude was examined across various models like TAM and TAM2, emphasizing their importance in shaping behavioral intentions toward technology use. The research highlighted the need for a deeper understanding and inclusion of attitude-related constructs in technology acceptance theories to explain users' behavioral intentions better. Bervell et al. (2020) illustrated that positive attitudes toward Learning Management Systems significantly enhanced the intention to use these technologies in distance education. Saleh et al. (2022) further stressed the significance of positive attitudes in sustaining higher education during the COVID-19 pandemic, calling for more research on the influences of self-efficacy and subjective norms on technology acceptance. Koca, Kılıç, and Dadandı (2023) investigated the relationships between attitudes toward distance education, academic life satisfaction, academic self-efficacy, and gender. Their study revealed that positive attitudes towards distance education, enhanced by high self-efficacy, lead to greater academic life satisfaction. They also found that gender moderated this relationship, indicating different impacts for male and female students.

Although this study focuses on educational contexts, looking externally to understand the broader implications is essential. In healthcare, Burton-Jones and Hubona (2006) showed that organizational support and user training indirectly influenced technology acceptance by shaping user attitudes. Similarly, Holden and Karsh (2010) demonstrated that positive attitudes toward health information technologies, driven by PEOU and PU, were essential for successful implementation. Within healthcare, the mediating role of attitude was critical. Singh and Ravi (2022) emphasized that PEOU and PU shaped medical practitioners' attitudes toward e-health platforms, which drove their adoption. Retail contexts also highlighted the importance of attitude. Kim et al. (2017) found that while beliefs about smart in-store technology influenced attitudes, it was attitudes that more strongly predicted adoption behavior. Through a comprehensive meta-analysis, King and He (2006) also affirmed that attitude was a crucial mediator, effectively bridging the gap between user perceptions (like PEOU and PU) and actual technology adoption behaviors. Their findings highlighted that a positive attitude towards technology facilitated initial acceptance and encouraged sustained usage.

From an attitude strength perspective, Kim et al. (2009) explored the impact of attitude strength on technology acceptance, extending the traditional TAM framework. They posited that the strength and confidence of users' attitudes toward technology were critical determinants of initial acceptance and sustained use. The researchers found that solid and well-formed attitudes enhanced the predictive accuracy of TAM by not only influencing immediate behavioral intentions and ensuring long-term engagement with technology. Their findings suggested that fostering positive attitudes through targeted interventions, such as comprehensive training programs and ongoing support, could significantly improve technology adoption rates. The study stressed the need for organizations to build robust user attitudes to facilitate smoother transitions to new technological systems and maintain high levels of user satisfaction and commitment over time.

Guo and Zhou (2016) re-examined the role of attitude in information system acceptance through a satisfaction-dissatisfaction lens, offering a fresh perspective on how users' emotional responses shaped their technology adoption behaviors. They introduced a model that integrated user satisfaction and dissatisfaction as pivotal factors influencing attitude. They posited that positive experiences with information systems fostered favorable attitudes, which enhanced acceptance and usage. Conversely, negative experiences led to dissatisfaction, adversely affecting attitudes and deterring adoption. The study provided a comprehensive framework for understanding the complex dynamics of information system acceptance by addressing satisfaction and dissatisfaction. The findings emphasized the importance of managing user experiences to cultivate positive attitudes, suggesting that organizations should prioritize user satisfaction and promptly address sources of dissatisfaction to ensure successful system implementation and sustained use. The research highlighted the multifaceted nature of attitude formation and its critical impact on information systems' acceptance and long-term utilization.

Although attitude was critical in earlier TAM versions, Fred Davis was somewhat silent about why ATU was left out or the reason behind it in later TAM, TAM2, and UTAUT iterations. This omission raises essential questions about the evolving understanding of technology acceptance mechanisms. Was the exclusion due to empirical findings suggesting that PEOU and PU alone were sufficient to predict technology adoption? Or was it an effort to simplify the model for broader application? These unanswered questions make it compelling to revisit and reassess the role of attitude in TAM. This study aims to deepen the understanding of TAM by focusing on the role of attitude as a mediator. Using OSMASEM, this study will assess the robustness and consistency of TAM constructs in educational settings. This approach not only updates our understanding of technology acceptance factors but also aims to affirm TAM's theoretical framework, offering insights crucial for researchers and practitioners in optimizing technology adoption strategies in educational contexts.

OSMASEM

OSMASEM is an advanced analytical approach that combines meta-analysis methods with structural equation modeling (SEM) (Cheung, 2015; Cheung, 2021; Jak & Cheung, 2020). OSMASEM integrates meta-analysis and SEM into a comprehensive analysis, which estimates multiple relationships among variables across studies. This approach provides a detailed and integrated understanding of how these variables relate, offering a robust statistical analysis that synthesizes and quantifies the relationships between critical constructs in TAM (Cheung, 2015; Scherer et al., 2019). By pooling data from multiple studies, OSMASEM offers a more generalizable understanding of how attitude influences technology acceptance (Cheung, 2015; Jak & Cheung, 2020; Scherer et al., 2019). It also examines complex relationships between variables, providing insights into attitude's direct and indirect effects on technology use (Cheung, 2015; Al-Emran et al., 2018; Scherer et al., 2019). The application of OSMASEM in exploring TAM within educational settings provides several distinct advantages. OSMASEM allows for data consolidation across a broad spectrum of studies, making it possible to incorporate findings from different educational institutions, contexts, and demographic groups. This integration is particularly effective in creating more robust and generalized insights into the dynamics of technology acceptance in educational environments. By pooling data from multiple sources, OSMASEM significantly enhances the research's statistical robustness, enabling the detection of finer, more subtle relationships within the data that might not be observable in studies with smaller sample sizes. This capability is crucial in TAM studies, as it helps uncover intricate interactions among key constructs like PU, PEOU, ATU, ITU, and ASU. Moreover, OSMASEM, with the application of structural equation modeling, helps accurately estimate the relationships between these constructs. This methodological approach facilitates the calculation of summary effect sizes, clearly depicting the magnitude and direction of the relationships among the constructs.

The Present Study of TAM with OSMASEM

This research integrates and analyses existing data on TAM as applied in educational environments, utilizing the advanced capabilities of correlation-based OSMASEM proposed by Jak et al. (2021). This comprehensive meta-analysis seeks to explore several critical inquiries:

1. How do the relationships among TAM constructs, represented in pooled correlation matrices, compare to those observed in previous empirical TAM studies, specifically through the OSMASEM lens?
2. To what degree does TAM align with and fit the aggregated data derived from these pooled correlation matrices when examined via the OSMASEM methodology?
3. How do the outcomes and structural connections within TAM change when the ATU construct is included versus its exclusion, mainly when assessed in educational settings through the OSMASEM approach?

Method

Literature Search and Screening Procedures

The exploration for studies on TAM in education spanned from 1986 to 2024, utilizing a specific search string on Primo by Ex Libris: "technology" AND "acceptance" AND "model" AND "attitude" AND “education.” This search was conducted across numerous databases to ensure an exhaustive literature capture. The databases included 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. Search filters such as English language, article document type, open access, peer-reviewed, and specified years ensured the relevance and scope of the study.

The database selection and search parameters produced a pool of literature to be further reviewed and analyzed for the meta-analysis. An initial abstract screening of 6894 identified studies was conducted based on these criteria:

(1) studies must focus on technology acceptance in school or university settings;
(2) detailed examination and correlation analysis of TAM constructs;
(3) inclusion of "attitude" as one of the constructs;
(4) utilization of quantitative research methods; and
(5) discussion and reporting of findings in English.

This screening yielded 186 eligible empirical studies. Further exclusions were made based on the following criteria:

(1) 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) studies were not based on TAM models;
(4) insufficient statistical reporting of correlations between TAM constructs;
(5) correlations were negative where the R package metaSEM could not compute; and

(6) absence of original TAM endogenous constructs in the measured model, specifically ITU and ASU.

Figure 3 summarizes the literature search and screening procedures. Table 1 lists the various research sources used in this OSMASEM study, and ultimately, only 20 articles were selected.

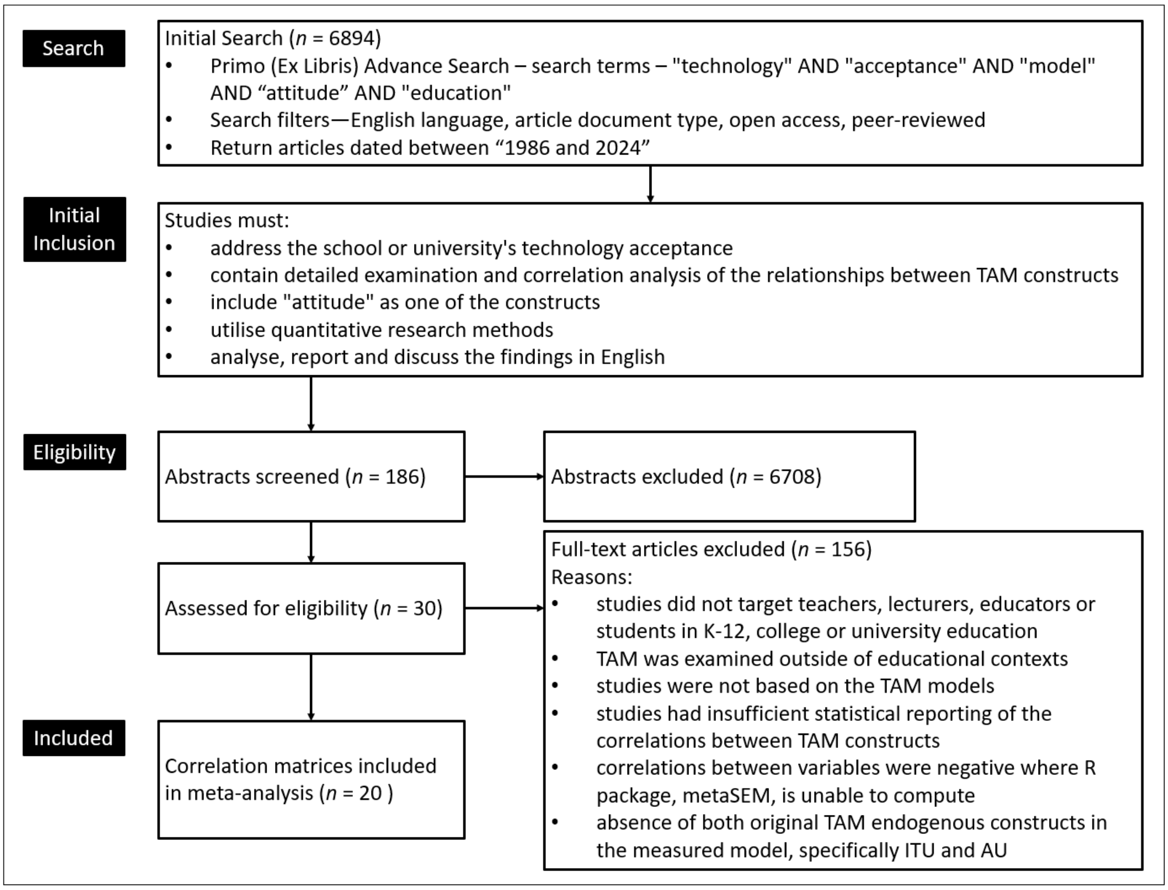

Figure 3. Diagram Describing the Literature Search and the Selection of Eligible Studies for Meta-Analysis

Table 1. TAM Studies from Which Data are Used

S/N	Sample Size	Study
1	174	Almulla, M. (2021). Technology Acceptance Model (TAM) and e-learning system use for education sustainability. *Academy of Strategic Management Journal, 20*(4), 1–13.
2	161	Mailizar, M., Almanthari, A., & Maulina, S. (2021). Examining teachers' behavioral intention to use E-learning in the teaching of mathematics: An extended TAM model. *Contemporary educational technology, 13*(2), ep298.
3	230	El-Gayar, O. F., & Moran, M. (2007). Examining students' acceptance of tablet PCs using TAM.
4	392	Kalsi, P. S., & Kaur, R. (2024). Structural Equation Modelling (SEM) Based

S/N	Sample Size	Study
		Assessment Of Students' M-Learning Behavioural Adoption Using An Extended-Simplified TAM. *Migration Letters, 21*(S2), 1333-1344.
5	515	Rabaa'i, A. A. (2016). Extending the technology acceptance model (TAM) to assess students' behavioral intentions to adopt an e-learning system: The case of moodle as a learning tool. *Journal of emerging trends in engineering and applied sciences, 7*(1), 13-30.
6	480	Zobeidi, T., Homayoon, S. B., Yazdanpanah, M., Komendantova, N., & Warner, L. A. (2023). Employing the TAM in predicting the use of online learning during and beyond the COVID-19 pandemic. *Frontiers in Psychology*, 14, 1104653.
7	159	Yaakop, A. Y., Ariffin, Z. Z., Mahadi, N., Abu Hasan, Z. R., & Harun, M. Web 2.0 Educational Tools Continuance Intention: Integrating TTF Model And TAM. *European Proceedings of Social and Behavioural Sciences*.
8	481	Lau, S. H., & Woods, P. C. (2008). An investigation of user perceptions and attitudes towards learning objects. *British journal of educational technology*, *39*(4), 685–699.
9	153	Teo, T., & Noyes, J. (2011). An assessment of the influence of perceived enjoyment and attitude on the intention to use technology among pre-service teachers: A structural equation modeling approach. *Computers & education, 57*(2), 1645-1653.
10	705	Muhaimin, H., Mukminin, A., Pratama, R., & Asrial, H. (2019). Predicting factors affecting intention to use Web 2.0 in learning: evidence from science education. *Journal of Baltic Science Education*, *18*(4), 595.
11	386	Naveed, Q. N., Alam, M. M., & Tairan, N. (2020). Structural equation modeling for mobile learning acceptance by university students: An empirical study. *Sustainability, 12*(20), 8618.
12	197	Teo, T., Faruk Ursavaş, Ö., & Bahçekapili, E. (2011). Efficiency of the technology acceptance model to explain pre-service teachers' intention to use technology: A Turkish study. *Campus-Wide Information Systems*, *28*(2), 93-101.
13	487	Buabeng-Andoh, C. (2018). Predicting students’ intention to adopt mobile learning: A combination of theory of reasoned action and technology acceptance model. *Journal of Research in Innovative Teaching & Learning*, *11*(2), 178-191.

S/N	Sample Size	Study
14	220	Mukminin, A., Habibi, A., Muhaimin, M., & Prasojo, L. D. (2020). Exploring the drivers predicting behavioral intention to use m-learning management system: Partial least square structural equation model. *IEEE Access,* 8, 181356-181365.
15	150	Zogheib, B. (2019). Using structural equation modeling to study the influence of perceived usefulness and perceived compatibility on students'attitudes towards using iPad. *Innovations, Technologies, and Research in Education,* 4, 53-66.
16	318	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.
17	487	Teo, T., Ursavaş, Ö. F., & Bahçekapili, E. (2012). An assessment of pre-service teachers' technology acceptance in Turkey: A structural equation modeling approach. *Asia-Pacific Education Researcher, 21*(1), 191-202.
18	250	Teo, T., & Van Schalk, P. (2009). Understanding technology acceptance in pre-service teachers: A structural equation modeling approach. *Asia-Pacific Education Researcher, 18*(1), 47-66.
19	192	Felea, M., Bucur, M., Negruţiu, C., Nitu, M., & Stoica, D. A. (2021). Wearable technology adoption among Romanian Students: A structural model based on TAM. *Amfiteatru Economic, 23*(57), 376-391.
20	151	Sharma, B. K., Kumar, V. R., & Bhatt, V. K. (2023). Factors Influencing E-learning Technology Among Youth in India: An Extended TAM Model. *Management and Labour Studies*, 0258042X231208588.

Results

Internal Structure

Following the names of TAM variants used by López-Bonilla and López-Bonilla (2017), this study will use the model references TAM-O (with the attitude construct) and TAM-R (without the attitude construct). The terms provide a clear distinction between the two variations of TAM, facilitating more precise discussions and comparisons in the literature. By differentiating TAM-O and TAM-R, researchers can better analyze and report on the influence of the attitude construct on the model's predictive power and applicability in various contexts. The evaluation of both models utilizing historical data was performed using R Studio (version 2024.04.1, Build 748) and R (version 4.4.0) through the application of the “metaSEM” package (version 1.3.0). This detailed examination aimed to validate the models' theoretical framework by statistically comparing observed correlations against the proposed measurement models.

The objective was to ascertain the alignment of the actual factor structure and factor loadings with the theoretical expectations, drawing on seminal works such as those by Albright and Park (2009), Bollen (1989), Hair et al. (2006), and Kline (2005). The analysis employed five key indices to evaluate the fit of the model to the data. The Chi-square to Degrees of Freedom Ratio (χ^2/df) was used due to its capacity to account for the complexity of the model relative to the sample size. Given the χ^2 statistic's sensitivity to sample size, the χ^2/df ratio was specifically utilized, with values below 3 considered indicative of an acceptable model fit, as proposed by Kline (2005). The Root Mean Square Error of Approximation (RMSEA) was also assessed, following Steiger's (1990) guidelines: RMSEA values below .050 denote a close fit, values between .050 and .080 indicate a good fit, values from .080 to .100 suggest a mediocre fit and values exceeding .100 reflect an unacceptable fit. This metric assesses how well the model, with unknown but optimally chosen parameter estimates, would fit the population covariance matrix.

The Standardized Root Mean Square Residual (SRMR) also provided the standardized difference between the observed and predicted correlations, offering a direct assessment of model fit. The Comparative Fit Index (CFI), proposed by Bentler (1990), was used to compare the fit of the specified model to that of an independent (null) model, with values greater than .950 suggesting an acceptable fit, indicating that the model significantly improves the fit over the null model. The Tucker-Lewis Index (TLI), also known as the Non-Normed Fit Index (NNFI), as defined by Bentler and Bonett (1980), adjusts the Comparative Fit Index (CFI) for model complexity, with values over .950 indicating an acceptable model fit.

The analytical process involved comparing these indices against established thresholds to assess the fit of the proposed measurement model. The TAM-O model's indices ($\chi2/df$ = 2.700; RMSEA = .014; SRMR = .092; CFI = .983; TLI = .958) indicated its fit within acceptable thresholds (Table 1). Reliability assessment conducted with IBM SPSS (version 28.0.1.1) demonstrated high data reliability (N = 20; α = .925). The TAM-R model's indices ($\chi2/df$ = 2.500; RMSEA = .015; SRMR = .096; CFI = .979; TLI = .936) also indicated its fit within acceptable thresholds (Table 1). TAM-R's reliability assessment conducted with IBM SPSS (version 28.0.1.1) demonstrated high data reliability (N = 20; α = .908).

Table 2. Goodness-of-fit Indices

Measure	Threshold	TAM-O	TAM-R
χ^2	--	9.079	5.000
df	--	4	2
χ^2/df	< 3.000	2.700	2.500
p-value	> .050	.059	.082
RMSEA	< .050	.014	.015
SRMR	<.080	.092	.096
CFI	> .950	.983	.979
TLI	> .950	.958	.936

The correlation matrices derived from the TAM studies were analyzed using the R package 'metaSEM' (version 1.3.1), facilitating the implementation of the OSMASEM method. The 'metaSEM' package integrates several functions for comprehensive meta-analysis, including univariate and multivariate techniques, three-level meta-analysis, two-stage SEM, and OSMASEM, employing SEM through the 'OpenMx' package in R. The selection of the OSMASEM approach was particularly appropriate for this study due to its efficacy in processing longitudinal data and mapping the evolution of relationships between variables over continuous time points for the TAM studies (Cheung, 2014). It is especially relevant given that our empirical data spans 17 years from 2007 to 2024, encapsulating extensive longitudinal trends.

In the analytical process, 'metaSEM' utilizes maximum likelihood estimation, opting to sum the sample sizes across studies instead of averaging them. This methodological choice is crucial for computing the standard errors associated with the path coefficients in the structural equation model. Such an approach enhances the precision of significance testing, allowing for a more sensitive and accurate determination of the robustness of the observed relationships within the TAM studies. This heightened sensitivity is essential for detecting significant effects and patterns within the wide temporal range of the dataset.

The meta-analysis of TAM-O revealed some notable differences in the variance explained by PU and ASU compared to Davis's (1986) original TAM. For PU, the original TAM explained 40% of the variance, indicating a strong relationship between users' perceptions of the usefulness of the technology and their acceptance of it. In contrast, the TAM-O model explained 30.7% of the variance in PU. It suggested that while PU remained an important factor in technology acceptance, its influence was less pronounced in TAM-O than in the original model. Conversely, when addressing ASU, TAM-O demonstrated a stronger explanatory power. The variance explained by TAM-O for ASU was 48.2%, significantly higher than the 36.1% explained variance for ASU in the original TAM.

Table 3. Comparison of Variances Explained

	Variance Explained (R^2)	
	Original Model	**TAM-O**
PU	.400	.307
ASU	.361	.482

In TAM-O, PEOU significantly influenced PU (β=.554; p<.001), indicating a strong positive relationship. The relationship was statistically significant, meaning the observed effect was highly unlikely to be due to chance. Additionally, PEOU had a significant favorable influence on ATU (β=.387; p<.001), suggesting that ease of use directly enhanced users' positive attitudes towards using the technologies. PU significantly impacted ATU (β=.370; p<.0011). Furthermore, PU directly affected ITU (β=.328; p<.001), highlighting that the perceived benefits of the technologies motivated users to intend to use it. ATU, in turn, significantly impacted ITU (β=.401; p<.001). ITU strongly predicted ASU (β=0.694; p<.001). ATU served as a mediator between PU, PEOU, and ITU. The visual representation in Figure 3 summarizes these pathways, demonstrating the direct and mediated effects within the model.

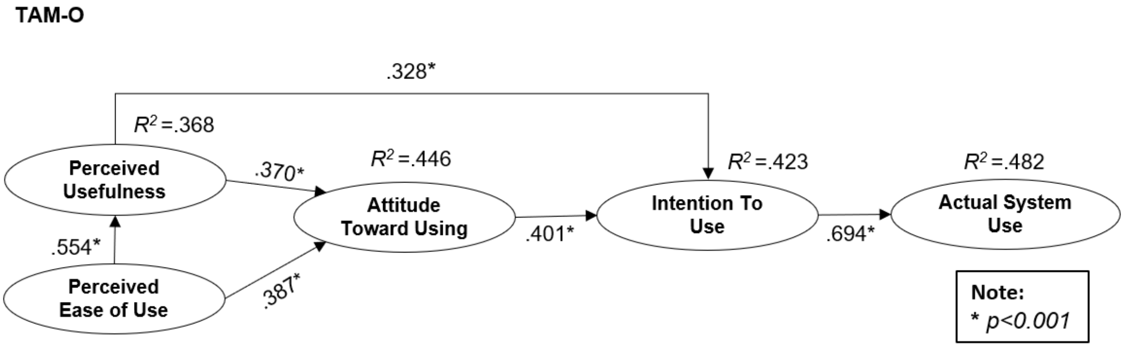

Figure 3. Path Diagram of TAM-O

As shown in Table 5, TAM-R, which removed the ATU component, explained 28.8% of the variance in PU (R^2= .288). It was the lowest among the three models, suggesting that ATU contributed to a better understanding of PU. For ASU, TAM-R explained 41.9% of the variance (R^2=.419), which was higher than the original model but lower than TAM-O. It implied that while removing attitude simplified the model, it retained a substantial predictive power for ASU, though less than the model with the ATU component included. The comparison indicated that incorporating ATU (as in TAM-O) enhanced the model's ability to predict ASU, although it slightly reduced the variance explained of PU. Removing ATU (as in TAM-R) simplified the model but decreased its explanatory power for PU while maintaining a strong ASU prediction. It suggested that attitude was crucial in predicting acceptance and actual use of technology.

Table 5. Comparison of Model Variances Explained

	Variance Explained		
	Original Model	**TAM-O**	**TAM-R**
PU	.400	.307	.288
ASU	.361	.482	.419

In TAM-R, the relationship between PEOU and PU was likewise notable (Figure 4). PEOU had a significant influence on PU (β=.537; p<.001), which indicated a strong positive relationship, suggesting that users who found the technologies easy to use were more likely to perceive them as useful. The influence of PU on ITU was also significant (β= .419; p<.001). It again indicated that users who perceived the technologies as useful were more likely to intend to use them. Additionally, PEOU directly influenced ITU (β =.254; p<.001), although the effect was smaller than the influence of PU on ITU. The relationship between ITU and ASU was strong (β=.647; p< .001). In TAM-R, removing the ATU component simplified the model by focusing directly on the relationships between PEOU, PU, ITU, and ASU. Despite this simplification, the model retained substantial explanatory power, particularly in ASU. The significant path coefficients indicated that PEOU and PU are crucial determinants of ITU, with PU having a slightly stronger effect. The strong influence of ITU on ASU highlighted the importance of intention in driving ASU, which was consistent with the premise of the original TAM. It implied that TAM-R was particularly useful in contexts where attitudes might be challenging to measure or less relevant to the adoption decision. One such instance could be a situation where the usage of the technology or system is mandatory in the organization.

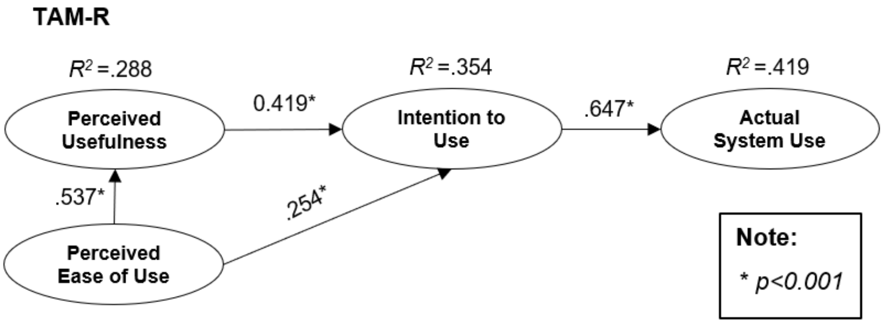

Figure 4. Path Diagram of TAM-R

The study also evaluated the impact of each independent variable on the dependent variables by examining their direct, indirect, total indirect, and cumulative effects. A connecting coefficient represents the direct influence of one factor on another within the models. Indirect influence describes how a factor impacts a target variable through its effect on other variables within the model. The total indirect impact of a variable is determined by multiplying its indirect impacts, while the total impact includes both direct and indirect effects. According to Cohen (1988), effect sizes of .200 are considered small, .500 represents a moderate effect, and values of .800 or higher are large. These effects are summarized in Table 6.

Table 6. Direct, Indirect, and Total Effects Implied in TAM-O & TAM-R

		TAM-O	**TAM-R**
Direct Effects	**PEOU → PU**	.554*	.537*
	PEOU → ITU	-	.254*
	PEOU → ATU	.387*	-
	PU → ITU	-	.419*
	PU → ATU	.370*	-
	ATU → ITU	.401*	-
	ITU → ASU	.694*	.647*
Indirect Effect	**PEOU → AU**	.164*	.146*
Total Effect	**PEOU → AU**	.164*	.310*

*Note: * $\beta < .001$*

In the TAM-O model, several vital direct effects are observed. The path coefficient from PEOU to PU is .554, indicating a strong positive relationship. The path from PEOU to ATU had a coefficient of .387, showing that ease of use significantly influences the user's attitude towards using the system. PU's influence on ATU was also notable, with a coefficient of .370, emphasizing that PU played a critical role in shaping the user's attitude. ATU directly affected ITU, as indicated by a coefficient of .401, which meant a positive ATU increased the user's intention to use it. Finally, ITU had a strong direct effect on ASU, with a coefficient of .694, indicating that a user's intention to use the system strongly predicted ASU.

For TAM-R, the direct effects included the path from PEOU to PU, which was .537, similar to TAM-O, reinforcing the importance of PEOU in determining PU. PEOU also directly impacted ITU, with a coefficient of

.254, suggesting that PEOU could directly influence the user's intention to use the system without necessarily changing their attitude. PU to ITU had a coefficient of .419, indicating that PU directly influenced ITU. The relationship between ITU and ASU was .647, showing that ITU remained a strong predictor of ASU, similar to TAM-O.

The indirect effects further illustrated the nuanced relationships in these models. In TAM-O, the total indirect effect of PEOU on ASU was .164, mediated through ATU and ITU. This value was derived from the combination of multiple paths: PEOU → ATU → ITU → ASU and PEOU → PU → ATU → ITU → ASU, highlighting the interplay of user perceptions and attitudes that drove technology use. In TAM-R, the indirect effect of PEOU on ASU was .146, primarily mediated through PU and ITU, indicating that PEOU influenced ASU indirectly by enhancing PU and ITU. The absence of ATU in these indirect paths in TAM-R highlighted a more streamlined influence route.

When combining direct and indirect effects to understand the total influence, in TAM-O, the total effect of PEOU on ASU remained at .164, as there was no direct path from PEOU to ASU in the model. In TAM-R, the total effect of PEOU on ASU was .310, which included both the direct effect of PEOU on ITU and the indirect effect through PU and ITU. The results emphasized the importance of PEOU and PU in influencing user attitudes, intentions, and actual usage of a system. The distinctions between TAM-O and TAM-R highlighted different pathways through which the perceptions affected user behavior. TAM-O emphasized attitudinal mediation through ATU, and TAM-R highlighted a more direct path from PEOU to ITU.

Discussion

The primary distinction between TAM-O and TAM-R lies in including the ATU component in TAM-O. By including ATU, TAM-O captured the psychological processes underlying users' acceptance of technology more nuancedly. TAM-O recognizes that users' positive attitudes towards a system are pivotal in forming their intentions to use it, eventually leading to ASU. For instance, in TAM-O, the path from PEOU to PU is strong (β=.554), indicating that PEOU significantly boosted the PU. Subsequently, PU impacted ATU (β=.370), and ATU significantly influenced ITU (β=.401). The chain of effects illustrated how perceived characteristics of the system lead to positive attitudes, which then translate into intentions to use the system.

In contrast, TAM-R simplified the model by excluding the ATU component, focusing directly on the relationships between PEOU, PU, and ITU. Its streamlined approach emphasized the direct effects of perceived technological characteristics on users' intentions and subsequent usage. Without ATU, TAM-R posited that PEOU and PU independently influenced ITU without the mediating effect of ASU. For example, in TAM-R, PEOU impacted PU with a slightly lower coefficient (β=.537) compared to TAM-O, and both PEOU (β=.254) and PU (β=.419) directly affected ITU. The model highlighted the importance of perceived characteristics without delving into the intermediary role of attitudes, presenting a more simplified view of technology acceptance.

While TAM-R maintained substantial explanatory power, particularly in predicting ASU (β=.647), it might overlook the complex mediating role of attitudes in the acceptance process. By focusing on direct relationships, TAM-R might miss out on understanding how users' internal evaluations and attitudes toward the system influence their behavioral intentions. A critical consideration in the choice between TAM-O and TAM-R is the context of technology use, mainly whether the use is voluntary or mandatory. ATU (as included in TAM-O) might be less influential in settings where technology use is mandatory because users must use the system regardless of their attitudes. In such contexts, the simplified approach of TAM-R, which focuses on direct relationships between system characteristics and behavioral intentions, could be more relevant. On the other hand, in voluntary use contexts, users' attitudes significantly impact their decision to use the technology, making TAM-O more appropriate for capturing the nuances of acceptance behavior.

From the analysis, it could be concluded that TAM-O provided a more detailed and psychologically rich framework for understanding technology acceptance by incorporating users' attitudes. On the other hand, TAM-R offered a more straightforward approach by emphasizing direct relationships, making it simpler but potentially less comprehensive in capturing the nuances of user behavior. The choice between TAM-O and TAM-R depends on the research context and the specific aspects of user behavior and technology acceptance that researchers or practitioners aim to understand. TAM-O would be more appropriate if the goal is to capture the detailed psychological processes and the mediating role of attitudes. However, TAM-R might be preferred if the focus is on a straightforward analysis of direct influences, especially in mandatory-use contexts.

The role of ATU in TAM is significant, as it provides insight into how users' perceptions and feelings about a system influence their intention and actual use of the system. Based on the analysis of the TAM-O and TAM-R models, several points suggest that ATU should indeed be considered for inclusion in future iterations of TAM. ATU is crucial in mediating the relationship between PEOU and ITU in TAM-O. The path coefficients from PEOU to ATU (.387*) and from ATU to ITU (.401*) highlight that users' attitudes significantly influence their intention to use the system. This mediation effect suggests that users who find the system easy to use develop a positive attitude toward it, enhancing their intention to use it. Including ATU captures this attitudinal aspect, providing a more comprehensive understanding of the factors driving system adoption.

Secondly, the absence of ATU in TAM-R results in a more direct influence path, but this omission may overlook critical motivational aspects. While TAM-R shows that PEOU directly affects ITU (.254*) and indirectly influences ASU through PU and ITU, the indirect effect mediated by ATU in TAM-O (.164*) indicates that attitudes form a vital link in the acceptance process. By excluding ATU, TAM-R might miss out on capturing how users' positive or negative feelings towards the system influence their decision-making process.

Furthermore, the inclusion of ATU aligns with psychological theories of behavior, such as the Theory of Planned Behaviour (TPB), which posits that attitudes significantly predict intentions and behaviors. Attitudes are shaped by beliefs about the outcomes of using the system; thus, integrating ATU in TAM aligns with well-established behavioral frameworks and enhances the model's theoretical robustness (Ajzen, 1991; Fishbein & Ajzen, 1975; King & He, 2006). However, it is also essential to consider the model's parsimony. Including ATU adds complexity, and the decision to incorporate it should weigh the benefits of capturing additional explanatory power against the simplicity and ease of applying the model. A simpler model without ATU might be more beneficial in practical applications, especially when rapid assessments are needed. The decision to use TAM-O or TAM-R is summarised in Figure 5. The simple flowchart provides a clear and concise guide for determining which model to apply based on the context of technology use and the specific analytical needs. It helps to clarify whether the inclusion of ATU is beneficial for capturing users' internal evaluations and attitudes in voluntary use contexts or if a more simplified approach without ATU is sufficient, particularly in mandatory use scenarios.

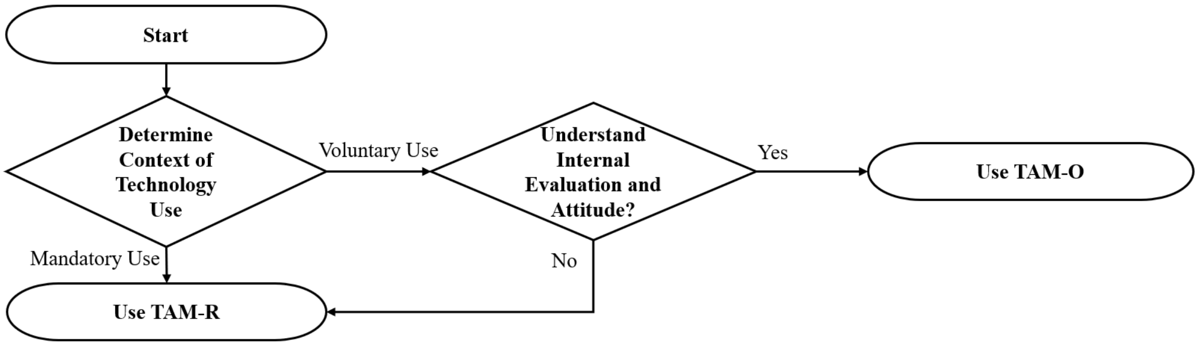

Figure 5. Decision Flowchart for Selecting TAM-O or TAM-R Based on Context and Evaluation Needs

Limitations

While the OSMASEM approach offers numerous benefits for exploring TAM within educational settings, it is crucial to consider its constraints. One significant challenge is the dependency on the availability and quality of relevant primary studies that provide sufficient and consistent data. In many TAM studies, the ASU construct is often omitted. As such, not all studies may offer detailed information or present it uniformly, complicating the data extraction and synthesis processes. The integrity and thoroughness of the selected studies profoundly influence the reliability and applicability of OSMASEM findings, as some studies might omit essential statistics or details required for OSMASEM, such as correlation matrices, path coefficients, or standard errors.

Examining TAM with OSMASEM presents further limitations, especially considering methodological insights from López-Bonilla and López-Bonilla (2017). Their study revealed that the choice of statistical method significantly impacts model performance, with PLS-SEM favoring TAM with the attitude construct (TAM-O) and CB-SEM favoring TAM without it (TAM-R). This divergence highlights the limitations of relying on a single analytical approach like OSMASEM, which is more inclined to PLS-SEM, which may not capture distinctions revealed by multiple methods, potentially leading to biased interpretations and less robust conclusions.

Moreover, OSMASEM requires proficiency in both SEM and meta-analysis, posing a barrier for less experienced researchers. While robust, the “metaSEM” package within the R software environment introduces additional complexity that requires a firm foundation in both methodologies. The complexity of OSMASEM, demanding substantial resources and time, further limits its feasibility for some researchers. Assumptions underlying SEM and meta-analysis, such as normality, independence of observations, and adequate sample size, must be met to ensure valid results. Violations can lead to biased estimates and incorrect conclusions.

Conclusions

In Davis' revisitation of TAM, it was mentioned that compelling design features could indirectly influence ATU, fostering positive acceptance (Davis & Granić, 2024). Specific beliefs about a system's PU and PEOU were more predictive of user behavior than general attitudes, making precise measurement and definition crucial. Factors significantly shaped ATU, including trust, perceived risk, training, demographics, compatibility, IT competency, education level, intrinsic motivation, perceived aesthetics, concentration, and mood. Davis and Granić (2024) introduced the Seven Pillars Framework that offered actionable principles for tailoring TAM to specific contexts, emphasizing the importance of core TAM constructs to avoid biases and ensure accurate predictions. They highlighted the importance of understanding and leveraging user attitudes by focusing on PU and PEOU, considering specific influencing factors, and using a structured framework to enhance technology acceptance.

With that in the background, this study set out to re-examine the role of attitude in TAM from a pragmatic standpoint. The choice between incorporating ATU depends on the research context and objectives. TAM-O, with ATU, offers a detailed and psychologically rich framework, ideal for understanding the nuanced mediation of attitudes between perceived system characteristics and behavioral intentions. This makes it suitable for contexts where capturing the psychological processes behind technology acceptance is crucial. Conversely, TAM-R provides a more straightforward approach by focusing on direct relationships, which may be preferable in mandatory use contexts or when simplicity and direct influence analysis are prioritized. Thus, ATU should be considered for inclusion in TAM when the goal is to gain a comprehensive understanding of the factors driving system adoption, particularly the attitudinal influences on user intentions.

The current study utilized the OSMASEM to study the role of attitude in TAM. In the educational context, OSMASEM has proven to be an increasingly popular tool in understanding technology acceptance by synthesizing data across multiple studies. Notably, past research has highlighted the significant role of attitudes within the technology acceptance models, such as in UTAUT, which is a later iteration of TAM (Or, 2023). The OSMASEM approach offers a robust method for aggregating and analyzing findings from various research efforts, enhancing the generalizability and reliability of conclusions drawn about technology acceptance in educational settings. In education research, OSMASEM can be particularly valuable for exploring the interplay between educational interventions, student characteristics, and learning outcomes. By leveraging the power of this technique, researchers can generate more comprehensive insights and evidence-based recommendations that can inform policy, improve educational practices, and ultimately enhance student achievement.

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