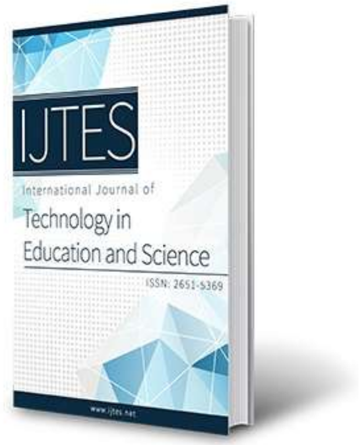

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The Strange Case of the Unified Theory of Acceptance and Use of Technology 3: Unpacking Informal Model Extensions in Artificial Intelligence and Educational Technologies

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To cite this article:

Or, C. (2025). The strange case of the Unified Theory of Acceptance and Use of Technology 3: Unpacking informal model extensions in artificial intelligence and educational technologies. *International Journal of Technology in Education and Science (IJTES), 9*(3), 354-373. https://doi.org/10.46328/ijtes.632

IJTES
International Journal of Technology in Education and Science
2025, Vol. 9, No. 3, 354-373 https://doi.org/10.46328/ijtes.632

The Strange Case of the Unified Theory of Acceptance and Use of Technology 3: Unpacking Informal Model Extensions in Artificial Intelligence and Educational Technologies

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Article Info

Article History

Received:
17 January 2025
Accepted:
5 May 2025

Keywords

Unified Theory of Acceptance and Use of Technology
UTAUT
UTAUT2
UTAUT3
Artificial intelligence in education
Technology acceptance

Abstract

The Unified Theory of Acceptance and Use of Technology (UTAUT) and its successor, UTAUT2, were widely recognised frameworks for understanding technology adoption in organisational and consumer contexts. UTAUT2 extended the original framework by introducing constructs such as hedonic motivation, price value, and habit, broadening its applicability in individual decision-making processes. Informal extensions of UTAUT2, often labelled as "UTAUT3," had emerged to examine the adoption of educational technologies, including artificial intelligence tools and e-learning platforms. Despite the potential of these extensions, "UTAUT3" lacked formal endorsement by its original developers and did not constitute an officially validated framework. This study examined the informal UTAUT3 model, particularly its application in educational technologies. Using meta-analytic structural equation modelling and bootstrapping, the study evaluated the model's explanatory power and theoretical consistency. The findings revealed that the informal UTAUT3 model exhibited structural inconsistencies, including the absence of direct paths from FC and H to UB and an inflated path coefficient from BI to UB, raising concerns about possible multicollinearity and model over-specification. The study highlighted the need for a cautious interpretation of the informal UTAUT3 model's findings and called for theoretical refinement, including re-evaluating the role of personal innovativeness, often included as a construct in the informal UTAUT3.

Introduction

The Unified Theory of Acceptance and Use of Technology (UTAUT) and its successor, UTAUT2, are widely recognised as foundational frameworks for studying technology acceptance (Venkatesh et al., 2003; Venkatesh et al., 2012). These models provide valuable insights into how users adopt and use new technologies by examining key constructs such as performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC).

UTAUT2 further extended this framework by incorporating additional constructs such as hedonic motivation (HM), price value (PV), and habit (H), making it particularly useful for studying consumer behaviour in technology adoption. Over the years, researchers have applied UTAUT and UTAUT2 to a variety of emerging technologies, adapting their constructs to address domain-specific challenges. Among these adaptations, some studies have informally referred to their extended versions as "UTAUT3," particularly in contexts where constructs were added to explore newer educational technologies like learning management systems (LMS) and artificial intelligence (AI) tools (Maisha & Shetu, 2023; Tan et al., 2024). This proliferation of informal extensions has sparked some interest and following. It is important to note that "UTAUT3" has not been officially proposed or endorsed by Venkatesh or his collaborators, the original proponents of the UTAUT framework. Instead, the term "UTAUT3" has been used informally in academic literature to describe extensions of the UTAUT2 framework.

Some researchers have extended UTAUT2 by incorporating constructs such as trust, transparency, and usability, with these adaptations being informally labelled as UTAUT3. For example, Gunasinghe et al. (2020) focused on content quality, collaboration, and academic workload compatibility in the context of academic e-learning adoption. Tetteh et al. (2022) then added trust, usability, and adaptability during crises to examine virtual learning adoption during the pandemic. Maisha and Shetu (2023) examined technological preparedness and socioeconomic barriers in e-learning adoption within developing countries, while Gupta et al. (2023) introduced e-leadership and virtual communication readiness to address educator-focused adoption. Tan et al. (2024) incorporated constructs from the Information System Success model in their exploration of ChatGPT adoption in higher education. However, as of now, there is no cohesive or formalised theoretical framework that constitutes an official UTAUT3. Although UTAUT3 has been referenced in some academic works, it remains an informal term used to describe diverse extensions of the UTAUT2 framework.

This paper seeks to explore these extensions of UTAUT2, often referred to as UTAUT3, in the context of educational technologies. Specifically, the paper focuses on their applicability to AI systems and tools used in education, such as adaptive learning platforms and AI-based tutoring systems. By synthesising these adaptations, this paper aims to identify recurring themes and challenges in educational technology acceptance and to discuss the potential need for a formalised version of UTAUT3.

Literature Review

UTAUT and its successor, UTAUT2, are well-established frameworks for understanding technology acceptance. UTAUT was first introduced by Venkatesh et al. (2003) as a synthesis of eight competing models of user acceptance. It identifies four core constructs, PE, EE, SI and FC, that influence behavioural intention (BI) and use behaviour (UB). Venkatesh et al. (2012) extended UTAUT into UTAUT2 by incorporating additional constructs: HM, PV, and H. UTAUT2 was designed to better address consumer contexts, enhancing its applicability to a broader range of technologies beyond workplace adoption (see Figure 1).

PE, defined as the belief that using technology enhances performance, continued to play a pivotal role in predicting BI, as established in the original UTAUT model (Venkatesh et al., 2003). EE, which captures the perceived ease of technology use, and SI, which reflects the influence of others' opinions, also remained significant predictors of

BI. FC, initially conceptualised as a determinant of UB, was modified in UTAUT2 to directly affect both BI and UB, reflecting the importance of available resources and support in facilitating technology use.

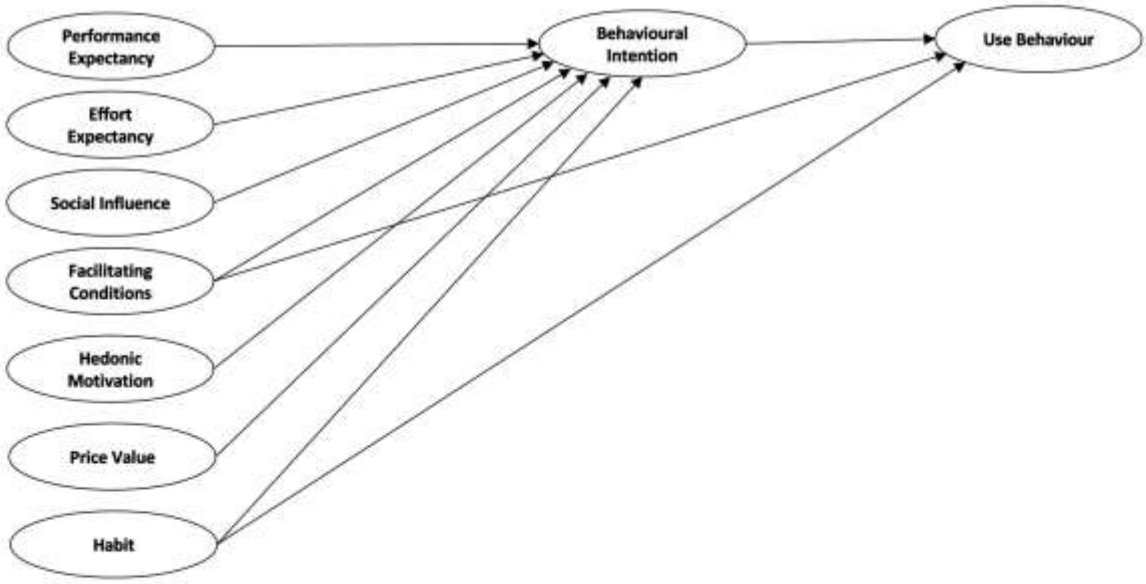

Figure 1. The UTAUT2 Model

Note: Adapted from Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157–178.

HM, a new construct introduced in UTAUT2, acknowledged the role of intrinsic enjoyment and pleasure in technology adoption. Empirical studies have consistently validated HM, demonstrating that technologies offering enjoyable user experiences are more likely to be adopted (Brown & Venkatesh, 2005; Venkatesh et al., 2012). PV, which captures the trade-off between the benefits and costs of using technology, further enhanced the consumer focus of UTAUT2. This construct is particularly significant in cost-sensitive contexts, such as mobile apps or subscription-based services (Dwivedi et al., 2019). H, representing the extent to which behaviours become automatic over time, added a behavioural dimension to UTAUT2. Research has shown that H significantly influences both BI and UB, highlighting the importance of prior experience and repeated usage in shaping technology adoption patterns (Limayem et al., 2007; Venkatesh et al., 2012).

Both UTAUT and UTAUT2 have been widely applied across domains, offering a robust foundation for understanding user acceptance of technologies (Abbad, 2021; Arain et al., 2019; Kittinger & Law, 2024; Raman & Don, 2013). Although UTAUT2 has been widely adopted, it has faced criticism for its complexity and potential overfitting due to the inclusion of multiple constructs (Tamilmani et al., 2021). Even in light of these critiques, some researchers have proposed expanding the model's focus on intention and behaviour by integrating additional constructs to enhance its explanatory power (Dwivedi et al., 2017). Nonetheless, UTAUT2 has been extensively validated across diverse domains, including mobile banking (Hilal & Varela-Neira, 2022). Understanding consumer adoption of mobile banking: extending the UTAUT2 model with proactive personality.

Sustainability, *14*(22), 14708.), e-learning (Ramírez-Correa et al., 2015), and healthcare technology (Hoque & Sorwar, 2017), demonstrating its robustness and adaptability.

In retrospect, Venkatesh et al. (2016) synthesised the foundational aspects of UTAUT and UTAUT2 and critiqued the lack of consideration for group-level or organisational-level factors. To address these gaps, they proposed a multi-level framework and encouraged future UTAUT research that explored contextual factors, such as culture and organisational dynamics, as well as new constructs that align with emerging technologies. They advocated for extending UTAUT beyond individual-level analysis, urging a shift towards meso- and macro-level dynamics to capture broader behavioural trends. More recently, Venkatesh (2022) discussed the unique challenges posed by the adoption of AI tools, including issues of trust, transparency, and resistance to algorithm-driven decision-making. He highlighted the complexities of AI technologies, such as biases, model errors, and the opacity of black-box algorithms, which often led users to rely on personal judgment over AI recommendations, and at the same time, noted the necessity of addressing AI-specific contextual factors. These factors included individual traits like openness to experience, technology characteristics such as algorithm transparency, and environmental influences like organisational culture. Ventakesh (2022) also proposed a research agenda integrating these elements into UTAUT to guide AI adoption studies, emphasising the need for interventions such as training programs and change management strategies to overcome resistance and foster trust.

As mentioned by Ventakesh (2022), researchers have sought to adapt UTAUT2 to emerging technologies, particularly those in fields like AI and educational systems, in recent years. In these efforts, informal extensions of UTAUT2 have sometimes been labelled as "UTAUT3." For instance, studies exploring AI-driven tools, such as ChatGPT, have incorporated additional constructs from the Information System Success model (Tan et al., 2024). While these extensions are valuable in contextualising UTAUT2 for cutting-edge technologies, it is important to note that UTAUT3 has not been formally proposed or recognised as an official framework by the original developers.

In the context of theoretical frameworks like UTAUT, an official model refers to a formalised framework that has been explicitly proposed, developed, and validated by its original proponents or through recognised academic consensus (Dubin, 1978; Gregor, 2006; Whetten, 1989). An official model is distinguished by its rigorous theoretical foundations, standardised constructs, empirical validation, and widespread recognition in academic literature (Whetten, 1989; Dubin, 1978). For example, UTAUT and UTAUT2 were introduced and developed by Venkatesh and his collaborators (Venkatesh et al., 2003; Venkatesh et al., 2012) through comprehensive research that synthesised multiple pre-existing models of technology acceptance. These models were disseminated through peer-reviewed publications, with their constructs empirically validated across various studies, establishing their generalisability and robustness. As a result, both UTAUT and UTAUT2 have become widely recognised and adopted across multiple domains of research and practice.

An official model is typically characterised by several critical components. First, theoretical foundations are essential, as the model must build upon or synthesise established theories to offer a comprehensive explanation of a phenomenon (Whetten, 1989). For instance, UTAUT was grounded in eight competing models of technology acceptance, such as the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (Ajzen, 1991; Davis, 1989; Venkatesh et al., 2003). Second, an official model defines its constructs with precision and consistency to ensure clarity and reliability in application. For example, UTAUT operationalises constructs like PE, EE, SI and FC, with these constructs tested for reliability and validity across studies, like Ventakesh and Zhang (2010) tested UTAUT in both the US and China. Third, empirical validation is a hallmark of an official model. A framework must be rigorously tested in diverse contexts to demonstrate its applicability and reliability (Dubin, 1978). For example, UTAUT2 extended its predecessor by incorporating new constructs, HM, PV and H, specifically validated for consumer behaviour contexts (Venkatesh et al., 2012). Finally, formal recognition is achieved through peer-reviewed dissemination and widespread citation within the academic community, as evidenced by the prominence of UTAUT and UTAUT2 in technology acceptance research (Bornmann & Daniel, 2008; Cronin, 1984; Garfield, 2006; Merton, 1973; Small, 1978).

Venkatesh and his collaborators (e.g., Venkatesh et al., 2003; Venkatesh et al., 2012) have not officially proposed, endorsed, or recognised the term "UTAUT3" in their academic publications. The adaptations and extensions of UTAUT2 that some researchers have labelled as "UTAUT3" are informal and have not been formalised into a cohesive theoretical framework by Venkatesh or his collaborators. In fact, there is no evidence in their work to suggest that they have engaged in any significant effort to develop or support a third iteration of UTAUT. Instead, Venkatesh et al. (2012) have focused on ensuring the broad applicability of UTAUT and UTAUT2 across organisational, consumer, and individual contexts. Beyond this, there has been no formal announcement or publication from Venkatesh and collaborators suggesting the existence or development of UTAUT3.

Tracing back to how it all started in the educational context, Farooq et al. (2017) first introduced the construct of "Personal Innovativeness" (PI) as part of their extension of the UTAUT2 to examine lecture capture systems (Figure 2). It was named "Proposed theoretical framework for UTAUT3 (UTAUT2)", even though the article title was "Acceptance and use of lecture capture system (LCS) in executive business studies: Extending UTAUT2". However, it remains unclear today whether the uptake was fully intended by the original authors or whether subsequent researchers might have misinterpreted or overextended the inclusion of PI as a formal and defining characteristic of a new UTAUT2 iteration, often referred to as "UTAUT3." The ambiguous naming of their framework as the "Proposed theoretical framework for UTAUT3 (UTAUT2)" may have contributed to this interpretive divergence, with researchers potentially misconstruing it as an endorsement of a distinct model rather than a contextual extension of UTAUT2. This uncertainty highlighted how subtle variations in naming and framing can influence the trajectory of theoretical models in academic research, leading to both intentional advancements and unintentional reinterpretations.

The concept of PI is not novel and has been pervasive in the technology acceptance literature well before its inclusion in Farooq et al.'s study. For instance, Agarwal and Prasad (1998) were among the first to operationalise PI in the context of information technology, defining it as an individual's willingness to try out new technologies. Since then, the construct has been incorporated in studies focusing on innovation adoption, particularly in research using frameworks such as TAM (Davis, 1989; Jeung-tai & Chihui, 2009; Joo et al., 2014; Kishore & McLean, 2001).

Past studies have incorporated PI but typically as a supplementary variable rather than a core construct. For example, research by Lu et al. (2005) on wireless internet adoption found that while PI was positively associated with technology use, its impact was secondary to constructs such as perceived usefulness and ease of use. This suggested that while PI captured individual tendencies towards openness to new technologies, it often failed to provide meaningful insights beyond those offered by primary constructs that directly address contextual or functional aspects of the technology.

Furthermore, the lack of consistent operationalisation and standardised measurement for PI has contributed to its diminished importance in the literature. For example, while some studies defined the construct as a general disposition towards technological innovation, others interpreted it as a context-specific attitude (Agarwal & Prasad, 1998; Ciddi, 2025). This inconsistency made it challenging to draw generalisable conclusions about the construct's role in technology acceptance, reducing its theoretical utility.

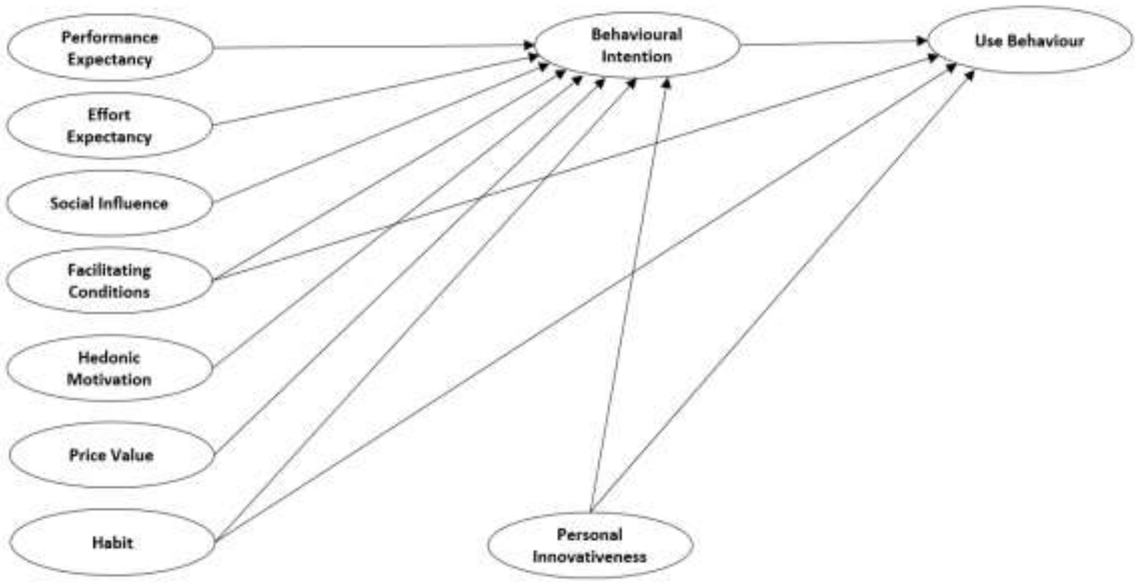

Figure 2. The Informal UTAUT3 Model

Note: Adapted from Farooq, M. S., Salam, M., Jaafar, N., Fayolle, A., Ayupp, K., Radovic-Markovic, M., & Sajid, A. (2017). Acceptance and use of lecture capture system (LCS) in executive business studies: Extending UTAUT2. *Interactive Technology and Smart Education, 14(*4), 329-348.

In many cases, PI appears to function as a proxy for deeper psychological traits, such as openness to experience, or as an indirect predictor of technology use mediated by other constructs like HM or H. Studies like Bhat et al. (2024) provided key insights into the mediating effects of PE, HM and H. However, a broader analysis is required to generalise these findings across contexts. The One-stage Meta-analytic Structural Equation Modelling (OSMASEM) approach offers a robust framework by synthesising data from multiple studies.

Through integrating diverse datasets, OSMASEM enables the analysis of PI alongside UTAUT2's core constructs in the informal UTAUT3, offering a deeper understanding of their collective and unique impacts on BI and UB.

OSMASEM provides a powerful methodological approach to address this issue by pooling findings from multiple studies and assessing the relationships between constructs across contexts. OSMASEM enables the integration of diverse datasets, allowing researchers to examine both the core constructs of informal UTAUT3 and the added construct, PI.

This study will examine how PI as a construct affects the official UTAUT2 framework in terms of explanatory power. This research also explores the consistency of relationships between constructs in the informal UTAUT3 across studies, settings, and technologies. Ultimately, this approach seeks to address the gaps in current knowledge by synthesising and evaluating the informal UTAUT3, offering insights into the theoretical and practical implications of the adoption of AI and educational technologies. To achieve these objectives, the study addresses the following research questions:

- To what extent does the inclusion of an additional construct in UTAUT3 improve the overall model fit when compared to UTAUT2, as measured using OSMASEM and bootstrapping?
- How do the core constructs of the informal UTAUT3 perform in explaining BI and UB as compared to the official UTAUT2 in the educational contexts?
- What is the relative explanatory power of the added construct in UTAUT3 compared to the core constructs in UTAUT2 when predicting BI and UB in the education contexts?

Method

A literature search on UTAUT3 in education was conducted using Primo by Ex Libris with the search string: "UTAUT3" AND "education". The databases included the DOAJ, IngentaConnect Journals, Springer Ejournals, Journals@Ovid Ovid Autoload, Springer Nature OA/Free Journals, ScienceDirect Ejournals, CINAHL Complete, Wiley Online Library - AutoHoldings Journals, Public Library of Science, Taylor & Francis Online, Business Source Complete, IOP Publishing Free Content, BMJ Journals, Taylor & Francis Open Access, Wiley Online Library Open Access, SAGE Journals PREM24 Premier 2024, and Oxford Journals Online. The search filters were English language, article document type, open access and peer-reviewed. The initial screening of the 183 identified studies was based on the following criteria:

(1) the studies examined UTAUT3 in school or university settings;
(2) the studies reported detailed examinations and correlations of UTAUT3 constructs;
(3) the studies utilised quantitative research methods; and
(4) the studies were analysed, reported with findings discussed in English.

This resulted in 54 eligible empirical studies.

Further exclusion criteria were: (1) the studies did not target teachers, lecturers, educators, or students in K-12, college, or university education; (2) UTAUT3 was examined outside of educational contexts; and (3) insufficient statistical reporting of correlations. Finally, 7 studies were included in the meta-analysis using correlation matrices. Figure 3 shows PRISMA, which describes the literature search and selection process. The list of UTAUT3 studies is shown in Table 1.

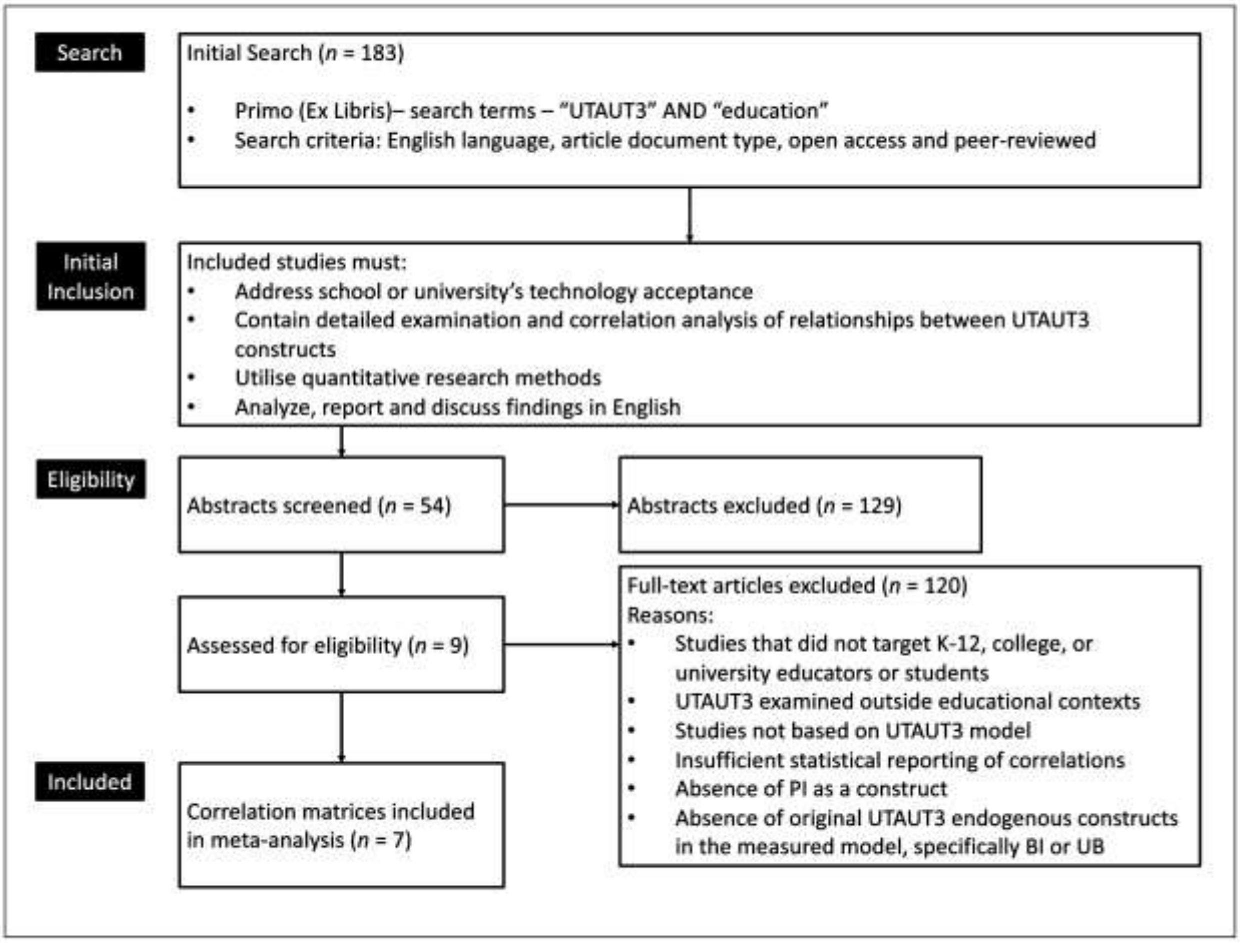

Figure 3. PRISMA Diagram

Table 1. List of UTAUT3 Studies

S/N	Technology	Sample Size	Reference
1	Lecture Capture System	481	Farooq, Muhammad Shoaib, et al. "Acceptance and use of lecture capture system (LCS) in executive business studies: Extending UTAUT2." *Interactive Technology and Smart Education 14*.4 (2017): 329-348.
2	e-learning	441	Gunasinghe, A., Hamid, J. A., Khatibi, A., & Azam, S. F. (2020). The adequacy of UTAUT-3 in interpreting academician's adoption of e-learning in higher education environments. *Interactive Technology and Smart Education, 17*(1), 86-106.
3	e-learning	191	Kamalasena, B. D. T. M., & Sirisena, A. B. (2021). Factors influencing the adoption of e-learning by university students in Sri Lanka: Application of UTAUT-3 model during Covid-19 pandemic. *Wayamba Journal of Management, 12*(2), 99-124.
4	Virtual Learning Environment	1874	Tetteh, F., Otysina, F., Baffoe, S., & John, A. (2022). Adoption and use of virtual learning environment during the Covid-19

S/N	Technology	Sample Size	Reference
			pandemic: a perspective of UTAUT3. *ADRRI Journal (Multidisciplinary), 31*(2 (8), April, 2022-June), 111-135.
5	Virtual Communication	380	Gupta, S., Mathur, N., & Narang, D. (2023). E-leadership and virtual communication adoption by educators: a UTAUT3 model perspective. *Global Knowledge, Memory and Communication, 72*(8/9), 902-919.
6	e-learning	285	Maisha, K., & Shetu, S. N. (2023). Influencing factors of e-learning adoption amongst students in a developing country: the post-pandemic scenario in Bangladesh. *Future Business Journal, 9*(1), 37.
7	Artificial Intelligence	388	Tan, C. N. L., Tee, M., & Koay, K. Y. (2024). Discovering students' continuous intentions to use ChatGPT in higher education: a tale of two theories. *Asian Education and Development Studies, 13*(4), 356-372.

Analysis Using metaSEM for OSMASEM and Bootstrap

The R package metaSEM (Cheung, 2015; version 1.3.1) was used to analyse correlation matrices from TAM studies, leveraging R software (R Core Team, 2024; version 4.4.2). This package employs the OSMASEM method, integrating meta-analysis and SEM with the OpenMx package. A meta-analysis combines findings from independent studies to estimate overall effect sizes and trends (Borenstein et al., 2021), offering greater statistical power and reliability than individual studies. The metaSEM package extends this by evaluating complex relationships between observed and latent variables using SEM. OSMASEM is particularly relevant as it processes past data and maps variable relationships over time (Jak & Cheung, 2020), treating pooled data from multiple studies as if from one large dataset. This retains data richness while enhancing statistical power to detect significant effects. Correlation matrices were inspected for completeness and consistency, with missing data handled through imputation or exclusion. Standardisation ensured comparability across studies. The OSMASEM method aggregated data using maximum likelihood estimation, summing sample sizes across studies rather than averaging them. This approach improved the accuracy of standard error computations for SEM path coefficients.

To assess the stability and robustness of the model, bootstrap resampling was also performed. Bootstrapping involves resampling the data with replacement to generate additional datasets that approximate the variability inherent in the original dataset (Efron & Tibshirani, 1993). This approach allowed for insights into the generalizability of the model's parameters across resampled datasets. Bootstrapping is particularly valuable when working with small datasets, as it compensates for limited variability by introducing resampling-based variation. Moreover, bootstrapping has been widely recognised as a nonparametric method that does not rely on stringent assumptions of normality, making it particularly suited for SEM in the presence of small sample sizes or when data distributions deviate from normality (Westfall & Young, 1993). By resampling multiple times, bootstrapping provides an empirical approximation of the sampling distribution of parameter estimates, which can be used to construct robust confidence intervals and reduce bias in inference (Cheung, 2009). This iterative approach is essential for assessing the generalizability of model parameters, particularly in meta-analytic structural equation modelling (OSMASEM), where heterogeneity across studies can impact the stability of aggregated results (Jak & Cheung, 2020). Bootstrapping is also an effective tool for diagnosing model sensitivity, as it reveals how parameters behave under slight variations in the data. This is especially important when analysing models with complex structures or a high number of parameters relative to the sample size, as small data perturbations can significantly affect parameter stability and model fit (Nevitt & Hancock, 2001). Therefore, bootstrapping not only strengthens the reliability of parameter estimates but also provides a clearer understanding of the limitations and robustness of the model in addressing real-world variability.

Results

The model fit for the informal UTAUT3 was evaluated using a range of standard goodness-of-fit indices. These indices provided insights into the degree to which the proposed model aligned with the data. The results are summarised in the table below and discussed in detail in Table 2. The chi-square (χ^2) statistic for the model was 5.112 with 5 degrees of freedom (*df*), resulting in a χ^2/df ratio of 1.022. Typically, a χ^2/df ratio below 3.000 is indicative of an acceptable fit (Schumacker & Lomax, 2010). The chi-square-to-degrees-of-freedom ratio (χ^2/df) was 1.022, which fell well below the threshold of 3.000, indicating an excellent model fit (Schumacker & Lomax, 2010). In this case, the p-value for the χ^2 test was 0.402, which was greater than the threshold of 0.05, indicating that the fit of the model was not significantly worse than a perfect fit.

Table 2. Goodness-of-fit Indices of Informal UTAUT3

Measure	Threshold	Value
χ^2	--	5.112
df	--	5
χ^2/df	< 3.000	1.022
***p*-value**	> .050	.402
RMSEA	< .050	.002
SRMR	<.080	.022
CFI	> .950	.999
TLI	> .950	.999

The RMSEA value for the informal UTAUT3 model was .002, which was well below the threshold of .050 for a good model fit (Browne & Cudeck, 1993). This suggested that the model demonstrated an excellent fit when considering the complexity of the model in relation to the data. The low RMSEA value reflected the minimal error of approximation in the population. The SRMR value was .022, significantly below the threshold of .080. This value indicated a very good fit between the observed and predicted correlation matrices (Hu & Bentler, 1999). The SRMR being close to zero reflected a strong consistency between the model and the data, further supporting the model's adequacy. The CFI and TLI were both .999, surpassing the threshold of .950 for excellent model fit (Bentler, 1990). These indices compared the specified model to a null model (one assuming no relationships among variables) and indicated that the informal UTAUT3 model captured almost all of the covariation in the data. The values suggested that the model's structure aligned closely with the data, providing strong evidence of a good fit. The overall fit indices suggested that the informal UTAUT3 model provided an excellent fit to the data, as evidenced by the RMSEA, SRMR, CFI, and TLI values (Hair et al., 2019).

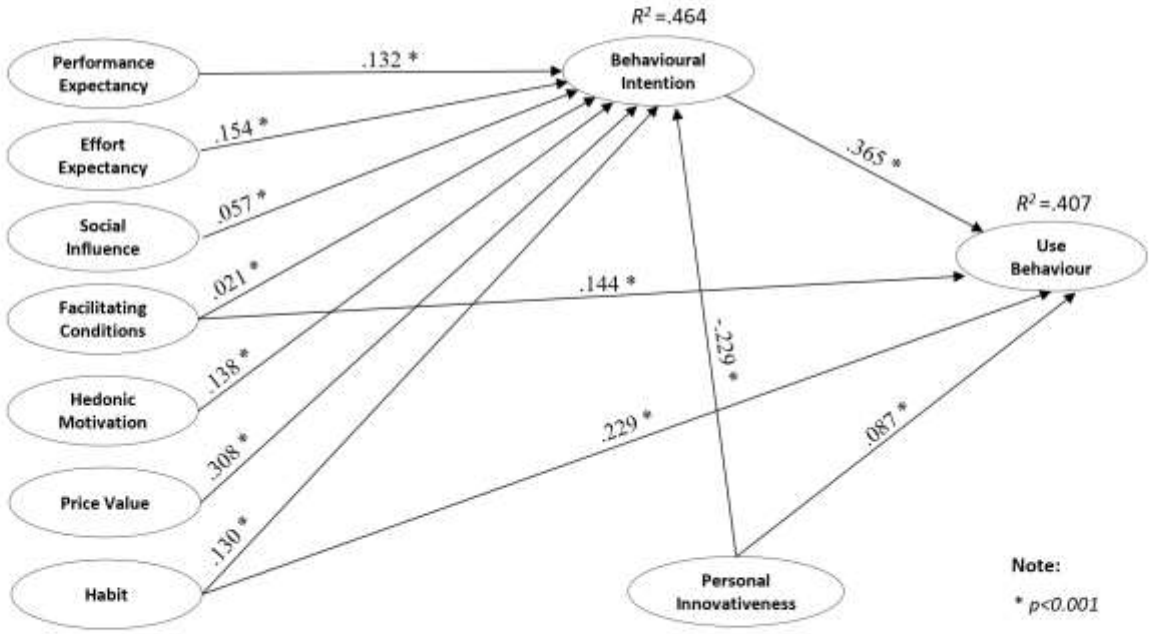

Figure 4. Path Analysis of Informal UTAUT3

The model was assessed using path coefficients and explained variances (R^2) for the dependent variables, BI (R^2 =.464) and UB (R^2 =.407) (Figure 4). For BI, several factors showed significant positive effects. PE (β =.132, p<.001), EE (β =.154, p<.001), and SI (β =.057, p<.001) emerged as strong predictors, aligning with previous UTAUT research (Venkatesh et al., 2003; Venkatesh et al., 2012). HM (β =.138, p<.001) and PV (β =.308, p<.001) also influenced BI, highlighting the importance of perceived enjoyment and economic value. H (β =.130, p<.001) made a notable contribution, consistent with findings that habitual behaviour predicts intention (Venkatesh et al., 2012). The negative coefficient for PI (β = −.229, p<.001) suggested a counterintuitive relationship with UB, indicating that higher levels of PI did not directly translate into increased technology use. This possibly reflected complexities such as overconfidence, which might have led to less reliance on provided resources, or the likelihood that highly innovative individuals were more selective or critical in their technology adoption. Alternatively, the negative association might have pointed to an indirect effect, where PI influenced UB through other pathways. For UB, BI (β =.365, p<.001) had a strong, direct effect, consistent with UTAUT's core premise that intention predicted behaviour. FC (β =.144, p<.001) significantly influenced UB, highlighting the importance of resource availability and support. H (β =.087, p<.001) also contributed positively, reinforcing its dual role as a predictor of both intention and behaviour.

The comparison of variances explained (R^2) for BI and UB between UTAUT2 and the informal UTAUT3 models highlighted the impact of adding PI on predictive power (Table 3). UTAUT2 explained 74.0% of the variance in

BI and 52.0% in UB, demonstrating strong predictive accuracy and a robust theoretical structure (Ventakesh et al., 2012). In contrast, the informal UTAUT3 model, which incorporated PI, explained only 46.4% of BI and 40.4% of UB, reflecting reduced explanatory power. The addition of PI in the informal UTAUT3 model appeared to weaken the predictive strength of core constructs from UTAUT2. Although PI provided a useful individual-level perspective, its inclusion disrupted the structural consistency of the model, possibly introducing complexity or multicollinearity.

Table 3. Variances Explained for UTAUT2 and UTAUT3

	Variances Explained (R^2)	
	UTAUT2	**Informal UTAUT3**
BI	.740	.464
UB	.520	.404

In the current study, bootstrapping was applied to generate 50 resampled datasets based on the 7 original studies included in the OSMASEM. Bootstrapping estimated the stability and generalizability of model parameters despite the limited number of available studies. While having only 7 studies could limit the generalizability of traditional meta-analytic methods, bootstrapping mitigated this issue by creating resampled datasets that reflected the variability within the original studies. This was particularly valuable for calculating confidence intervals and assessing model fit indices. By doing so, bootstrapping addressed the uncertainty inherent in small datasets and provided a more reliable basis for drawing inferences about the population-level effects. The decision to use 50 bootstrap samples aligned with recommendations in the literature, which suggested that for small datasets, bootstrapping could provide robust standard errors and confidence intervals (Nevitt & Hancock, 2001). Moreover, increasing the number of bootstrap replications enhanced the precision of parameter estimates without introducing bias, making it an appropriate method for studies with limited sample sizes, which, in this case, 7 studies.

After performing the bootstrapping procedure with 50 resampled datasets, the model fit indices (e.g., CFI, TLI, RMSEA) fell below acceptable thresholds (e.g., Hu & Bentler, 1999) (Table 4). This observation suggested that the variability introduced through the resampling process might have highlighted structural or data-related weaknesses that were less apparent in the analysis of the initial 7 studies alone. When the model fit indices fell below acceptable thresholds, it raised important concerns about the validity of the model and the reliability of the estimated relationships and suggested that the model did not adequately capture the underlying structure of the data. The poor fit of the bootstrap model could imply that the coefficients and relationships could be biased or unreliable due to structural misfit. Given this, the estimated path coefficients and relationships among constructs in the informal UTAUT3 model could not be interpreted as valid or reliable representations of the underlying data structure. In SEM, poor model fit indicates that the hypothesised model fails to adequately represent the relationships in the observed data (Byrne, 2010). Consequently, any analysis or interpretation of the path coefficients or relationships would be misleading and potentially erroneous. As such, the analysis of path coefficients and relationships should be interpreted with caution. It was not ideal to accept the coefficients or UTAUT3 relationships as confirmatory findings because the poor model fit undermined the validity of the relationships.

Table 4. Model Fit Indices for Bootstrap Model of 50 Resampled Data

Measure	**Threshold**	**Value**
χ^2	--	439.472
df	--	33
χ^2/df	< 3.000	13.317
***p*-value**	> .050	.000
RMSEA	< .050	.055
SRMR	<.080	.400
CFI	> .950	.341
TLI	> .950	.101

The UTAUT3 bootstrap model provided some insights into the relationships among key constructs despite its fit indices falling below thresholds (see Figure 5). PE (β = .491, p<.001) was demonstrated as a strong predictor of BI, aligning with UTAUT-based findings (Venkatesh et al., 2003). EE (β = .514, p<.001) showed a substantial positive impact on BI, while SI (β= .380, p<.001) highlighted the role of peer and societal expectations. FC (β = .471, p<.001) contributed positively to BI, emphasising the role of resources and infrastructure. HM (β= .463, p<.001) showed that the enjoyment derived from using the technology strongly influenced BI, emphasising intrinsic motivation. PV (β= .653, p<.001) emerged as the strongest predictor, suggesting that cost-benefit considerations were pivotal in shaping BI. H (β= .561, p<.001) demonstrated a significant contribution to BI, highlighting the automaticity of technology use. PI (β= .413, p<.001) highlighted the role of individual traits, where more innovative individuals were more likely to form stronger intentions to use technology. However, the bootstrapped UTAUT3 model omitted key relationships expected from theoretical UTAUT2 foundations.

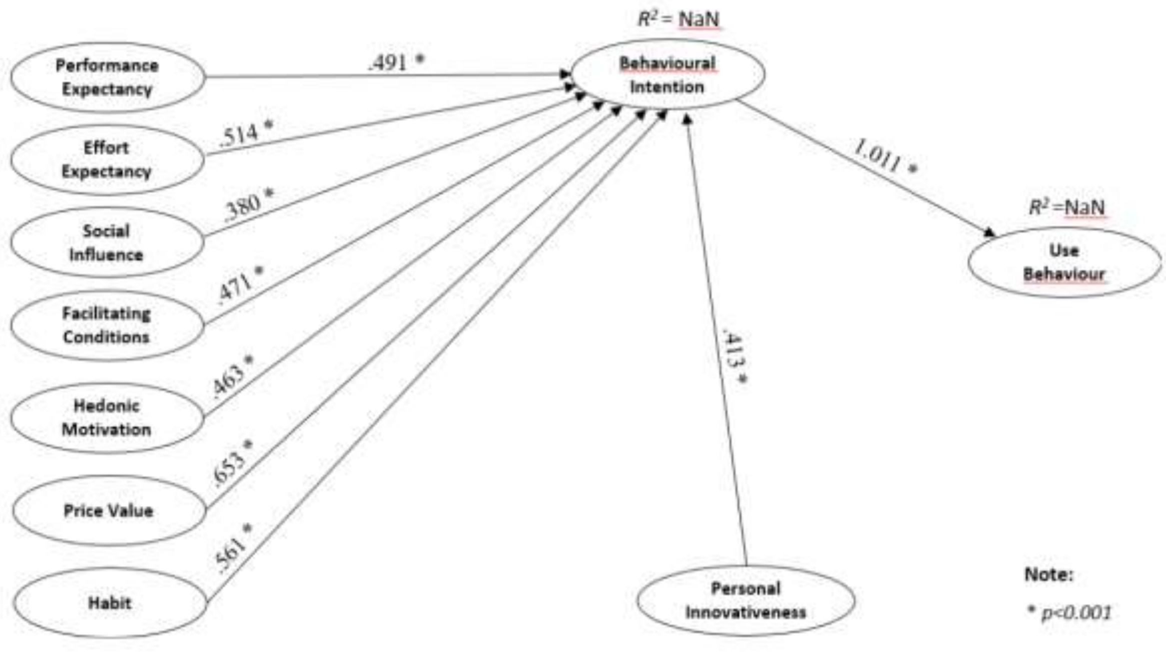

Figure 5. Path Analysis of Informal UTAUT3 Bootstrap Model

Specifically, FC, which often directly influences UB, was not linked to UB in the bootstrapped UTAUT3 model.

This contradicted prior UTAUT2 research emphasising the role of FC (e.g., resource availability, support) in enabling technology use (Venkatesh et al., 2012). Additionally, the model excluded a direct path from H to UB despite H being a strong determinant of UB beyond its influence on BI. These omissions might lead to an incomplete understanding of UB, as the model relied heavily on BI.

While the BI to UB path (β= 1.011, p<.001) was significant and indicated an exceptionally strong relationship, the coefficient exceeding 1 was unusual and might suggest issues such as over-specification of the model or multicollinearity among predictors. The inflated BI to UB coefficient highlighted potential model issues. While performing the calculation of the explained variances (R^2) after performing a bootstrapping of 50 data samples, the results could not be determined. (i.e. *NaN; not a number*). It indicated that there were structural issues within the informal UTAUT3 model. One plausible explanation is that bootstrap R^2 values BI and UB could not be calculated due to the structural inconsistencies within the model. This again indicated that the informal UTAUT3 path model might not adequately define the relationships between variables to calculate explained variances. With these observations, it is important to note that the results of the bootstrapped UTAUT3 model must be interpreted with caution due to key theoretical omissions and below-threshold fit indices.

Discussion

The meta-analysis revealed the negative coefficient for the path from PI to BI ($\beta = -.229$, $p < .001$), and it raised important considerations regarding its role within the informal UTAUT3 framework. While PI is theoretically associated with openness to adopting new technologies (Agarwal & Prasad, 1998), its negative relationship with BI suggested complexities that warranted further investigation. One possible explanation was that individuals with high levels of PI might demonstrate overconfidence in their ability to adopt and use technologies, potentially leading to reduced reliance on available resources or support systems. This overconfidence could, in turn, hinder sustained intentions, particularly in environments where external facilitation or ease of use played a significant role in technology adoption. Moreover, the negative coefficient might indicate that PI's influence on UB operated indirectly through other constructs. Prior studies noted that individual traits like PI often exerted their effects through mediating or moderating pathways rather than serving as direct predictors of BI (Agarwal & Prasad, 1998; Bhat et al., 2024). For example, individuals with high PI might prioritise exploration and experimentation with technology but remain selective or critical in committing to regular use, particularly when the technology fails to meet their expectations.

The inclusion of PI in the informal UTAUT3 model represented an unqualified theoretical extension of the UTAUT2 framework. While PI is relevant in modern contexts, where individual differences in openness to innovation play a critical role in shaping technology adoption, its inclusion in the informal UTAUT3 model warranted scrutiny for several reasons. For instance, it has not been formally included in the UTAUT2 model (Venkatesh et al., 2012). Thus, its incorporation into the informal UTAUT3 model required additional empirical validation to establish its explanatory power and role in predicting BI and UB. The results of this study suggested that the inclusion of PI in the informal UTAUT3 model did not yield stable relationships or improve model fit, particularly during bootstrapping. This raised questions about whether PI consistently contributed to explaining technology adoption across diverse contexts or if its effects were moderated by contextual factors (e.g., culture, type of technology).

The evaluation of the informal UTAUT3 model's fit indices presented a mixed interpretation of the proposed framework. While the initial model fit indices with 7 studies suggested excellent alignment with the data, the results of the bootstrapped model revealed significant concerns. Specifically, the bootstrap model fit indices below acceptable thresholds indicated substantial discrepancies in the informal UTAUT3 model's structure (Hu & Bentler, 1999). These findings suggested that while the informal UTAUT3 model initially appeared to align well with the observed data, the variability introduced through bootstrapping revealed underlying structural weaknesses. PE, EE, and SI emerged as significant predictors of BI, which was consistent with prior UTAUT2 research demonstrating the significance of these constructs in predicting intention (Venkatesh et al., 2012; Williams et al., 2015). Additionally, intrinsic and economic motivators, represented by HM and PV, respectively, strongly influenced BI. These results reinforced prior findings that intrinsic enjoyment (HM) and cost-benefit trade-offs (PV) were critical to understanding consumer technology adoption (Brown & Venkatesh, 2005). H, also contributed significantly to BI, which aligns with research emphasising the role of automaticity in shaping user intentions (Limayem et al., 2007; Venkatesh et al., 2012).

Despite confirming some usual significant relationships within the UTAUT2 framework, the bootstrapped model omitted critical paths that are well-established in the UTAUT2 framework. One notable omission was the absence of a direct path from FC to UB, which undermined the model's ability to account for resource availability and support in driving actual behaviour. Prior studies have consistently emphasised the importance of FC in facilitating technology use, particularly in voluntary contexts where access to resources can be a determining factor (Venkatesh et al., 2012; Dwivedi et al., 2017). Similarly, the exclusion of a direct path from H to UB is a critical limitation. Research has demonstrated that H not only predicts BI but also directly influences UB, as habitual behaviours often bypass conscious intention (Limayem et al., 2007; Venkatesh et al., 2012). These omissions suggested that the model provided an incomplete representation of the factors influencing UB, heavily relying on BI to explain behavioural outcomes.

The bootstrap model also revealed that the BI to UB path was significant but unusually high, with the coefficient exceeding 1. This anomaly suggested potential issues such as multicollinearity or model over-specification, both of which could distort path estimates (Hair et al., 2019). Such a result called into question the stability and reliability of the relationships within the informal UTAUT3 model. Furthermore, the inability to calculate R^2 values for BI and UB in the bootstrap model pointed to structural inconsistencies, indicating that the model's relationships might not adequately capture the underlying data structure.

The current study is not the first to analyse UTAUT3, Khan et al. (2022) conducted a meta-analysis of mobile learning adoption in higher education based on the informal UTAUT3. The study's reference to the informal UTAUT3 as its underlying framework highlighted an interesting direction for research but could benefit from further clarification, given UTAUT3's informal and unofficial status. Notably, the meta-analysis utilised UTAUT and UTAUT2 past studies as proxies and assumed that the constructs and relationships in UTAUT3 were identical or sufficiently aligned with those of its predecessors. However, UTAUT3 includes constructs such as PI, which are not part of the original UTAUT or UTAUT2 frameworks. Such an approach risks mixing different theoretical models and weakening UTAUT3's unique contributions. Furthermore, the approach might obscure the exploratory nature of the informal UTAUT3, leading to the misinterpretation that its constructs and relationships had already been empirically validated when, in fact, they had not. Presenting it as a formalised model might inadvertently lead other researchers to adopt it without critically evaluating its constructs or rigorously testing its validity. This might result in varying interpretations, which could pose challenges for theoretical consistency in technology adoption research.

The analysis in this study revealed several limitations in the informal UTAUT3 model, including poor model fit, inability to calculate R^2, and inconsistencies in relationships. These issues indicated that the model required further refinement and validation before it could be considered a reliable framework for understanding technology acceptance. Using the label "UTAUT3" without formal recognition could lead to confusion in the literature and detract from the credibility of both the current model and the broader UTAUT framework. The term, “UTAUT3”, carries significant implications, as it suggests a formal, widely validated, and theoretically accepted extension of the UTAUT framework. The informal UTAUT3 model in its current state does not meet these criteria. Specifically, unlike UTAUT and UTAUT2, which were rigorously tested and supported by strong empirical evidence (Venkatesh et al., 2003; Ventakesh et al., 2012), the informal UTAUT3 model lacks widespread validation or consensus in the academic community. Referring to the model as "UTAUT3" could mislead researchers into assuming that it has been formally recognised, which is not the case.

Conclusion

The informal UTAUT3 model represents an extension of existing technology adoption frameworks; however, it is critical that it is referred to appropriately to avoid misleading future research. Specifically, the model should be described as an "extended UTAUT2 model" to emphasise its preliminary and exploratory nature rather than suggesting it is a formally validated and established framework. This distinction is essential to prevent misrepresentation and to encourage researchers to interpret its findings with caution.

Additionally, the role of PI in the extended UTAUT2 model requires further theoretical and empirical refinement. As a construct, PI captures an individual’s propensity to embrace and experiment with new technologies, making it a valuable addition to technology adoption frameworks. However, its inconsistent performance in the current analysis raised questions about its operationalisation and contextual relevance. Future research should investigate PI’s role in greater depth, particularly exploring whether its influence varies across populations, types of technology, or cultural contexts, which could strengthen the theoretical coherence and predictive power of the extended UTAUT2 model.

Future studies must also address the informal UTAUT3 (i.e. extended UTAUT2 with PI as a construct) model's limitations by expanding the dataset, refining its theoretical structure, and employing advanced analytical techniques to improve its robustness and generalizability across diverse contexts and populations. These steps are necessary to establish the validity of the extended UTAUT2 model and to ensure that it aligns with the rigorous standards expected of formalised extensions of the UTAUT framework. Only through such efforts can the extended UTAUT2 model be considered a reliable and widely applicable tool for understanding technology adoption.

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