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Theoretical Convergence or Complexity? Integrating Task-Technology Fit into Unified Theory of Acceptance and Use of Technology 2 for Educational Technology Adoption

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Abstract

This study examined the integration of Task-Technology Fit (TTF) into the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) in the context of educational technology adoption. While UTAUT2 provided a behavioural perspective on technology acceptance, TTF offered a task-specific approach, highlighting the alignment between technology and user needs. The convergence of these models introduced theoretical and methodological challenges, particularly concerning construct overlap and model complexity. The analysis of existing literature on UTAUT2-TTF integration identified gaps in structural validity and construct differentiation. The findings indicated that while TTF enhanced the explanatory power for technology use behaviour (UB), its integration into UTAUT2 introduced redundancy, particularly between performance expectancy and task-technology fit. The study suggested that future research should refine model constructs to improve clarity and parsimony, ensuring theoretical coherence and empirical rigour. A meta-analytic structural equation modelling approach (MASEM) was recommended to enhance the evaluation of integrated models across multiple contexts. This study contributed to the ongoing discourse on technology adoption models, advocating for a balanced approach that maintained explanatory power while minimising complexity.

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Introduction

The rapid advancement of technology has profoundly transformed educational environments, creating a pressing need for robust models to understand and predict technology adoption (Alam & Mohanty, 2023; George & Wooden, 2023; Grassini, 2023). Among the most prominent models in this field are the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and Task-Technology Fit (TTF) theory (Goodhue & Thompson, 1995; Ventakesh et al., 2012). Both models have independently offered valuable insights into how and why individuals adopt and use technologies (Castanha et al., 2020; Furneaux, 2012; Spies et al., 2020; Tamilmani et al., 2021). Exploring the convergence of these two theoretical frameworks presents an opportunity to deepen our understanding of technology adoption processes (Bhimasta & Suprapto, 2016; Bu, 2022; Faqih & Jaradat, 2021; Gengfu & Chotiyaputta, 2019; Gerhart et al., 2015; Sharif et al., 2019; Wang et al., 2022). UTAUT2, an extension of the original UTAUT model, incorporates additional constructs such as hedonic motivation (HM), price value (PV), and habit (H) to explain user intentions and behaviours more comprehensively (Venkatesh et al., 2012). While UTAUT2 has been extensively applied across diverse contexts, it has faced criticism for its complexity and the potential redundancy among its constructs (Dwivedi et al., 2019). Conversely, TTF theory posits that technology adoption is more likely when the technology effectively supports the tasks it is designed to facilitate (Goodhue & Thompson, 1995). This theory emphasises the alignment between task characteristics and technological capabilities, which is instrumental in predicting user satisfaction and usage (Gebauer et al., 2010).

Past studies have shown that integrating TTF into the UTAUT2 framework could offer a more nuanced understanding of technology adoption in educational settings (Bhimasta & Suprapto, 2016; Faqih & Jaradat, 2021; Gengfu & Chotiyaputta, 2019; Gerhart et al., 2015; Sharif et al., 2019; Wang et al., 2022). This integration addresses potential theoretical overlaps, such as the constructs of performance expectancy in UTAUT2 and task-technology fit in TTF, while evaluating their combined explanatory power (Faqih & Jaradat, 2021; Wang et al., 2022). By examining the synergy between these models, this paper proposes a comprehensive approach to studying the adoption of educational technology, ultimately providing insights for researchers and practitioners seeking to enhance technology use in learning environments.

Literature Review

Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

UTAUT2 was introduced by Venkatesh et al. (2012) as an extension of the original UTAUT model to better capture the complexities of technology acceptance and use in consumer contexts (Venkatesh et al, 2003). UTAUT2 expanded the original model by adding three constructs: HM, PV, and H, while retaining the core constructs of performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) from UTAUT. The dependent variables include behavioural intention (BI) and usage behaviour (UB), which are often moderated by variables such as age, gender, experience, and voluntariness of use.

PE refers to the degree to which technology use enhances task performance, while EE measures the ease of use associated with the technology. SI captures the degree to which individuals perceive that significant others expect them to use the technology. FC assess the availability of resources and infrastructure to support technology use. HM addresses the intrinsic enjoyment derived from using the technology, PV reflects the trade-off between cost and benefits, and H examines the extent to which technology use becomes automatic over time (Venkatesh et al., 2012).

Empirical studies have validated the predictive power of UTAUT2 in various contexts, including mobile applications, e-learning systems, and e-commerce platforms (Dwivedi et al., 2019). However, UTAUT2 has been critiqued for its increasing complexity, the potential overlap of constructs, and the need for contextual adaptations (Tamilmani et al., 2021). For instance, PE and EE may correlate strongly in systems that are both efficient and easy to use, raising questions about construct redundancy (Tamilmani et al., 2021).

Task-Technology Fit (TTF)

The TTF theory, proposed by Goodhue and Thompson (1995), provides a complementary perspective on technology adoption by emphasising the alignment between the characteristics of the task and the capabilities of the technology. TTF suggests that technology adoption and utilisation are more likely when the technology supports the specific tasks users aim to perform. Unlike UTAUT2, which focuses on user perceptions and behavioural constructs, TTF centres on the task characteristics (TAC) and technology characteristics (TEC). Task characteristics refer to the nature and requirements of the tasks that need to be completed using the technology, such as their complexity, interdependence, and structuredness. Technology characteristics represent the technological attributes and functionalities that facilitate task execution, including ease of use, system reliability, and adaptability to user needs.

The core construct, TTF, captures the degree to which the technology enables task completion effectively and efficiently. Empirical studies have consistently shown that TTF is a strong predictor of user satisfaction, individual performance, and usage behaviour (Dishaw & Strong, 1999; Gebauer et al., 2010). For example, in enterprise resource planning (ERP) systems, TTF has been found to significantly enhance task performance by aligning system capabilities with organisational workflows (Zigurs & Buckland, 1998). While TTF provides a useful lens for understanding adoption in task-specific contexts, its scope has been critiqued for neglecting broader behavioural factors, such as SI or intrinsic motivation, which are also central to UTAUT2. For instance, the integration of models like UTAUT2 provides a comprehensive framework to examine both technological and behavioural factors, enabling better predictions of adoption and use behaviour, especially in diverse contexts such as augmented reality in education or e-books (Meng & Chotiyaputta, 2019; Gerhart et al., 2015). Another criticism is that TTF's explanatory power is insufficient in complex socio-technical systems (Faqih & Jaradat, 2021; Wang et al., 2022). For example, in learning management systems, TTF alone might highlight the technological fit but failed to account for SI or EE, which significantly impact adoption (Sharif et al., 2019).

Within educational contexts, TTF has also proven valuable for assessing how well online learning platforms and instructional tools support the specific tasks associated with both teaching and learning (McGill & Klobas, 2009; Teo & Zhou, 2014). By examining the alignment between course objectives, learning activities, and the technological functionalities offered, educators can tailor instructional design to facilitate active learning, collaboration, and timely feedback. This alignment is especially vital in distance or blended learning environments, where technology mediates much of the instructional process (Almaiah & Alismaiel, 2019; McGill & Klobas, 2009). When technology is well-matched to the tasks at hand, such as delivering multimedia content, fostering interactive discussions, or administering assessments, learners tend to show higher levels of engagement, motivation, and overall performance (Dishaw & Strong, 1999; Goodhue & Thompson, 1995; McGill et al., 2014; Wu & Chen, 2017)

Integration of UTAUT2 and TTF in the Educational Contexts

Integrating UTAUT2 and TTF offers a promising avenue for advancing our understanding of technology adoption by combining their strengths (Faqih & Jaradat, 2021; Sharif et al., 2019) (Figure 1). UTAUT2 excels at explaining user-centric factors, such as HM, SI, and H, while TTF provides a task-oriented framework that emphasises the alignment between technology and tasks (Goodhue & Thompson, 1995; Ventakesh et al., 2012). By synthesising these frameworks, researchers can address the limitations of each and gain a more holistic view of adoption. While the theoretical convergence of UTAUT2 and TTF may promise further insights and a new understanding of technology adoption, one might argue that there are overlapping constructs (Dishaw & Strong, 1999). For instance, PE in UTAUT2 and task-technology fit in TTF both focus on the perceived usefulness of technology, albeit from different angles. PE reflects the user's perception of the overall benefits of technology, while TTF assesses the alignment between specific tasks and technological capabilities. Additionally, EE and TAC share a common emphasis on ease of use, learnability, and system complexity.

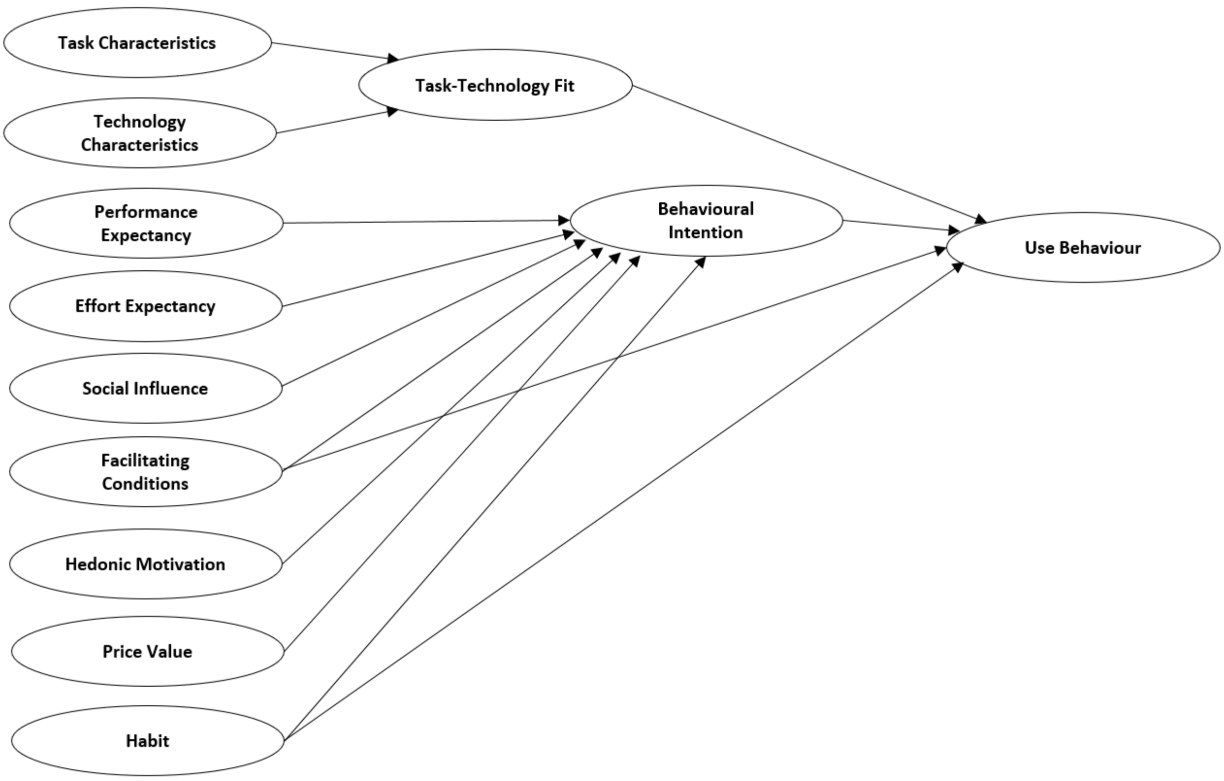

Figure 1. UTAUT2-TTF Integrated Model

Empirical studies on UTAUT2-TTF integration in educational contexts are emerging but remain limited. For example, Gengfu et al. (2019) investigated e-learning adoption in universities by combining TTF and UTAUT2 constructs. Their findings revealed that TTF constructs, particularly TTF, acted as significant mediators between UTAUT2 predictors (e.g., PE and EE) and BI. Similarly, Bhimasta and Suprapto (2016) demonstrated that integrating TTF into UTAUT2 enhanced the model's explanatory power in predicting mobile e-textbook adoption. These studies suggest that integrating TTF into UTAUT2 could potentially enhance predictive accuracy.

Faqih and Jaradat (2021) explored the adoption of augmented reality (AR) in educational settings using the integrated UTAUT2-TTF model. They found that TTF was directly related to UB and acted as a mediator between UTAUT2 predictors, such as PE and BI. It was in their findings that a significant overlap between TTF and PE was revealed, suggesting the need to address multicollinearity issues in the combined model. Furthermore, their study highlighted the potential of integrating task-specific constructs into UTAUT2 to enhance predictive power in advanced technological contexts, such as AR.

Other past studies revealed the emergence of TTF as a predictor of BI. Sharif et al. (2019) applied the integrated UTAUT2-TTF framework to evaluate the adoption of learning management systems in higher education. They found that TTF was a critical determinant of BI. Bu (2022) extended the integrated UTAUT2-TTF model to the context of the metaverse in university football training. The study revealed that HM and TTF jointly influenced BI, with TTF emerging as the strongest predictor of BI. The research emphasised that task-technology alignment in a metaverse environment was instrumental in determining the perceived usefulness and adoption of the system by students and trainers, further supporting the value of integrating TTF with UTAUT2. Wang et al. (2022) investigated tablet adoption in rural and urban education settings using the integrated UTAUT2-TTF framework. Their results also showed that TTF was a significant predictor of both BI and UB in both contexts. However, they observed that the significances varied between rural and urban areas, with rural users relying more on FC and urban users placing greater emphasis on TTF. This finding highlighted the importance of considering contextual factors when integrating TTF into UTAUT2.

While past studies integrating UTAUT2 and TTF showed potential in highlighting new construct relationships, they also revealed significant gaps in addressing model fit, which undermined the rigour and generalisability of their findings. Most studies did not report critical fit indices, like SRMR, RMSEA, CFI, TLI, and χ^2/df, which are essential for evaluating the structural validity of the integrated models. Of the 7 studies, only Sharif et al. (2019) partially addressed this by reporting RMSEA and CFI, but it omitted key indices such as SRMR and χ^2/df. The absence of comprehensive fit evaluation in the remaining studies, including those by Gengfu et al. (2019), Bhimasta and Suprapto (2016), Bu (2022), Faqih and Jaradat (2021), Wang et al. (2022), and Gerhart et al. (2015), highlighted a critical methodological shortcoming.

In retrospect, the integration of UTAUT2 and TTF in these reviewed studies added model complexity by introducing additional constructs and relationships. However, few studies offered theoretical justification or empirical evidence to support this increased complexity. For example, while Bhimasta and Suprapto (2016) highlighted the improved explanatory power of integrating TTF but did not evaluate how the added complexity impacted model interpretability or fit. Context-specific fit was also insufficiently addressed. Studies such as Wang et al. (2022), which examined rural and urban educational settings, failed to evaluate model fit across these distinct user groups. Furthermore, none of the studies employed cross-validation procedures to test the stability of the integrated models across independent datasets or subsamples. This omission raised concerns about the robustness and broader applicability of the findings.

There is a critical need for a study that empirically examines the integration of UTAUT2 and TTF to address key methodological gaps. Such a study should prioritise the reporting of comprehensive model fit indices, such as SRMR, CFI, TLI, and χ^2/df, to ensure methodological rigour and replicability. Furthermore, research needs to empirically justify the added complexity of integrating TTF into UTAUT2 by demonstrating its contribution to explanatory power without sacrificing model interpretability. Evaluating model fit across diverse user groups and contexts is equally important to establish the robustness and generalisability of the integrated model. Cross-validation procedures should be employed to test the stability of findings across independent datasets, ensuring that the results are not context-dependent or sample-specific. A study addressing these methodological refinements would provide valuable insights into the theoretical and practical implications of combining UTAUT2 and TTF, offering a stronger and more generalisable framework for understanding technology adoption.

As such, a study utilising a One-stage Meta-analytic Structural Equation Modelling (OSMASEM) approach to investigate the integration of UTAUT2 and TTF could effectively address existing gaps by reporting comprehensive model fit indices, testing construct validity, and incorporating cross-validation procedures. OSMASEM is an advanced statistical method that integrates meta-analytic techniques with structural equation modelling to synthesise data and evaluate theoretical frameworks across multiple studies (Cheung, 2015; Jak & Cheung, 2020; Jak et al., 2021). Unlike conventional meta-analysis, which primarily summarises effect sizes from primary studies, OSMASEM allows researchers to simultaneously estimate relationships among multiple constructs while accounting for heterogeneity in study designs, sample characteristics, and measurement tools (Jak & Cheung, 2020). This approach is particularly useful when dealing with complex models, such as UTAUT2 and TTF, as it enables the evaluation of structural validity and inter-construct relationships (Or, 2023; Or, 2024).

The OSMASEM method would enhance understanding of the theoretical and practical implications of combining TTF with UTAUT2, offering a more generalisable framework for predicting technology adoption. In the context of educational research, OSMASEM has been applied to synthesise evidence on key factors influencing technology adoption, teaching practices, and learning outcomes. For instance, Or (2023) utilised the OSMASEM approach to synthesise 39 past empirical UTAUT2 studies in the educational contexts. In the study, besides confirming the existing UTAUT2 relationships, PE, HM, SI and PV were also found to have significant effects on UB.

This study examines the theoretical and methodological challenges of integrating TTF into UTAUT2 in the context of educational technology adoption, with the goal of assessing whether this integration enhances the model's explanatory power in predicting BI and UB. By employing OSMASEM, the study aims to address critical gaps in prior research, including the lack of comprehensive model fit indices and cross-context validation, thereby enabling a systematic examination of task-specific and user-centric factors in technology adoption. This approach not only refines the theoretical and empirical foundations of UTAUT2-TTF integration but also provides deeper insights into the drivers of adoption, ultimately advancing both research and practice in educational technology.

The following are the specific research questions:

- What are the theoretical and methodological challenges of integrating TTF into UTAUT2 for studying educational technology adoption?
- How does the integration of TTF into UTAUT2 influence the model's ability to predict technology adoption and use behaviour?
- What are the key construct overlaps between UTAUT2 and TTF, and how do they affect the clarity and parsimony of the integrated model?
- What modifications can be made to improve the theoretical and empirical robustness of the UTAUT2-TTF integration?
- How can the OSMASEM approach be applied to evaluate the structural validity and inter-construct relationships of the integrated model?

Method

A literature search on UTAUT2-TTF in education was conducted using Primo by Ex Libris with the search string: "UTAUT2" AND "TASK TECHNOLOGY FIT" AND “EDUCATION” between the period 2012 to 2024. The databases included the DOAJ, IngentaConnect Journals, Springer Ejournals, Journals@Ovid Ovid Autoload, Springer Nature OA/Free Journals, ScienceDirect E-Journals, 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 set for the English language, article document type, open access, and peer-reviewed status.

The initial screening of the 559 identified studies was based on the following criteria:

(1) the studies examined UTAUT2 and TTF in school or university settings;
(2) the studies reported detailed examinations and correlations of UTAUT2 and TTF constructs;
(3) the studies utilised quantitative research methods; and
(4) the studies were analysed, reported with findings discussed in English.

This resulted in 196 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) UTAUT2 and TTF were 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 2 illustrates the PRISMA flow diagram, which outlines the process for conducting the literature search and selection. The list of UTAUT2-TTF studies is shown in Table 1.

Table 1. List of UTAUT2-TTF Studies

S/N	Technology	Sample Size	Reference
1	e-textbook	326	Bhimasta, R. A., & Suprapto, B. (2016, November). An empirical investigation of student adoption model toward mobile e-textbook: UTAUT2 and TTF model. *In proceedings of the 2nd international conference on communication and information processing (pp. 167-173*).
2	e-book	257	Gengfu, M., & Chotiyaputta, V. (2019). Acceptance and use predictors of E-books: a case at universities in Sichuan, China. *Asian Administration & Management Review, 2*(2).
3	Learning Management System	178	Sharif, A., Afshan, S., & Qureshi, M. A. (2019). Acceptance of learning management system in university students: an integrating framework of modified UTAUT2 and TTF theories. *International Journal of Technology Enhanced Learning, 11*(2), 201-229.
4	Augmented Reality	281	Faqih, K. M., & Jaradat, M. I. R. M. (2021). Integrating TTF and UTAUT2 theories to investigate the adoption of augmented reality technology in education: Perspective from a developing country. *Technology in Society, 67*, 101787.
5	Meta-Universe	295	Bu, F. Investigating the Acceptance of Meta-Universe Technology for Football Course Training among University Physical Education Teachers: A UTAUT2 and TTF Model Approach.
6	Tablet Computers	232 (Rural) 214 (Urban)	Wang, F., Wijaya, T. T., Habibi, A., & Liu, Y. (2022). Predictors influencing urban and rural area students to use tablet computers as learning tools: combination of UTAUT and TTF models. *Sustainability, 14(*21), 13965.
7	e-textbook	397	Gerhart, N., Peak, D. A., & Prybutok, V. R. (2015). Searching for New answers: the application of task-technology fit to E-Textbook usage. Decision Sciences *Journal of Innovative Education, 13*(1), 91-111.

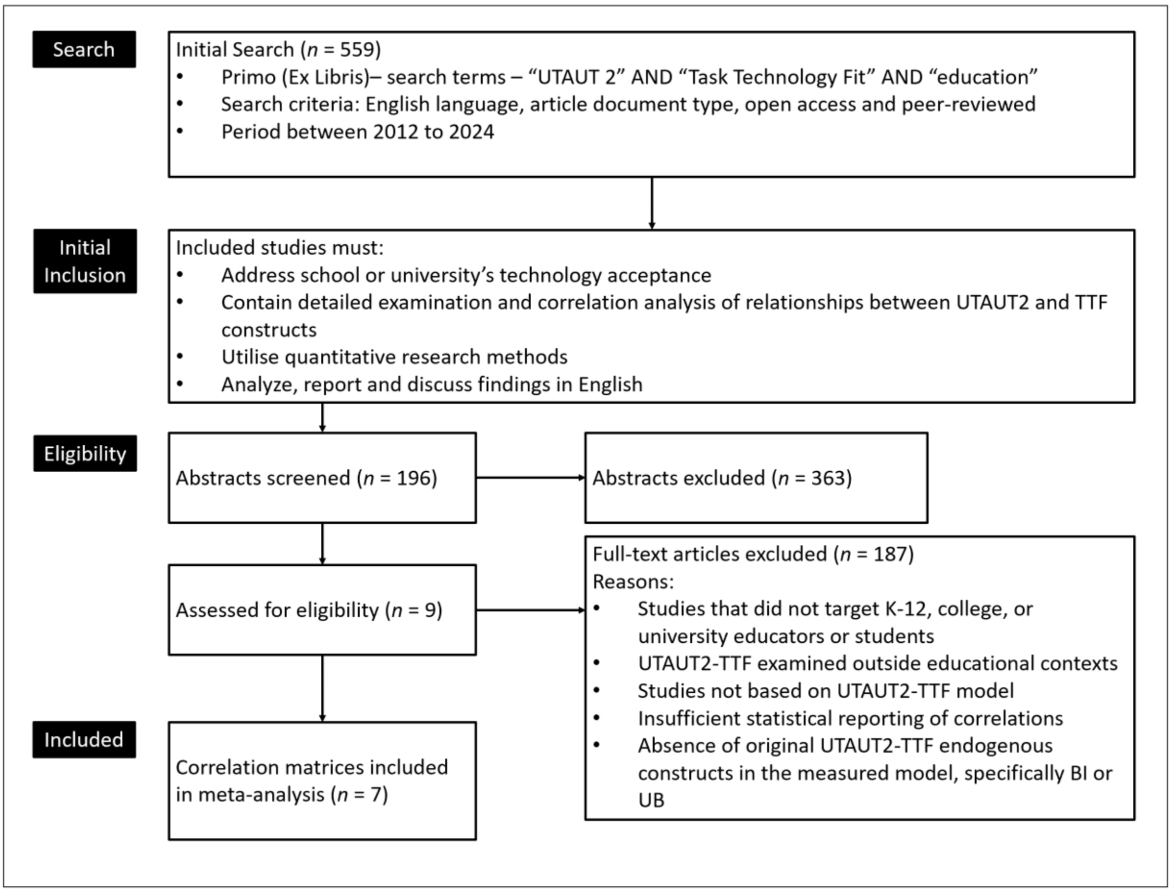

Figure 2. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) Flow Diagram

Results

The findings from Model 1, which evaluated TTF as a predictor of UB, revealed mixed model fit results (see Table 2).

Table 2. Model Fit Indices for Model 1 (TTF as a Predictor of UB)

	Threshold	Value
χ^2	-	45.374
df	-	17
χ^2/df	< 3.000	2.669
p-value	> .050	.000
CFI	> .950	.973
TLI	> .950	.896
RMSEA	< .050	.023
SRMR	< .080	.052

The chi-square value was statistically significant, χ^2 (17) = 45.37, $p < .001$, indicating a lack of exact fit. However, other fit indices suggested the model was acceptable overall. The comparative fit index (CFI) was .973, exceeding the recommended threshold of .950 (Hu & Bentler, 1999). Similarly, the root mean square error of approximation (RMSEA) was .023, falling below the acceptable limit of .050 (Browne & Cudeck, 1993). The standardised root mean square residual (SRMR) was .052, within the criterion of .080 or less. The Tucker-Lewis index (TLI), however, was below the acceptable threshold at .896, suggesting potential limitations in model parsimony (Bentler & Bonett, 1980). These results indicated that while the model performed well in terms of approximate fit measures (e.g., RMSEA and SRMR), it failed to meet the criterion for TLI, suggesting the need for further refinement to improve the balance between fit and complexity.

The structural model results demonstrated significant relationships between TTF, BI, and UB. TTF was strongly predicted by task characteristics (β = .916, p< .001) and weakly by TEC (β = .068, p< .001) (Figure 3). TTF significantly influenced BI (β = .147, p < .001) but had a more substantial direct effect on UB (β = .356, p< .001). Among the UTAUT2 predictors, PE (β = .244, p< .001), EE (β = .118, p< .001), SI (β = .183, p< .001), FC (β = .210, p< .001), HM (β = .049, p < .001), PV (β = .036, p< .001), and H (β = .199, p< .001) all had significant effects on BI. H also directly influenced UB (β = .165, p< .001). Model 1 explained 56% of the variance in BI (R^2 = .560) and 62.3% of the variance in UB (R^2 = .623), demonstrating moderate explanatory power. These findings were consistent with prior research emphasising the critical roles of task-specific and behavioural constructs in predicting technology adoption (Venkatesh et al., 2012; Goodhue & Thompson, 1995). However, the observed model fit issues revealed the importance of refining the framework and addressing construct overlap to enhance the robustness of these findings.

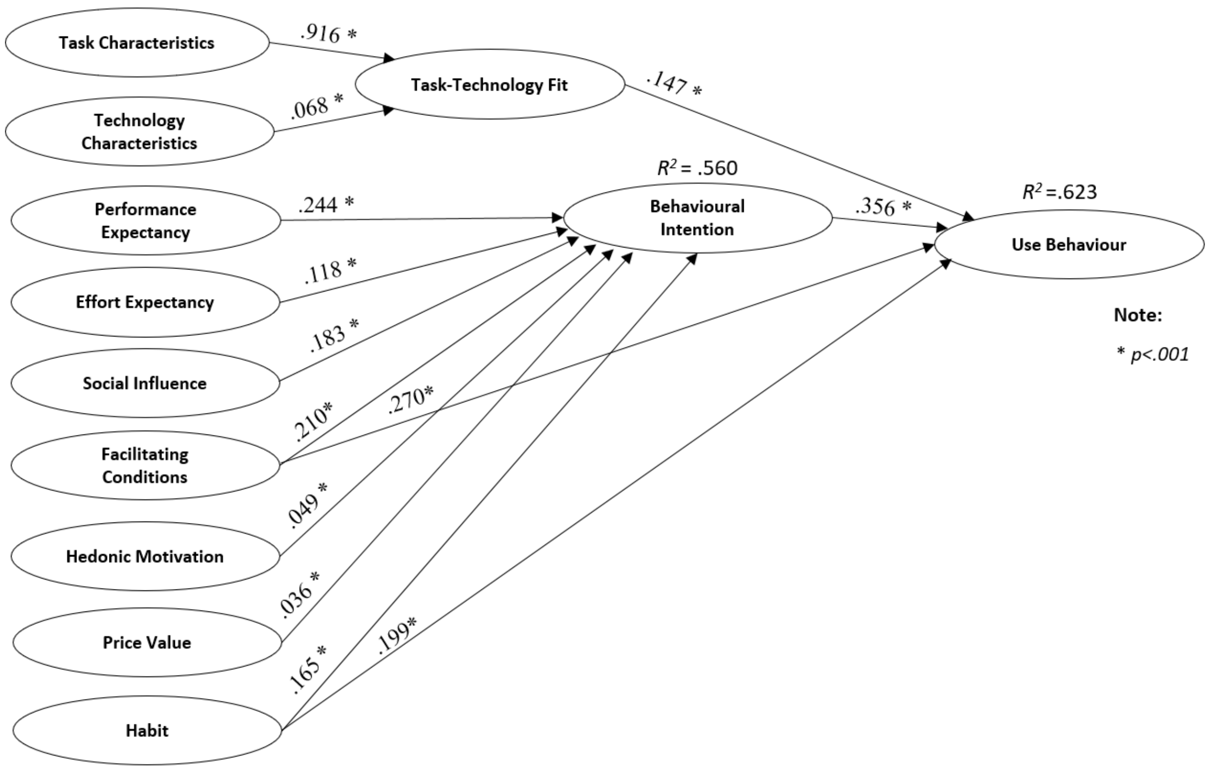

Figure 3. Structural Model 1 Results (TTF as a Predictor of UB)

Some model fit indices for Model 2, which evaluated TTF as a predictor of BI, were also below acceptable thresholds (Table 3). The chi-square value was significant, χ^2 (17) = 39.38, p= .002, indicating a lack of exact fit. While CFI was .979, exceeding the recommended threshold of .950 (Hu & Bentler, 1999), RMSEA was .025, well below the recommended maximum of .050 (Browne & Cudeck, 1993). Similarly, SRMR was .050, meeting the criterion of less than .080. TLI was slightly below the recommended threshold of .950, with a value of .918. This indicated that there was some room for improvement in balancing model complexity and parsimony (Bentler & Bonett, 1980). These results suggested that caution should be taken when interpreting the findings, particularly considering the significant chi-square value and suboptimal TLI.

Table 3. Model Fit Indices for Model 2 (TTF as a Predictor of BI)

	Threshold	**Value**
χ^2	-	39.380
df	-	17
χ^2/df	< 3.000	2.316
p-value	> .050	.002
CFI	> .950	.979
TLI	> .950	.918
RMSEA	< .050	.025
SRMR	< .080	.050

When comparing the model fit indices for Model 1 (TTF as a predictor of usage behaviour, UB) and Model 2 (TTF as a predictor of behavioural intention, BI), it was evident that neither model achieved an optimal level of fit across all indices. However, Model 2 demonstrated slightly better performance in some areas. Both models failed the chi-square test, indicating that their structure did not fully align with the data, a significant limitation that could not be overlooked, even considering that chi-square is sensitive to sample size. Both models achieved high CFI values, with Model 1 at .973 and Model 2 slightly higher at .979, both surpassing the recommended threshold of .950. Similarly, RMSEA values were within excellent ranges, with Model 1 at .023 and Model 2 at .025, both comfortably below the .050 threshold. The SRMR values also indicated acceptable fit, with Model 1 at .052 and Model 2 at .050, both meeting the criterion of less than .080. While these approximate fit indices suggested reasonable alignment of the models with the data, they do not fully compensate for the inadequacies indicated by the chi-square and other indices. The most critical issue lies in TLI, which assesses model parsimony. For Model 1, the TLI was .896, and for Model 2, it was .918, both falling short of the recommended .950 threshold. This indicated that neither model strikes an adequate balance between fit and complexity, suggesting potential overfitting or structural inconsistencies. The suboptimal TLI values were particularly concerning, as they undermine the reliability of the models despite the positive indications from other indices.

Model 2 demonstrated a higher R^2 for UB (.657) compared to Model 1 (.623), indicating that it explained more variance in UB (see Figure 4). This suggested that Model 2 better captured the relationships leading to actual technology use. Additionally, TTF had a stronger direct influence on UB in Model 2 (β = .456, p< .001) compared to Model 1 (β = .356, p< .001). While Model 1 highlighted a modest direct relationship between TTF and BI (β = .147, p< .001), Model 2 showed a slightly stronger effect of TTF on BI (β = .164, p< .001), indicating better integration of task-specific factors into BI pathways.

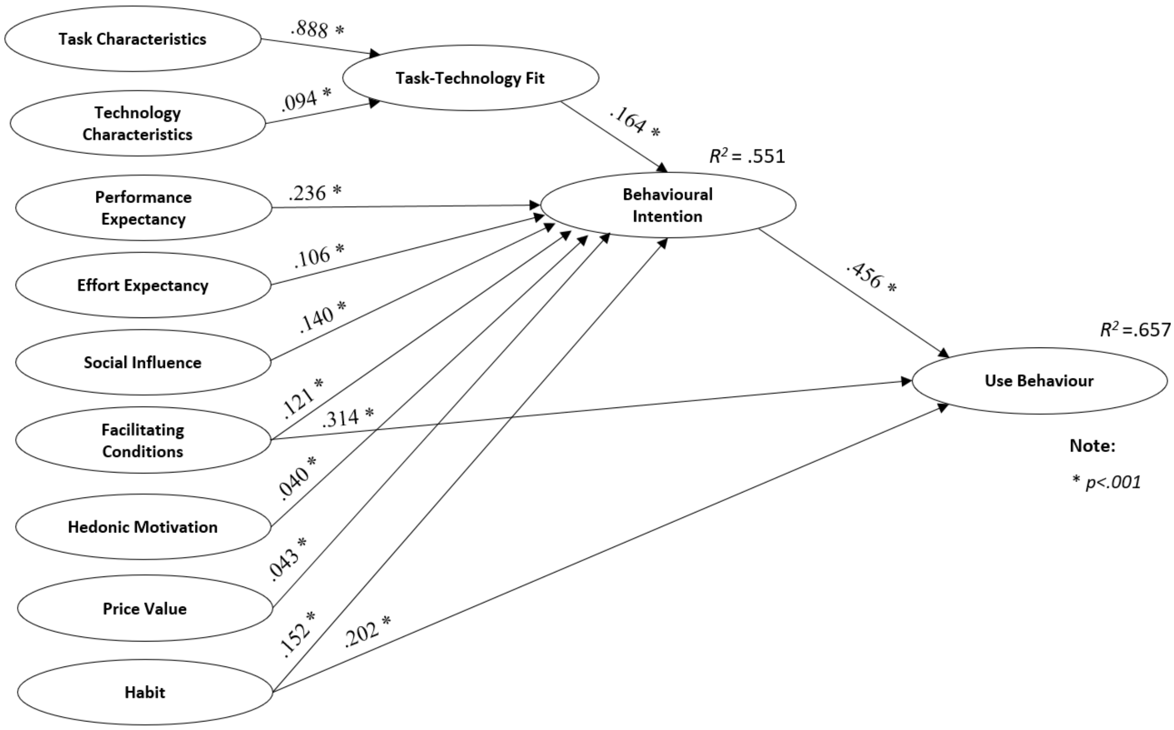

Figure 4. Structural Model 2 Results (TTF as a Predictor of BI)

From the perspective of UTAUT2 constructs, both models produced consistent results across most predictors. However, Model 2 provided slightly better integration of FC (β = .121), H (β = .202 for BI, β = .152 for UB), and SI (β = .140), which collectively contributed to its higher explanatory power for UB. Despite these advantages, it was crucial to emphasise the limitations of Model 2. TLI for Model 2 was .918, falling below the recommended threshold, and the chi-square value was significant, indicating suboptimal fit. Model 1 also suffered from similar limitations, with a lower TLI and a significant chi-square value. Neither model achieved ideal parsimony or structural validity, which necessitates careful interpretation of the results and potential revisions to enhance fit.

Given the higher explanatory power for UB and slightly better structural integration, Model 2 was the relatively preferred model in this study. As such, a bootstrap analysis of Model 2, using a 50-studies resample, was conducted to evaluate the relationships within the UTAUT2-TTF model (Figure 5). While most paths demonstrated significant relationships, two key anomalies emerged during bootstrapping: the R^2 values for BI and UB were returned as "NaN" (not a number), and the path coefficient from BI to UB exceeded 1 (β=1.155, p<.001). These anomalies raised important concerns about the model's validity and structural stability, warranting further investigation. “NaN” in SEM or path analysis typically occurs due to issues in model specification, estimation processes, or data handling. Such outcomes often signal violations of underlying assumptions, leading to invalid computations. R^2 values being "NaN" usually result from negative residual variances, also referred to as Heywood cases. Residual variances are critical to the calculation of R^2, which is expressed as $R^2 = 1 -$ (Residual Variance/Total Variance). When residual variances are negative, the formula becomes invalid, resulting in "NaN" values. This can stem from model misspecification, such as incorrectly specified paths or overfitting, multicollinearity among constructs, or overly restrictive constraints (Byrne, 2016; Kline, 2016). In SEM, missing or incomplete data, dividing by zero due to zero variance in a variable, or ill-conditioned covariance matrices further aggravate these computational issues (Little & Rubin, 2020; Hu & Bentler, 1999).

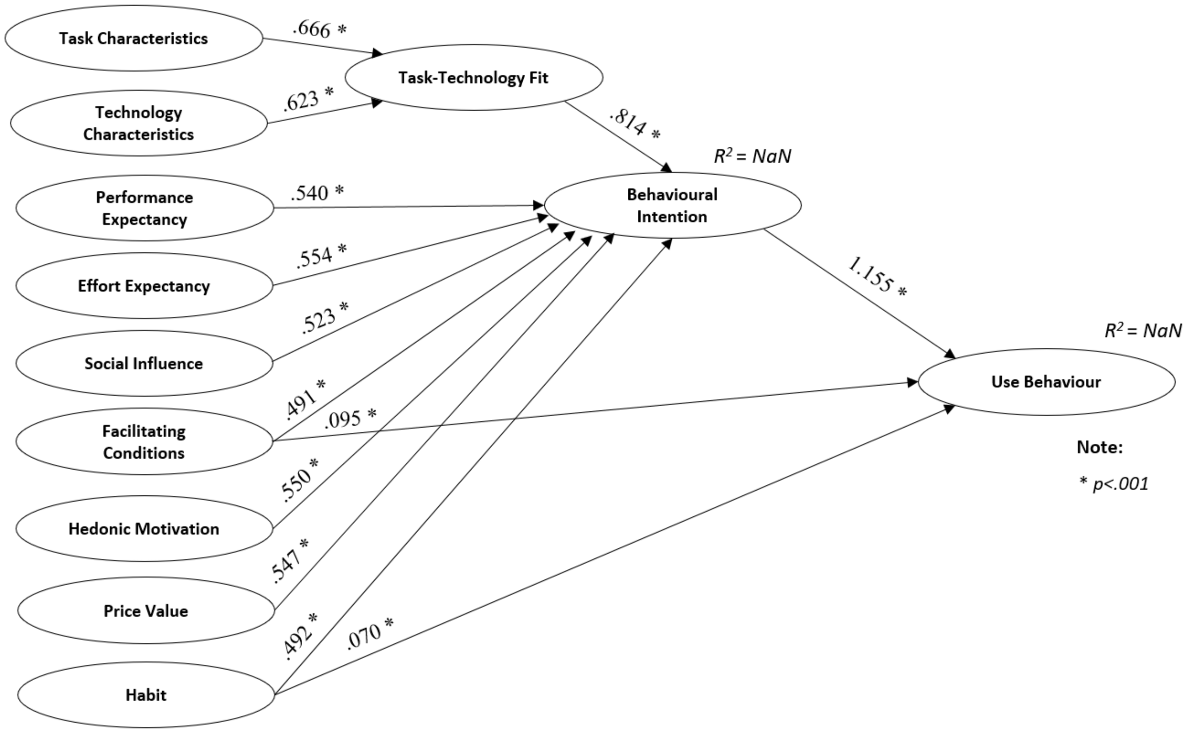

Figure 5. Structural Model Results with Bootstrap Resampling (50 Studies)

The path coefficient from BI to UB exceeding 1 (β=1.155, p< .001) was another concerning anomaly. In SEM, standardised coefficients are expected to fall within the range of -1 to 1. When coefficients exceed this range, it typically indicates problems such as high multicollinearity among predictors, errors in the standardisation process, or improper model constraints (Kline, 2016; Byrne, 2016). Overlapping constructs among latent variables and incorrectly specified paths can further inflate coefficients, distorting their interpretability. Sampling or measurement errors, particularly with small sample sizes or unreliable measures, can also produce unstable or inflated estimates (Brown, 2015).

Discussion

While past research examined the integration of TTF into the UTAUT2 framework, aiming to bridge task-specific and user-centric perspectives on technology adoption, the results revealed significant concerns regarding structural validity and methodological robustness. Model 1, which examined TTF as a predictor of UB, demonstrated acceptable fit based on the CFI (.973), RMSEA (.023), and SRMR (.052) but failed to meet TLI threshold (.896) and exhibited a significant chi-square value ($\chi 2(17) = 45.37$, p<.001). Similarly, Model 2, where TTF predicted BI, fell short of the recommended threshold of .950. These results pointed out an imbalance between model complexity and fit (Bentler & Bonett, 1980; Hu & Bentler, 1999).

A key issue identified within the integrated UTAUT2-TTF framework was the redundancy of certain constructs. Specifically, PE and TTF both centre on how well a technology supports task performance, while FC and TTF converge in their focus on resource availability and a technology's functional adequacy for completing tasks. Additionally, EE and TAC overlap in their emphasis on ease of use, learnability, and system complexity, contributing to the high degree of multicollinearity observed. Although each construct is theoretically distinct, their strong intercorrelations suggest that participants in previous studies might have perceived them as interchangeable. Both FC and TTF address resource availability and the functionality of technology for task execution, further compounding their redundancy in measurement. This overlap not only diminished the parsimony of the model but also distorted parameter estimates, as demonstrated by the unusually large path coefficient from BI to UB ($\beta = 1.155$, $p < .001$) in the bootstrap analysis of Model 2. Such inflated coefficients are indicative of multicollinearity, making it difficult to differentiate the unique contributions of each predictor (Byrne, 2016; Kline, 2016).

The issue of overspecification further aggravated these challenges. Overspecification occurs when a model includes too many parameters relative to the available data, reducing parsimony and increasing the likelihood of estimation problems (Bentler & Bonett, 1980). The integration of task-specific constructs, such as TTF, into an already complex UTAUT2 framework introduced numerous paths and potential interdependencies, which likely contributed to suboptimal fit indices. Overspecification not only limited the interpretability of results but also increased the risk of unreliable findings, as the estimation process becomes sensitive to small variations in the data (Hu & Bentler, 1999). Reducing complexity by merging overlapping constructs or eliminating non-significant paths could improve the framework's parsimony and enhance its theoretical coherence.

The original UTAUT2 framework demonstrated strong explanatory power, accounting for 74% of the variance in BI and 52% of the variance in UB (Venkatesh et al., 2012). With the integration of TTF, Model 1 improved on the explained variance in UB (62.3%), highlighting TTF's complementary role in enhancing the understanding of technology use. Model 2 further increased the explanatory power for UB, reaching 65.7%, though its improvement for BI was modest (55.1%). In contrast, the bootstrap model encountered computational anomalies, producing "NaN" R^2 for both BI and UB. These issues likely resulted from negative residual variances, known as Heywood cases, which stem from overspecification, multicollinearity, or insufficient model identification (Hu & Bentler, 1999). Such anomalies highlighted the challenges of integrating complex constructs, such as TTF, into an already comprehensive framework.

Practically, the findings provided significant implications for policymakers, educators, and organisations relying on technology adoption models for decision-making. The computational anomalies, such as "NaN" R^2 values and inflated path coefficients, undermine the reliability of the model's predictions. Without addressing these issues, stakeholders risk basing their strategies on flawed assumptions, particularly regarding the importance of task-technology alignment in influencing behaviour. While TTF undoubtedly provides valuable insights into UB, its integration into UTAUT2 must be approached with caution until the framework's structural and computational limitations are resolved.

The integration of TTF into the UTAUT2 framework raises critical questions about the practical and theoretical implications of adding complexity to an already robust model. While the integrated models demonstrated enhanced explanatory power for UB, the methodological and structural challenges exposed in this study limit their practical applicability and theoretical generalisability. These issues demand a rethinking of the framework's utility in both research and practice. Theoretical implications of the integrated framework remained questionable due to significant redundancy among constructs such as PE, FC and TTF. While TTF's inclusion highlighted task-specific nuances, its overlap with core UTAUT2 predictors blurred theoretical boundaries, making it difficult to ascertain unique contributions. Such redundancy diminished the theoretical coherence of the model, thereby complicating its use for deriving clear and actionable insights. The limited added value of TTF for BI, in particular, suggests that TTF may not be well-suited as a direct predictor in this framework. Future research should focus on simplifying the integrated framework to ensure parsimony and interpretability. Construct overlaps must be addressed by re-evaluating the operational definitions of predictors and considering whether constructs such as PE and TTF can be combined, or EE and TAC, reframed. The model's complexity could be reduced by treating TTF as a moderating or mediating variable rather than a direct predictor.

Conclusion

The findings from this study highlighted the complexities of integrating TTF into the UTAUT2 framework for understanding technology adoption in educational contexts. While the integration provides an opportunity to capture both task-specific and behavioural factors, it raises significant challenges that need to be addressed to ensure the framework's robustness and utility. The results demonstrated the potential of TTF to enhance the explanatory power of UTAUT2, particularly in predicting UB. However, the methodological and structural issues observed, including suboptimal fit indices, overlapping constructs, and computational anomalies, raise doubts about the validity of the integrated framework in its current form.

These findings emphasised the importance of striking a balance between complexity and parsimony in model development. Overspecification, as observed in this study, reduced interpretability, increased estimation challenges, and ultimately undermined the reliability of the results. A more streamlined framework, with clearly defined constructs and reduced redundancy, would provide a stronger foundation for future research. The observed anomalies, such as inflated path coefficients and "NaN" residuals, further highlighted the need for rigorous model testing and validation, particularly in diverse contexts and with independent datasets.

While this study affirmed the theoretical importance of integrating task-specific and user-centric constructs, it also revealed the limitations of relying on traditional structural equation modelling approaches to evaluate complex frameworks. Advanced methodologies, such as Bayesian SEM or OSMASEM, offer promising alternatives for addressing issues of multicollinearity and model misspecification. By adopting these methods, future research could provide more stable and reliable parameter estimates, enabling a deeper understanding of the interplay between task characteristics and user behaviour.

This study contributes to the ongoing discourse on technology adoption by demonstrating the potential and limitations of integrating TTF into the UTAUT2 model. While the combined framework offered valuable insights, the challenges it presented showed the need for theoretical refinement and methodological innovation. Future research should prioritise simplifying the model, ensuring construct clarity, and employing advanced analytical techniques to realise the full potential of this integration in understanding technology adoption behaviour.

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