ANALYZING THE DETERMINANTS OF HEALTHCARE TECHNOLOGY ADOPTION USING THE TASK-TECHNOLOGY FIT (TTF) MODEL: A SYSTEMATIC REVIEW AND META-ANALYSIS

DOI
https://doi.org/10.18690/um.fov.4.2025.15

ISBN
978-961-286-998-4

AYESHA THANTHRIGE, NILMINI WICKRAMASINGHE
La Trobe University, School of Computing, Engineering and Mathematical Sciences, Victoria, Australia
thanthrige87@gmail.com, n.wickramasinghe@latrobe.edu.au

This study aims to investigate the determinants of healthcare technology adoption using an extended Task-Technology Fit (TTF) model through a Systematic Literature Review (SLR) and meta-analysis, focusing on healthcare-specific tasks and their alignment with technology characteristics. While TTF has been widely applied across various domains, its application within healthcare is limited, with inconsistent findings. Addressing this research gap, the study provides a clearer understanding of how healthcare-specific tasks align with Technology Characteristics (TechC) to influence adoption among individuals. The extended model includes Behavioral Intention (BI) to assess users' intention to adopt healthcare technologies. The analysis reveals that TTF is a significant predictor of technology use, offering novel insights into the factors that drive successful healthcare technology adoption. The findings contribute to both theoretical advancements in TTF and offer practical implications for improving the design and implementation of digital healthcare solutions. Healthcare solution designers are encouraged to apply the TTF framework when evaluating new technologies to guide technology design and evaluation in real-world healthcare environments.

Keywords:
task-technology fit (TTF),
technology adoption,
digital health solutions,
systematic literature review (SLR),
technology characteristics (TechC)

University of Maribor Press

1 Introduction

This study focuses on healthcare professionals broadly to capture diverse task requirements across various roles such as clinicians, nurses, and administrators, as TTF's applicability varies depending on specific tasks performed. The Task-Technology Fit (TTF) model offers an important framework for understanding how alignment between task requirements and technology functionality influences adoption. Originally introduced by Goodhue & Thompson (1995), TTF suggests that technology is more likely to be adopted when its capabilities match users' specific tasks. The better the fit between task characteristics (TC) and technology features, the more likely users find the technology beneficial, enhancing performance and increasing adoption likelihood. Unlike other adoption models, TTF uniquely focuses on alignment between tasks and technology capabilities. While the Technology Acceptance Model (TAM) emphasizes perceived usefulness and ease of use, and the Unified Theory of Acceptance and Use of Technology (UTAUT) examines performance expectancy, effort expectancy, social influence, and facilitating conditions, TTF specifically addresses how well technology features support task requirements. This distinctive focus makes TTF particularly valuable for understanding adoption in healthcare, where specific functionalities must closely match clinical workflows and patient management requirements. Healthcare heavily relies on technology to improve patient care, enhance clinical decision-making, and streamline efficiency. Technologies like Electronic Health Records (EHR), telemedicine platforms, mobile health applications, wearables, and health information systems are increasingly integrated into healthcare settings (Gu et al., 2021). Despite these advances, adoption and sustained use remain inconsistent (Alkhalifah & Bukar, 2022), suggesting further research is needed to explore determinants of technology adoption in healthcare contexts. TTF is particularly relevant to healthcare due to the diverse and complex tasks performed by healthcare professionals and patients. Clinicians manage patient records, coordinate care, conduct diagnostics, and ensure treatment compliance. Patients with chronic conditions monitor health metrics, adhere to medication schedules, track dietary intake, and manage appointments. A strong fit between these tasks and supporting technologies is critical for effective adoption and use (Janssen et al., 2021). While TTF has been applied in healthcare settings, its application remains limited compared to other domains, leading to inconsistent findings. For example, some studies suggest TTF significantly influences healthcare technology adoption, while others indicate this relationship may be moderated by factors such as organizational support, user training, or technology complexity (Farivar et al., 2020). Additionally, less attention has been paid to TTF's role in predicting long-term usage. This research gap highlights the need for more comprehensive studies examining how healthcare-specific tasks align with technology features and how this alignment influences both adoption and sustained use (Wang et al., 2023). The application of TTF to healthcare technologies can provide valuable insights into how different stakeholders such as clinicians, patients, and healthcare administrators interact with digital health solutions. For clinicians, the fit between the technology and their tasks might relate to how well the technology supports clinical decision-making, patient monitoring, or data entry. For patients, particularly those managing chronic illnesses, technology needs to align with their daily health tasks, such as tracking blood sugar levels, managing diet, or scheduling medical appointments. Understanding these different dimensions of TTF can help identify the factors that drive successful adoption and long-term use, leading to better patient outcomes and more efficient healthcare delivery (Winckler, 2022). Despite the growing interest in digital health solutions, there remain significant challenges to their widespread adoption in healthcare. Many healthcare professionals and patients are hesitant to use new technologies due to concerns about ease of use, data security, and the perceived benefits of the technology. Additionally, organizational factors such as the availability of technical support, the provision of adequate training, and the compatibility of new technologies with existing systems can influence whether a technology is adopted or rejected (Lambert et al., 2023). Addressing these challenges requires a deeper understanding of how healthcare-specific tasks align with the functionality of the technologies being introduced.

2 Research Model and Hypotheses

This study focuses on understanding how TTF influences Behavioral Intention (BI) in healthcare contexts. The TTF model theorizes that individuals are more likely to use technology when they perceive a strong fit between their task requirements and the technology's functionalities. Our model extends the traditional TTF framework by incorporating BI, which has been widely used in models such as UTAUT. While the original TTF model focuses on how alignment between TC and Technology Characteristics (TechC) impacts performance, our extended model investigates how this alignment influences users' intention to adopt healthcare technologies. Including

BI provides a crucial link between TTF and actual technology adoption, particularly important in healthcare where successful implementation depends on both improved performance and user acceptance. This approach keeps the model focused on adoption behaviors while providing insights into how task-technology alignment influences engagement and usage intentions. Our model brings a unique perspective compared to TAM and UTAUT by emphasizing the fit between healthcare tasks and technology features rather than focusing primarily on perceptions or social factors. This task-technology alignment is particularly critical in clinical environments where workflow integration directly impacts adoption outcomes. By incorporating BI into the TTF framework, we capture both the functional fit aspects and the behavioral aspects of technology adoption in healthcare contexts. Our research examines relationships between TC, TechC, TTF, and BI in healthcare technology adoption (Figure 1). TC refers to healthcare-related tasks users need to perform, while TechC encompasses features and functionalities designed to support these tasks. TTF represents the degree to which technology features align with and support user task requirements, and BI reflects users' intention to adopt and use healthcare technologies. The association between TC and TTF is particularly important in healthcare settings where tasks are often complex, interdependent, and time sensitive. When tasks require significant information processing, coordination across multiple parties, or rapid decision-making, technology's ability to support these specific requirements becomes critical for adoption. Similarly, the alignment between TechC and TTF highlights how technology features directly influence perceived fit with healthcare tasks. This study excludes organizational context to maintain a focus on task-technology alignment, as organizational factors such as culture or support are secondary to the core TTF constructs.

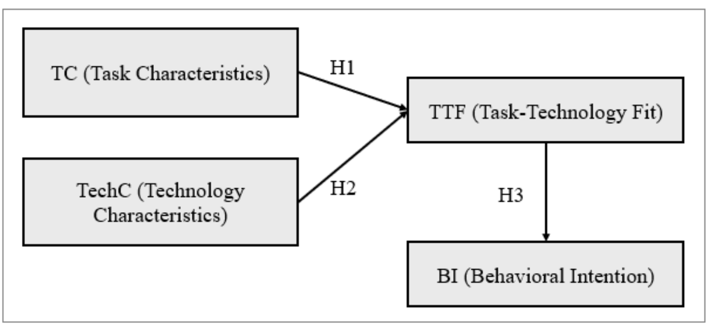

Figure 1: Research model

Based on this framework, we propose the following hypotheses:

H1: TC will be positively associated with TTF.

H2: TechC will be positively associated with TTF.

H3: TTF will be positively associated with BI.

3 Methodology

3.1 Research Question

How effectively does the TTF model predict healthcare technology adoption in the context of healthcare tasks?

3.2 Study Selection

This study follows a systematic literature review (SLR) and meta-analysis approach, adhering to the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. Appendix B provides the PRISMA checklist, detailing how each item was addressed. The methodology was structured based on prior meta-analytic practices to ensure comprehensive and unbiased analysis (Dwivedi et al., 2019). We aimed to review studies focusing on the TTF model's application in healthcare settings, including the relationships between TC, TechC, TTF, and BI. The search strategy involved querying multiple databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, PubMed, and Google Scholar. These databases were selected based on their comprehensive coverage of technology adoption and healthcare literature. Keywords included combinations of "Task-Technology Fit", "TTF", "healthcare technology adoption", "mHealth", "telehealth", and "technology characteristics" and "chronic disease management" to capture studies relevant to chronic conditions such as diabetes. Controlled vocabularies (e.g., MeSH terms in PubMed) were used to enhance search accuracy. Hand-searching of bibliographies was also conducted to identify additional relevant studies. Search results were imported into the reference management software EndNote for the removal of duplicates, after which they were screened using Covidence software to manage and streamline the review process. The initial phase involved screening titles and abstracts for relevance against the inclusion and exclusion criteria. To ensure unbiased selection, titles and abstracts were screened independently by two reviewers against inclusion and exclusion criteria, with discrepancies resolved through discussion or by a third reviewer.

Studies were included if they met the following criteria:

- Focused on healthcare technologies, such as EHR, mHealth applications, telehealth, or other digital health innovations, including those supporting chronic disease management.
- Published in English between 2012 and 2025.
- Provided quantitative data, including sample sizes, standardized path coefficients (β), and reliability statistics such as Composite Reliability (CR) or Cronbach's α.
- Examined relationships related to TTF, TC, TechC, BI.

Exclusion criteria were:

- Studies not focused on TTF or healthcare technology adoption.
- Non-quantitative studies or those lacking standardized β coefficients.
- Studies published before 2012 or not in English.

A full-text review of screened articles was conducted by two independent reviewers, with discrepancies resolved by a third reviewer to ensure impartiality. Our analysis identified 15 studies meeting all inclusion criteria.

3.3 Coding Data

For each included study, we extracted publication details, study characteristics, and quantitative data focusing on relationships between independent and dependent variables, with particular attention to the TTF model. Appendix C provides the data extraction template. We harmonized constructs with similar conceptualizations but different labels to maintain consistency across studies. Our analysis included 15 studies providing 43 unique path coefficients. While this sample is smaller than ideal for meta-analysis, it represents the current state of quantitative research explicitly applying TTF in healthcare contexts. The meta-analysis of these studies offers valuable preliminary insights while highlighting the need for more research in this area.

3.4 Statistical Analysis

This approach is appropriate given the variability in study designs, populations, and healthcare contexts represented. Meta-analysis is particularly valuable for this study as it allows us to systematically combine findings across diverse studies, revealing patterns that might not be apparent in individual studies. By statistically synthesizing results, meta-analysis provides more precise estimates of effect sizes and identifies sources of heterogeneity, highlighting contextual factors that might influence relationships between key constructs. While our sample size is limited, meta-analysis still provides valuable insights by systematically integrating available evidence. The meta-analysis was conducted using R Software.

4 Results

4.1 Study Identification and Screening

The systematic review began by identifying 691 potential studies across various databases, including Scopus (41%), Science Direct (22%), Web of Science (6%), CINAHL (6%), IEEE Xplore (3%), PubMed (19%), and Google Scholar (3%). Following the removal of duplicates (171, 25%), the titles and abstracts of 520 articles were reviewed to assess their relevance to the TTF model in healthcare technology adoption. After this initial screening, 361 full-text articles were reviewed, resulting in 15 studies (4% of the full-text articles assessed) being included in the final meta-analysis. Figure 2 provides the PRISMA flow diagram, summarizing the study selection process.

4.2 Descriptive Analysis

The included studies span several geographical regions and methodologies, offering insights into TTF's role in healthcare technology adoption. The range of technologies studied includes EHR, mHealth apps, telemedicine, and other digital health platforms, with several studies focusing on chronic disease management, such as diabetes care. Appendix A summarizes key information for each included study, including objectives, study design, sample size, outcomes, key findings, and statistical results, with detailed β values. Age and gender were the most consistently reported demographic factors, with 13 and 14 studies respectively providing data on these categories, while variables such as education, occupation, income, nationality, and usage experience were less frequently reported.

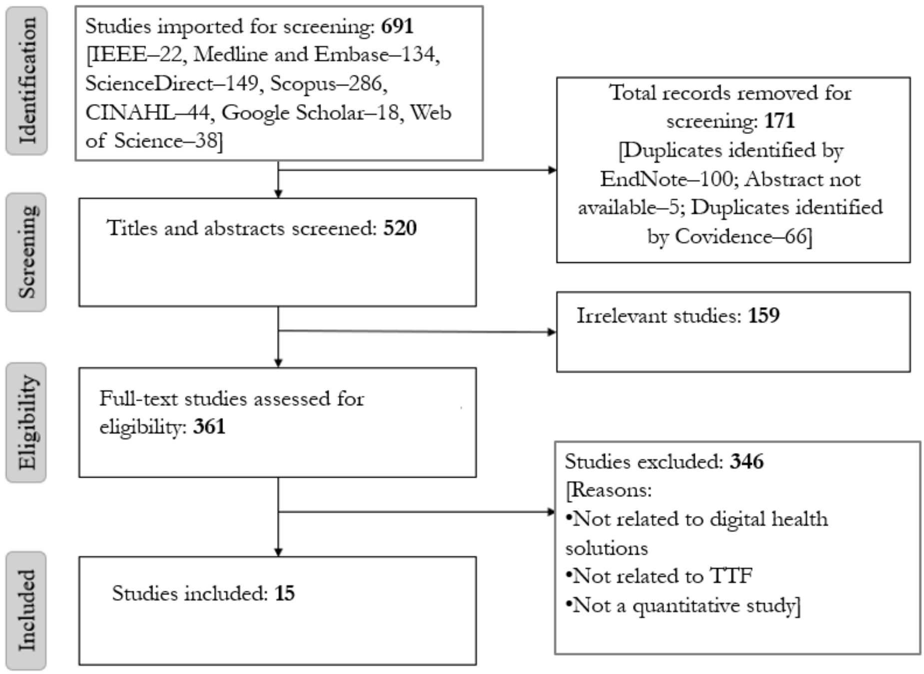

Figure 2: PRISMA Flow Diagram

4.3 Path Coefficients and Statistical Significance

Table 1 summarizes the β reported across the included studies, focusing on the relationships between TC, TechC, TTF, BI. The β exhibited significant variation across the studies. For example, the relationship between TC and TTF (H1) ranged from -0.007 to 0.525, while the relationship between TechC and TTF (H2) ranged from 0.199 to 0.780. Similarly, the relationship between TTF and BI (H3) ranged from -0.209 to 0.712, indicating both positive and negative associations across different contexts. These variations suggest that the impact of task and TechC on

TTF, and subsequently on BI, is highly context dependent. The differences in these β highlight how diverse study settings and technology implementations can affect the fit between tasks and technology, as well as the intention to use the technology.

The number of studies examining each relationship showed slight differences. For example, 15 studies analyzed the relationship between TC and TTF (H1). However, 14 studies explored the relationship between TechC and TTF (H2) and an equal number (14) examined the link between TTF and BI (H3). Most studies supported the hypothesized relationships, with higher than 90% of the β demonstrating statistical significance at $p < 0.01$. Specifically, 93% of the studies examining the relationship between TC and TTF (H1) found it to be positive and significant, while 100% of the studies analyzing the relationship between TechC and TTF (H2) supported the hypothesis. Additionally, 93% of the studies exploring the relationship between TTF and BI (H3) found it statistically significant, reinforcing the importance of TTF in predicting BI. Table 1 offers a comprehensive overview of the path coefficients, their significance, and the average effect sizes across the studies.

Table 1: Summary of Path Coefficients, Sample Sizes, Significance, and Weight Analysis

Path	n	Range of β values		Avg β	Sample size				Positive sig β		Negative sig β	
					Min	Max	Avg	Total	No.	%	No	%
Tech C - TTF	15	0.199	0.780	0.438	102	487	262.3	4041	15	100%	0	0%
TC-TTF	14	-0.007	0.525	0.291	102	487	253.7	3658	13	93%	1	7%
TTF - BI	14	-0.209	0.712	0.327	113	487	273.8	3939	13	93%	1	7%

n = Number of studies; AVG β = Arithmetic mean of β values; MIN = Minimum; MAX = Maximum; AVG = Average values; Total= Total sample size; Sig = Significance

4.4 Meta-Analysis Outcomes

The meta-analysis results (see Table 2) confirmed the hypothesized relationships in the TTF model. Figure 3 presents the meta-analytic outcomes, highlighting the relative strength of the relationships within the TTF model. The relationship between TechC and TTF (H2) was the strongest, with a meta-analytic effect size of $\beta = 0.445$ ($p < 0.001$), indicating a robust positive relationship across the studies. The relationship between TTF and BI (H3) also demonstrated a significant effect, with β = 0.271 (p < 0.001). Although the relationship between TC and TTF (H1) was weaker, it remained statistically significant, with β = 0.263 (p < 0.001). The heterogeneity tests revealed high variability across studies, with I^2 values ranging from 86.15% to 94.87%, suggesting that contextual factors may influence the strength of these relationships. Overall, the meta-analysis provides strong support for the hypothesized relationships in the TTF model, reinforcing its relevance in understanding healthcare technology adoption.

Table 2: Meta-Analysis of Path Coefficients, Total Sample Sizes, Significance, and Confidence Intervals

Path	n	TSS	Meta β	p-value β	95% CI β		Heterogeneity test		
					Lower	Upper	Q-value	df (Q)	I^2 (%)
TechC -TTF	15	4041	0.445	0.00	0.414	0.476	155.61	14	91.00
TC-TTF	14	3658	0.263	0.00	0.231	0.296	93.83	13	86.15
TTF - BI	14	3939	0.271	0.00	0.237	0.299	253.29	13	94.87

n = No. of occurrences; TSS = Total sample size; Meta β = Weighted mean effect size; CI = Confidence interval, Q - Total amount of heterogeneity

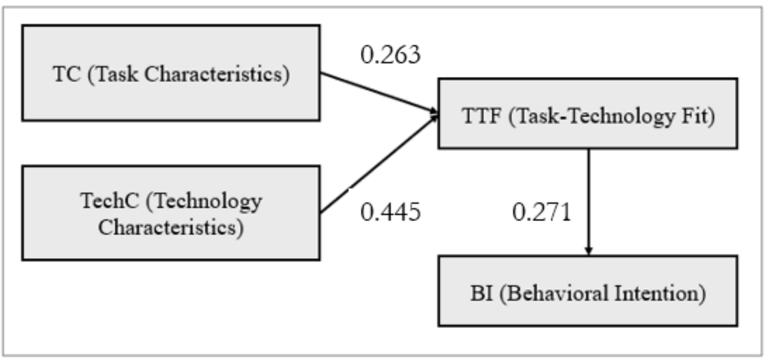

Figure 3: The meta-analytic outcomes

5 Discussion

5.1 Theoretical Contributions

This study contributes to technology adoption theory by validating and extending the TTF model in healthcare contexts. By confirming relationships between TC, TechC, TTF, and BI, we demonstrate TTF's value as a framework for understanding healthcare technology adoption. The significant influence of TTF on BI shows that task-technology alignment is crucial for adoption decisions, complementing insights from other adoption models such as TAM and UTAUT. Compared to prior studies, our findings align with Wang et al. (2020) and Tao et al. (2023) which emphasize TTF's role in mHealth and wearable adoption, particularly for chronic disease management, but extend these by integrating BI to capture user intentions more explicitly. Our findings highlight the relative importance of technology characteristics compared to task characteristics in determining TTF. In healthcare settings, technology design and functionality appear to play a more influential role in task-technology alignment than the inherent characteristics of healthcare tasks. The high heterogeneity in TechC-TTF, $I^2=91.00\%$ and TTF-BI, $I^2=94.87\%$ relationships suggests that study-specific factors, such as technology type (e.g., EHR vs. mHealth) or user demographics, moderate these effects, warranting further investigation into contextual influences (Howard et al., 2019). This finding carries important implications for technology design and implementation. The substantial heterogeneity observed across studies indicates that TTF's application in healthcare is context dependent. While our sample size is limited, this analysis represents an important first step in systematically examining TTF in healthcare contexts. The consistent patterns observed across our sample suggest that these relationships are robust, though further research with larger samples is needed to strengthen these conclusions.

5.2 Practical Implications

This study provides valuable practical insights for healthcare organizations, decision-makers, and technology providers aiming to improve the adoption and use of healthcare technologies. The research emphasizes the importance of aligning healthcare technologies with the specific tasks of healthcare professionals, such as EHR or telemedicine platforms, to enhance TTF and drive higher adoption rates. For instance, technologies supporting chronic disease management, like diabetes-focused mHealth apps, must align with tasks such as glucose monitoring and medication adherence to improve adoption. User-centered design is also critical; technologies must prioritize ease of use, interoperability, and seamless integration into clinical workflows to reduce cognitive load and increase both BI and actual usage. Comprehensive training and ongoing support are essential to ensure that even well-fitted technologies are adopted successfully. Training should focus on skill development while providing continuous technical support to address potential resistance due to unfamiliarity with new systems. The study also highlights the need for continuous monitoring and adaptation of technologies to maintain alignment with evolving healthcare tasks, ensuring that technologies remain relevant and useful over time. By incorporating BI into the TTF framework, healthcare organizations can more accurately predict adoption by not only evaluating task-technology alignment but also understanding users' intentions, allowing for more targeted strategies. Decision-makers must also balance feature complexity with usability, ensuring technologies are equipped with essential, task-aligned features without overwhelming users. Addressing these factors can significantly improve technology adoption, enhance patient outcomes, and boost operational efficiency, especially in critical areas like chronic disease management.

5.3 Limitations and Future Research

Despite the valuable insights provided by this meta-analysis, several limitations should be noted. Studies were excluded if they did not focus on TTF, did not relate to healthcare technology adoption, or were not quantitative studies. The relatively small number of research studies found that applying the TTF model in the context of healthcare technology adoption, with only 15 studies meeting the inclusion criteria, highlights a significant gap in literature. This limited number of studies may reflect the emerging application of TTF in healthcare and underscores the need for more quantitative studies to validate these findings. The study protocol was not registered, which may limit transparency. The absence of a formal methodological quality assessment of included studies, due to the focus on quantitative data, may affect the credibility of results. The predominance of studies from Asia, particularly Taiwan, may limit generalizability, as regional differences in infrastructure, policy, or digital literacy could influence adoption outcomes. This finding highlights a significant gap in the literature regarding quantitative applications of TTF in healthcare contexts. The small sample emphasizes the need for more research explicitly applying TTF to the adoption of healthcare technology. The study focused primarily on quantitative studies that reported standardized β and other statistical data related to TTF. As a result, qualitative insights into how task and TechC influence healthcare technology adoption were not included.

6 Conclusion

This systematic review and meta-analysis provide valuable insights into TTF's role in healthcare technology adoption. By extending TTF to incorporate BI, we bridge theoretical perspectives on technology alignment and adoption decisions. Our findings confirm that TTF significantly influences adoption intentions in healthcare settings, with technological characteristics playing a particularly important role in determining the fit. The results highlight the importance of designing healthcare technologies that align with specific task requirements, whether for healthcare professionals or patients. Implementation strategies should emphasize this alignment to enhance adoption. While our study advances understanding of healthcare technology adoption through the TTF lens, it also reveals the limited application of TTF in quantitative healthcare technology research. This gap presents important opportunities for future research to expand the evidence base and further refine our understanding of how task-technology fit influences healthcare technology adoption. As healthcare systems increasingly rely on digital technologies, understanding the determinants of successful adoption becomes increasingly important. The task-technology fit perspective offers valuable insights into how alignment between technology capabilities and healthcare tasks can drive adoption and ultimately improve healthcare delivery.

References

Al-Emran, M. (2021). Evaluating the Use of Smartwatches for Learning Purposes through the Integration of the Technology Acceptance Model and Task-Technology Fit. International Journal of Human-Computer Interaction, 37(19), 1874-1882. https://doi.org/10.1080/10447318.2021.1921481

Alhendawi, K. M. (2022). Task-technology fit model: Modelling and assessing the nurses' satisfaction with health information system using AI prediction models [Article]. International Journal of Healthcare Management. https://doi.org/10.1080/20479700.2022.2136881

Aljarboa, S., & Miah, S. J. (2020, 16-18 Dec. 2020). Assessing the Acceptance of Clinical Decision Support Tools using an Integrated Technology Acceptance Model. 2020 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE),

Alkhalifah, A., & Bukar, U. A. (2022). Examining the Prediction of COVID-19 Contact-Tracing App Adoption Using an Integrated Model and Hybrid Approach Analysis. Frontiers in public health, 10, 847184. https://doi.org/https://dx.doi.org/10.3389/fpubh.2022.847184

Alkhwaldi, A. F., & Abdulmuhsin, A. A. (2022). Understanding User Acceptance of IoT Based Healthcare in Jordan: Integration of the TTF and TAM. Studies in Computational Intelligence,

Antoniadis, K., Zafiropoulos, K., & Mitsiou, D. (2022). Measuring Distance Learning System Adoption in a Greek University during the Pandemic Using the UTAUT Model, Trust in

Government, Perceived University Efficiency and Coronavirus Fear [Article]. Education Sciences, 12(9), Article 625. https://doi.org/10.3390/educsci12090625

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): Towards a Revised Theoretical Model. Information Systems Frontiers, 21(3), 719-734. https://doi.org/10.1007/s10796-017-9774-y

Edo, O. C., Ang, D., Etu, E.-E., Tenebe, I., Edo, S., & Diekola, O. A. (2023). Why do healthcare workers adopt digital health technologies - A cross-sectional study integrating the TAM and UTAUT model in a developing economy. International Journal of Information Management Data Insights, 3(2), 100186. https://doi.org/https://doi.org/10.1016/j.jjimei.2023.100186

El-Masri, M., Al-Yafi, K., & Kamal, M. M. (2023). A Task-Technology-Identity Fit Model of Smartwatch Utilisation and User Satisfaction: A Hybrid SEM-Neural Network Approach. Information systems frontiers : a journal of research and innovation, 25(2), 835-852. https://doi.org/https://dx.doi.org/10.1007/s10796-022-10256-7

El Kurdi, B., Babar, S., El Iskandarani, M., Bataineh, A., Lerch, M. M., Young, M., & Singh, V. P. (2019). Factors That Affect Prevalence of Small Intestinal Bacterial Overgrowth in Chronic Pancreatitis: A Systematic Review, Meta-Analysis, and Meta-Regression. Clinical and translational gastroenterology, 10(9), e00072-e00072. https://doi.org/10.14309/ctg.0000000000000072

Goodhue, D. L., & Thompson, R. L. (1995). Task-Technology Fit and Individual Performance. MIS quarterly, 19(2), 213-236. https://doi.org/10.2307/249689

Gu, D., Khan, S., Khan, I. U., Khan, S. U., Xie, Y., Li, X., & Zhang, G. (2021). Assessing the Adoption of e-Health Technology in a Developing Country: An Extension of the UTAUT Model [Article]. SAGE Open, 11(3). https://doi.org/10.1177/21582440211027565

Habeeb, R. J. H., Hilles, S. M. S., & Momani, A. M. (2021). Social Commerce Adoption Based UTAUT Model for Consumer Behavior: Iraq Small and Medium Enterprise. 2nd International Informatics and Software Engineering Conference, IISEC 2021,

Howard, M. C., & Rose, J. C. (2019). Refining and extending task–technology fit theory: Creation of two task–technology fit scales and empirical clarification of the construct. Information & Management, 56(6), 103134. https://doi.org/10.1016/j.im.2018.12.002

Hsiao, J. L., & Chen, R. F. (2012). An investigation on task-technology fit of mobile nursing information systems for nursing performance [Article]. CIN - Computers Informatics Nursing, 30(5), 265-273. https://doi.org/10.1097/NCN.0b013e31823eb82c

Janssen, A., Keep, M., Selvadurai, H., Kench, A., Hunt, S., Simonds, S., Marshall, T., Hatton, L., Dalla-Pozza, L., McCullagh, C., & Shaw, T. (2021). Factors That Influence Use of a Patient Portal by Health Professionals. International Journal of Environmental Research and Public Health, 18(4). https://doi.org/https://dx.doi.org/10.3390/ijerph18041877

Kamal, M., & Subriadi, A. P. (2021). UTAUT Model of Mobile Application: Literature Review. Proceedings - IEIT 2021: 1st International Conference on Electrical and Information Technology,

Lambert, S. I., Madi, M., Sopka, S., Lenes, A., Stange, H., Buszello, C.-P., & Stephan, A. (2023). An integrative review on the acceptance of artificial intelligence among healthcare professionals in hospitals. NPJ digital medicine, 6(1), 111. https://doi.org/https://dx.doi.org/10.1038/s41746-023-00852-5 (Erratum in: NPJ Digit Med. 2023 Jul 11;6(1):125 PMID: 37433964 [https://www.ncbi.nlm.nih.gov/pubmed/37433964])

Semiz, B. B., & Semiz, T. (2021). Examining consumer use of mobile health applications by the extended UTAUT model. Business & management studies: an international journal, 9(1), 267-281. https://doi.org/10.15295/bmij.v9i1.1773

Shapira, S., & Cauchard, J. R. (2022). Integrating drones in response to public health emergencies: A combined framework to explore technology acceptance. Frontiers in public health, 10, 1019626. https://doi.org/https://dx.doi.org/10.3389/fpubh.2022.1019626

Tao, D., Chen, Z., Qin, M., & Cheng, M. (2023). Modeling Consumer Acceptance and Usage Behaviors of m-Health: An Integrated Model of Self-Determination Theory, Task–Technology Fit, and the Technology Acceptance Model [Article]. Healthcare (Switzerland), 11(11), Article 1550. https://doi.org/10.3390/healthcare11111550

Wang, H., Tao, D., Yu, N., & Qu, X. (2020). Understanding consumer acceptance of healthcare wearable devices: An integrated model of UTAUT and TTF [Article]. International Journal of Medical Informatics, 139, Article 104156. https://doi.org/10.1016/j.ijmedinf.2020.104156

Wang, S. L., & Lin, H. I. (2019). Integrating TTF and IDT to evaluate user intention of big data analytics in mobile cloud healthcare system [Article]. Behaviour and Information Technology, 38(9), 974-985. https://doi.org/10.1080/0144929X.2019.1626486

Wang, X., Lee, C. F., Jiang, J., Zhang, G., & Wei, Z. (2023). Research on the Factors Affecting the Adoption of Smart Aged-Care Products by the Aged in China: Extension Based on UTAUT Model [Article]. Behavioral Sciences, 13(3), Article 277. https://doi.org/10.3390/bs13030277

Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): a literature review. Journal of Enterprise Information Management, 28(3), 443-488. https://doi.org/10.1108/JEIM-09-2014-0088

Winckler, D. (2022). Not another box to check! Using the UTAUT to explore nurses' psychological adaptation to electronic health record usability. Nursing Forum, 57(3), 412-420. https://doi.org/https://dx.doi.org/10.1111/nuf.12686

Yamin, M. A. Y., & Alyoubi, B. A. (2020). Adoption of telemedicine applications among Saudi citizens during COVID-19 pandemic: An alternative health delivery system. Journal of infection and public health, 13(12), 1845-1855. https://doi.org/https://doi.org/10.1016/j.jiph.2020.10.017

Appendix A- Data used for analysis

ID	Author & Year	Aims & Objectives	Sample Size	Demographic Variables	Path Coefficient (Beta)	Study Design	Country	Methodology	Key Findings
1	Hailiang Wang et al., 2020	To develop and empirically test an integrated model of UTAUT and TTF to understand consumer acceptance of healthcare wearable devices (HWDs).	406	Gender, Age, Education, Occupation, HWD usage experience	Tech - TTF: 0.726 TC - TTF : 0.118 TTF - BI : 0.219	Cross-sectional survey design	China	Self-administered questionnaire survey	The study shows that performance expectancy, effort expectancy, social influence, facilitating conditions, and task-technology fit positively influence the acceptance of healthcare wearable devices (HWDs). These factors explained 68% of the variance in behavioral intention to use HWDs.
2	Shu Lin Wang & Hsin I Lin, 2019	To integrate Task-Technology Fit (TTF) and Innovation Diffusion Theory (IDT) to evaluate young users' intention to use a mobile cloud healthcare system for diabetes preventive care.	423	Age (15-40 years), Gender, Education Level	Tech - TTF: 0.780 TC - TTF : 0.193 TTF - BI : 0.407	Cross-sectional survey design	Taiwan	Questionnaire survey	Task characteristics, technology characteristics, and relative advantage positively influence task-technology fit, which in turn influences intention to use the mobile healthcare system. Observability had no significant effect.
3	Kamal Mohammed Alhendawi, 2022	To extend the TTF model by incorporating nurses' attitudes and evaluate the predictive power of regression and neural network models for nurse satisfaction with HIS.	164	Age, Gender, Occupation	Tech - TTF: 0.494 TC - TTF : 0.261 TTF - BI : 0.697	Cross-sectional survey	Palestine (Gaza Strip)	Questionnaire survey with AI prediction models	Task and technology characteristics, along with nurses' attitudes and task-technology fit, influence nurses' satisfaction with HIS. ANN model outperforms regression in predictive accuracy.
4	Mohammadhiwa Abdekhoda, Afsaneh Dehnad, Javad Zarei, 2022	To identify the key determining factors influencing faculty members' intention to adopt e-learning during COVID-19 by integrating UTAUT and TTF models.	143	Gender, Age, Teaching Experience	Tech - TTF: 0.652 TC - TTF : 0.525 TTF - BI : 0.244	Descriptive-analytical, cross-sectional survey	Iran (Ahwaz University of Medical Sciences)	Questionnaire survey	Technology and task characteristics, task-technology fit, social influences, effort expectancy, performance expectancy, and facilitating conditions positively influence e-learning adoption.
5	Yvonne O'Connor, Pavel Andreev, Philip O'Reilly, 2020	To develop and validate a conceptual model exploring how mHealth affects physicians' perceived quality of care (PQoC) in a hospital setting.	102	Age, Gender, Professional role	Tech - TTF: 0.479 TC - TTF : 0.337	Quasi-experimental posttest-only	Canada	Observational survey	Task-technology fit (TTF) and mHealth utilization positively impact physicians' perceived quality of care (PQoC). Self-efficacy is crucial in mHealth utilization.

ID	Author & Year	Aims & Objectives	Sample Size	Demographic Variables	Path Coefficient (Beta)	Study Design	Country	Methodology	Key Findings
6	Ali Alkhalifah, Umar Ali Bukar, 2022	To predict the factors influencing adoption of the Tawakkalna COVID-19 contact-tracing app in Saudi Arabia using TAM, PCT, and TTF, and validate using SEM and ANN.	309	Age, Gender, Nationality	Tech - TTF: 0.430 TC - TTF : 0.450 TTF - BI : 0.269	Cross-sectional survey design	Saudi Arabia	Questionnaire survey	Perceived ease of use, usefulness, task features, and mobility positively impact intention to adopt the app; privacy risk was not significant
7	Lianna Wijaya, Kah Choon Ng, Pardomuan Robinson Sihombing, 2023	To explore factors affecting the continuance usage intention (CUI) of telemedicine apps in Jakarta using Task-Technology Fit (TTF) theory.	137	Gender, Age, Education Level	Tech - TTF: 0.396 TC - TTF : 0.104 TTF - BI : 0.191	Cross-sectional survey	Indonesia	Online questionnaire survey	Technology characteristics and self-efficacy significantly impact telemedicine continuance usage, while task characteristics and awareness have minimal effects.
8	Mazen El-Masri, Karim Al-Yafi, Muhammad Mustafa Kamal, 2023	To develop and validate a Task-Technology-Identity Fit (TTIF) model that predicts smartwatch utilisation and satisfaction using both SEM and ANN analysis.	248	Gender, Age, Occupation, Nationality	Tech - TTF: 0.382 TC - TTF : 0.382 TTF - BI : 0.680	Cross-sectional survey design	Qatar	Questionnaire survey	Task-technology fit and technology-identity fit both significantly affect user satisfaction with smartwatches. Identity fit has a stronger effect on satisfaction, while actual task fit impacts smartwatch choice.
9	Tung-Cheng Lin, 2014	To investigate the effectiveness of mobile nursing information systems (MNIS) using an extended TTF model that includes organizational readiness and separates TTF into task-technology fit (TaTeF) and technology-individual fit (TeIF).	144	Gender, Education, Work Experience	Tech - TTF: 0.298 TC - TTF : 0.352 TTF - BI : 0.300	Cross-sectional survey	Taiwan	Questionnaire survey	Technology-individual fit and organizational readiness significantly influence MNIS usage; organizational support plays a crucial role in adoption.
10	Mohammad Ali Yousef Yamin, Bader A. Alyoubi, 2020	To investigate Saudi citizens' behavioral intention to adopt wireless sensor network (WSN)-based telemedicine apps during COVID-19, extending UTAUT with TTF.	348	Age, Gender	Tech - TTF: 0.209 TC - TTF : 0.489 TTF - BI : 0.508	Cross-sectional survey	Saudi Arabia	Online questionnaire survey	Task-technology fit and facilitating conditions are crucial for the adoption of telemedicine apps based on wireless sensor networks; R^2 explains 79.5% of variance in adoption behavior.
11	Muhammad Shahbaz et al., 2021	To propose a big data analytics (BDA) system for environmental air pollution (EAP) management and examine user adoption behavior using TTF and UTAUT frameworks.	412	Gender, Age, Education Level	Tech - TTF: 0.267 TC - TTF : 0.284 TTF - BI : 0.140	Cross-sectional survey	Pakistan	Structured questionnaire survey	Task-technology fit, along with UTAUT factors, strongly influences the adoption of the BDA-EAP management system. Resistance to change negatively impacts adoption, while extrinsic motivation positively moderates adoption.

ID	Author & Year	Aims & Objectives	Sample Size	Demographic Variables	Path Coefficient (Beta)	Study Design	Country	Methodology	Key Findings
12	Ju-Ling Hsiao, Rai-Fu Chen, 2012	To investigate the relationship between nursing task characteristics, m-NIS characteristics, TTF, and nursing performance using a modified TTF model.	219	Gender, Age, Work Experience	Tech - TTF: 0.270 TC - TTF : 0.308 TTF - BI : 0.312	Cross-sectional survey design	Taiwan	Questionnaire survey	Task-technology fit (TTF) positively influences nursing performance through factors such as information identification, acquisition, integration, and interpretation.
13	Hyo-Jin Kang, Jieun Han, Gyu Hyun Kwon, 2022	To analyze the user acceptance behavior of smart home health care services (SHHSs) in South Korea using an integrated UTAUT and TTF model.	487	Gender, Age, Marital Status	Tech - TTF: 0.517 TC - TTF : -0.007 TTF - BI : -0.209	Cross-sectional survey	South Korea	Online survey	Performance expectancy, effort expectancy, social influence, and task–technology fit significantly influence the behavioral intention and adoption of SHHS. Task characteristics did not affect task–technology fit.
14	Al-Rahmi et al., 2022	To integrate UTAUT and TTF models to evaluate social media use in teaching and learning in higher education and assess their impact on academic performance.	383	Gender, Age (18â€"41+), Discipline (Engineering, Science, Management, Social Sciences)	Tech - TTF: 0.199 TTF - BI : 0.107	Survey-based SEM (SmartPLS 3.3.3)	Malaysia	Structural Equation Modeling integrating UTAUT and TTF	Task-Technology Fit (TTF) and Behavioral Intention (BI) significantly impact Academic Performance (AP). PEX, EEX, Social Characteristics, and Technology Characteristics influence TTF and BI. Strong interrelationships among UTAUT and TTF constructs improve student performance via social media use.
15	Hsieh & Lin, 2020	To examine the performance impact and user resistance behavior toward the epidemic prevention cloud (EPC) using an integrated Task-Technology Fit (TTF) and Status Quo Bias (SQB) model.	116	Gender, Age, Education, Position, Work Experience	Tech - TTF: 0.474 TC - TTF : 0.277 TTF - BI : 0.712	Cross-sectional field survey using SmartPLS	Taiwan	Integrated TTF and Status Quo Bias (SQB) theoretical model	Task and technology characteristics positively influence TTF. TTF enhances utilisation and performance while reducing resistance to use. Resistance is influenced by uncertainty costs (positive), perceived value (negative), but not sunk costs. Resistance negatively affects utilisation but not performance. Utilisation and TTF significantly affect performance.

Appendix B

Section and Topic	Item #	Checklist item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	Analyzing the Determinants of Healthcare Technology Adoption Using the Task-Technology Fit (TTF) Model: A Systematic Review and Meta-Analysis.
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	The abstract follows PRISMA 2020 for Abstracts guidelines, providing a structured summary including background (TTF's limited application in healthcare), objectives (investigate determinants of healthcare technology adoption), methods (SLR and meta-analysis), results (TTF as a significant predictor), and conclusions (theoretical and practical implications).
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	Section 1 describes the rationale, highlighting TTF's limited application in healthcare compared to other domains, inconsistent findings, and the need to understand task-technology alignment for adoption
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	Section 1 explicitly states the objective: to investigate determinants of healthcare technology adoption using an extended TTF model via SLR and meta-analysis, focusing on healthcare-specific tasks and technology characteristics. The research question is specified in Section 3.1.
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	Section 3.2 lists inclusion criteria (healthcare technologies, English, 2012–2025, quantitative data with β coefficients) and exclusion criteria (non-TTF, non-healthcare, non-quantitative, pre-2012, non-English). Studies were grouped by TTF relationships (TC, TechC, TTF, BI) for meta-analysis
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	Section 3.2 specifies databases searched: Scopus, Web of Science, IEEE Xplore, ScienceDirect, PubMed, and Google Scholar. The paper does not specify the exact date of the last search, but studies span 2012–2025.
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	keywords ("Task-Technology Fit," "TTF," "healthcare technology adoption," "mHealth," "telehealth," "technology characteristics," "chronic disease management") and use of controlled vocabularies (e.g., MeSH terms in PubMed). Hand-searching of bibliographies was also conducted to identify additional relevant studies
Selection process	8	Specify the methods used to decide whether a	Section 3.2 describes the selection process: two reviewers independently screened titles and abstracts

Section and Topic	Item #	Checklist item	Location where item is reported
		study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	using Covidence software, with discrepancies resolved by discussion or a third reviewer. Full-text reviews were also conducted by two independent reviewers. No automation tools were used.
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	Section 3.3 outlines data collection: two reviewers extracted publication details, study characteristics, and quantitative data (e.g., β coefficients) independently, using a template (Appendix A). No contact with study investigators is mentioned. Covidence and EndNote were used for data management
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	Section 3.3 defines outcomes sought: β coefficients for relationships between TC, TechC, TTF, and BI. All compatible results (e.g., standardized path coefficients) were sought from each study
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	Additional variables: publication details, study characteristics (e.g., technology type), sample size, reliability statistics (CR or Cronbach's α). Constructs with similar labels were harmonized. No assumptions about missing data are explicitly stated.
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if	Section 5.3 notes no formal methodological quality assessment was conducted due to the focus on quantitative data, a limitation. No specific tools or independent reviewer processes for bias assessment are described.

Section and Topic	Item #	Checklist item	Location where item is reported
		applicable, details of automation tools used in the process.	
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	Section 4.4 specifies the effect measure: standardized path coefficients (β) for TC-TTF, TechC-TTF, and TTF-BI relationships, with significance levels ($p < 0.01$) and confidence intervals in Table 2.
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	Section 3.2 describes eligibility for synthesis: studies providing β coefficients for TTF relationships were included, grouped by path (TC-TTF, TechC-TTF, TTF-BI).
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	Section 3.3 notes data preparation: constructs with similar conceptualizations were harmonized to ensure consistency. No handling of missing statistics is described.
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	Section 4 presents results visually in tables (Table 1 for β coefficients, Table 2 for meta-analysis results).
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	Section 3.4 describes synthesis: meta-analysis used a random-effects model to estimate weighted mean β values, with heterogeneity assessed via I 2 and Q statistics. The choice of meta-analysis is justified by the need to combine diverse study findings. meta-analysis was conducted using R.
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	Section 5.1 explores heterogeneity causes, suggesting technology type (e.g., EHR vs. mHealth) and demographics as moderators, but no formal subgroup analysis or meta-regression is conducted.
	13f	Describe any sensitivity analyses conducted to assess robustness of the	No sensitivity analyses are described to assess the robustness of synthesized results.

Section and Topic	Item #	Checklist item	Location where item is reported
		synthesized results.	
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	No methods are described to assess reporting bias (e.g., publication bias via funnel plots or Egger's test), a limitation not explicitly noted
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	No formal certainty assessment (e.g., GRADE) is described. Section 5.3 acknowledges the small sample size (15 studies) and lack of quality assessment as limiting result credibility.
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	Section 4.1 describes the search process: 691 records identified, 171 duplicates removed, 520 screened, 361 full-text reviewed, and 15 studies included. Figure 2 (PRISMA Flow Diagram) visualizes this.
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	Section 4.1 does not cite specific excluded studies or reasons beyond general criteria (e.g., non-TTF, nonquantitative)
Study characteristics	17	Cite each included study and present its characteristics.	Section 4.2 and Appendix A cite all 15 included studies and present characteristics (e.g., sample size, β coefficients), objectives, design, outcomes, and findings.
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	No risk of bias assessments are presented for included studies, consistent with the limitation in Section 5.3
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	Section 4.3 and Appendix A present β coefficients, sample sizes, and significance for each study. Table 1 summarizes ranges, averages, and significance. Table 2 provides meta-analytic β estimates with 95% confidence intervals.
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	Section 4.2 summarizes study characteristics (e.g., technologies, geographic distribution). No risk of bias assessment is included.
	20b	Present results of all	Section 4.4 and Table 2 present meta-analysis results:

Section and Topic	Item #	Checklist item	Location where item is reported
		statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	β = 0.445 (TechC-TTF), β = 0.263 (TCTTF), β = 0.271 (TTF-BI), with 95% CIs and I 2 values (86.15%–94.87%) indicating high heterogeneity.
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	Section 5.1 discusses heterogeneity, attributing it to technology type and demographics, but no statistical analysis (e.g., subgroup analysis) is presented.
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	No sensitivity analyses are reported.
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	No assessment of reporting biases is presented for the syntheses.
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	No formal certainty assessment is provided. Section 5.3 notes limitations (small sample, no quality assessment) affecting confidence in results
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	Section 5.1 interprets results in context, comparing findings to prior studies (e.g., Wang et al., 2020; Tao et al., 2023) and emphasizing TTF's role in healthcare.
	23b	Discuss any limitations of the evidence included in the review.	Section 5.3 discusses limitations of included evidence: small sample (15 studies), predominance of Asian studies, and focus on quantitative data
	23c	Discuss any limitations of the review processes used.	Section 5.3 discusses review process limitations: no protocol registration, no quality assessment, and limited geographic diversity.
	23d	Discuss implications of the results for practice, policy, and future research.	Sections 5.1 and 5.2 discuss implications for theory (extending TTF with BI), practice (user-centered design, training), and future research (qualitative studies, broader demographics).
OTHER INFORMATION			
Registration and	24a	Provide registration information for the	Section 5.3 states the review was not registered.

Section and Topic	Item #	Checklist item	Location where item is reported
protocol		review, including register name and registration number, or state that the review was not registered.	
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	No protocol is mentioned or accessible, consistent with the limitation in Section 5.3
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	No amendments are mentioned, as no protocol was prepared.
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	No financial or non-financial support is mentioned in the paper.
Competing interests	26	Declare any competing interests of review authors.	No competing interests are declared in the paper.
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	Appendix A provides extracted data (study IDs, authors, β values, sample sizes). No analytic code or additional materials are mentioned as publicly available.

From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71