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Systematic Literature Review

Task Technology Fit and Financial Technology Adoption: A Systematic Literature Review on E-Money Contexts (2020-2025)

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INFORMASI ARTIKEL

Diterima Redaksi: 30 Oktober 2025
Revisi Akhir: 04 Januari 2025
Diterbitkan *Online*: 06 Januari 2026

KATA KUNCI

Task Technology Fit (TTF)
Financial Technology
E-Money
Technology Adoption

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A B S T R A K

The rapid advancement of financial technology has positioned electronic money (e-money) as a critical innovation in modern payment systems, making the alignment between technological capabilities and user requirements essential for successful adoption. This study conducts a systematic literature review to examine the application of Task–Technology Fit (TTF) theory in e-money and digital payment research published between 2020 and 2025, with the aim of synthesizing empirical evidence and identifying theoretical and methodological gaps in the existing literature. Following the systematic review protocol proposed by Kitchenham and Charters, a comprehensive search was conducted in the Scopus database using predefined keywords related to TTF and fintech, yielding 1,424 articles that were subsequently filtered through inclusion and exclusion criteria to obtain 26 primary studies. Quality assessment was performed using five predefined criteria, and data extraction addressed five research questions concerning TTF model types, research focus, theoretical integration, methodological approaches, and knowledge gaps. The findings indicate that 80.8% of the reviewed studies employed extended or hybrid TTF models integrated with behavioral theories, particularly UTAUT/UTAUT2 and TAM. Most studies focused on technology adoption, followed by utilization and fit-related analyses, with quantitative approaches dominating the literature and SEM-PLS emerging as the most frequently used analytical technique. Geographically, research was concentrated in European countries, notably the United Kingdom, the Netherlands, and Switzerland, with a marked increase in publications observed in 2024. Despite the robustness of TTF in explaining e-money adoption, the review identifies persistent gaps related to contextual factors such as digital literacy and trust, limited cross-cultural perspectives, and a lack of longitudinal and experimental designs, highlighting the need for stronger theoretical integration and broader methodological approaches to advance fintech adoption research across diverse socio-economic contexts.

INTRODUCTION

The growth advancement of financial technology (fintech) has brought significant transformation to the payment system landscape, with electronic money (e-money) emerging as one of the most widely adopted innovations. E-money enables users to perform transactions quickly, securely, and efficiently without relying on physical cash. In Indonesia, the adoption of e-money has grown remarkably, driven by the increasing penetration of smartphones, enhanced internet connectivity, and government initiatives promoting cashless transactions. This development reflects a broader shift toward virtual financial services, in which digital payment systems play a crucial role in supporting everyday economic activities.

The increasing reliance on virtual transactions highlights the necessity of technologies that align with user needs in terms of convenience, security, and accessibility. However, the effectiveness of a technology is not solely determined by its availability, but by the extent to which it fits the tasks users aim to accomplish. In this regard, the Task–Technology Fit (TTF) theory serves as a relevant framework for assessing how well a technology supports users in achieving their intended goals. TTF posits that technology adoption and performance outcomes are significantly influenced by the degree of alignment between task characteristics and technological capabilities [1].

Given these dynamics, applying the TTF framework is essential for evaluating whether the characteristics of e-money truly correspond to the needs and tasks of its users. The selection of TTF as a theoretical foundation is based on its strong explanatory power in linking technological features, task characteristics, and user performance, thereby offering valuable insights into technology adoption behaviors at both individual and organizational levels [1].

Ideally, e-money systems should not only ensure user compliance but also deliver convenience, efficiency, and enhanced user satisfaction. Examining e-money adoption through the TTF lens provides a deeper understanding of how the alignment between task and technology influences user acceptance and performance outcomes. Several studies have explored this relationship, offering substantive perspectives on TTF within the context of digital financial services. For instance, Shaikh *et al*. [2] conducted a qualitative literature review of studies published between 2009 and 2020, revealing a strong interconnection between task–technology alignment and the effectiveness of digital financial services. Furthermore, Wijayanti *et al.* [3] emphasized that a higher level of task–technology fit enhances users' perceived usefulness of the system, thereby improving organizational performance and sustainability in microfinance institutions.
The present study aims to systematically compile, analyze, and synthesize existing empirical evidence on the application of the Task Technology Fit (TTF) model within the context of e-money and digital payment systems from 2020 to 2025. The objective is to provide a comprehensive overview of the current state of research that employs the TTF framework to explain user adoption, utilization, and performance outcomes in e-money systems, and to identify the theoretical and methodological gaps that open avenues for future investigations.
To achieve these objectives, the following six research questions (RQs) are formulated:

RQ1: What types of Task Technology Fit (TTF) models have been used in the selected studies?

RQ2: What is the main area of investigation (fit focus/utilization/adoption) in the selected studies that applied the Task
Technology Fit model in the context of E-Money, Fintech, and Digital payment systems?

RQ3: Which theories have been integrated with the TTF model in the context of e-money, fintech, and digital payment systems?

RQ4: What research methods and analytical techniques have been employed in the selected studies?

RQ5: What are the knowledge gaps identified in previous studies regarding the application of the Task–Technology Fit theory?

This SLR paper is constructed as follows. Section II presents an overview of task technology fit model. Section III describes the research methodology employed. Section IV illustrates the descriptive results and the findings related to the RQs. Section V discusses the limitations of this review and presents the implications of the SLR findings and a conclusion.

LITERATURE REVIEW

Task Technology Fit Model

Task–Technology Fit (TTF) model, originally proposed by Goodhue and Thompson [4], is one of the most widely recognized frameworks for assessing information system success through the alignment between technological capabilities and user task requirements. The model posits that an information system yields higher utilization and improved performance when the technology provides functionalities that adequately support the tasks users are required to perform. Within this framework, task characteristics describe the nature, complexity, and interdependence of user activities, while technology characteristics refer to the technical features and capabilities that facilitate those activities. The degree of alignment between these two components—known as task–technology fit—determines the extent to which users perceive the system as useful and effective in achieving their goals [1].

Recent studies have applied the TTF framework extensively in the domain of digital financial services, including e-money and e-wallet systems. For instance, Yaakop *et al.* [5] integrated the TTF and Technology Acceptance Model (TAM) to investigate e-wallet adoption among Malaysian youth during the COVID-19 pandemic, revealing that a strong task–technology alignment significantly enhanced users' adoption intentions. Similarly, Van dat *et.al* [6] found that the degree of task–technology fit positively influences users' continuance intention toward e-wallet use, highlighting that technological functionalities such as ease of transaction, system reliability, and perceived security must align with users' financial transaction needs. In addition, a study by Xia *et al.* [7] emphasized that the success of digital payment adoption depends not only on the availability of technology but also on the perceived compatibility between system capabilities and user tasks.

In this regard, the TTF framework provides a robust theoretical lens for examining how specific technological features such as usability, transaction speed, and data security, correspond to the practical requirements of digital financial transactions. When this alignment is achieved, users tend to perceive e-money as more efficient, reliable, and beneficial for daily financial activities, thereby fostering higher adoption and satisfaction levels [3], [1]. Hence, TTF remains a critical foundation for understanding the interplay between user tasks, technological functionalities, and performance outcomes in the evolving digital financial ecosystem.

In the evolving landscape of digital technology research, understanding how the interaction between technology, tasks, and users influences performance has become increasingly significant. Earlier studies emphasized technology utilization as the main predictor of performance outcomes; however, more recent investigations highlight the importance of contextual alignment between user needs, task demands, and technological capabilities. This perspective underscores that performance effectiveness is achieved when technologies adequately support the cognitive and operational requirements of their users [4], [1], [8]. Building on these theoretical advancements, contemporary models conceptualize technology adoption and use not merely as behavioral responses, but as outcomes of fit between technological affordances and task characteristics. The following figure illustrates these conceptual models, demonstrating the transition from utilization-centered frameworks to integrative approaches grounded in the Task–Technology Fit (TTF) theory.

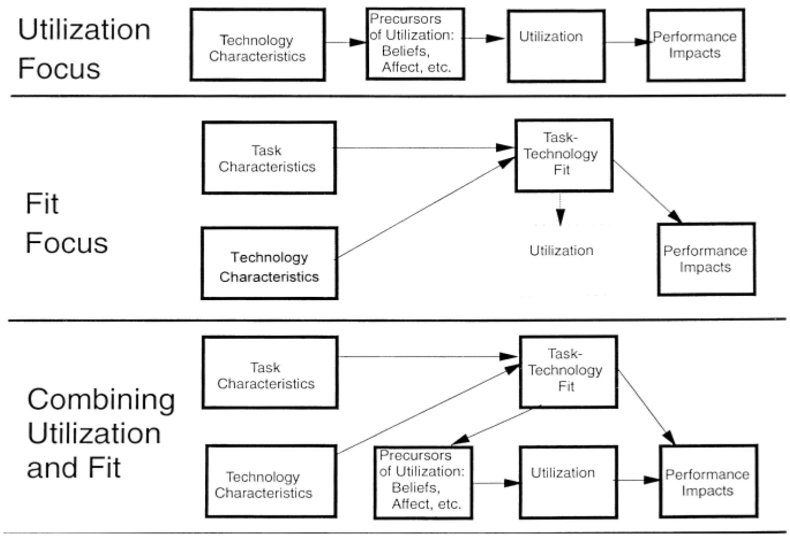

Figure 1. Three Models of the link From Technology to Performance

Figure 1 illustrates three conceptual models linking technology to performance: the Utilization Focus, the Fit Focus, and the Combined Utilization and Fit model. The Utilization Focus model posits that technology characteristics influence users' beliefs, affect, and other precursors of utilization, which subsequently drive technology use and impact performance. The Fit Focus model emphasizes the alignment between task and technology characteristics, suggesting that a high level of task-technology fit leads to greater utilization and improved performance outcomes. The Combined model integrates both perspectives, proposing that task and technology characteristics jointly determine task-technology fit and user beliefs, which together influence utilization and ultimately performance. This integrated framework provides a more comprehensive understanding of how technology and contextual factors interact to affect organizational performance [4].

METHODS

The current study utilises a systematic literature review (SLR) methodology, a formalised process designed to identify, evaluate, and interpret all relevant published studies on a clearly defined research question or topic [9]. This method is

 https://doi.org/10.56211/factory.v4i2.1349

employed to thoroughly address the research questions introduced in Section I by systematically organising available evidence, exposing research gaps, and offering directions for future work. Adopting the procedural framework , the review is structured around three sequential phases: planning the review, conducting the review, and reporting the results [9]**.** Before conducting an SLR, it is essential to design a clear and systematic review protocol to minimize potential bias. This protocol includes defining the research focus, formulating research questions, developing search strategies, determining inclusion and exclusion criteria, assessing study quality, extracting relevant data, and synthesizing the findings. The identification of the research focus and research questions (RQ1–RQ5) was presented in Section I, while the subsequent sections elaborate on the remaining stages of the review process.

Table 1. Inclusion and exclusion criteria for this study.

Inclusion criteria	Published 2020 – 2025
	Written in English
	Subject area in Business, accounting and management
	Available as full text
	Published as refereed international journal in Scopus
	Involved the use of task technology fit Model in E-money
Exclusion criteria	Outside the selected time frame
	Not written ini English
	Duplicative studies
	Not related to the topic of this SLR and its research question
	Not avalilable full text
	Conceptual studies with no result

Inclusion and Exclusion Criteria of The Study

These phases are an essential part of the SLR writing process. The inclusion and exclusion criteria serve a key function in ensuring that all selected studies are relevant and aligned with the research objectives. This SLR aims to identify various issues discussed in studies that applied the Task Technology Fit (TTF) model within the fintech sector, particularly in the context of e-money. The inclusion criteria were applied to journal articles and conference papers published in selected databases between 2010 and 2020, written in English. Studies without full-text access, those outside the research period, or those that were duplicated were excluded from the analysis. Table 1 presents a detailed summary of the inclusion and exclusion criteria applied in this study.

Search Strategy

First, a specific keyword query was applied in the Scopus database search field: TITLE-ABS-KEY("task technology fit") AND (LIMIT-TO(SUBJAREA, "BUSI")) AND (LIMIT-TO(DOCTYPE, "ar")) AND (LIMIT-TO(LANGUAGE, "English")) AND (LIMIT-TO(OA, "all")). The retrieved database consisted of all studies discussing the Task–Technology Fit (TTF) framework in relation to various subjects within the fields of business, management, and accounting. Second, the database was further refined based on the Systematic Literature Review (SLR) context using additional keywords: *financial technology, fintech, e-money, e-wallet,* and *digital payment*. Third, all studies that met the inclusion criteria and passed the screening process were selected for inclusion in this SLR.

To ensure the comprehensiveness of the literature search, a manual search was also conducted using the backward and forward search approaches proposed by Webster and Watson [10] . Through the backward-reference search, the reference lists of each selected study were examined to identify additional relevant publications. Meanwhile, through the forward-reference search, citations of each study were tracked using Google Scholar to locate further related research. Accordingly, this study applied a combination of automatic and manual search methods to ensure completeness and accuracy in the literature identification process, in line with the systematic review guidelines proposed by Kitchenham and Charters [9]and Webster and Watson [10].

Study Election Process

Following the automatic search process using a query based on the Task Technology Fit (TTF) theory, a total of 1,424 articles were initially identified. Subsequently, the results were refined by limiting the publication period to the last five years, reducing the number of relevant articles to 739. In the next stage, further filtering was applied based on document type, subject area, and open access status, resulting in 90 articles.

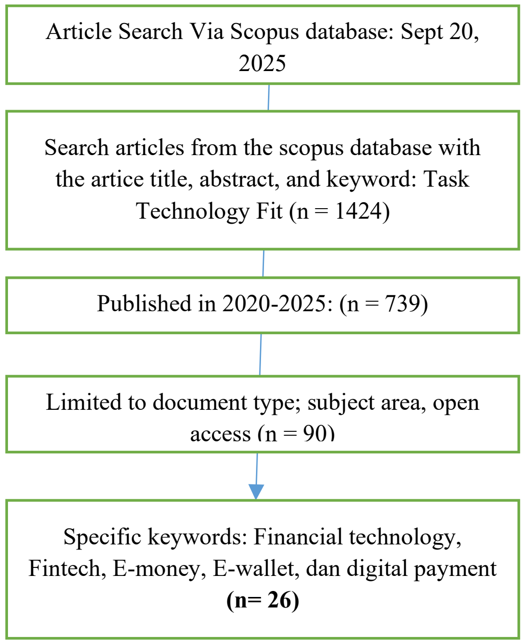

Figure 2. Search protocol and criteria for study selection

As the focus of this Systematic Literature Review (SLR) is the application of the TTF theory in the e-money context, an additional screening using related special keywords was conducted. Consequently, 26 articles were found to meet the relevance criteria. Therefore, a total of 26 studies were finally selected for in-depth analysis. The following figure presents the search strategy and study selection procedures employed in this research.

Quality Assesment

The primary purpose of the Quality Assessment (QA) is to ensure accurate evaluation of the overall quality of the selected studies (N = 26). This Systematic Literature Review (SLR) established five QA criteria to assess the methodological and theoretical rigor of the reviewed papers, as presented below:

QA1: Is the study's topic related to the application of the Task Technology Fit (TTF) model in the e-money or digital payment context?

QA2: Does the study clearly describe the technological characteristics of the e-money system examined (e.g., type of platform, usability, accessibility, or functionality)?

QA3: Are the task characteristics and technology characteristics explicitly identified and properly aligned within the research model?

QA4: Does the paper clearly present the research methodology, including data collection and analysis techniques?

QA5: Are the measurement items or indicators used to assess task–technology fit and user outcomes clearly described?

The quality of each study was evaluated using a three-level quality scale: high, medium, and low, based on the QA scores. A score of 1 was assigned if a study fully met a quality criterion, 0.5 if it partially met the criterion, and 0 if it did not meet the criterion. With five criteria, the maximum score for each study was 5, and the minimum score was 0. Based on the scoring results, studies with a total score of 3 or above were categorized as high-quality, those scoring between 1 and 3 as medium-quality, and those scoring below 1 as low-quality.

 https://doi.org/10.56211/factory.v4i2.1349

Table 2. Quality Assesment Score

SID	QA1	QA2	QA3	QA4	QA5	Total Score	Category
S1	1	0,5	1	1	1	4.5	High
S2	1	1	1	1	1	5	High
S3	1	1	0	1	0	3	Medium
S4	1	1	1	1	1	5	High
S5	0	0,5	0	1	0	1,5	Medium
S6	1	0,5	0	1	0	2,5	Medium
S7	1	1	0	1	0	3	Medium
S8	1	1	0	1	0	3	High
S9	1	1	1	1	1	5	High
S10	0	0,5	0	1	0	1,5	Medium
S11	0	1	0,5	1	0	2,5	Medium
S12	0	0,5	0	1	0	1,5	Medium
S13	0	1	0	1	0	2	Medium
S14	0	1	0	1	0	2	Medium
S15	0	0,5	0	1	0	1,5	Medium
S16	1	1	1	1	1	5	High
S17	1	1	0	1	0	3	High
S18	1	1	0	1	0	3	High
S19	1	1	0	1	0	3	High
S20	1	1	0	1	0	3	High
S21	1	1	1	1	1	5	High
S22	0	1	0	1	1	3	High
S23	1	1	0	1	0	3	High
S24	1	1	0,5	1	0,5	4	High
S25	1	1	0,5	1	0,5	4	High
S26	0	1	0	1	0	2	Medium

Based on the results of the Quality Assessment (QA) applied to the 26 selected studies, it was found that 14 studies (54%) were categorized as high-quality, while 12 studies (46%) were identified as medium-quality. No study was classified as low-quality. Therefore, all 26 studies were retained for further analysis. Accordingly, this Systematic Literature Review (SLR) comprises 26 primary studies that met the established quality criteria.

Data Extraction and Synthetis for SLR Data

The data extraction process represents a crucial stage in conducting a Systematic Literature Review (SLR), as it ensures the accuracy and consistency of the information collected from each selected study. At this stage, a data extraction form is employed as the primary instrument to systematically and structurally document the relevant research information [9]**.** This stage began with a comprehensive reading of the 26 selected studies. Subsequently, all studies were organized and processed using Mendeley and Microsoft Excel. To facilitate the retrieval of relevant information, a structured mapping process was carried out, covering key elements such as year of publication, author(s), study title, variables, theoretical foundation, research method, main findings, journal name, journal indexation, remarks, and the URL address of each article.

RESULT AND DISCUSSION

Descriptive Findings of The Selected Studies

Once data extraction was finalized, the gathered information from the selected primary studies was examined using further analysis.

1. Publication Source Overview

From the 26 selected studies that applied the Task–Technology Fit (TTF) model based on the defined keywords, the publications were distributed across several reputable publishers. The results reveal that the analyzed studies were published in various well-established international journals. Among them are the *South African Journal of Economic and Management Sciences*, *Global Business and Finance Review*, and *Uncertain Supply Chain Management*. In addition, several articles appeared in the *International Journal of Information Management Data Insights*, *International Journal of Law and Management*, *Technological Forecasting and Social Change*, and *Quantitative Finance and Economics*. Other publications were identified in journals such as *Banks and Bank Systems*, *Humanities and Social Sciences Communications (Springer Nature)*, *International Journal of Technology Marketing*, *International Journal of Hospitality Management*, and *International Journal of Research in Marketing*. Further contributions also came from the *Journal of Risk and Financial Management (JRFM)*, *Financial Innovation*, *International Journal of Asian Business and Information Management*, and the *International Journal of Retail and Distribution Management*. Interestingly, a considerable number of studies were published in *Cogent Business & Management* and the *Journal of Theoretical and Applied Electronic Commerce Research*, indicating that these two journals serve as major sources of research dissemination within this topic area.

2. Chronological View

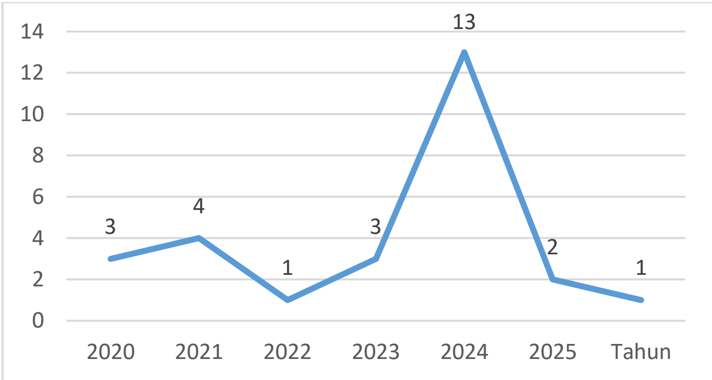

Figure 3. Distribution of Publication

Figure 3 presents the distribution of studies by publication year from 2020 to 2025. The trend indicates a fluctuating yet generally increasing research interest over time. During the early phase (2020–2022), the number of publications remained relatively low and stable, ranging from 1 to 4 studies per year. A notable decline occurred in 2022, suggesting limited academic attention during that period. However, a significant surge was observed in 2024, with a total of 13 studies published, representing the peak of scholarly attention within the examined timeframe. This sharp increase may reflect the growing relevance of the topic and the emergence of new research frameworks or policy developments during that year. The number of studies then decreased in 2025, suggesting a potential saturation of the topic or a shift in research focus toward related areas. Overall, the chronological analysis demonstrates a dynamic evolution of interest, with 2024 serving as the pivotal year for research output in this domain.

3. Research Methodologies

Table 3. Methodologies and Data Collection Strategy

	Research Method	Analytical Technique	Frequency
1	**Quantitative – Survey**	SEM-PLS, SEM-AMOS, SEM, Regression, PPM-TTF, Integrated Models (UTAUT, TAM, ECM, etc.)	**12**
2	**Quantitative (General)**	Descriptive / Statistical Analysis	**8**
3	**Quantitative – Online Survey**	Web-based Survey Analysis	**2**
4	**Quantitative – Structural Model**	SEM-AMOS	**1**
5	**Quantitative – Multi-Data Study**	Multi-source Data Analysis	**1**
6	**Experimental Study**	Scenario-based Moderation and Mediation Analysis	**1**

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7	**Experimental – Between-Subjects Design**	2×2×2 Factorial Analysis	**1**

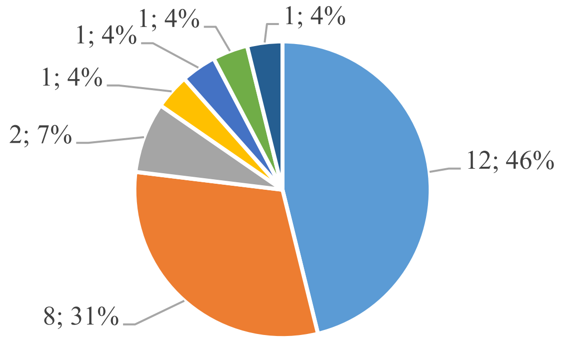

Figure 4. Distribution of Research Methodologies

Based on the classification of research methods, the majority of the studies analyzed in this review applied quantitative approaches, as summarized in table 3 and illustrated in Figure 4. Out of the 26 selected studies, 46% (n = 12) employed quantitative survey methods, using analytical techniques such as SEM-PLS, SEM-AMOS, regression analysis, and various integrated models including PPM-TTF, UTAUT, TAM, and ECM. This demonstrates a strong emphasis on empirical validation through structural and causal testing. Meanwhile, 31% (n = 8) of the studies used general quantitative approaches, which primarily relied on descriptive or statistical analysis to examine relationships among key variables. In addition, 7% (n = 2) of the studies conducted web-based online surveys, reflecting the increasing use of digital data collection methods in recent research. The remaining studies, each accounting for 4% (n = 1), employed diverse methods such as quantitative structural modeling using SEM-AMOS, multi-source data analysis, scenario-based experimental studies that examined moderation and mediation effects, and between-subject factorial designs (2×2×2). These findings indicate that while quantitative survey-based studies dominate the literature, there is a growing methodological diversification, incorporating both advanced statistical modeling and experimental approaches to strengthen the empirical robustness and contextual understanding of Task–Technology Fit (TTF)–related research.

4. Coverage of Studies by Geographical Regions

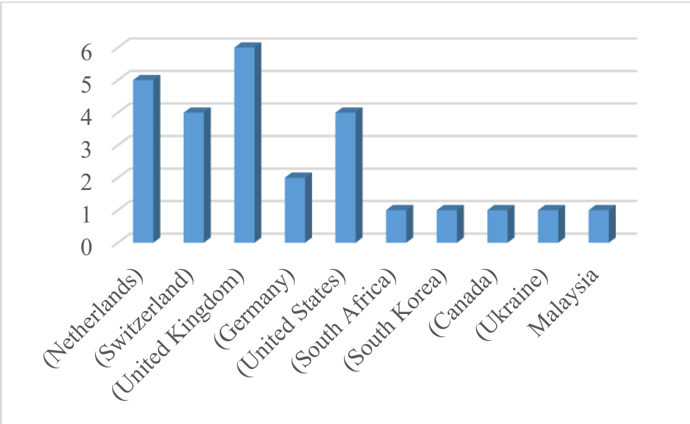

Figure 5. Coverage of Studies by Geographical Regions

The geographical distribution of the selected studies is presented in the figure above. In this review, ten countries were identified as the primary locations of the analyzed research. The United Kingdom contributed the highest number of studies (N = 6), followed by the Netherlands (N = 5) and Switzerland (N = 4). The United States also accounted for four studies (N=4), while Germany contributed two (N=2). Other countries, including South Africa, South Korea, Canada, Ukraine, and Malaysia, each contributed one study. These findings indicate that research related to the analyzed topic demonstrates a broad international distribution, with a notable concentration in European and North American regions, reflecting a strong global academic interest in the subject area.

Findings from The Proposed Research Questions

1. what is types of Task–Technology Fit (TTF) Models Used in the Selected Studies? (RQ1)

According to a systematic review of 26 primary studies, the Task–Technology Fit (TTF) models employed in prior research can be classified into two main categories: the original TTF model and the extended or hybrid TTF model integrated with other theoretical frameworks. Studies that adopted the original TTF model without modification were relatively few, whereas the majority of recent research has tended to develop hybrid models to better align with specific research contexts, enhance the explanatory power of the model, and capture the more complex dynamics of user behavior**.**

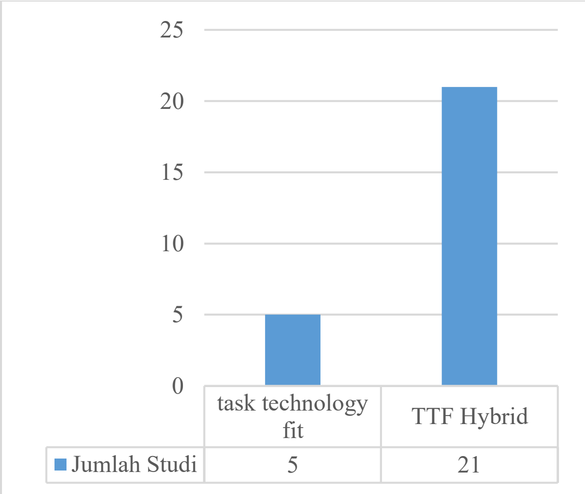

Figure 6. Distribution of The Selected Studies by Task Technology Fit Used

As illustrated in Figure 6, the findings of this systematic literature review reveal that only five studies (19.2%) applied the Task–Technology Fit (TTF) model in its original, unmodified form. In contrast, twenty-one studies (80.8%) developed hybrid or extended models by integrating additional theoretical frameworks such as the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Theory of Planned Behavior (TPB), and the Expectation–Confirmation Model (ECM). This integration aimed to enhance the explanatory power of the model by incorporating behavioral and contextual factors relevant to technology use. The tendency to extend or hybridize the TTF model aligns with previous scholars' recommendations to continuously adapt and expand the framework to better capture the increasing complexity of modern technological phenomena. Consequently, many researchers have extended the TTF model to improve its empirical relevance and explanatory capacity regarding technology adoption and usage behaviors in both organizational and individual contexts.

The trend toward extended TTF models has become increasingly evident in recent years. For instance, Munday *et al.* [11] combined UTAUT2 with TTF to analyze the factors influencing users' continuance intention toward food delivery applications during the COVID-19 pandemic. Their findings revealed that, beyond task–technology alignment, factors such as performance expectancy and habit played dominant roles in shaping users' continued usage intentions. Similarly, Ojiaku *et al.* [12] integrated TTF with UTAUT in the context of fintech adoption in developing countries. Their study found that task characteristics significantly influenced effort expectancy and performance expectancy, although the direct relationship between TTF and usage intention was not consistently significant.

Moreover, Baxi *et al.* [13] demonstrated that incorporating TTF constructs into the UTAUT framework enhanced the model's explanatory power in predicting digital wallet adoption. Their results showed that TTF not only had a direct effect on behavioral intention but also an indirect effect through perceived usefulness and ease of use. Additionally, Van dat *et al.* [14] emphasized that in organizational and cultural contexts, the fit-based models such as TTF should be adapted to include internal and external environmental factors to remain empirically valid. Their study highlighted the importance of integrating resource management theories with technology adoption frameworks to broaden the applicability of TTF in diverse settings.

Overall, these findings indicate that the development of hybrid TTF models serves three primary purposes. First, to incorporate contextual factors such as organizational environment, user identity, and facilitating conditions that are not included in the original TTF constructs. Second, to link task–technology alignment with users' perceptual and acceptance

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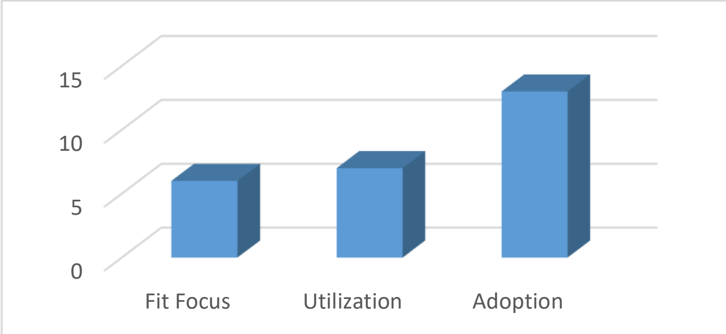
mechanisms through frameworks such as TAM, UTAUT, and UTAUT2. Third, to expand the model structure by adding mediating or moderating constructs (e.g., user satisfaction, experience, or leadership) to improve its predictive capability regarding technology use outcomes. Hence, the adapted and extended TTF models have demonstrated superior explanatory power compared to the conventional TTF model, particularly in addressing the complex and dynamic nature of modern information systems research.

2. What the main area of investigation (fit focus/utilization/adoption) in the selected studies that applied the Task–Technology Fit model in the context of E-Money, Fintech, and Digital payment systems? (RQ2)



Figur 7. Main Area of Investigation Distributed by Afit Focus, Utilization, And Adoption

As illustrated in Figure 7, the results of this systematic literature review reveal that among the 26 studies employing the Task–Technology Fit (TTF) model, three main research areas were identified: fit focus, utilization, and adoption. The adoption category represents the largest portion, encompassing 13 studies (50%), which primarily focus on the early stages of technology acceptance and evaluation based on the perceived alignment between tasks and technology. Studies within this category investigate factors such as intention to use, perceived ease of use, perceived usefulness, user trust, and readiness to adopt new systems across various contexts, including online learning, digital financial services, and technology-based business platforms.

The utilization category includes 7 studies (26.9%), which emphasize the influence of task–technology alignment on the intensity and continuity of system use. Research in this area demonstrates that a higher level of task–technology fit tends to increase users' willingness to continuously utilize the technology, as it effectively supports their work requirements and enhances task efficiency. Meanwhile, the fit focus category comprises 6 studies (23.1%), concentrating on the direct measurement of task–technology alignment and its impact on work effectiveness, productivity, and output quality. Studies within this category typically aim to empirically test the extent to which the congruence between task characteristics and technological capabilities improves individual or organizational performance.

Overall, these findings indicate that most TTF-related studies have predominantly emphasized the technology adoption process, while aspects related to technology utilization and direct task–technology alignment remain relatively underexplored. This trend reflects a broader shift in TTF research from a purely technical analysis toward a contextual and behavior-oriented approach, aimed at explaining the mechanisms of adoption, continued use, and successful implementation of digital technologies across diverse domains.

For instance, Xiong *et al.* [15] identified several key factors such as task characteristics, technology characteristics, perceived usefulness, confirmation, system quality, information quality, and user satisfaction as major determinants of continued usage intention in e-money and fintech payment applications. Their findings suggest that when the technology effectively supports users' financial tasks, the perceived efficiency and convenience encourage users to continue using the digital payment system. Similarly, Wu *et al.*[16] examined the impact of task–technology fit on the actual use of digital payment systems among young users. Their study found that a higher degree of fit between users' tasks and the technology's capabilities significantly enhances perceived usefulness and ease of use, leading to greater user experience quality and usage intensity. Moreover, trust and perceived security were identified as essential mediating factors that strengthen the relationship between task–technology fit and users' intention to continue using fintech services. In addition, Yamin *et al.* [17] emphasized that in the initial adoption stage of e-money, task technology fit plays a critical role in shaping users' intention to adopt financial technology. Their research demonstrated that when the technology aligns with users' needs and daily financial activities, it positively influences perceived value, attitude toward use, and behavioral intention, especially when supported by strong perceptions of security, system reliability, and accessibility. Overall, these studies highlight that within the context of fintech and e-money, the task–technology fit construct serves as a central mechanism linking system characteristics with user behavior. It influences not only the adoption and continued use of financial technologies but also their overall success and sustainability in digital financial ecosystems.

3. Which theories have been integrated with the TTF model in the context of e-money, fintech, and digital payment systems? (RQ3)

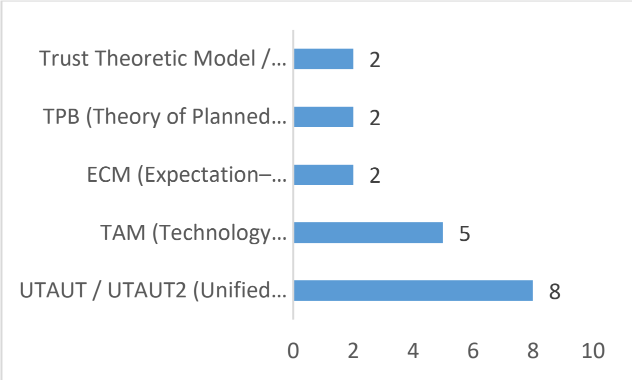


Figure 8. The five most prevalent theories integrated with the Task–Technology Fit (TTF) model.

Table 4. List theory/ model integrated with task technology fit

Theory/Model integrated with TTF	Study Collected	No Article
UTAUT / UTAUT2 (Unified Theory of Acceptance and Use of Technology)	8	S5 S6 S9 S16 S19 S21 S23 S26
TAM (Technology Acceptance Model)	5	S1 S19 S17 S7 S15
ECM (Expectation–Confirmation Model)	2	S20 S26
STPB (Theory of Planned Behavior)	2	S10 S3
Trust Theoretic Model / Trust Theory	2	S10 S3
Marketing / Branding Capabilities Theory	1	S13
Theory of Mind Perspective	1	S2
APCO Model (Antecedent Privacy Concerns and Outcomes)	1	S8
PPM (Push-Pull-Mooring) Framework	1	S18
CASA (Computers Are Social Actors)	1	S22

Based on the results of this *Systematic Literature Review* (SLR) involving 26 selected studies, it was found that the *Task–Technology Fit* (TTF) model is frequently integrated with several behavioral and technological theories to explain the adoption and utilization of financial technologies, particularly in the context of e-money and fintech. The integration of these theoretical frameworks aims to provide a more comprehensive understanding of how the alignment between tasks and technology interacts with behavioral and perceptual factors that influence user decision-making. Among the reviewed studies, TTF was most frequently combined with the *Unified Theory of Acceptance and Use of Technology* (UTAUT/UTAUT2), followed by the *Technology Acceptance Model* (TAM) as the second most utilized theory.

As shown in Figure 8, five major theoretical frameworks have been most frequently associated with the Task–Technology Fit (TTF) model in the examined literature. Among these, the Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2) appeared as the most frequently integrated model, cited in eight studies, followed by the Technology

Acceptance Model (TAM) with five studies. The Expectation Confirmation Model (ECM), Theory of Planned Behavior (TPB), and Trust Theory each appeared in two studies. These integrations indicate that researchers often combine TTF with behavioral intention models to better explain technology adoption and usage behavior in e-money and fintech contexts. Such combinations allow for a more holistic understanding that connects system quality and task alignment with psychological and perceptual factors influencing user decisions. This approach aligns with Baxi *et.al* [8], who emphasized that integrating behavioral and technological models enhances explanatory power when analyzing digital payment adoption, particularly in environments where trust, usability, and performance expectancy play central roles.

The integration of these models demonstrates that researchers tend to combine TTF with user behavior theories to provide a more comprehensive understanding of the adoption and sustained use of financial technologies. This approach highlights that the alignment between task requirements and technological capabilities is not only influenced by system characteristics but also by psychological factors such as performance expectancy, trust, and perceived ease of use. In this regard, the combination of TTF and UTAUT underscores the significance of facilitating conditions and behavioral intention, while the integration of TTF and TAM emphasizes perceived usefulness and usability as key predictors of adoption. These theoretical synergies provide a more holistic view of how technology–task alignment affects user engagement and satisfaction in digital financial ecosystems.

Consistent with this trend, Baxi *et al.* [8] confirmed that the integration of behavioral models with TTF substantially improves the model's ability to predict user adoption and continuous usage of digital payment systems. Their study found that the degree of alignment between technological features and users' financial tasks strengthens perceptions of usefulness, trust, and ease of use, ultimately enhancing users' intention to adopt and consistently utilize fintech and e-money platforms.

Overall, the findings of this systematic literature review affirm that integrating behavioral theories with the TTF model provides a more comprehensive understanding of the determinants of digital financial technology implementation success. It not only highlights the functional fit of the system but also emphasizes the roles of psychological and social factors—such as trust, ease of use, and user satisfaction—in enhancing the sustainability of fintech and e-money adoption [8], [11], [1]. Based on the synthesis of 26 selected studies, this review therefore proposes an integrated conceptual model that illustrates how TTF interacts with key constructs derived from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) within the e-money adoption context (see Figure 9).

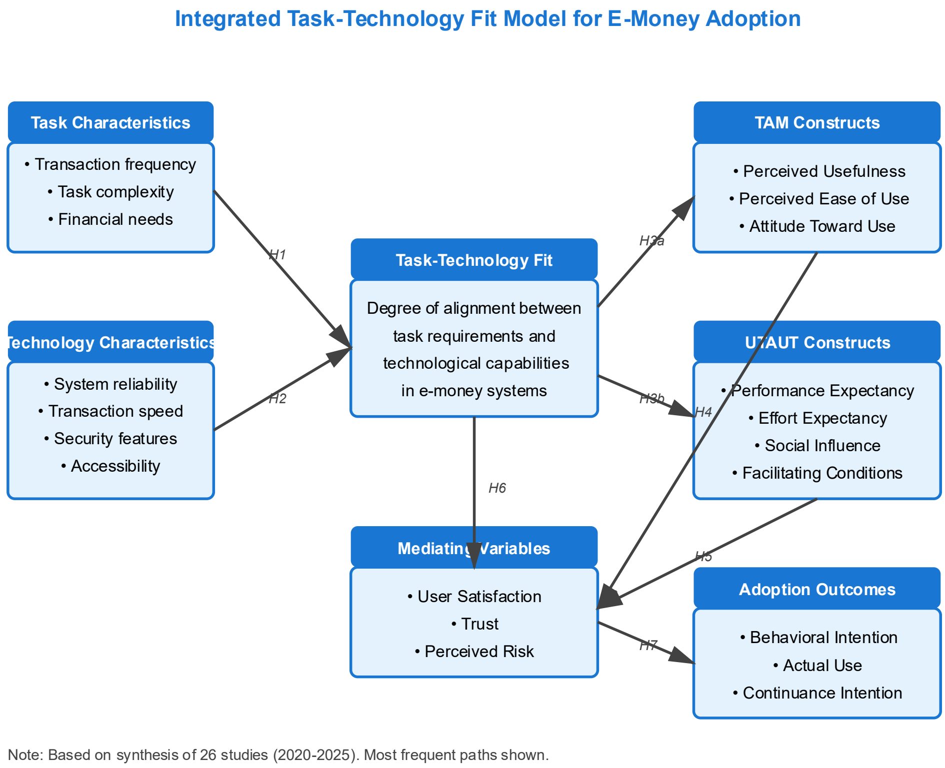


Figure 9. Integrated Conceptual Framework of TTF in E-Money Adoption

The synthesized framework identifies a set of interrelated pathways through which Task–Technology Fit (TTF) influences e-money adoption. At the antecedent level, task characteristics—such as transaction frequency, task complexity, and users' financial needs—significantly shape perceptions of task–technology alignment. When e-money systems effectively support diverse financial tasks, including bill payments, peer-to-peer transfers, and merchant transactions, users report higher levels of perceived fit. In parallel, technology characteristics also play a critical role in determining TTF. Prior studies indicate that system reliability, transaction speed, security mechanisms, and accessibility directly enhance task–technology alignment, particularly when advanced features such as biometric authentication, instant settlement, and offline functionality are incorporated into e-money platforms.

Building on these antecedents, TTF emerges as a pivotal construct influencing users' behavioral beliefs. Empirical evidence consistently demonstrates that TTF acts as a strong antecedent to constructs derived from the Technology Acceptance Model, namely perceived usefulness and perceived ease of use. When users perceive a high degree of alignment between e-money functionalities and their financial tasks, they are more likely to evaluate the system as useful and easy to use, with robust effect sizes reported across multiple studies. Similarly, TTF positively influences key constructs from the Unified Theory of Acceptance and Use of Technology, particularly performance expectancy and effort expectancy. High task–technology fit enhances users' expectations that e-money systems will improve transaction efficiency while reducing cognitive effort.

The framework further shows that TAM- and UTAUT-related constructs operate through a set of mediating variables that translate cognitive evaluations into adoption-related outcomes. Perceived usefulness and ease of use contribute to higher levels of user satisfaction and trust while reducing perceived risk, especially in contexts where financial security concerns are salient. In addition, performance expectancy and social influence strengthen satisfaction and trust, whereas facilitating conditions moderate the relationship between TTF and continuance intention. Beyond these indirect effects, several studies also identify direct influences of TTF on user satisfaction and trust, suggesting that task–technology alignment independently shapes positive user attitudes beyond the explanatory power of TAM and UTAUT.

At the outcome level, user satisfaction consistently emerges as the strongest predictor of behavioral intention, actual usage, and continuance intention across the reviewed studies. Trust further moderates the relationship between TTF and adoption outcomes, particularly in developing-country contexts where digital financial literacy remains limited. Mediation analyses indicate the presence of a double mediation mechanism, whereby the effect of TTF on adoption outcomes is largely transmitted through sequential pathways involving TAM and UTAUT constructs followed by mediating variables, as well as through direct pathways from TTF to mediating variables.

Overall, the integrated framework highlights the theoretical complementarity of combining TTF with TAM and UTAUT. While TTF captures the functional alignment between tasks and technology, TAM explains users' perceptions of usefulness and ease of interaction, and UTAUT accounts for performance expectations and contextual enablers. Together, this multi-theoretical approach offers a more comprehensive explanation of e-money adoption and provides actionable guidance for fintech providers to design systems that align with users' transaction patterns, enhance perceived value, and foster sustainable usage.

4. What research methods and analytical techniques have been employed in the selected studies? (RQ 4)

Table 5. Analysis Type and Software Used

Analysis Type	Software Used	Number of Articles
Structural Equation Modeling (SEM-PLS)	SmartPLS	13
	WarpPLS	2
	PLS-Graph	1
Structural Equation Modeling (SEM-AMOS)	AMOS	6
	LISREL	1
Regression / Moderation / Mediation Analysis	SPSS (Multiple / Hierarchical Regression)	2
	PROCESS Macro (Hayes Model)	1

As shown in Table 5, most of the selected studies employed quantitative approaches using multivariate statistical techniques. The dominant analytical method identified was Structural Equation Modeling (SEM-PLS), applied in 13 studies through SmartPLS, 2 studies using WarpPLS, and 1 study using PLS-Graph, totaling 16 articles adopting a

 https://doi.org/10.56211/factory.v4i2.1349

variance-based SEM approach. This dominance indicates that recent research on digital financial technology and the Task Technology Fit (TTF) model emphasizes predictive modeling and the exploration of complex structural relationships between latent constructs [8], [11].

Meanwhile, covariance-based SEM (SEM-AMOS) appeared in 6 studies using AMOS and 1 using LISREL, accounting for 7 articles. These studies typically focus on theory confirmation, testing model fit, and evaluating causal relationships among behavioral constructs, such as perceived usefulness, trust, and continuance intention in fintech or e-money adoption [1].

In addition, three studies utilized regression-based analyses, including multiple or hierarchical regression (2 studies) and PROCESS macro (1 study) to test moderation and mediation effects. These approaches were mostly applied in studies with fewer variables or smaller sample sizes where SEM was not required.
Overall, this pattern demonstrates that the TTF model and its extensions are predominantly examined using SEM-based techniques, especially PLS-SEM, which allows researchers to assess both measurement validity and predictive power simultaneously. This analytical preference aligns with the integrative and exploratory nature of TTF research in digital financial contexts, where constructs such as trust, perceived ease of use, and user satisfaction play significant roles in explaining technology adoption and continuance behavior [8], [11], [1].

5. What are the knowledge gaps identified in previous studies regarding the application of the Task–Technology Fit theory? (RQ5)
The analysis reveals a fluctuating pattern in the number of studies applying the Technology-Task Fit (TTF) framework within the context of e-money adoption in financial technology during the 2020–2025 period. A modest number of studies were published in the early years (2020–2022), followed by a significant surge between 2023 and 2024, reaching a total of ten articles. However, this growth was not sustained, as the number of publications dropped sharply in 2025, indicating a notable shift in research focus.

This pattern suggests that scholars' interest in TTF-based analysis of e-money adoption peaked in the post-pandemic recovery period, where digital financial solutions gained widespread attention as tools for cashless transactions and economic resilience. During 2023–2024, the global emphasis on digital transformation, combined with government initiatives promoting cashless ecosystems, likely stimulated academic inquiry into how well technological features of e-money systems aligned with users' financial tasks [3], [1].

However, the subsequent decline in 2025 may be attributed to several factors. First, the theoretical saturation of TTF applications in the fintech domain has led many researchers to seek new theoretical integrations, such as combining TTF with Unified Theory of Acceptance and Use of Technology (UTAUT) or Theory Acceptance Model (TAM), to capture more complex behavioral dimensions. Second, the emergence of new fintech modalities—such as digital investment apps, blockchain-based wallets, and AI-driven financial assistants—may have shifted the research focus away from traditional e-money studies toward more advanced financial technologies.

Furthermore, the decline could reflect a regional redistribution of research priorities, where developing economies that had previously been active in e-money studies began redirecting their efforts toward evaluating policy effectiveness and consumer protection in digital financial systems rather than examining task–technology alignment. while the period of 2023–2024 marked the peak of scholarly engagement with the TTF model in e-money contexts, the sharp drop in 2025 underscores a maturing research field that now demands conceptual expansion and cross-framework integration to address evolving fintech phenomena.

Despite the extensive application of the *Task–Technology Fit (TTF)* model in examining user adoption and success of digital financial systems, the present review identifies several persistent knowledge gaps in the existing literature, particularly concerning the use of *e-money* within the broader *fintech* ecosystem.

First, previous studies predominantly emphasize the direct linkage between task–technology fit and behavioral outcomes such as intention to use or user satisfaction. However, limited attention has been paid to contextual and moderating variables, including *digital financial literacy*, *trust*, *perceived risk*, and *technological readiness*. These variables are essential to capture the complex behavioral mechanisms underpinning users' interaction with financial technologies. Second, the geographical and cultural scope of current research remains narrow. Most investigations have been conducted in developing countries particularly Indonesia, Malaysia, and China resulting in findings that may not be generalizable across diverse socio-economic or regulatory contexts. Comparative and cross-cultural research remains scarce, despite the influence of financial culture, infrastructure readiness, and national regulations on the perceived fit between technology and user tasks. Third, the majority of studies adopt a functionally oriented perspective on TTF, focusing primarily on utilitarian aspects such as efficiency, ease of use, and transaction speed. Conversely, affective and social dimensions such as digital identity, perceived psychological safety, and social influence have received minimal scholarly attention. These factors may significantly affect users' trust and the long-term sustainability of e-money adoption. Fourth, the literature still relies heavily on the standalone use of the TTF model, with insufficient integration into complementary frameworks such as the *Unified Theory of Acceptance and Use of Technology (UTAUT)*, *Technology Acceptance Model (TAM)*, or *Expectation–Confirmation Model (ECM)*. Theoretical integration between TTF and behavioral models could provide a more comprehensive understanding of cognitive, affective, and contextual determinants influencing technology adoption in fintech.

From a methodological perspective, most studies employ cross-sectional survey designs analyzed using *Structural Equation Modeling (SEM)*. Few have adopted longitudinal, experimental, or data-driven approaches (e.g., behavioral analytics or machine learning) to examine temporal changes and causal relationships in user behavior. Such methods could strengthen empirical validity and provide richer insights into dynamic user interactions within digital finance ecosystems.

Finally, the current body of research offers limited exploration of digital financial inclusion through the TTF lens. Studies have primarily focused on technologically proficient users, overlooking vulnerable segments such as rural populations, older adults, and micro-entrepreneurs. Future research should extend TTF applications to these groups to ensure that fintech innovations foster equitable access, inclusion, and empowerment in the digital economy.
In summary, while the TTF framework remains theoretically robust for analyzing technology adoption in fintech, its application has been largely functional, context-specific, and methodologically limited. Future studies should adopt integrated, multidimensional, and cross-contextual approaches that incorporate social, psychological, and cultural factors alongside functional fit. Such advancements would enable the TTF model to evolve into a more holistic and empirically grounded framework for understanding the sustained adoption and success of e-money in the global fintech landscape.

IMPLICATIONS, LIMITATIONS, AND CONCLUSION

This systematic review offers significant insights into the application of the *Task–Technology Fit (TTF)* theory within the domain of financial technology, with a specific focus on the use of *E-money*. The findings demonstrate that the degree of fit between technological features such as usability, transaction speed, and system reliability and users' financial tasks substantially determines the success of E-money adoption. Theoretically, this review reinforces the relevance of TTF as a foundational model in explaining technology-driven financial behavior. However, it also reveals that the explanatory strength of TTF can be expanded through integration with behavioral frameworks such as the *Technology Acceptance Model (TAM)* or *Unified Theory of Acceptance and Use of Technology (UTAUT)* to capture users' psychological and contextual dimensions. Practically, the results highlight that policymakers and fintech providers should not only enhance technical efficiency but also ensure perceived security, trust, and regulatory transparency to strengthen user confidence in E-money systems.

Despite its contributions, this review acknowledges several limitations. The majority of the analyzed studies were cross-sectional in nature and heavily concentrated in developing countries, particularly in Southeast Asia. Such contextual dominance may limit the generalizability of findings to advanced economies or regions with different digital infrastructures and regulatory frameworks. Additionally, most studies relied on self-reported survey data, which may not fully reflect actual user behavior in real transaction environments. Future research should therefore adopt longitudinal designs, incorporate objective usage data, and expand the scope to comparative cross-country analyses. Integrating advanced analytical tools such as *structural equation modeling* with *machine learning* approaches may also provide deeper insights into the evolving dynamics of task–technology alignment in digital payment ecosystems.

In conclusion, the application of the *Task–Technology Fit* theory to E-money research has proven instrumental in advancing understanding of user–technology interaction within the fintech landscape. However, the existing body of knowledge remains fragmented and often limited to functional evaluations of technology. Future studies should move toward more holistic frameworks that consider socio-cultural, behavioral, and policy-related variables influencing E-

 https://doi.org/10.56211/factory.v4i2.1349

money adoption. By addressing these gaps, scholars can strengthen the theoretical robustness of TTF while offering actionable guidance for fintech innovators and regulators seeking to optimize digital payment systems that are adaptive, inclusive, and sustainable.

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