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Fit for the future: Examining the impact of task-technology fit on bank employee intentions to use FinTech

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Background: FinTech revolutionizes banking by transforming traditional practices, making it crucial to understand how bank employees adopt these innovations for enhanced operational effectiveness.

Aim: This study examines the intention to use FinTech among employees, utilising an integrated task-technology fit (TTF) and technology acceptance model (TAM). Unlike previous studies, it examines the influence of TTF at three levels (underfit, overfit and ideal fit) on TAM and the intention to use FinTech from the perspectives of bank employees.

Setting: The research focuses on three major banks in Ethiopia, a developing economy with growing FinTech adoption in the banking sector.

Method: The study employed a quantitative research method, gathering data via a questionnaire survey of 213 bank employees in Ethiopia. The analysis was conducted using structural equation modelling via Smart-PLS software.

Results: The findings reveal that an ideal fit significantly and positively impacts perceived usefulness, ease of use and intention to adopt FinTech. Underfit negatively influences perceived usefulness, while overfit shows no significant impact on perceived usefulness, ease of use or adoption intention. In addition, perceived usefulness directly and significantly affects the intention to use FinTech.

Conclusion: FinTech adoption in banks is optimised when the technology is ideally suited to employees' tasks. Excessive or insufficient task-technology alignment can hinder FinTech adoption in the emerging economy context.

Contribution: The study advances theoretical understanding by integrating TTF and TAM, introducing the concept of varying TTF levels. It also broadens the framework's application to emerging economies, offering practical insights for optimising FinTech adoption in banking.

Keywords: FinTech; task-technology fit; technology acceptance model; perceived usefulness; intention to use.

Introduction

The rapid evolution of workplaces driven by emerging technologies and increasing competitive pressures has triggered a paradigm shift in financial technologies (Jerene & Sharma 2020). FinTech has become a pivotal and transformative phenomenon within the global financial sector (Hu et al. 2019). Literature evidenced that FinTech-enabled companies could reach a broader customer base, including underserved populations, by providing seamless digital platforms accessible via mobile devices (Ashta & Herrmann 2021; Jangir et al. 2023; Lim et al. 2019; Nasrullah & Dar 2023; Wang et al. 2019). Effective FinTech, which can be deemed as an innovative approach, involves leveraging the internet, smartphones and mobile applications to deliver a range of services, such as payments, savings, loans and investment opportunities, to customers (Tiwari 2021; Wang et al. 2019). Such innovations aimed to garner a high standing of firm effectiveness, simplify traditional financial processes, increase automation, reduce costs and provide individualised, user-friendly experiences for customers and organisations (Balaskas et al. 2024; Jangir et al. 2023; Nasrullah & Dar 2023). By transforming financial technologies, financial firms can foster a work environment that enhances employee performance, thereby benefiting the organisation.

Extant literature has shown that FinTech positively influences financial institutions to provide customers with seamless access to financial services, regardless of time and distance constraints

(Jerene & Sharma 2020) while also increasing efficiency and customer experience (Alalwan et al. 2016; Davis, Bagozzi & Warshaw 1989). Therefore, FinTech is important for banking employees, who are facing ongoing pressure to stay updated with evolving technologies (Kim et al. 2010) and deal with the increased demands of customers (Hu et al. 2019). In short, FinTech tends to facilitate employees' establishing positive relationships of high standing with banking clients and achieving organisational success (King & Previati 2021). Although the body of literature on FinTech is expanding, our understanding of its relative significance concerning employees' intention to adopt and utilise it remains limited. Therefore, there is a need to explore the impact of FinTech on employees' intention to use it.

Employee technology intention to use refers to the willingness or leaning of employees to adopt and utilise a specific technological solution within their work environment (Venkatesh & Davis 2000). By adopting the technologies to jobs, employees can deal with the existing job demands and thus show intention to mitigate customer complaints (Kim et al. 2010). Customer complaints are common in the Ethiopian banking industry (Menza, Jerene & Oumer 2024). High digital literacy is observed among employees. Given the rapid evolution of FinTech globally, it is crucial for Ethiopian banks to stay aligned with technological advancements in order to meet customer expectations and maintain their competitive edge. As FinTech continues to reshape employees' roles, it also impacts their job duties, attitudes, behaviours and skill requirements (Bhutto, Jamal & Ullah 2023). Therefore, understanding employees' acceptance behaviour towards utilising FinTech is crucial for ensuring its successful integration into the banking sector. Furthermore, previous studies have primarily focused on customers' perspectives on the adoption of FinTech based on different theories. For example, Gebrekidan (2022) used a modified version of the UTAUT2 model to explore users' intentions to adopt digital financial services in Ethiopia. The study identified performance expectancy, effort expectancy, facilitation conditions, hedonic motivation and price value as strong predictors of users' intentions to adopt digital payment services. Similarly, Jerene and Sharma (2020) applied the TAM to investigate bank customers' acceptance of FinTech in Ethiopia, finding that customer awareness, subjective norms and perceived usefulness significantly influenced adoption intentions. In addition, there is extensive research on technology acceptance from customer perspectives using models like the TAM (Bastari et al. 2020; Daradkeh 2019; Yen et al. 2010) and task-technology fit (TTF) model (Lee, Cheng & Cheng 2007; Wu & Chen 2017). However, while these studies provide significant insights into financial technology adoption from the customers' perspectives, it is surprising that limited research has been conducted on FinTech acceptance from the employees' standpoint (Kitsios, Giatsidis & Kamariotou 2021).

Prior studies for example (Daradkeh 2019; Shih & Chen 2013; Witjaksono, Agus Sihabuddin & Azhari Azhar 2021; Wu & Chen 2017) assume a single-level relationship among task characteristics, technical characteristics and TTF to investigate consumers' intention to use digital finance. However, while these studies offer significant insight into the customers' technology acceptance behaviour, it is startling there is no research conducted based on varying degrees of fit (underfit, ideal fit and overfit) that may exist in different contexts to influence the employees' FinTech acceptance behaviour. Interestingly, we propose to test whether these varying levels of TTF may significantly influence employees' intention to use FinTech.

Overall, our study aims to fill these gaps by investigating the impact of different TTF degrees (underfit, ideal fit and overfit) on users' beliefs regarding FinTech adoption in the banking sector, integrating TTF and TAM models from the perspective of bank employees in the study area. The TTF evaluates how well a user's task aligns with the specific attributes of a technology (Sinha et al. 2017; Huang 2017). If an ideal TTF exists, then employees will reflect on whether FinTech is a useful and/or easy-to-use FinTech solution, which relates to technology acceptance (Fang 2017). Likewise, TAM is a concept that was developed and empirically validated to identify factors influencing technology implementation (Davis et al. 1989; Venkatesh & Davis 2000). Numerous studies utilise it to identify the determinants of technology acceptability; hence, this study employs TAM to examine the acceptance of FinTech among bank employees. The combination of these two models provides a thorough knowledge of the causal mechanisms that underpin the interactions involved, providing new insights that cannot be achieved from a single theory-driven approach (Dishaw & Strong 1999; Wang et al. 2019).

This study provides significant theoretical contributions to the information system literature in various features. Firstly, by integrating the TTF and Technology TAM, it presents a dual-theoretical framework that enhances understanding of FinTech adoption from an employee perspective. Furthermore, the study introduces three levels of TTF (underfit, ideal fit and overfit), highlighting new insight into the varying impacts on employees' intention to use FinTech. The findings confirm that the direct effect of ideal fit positively and significantly influences perceived usefulness, perceived ease of use and intention to use FinTech, while underfit negatively affects perceived usefulness.

Secondly, this study expands the TTF-TAM framework to the Ethiopian FinTech sector, thereby broadening the application of these models to emerging economies. Additionally, the study offers practical guidance for bank managers and FinTech providers to design and manage their digital platforms effectively to enhance their customer service.

Literature review and theoretical background

FinTech

FinTech is a term that describes cutting-edge technologies intended to boost and automate the supply and application of financial services (Balaskas et al. 2024). It has transformed the financial sector, changing the way financial services are delivered and utilised (Agarwal & Zhang 2020). This emergence of FinTech has led to the creation of new products, services, processes and business models (Gomber, Koch & Siering 2017; Thi & Minh 2021). Fundamentally, it indicates the application of advanced software and algorithms on computers and smartphones, such as cryptocurrencies, Internet banking, mobile payments, crowdfunding, Robo-Advisory, blockchain and cloud computing, to benefit businesses, entrepreneurs and customers to more effectively manage their lives, businesses and financial procedures (Balaskas et al. 2024; Banu, Mohamed & Parayitam 2019; Jourdan et al. 2023; Nalluri & Chen 2024). Ultimately, FinTech increases the efficiency of financial markets in providing faster financial service delivery to customers in this era of digitalisation, in contrast to traditional banking services (Dandapani 2017; David-West & Nwagwu 2018; Thakor 2020).

Many scholars agree that these financial technologies, with their emphasis on quick and convenient services, can enhance revenue and operational efficiency, reduce costs and improve service quality (Mohammed & Ward 2006; Sumra et al. 2011). FinTech is currently having a significant impact on the global banking business, with developing nations, predominantly India and China, experiencing the most notable impact (Ashta & Herrmann 2021), where these technology companies have extended finance services in emerging economies.

In Ethiopia, FinTech is revolutionising the banking landscape by enhancing efficiency, promoting financial inclusion and broadening entree to banking services. Major advancements in Ethiopia include mobile banking, digital payments and remittances and alternative lending models (Oshora et al. 2021). Mobile money systems in Ethiopia have become increasingly popular, allowing individuals to carry out essential financial services, payments and transactions via mobile devices, mainly in rural areas where traditional banking infrastructure is inadequate (Hordofa 2023). FinTech solutions have also facilitated the expansion of digital payments and remittances, reducing reliance on cash-based transactions (Damtew 2020). Furthermore, the Ethiopian government has introduced policies and procedures to regulate digital financial services, with the National Bank of Ethiopia ensuring consumer protection and financial system stability (Oshora et al. 2021).

Bank employees have recognised that FinTech solutions can enhance efficiency, streamline processes and reduce manual work. Ethiopian banks are investing in training to bridge the digital technology skills gap and promote FinTech adoption. Moreover, employees' awareness of the growing customer preference for digital banking, particularly among younger customers, has led to increased FinTech adoption. However, challenges such as low Internet penetration, limited digital literacy and poor infrastructure pose obstacles to mainstream FinTech adoption in Ethiopia. Addressing these issues will be essential to fully harness FinTech's potential and advancing nationwide financial inclusion (Damtew 2020).

Scholars attempted to describe technology use and acceptance using various theoretical foundations in the previous information systems literature. These theories have been successful to varying degrees in identifying the factors that influence users' intentions and behaviours regarding technology adoption (Ojiaku et al. 2024). However, the changing nature of technology and consumer behaviour has decreased the effectiveness of a single theoretical model in addressing the intention to adopt technology (Sharif, Afshan & Qureshi 2019). Therefore, integrating a theoretical framework is crucial for understanding issues that impact the intention to use technology (Sharif et al. 2019; Wang et al. 2019; Zhou, Lu & Wang 2010). Consequently, we integrated TTF and TAM to explore the variables influencing the employees intention to use FinTech in the Ethiopian banking sector.

Task-technology fit

The TTF model, established by Goodhue (1998), asserts that for technology adoption to succeed, the qualities of a task must align with the capabilities of the technology. Goodhue and Thompson (1995) expanded on the TTF model to describe the effect of information systems on performance, building on performance impact theory, which stands for TTF and measures how well technology matches the requirements of a task, determining usage and performance impact. They define TTF as the extent to which the technology's capabilities align with the user's tasks. According to this study, two constructs, task and technology characteristics, affect TTF. By assessing the alignment between task and technology features, this model widely evaluates how information technology contributes to performance (Lee et al. 2007; Wu & Chen 2017). Task characteristics define the steps users take to convert information into output using IT, while technological characteristics refer to the tools or machinery used to perform various functions (Oh et al. 2023).

In the context of FinTech, tasks involve real-time data processing, continuous monitoring of financial information and security threats and facilitating digital financial transactions to offer seamless services to customers. Technology characteristics encompass digitalisation (such as mobile banking and online payments), automation, cloud computing, artificial intelligence and cybersecurity utilised by financial institutions. When technology supports user tasks effectively, it can boost task efficiency and effectiveness and decrease operational costs. Users are more inclined to adopt technology that offers considerable benefits in task completion, while technology lacking significant advantages may not be adopted (Daradkeh 2019; Goodhue & Thompson 1995).

Previous studies have extensively applied the TTF model to explore various aspects of technology usage, such as investigating user adoption of VR English language learning systems, exploring the business value of big data analytics, examining e-learning acceptance in higher education, studying mobile banking for individual performance (Alyoussef 2023; Muchenje & Seppänen 2023; Tam & Oliveira 2016; Wang, Huang & Lin 2020) and integrating TTF with other models like UTAUT (Ojiaku et al. 2024; Sachitra & Wimalasena 2024). Moreover, the integration of TTF and TAM models has been particularly valuable in understanding user behaviour when utilising information technology. Dishaw and Strong (1999) proposed a combined model that takes into account both attitudes towards information technology and the alignment among technology and task characteristics. Their research revealed that the combined model prominently enhanced the variation clarified by TTF or TAM alone, and also that TTF was a substantial interpreter of intention to use and perceived ease of use. Surprisingly, an unexpected finding was the nonappearance of a direct relationship between TTF and perceived usefulness. The study by Yen et al. (2010) found that TTF has a significant direct impact on the behavioural intention to adopt wireless technology; however, in this study, no significant effect of TTF on perceived usefulness (PU) and perceived ease of use (PEOU) was observed. Furthermore, studies have shown that TTF is consistently correlated with PU, PEOU and intention to use technology, meaning that users will perceive technology as helpful and simple to use when it helps perform tasks (Daradkeh 2019; Shih & Chen 2013; Witjaksono et al. 2021; Wu & Chen 2017).

However, different levels of task and technology combinations can result in varying degrees of fit, impacting employees' acceptance and intention to use technology. Junglas, Abraham and Watson (2008) classified task technology fit into ideal fit, overfit and underfit levels based on different dimensions of the task and technical features and studied the impact of different matching levels on technology usage. According to him, ideal fit refers to the exact matching between task requirements and technology functionality. Overfit occurs when technology provides an excessive amount of features beyond what is necessary for a given task, while underfit happens when the technological functionality does not meet the task requirements (Muchenje & Seppänen 2023). On the other hand, underfit has been categorised as 'too little' to specify that technology has fewer features, causing employees to be unable to perform the task, and overfit has been categorised as 'too much' to specify that technology provides much more than is needed to complete the task (Howard & Rose 2019).

Therefore, this study makes modifications to the TTF model, no longer categorising the relationship between task features, technical features and matching degree as a single-level effect but dividing it into different degrees of matching and studying the influence of different degrees of TTF on employee technology acceptance and usage intention in the study area. In the context of FinTech adoption, employees' intentions to use it will be positively impacted if they believe that its capabilities fit their task requirements to a sufficient degree. The greater the fit between FinTech and the tasks of employees, the more employees feel that a tool's specified purpose and capabilities are beneficial for their work. As a result, based on the TTF model, the following hypotheses are proposed:

H1: When the characteristics of technology fall short of the task characteristics, this underfit negatively affects bank employees' TAM and their intention to use FinTech.

H1a: Underfit negatively influences bank employees' PU of FinTech.

H1b: Underfit negatively influences bank employees' PEOU of FinTech.

H1c: Underfit negatively influences bank employees' intention to use FinTech.

H2: When the technology characteristics (TE) align well with the task characteristics (TA), this ideal fit positively influences bank employees' TAM and their intention to use FinTech.

H2a: The ideal fit positively affects bank employees' PU of FinTech.

H2b: The ideal fit positively affects bank employees' PEOU of FinTech.

H2c: The ideal fit positively affects bank employees' intention to use FinTech.

H3: When the technology characteristics (TE) exceed the task characteristics (TA), this overfit negatively impacts bank employees' TAM and their intention to use FinTech.

H3a: Overfit negatively affects bank employees' PU of FinTech.

H3b: Overfit negatively affects bank employees' PEOU of FinTech.

H3c: Overfit negatively affects bank employees' intention to use FinTech.

Technology acceptance model

The TAM, initially announced by Davis (1986) in his doctoral proposal, is a prominent framework for explaining and predicting users' acceptance and adoption of technology within organisations. Its foundation is rooted in Ajzen and Fishbein's (1975) Theory of Reasoned Action (TRA) and the Theory of Planned Behaviour (TPB) (Schifter & Ajzen 1985). Davis et al. (1989) later refined the model, highlighting behavioural intention, perceived usefulness and perceived ease of use as the critical constructs in explaining user behaviour. Consequently, TAM focuses on assessing users' perceptions of usefulness and ease of use to understand technology adoption dynamics (Awad 2020).

Perceived usefulness (PU), according to TAM, refers to the degree to which an individual believes that using technology will improve their performance or productivity (Davis et al. 1989). This construct plays a vital role in technology adoption (Venkatesh & Davis 2000), significantly influencing employees' intentions to use technology. Similarly, PEOU reflects the belief that using the technology requires minimal effort (Davis et al. 1989). Systems perceived as user-friendly and effortless to operate are more likely to be adopted (Yen et al. 2010). The convenience, user-friendliness and ease of use of a FinTech service are crucial factors that influence user adoption (Riquelme & Rios 2010). The behavioural intention in this context refers to bank employees' willingness or plan to use FinTech services while performing their duties (Al-Rahmi et al. 2021). Understanding behavioural intention is vital for FinTech companies to develop effective strategies that promote technology adoption.

Empirical research has consistently supported the TAM hypothesis, demonstrating that PU and PEOU have a significant influence on users' intentions to adopt new technologies (Akturan & Tezcan 2012; Alsmadi et al. 2022; Awad 2020; Bastari et al. 2020; Daradkeh 2019; Huang 2017; Singh, Sahni & Kovid 2020; Szopiński 2016; Yen et al. 2010). Given the extensive availability and convenience of FinTech services, it is important to investigate how PU and PEOU influence bank employees' intentions to use in the context of FinTech services. Consequently, we proposed the following hypotheses based on the TAM model:

H4: Perceived usefulness positively impacts bank employees' intention to use FinTech.

H5: Perceived ease of use positively impacts bank employees' intention to use FinTech.

Conceptual model

Dishaw and Strong's (1999) integrated model serves as the primary inspiration for the research model in this study. However, we have made significant modifications to adapt the model to the current study's context.

Firstly, we remove the tool experience construct from Dishaw and Strong's (1999) model. Goodhue and Thompson (1995) focused on task and technology characteristics, excluding individual characteristics. The study found unclear effects of individual characteristics on TTF, leading to the exclusion of this construct in current research. Because bank employees use many different financial technologies, it is more useful to look at the connection between TTF and users' intention to adopt FinTech instead of the relationship between TTF and actual usage (Yen et al. 2010). Secondly, in contrast to the utilisation of tool functionality in Dishaw and Strong (1999), this study adopts the term technology characteristics, consistent with the original construct designation in Goodhue and Thompson (1995). Thirdly, this study introduces modifications to the TTF by restructuring the relationship between task features, technological features and matching degrees. Unlike the traditional approach of treating this relationship as a single-level effect, we now segment it into varying degrees of matching. Junglas et al. (2008) classified the TTF into ideal fit, overfit and underfit levels based on diverse tasks and technological features. We thoroughly investigate the impact of these distinct matching levels of TTF on employees' FinTech adoption intentions within the banking sector as shown in Figure 1.

Methods

Measure development

This study utilised a quantitative research method, such as a self-administered questionnaire survey, to gather data and evaluate the proposed research framework regarding employees' intention to adopt FinTech in commercial banks in Ethiopia. We structured the questionnaire into two main parts. The first part focused on collecting demographic information from the participants, encompassing details such as age, gender, education level, job role and working years of experience. The second part included details on the latent constructs, task and technology characteristics of TTF (categorised as underfit, ideal fit and overfit), as well as the components of TAM, including PU, PEOU and intention to use FinTech.

The questionnaire items were designed as Likert-type statements, utilising a five-point scale from 1 (strongly disagree) to 5 (strongly agree). To assure the accuracy and reliability of information, we selected all survey items from prior research and made slight modifications to better align with the specific context of FinTech.

The scale used to measure underfit, ideal fit and overfit was adopted from the research conducted by Howard and Rose (2019). Similarly, the TAM model constructs measures of PU (three items), PEOU (three items) and intention to use (three items) based on the research conducted by Davis et al. (1989).

Data collection

The study's sample comprises employees from the top three technology-leading commercial banks in Ethiopia, namely the Commercial Bank of Ethiopia (CBE), Bank of Abyssinia (BOA) and Awash International Bank (AIB). Initially, we purposefully selected the aforementioned three banks because of their high rankings in technology utilisation.

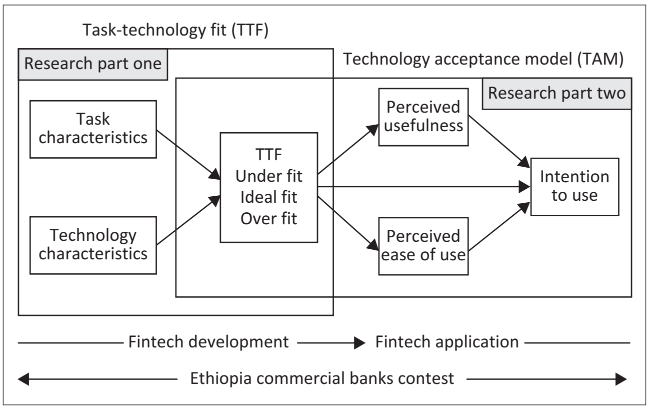


FIGURE 1: Proposed research model by integrating task-technology fit and technology acceptance model.

We then used a proportional sampling method to select participants from each bank. Next, we employed a stratified sampling technique to allocate respondents from various branches of the banks in Addis Ababa, the capital city of Ethiopia. We distributed 300 paper-based questionnaires to the participants from January to March 2023, resulting in the collection of 254 questionnaires with an 84% response rate. Out of these, 213 valid responses were considered for evaluating the proposed model.

The composition of the respondents shows that the majority are male (62%), youth between the ages of 18 and 30 (51%) and 80% are bachelor's degree holders in four major business disciplines (accounting, management, economics and marketing, in this order of relevance). The average work experience of the bank workers in the sample is 4.7 years (see Table 1).

Ethical considerations

Informed consent statement

The authors sought and obtained informed consent before and throughout the data collection process. The researcher assured them of anonymity and that their responses would be solely used for academic purposes.

Institutional review board statement

The research adhered to the following protocols: (1) Participants were fully informed about the study's purpose and procedures prior to completing the survey; (2) the study utilised a simple questionnaire collecting non-identifiable data, with no personal information such as names or addresses; (3) absolute confidentiality of the collected data was maintained throughout the research process; and (4) the questionnaire and methodology were reviewed and deemed appropriate by the researchers' affiliated institution.

As this research does not involve sensitive or private information, risks, or contentious issues, formal ethical approval is not required.

TABLE 1: Demographic characteristics across sample.

Variables	Frequency	%	Cumulative
Bank name			
Abyssinia	63	29.58	29.58
CBE	126	59.15	88.73
AIB	24	11.27	100.00
Gender			
Male	132	61.97	61.97
Female	81	38.03	100.00
Age (years)			
18–30	109	51.17	51.17
31–40	99	46.48	97.65
41–50	5	2.35	100.00
Education			
Diploma	1	0.47	0.47
Bachelor	170	79.81	80.28
Masters	42	19.72	100.00
Specialisation			
Marketing	15	7.04	7.04
Accounting	82	38.50	45.54
Economics	34	15.96	61.50
Management	76	35.68	97.18
Others	6	2.82	100.00

CBE, Commercial Bank of Ethiopia; AIB, Awash International Bank.

Data analysis and results

The obtained data were analysed using the partial least square structural equation modelling (PLS-SEM) method with Smart-PLS4 software. These SEM techniques, as suggested by Anderson, Kellogg and Gerbing (1988), were applied to validate the hypothetical model proposed in this study and to assess the correlation effects of TTF and TAM constructs on employees' intentions to use FinTech. The SmartPLS4 results demonstrate a perfect alignment of the items with their respective constructs, with item values surpassing the allowed threshold of 0.6 (Hair et al. 2019).

Measurement model

Table 2 shows that all reliability tests, including Cronbach's alpha, composite reliability and average variance extracted (AVE), exceed the recommended thresholds. According to Hair et al. (2021) and Bagozzi and Yi (1988), Cronbach's alpha and composite reliability values should be above 0.7, and AVE should exceed 0.5, in line with the standards set by Fornell and Larcker (1981). Furthermore, the factor loadings for the items exceed the critical threshold of 0.708. The measurement model presented in Table 2 meets all these requirements.

Average variance extracted is a test of convergent validity, which measures the extent of variation measured by items within a construct. We expect this measure to have the highest possible value. All the values in Table 3 exceed 0.7, confirming the model's convergent validity.

To carry out a discriminant validity test, we utilise a heterotrait-monotrait (HTMT) ratio of correlations approach (Hair et al. 2019). The findings reveal that all HTMT values are below the required threshold of 0.85 (Hair et al. 2019), as indicated in Table 3. Thus, the standard for discriminant validity was met.

Consequently, we confidently assert that our model fulfils the necessary criteria for validating and confirming the reliability of the measurement model, thereby enabling us to proceed with the evaluation of the structural model.

Structural model

We evaluate the proposed structural path by conducting structural equation modelling using Smart-PLS. The assessment of the structural model involves an examination of *R*-squared (R^2) values, which quantify the degree to which independent variables account for the observed variance in the dependent variable. According to Hair et al. (2021),

TABLE 2: Evaluation of convergent validity and reliability.

Construct	Items	Factor loadings	Cronbach's alpha	Composite reliability	AVE
Under fit	UF1	0.91	0.89	0.90	0.82
	UF2	0.88	-	-	-
	UF3	0.93	-	-	-
Ideal fit	IF1	0.87	0.84	0.84	0.76
	IF2	0.87	-	-	-
	IF3	0.86	-	-	-
Over fit	OF1	0.83	0.82	0.83	0.73
	OF2	0.90	-	-	-
	OF3	0.84	-	-	-
Perceived usefulness	PU1	0.90	0.88	0.89	0.81
	PU2	0.85	-	-	-
	PU3	0.95	-	-	-
Perceived ease of use	PEOU1	0.89	0.85	0.85	0.77
	PEOU2	0.86	-	-	-
	PEOU3	0.89	-	-	-
Intention to use	IU1	0.93	0.90	0.91	0.83
	IU2	0.84	-	-	-
	IU3	0.95	-	-	-

AVE, average variance extracted; IU, intention to use; PEOU, perceived ease of use; PU, perceived usefulness; OF, over fit; UF, under fit; IF, ideal fit.

TABLE 3: Heterotrait-Monotrait discriminant validity tests.

Construct	IF	IU	OF	PE	PU	UF
Ideal fit	-	-	-	-	-	-
Intention to use	0.80	-	-	-	-	-
Over fit	0.28	0.21	-	-	-	-
Perceived ease of use	0.85	0.79	0.28	-	-	-
Perceived usefulness	0.80	0.88	0.20	0.89	-	-
Under fit	0.12	0.19	0.11	0.10	0.22	-

IU, intention to use; PEOU, perceived ease of use; PU, perceived usefulness; OF, over fit; UF, under fit; IF, ideal fit.

the R^2 ranges from 0 to 1, with higher levels demonstrating a higher degree of illustrative power. Generally speaking, R^2 values of 0.75, 0.50 and 0.25 can be classified as substantial, moderate and weak, respectively (Hair, Ringle & Sarstedt 2011; Henseler, Ringle & Sinkovics 2009).

The R^2 for the main dependent variable, intention to use, is about 0.679. All variables (overfit, ideal fit, underfit, PU and PEOU) together explain 67.90% of the variation in intention to use. A threshold exceeding 0.5 denotes a moderate effect, in line with the criteria set forth by Hair et al. (2021), necessitating the independent variables to elucidate at least half of the variance in the dependent variable. Furthermore, the R^2 values for perceived usefulness and perceived ease of use amount to 0.646 and 0.519, respectively, indicating a moderate impact on these constructs and elucidating more than half of their variability (64.6% and 51.9%, respectively). Therefore, the R^2 values obtained in the current investigation were statistically significant.

Moreover, the structural model exhibits favourable indices, with a standardised root mean square residual (SRMR) of 0.05 and a normed fit index (NFI) of 0.81. As per the benchmarks established by Hu and Bentler (1999) and Browne and Cudeck (1992), SRMR values should not exceed 0.08, while NFI values should approach 0.9. In addition, the results of correlation tests measured by a variance inflation factor (VIF) show the values for all items are below 5. This suggests that our model is free from multicollinearity issues, as recommended by Hair et al. (2011).

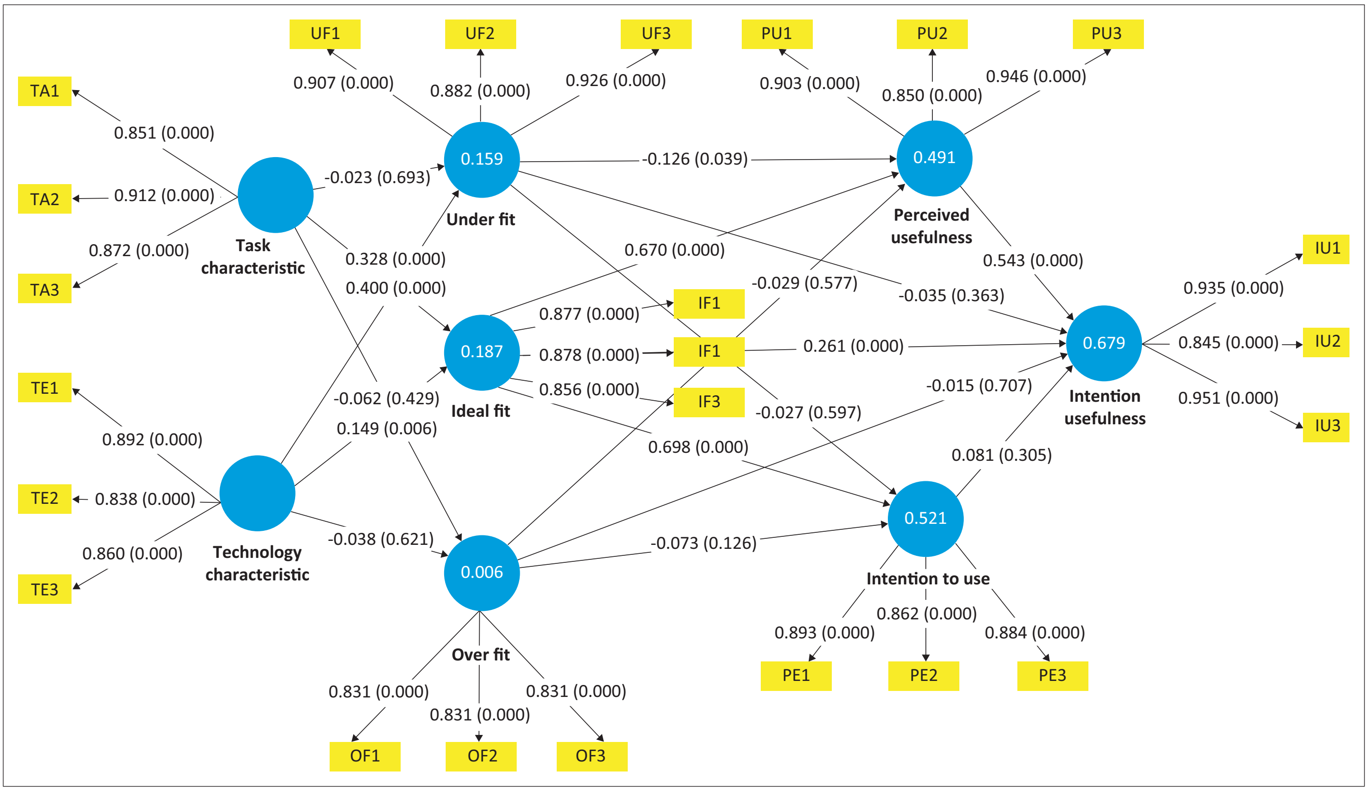
In this study, structural equation modelling (SEM) was used to test the proposed hypotheses. The expected correlations are presented in Table 4, with path coefficients calculated through bootstrapping using 5000 subsamples, as depicted in Figure 2. Moreover, the results of this study revealed that TTF may operate through multiple loops or pathways, i.e., through the ideal fit and under-fit scenarios. This underscores the significance of employing and validating the use of disaggregated TTF (over, ideal and underfit) instead of the traditional aggregate variable TTF in previous studies. The conclusive results of this study can be briefly summarised as follows:

When the technology characteristics are lower than the task characteristics, the underfit negatively affects bank employees' TAM and intention to use FinTech. The findings indicate that the underfit (H1a) has a negative and significant impact (β = –0.126, $p < 0.05$) on bank employees' PU of FinTech. Hence, H1a was supported. The underfit has a negative and statically insignificant impact on bank employees' PEOU (H1b) (β = –0.027, $p > 0.05$) and intention to use (H1c) (β = –0.035, $p > 0.05$). Therefore, H1b and H1c were not supported.

When the technology characteristics well match the task characteristics, the ideal fit has a positive impact on bank employees' TAM and intention to use. That is, the ideal fit has a positive and significant impact on bank employees' PU (H2a) (β = 0.275, $p < 0.001$), PEOU (H2b) (β = 0.697, $p < 0.001$) and intention to use FinTech (H2c) (β = 0.261, $p < 0.001$). Therefore, H2a, H2b, and H2c were supported. However, the overfit has a statically insignificant impact on bank employees' PU (H3a) (β = 0.013, $p > 0.05$) PEOU (H3b) (β = –0.073, $p > 0.05$), and intention to use (H3c) (β = –0.015, $p > 0.05$). Hence, H3a, H3b, and H3c were not supported.

TABLE 4: Results of hypothesis testing.

Hypothesis	Relationships	Beta (β)	*T* statistics	*p*-value	Decision
(H1a)	Under fit -> Perceived usefulness	-0.13	2.12	0.04	Accepted
(H1b)	Under fit -> Perceived ease of use	-0.03	0.53	0.57	Rejected
(H1c)	Under fit -> Intention to use	-0.03	0.91	0.36	Rejected
(H2a)	Ideal fit -> Perceived usefulness	0.27	3.82	0.00	Accepted
(H2b)	Ideal fit -> Perceived ease of use	0.70	16.21	0.00	Accepted
(H2c)	Ideal fit -> Intention to use	0.26	3.51	0.00	Accepted
(H3a)	Overfit -> Perceived usefulness	0.01	0.28	0.78	Rejected
(H3b)	Overfit -> Perceived ease of use	-0.07	1.53	0.13	Rejected
(H3c)	Overfit -> Intention to use	-0.01	0.38	0.71	Rejected
(H4)	Perceived Usefulness -> Intention to use	0.54	7.66	0.00	Accepted
(H5)	Perceived ease of use -> Intention to use	0.08	1.02	0.31	Rejected



IU, intention to use; PEOU, perceived ease of use; PU, perceived usefulness; OF, over fit; UF, under fit; IF, ideal fit; TE, technology characteristics; TA, task characteristics.

FIGURE 2: Results of the research model.

The PU positively and significantly influences bank employees' intention to use (H4). This hypothesis is proved correct with a positive and significant coefficient ($\beta = 0.542$, $p < 0.001$). Thus, H4 was supported. The results do not support our hypothesis (H5) that PEOU will influence employees' intentions to use.

Figure 2 displays the results of the research model.

Discussion

FinTech is widely recognised as an instrument for improving financial inclusion, aiming to broaden the availability of financial services to all individuals, especially those historically marginalised. Despite these advancements, the adoption of FinTech remains uneven and limited, particularly in developing countries. This study delves into the intricate and varied dimensions of human behaviour, concentrating on the factors that shape individuals' perceptions, utilisation and acceptance of FinTech services. By incorporating the TTF and TAM models, this research provides a nuanced insight into the determinants influencing employees' willingness to adopt FinTech within the banking industry.

Our results align with previous studies emphasising the influence of TTF (in this case, the ideal fit) on technology adoption intention (Daradkeh 2019; Shih & Chen 2013; Witjaksono et al. 2021; Wu & Chen 2017). Particularly, we found that an ideal fit positively and significantly impacts PU, PEOU and employees' intentions to use. This suggests that when FinTech aligns well with employees' tasks, they are more likely to perceive these technologies as useful and easy to use, ultimately increasing their intention to adopt them. Interestingly, our study also revealed that the underfit negatively and significantly impacts PU. This finding highlights the importance of ensuring that FinTech adequately meets the needs and requirements of bank employees. When FinTech is perceived as not aligning well (when the task and technology characteristics are mismatched) with the employees' tasks, they may be viewed as less useful, thereby hindering their adoption. Unexpectedly, our findings did not reveal a significant relationship between overfit and PU, PEOU or intention to use FinTech. This unexpected result suggests that providing excessive features and functionalities beyond what is necessary for employees' tasks may not necessarily enhance their perception of usefulness or intention to use. This finding underscores the importance of striking a balance between providing sufficient capabilities for technologies to meet employees' needs without overwhelming them with unnecessary features.

Moreover, as expected and consistent with prior research (Alalwan et al. 2016; Alsmadi et al. 2022; Davis et al. 1989; Singh et al. 2020; Yen et al. 2010) on technology acceptance, our study confirms the significant role of PU in determining employees' intention to use FinTech context. However, the effect of PEOU on intention to use was found to be insignificant, which is inconsistent with the previous studies (Alalwan et al. 2018) conducted on the customer adoption of mobile Internet. The reason for the unexpected finding may be attributed to the fact that PEOU strongly influences customers' IU, while, from the perspective of bank employees and the FinTech context, PU may be vital because of task requirements. Through learning and training, employees can increase their intention to utilise FinTech, which is useful but not user-friendly. Thus, employees' PU affects IU more than PEOU, but from the customers' perspective, PEOU affects IU more.

Implications

This study offers significant theoretical contributions to the information system literature in various features. Firstly, by integrating the TTF and Technology TAM, it presents a dual-theoretical framework that enhances understanding of FinTech adoption from an employee perspective. Secondly, the existing literature on FinTech inadequately addresses the influence of varying degrees of TTF on employees' PU, PEOU and intention to adopt financial technology. This study advances the literature by introducing a comprehensive framework for evaluating FinTech adoption through the lens of TTF at three levels: underfit, overfit and ideal fit. It explores employees' perspectives on FinTech adoption, thereby extending the TTF model and contributing theoretically. The findings confirm that the direct effect of ideal fit positively and significantly influences PU, PEOU and intention to use FinTech, while underfit negatively affects perceived usefulness. Thirdly, this study extends the TTF-TAM model to the Ethiopian FinTech sector, thereby broadening the application of these models to emerging economies.

From a practical perspective, the study provides valuable insights for practitioners in the banking sector to enhance FinTech adoption among employees. The study's findings underscore the significance of aligning tasks with technology to optimise employees' PU, PEOU and intention to use FinTech. Organisations can leverage these insights to design and implement FinTech that aligns with employees' needs and preferences, ultimately fostering the successful adoption of these technologies into their organisations. The study also underscores the negative impact of the underfit on perceived usefulness, emphasising the importance of addressing task-technology misalignments. Practitioners can use this information to tailor training programmes, improve digital literacy and create awareness about the benefits of FinTech to overcome adoption barriers. By incorporating the practical implications derived from the study, the banking sector can effectively promote and facilitate the adoption of FinTech in Ethiopian commercial banks, leading to enhanced efficiency and customer satisfaction.

Conclusion

In summary, this research investigates factors that influence the acceptance of FinTech among bank employees in Ethiopia, with a specific focus on incorporating TAM and TTF models. By utilising primary data collected from 213 employees across three major commercial banks in Ethiopia, the study uncovers a nuanced relationship.

The findings indicate that the ideal fit positively and significantly influences PU, PEOU and employees' intentions to use FinTech. When there is an optimal or ideal fit between the technology's abilities and the demands of the task, employees are more likely to perceive FinTech as useful and easy to use. This, in turn, increases their willingness to adopt and use it. These findings have significant implications for financial organisations seeking to promote the adoption of FinTech among their employees. By carefully aligning the features and functionalities of FinTech with the specific tasks and requirements of the employee, organisations can foster a sense of ideal fit, which is likely to enhance the PU and PEOU of the technology. This, in turn, can contribute to higher levels of technology adoption and, ultimately, more successful FinTech implementation within the organisation.

The study's key additional finding is that underfit has a negative and significant impact on PU. This underlines the critical importance of ensuring that FinTech adequately meets the needs and requirements of bank employees. Employees may perceive FinTech as less useful if it does not align well with their tasks, which could hinder its overall adoption within the organisation. Surprisingly, we found an insignificant relationship between overfit and PU, PEOU or intention to use FinTech, suggesting that excessive features may not enhance employees' perception of usefulness or intention to use FinTech. Moreover, our study also confirms that PU is a crucial factor in influencing employees' intention to adopt FinTech.

This study is anticipated to offer valuable insights for future research efforts. By affirming the importance of categorising TTF as underfit, ideal fit or overfit rather than assuming a linear correlation between TTF and TAM, this research contributes a unique perspective. In addition, the emphasis on employees' perspectives rather than customers distinguishes this article from most previous studies. By shedding light on the intricate dynamics of technology adoption in emerging markets, this study enriches the existing literature. Moreover, these findings hold important implications for policymakers and industry practitioners seeking to promote the effective adoption and use of FinTech in the banking sector, thereby enhancing financial inclusion and driving economic development in Ethiopia and beyond.

Nevertheless, it is crucial to acknowledge certain limitations of this study. Firstly, the sample was confined to employees of three commercial banks in Ethiopia, potentially constraining the generalisability of the findings. Future research could broaden the sample to encompass employees from a broader spectrum of financial institutions and industries. In addition, the use of self-reported data may introduce the potential for social desirability bias. Subsequent research could integrate objective measures of technology adoption behaviour to mitigate this bias. Future research could also further examine the role of organisational factors and cultural influences on FinTech adoption to offer a more comprehensive understanding of technology adoption dynamics in emerging markets.

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Authors' contributions

A.A.S. and S.W. conceptualised the study and methodology, collected and analysed the data and wrote the original and revised manuscripts. N.Z. performed the statistical analysis, curated the data and supervised the study. L.W. designed the study, conducted the data analysis and interpretation and wrote the original and revised manuscripts. All authors read and approved the final version of the manuscript.

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Data availability

Data are available upon reasonable request from the corresponding author, L.W.

Disclaimer

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