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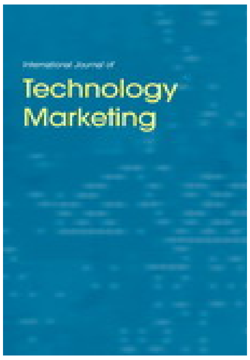

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Integrating TTF and UTAUT models to illuminate factors that influence consumers' intentions to adopt financial technologies in an emerging country context

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Abstract: Previous studies show that although financial technologies (Fintech) bridge the financial inclusion gap, its rate of adoption is low. This study aims to develop understand of factors that influence consumers' intentions to adopt financial technologies (Fintech) for savings, loans, and investment by testing a model that integrates the unified theory of acceptance and usage of technology (UTAUT) and task-technology fit (TTF) model. Data was collected from a cross-section of 324 respondents online. Structural equation modelling via smart PLS 3.0 was used to test the hypothesised relationship. The result showed that the TTF and UTAUT integrative model is robust and adequately explained Fintech adoption. Performance expectancy and social influence significantly affected behavioural intentions, and effort expectancy significantly predicts performance expectancy. Interestingly, TTF predicts use behaviour but not significant on adoption intention. Finally, task characteristics strongly predict effort expectancy and performance expectancy. Focusing on user perceptions of the technology and neglecting the effect of the task technology fit, as commonly done in extant literature, may be not enough. Thus, this study fills this gap and integrates both UTAUT and TTF to facilitate understanding of illuminate factors that influence consumers' intentions to adopt financial technologies in an emerging country context.

Keywords: task-technology fit; TTF; UTAUT; performance expectancy; effort expectancy; financial technologies; Fintech; adoption intention; consumers' intentions; emerging country context.

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1 Introduction

The neo-classical theorist Joseph Schumpeter (1883–1950) commented on the effect of technical innovation on economic growth and fluctuation by arguing that innovation places companies in a state of dynamic disequilibrium. Firms, thus, continually dismantle the old order of economic activity (technological, organisational and managerial) and simultaneously invent and build a new one [Nolan (1996) cited in Osarenkhoe (2006, p.116)]. "In the past few thousand years, the way we pay has changed just three times – from coins to paper money, to plastic cards. Now we're on the brink of the next big shift that is the use of mobile payment services" [Sharma et al. (2018) cited in Srivastava and Singh (2020, p.378)].

The internet and its Web 2.0 technologies such as social media, smartphones, and mobile applications have revolutionised and simplified consumer behaviour on the one hand. On the other hand, it has cropped-up a generation of empowered consumers who are more sophisticated and readily amenable to changes in consumption trends (Porter, 2008). Consumers now practically deploy these digital technologies to transform almost every facet of their daily lives (Hanafizadeh and Kim, 2020): From commuting to communicating; from finding things to financial transactions. The use of the internet and its enabling technology for financial transactions, cut across such services as investing, savings, borrowing, paying bills, transferring funds, and asset management (Patil et al., 2020; Srivastava and Singh, 2020). This marriage between finance and technology, christened 'Fintech', has disrupted the financial ecosystem and led to the growth and proliferation of online savings, loans, and investment schemes across the globe (OSIP). Consequently, the Fintech sector has attracted over US$55 billion in investment globally, with much of the funding in China and strong gains in other markets, including Nigeria (Accenture, 2019). For instance, investment in the Nigeria Fintech market grew by more than 25% to over US$600 million between 2014 and 2019 (Kola-Oyeneyin et al., 2020).

Fintech is a line of business that uses software to provide financial services. Financial Stability Board (2017) defined Fintech as technology-enabled innovation in financial services that could result in new business models, applications, processes or products with an associated material effect on providing financial assistance. In this study, Fintech refers to the innovative financial service providers that leverage on the internet, smartphones, and mobile apps to provide savings, loans, and investment opportunities to customers (Wang et al., 2019; Srivastava and Singh, 2020). Where customers can conveniently save money with discipline, make loan request, and make investments. Examples of Fintech offering such service as *Piggyvest*, *Crowdyvest*, *Kuda*, *Carbon*, *Alat* and *Vult*. Generally, Fintech offers innovative solutions in payment, wealth management, lending, crowd-funding, capital market, and insurances using mobile applications (Lee and Shin, 2018; Srivastava and Singh, 2020). Despite its growing importance, the impact made by Fintech is still only a fraction of its potential (Kola-Oyeneyin et al., 2020) and the scale of adoption is still very limited. Similar observation was made in India by Patil et al. (2020). In the Nigerian context, with a population of over 200 million, more than 40% of Nigerians are still underserved and unbanked.

1.1 Research gap

Notwithstanding the growing importance of Fintech, empirical research examining the phenomenon, especially regarding consumer behaviour is relatively scant (Gimpel et al., 2018). Prior study in this domain investigated Fintech adoption predictors (Stewart and Jürjens, 2018; Mazambani and Mutambara, 2019) or Continuance intention (Ryu, 2018; Wang and Guan, 2019) from the perspectives of theory of reasoned action (TRA), theory of planned behaviour (TPB), net valence framework. Moreover, these studies focused on the psychological factors of Fintech adoption. Given that Fintech require the use of information systems to perform financial tasks online, empirical and anecdotal evidence suggests that consumers rarely complete online tasks due to the perceived difficulty of using a technology (Aljukhadar et al., 2014). Therefore, it is essential to understand the extent consumers believe the information systems, financial tasks requirement, and the fit between the tasks and technology will help improve their performance (Rahman et al., 2021; Srivastava and Singh, 2020; Zhou et al., 2010).

The task-technology fit (TTF) model posits that individuals will use a technology based on the fit between the technological characteristics and task requirements

(Goodhue, 1995; Goodhue and Thompson, 1995). In this study, the TTF model has been integrated with the technology acceptance model (TAM), unified theory of acceptance and usage of technology (UTAUT), social cognitive theory (SCT) and DeLone and McLean (D&M) model (Tam and Oliveira, 2016a, 2016b; Zhou et al., 2010) to explain technology adoption intention in an emerging market context. The rationale for intergrating these models is that it yields a better assessment and a more robust account underlying cause-and-effect relationships which a single model cannot provide (Wang et al., 2019). For instance, the TAM and UTAUT highlights technology adoption intention but not use of technology, but the TTF emphasises on technology use. Moreover, the TTF has been used in the context of involuntary use of technology such as work environment, integrating it with UTUAT gives it the validity it needs in the voluntary environment (Baxi and Patel, 2021). In addition, the TTF model helps us predict both current and future use of technology (Aljukhadar et al., 2014).

1.2 Objective of the study

This study aims to develop understand of factors that influence consumers' intentions to adopt financial technologies (Fintech) for savings, loans, and investment by testing a model that integrates the unified theory of acceptance and usage of technology (UTAUT) (Venkatesh et al., 2003) and task-technology fit (TTF) model (Goodhue and Thompson, 1995). Specifically, the study examined the technology and task characteristics fits, and the extent this fit predicts Fintech adoption intention and actual use behaviour.

1.3 Contributions of this study

Simply focusing on user perceptions of the technology and neglecting the effect of the task technology fit, as commonly done in extant literature, may not be enough. Thus, this study fills this gap and integrates both UTAUT and TTF to facilitate understanding of illuminate financial technologies user adoption factors that influence consumers' intentions to adopt financial technologies in an emerging country context. A second contribution is to fill the research gap identified in AlSaleh and Thakur (2019) by examining consumers effort and performance expectancy, social influence, and facilitating conditions effect on behavioural intention. Thirdly, the relationship between the effort and performance expectancy and technology characteristics was also examined. Fourthly, in comparison with the fragmented TTF and UTAUT models, the integrated model illuminates additional dimensions of user adoption, showing the explanation advantage of the integrated model.

2 Literature review and theoretical background

Mobile payments (mobile wallet or m-payment services) for financial transactions have transformed mode of transaction from physical cash mode to digital mode of payments (Sharma et al., 2018) within different domains like the consumer to business (C2B), consumer to consumer (C2C), consumer to machine (C2M) and consumer to online (C2O) services (Shin, 2009).The rise in smartphone ownership and increased internet penetration ushered in the Fintech 3.0 era. This era saw the prominence of mobile payments, increased start-up activity and innovation, financial inclusion and regulation (Srivastava and Singh, 2020).

The Information systems literature encompasses studies that attempt to explain technology use and adoption using various theoretical underpinnings. These theories have succeeded at varying levels in highlighting the factors that affect customer adoption intention and technology use behaviour. However, the changing nature of consumer psychology and complexity of human behaviour has shrunk the efficacy of a single theoretical framework in explaining intention towards adopting technology (Sharif et al., 2019). This calls for an integrative theoretical framework for understanding factors that influences intention to adopt (see Zhou et al., 2010; Oliveira et al., 2014; Sharif et al., 2019). Accordingly, we integrate the UTAUT and TTF to examine the adoption and use of financial technologies.

2.1 Unified theory of acceptance and use of technology

The UTAUT advanced the TAM and seven other competing models to explain drivers of IS technology adoption (Venkatesh et al., 2003). The theory posits that performance expectancy, effort expectancy, social influence and facilitating conditions are direct determinants of IS/IT adoption and usage (AlSaleh and Thakur, 2019; Venkatesh et al., 2003). The UTAUT model has been widely used across various discipline for its robustness in streamlining overlapping constructs from existing IS theories into a unified model. Previous studies have used the UTAUT model to explain internet banking, mobile banking (Al-Saedi et al., 2020; Purwanto and Loisa, 2020), mobile payment (Morosan and Defranco, 2016; Srivastava and Singh, 2020), and cashless payment (Rahman et al., 2020). Other studies have extended the UTAUT model by merging it with other models such as the TTF (Sharif et al., 2019; Wang et al., 2020; Zhou et al., 2010), TPB (Kaye et al., 2020), DeLone and McLean IS theory (Slade et al., 2015; Tam and Oliveira, 2016) or with other variables such as trust, innovativeness, and anxiety (Patil et al., 2020; Tabrani et al., 2018; Papadopoulou and Kanellis, 2018). Despite its widespread use and validation across discipline, it has rarely been used to investigate Fintech adoption.

2.2 Task-technology fit

Task-technology fit model posits that the functions of a technology should match the tasks that individuals perform (Goodhue, 1995; Goodhue and Thompson, 1995). It indicates the task and technology characteristics as the key aspects in forming task-technology fit (Wang et al., 2020). The theory believes that technology's acceptance and use relies on the technology's perceived ability to perform some assigned functions optimally. TTF consist of four basic constructs which are task characteristic, technology characteristic, performance benefits, and technology use. Task is context specific and varies. For Fintech, it relates to the ease and convenience of performing financial transactions such as taking a loan, saving money, or managing ones account. Technology characteristic represents the designs, interface, quality, and features of financial applications on digital devices. The TTF has also been richly used to examine the adoption and use of technology in previous studies. For instance, Aljukhadar et al. (2014) investigated successful completion of online task, Bere (2018) examined online learning, and Tam and Oliveira (2016) examined mobile banking. The TTF and has been combined with different competing models with better explanatory power such as with TAM (Vanduhe et al., 2020; Wu and Chen, 2017; Yen et al., 2010), D&M IS theory (Tam and Oliveira, 2016), and UTAUT (Wang et al., 2020; Zhou et al., 2010).

3 Conceptual framework and hypotheses development

3.1 Performance expectancy

According to Venkatesh et al. (2003), performance expectancy (PE) is the extent an individual believes the use of a system will help achieve stated goals. Performance expectancy is akin to the perceived useful in TAM and relative advantage in IDT (Baumgartner and Green, 2008) and outcome expectation in SCT (Venkatesh et al., 2003). In the context of online savings and investment (OSIP) Fintech adoption, performance expectancy is related to the degree users belief that using financial technologies will help them achieve their savings, investment, and wealth management goals. Previous research has shown positive effect of PE on consumer behaviour (Al-saedi et al., 2020; Wang et al., 2020; Keong, 2016; Zhou et al., 2020). Al-saedi et al. (2020) and Rahman et al. (2020) found it to be the strongest predictor of M-payment usage intention. In a similar vein, Keong (2016) found that P.E. impacts individual intention to adoption technology while Wang et al. (2020) found it positively predicts behavioural intention to use HWD. In light of the current study, this hypothesis was developed.

H_1 Performance expectancy has a positive influence on Fintech adoption intention.

3.2 Effort expectancy

Effort expectancy is the degree of ease related to the use of a technology (Wang et al., 2020). The higher a technology is expected to make a task easy, the higher the chances users' would use it (Al-saedi et al., 2020). When using Fintech, consumers expect that the system will require little effort to save and invest. Recent studies have acknowledged the germane role of effort expectancy in influencing technology adoption intention (Al-saedi et al., 2020; Wang et al., 2020; Patil et al., 2020). Al-saedi et al. (2020) found a positive and significant effect between effort expectancy and m-payment usage. Similarly, Patil et al. (2020) found EE to significantly predict attitude towards m-payment adoption. Also, Wang et al. (2020) found that EE positively influenced consumers' intention to use high definition wearable device.

Furthermore, the degree to which an IS system is believed to require minimal effort will affect how useful it is perceived to facilitate goal attainment. In other words, effort expectancy should predict performance expectancy. Previous research shows significant effect for effort expectancy on performance expectancy, similar with previous studies (Akinwale and Kyari, 2020; Wang et al., 2020; Zhou et al., 2010). In line with the above analysis, this hypothesis was formulated:

H_2 Effort expectancy has a positive effect on Fintech adoption intention.

H_3 Effort expectancy has a positive effect on performance expectancy.

3.3 Social influence

Social influence is defined as the degree to which consumers perceive that their important others (e.g., family, friends, colleagues, etc.) support their specific behaviour such as using specific technology (Wang et al., 2020; Patil et al., 2020; AlSaleh and Thakur, 2019). Rahman et al. (2020) defined it as the degree to which referent others believe that an individual should adopt and use a new system. It is when consumers regard the opinions of their significant others and believe they would support their use of certain technology. Consumers would use a technology and strengthen their relationships with important others when they perceive their important others believe they have the self-efficacy to do so (Wang et al., 2020). Previous studies show mixed result for the effect of social influence on behaviour intentions (Al-saedi et al., 2020; Wang et al., 2020; Wu and Chen, 2017; AlSaleh and Thakur, 2019). While Al-saedi et al. (2020), Rahman et al. (2020) and Wang et al. (2020) reported a positive and significant effect for social influence on intention to use a technology, in contrast, Huang and Chang (2017) and Wu and Chen (2017) observed that social influence does not in any way determines adoption intention. However, we expect social influence to positively predict Fintech adoption intention and hypothesise as follows:

H_4 Social influence has a positive effect on Fintech adoption intention.

3.4 Facilitating conditions

This is the extent to which an individual believes that organisational and technical infrastructures are available to support the use of a system (Venkatesh et al., 2003). Similarly, it refers to environmental and technical resources that encourage system use (Verkijika, 2018). Fintech ecosystem consists of startups, technology developers, government, customers, and traditional financial institutions (Lee and Shin, 2018). A significant part of this ecosystem provides the technical facilities and organisational support for a seamless use of the technology. This suggests that as the presence of an operational infrastructure facilitates the use of Fintech, the behavioural intention to adopt it will increase (Oliveira et al., 2016; Patil et al., 2020). Existing literature mostly found a positive effect for facilitating condition on behavioural intention (Patil et al., 2020; Rahman et al., 2020; Zhou et al., 2010; Wang et al., 2020). However, Oliveira et al. (2014) found a non-significant influence of facilitating condition on behavioural intentions among university students and alumni. The present study argues for a significant and positive effect of facilitating condition on behavioural intention using data from consumers of diverse background. Thus, we hypothesised as follows:

H_5 Facilitating condition has a positive effect on Fintech adoption intention.

3.5 Task-technology fit

Task-technology fit is the degree the capabilities of a technology supports the tasks that individuals perform, indicating that task and technology characteristics are two fundamental aspects of task-technology fit (Wang et al., 2020). Goodhue and Thompson (1995) added that an IT system can only be adopted when its functionality meets the needs of the task. In other words, when the task and technology are fit, users' performance can be strengthened (Wang and Lin, 2020). The TTF consists of the relationship between individuals, tasks requirement, and technology characteristics (Goodhue, 1995; Goodhue and Thompson, 1995).

The technology characteristics can be defined as the feature, attributes and qualities of the technology that makes it suitable to perform the task effectively and efficiently (Bere, 2018). Thus, the more a technology shows appropriateness for the specific task, the higher the chances of using such technology. In contrast, a complex technology will decrease the task technology fit (Goodhue, 1995; Goodhue and Thompson, 1995). In other words, when technologies become too complex and difficult to use, then the tasks will hardly be accomplished with it. In addition, the characteristics of a technology should minimise effort and facilitate the production of the intended output. Thus, technology characteristics should relate positively with effort expectancy and performance expectancy. On the other hand, Task characteristics are generally determined as the actions people take to convert inputs into outputs (Al-maatouk et al., 2020). In the context of online savings and investment Fintech, task characteristics refers to the information-based task of finding high-yielding savings and investment products and transaction-based task of saving, investing, and retrieving money with a provider.

In the TTF model, the task and technology characteristics usually predicts the TTF and TTF predicts utilisation as confirmed in previous studies (e.g., Al-maatouk et al., 2020; Bere, 2018; Tam and Oliveira, 2016; Lu and Yang, 2014). However, Wang et al. (2020) found a non-significant effect between task characteristics and TTF while Zhou et al. (2020) found a negative relationship. Furthermore, technology characteristics has been found to positively influence effort expectancy (Wang et al., 2020; Vanduhe et al., 2020; Yen et al., 2010; Zhou et al., 2010) and performance expectancy (Yen et al., 2010) or their surrogates. Accordingly, we hypothesise as follows:

H_6 Task characteristics have a positive effect on task-technology fit.

H_7 Technology characteristics have a positive effect on task-technology fit.

H_8 Technology characteristics have a positive effect on effort expectancy.

H_9 Technology characteristics have a positive effect on performance expectancy.

H_{10} Task-Technology fit has a positive effect on Fintech adoption intention.

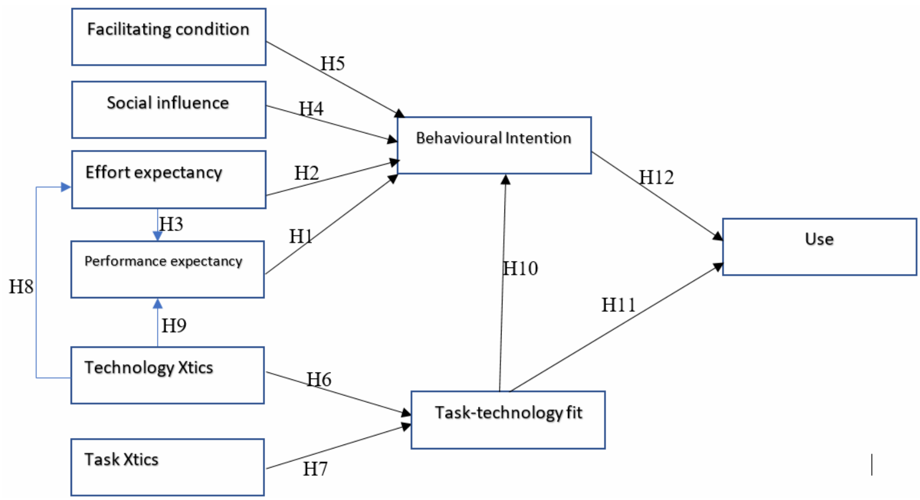
H_{11} Task-technology fit has a positive effect on user behaviour.

3.6 Adoption intention and use behaviour

Adoption intention is defined as the conscious plan to indulge or not indulge a specific future behaviour (Slade et al., 2015). It can also be described as a deliberate plan to use or not to use technology in the process of performing a duty. If the adoption intention is positive, individual shall surely use the technology and vice versa. Expectedly, many contemporary studies have scrutinised and identified the impactful effect of adoption intention on actual usage of technology. Thus, adoption intention is a proper antecedent of the actual use of technology. Existing studies substantiate the impactful effect of adoption intention on actual technology usage (Phua et al., 2012; Huang and Chang, 2017). Investigating these assertions, we hypothesise:

H_{12} Fintech adoption intention has a positive effect on user behaviour.

Figure 1 Research model (see online version for colours)



4 The context of the study – emerging market of Nigerian Fintech industry

The Nigeria Fintech industry is among the top three in Sub-Saharan Africa coming behind Kenya and South Africa. However, the country is the largest player in the region with over 200 million people (Wayne et al., 2020) and a huge potential for Fintech. Its Fintech revolution can first be traced back to the pre-1980s when analogue systems such as landline and telegragh were used to facilitate banking operations. The Fintech 2.0 era spanned between late 1980s to around 2007 when banks deployed technology such as analogue phones and computer to facilitate their bank-end and front-end operations (Monye, 2019) up to when banking was gradually moved outside the banking hall using ATM, payment, and switching solutions powered by the internet. The Fintech space in this era was dominated by payment solution providers such as *Interswitch*, *E-tranzact*, and *Systemspec*.

The rise in smartphone ownership and increased internet penetration ushered in the Fintech 3.0 era. This era saw the prominence of mobile payments, increased start-up activity and innovation, financial inclusion and regulation. This era is characterised by the rise in Fintech start-ups consisting of around 250 firms with a lot of investment and funding. McKinsey report that the Nigeria Fintech firms raised over $600 million between 2014 to 2019 after Kenya which was the second-highest in Africa with over $149 million funding in 2019 alone (Santosdiaz, 2021). Santosdiaz, (2021) also reported that *Stripe* (a US-based firm) acquired Nigeria's *Paystack* for $200 million in 2021. Recently, Flutterwave collaborated with Paypal to ease cross-bounder payment on Paypal platforms for Africa merchants. Some of the major players in the Fintech sector are *Piggyvest*, *Paystack*, *Kudabank*, *Carbon*, *Remita*, *Flutterwave* and *Kuda*. In addition, this era witnessed concerted attempts to regulate the Fintech landscape. The CBN and SEC are at the forefront of this regulation. Other regulatory agencies include the Nigerian Deposit Insurance Corporation (NDIC), National Insurance Commission (NAICOM), Nigerian Communication Commission (NCC) and National Information Technology Development Agency (NITDA).

Similar to the successes of Safaricom's M-Pesa in Kenya and MTN's Mobile Money in Ghana. The near future of Fintech in Nigeria is expected to be led by the telecommunication service providers (Fintech 3.0). While most Sub-Saharan African economies are already reaping dividends of the mobile payment platform, the Nigerian Fintech is still foot-dragging. Though, the CBN payment service bank regulation was gazette in 2018, telcos are yet to explore this space. Rather, telcos have partnered with mobile banking agents to reach customers through point-of-sales machine and PIN pads using their smartphones and internet (Wayne et al., 2020). Nevertheless, the mobile money when launched is expected to further disrupt the Fintech ecosystem and usher more opportunities and growth. Furthermore, as new technologies such as artificial intelligence, cloud technology, advanced robotics, virtual reality systems, 3D printing, miniaturisation of sensors, voice recognition, block-chain technology, and crypto-currency grow and mature, the fourth Fintech revolution will be birthed to provide more efficient financial services (Mehdiabadi et al., 2020).

5 Methodology

5.1 Measure development

The measures for this study were developed based on the UTAUT and TTF model. Scale items from existing literature were adapted for the Fintech context. Items for the UTAUT model constructs were adapted from Venkatesh et al. (2003), Zhou et al. (2010) and Wang et al. (2020). TTF model constructs of technology characteristics was measured with items adapted from Wang et al. (2020) and Zhou et al. (2020) and task-technology fit items were assessed using items adapted from Wang et al. (2020) and Zhou et al. (2020). Task characteristics were assessed with items developed by the researchers for the study following the task requirements of group buying (Spies et al., 2020). Adoption intention was measured with items adapted Al-Saedi et al. (2020) and Venkatesh et al. (2003). To avoid retaining a high rate of measurement error, all constructs were measured using more than two-items (Churchill, 1979). All measurement items were measured on a 7-point Likert scale with anchors ranging from strongly agree (7) to strongly disagree (1). The questionnaire items are in the appendix.

5.2 Survey administration

Since we are interested in examining Fintech adoption intention, we collected data from consumers with one or more active Fintech app using links sent to WhatsApp groups, contacts, and Facebook feeds. Specifically, we sent the survey link to various WhatsApp groups and also sent personalised invitation to participants on their personal WhatsApp accounts. The survey link was also shared on Facebook newsfeed and timeline of the researchers. The online survey offers the benefits of fast response time, cost-efficiency, an absence of geographical boundaries, and the elimination of data entry and processing requirements (Shiau and Meiling, 2012). The survey was developed using Google Forms and distributed between May and June 2020. To ensure we sampled Fintech users in Nigeria, we included a screening question – 'which of this Fintech do you use …' – to screen out invalid responses. Also, we tested for non-response bias by comparing the sample distribution for the early and late responses using independent sample t-test. The result showed no statistically significance ($p > 0.01$) for the two groups. Hence, indicating that we do not have problems of non-response bias.

In total, 324 responses were collected as valid and used for the data analysis. Table 1 summarises the characteristics of respondents. About two-third of the respondents are male (63%) with most of them single (85%). They are mainly young adults the ages of 18 and 35 years (90%) and mostly educated to tertiary levels (88%). More than 50% are employed and work in the private or public sector.

Table 1 Profile of respondents

Variable		*Frequency*	*Valid percent*	*Mean*	*S.D*
Gender	Female	120	37.0	.63	.48
	Male	204	63.0		
Age	18–25 years	108	33.3	1.79	.71
	26–35 years	189	58.3		
	36–45 years	18	5.6		
	46–55 years	6	1.9		
	55 years and above	3	.9		
Marital status	Single	276	85.2	1.15	.36
	Married	48	14.8		
Educational qualification	WAEC	39	12.2	2.26	.66
	HND/BSC	160	50.0		
	Post-graduate	125	37.8		
Occupation	Civil servant	120	37.4	2.51	1.49
	Private employee	54	15.8		
	Self-employed	75	23.4		
	Unemployed	15	4.7		
	Student	60	18.7		
Total		324	100		

6 Results

We analysed our data using PLS-SEM technique via SmartPLS 3.0 (Ringle et al., 2005). The PLS-SEM technique's choice was based on the following rationale: First, SEM accounts for measurement error in latent variables that we do not measure directly and assess the relationships among variables simultaneously (Gebauer and Tang, 2008). Second, our model is complex involving latent variables, indicators, and structural relationships. Third, our structural model explores the UTAUT and TTF theories in Fintech and PLS-SEM is considered suitable for theory development. Finally, we test our analysis from a prediction perspective (Hair et al., 2019).

Table 2 Evaluation of Constructs internal consistency, reliability and convergent validity

Construct	*Construct code*	*Items-loading*	*Cronbach's*	*rho_A*	*C.R*	*AVE*
Effort expectancy	EFX1	0.702	0.687	0.699	0.808	0.515
	EFX2	0.748				
	EFX3	0.778				
	EFX4	0.634				
Facilitating conditions	FAC1	0.744	0.772	0.774	0.853	0.592
	FAC2	0.797				
	FAC3	0.768				
	FAC4	0.766				
Behavioural intentions	INT1	0.859	0.8	0.8	0.883	0.715
	INT2	0.873				
	INT3	0.803				
Performance expectancy	PEX1	0.738	0.846	0.848	0.897	0.687
	PEX2	0.864				
	PEX3	0.835				
	PEX4	0.871				
Social Influence	SIF1	0.853	0.755	0.774	0.861	0.677
	SIF2	0.899				
	SIF3	0.704				
Technology characteristics	TCC2	0.878	0.766	0.78	0.866	0.683
	TCC3	0.855				
	TCC4	0.741				
Task characteristics	TKC1	0.878	0.869	0.871	0.92	0.792
	TKC2	0.89				
	TKC3	0.902				
Task-technology fit	TTF1	0.839	0.834	0.845	0.89	0.67
	TTF2	0.862				
	TTF3	0.852				
	TTF4	0.713				
Use behaviour	USE1	0.837	0.862	0.893	0.907	0.711
	USE2	0.912				
	USE3	0.902				
	USE4	0.704				

6.1 Measurement model assessment

To prepare and confirm our data for a PLS analysis, we first conduct a measurement model analysis to ensure the latent constructs' reliability and validity. The internal consistency or reliability of construct measures the extent the manifest variables determine the latent constructs in the measurement model (Hair et al., 2019). Since all action was conceptualised reflectively, we report the indicator loadings, then internal consistency reliability using Cronbach alpha and composite reliability to validate the measurement instrument. The result shows that each item's loading is higher for the construct it was meant to measure. The loadings for most of the items are above the threshold of 0.708. As Table 2 shows the composite reliability ranges between 0.80 and 0.92. The Cronbach's alpha and rho_A were all above the threshold value of 0.70 except for the effort expectancy construct with marginal values of 0.687 and 0.699 for Cronbach alpha and rho_A, respectively. The values generally suggest that the model has adequate consistency and reliability.

Furthermore, we assessed the measurement model's convergent and discriminant validity. The average variance extracted was used to validate the measurement items convergence. As a rule, the AVE must be 0.5 (50%) or higher, suggesting that the construct explains not less than 50% of each indicator's variance (Hair et al., 2019). As table 2 also shows, the AVE values for all of the hands were all above 0.5. Hence, all the constructs share more variance with the items supposedly measuring specific constructs than with other constructs. Thus, the convergent validity of the model is verified.

Table 3 Evaluation of constructs internal consistency, reliability and convergent validity

	AI	*EE*	*PE*	*SI*	*TSK Xtics.*	*TTF*	*TCH Xtics.*	*UB*	*FC*
Adoption intention	*0.846*								
Effort expectancy	0.486 (0.638)	*0.717*							
Performance expectancy	0.624 (0.754)	0.559 (0.723)	*0.829*						
Social influence	0.542 (0.694)	0.484 (0.677)	0.374 (0.465)	*0.823*					
Task characteristics	0.593 (0.711)	0.527 (0.651)	0.589 (0.685)	0.357 (0.431)	*0.839*				
Task-technology fit	0.473 (0.57)	0.406 (0.527)	0.452 (0.525)	0.443 (0.562)	0.459 (0.532)	*0.819*			
Technology characteristics	0.534 (0.682)	0.552 (0.756)	0.596 (0.731)	0.383 (0.51)	0.559 (0.669)	0.714 (0.89)	*0.827*		
Use behaviour	0.556 (0.654)	0.351 (0.452)	0.638 (0.728)	0.385 (0.477)	0.525 (0.465)	0.606 (0.702)	0.584 (0.699)	*0.843*	
Facilitating condition	0.439 (0.546)	0.505 (0.679)	0.514 (0.634)	0.557 (0.437)	0.485 (0.591)	0.481 (0.585)	0.484 (0.612)	0.658 (0.535)	*0.769*

Note: HTMT in parenthesis.

Discriminant validity measures the extent a latent variable is empirically different from other constructs in the model (Hair et al., 2019). We assessed the discriminant validity using the Fornell and Larcker (1981) criteria and the heterotrait-monotrait ratio (HTMT) (Henseler et al., 2015). Table 3 reports that the correlation between the diagonal constructs is more significant than the correlation between the off-diagonal constructs. This showed that the average variance shared between a construct and its measures are more significant than the construct's variance and any other constructs in the model. Also, As shown in Table 3, the HTMT are all below the threshold of 0.85 benchmarks except for the correlation between task-tech fit and tech characteristics (0.89) below the threshold of 0.90 for constructs conceptually similar (Hair et al., 2019; Henseler et al., 2016). These results demonstrate that there are no discriminant validity problems. Therefore, it is safe to conclude that our model satisfies the condition for validating and confirming the measurement model's reliability to continue with the structural model assessment.

6.2 Structural model assessment

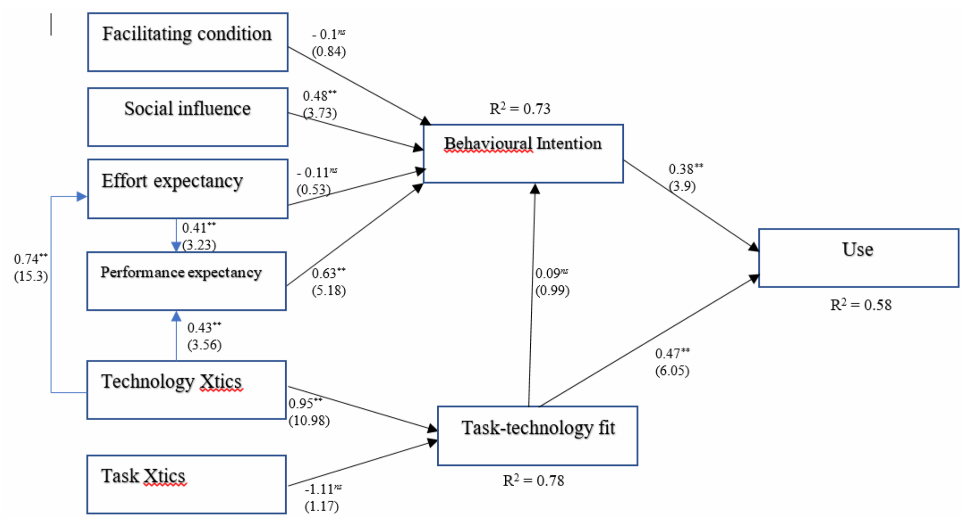
The hypothesised structural path is assessed using structural equation modelling run through partial least squares via SmartPLS version 3.0 (Ringle et al., 2005). The structural model is evaluated through the R^2 values, representing the variance explained in the endogenous constructs. The path coefficient significance shows the strength and direction of the relationship between the dependent variables and the independent variables. The path coefficients in a PLS model are the same as the standardised beta coefficients in regression analysis (Hair et al., 2011; Hussain et al., 2020). The t-statistics and the 95% confidence interval (C.I.s) tests the significance of the hypotheses in the structural paths at the 0.05 level. The model testing result showed that the R^2 values are generally accepted because they are more significant than the recommended 10% (Falk and Miller, 1992; Hussain et al., 2020). The R^2 statistics was 58% for use behaviour, 73% for behavioural intention, 61% for performance expectancy, 55% for effort expectancy, and 78% for TTF. According to Chin (1998), R^2 values of 0.19, 0.33 and 0.67 can be translated as weak, moderate, and substantial, respectively. Therefore, the R^2 values for the current study were most significant.

Table 4 Result of hypotheses testing and confidence interval

Hypotheses	*Paths*	*B*	*T*	*p*	*Confidence interval*		*Decision*
					2.50%	*97.50%*	
H1	Performance expect → Adoption int.	0.625	5.182	0.000	0.437	0.911	Accept
H2	Eff expect → Adoption int.	–0.110	0.531	0.595	–0.605	0.151	Reject
H3	Eff expect → Performance expect	0.410	3.234	0.001	0.156	0.655	Accept
H4	Social influence → Adoption int.	0.482	3.732	0.000	0.295	0.775	Accept
H5	Fac. cond. → Adoption int.	–0.100	0.843	0.399	–0.301	0.157	Reject
H6	Task Xtics → Task-tech. fit	–0.111	1.177	0.239	–0.304	0.063	Reject
H7	Tech Xtics →Task-tech. fit	0.952	10.98	0.000	0.790	1.130	Accept
H8	Tech. Xtics → Effort expect	0.742	15.73	0.000	0.647	0.830	Accept
H9	Tech. Xtics → Perf expect	0.429	3.558	0.000	0.196	0.671	Accept
H10	Task-Tech. fit → Adoption int.	0.089	0.996	0.319	–0.090	0.254	Reject
H11	Task-Tech. fit → Use behaviour	0.474	6.051	0.000	0.320	0.631	Accept
H12	Adoption Int. → Use behaviour	0.383	3.902	0.000	0.182	0.566	Accept

Figure 2 illustrates the hypothesised relationships with path coefficients estimated using 5,000 subsamples bootstrapping. The SEM analysis findings show that performance expectancy had a strong positive relationship with behavioural intention (β = 0.625, T = 5.182, p < 0.05). Hence, the result supported H1. Effort expectancy was not statistically significant related to behavioural intention (β = –0.11, T = 0.531, p = 0.595). Thus, H2 was not supported. However, the relationship between effort expectancy and performance expectancy (β = 0.41, T = 3.23, p < 0.05) was positive and significant supporting H3. H4 predicted a positive relationship between social influence and behavioural intentions. The result revealed a positive significant effect for social influence (β = 0.482, T = 3.732, p < 0.05) supporting H4. Hypothesis 5 predicted that facilitating condition would affect adoption intention. The result showed facilitating condition does not have statistically significant effect on adoption intention (β = –0.1, T = 0.843, p = 0.399). Therefore, H5 was not supported.

Figure 2 Result of hypotheses test (see online version for colours)



Notes: *p < 0.01, ns – not significant, t-value in parentheses.

Regarding the hypotheses addressing the relationship in the TTF, and their relationship with effort expectancy, performance expectancy, adoption intention and use behaviour, the result showed that technology characteristics was positively related to task-technology characteristics (β = 0.952, T = 10.98, p < 0.01), which supports H7. In contrast, task characteristics was not significantly related to task-technology fit (β = –0.11, T = 1.177, p = 0.239). Thus, H6 was not supported.

The integrative UTUAT and TTF model shows a strong model fit and adequately explains Fintech adoption intention. Technology characteristics related positively with effort expectancy (β = 0.742, T = 15.74, p < 0.01) and performance expectancy (β = 0.429, T = 3.558, p < 0.01), supporting supports H8 and H9. Contrarily to our prediction in H10, the hypothesis regarding the effect of task-technology fit on behavioural intention was not significant. Thus, H10 was not supported. However, the relationship between task-technology fit and actual usage was positive and significant (β = 0.474, T = 6.051, p < 0.01), supporting H11. Finally, the path from behavioural intention to use behaviour showed a statistically significant positive relationship, which supports H12. Furthermore, to permits the generalisation of the results, the C.I.s of the path coefficients also confirms the significance of the structural relationships at 95% CI as shown in Table 4.

7 Discussion

The distortions created by recent advances in internet technology in the financial industry ecosystem portend increasing challenges for traditional financial firms and redefined financial services consumption. The Fintech is believed to improve financial inclusion and serve the underserved by making financial services reach more consumers. Despite these developments, Fintech adoption is still patchy and relatively low, especially across emerging economies. This study integrates the TTF model and the UTAUT model to explain Fintech adoption. Findings from this study show that the UTAUT model explains adoption intention. As expected, performance expectancy has a positive and significant effect on behaviour intention, confirming previous results (Al-Saedi et al., 2020; Rahman et al., 2021; Wang et al., 2020; Zhou et al., 2020). In the UTAUT model, the effect of performance expectancy was strongest on behavioural intention corroborating Rahman et al. (2021) who found a more profound effect of performance expectancy on cashless payment adoption.

Similarly, consistent with previous research effort expectancy relates positively to performance expectancy (Srivastava and Singh, 2020; Akinwale and Kyari, 2020; Wang et al., 2020; Zhou et al., 2020). However, the effect of effort expectancy on behavioural intention was not significant. This result supports Zhou et al. (2010) but contradicts other contemporary literature that finds positive effects for effort expectancy on behaviour intention (Al-Saedi et al., 2020; Patil et al., 2020; Wang et al., 2020; Zhou et al., 2020).

The non-significant direct effect of effort expectancy suggests that effort expectancy influences behavioural intention through performance expectancy. A plausible explanation for the insignificant direct effect for effort expectancy could be the small screen interface and the procedural hassles of downloading, subscribing, and using a Fintech app. The downtime associated with internet connectivity, the many security features required to set-up a Fintech app, and sometimes the need to remember several passcodes may make consumers perceive the expected effort for using a Fintech app seem too complex and inhibit their desire to use the technology. The effect of social influence on behaviour intention is positive and significant supporting previous research (AlSaleh and Thakur, 2019; Al-Saedi et al., 2020; Wang et al., 2020; Verkijika, 2018) but contradicts findings by Huang and Chuang (2017) and Wu and Chen (2017). Consumers will adopt Fintech once significant others support their use of the technology. The facilitating condition was found to have an insignificant effect on behaviour intention, contradicting previous findings (Patil et al., 2020; Wang et al., 2020; Rahman et al., 2021; Verkijika, 2018) but supports Oliveira et al. (2014). The non-significant impact for facilitating condition suggests the apparent inadequacy of resources such as stable, efficient, and affordable internet and problems associated with the complexity of using I.T. systems.

The TTF model also adequately explained the behavioural intention. This study found that technology characteristics significantly affect TTF in line with previous research (Al-maatouk et al., 2020; Bere, 2018; Tam and Oliveira, 2016; Lu and Yang, 2014). As expected, the features of Fintech are believed to relate positively with the match of performing financial savings, loans, and investment transactions via an app on a smartphone. Consumers will use IT systems to perform financial tasks once it can provide secure, prompt, and ubiquitous services in real-time. However, contrary to our expectation, the financial tasks requirement did not relate significantly with the TTF confirming (Wang et al., 2020) but contradicts Zhou et al. (2020) who found a significant but negative relationship. This finding is surprising and counterintuitive. The non-significant result is plausibly related to the perceived complexity of using Fintech for financial tasks. The negative relationship between task characteristics and TTF in our model suggests that as technology's complexity increases, consumers become less likely to perform the task with the technology. Another plausible explanation is related to online data security issues, internet access, connectivity, and the complexity of the technology for completing the task. Security concerns portend severe impediments to the adoption of IT systems, especially as it relates to financial transactions. Therefore, the scepticism of losing money, system failure, and identity theft might explain the insignificant task characteristics-TTF path.

Similarly, using IT systems to perform financial tasks depend on the extent consumers can access and pay for a stable and reliable internet connection. In the context of this study, internet access is mainly via mobile data subscription which is mostly costly (Srivastava and Singh, 2020). Also, internet access is often epileptic and sometimes unavailable, which affects the reliability of the system for performing financial tasks. The insignificant path between facilitating condition and behavioural intentions further confirms this assertion.

Nonetheless, the UTAUT and TTF integrative model showed good fit and correlated significantly. Technology characteristics significantly affect performance and effort expectancy in line with extant studies (Vanduhe et al., 2020; Yen et al., 2010; Zhou et al., 2010). The functionality of the Fintech will determine the effort consumers expect to exert in using the technology and its expected performance. Furthermore, the technology-task fit showed a positive and significant effect on actual usage but does not predict behavioural intention. In other words, the perceived fit of using Fintech apps to perform financial tasks does not lead to positive behavioural intentions (i.e., TTF-B.I. path), but affects actual usage positively (i.e., TTF-use behaviour path). This is more like consumers find Fintech necessary despite the complexity or difficulty they encounter using it. Though, the TTF model was primarily used in context where IT use is non-volitional, their deployment for financial transactions are not voluntary per se. Financial service providers make their adoption inevitable, especially for traditional banking services such as transferring money, checking balances, and making payments (Rahman et al., 2021; Shin, 2009). Therefore, while consumers may not demonstrate behavioural intention using the technology to perform financial tasks, they find themselves using the technology for the purpose. Thus, the motivation to access loans and put money aside for some compelling reasons and invest in instrument with higher yields through Fintech apps outweighs consumers' weak intent to use the technology. Finally, in line with other studies on technology adoption (Phua et al., 2012), this study found that behavioural intention has a significant effect on actual usage.

8 Theoretical and practical implications

The TTF model is a significant theoretical contribution to understanding IT system adoption. This study integrates the TTF model and the UTAUT model to explain consumers' intentions to use technology to perform their financial tasks of savings, loans, and investment. We found that task characteristics have no direct effect on TTF; TTF has no direct impact on behavioural intention but actual usage. These results offer important insights into understanding the theories driving consumers' intention to adopt Fintech. First, while the TTF model has been used to explain technology adoption and use in another context, our work extends its application to the financial technology context. Our result shows a modest significance for the TTF construct on adoption intention and use behaviour. Specifically, we show that the TTF affects actual usage more than it affects consumers' adoption intentions. Thus, our result adds to theory by showing that though consumers may not express the intention to adopt Fintech, they would use the technology once they believe the technology functionalities are congruent with the task-technology fit.

Importantly, our study contributes to theory by showing that the integrative model of the TTF and UTAUT can be used to explain adoption and use of Fintech. The technology functionalities relate positively with the expected performance of Fintech apps and the effort one needs to exert to use the technology. Thus, our results highlight the mechanism through which financial technology's characteristics affect the expected performance and effort for using Fintech. Furthermore, our research provides richer insight to Fintech and I.S. research by empirically and theoretically validating an integrative model of the TTF and UTAUT model on Fintech adoption intention and use.

Our findings provide some practical implications for Fintech service providers. The study showed that technology characteristics strongly influenced TTF and effort expectancy. Also, TTF predicts actual use, but it is not a significant predictor of adoption intention. This implies that consumers' preferences to use Fintech are latent and manifest through actually usage depending on the technology's functionality. Thus, it is essential for Fintech firms to emphasise user-friendly design interfaces, promote the app's functionality and the value-added services it offers other than the traditional financial institutions, and incentivise consumers to download and try the Fintech app.

The study also showed that social influence is an essential influence on adoption intention. This is in line with AlSaleh and Thakur (2019). Therefore, Fintech firms must leverage on consumers social influence to stimulate interest and use of the technology. Using influencers, soliciting and displaying app and service reviews, and brand communities might provide an important avenue to influence consumer behaviour and get customers to try the Fintech apps. It is also important that Fintech firms pay attention to the design interface of their apps. The more user-friendly the app, the less the effort required to use the app, and the better the expected performance. In fact, designing simple and easy to use functions on the app would correlate strongly with the expected effort required to use the app. This implies that Fintech marketers should design financial service technology that requires less data consumption, easy to navigate, and secured.

9 Conclusions, limitations, and further studies direction

As Fintech becomes widespread and fill the financial inclusion gap, Fintech firms expect increased adoption. However, the adoption level has been rather low and patchy. This study shows that the TTF and UTAUT model adequately explained Fintech adoption intention and actual usage. Action was louder than intent to use for the perceived fit between the task requirements and technology. That is, user readily adopted and used a Fintech app even without manifesting intent.

This study aims to develop understand of factors that influence consumers' intentions to adopt Fintech for savings, loans, and investment by testing a model that integrates the unified theory of acceptance and usage of technology (UTAUT) and task-technology fit (TTF) model.

This research has its limitations. First, in the TTF model, tasks requirements are operationalised according to the context of the study. In this paper, we operationalised tasks characteristics based on saving, investment, loans, and wealth management task. Since, Fintech is ubiquitous and varied, we acknowledge that our operationalising may not adequately capture all the demand-side tasks of Fintech. Future studies may consider other operationalisation and focus on other forms of Fintech such as payment solutions, P2P lending, personal finance, and capital market Fintech. Furthermore, traditional banks use Fintech to leverage the services they provide to their customers. Some of these Fintech are used as a necessity. It would be interesting to know how consumers volition and tech savviness affect the adoption and use of Fintech.

Second, Fintech adoption in Nigeria is still at its infancy and the respondents participated in the study without any inducement which may reflect self-selection bias (Wu and Chen, 2017). Though, we tested for non-response bias and found it not to be a problem, we suggest future study should use probability random sampling as the population of Fintech users increases.

Third, Fintech adoption in Nigeria is still at its infancy. The respondents participated in the study without any inducement which may reflect self-selection bias (Wu and Chen, 2017). Though, we tested for non-response bias and found it not to be a problem, we suggest future study should use a probability random sampling as the population of Fintech users increases.

Finally, the study used a cross-sectional design which inadvertently makes it difficult to determine causal effects among construct. Future studies examining the model using longitudinal design should be worthwhile. Also, though our model explained 58% and 73% of the variance in use and behavioural intention, a significant part of the unexplained variance is possibly due to factors we did not account for in our model. Future study should extend the model with such other factors as *trust*, *attitude towards Fintech* and *internet penetration*. In addition, our study used Fintech user with online presence in Nigeria which limits the external validity of our findings. Future research may investigate other cultures and the unbanked who use Fintech through money agents, to account for financial inclusion.

References

Accenture (2019) *Global Fintech Investments Surged in 2018 with Investments in China Taking the Lead, Accenture Analysis Finds; UK Gains Sharply despite Brexit Doubts* [online] https://newsroom.accenture.com/news/global-fintech-investments-surged-in-2018-with-investments-in-china-taking-the-lead-accenture-analysis-finds-uk-gains-sharply-despite-brexit-doubts.htm (accessed 18 December 2020).

Akinwale, Y.O. and Kyari, A.K. (2020) 'Factors influencing attitudes and intention to adopt financial technology services among the end-users in Lagos State, Nigeria', *African Journal of Science, Technology, Innovation and Development*, DOI: 10.1080/20421338.2020.1835177.

Aljukhadar, M., Senecal, S. and Nantel, J. (2014) 'Is more always better? Investigating the task-technology fit theory in an online user context', *Information & Management*, Vol. 51, No. 4, pp.391–397.

Al-maatouk, Q., Othman, M.S., Aldraiweesh, A., Alturki, U., Al-rahmi, W.M. and Aljeraiwi, A.A. (2020) 'Task-technology fit and technology acceptance model application to structure and evaluate the adoption of social media in academia', *IEEE Access*, Vol. 8, pp.78427–78440.

Al-Saedi, K., Al-Emran, M., Ramayah, T. and Abusham, E. (2020) 'Developing a general extended UTAUT model for M-payment adoption', *Technology in Society*, Vol. 62, p.101293.

AlSaleh, D. and Thakur, R. (2019) 'Impact of cognition, affect, and social factors on technology adoption', *International Journal of Technology Marketing*, Vol. 13, No. 2, pp.178–200.

Baumgartner, I. and Green, P. (2008) 'Adoption of service oriented computing from the IT professionals' perspective: an e-government case study', in Avison, D., Kasper, G.M., Pernici, B., Ramos, I. and Roode, D. (Eds.): *Advances in Information Systems Research, Education and Practice*, Vol. 274, pp.189–201, Springer, New York.

Baxi, C. and Patel, J.D. (2021) 'Use of mobile wallet among consumers: underlining the role of task-technology fit and network externalities', *International Journal of Business Information Systems*, Vol. 37, No. 4, pp.544–563.

Bere, A. (2018) 'Applying an extended task-technology fit for establishing determinants of mobile learning: an instant messaging initiative', *Journal of Information Systems Education*, Vol. 29, No. 4, pp.239–252.

Chin, W.W. (1998) 'The partial least squares approach to structural equation modeling', in Marcoulides, G.A. (Ed.): *Modern Business Research Methods*, pp.295–336, Lawrence Erlbaum Associates, Mahwah, NJ.

Churchill Jr., G.A. (1979) 'A paradigm for developing better measures of marketing constructs', *Journal of Marketing Research*, Vol. 16, No. 1, pp.64–73.

Falk, R.F. and Miller, N.B. (1992) *A Primer for Soft Modeling*, University of Akron Press, Akron.

Financial Stability Board (2017) *Financial Stability Implications from Fintech: Regulatory and Supervisory Issues that Merit Authorities' Attention*, May [online] https://www.fsb.org/wp-content/uploads/R270617.pdf (accessed 15 May 2021).

Fornell, C. and Larcker, D.F. (1981) 'Evaluating structural equation models with unobservable variables and measurement error', *Journal of Marketing Research*, Vol. 18, No. 1, pp.39–50.

Gebauer, J. and Tang, Y. (2008) 'Applying the theory of task-technology fit to mobile technology: the role of user mobility', *International Journal of Mobile Communications*, Vol. 6, No. 3, pp.321–344.

Gebauer, J. and Tang, Y., (2008) 'Applying the theory of task-technology fit to mobile technology: the role of user mobility', International Journal of Mobile Communications, Vol. 6 No 3, pp.321-344.

Gimpel, H., Rau, D. and Röglinger, M. (2018) 'Understanding FinTech start-ups – a taxonomy of consumer-oriented service offerings', *Electronic Markets*, Vol. 28, pp.245–264.

Goodhue, D., L. (1995) 'Understanding User Evaluations of Information Systems', *Management Science*, Vol. 41, No. 12, pp.1827–1844.

Goodhue, D.L. and Thompson, R.L. (1995) 'Task-technology fit and individual performance', *MIS Quarterly*, pp.213–236.

Hair Jr., J.F., Ringle, C.M. and Sarstedt, M. (2011) 'PLS-SEM: indeed a silver bullet', *The Journal of Marketing Theory and Practice*, Vol. 19, No. 2, pp.139–152.

Hair, J.F., Ringle, C.M., Gudergan, S.P., Fischer, A., Nitzl, C. and Menictas, C. (2019) 'Partial least squares structural equation modeling-based discrete choice modeling : an illustration in modeling retailer choice', *Business Research*, Vol. 12, No. 1, pp.115–142, https://doi.org/10.1007/s40685-018-0072-4.

Hanafizadeh, P. and Kim, S. (2020) 'Digital business: a new forum for discussion and debate on digital business model and digital transformation', *Digital Business*, March, Vol. 1, p.100006.

Henseler, J., Hubona, G. and Ray, P.A. (2016) 'Using PLS path modeling in new technology research: updated guidelines', *Industrial Management & Data Systems*, Vol. 116, No. 1, pp.2–20.

Henseler, J., Ringle, C.M. and Sarstedt, M. (2015) 'A new criterion for assessing discriminant validity in variance-based structural equation modeling', *Journal of the Academy of Marketing Science*, Vol. 43, pp.115–135.

Huang, K.Y. and Chuang, Y.R. (2017) 'Aggregated model of TTF with UTAUT2 in an employment website context', *Journal of Data Science*, Vol. 15, No. 2, pp.187–204.

Huang, S.L. and Chang, C.Y. (2020) 'Understanding how people select social networking services: Media trait, social influences and situational factors', *Information & Management*, Vol. 57, No. 6, p.103323.

Hussain, S., Xuetong, W. and Hussain, T. (2020) 'Impact of skilled and unskilled labor on project performance using structural equation modeling approach', *SAGE Open*, pp.1–16, https://doi.org/10.1177/2158244020914590.

Kaye, S., Lewis, I., Forward, S. and Delhomme, P. (2020) 'A priori acceptance of highly automated cars in Australia, France, and Sweden: a theoretically-informed investigation guided by the TPB and UTAUT', *Accident Analysis and Prevention*, May, Vol. 137, p.105441.

Keong, W.Y. (2016) 'Factors influencing passengers' attitude and adoption intention of mobile taxi booking application', *The Social Sciences*, Vol. 11, pp.2769–2776.

Kola-Oyeneyin, T.K., Kuyoro, M. and Olanrewaju, T. (2020) *Harnessing Nigeria's Fintech Potential* [online] https://www.mckinsey.com/featured-insights/middle-east-and-africa/harnessing-nigerias-fintech-potential# (accessed 30 April 2021).

Lee, I. and Shin, J.Y. (2018) 'Fintech: ecosystem, business models, investment decisions, and challenges', *Business Horizons*, Vol. 61, No. 1, pp.35–46, https://doi.org/10.1016/j.bushor.2017.09.003.

Lu, H.P. and Yang, Y.W. (2014) 'Toward an understanding of the behavioral intention to use a social networking site: an extension of task-technology fit to social-technology fit', *Computers in Human Behavior*, Vol. 34, pp.323–332.

Mazambani, L. and Mutambara, E. (2019) 'Predicting FinTech innovation adoption in South Africa: the case of cryptocurrency', *African Journal of Economic and Management Studies*, Vol. 11, No. 1, pp.30–50.

Mehdiabadi, A., Tabatabeinasab, M., Spulbar, C. and Yazdi, A.K. (2020) 'Are we ready for the challenge of Banks 4.0? Designing a roadmap for banking systems', *Int. J. Financial Stud.*, Vol. 8, No. 32, pp.1–28.

Monye, C. (2019) *Lessons from Nigeria's Fintech History: Part 1* [online] https://www.future.africa/home/the-history-of-fintech-in-nigeria-part-1 (accessed 12 June 2021).

Morosan, C. and DeFranco, A. (2016) 'It's about time: revisiting UTAUT2 to examine consumers' intentions to use NFC mobile payments in hotels', *International Journal of Hospitality Management*, Vol. 53, pp.17–29.

Nolan, R.L. (1996) *The Process of Creative Destruction: Business Transformation*, December, pp.9–19, Harvard Business School.

Oliveira, T., Faria, M., Thomas, M.A. and Popovič, A. (2014) 'Extending the understanding of mobile banking adoption: when UTAUT meets TTF and ITM', *International Journal of Information Management*, Vol. 34, No. 5, pp.689–703.

Osarenkhoe, A. (2006) 'Customer-centric strategy: a longitudinal study of implementation of a customer relationship management solution', *Int. J. Technology Marketing*, Vol. 1, No. 2, pp.115–144.

Papadopoulou, P. and Kanellis, P. (2018) 'Online trust and the importance of interaction', *International Journal of Technology Marketing*, Vol. 13, No. 1, pp.21–50, DOI: 10.1504/IJTMKT.2018.099849.

Patil, P., Tamilmani, K., Rana, N.P. and Raghavan, V. (2020) 'Understanding consumer adoption of mobile payment in India: extending Meta-UTAUT model with personal innovativeness, anxiety, trust, and grievance redressal', *International Journal of Information Management*, Vol. 54, p.102144, DOI: 10.1016/j.ijinfomgt.2020.102144.

Phua, P.L., Wong, S.L. and Abu, R. (2012) 'Factors influencing the behavioural intention to use the internet as a teaching-learning tool in home economics', *Procedia – Social and Behavioral Sciences*, Vol. 59, pp.180–187, https://doi.org/10.1016/j.sbspro.2012.09.263.

Porter, M.E. (2008) 'The five competitive forces that shape strategy', *Havard Business Review*, January, Vol. 86, No. 1, pp.1–17.

Purwanto, E. and Loisa, J. (2020) 'The intention and use behaviour of the mobile banking system in Indonesia: UTAUT model', *Technology Reports of Kansai University*, Vol. 62, No. 6, pp.2757–2767.

Rahman, M., Ismail, I. and Bahri, S. (2020) 'Analysing consumer adoption of cashless payment in Malaysia', *Digital Business*, Vol. 1 No. 1, p.100004, https://doi.org/10.1016/j.digbus.2021.100004.

Rahman, M., Ismail, I. and Bahri, S. (2021) 'Analysing consumer adoption of cashless payment in Malaysia', *Digital Business*, Vol. 1, No. 1, p.100004. https://doi.org/10.1016/j.digbus.2021.100004.

Ringle, C.M., Wende, S. and Will, A., (2005) *SmartPLS 2.0 (M3) Beta*, University of Hamburg, Hamburg, Germany [online] http://www.smartpls.de (accessed 18 July 2022).

Ryu, H. (2018) 'What makes users willing or hesitant to use fintech ? The moderating effect of user type', *Industrial Management & Data Systems*, Vol. 118, No. 3, pp.541–569.

Santosdiaz, R. (2021) *An overview of Nigeria and the potential for Fintech*, May [online] https://thefintechtimes.com/category/world-menu/middle-east-africa/ (accessed 6 December 2021).

Sharif, A., Afshan, S. and Qureshi, M.A. (2019) 'Acceptance of learning management system in university students: an integrating framework of modified UTAUT2 and TTF theories', *International Journal of Technology Enhanced Learning*, Vol. 11, No. 2, pp.201–229.

Sharma, S.K., Mangla, S.K., Luthra, S. and Al-Salti, Z. (2018) 'Mobile wallet inhibitors: developing a comprehensive theory using an integrated model', *Journal of Retailing and Consumer Services*, Vol. 45, No. 2018, pp.52–63.

Shin, D.H. (2009) 'Towards an understanding of the consumer acceptance of mobile wallet', *Computers in Human Behavior*, Vol. 25, No. 6, pp.1343–1354, https://doi.org/10.1016/j.chb.2009.06.001.

Slade, E.L., Dwivedi, Y.K., Piercy, N.C. and Williams, M.D. (2015) 'Modeling consumers' adoption intentions of remote mobile payments in the United Kingdom: extending UTAUT with innovativeness, risk, and trust', *Psychology & Marketing*, Vol. 32, No. 8, pp.860–873.

Spies, R., Grobbelaar, S. and Botha, A. (2020) 'A scoping review of the application of the task technology fit theory', in Hattingh, M. and Al, E. (Eds.): *IFIP International Federation for Information Processing*, Vol. 1, pp.397–408, https://doi.org/10.1007/978-3-030-44999-5.

Srivastava, S. and Singh, N. (2020) 'From resistance to acceptance: role of moderating and mediating variables in intention to use mobile payment services', *International Journal of Technology Marketing*, Vol. 14, No. 4, pp.377–402.

Stewart, H. and Jürjens, J. (2018) 'Data security and consumer trust in FinTech innovation in Germany', *Information and Computer Security*, Vol. 26, No. 1, pp.109–128.

Tabrani, M., Amin, M. and Nizam, A. (2018) 'Trust, commitment, customer intimacy and customer loyalty in Islamic banking relationships', *International Journal of Bank Marketing*, Vol. 36, No. 5, pp.823–848, DOI 10.1108/IJBM-03-2017-0054.

Tam, C. and Oliveira, T. (2016) 'Understanding the impact of m-banking on individual performance: DeLone & McLean and TTF perspective', *Computers in Human Behavior*, Vol. 61, pp.233–244.

Tam, C. and Oliveira, T. (2016a) 'Understanding the impact of M-banking on individual performance: Delone & McLean and TTF perspective', *Computers in Human Behavior*, Vol. 61, pp.233–244, DOI: 10.1016/j.chb.2016.03.016.

Tam, C. and Oliveira, T. (2016b) 'Performance impact of mobile banking: using the task technology fit (TTF) approach', *International Journal of Bank Marketing*, Vol. 34, No. 4, pp.434–457, https://doi.org/10.1108/IJBM-11-2014-0169.

Vanduhe, V.Z., Nat, M. and Hasan, F.H. (2020) 'Continuance intentions to use gamification for training in higher education: integrating the technology acceptance model (TAM), social motivation, and task technology fit (TTF)', *IEEE Access*, Vol. 8, pp.21473–21484.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003) 'User acceptance of information technology: Toward a unified view', *MIS Quarterly*, Vol. 27, No. 3, pp.425–478, https://doi.org/10.2307/30036540.

Verkijika, S.F. (2018) 'Factors influencing the adoption of mobile commerce applications in Cameroon', *Telematics and Informatics*, Vol. 35, No. 6, pp.1665–1674.

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

Wang, Y. and Lin, K. (2020) 'Why people adopt VR English language learning systems: an extended perspective of task-technology fit', *Proceedings of the 53rd Hawaii International Conference on System Sciences*, pp.4919–4928.

Wang, Z. and Guan, Z.G. (2019) 'What determines customers' continuance intention of FinTech? Evidence from YuEbao', *Industrial Management & Data Systems*, Vol. 119, No. 8, pp.1625–1637.

Wang, Z., Guan, Z.(G)., Hou, F., Li, B. and Zhou, W. (2019) 'What determines customers' continuance intention of FinTech? Evidence from YuEbao', *Industrial Management & Data Systems*, Vol. 119, No. 8, pp.1625–1637, https://doi.org/10.1108/IMDS-01-2019-0011.

Wayne, T., Soetan, T., Bajepade, G. and Mogaji, E., (2020) 'Technologies for financial inclusion in Nigeria', *Research Agenda Working Papers*, Vol. 2020, No. 4, pp.40–56.

Wu, B. and Chen, X. (2017) 'Continuance intention to use MOOCs: integrating the technology acceptance model (TAM) and task technology fit (TTF) model', *Computers in Human Behavior*, Vol. 67, pp.221–232.

Yen, D.C., Wu, C., Cheng, F. and Huang, Y. (2010) 'Determinants of users' intention to adopt wireless technology: an empirical study by integrating TTF with TAM', *Computers in Human Behavior*, Vol. 26, No. 5, pp.906–915, https://doi.org/10.1016/j.chb.2010.02.005.

Zhou, M., Zhao, L., Kong, N., Campy, K.S., Xu, G., Zhu, G., Cao, X. and Wang, S., (2020) 'Understanding consumers' behavior to adopt self-service parcel services for last-mile delivery', *Journal of Retailing and Consumer Services*, Vol. 52, p.101911.

Zhou, T., Lu, Y. and Wang, B. (2010) 'Integrating TTF and UTAUT to explain mobile banking user adoption', *Computers in Human Behavior*, Vol. 26, No. 4, pp.760–767.