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Research article

The interplay of perceived benefit, perceived risk, and trust in Fintech adoption: Insights from Sub-Saharan Africa

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ABSTRACT

As financial technology (Fintech) continues to reshape the design and delivery of financial products, there is a growing interest in investigating the enablers and inhibitors of Fintech adoption in developing markets. This paper aims to empirically examine the risk-benefit factors associated with Fintech adoption. It further explores the mediating effect of trust in the relationship between risk-related factors and Fintech adoption intentions. The paper utilizes the survey approach to gather data across four countries in Sub-Saharan Africa (SSA). We employ partial least squares-structural equation modelling (PLS-SEM) and fuzzy-set qualitative comparative analysis (FSQCA) techniques to analyse our dataset. The study identified economic benefits, performance expectancy, and effort expectancy as important enablers of Fintech adoption. Conversely, perceived legal risk, security risk, and privacy concerns act as significant inhibitors of Fintech adoption. Furthermore, the findings provide support for the mediation model, suggesting that trust dampens the negative effect of perceived risk on Fintech adoption. The FSQCA results confirm the principle of equifinality as there are multiple causal configurations that can lead to high Fintech adoption. The estimated PLS-SEM model exhibits robustness, as there are no issues regarding unobserved heterogeneity, common method bias, or multicollinearity. Furthermore, the model demonstrates reasonable predictive accuracy as evidenced by acceptable R-square, F-square, and Q-square values. Policymakers, financial institutions, and Fintech firms can leverage the study's findings to shape their strategies, raise consumer awareness, and design innovative financial products that cater for the needs of consumers in Africa.

1. Background

Over the past decade, technology has infiltrated and transformed nearly every sector of our society, leading to significant changes in the way we communicate, interact, and undertake business transactions [1]. The financial sector, in particular, has experienced significant changes in respect of the design and delivery of financial products [2,3]. Improvement in technological infrastructure, coupled with cutting-edge mobile applications and enhanced internet connectivity, have resulted in the creation of new applications across the financial sector. Currently, the traditional approach of offering financial services, such as lending, savings, investment, payments, and borrowing, has been automated through the utilization of advanced technologies [4–6].

Fintech has recently emerged as a term to describe the technological advancements within the financial sector pioneered by

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specialized financial services providers, commonly referred to as Fintechs or Fintech firms [2,7]. These firms leverage advanced technologies such as machine learning, big data analytics, cloud computing, blockchain, and artificial intelligence (AI) to develop innovative financial models that offer seamlessly services to consumers [2,8,9]. In developing markets, Fintech has gained significant importance due to its potential to enhance financial inclusion [10,11], expand financial access [12], and promote efficiency and delivery of government services [13]. Individuals, businesses, and government institutions are leveraging these Fintech platforms to enhance their financial transactions [14–16].

Whereas the benefits associated with Fintech are expected to enhance adoption, risk-related factors—including financial, legal, security, and operational risks—may negatively impact Fintech adoption. For instance Ref. [17], highlight that legal uncertainty constitutes a significant barrier to Fintech adoption, particularly in markets such as Sub-Saharan Africa, where the regulatory framework for Fintech is still in its infancy. Even in advanced economies, lack of proper regulation has been identified as a major barrier to Fintech adoption [18]. Additionally, operational inefficiencies, threats such as data breaches, fraud, and cyberattacks, potential monetary losses incurred during financial transactions, and concerns regarding the misuse or inadequate protection of personal data may serve as impediments to the adoption of Fintech services.

The Fintech ecosystem consist of Fintech start-ups, government, traditional financial institutions, and technology developers [19]. Technology developers utilize advanced information technologies to create innovative products for consumers [1]. Fintech start-ups and traditional financial institutions such as banks, insurance firms and mobile network operators (MNOs), are responsible for implementing Fintech solutions. The government initiates legislations and regulations to safeguard financial consumers and ensure the stability of the financial system [1,20]. Consumers, including individuals, organizations, and government agencies, are the actual users of Fintech products. Their adoption and use of Fintech services is crucial in promoting financial inclusion, supporting and validating innovation, and enhancing the growth of the Fintech ecosystem [21,22].

While the rapid evolution of financial technology (Fintech) in Sub-Saharan Africa promises unprecedented opportunities for financial inclusion and economic development, the adoption of Fintech platforms such as crowdfunding and peer-to-peer lending in the region remains relatively low [23,24]. This presents a pressing challenge for region, as the potential of Fintech to revolutionize its financial sector can only be realized if adoption is enhanced. Effort aimed at enhancing Fintech adoption in the region not only promotes financial inclusion but also strengthens the competitiveness of the financial system [25]. In this study, we attempt to empirically identify the key drivers and inhibitors of Fintech adoption in SSA, thus highlighting some implications for policy initiation. By investigating the interplay of benefit, risk and trust factors in Fintech adoption in SSA, we attempt to address some important issues such as the key risk and benefit factors affecting Fintech adoption, and the role of trust in Fintech adoption, as well as the causal configurations that could promote high Fintech adoption. To address these objectives, a multi-method quantitative analysis is conducted relying on survey data from four SSA countries.

This paper contributes to the literature on Fintech adoption in three distinct ways. First, while there has been an increase in studies on Fintech adoption in the past decade, these studies have mostly focused on measuring perceived Fintech risk as a single construct, even though it is a multi-dimensional variable [26,27]. By treating risk as a multi-dimensional variable, the study provides a valuable contribution to the unified theory of acceptance and use of technology (UTAUT). Moreover, assessing risk constructs as part of the UTAUT framework is crucial as it informs the design and implementation of Fintech solutions, thereby facilitating increased adoption [28]. Secondly, although trust is a major factor influencing the adoption of technology-related services, few studies have explored its mediating role in the relationship between risk and adoption [29]. Most often, researchers examining the factors influencing Fintech adoption have treated trust as a predictor variable with a unidirectional role, with limited understanding of its mediating effects [30]. This paper treats trust as a mediating variable, thereby providing further insights into the role of trust in technology adoption. Furthermore, while the factors influencing Fintech adoption can be diverse and complex, existing research has primarily focused on the isolated effects of individual factors, without considering the different combinations of factors that may lead to high Fintech adoption [31]. By applying PLS-SEM and FSQCA techniques, this paper not only determine the net effect of individual constructs but also identifies different variable configurations that result in higher Fintech adoption, thus constructing a causal recipe for achieving high Fintech adoption.

The remaining parts of the study are organized as follows: Section 2 presents a review of the literature and introduces the key variables and their relationships. In Section 3, the paper presents the methodology by discussing the research design and the processes leading to the collection and analysis of the survey data. Additionally, issues relating to the validity and reliability of the study are also addressed in this section. Section 4 presents the results of the analysis and a discussion of the key findings. Section 5 presents the conclusion and implications of the research findings, while Chapter 6 highlights the limitations and opportunities for future research.

2. Literature review and hypothesis development

2.1. Theoretical underpinning

To understand the factors associated with innovation adoption, several theories have been put forth. For example [31], proposed the Technology Acceptance Model (TAM), which has become one of the most widely utilized models in terms of the adoption of information technology [32]. According to the TAM, a person's use of technology is influenced by factors such as perceived ease of use (PEOU), perceived usefulness (PU), beliefs, and attitudes. Davis [31] contends that perceived usefulness is based on the belief that the use of technology will enhance performance and provide greater satisfaction compared to existing methods. The second factor is perceived ease of use, which explains the belief that new technology can be used with minimal effort. However, the theory has been criticised for mainly focusing on ease of use (PEOU) and perceived usefulness (PU) [34,35]. In response to these criticisms and in pursuit of a more comprehensive model for technology acceptance [36], proposed the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The UTAUT has been widely applied in numerous studies and has been shown to possess high levels of validity and reliability in the field of technology adoption [37–39]. It identifies four key constructs that influence technology acceptance, namely performance expectancy, effort expectancy, social influence, and facilitating conditions. The UTAUT model, according to Ref. [37] is a tried and tested model explaining the intentions to adopt, use, and continue to use information system based systems. However, as indicated by Ref. [40], the application of UTAUT within the Fintech environment requires some modifications to examine the inherent risks associated with Fintech offerings. Thus, in this study, we propose an extension of the UTAUT model by incorporating trust, privacy concerns, and perceived risk-related factors to create a comprehensive model for predicting Fintech adoption in SSA.

The incorporation of risk and trust-related constructs into the Unified Theory of Acceptance and Use of Technology (UTAUT) represents a significant extension of the model, as it recognizes the increasing relevance of perceived risks in users' decisions to adopt new technologies, particularly in high-risk domains such as financial technology (Fintech). For example [27], has highlighted that legal, security, financial, and operational risks are crucial factors influencing user adoption and utilization of financial technology platforms. Moreover [41], have underscored the importance of trust issues in the context of technology adoption. However, the UTAUT model does not explicitly address the potential risks that users may perceive. By integrating risk and trust-related constructs, the model becomes more comprehensive and is better equipped to explain technology adoption within the SSA context, where trust, security, and risk are of paramount importance.

2.2. Hypothesis development

Recognizing that risk is a significant consideration for consumers in the realm of financial technology [42] the study investigates its influence on adoption within the UTAUT framework. Consequently, the study categorizes the factors anticipated to affect Fintech adoption into two groups: those related to benefits and those related to risks. Four benefit-related factors pertaining to Fintech adoption are examined, including performance expectancy, economic benefit, effort expectancy, and convenience. The risk-related factors encompass operational risk, legal risk, security risk, financial risk, and privacy concerns. Hence, the risk-benefit framework integrates the perceived drivers and inhibitors of intentions to adopt Fintech.

2.2.1. Benefit-related factors

2.2.1.1. Performance expectancy (PFE). This construct assesses the extent to which consumers believe that utilizing a particular system or technology will enhance their job performance. A higher level of performance expectancy increases the likelihood of individuals adopting a novel technology or system. The extent to which performance expectancy affects internet-based applications has be evaluated in the extant literature [43–46]. The majority of these studies have found a significant correlation between performance expectancy and technology adoption [42,47]. When consumers perceive that the adoption of financial technology will enhance the efficiency of their financial transactions, they are more likely to embrace such services. In this study, we posit that financial consumers are influenced by their performance expectancy concerning the adoption of Fintech services. Therefore, the following hypothesis is formulated:

Hypothesis H1a: Performance expectancy has a significant effect on consumer Fintech adoption intention in SSA.

2.2.1.2. Effort expectancy (EFE). The EFE construct refers to the level of effort required to use new technology [33]. Venkatesh et al. [36] also operationalizes effort expectancy as the extent to which one can easily use a technology. According to the UTAUT model, a higher perception of effort expectancy leads to greater adoption and use of a given technology. Effort expectancy has been examined in previous literature to understand its impact on the adoption of technology-related platforms. For example, studies such as [48] have found a significant relationship between effort expectancy and internet banking adoption. Additionally, qualitative findings also support this result, further aligning with the TAM theory by Ref. [33] and empirical studies conducted by Refs. [48,49]. Effort expectancy is grounded in the premise that users are more inclined to adopt technologies they perceive as user-friendly and requiring minimal effort. Consequently, consumers in Sub-Saharan Africa are likely to embrace Fintech services when they perceive a high degree of ease in utilizing such technology. The preceding discussion indicates that empirical evidence substantiates a relationship between effort expectancy and the intention to adopt Fintech services. Therefore, the proposed hypothesis is as follows:

Hypothesis H1b: Effort expectancy influences user intentions to adopt Fintech services in SSA.

2.2.1.3. Economic benefit (EBN). One significant factor that has been identified as exerting a substantial influence on the adoption of Fintech is economic benefit [27,50]. This factor refers to the perceived financial advantages expected from embracing a specific Fintech platform, as opposed to traditional banking services. It also conveys the understanding that the adoption of Fintech services will enhance the economic outcome for consumers. Frost [50] argues that the perception of economic benefit serves as a motivator for consumers to embrace technology-based financial services. Users are motivated to adopt technologies that offer clear financial advantages. When individuals perceive tangible financial gains or cost savings associated with the use of Fintech solutions as compared to traditional financial services, their likelihood of adoption increases. For example, the perception of lower transaction fees, cost savings, access to more affordable financial products, and enhanced investment opportunities linked to Fintech solutions may positively influence adoption intentions. In light of the above, the following hypothesis is posited.

Hypothesis H1c: Perceived economic benefit influences user intentions to adopt Fintech services in SSA.

2.2.1.4. Convenience (CVN). Within the scope of this research, convenience is defined as the flexibility associated with the use of Fintech platforms. Convenience can manifest in terms of flexibility in time or location [51]. Fintech services, including mobile payments, peer-to-peer lending, digital wallets, and robo-advisors, provide significant convenience by allowing users to manage their finances effortlessly via smartphones or computers. These services enable users to conduct transactions at any time and from any location, thereby eliminating the necessity of visiting a physical bank or enduring prolonged wait times. Several studies utilizing the TAM model have discovered that convenience drives the adoption of Fintech services. When consumers perceive that a technologically enabled service or product is easily accessible at any time and location, it may trigger adoption [52]. As a result, we propose the following hypotheses:

Hypothesis H1d: Perceived convenience of Fintech solutions has significant influence on user intentions to adopt Fintech services in SSA.

2.2.1.5. Perceived risk-related factors. Several empirical studies have indicated that the influence of risk-related factors on the adoption of innovation cannot be underestimated [27,40]. Risk, in the context of technology adoption, refers to the perception that adopting a new service comes with potential uncertainties and negative consequences. According to Ref. [28], most Fintech solutions possess inherent risks primarily due to the virtual nature of the transactions conducted. This perceived risk can decrease the desire for Fintech adoption among consumers as it undermines their trust in the technology [53]. Perceived risk has various aspects, and this study categorizes Fintech risk into five subconstructs: legal risk, operational risk, financial risk, security risk, and privacy concerns.

2.2.1.6. Operational risk. Operational risk is the perception that consumers may encounter uncertainties due to faults or errors on the part of Fintech service providers. It refers to a potential loss arising from inadequate or failed internal processes, personnel, or systems within the Fintech ecosystem, which could adversely affect consumers. Within the context of Fintech services, operational risks may emerge from technology failures, human error, cyberattacks, fraudulent activities, or disruptions in service delivery. Consumers may express concerns that such risks could compromise their efforts ([54]. Consequently, operational risk may significantly influence the adoption of Fintech services in Sub-Saharan Africa (SSA). Factors such as infrastructure challenges, cybersecurity threats, fraudulent activities, system failures, and customer service issues can all erode trust in Fintech platforms, rendering users hesitant to embrace these services. Therefore, we propose the following hypothesis:

Hypothesis H2a: Perceived operational risk associated with Fintech solutions influences user adoption intentions in SSA.

2.2.1.7. Legal risk. Legal risk refers to the fear that Fintech consumers may suffer financial consequences due to weaknesses in the existing regulatory and legal framework [27]. [17,18] has observed that legal risk and lack of regulatory framework within the Fintech ecosystem could serve as a major barrier to Fintech adoption. Legal risk could play a critical role in influencing the adoption of Fintech services, particularly in developing economies where the legal framework remains fragile. Factors such as regulatory uncertainty, compliance with financial and data protection laws, consumer protection concerns, and the complexities associated with cross-border transactions can significantly impact users' willingness to adopt these technologies. Therefore, if consumers perceive inadequate rules, data protection laws, and regulations governing Fintech provision, they are likely to hesitate in adopting Fintech solutions. The following hypothesis is therefore, formulated:

Hypothesis H2b: The perceived legal risk associated with Fintech solutions negatively impacts user adoption intentions in Sub-Saharan Africa (SSA).

2.2.1.8. Financial risk. Financial risk refers to the perception that consumers may lose money by using a particular Fintech platform. Security risk is the negative perception that Fintech services are susceptible to fraud and hacking activities, resulting in a security breach in financial transactions. If consumers believe that they may lose money due to the dishonest actions of hackers and fraudsters, they may not be motivated to adopt Fintech services [55]. Financial risk may significantly influence the adoption of Fintech services in Africa, as apprehensions regarding fraud, platform stability, hidden fees, currency fluctuations, and liquidity may dissuade potential users. This issue is particularly pertinent in the Sub-Saharan Africa (SSA) context, characterized by low financial literacy and high economic volatility. Consequently, we propose the following hypothesis.

Hypothesis H2c: Perceived financial risk negatively impacts users' intentions to adopt Fintech services in Sub-Saharan Africa (SSA).

2.2.1.9. Security risk. Fintech platforms manage sensitive financial information, including bank account details, credit card numbers, and transaction data, rendering them appealing targets for cybercriminals. Security risk refers to the potential for financial loss, data breaches, or unauthorized access to sensitive information associated with the use of Fintech platforms [27,56]. Users may harbour concerns that inadequate security measures could result in financial loss due to hacking, phishing, or fraud. If users perceive a high risk of unauthorized access to their accounts or financial resources, they are likely to be hesitant to adopt Fintech services. The potential for personal financial loss underscores the significance of security risk as a critical factor influencing the adoption of Fintech services. Given that SSA. In a region where digital infrastructure and regulatory oversight are still developing, concerns about financial loss, fraud, data breaches, and weak cybersecurity frameworks could potentially affect Fintech adoption negatively. Consequently, the following hypothesis is formulated.

Hypothesis H2d: Perceived security risks negatively influence users' intentions to adopt Fintech services in Sub-Saharan Africa.

2.2.1.10. Privacy concerns. Privacy concerns involve the potential fear that users' personal information could be accessed by unauthorized individuals, leading to a violation of their privacy [40,57,58]. Users may express concerns regarding the monitoring or sharing of their personal information with government agencies or third parties without their consent. This apprehension may arise from the perception that Fintech platforms facilitate increased surveillance, particularly if these platforms are believed to collect more data than necessary or to disseminate information to external entities. The potential for unauthorized access or surveillance can trigger significant concerns among users who prioritize privacy, ultimately leading them to refrain from adopting Fintech services. As privacy concerns escalate—whether due to regulatory deficiencies, previous data breaches, or a general mistrust of technology—Fintech adoption may decelerate, particularly among demographic groups that are already reticent about utilizing digital financial services. Consequently, the following hypothesis is formulated:

Hypothesis H2e: Privacy concerns has a negative influence on user adoption intentions of Fintech services in SSA.

2.2.1.11. Trust and Fintech adoption intentions. According to Ref. [59], perceived trust is the assurance on the part of the consumer that a service provider will take actions that will benefit the consumers and will not engage in activities that will jeopardize their interest. Dawood et al. [30] argue that since customers provide personal and financial information to service providers before accessing technology-based services, consumers will adopt such services if they are assured that such information will be secured from unauthorized access. Any doubt or concern regarding the trustworthiness of the service will negatively affect adoption [60]. If consumers believe that a particular technology platform is reliable and that adopting such a platform will secure their private information, they are more likely to use such platforms. Several studies such as [40,61–63] have observed a direct positive correlation between trust and the adoption intentions of consumers.

In the extant literature, there is a lack of consensus regarding the nature of the relationship between risk and trust. Whereas some studies have used risk as the predictor variable in the relationship, others have examined the effect of trust on risk. For instance, studies on e-commerce adoption have found that trust is a predictor of consumer risk [62,64,65]. However, others have found that risk negatively affects consumer trust with respect to adoption intentions [66]. Within the SSA context, there is a high inclination for people to avoid risk due to cultural beliefs, and there is a tendency for people to avoid risk in Fintech services. We thus argue that risk could have a negative effect on consumer trust in SSA.

While trust has been described as having a direct relationship with technology adoption intentions, it has also been identified as a possible mediator variable, as it mediates the relationship between risk factors and one's intentions to adopt Fintech services, as trust minimizes uncertainties or users' risk perception and positively affects their intentions to adopt Fintech services [67]. contend that risk perceptions of online banking services have an adverse effect on consumer adoption, as the more they perceive a service as risky, the less likely they are to trust such service. On the other hand, increased trust in the system will ultimately lead to its adoption, and this has been confirmed in various digital contexts, such as mobile banking, e-commerce and online banking [68,69]. Thus, trust could be

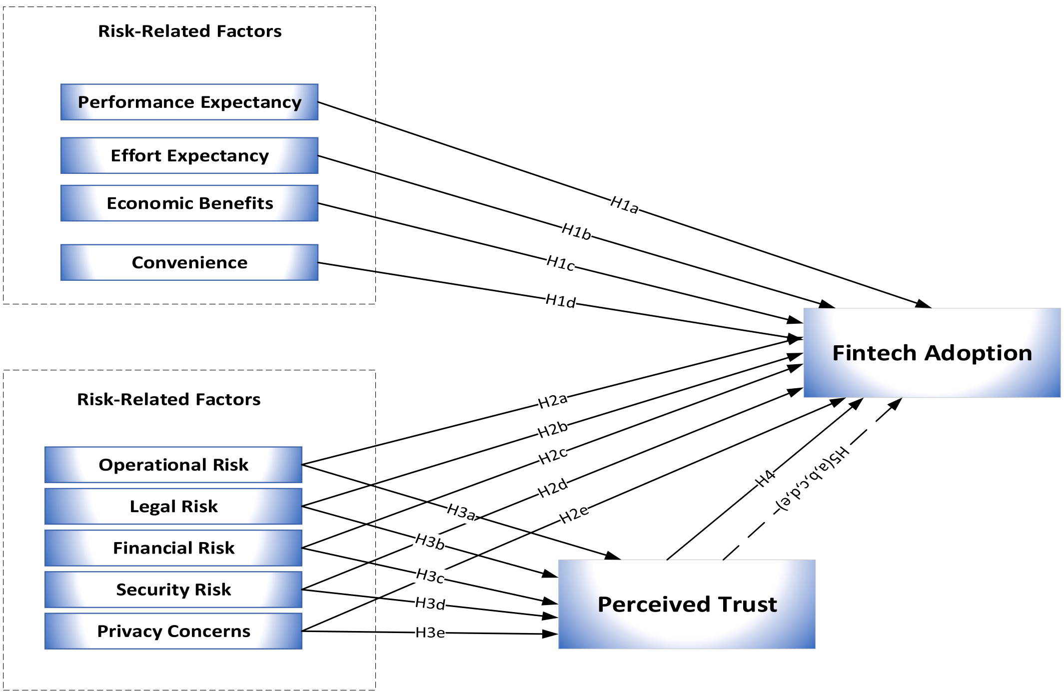

Fig. 1. Conceptual model indicating hypothesized relationships.

considered a mediator in the relationship between perceived risk and adoption intentions of Fintech services. Based on the above discussions, the following hypotheses are formulated:

Operational risk (H3a), legal risk (H3b), financial risk, (H3c), security risk (H3d), and privacy concerns (H3e) have negative effects on consumer trust.

Hypothesis H4: Trust is a significant predictor of Fintech adoption intentions in SSA.

Hypothesis H5: Trust significantly mediates the relationship between Operational risk (H5a), Legal risk (H5b), financial risk (H5c), security risk (H5d), privacy concerns(H5e), and Fintech adoption intentions in SSA.

2.2.1.12. Complexity analysis of Fintech adoption. Configurational theory underscores the complexity and flexibility of systems, challenging the notion of linear causality [70]. It is founded on three pivotal principles: conjectural causation, equifinality, and causal asymmetry [71]. The principle of conjectural causation posits that the impact of a single condition becomes apparent in the presence of other conditions. Equifinality suggests that various causal factors can yield the same outcome, albeit through different initial conditions and pathways. Causal asymmetry proposes that factors influencing the occurrence of a desired result may substantially diverge from those influencing its non-occurrence. This paper aims to scrutinize the configuration theory in relation to our data by investigating whether there exist multiple pathways leading to adoption outcome in the Fintech domain. Consequently, we formulate the following hypothesis: check references.

H6: There are different combinations/configurations of conditions that could contribute to high Fintech adoption.

2.3. Conceptual model

The conceptual model presented in this study (see Fig. 1) is derived from the literature, specifically focusing on risk and benefit factors influencing Fintech adoption intentions. In order to explain this relationship, the study proposes a comprehensive risk-benefit framework comprising eleven constructs. The main endogenous variable of interest in this model is Fintech adoption intentions. The exogenous variables encompass various risk-related factors, namely perceived financial risk, legal risk, security risk, operational risk, and privacy concerns. Perceived benefit-related factors are represented by exogenous variables such as perceived convenience, economic benefits, effort expectancy, and performance expectancy. Furthermore, perceived trust is designated as the mediating variable in this model.

Fig. 2. Selected countries for the study (shown in green).

3. Research methodology

This section is intended to explore the techniques and methodologies utilized to collect, measure, and analyse data. It also delineates how concerns regarding reliability and validity were addressed in this study. The chapter begins with an examination of the study area.

3.1. Study area

Four countries from Sub-Saharan Africa (SSA)—Ghana, Nigeria, Kenya, and South Africa—are the focus of this study (see Fig. 2). The selection of these nations is justified by their leadership roles in advancing the growth of financial technology (Fintech) solutions within the region [72]. Their rapidly expanding Fintech markets, characterized by increasing mobile and internet penetration, a rising consumer interest in digital financial services, and evolving financial landscape, render them ideal countries for this study. These countries not only provide a diverse array of Fintech solutions but also serve as benchmarks for the rest of the region. Ghana is progressively emerging as a significant player in the African Fintech landscape. The nation has experienced considerable growth in mobile money adoption, with transactions conducted via mobile wallets constituting a substantial portion of its Gross Domestic Product (GDP) [72]. Furthermore, Ghana's Fintech ecosystem is expanding, as evidenced by the increasing number of start-ups entering the market. These start-ups are focusing innovative payments, lending, and savings platforms to promote financial inclusion. Nigeria is the largest Fintech market in Africa, with a population exceeding 200 million and a burgeoning tech-savvy youth demographic. The country is home to more than 200 Fintech companies, including prominent platforms such as Flutter-wave and Interswitch [72]. Kenya is renowned for its pioneering role in mobile money services, M-Pesa, which has revolutionized financial transactions across the region. Launched by Safaricom a decade and a half ago, M-Pesa has significantly enhanced financial inclusion in the country, with approximately 82.9 % of the population now having access to financial services. The success of M-Pesa has spurred the emergence of numerous Fintech start-ups that utilize mobile technology for various financial services. South Africa features a well-established Fintech ecosystem, and a robust regulatory framework designed to foster Fintech growth. The country has been an early mover in Fintech regulation, creating the enabling environment for a thriving Fintech sector [23].

3.2. Data

This study utilized quantitative methodologies to validate our hypotheses and provide statistical evidence that can be applied in various contexts [73]. Consequently, structured questionnaires were employed to collect quantitative data. The survey instrument consisted of three sections. Section A included an introductory letter which specified the objective and nature of the study. It also contained statements seeking the consent of participants and the protection of their personal data from unauthorized access. Participants were freely allowed to decide whether they wish to be part of the study or not. Section B gathered demographic information from respondents, and Section C contained measurement items for the study. The measurement constructs were adapted from previous research. A 5-point Likert scale approach to measure the constructs was adopted, as this is a commonly used method for assessing individuals' attitudes and perceptions towards technology adoption [74,75]. The target population for this study comprised users of mobile financial technology (Fintech), peer-to-peer lending, and crowdfunding platforms in Nigeria, Ghana, Kenya, and South Africa. It includes individuals who currently utilize or are likely to utilize Fintech services within these four countries. Specifically, it encompasses consumers of digital financial services, such as mobile banking, mobile money transfers, online lending, and digital investment platforms. The study particularly focused on working professionals, small and medium-sized business owners, and students. A purposive sampling technique was employed to select individuals from the four countries who possess some knowledge and experience in the use of Fintech services.

To obtain a representative sample from the target population, a specific sample size procedure was employed. This procedure mandates that 5–10 respondents be included for each item measuring the constructs, in order to minimize sampling error [76]. In view of this, a sample size ranging from 170 to 340 participants is deemed sufficient for our study given that 34 item were employed. In all, 818 participants, including 230 Ghanaians, 200 Nigerians, 188 Kenyans, and 200 South Africans, successfully completed the questionnaires. Google Forms was utilized to administer the questionnaires, and the questionnaire link was distributed to potential participants via email and various social media platforms [77]. Only eligible participants were requested to complete the questionnaires.

To enhance the validity of the study, validated constructs from the extant literature were utilized. Performance expectancy, effort expectancy, and convenience constructs were adapted from the works of [75,78].). The items measuring risk-related constructs, including financial risk, operational risk, privacy concerns, legal risk, and security risk, were also adapted from Refs. [54,78]. Items measuring the trust construct were adapted from Ref. [62], while the privacy construct was assessed using validated items from Ref. [79]. Finally, the Fintech adoption construct was adapted from the study conducted by Ref. [78]. The number of items measuring each of the constructs and the sources of these items is presented in Appendix A.

3.3. Pilot study

During the pilot phase of this study, the content validity of the questionnaire was assessed. Content validity is the extent to which a measurement tool covers the entire range of the concept it is intended to measure [80]. To ensure content validity, the survey was piloted using 30 experts. These experts provided valuable feedback in respect to the order, content, wording, sentence structure, and layout of the questionnaire. The suggestions obtained from these experts were instrumental in enhancing the quality of the data collection instrument. For instance, the questionnaire initially consisted of 38 items that measured eleven constructs, but the number of items were reduced by 34 after the expert review.

3.4. Data analysis strategy and estimation techniques

The data analysis strategy for this study involves the evaluation of the measurement model for validity and reliability using indicators like Cronbach's Alpha, AVE, and composite reliability. This was followed by and assessment of the structural to determine the relationship between the study variables [81]. After estimating the structural model, its predictive power was then assessed using R-square, F-square, Q-square, and significance testing. The PLS-SEM approach was used for the data analysis because it is appropriate for conducting accurate multivariate analysis, even with a smaller sample size [76]. It is also recognized as an effective method for investigating complex relationships between latent and observed variables. Additionally, since the data used in this study did not follow a normal distribution, PLS-SEM is suitable for research data exhibiting non-normal distribution patterns [82]. The estimation process was conducted in three phases. After collecting the indicator variables through structured questionnaires, the measurement model was estimated to determine the number and nature of the latent variables. This phase was also crucial for assessing the validity and reliability of the constructs and measurement items. The SEM phase (structural model) was performed to estimate the relationship between the latent variables. Finally, in phase 3, the structural model was validated by calculating the model fit and robustness parameters.

The measurement model is estimated with the following equation:

$$\begin{aligned} k_1 &= \lambda_{11}.\gamma_1 + \lambda_{12}.\gamma_2 + \ldots + \lambda_{1d}.\gamma_d + \varepsilon_1 \\ k_2 &= \lambda_{21}.\gamma_1 + \lambda_{22}.\gamma_2 + \ldots + \lambda_{2d}.\gamma_d + \varepsilon_2 \\ k_3 &= \lambda_{31}.\gamma_1 + \lambda_{32}.\gamma_2 + \ldots + \lambda_{3d}.\gamma_d + \varepsilon_3 \\ \\ k_p &= \lambda_{p1}.\gamma_1 + \lambda_{p2}.\gamma_2 + \ldots + \lambda_{pd}.\gamma_d + \varepsilon_p \end{aligned} \tag{1}$$

Table 1
Factor loadings.

	AIT	CVN	EBN	EFE	FRK	LRK	ORK	PFE	PVC	SRK	TRS
AIT	0.890										
AIT	0.921										
AIT	0.883										
AIT	0.794										
CVN1		0.925									
CVN2		0.910									
CVN3		0.951									
EBN1			0.869								
EBN2			0.894								
EBN3			0.918								
EFE1				0.872							
EFE2				0.916							
FRK1					0.810						
FRK2					0.840						
FRK3					0.885						
LRK1						0.807					
LRK2						0.693					
LRK3						0.898					
ORK1							0.878				
ORK2							0.891				
ORK3							0.892				
PVC1									0.844		
PVC2									0.878		
PVC3									0.766		
PFE1								0.804			
PFE2								0.835			
PFE3								0.922			
PFE4								0.855			
SRK2										0.899	
SRK2										0.961	
TRS1											0.915
											0.912
TRS2											
											0.919
TRS3											
											0.922
TRS4											

PFE-Performance expectancy; EFE-Effort Expectancy; EBN-Economic Benefit; CVN-Convenience; ORK-Operational risk; LRK-Legal risk; FRK-Financial risk; SRK-Security risk; PVC-Privacy concerns; TRS-Trust; AIT-Adoption intentions.

where:

$k_i, i = 1, \ldots, p$ are the observed variables,

$\gamma_j, j = 1, \ldots, d$ are latent variables,

$\lambda_{ij}, i = 1, \ldots, p, j - 1, \ldots, d$ are the factor loadings.

$\lambda_i, i = 1, \ldots, p.$

A matrix representation of the equations above can be given as:

$$k = \delta.f + e \quad (2)$$

where k is the measurement variable; δ is the matrix of factor loading for latent variables; f is the factor loading; and λ is the factor loading. In this paper, the factor loadings are estimated, and loadings below 0.7 are dropped [76]. After confirming the structure of the structural model, SEM analysis was performed. Here, we estimate the relationship among the latent variables. The structural equation, with γ as the dependent variable, is given as:

$$\gamma : = \beta_{\gamma x}.X + \beta_{\gamma z}.Z + \varepsilon_\gamma$$

where $\beta_{\gamma x}.$ and $\beta_{\gamma z}$ are the path coefficients, and ε_γ is the error term. The path coefficients provide indications regarding the direction and strength of the relationship between the latent variables.

X and Z are the independent variables, while γ is the dependent variable. In phase 3, the estimated relationship is validated using various fit indicators as recommended by Ref. [76].

In addition to the PLS-SEM technique, we use FSQCA techniques to investigate the diverse solutions that achieve higher Fintech adoption. We follow the procedure outlined by Pappas and Woodside (2021) to calibrate our dataset, create a truth table, and present the results.

3.5. Validity and reliability of constructs – measurement model

The reliability and validity of the constructs were assessed using factor loadings, internal consistency, discriminant validity, and convergent validity. We utilized SmartPLS 3 to conduct all the relevant estimates. In Tables 1 and 2, the results revealed that all items exhibit significant loadings on their respective constructs, with all loadings surpassing 0.5. Secondly, the estimated average variance extracted (AVE) for each of the constructs exceeded 0.5. Furthermore, both composite reliability (CR) and Cronbach's alpha values exceeded 0.70 [76,83], providing a strong argument for construct validity and reliability.

The discriminant validity of the constructs was assessed using the criteria suggested by Refs. [83,84]. According to Ref. [83], discriminant validity is established when the square root of the Average Variance Extracted (AVE) for each construct exceeds the correlations between that construct and any other construct in the model. As presented in Table 3, the square root of the AVE (highlighted) ranges from 0.801 to 0.929, which is greater than the correlations with any other construct, thereby confirming discriminant validity within the model. In addition to utilizing the Fornell and Larcker criteria, we also employed the Heterotrait-Monotrait ratio (HTMT) to further investigate discriminant validity. According to Ref. [85], discriminant validity is achieved when HTMT values are 0.85 or below. The results reported in Table 4 indicate that the HTMT values range from 0.038 to 0.832, which are below 0.85, confirming that discriminant validity is achieved between the constructs in the model.

In addition to evaluating the validity and reliability of the study constructs, we also examined the presence of common method bias (CMB), given that the same instrument was utilized to measure all dependent and independent variables. Common method bias occurs when both independent and dependent variables are evaluated using the same instrument, such as a survey or questionnaire. The presence of CMB may undermine the validity of the estimates derived from the analysed relationships [86]. In this study, we assessed the potential for CMB by applying the collinearity assessment criteria proposed by Ref. [86]. According to these criteria, variance

Table 2
Construct reliability and validity.

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AIT	0.895	0.906	0.928	0.763
CVN	0.920	0.923	0.950	0.863
EBN	0.874	0.89	0.922	0.799
EFE	0.752	0.772	0.889	0.800
FRK	0.800	0.843	0.881	0.713
LRK	0.747	0.89	0.842	0.642
ORK	0.866	0.892	0.917	0.786
PFE	0.876	0.879	0.916	0.731
PVC	0.773	0.792	0.869	0.690
SRK	0.851	0.904	0.929	0.868
TRS	0.937	0.938	0.955	0.841

Note: PFE-Performance expectancy; EFE-Effort Expectancy; EBN-Economic Benefit; CVN-Convenience; ORK-Operational risk; LRK-Legal risk; FRK-Financial risk; SRK-Security risk; PVC-Privacy concerns; TRS-Trust; AIT-Adoption intentions.

Table 3
Discriminant validity of constructs (Correlation and Square root of AVE).

	AIT	CVN	EBN	EFE	FRK	LRK	ORK	PFE	PVC	SRK	TRS
AIT	**0.873**										
CVN	0.623	**0.929**									
EBN	0.668	0.694	**0.894**								
EFE	0.454	0.593	0.692	**0.894**							
FRK	0.277	0.461	0.389	0.39	**0.844**						
LRK	0.176	0.36	0.358	0.292	0.638	**0.801**					
ORK	0.18	0.29	0.317	0.31	0.33	0.452	**0.887**				
PFE	0.602	0.635	0.738	0.767	0.408	0.29	0.254	**0.855**			
PVC	0.523	0.471	0.573	0.508	0.274	0.299	0.499	0.454	**0.83**		
SRK	0.207	0.308	0.276	0.291	0.593	0.717	0.22	0.273	0.125	**0.932**	
TRS	0.504	0.411	0.497	0.525	0.241	0.179	0.473	0.438	0.778	0.034	**0.917**

Note: PFE-Performance expectancy; EFE-Effort Expectancy; EBN-Economic Benefit; CVN-Convenience; ORK-Operational risk; LRK-Legal risk; FRK-Financial risk; SRK-Security risk; PVC-Privacy concerns; TRS-Trust; AIT-Adoption intentions.

Table 4
HTMT result.

	AIT	CVN	EBN	EFE	FRK	LRK	ORK	PFE	PVC	SRK	TRS
AIT											
CVN	0.664										
EBN	0.769	0.668									
EFE	0.597	0.590	0.789								
FRK	0.277	0.358	0.355	0.335							
LRK	0.115	0.231	0.237	0.217	0.832						
ORK	0.258	0.272	0.326	0.289	0.487	0.719					
PFE	0.604	0.52	0.715	0.624	0.329	0.391	0.552				
PVC	0.653	0.555	0.779	0.837	0.395	0.208	0.321	0.513			
SRK	0.224	0.221	0.227	0.226	0.831	0.567	0.446	0.231	0.214		
TRS	0.528	0.31	0.53	0.521	0.198	0.048	0.458	0.642	0.421	0.141	

Note: PFE-Performance expectancy; EFE-Effort Expectancy; EBN-Economic Benefit; CVN-Convenience; ORK-Operational risk; LRK-Legal risk; FRK-Financial risk; SRK-Security risk; PVC-Privacy concerns; TRS-Trust; AIT-Adoption intentions.

inflation factor (VIF) values exceeding 3.3 indicate the presence of CMB, whereas values below 3.3 suggest its absence. Our results indicate that common method bias is not present, as the VIF values for the variables range from 1.0202 to 2.452 (see Table 5), which are significantly below the established threshold of 3.3.

4. Results

The demographic information of the participants is comprehensively presented in Table 6. A total of 818 participants successfully completed all relevant sections of the questionnaires. Out of this sample, 469 individuals (57.3 %) were identified as males, while the remaining participants were identified as females. Additionally, it was observed that the majority of participants (52 %) fell within the

Table 5
CMB assessment using VIF.

Construct	VIF
CVN	1.45
EBN	2.12
EFE	1.02
FRK	2.19
LRK	1.75
ORK	2.01
PFE	1.45
PVC	2.22
SRK	2.87
TRS	1.65

Note: PFE-Performance expectancy; EFE-Effort Expectancy; EBN-Economic Benefit; CVN-Convenience; ORK-Operational risk; LRK-Legal risk; FRK-Financial risk; SRK-Security risk; PVC-Privacy concerns; TRS-Trust; AIT-Adoption intentions.

age group of 26–35 years. Furthermore, a significant proportion of the participants (58.3 %) possessed a first-degree qualification. Regarding the prevalent Fintech platforms utilized by respondents, it was ascertained that 678 individuals, amounting to 82.9 % of the total respondents, utilized mobile payment platforms. Furthermore, 9.3 % and 7.8 % of the participants utilized peer-to-peer and crowdfunding platforms, respectively. Consequently, these results clearly confirm that mobile payment Fintech currently dominates the Fintech landscape in SSA.

Table 7 presents the descriptive statistics of the various constructs examined in this study. In total, there are 11 constructs, consisting of 9 independent variables, 1 mediating variable, and 1 dependent variable. The descriptive statistics primarily focus on the mean and standard deviation of these variables. The items were measured using a five-point scale, where 1 indicates strong disagreement and 5 represents strong agreement. The results reveal that the construct with the highest mean rating is 'Convenience' (M = 3.78, SD = 1.01), indicating that respondents generally agree that Fintech services are convenient to use. Following closely behind are 'Economic benefit' (M = 3.71, SD = 0.99) and 'Performance expectancy' (M = 3.54, SD = 1.00), which received the second and third highest mean ratings, respectively. Furthermore, the construct 'Operational risk' obtained the lowest mean rating (M = 2.85, SD = 1.06).

4.1. Estimation of the structural model

To determine the nature of the relationship between the latent variables and test the hypothesis proposed in section 1, we evaluated the structural model using SmartPLS 3. The results are presented in Table 8 and Fig. 3. We tested the hypotheses using the usual rule of thumb in regression analysis. If the t value is greater than 1.96 ($t \geq 1.96$), the coefficient (β) is significant at ($p \leq 0.05$). If $t \geq 2.58$, then β is significant at $p \leq 0.01$. Additionally, if $t \geq 3.1$, then β is significant at $p \leq 0.001$ (Hu et al., 2019).

We found from the results that all the benefit factors (i.e., economic benefit, performance expectancy, convenience and effort expectancy) have a significant positive effect on Fintech adoption intentions, as all these variables have a positive coefficient with t values larger than 1.96 ($t \geq 1.96$). The results imply that H1a, H1b, H1c and H1a are supported based on the structural model estimations. The results show that the economic benefit variable has the most impact on Fintech adoption intentions ($\beta = 0.348, t = 8.086$, $p = 0.01$). The implication of this result is that consumers see the economic benefit factor in Fintech services as the most important driver of their adoption of Fintech services. Put differently, consumers are more likely to adopt Fintech services if they believe that they are cheaper than conventional financial products, more convenient to use, require less effort to use, and are helpful in their day-to-day operations.

The results further show that while benefit factors are important positive drivers of Fintech adoption, some of risk factors such as legal risk ($\beta = -0.192$, $t = 3.45$, $p = 0.01$), security risk ($\beta = -0.196, t = 4.206, p = 0.01$) and privacy concerns ($\beta = -0.132, t = 3.403, p = 0.01$) all have a significant negative influence on Fintech adoption intentions, implying that these risk perceptions serve as barriers to Fintech usage. However, financial and operational risks are found to have an insignificant influence on Fintech adoption intentions.

The result further highlights the influence of perceived risk on consumers' perceived trust in Fintech services. We find that all but security risk constructs have a negative effect on trust: legal risk ($\beta = -0.136$, $t = 3.217$, $p = 0.01$), operational risk ($\beta = -0.151, t = 5.458, p = 0.01$) privacy concerns ($\beta = -0.72, t = 29.915, p = 0.01$) and financial risk ($\beta = -0.116, t = 4.198, p = 0.01$), providing support for H2b, H2d, and H2e. Furthermore, Table 7 presents the mediating effect of trust in the relationship between perceived risk elements and Fintech adoption intentions. We observed that trust is a significant mediator in the relationship between operational risk, legal risk, privacy concern on the one hand, and Fintech adoption intentions on the other (FRK - > TRS - >

Table 6
Demographic characteristics of student respondents (818).

Variable	Categorization	Frequency	Percentage
Gender	Male	469	57.3 %
	Female	349	42.7 %
Age group	25 and below	249	30.4 %
	26–35	425	52.0 %
	36–45	133	16.3 %
	Above 45	11	1.3 %
Education	Diploma/Certificate	257	31.4 %
	First Degree	477	58.3 %
	Second degree	76	9.3 %
	Third Degree	8	1.0 %
Income	\$100-\$500	491	60.0 %
	\$501-\$1000	244	29.8 %
	\$1001-\$2000	53	6.4 %
	\$2001-\$3000	23	2.8 %
	Above \$3000	7	0.9 %
Employment status	Employed	596	72.9 %
	Unemployed	222	27.1 %
Fintech Platform used	Mobile payment	678	82.9
	Peer-to-peer Lending	74	9.3
	Crowdfunding	66	7.8

Table 7
Descriptive statistics of study variables.

Variable	Min	Max	Mean	SD
EBN	1.00	5.00	3.71	0.99
EFE	1.00	5.00	3.32	1.03
PFE	1.00	5.00	3.54	1.00
CVN	1.00	5.00	3.78	1.01
FRK	1.00	5.00	3.22	1.10
SRK	1.00	5.00	3.05	1.08
LRK	1.00	5.00	2.91	0.93
ORK	1.00	5.00	2.90	1.06
PVC	1.00	5.00	3.16	0.97
TRS	1.00	5.00	3.23	1.08
AIT	1.00	5.00	3.59	0.95

Note: PFE-Performance expectancy; EFE-Effort Expectancy; EBN-Economic Benefit; CVN-Convenience; ORK-Operational risk; LRK-Legal risk; FRK-Financial risk; SRK-Security risk; PVC-Privacy concerns; TRS-Trust; AIT-Adoption intentions.

Table 8
Result of hypothesis testing (direct relationships).

Hypothesis	Relationship	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
H1a	PFE - > AIT	0.295***	0.048	6.151	0.001	Supported
H1b	EFE - > AIT	0.33***	0.041	8.054	0.001	Supported
H1c	EBN - > AIT	0.348***	0.043	8.086	0.001	Supported
H1d	CVN - > AIT	0.283***	0.038	7.538	0.001	Supported
H2a	ORK - > AIT	0.040	0.031	1.294	0.512	Not supported
H2b	LRK - > AIT	−0.192***	0.056	3.45	0.001	Supported
H2c	FRK - > AIT	0.032	0.038	0.826	0.409	Not supported
H2d	SRK - > AIT	−0.196***	0.047	4.206	0.001	Supported
H2e	PVC - > AIT	−0.132***	0.039	3.403	0.001	Supported
H3a	ORK - > TRS	−0.151***	0.028	5.458	0.001	Supported
H3b	LRK - > TRS	−0.136***	0.042	3.217	0.001	Supported
H3c	FRK - > TRS	−0.116***	0.028	4.198	0.001	Supported
H3d	SRK - > TRS	−0.06	0.034	1.791	0.073	Not supported
H3e	PVC - > TRS	−0.72***	0.024	29.915	0.001	Supported
H4	TRS - > AIT	0.244***	0.045	5.429	0.001	supported

Note: * and ** indicates significant at 0.01 and 0.05 respectively:** PFE-Performance expectancy; EFE-Effort Expectancy; EBN-Economic Benefit; CVN-Convenience; ORK-Operational risk; LRK-Legal risk; FRK-Financial risk; SRK-Security risk; PVC-Privacy concerns; TRS-Trust; AIT-Adoption intentions.

AIT: $\beta = 0.028, t = 3.868, p = 0.01$), (LRK - > TRS - > AIT: $\beta = -0.032, t = 2.901, p = 0.01$), (PVC - > TRS - > AIT: $\beta = 0.180, t = 8.511, p = 0.01$) (ORK - > TRS - > AIT: $\beta = 0.037, t = 4.802, p = 0.01$), providing support for H5a, H5b, H5c and H5e.

4.2. Robustness assessment

The estimated empirical model was further tested to determine how well it fits the data. Thus, in addition to the various reliability and validity tests, there was a need to investigate the robustness of the model using model fit indicators such as R-square, SRMR, and NFI. Table 9 shows the R-squared values and other fit indices of the model. The R-square value, also called the coefficient of determination, shows the percentage of variation in the dependent variable explained by the independent variable. Even though R-square values can range between 0 and 1 [76,84], posit that an R-square value of 0.7 is considered substantial, whereas values below 0.26 are considered weak. From our results, we observe that both trust ($R^2 = 0.647$) and adoption intentions ($R^2 = 0.704$) have a moderate level of explanatory power. Thus, we can surmise that over 60 percent of the variation in Fintech adoption intentions is explained by the exogenous variables (see Table 10).

Another important fit indicator generated is the SRMR (Standardized Root Mean Squared Residual). Hu & Bentler [87] have proposed that positive that SRMR values below 0.08 are suitable for assessing the fitness of a structural model, while values above 0.08 depict poor fit. It has been argued by some researchers that the recommended threshold for the SRMR to be acceptable is below 0.1 [87]. From the result in Table 4 it is observed that an SRMR value of 0.065 was obtained, which is lower than 0.08 and support the fitness of the model. The NFI value, according to must be higher than or equal to 0.9. Specifically, the closer it is to 1, the better. From our results, a value of 0.98 was obtained. Thus, almost all the fitness indices provide support for the fitness of the structural model.

In addition to the model fit indices estimated above, F^2 and Q^2 metrics were calculated to evaluate model performance and predictive relevance. The F-square statistic serves as a measure of effect size, indicating the extent to which the removal of an exogenous variable impacts the R-square value of an endogenous variable [88]. This metric quantifies the contribution of a specific predictor variable to the explained variance in the dependent variable. The F-square metric is significant as it helps researchers discern which variables exert considerable influence on the model's outcomes [88]. The effect of the predictor variable at the structural level is

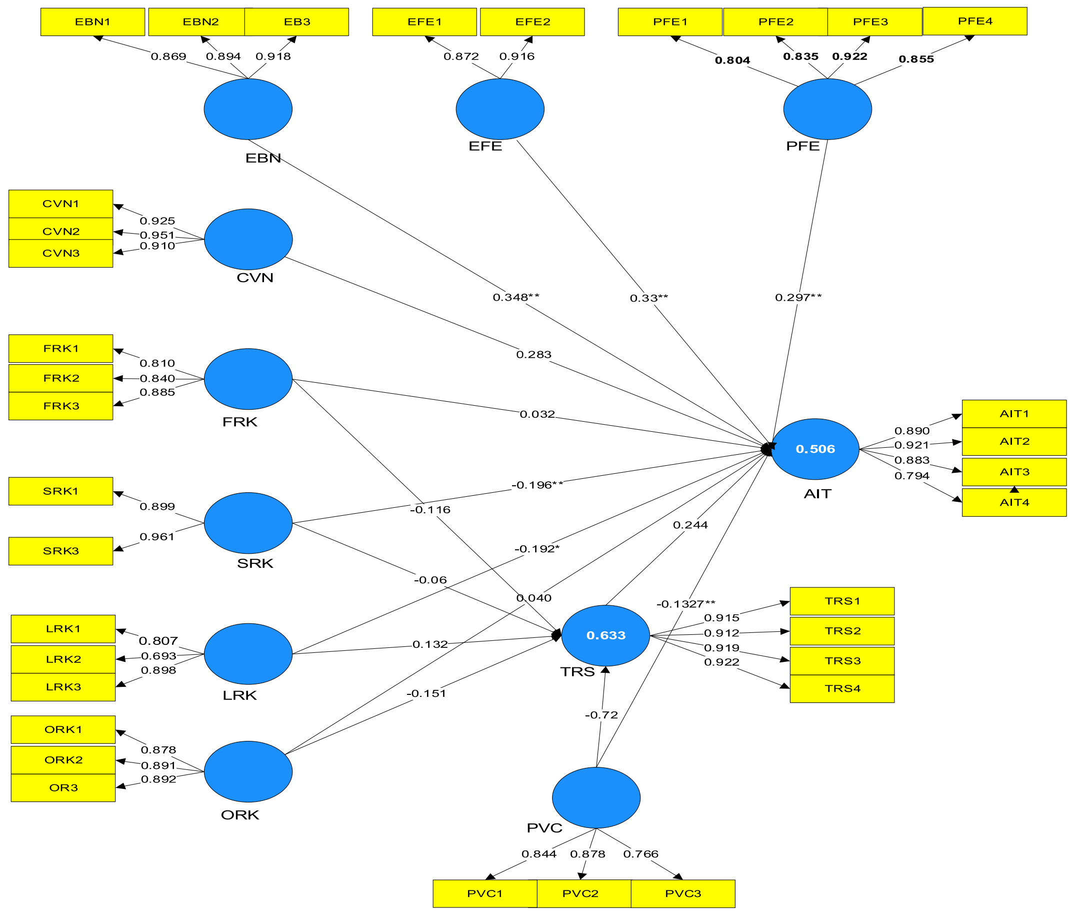

Fig. 3. Estimated structural model with hypothesized relationship.

Table 9
Indirect effect (mediation results).

Hypothesis	Indirect Relationships	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
H5a	ORK - > TRS - > AIT	0.037***	0.008	4.802	0.000	Supported
H5b	LRK - > TRS - > AIT	0.032***	0.011	2.901	0.004	Supported
H5c	FRK - > TRS - > AIT	0.028***	0.007	3.868	0.000	Supported
H5d	SRK - > TRS - > AIT	0.014	0.009	1.567	0.117	Not supported
H5e	PVC - > TRS - > AIT	0.18***	0.021	8.511	0.000	supported

Note: * indicates significant at 0.01:** ORK-Operational risk; LRK-Legal risk; FRK-Financial risk; SRK-Security risk; PVC-Privacy concerns; TRS-Trust; AIT-Adoption intentions.

Table 10
Fit indices.

Fit Indices	Fit Criteria	Estimated Model
χ^2		7244
Prob. χ^2	≤ 0.05	0.001
SRMR	≤ 0.08	0.06
NFI	≥ 0.9	0.98
R^2	≥ 0.5	0.506, 0.633

Note: χ^2-Chi-Square; SRMR-Standardized Root Mean Square Residual; NFI-Normed Fit Index.

classified as high if the F-square value is 0.35, medium if it is 0.15, and small if it is 0.02 [89]. The results presented in Table 11 indicate that the F-square effect sizes ranged from 0.0012 to 0.528. The predictive relevance of the model was assessed using the Q-square statistic. A high Q-square value suggests that the model not only fits well with existing data but is also capable of generalizing to new data, thereby enhancing its utility in decision-making processes [90]. A Q-square value greater than 0 ($Q^2 > 0$) indicates that the model possesses predictive relevance for a specific endogenous construct. Conversely, a Q-square value of 0 ($Q^2 = 0$) suggests that the model does not provide any predictive relevance for the endogenous construct. Additionally, a Q-square value less than 0 ($Q^2 < 0$) signifies that the model lacks predictive relevance. Generally, a Q^2 value greater than zero indicates that the model has predictive relevance for the corresponding endogenous construct. The higher the Q^2 value, the greater the model's predictive capability. Our Q-Square value of 0.542 suggest that the model is not only statistically significant but also practically useful for prediction [76].

Furthermore, to ascertain the existence of heterogeneity issues across the four countries—Ghana, Nigeria, Kenya, and South Africa—concerning Fintech adoption intentions, a multi-group analysis was conducted. In SmartPLS 3, we conducted separate PLS-SEM analysis for each of the countries (Ghana, Nigeria, Kenya, and South Africa). We then compared path coefficients and p-values across the groups to ascertain whether possible unobserved heterogeneity exist in the data. This analysis aimed to examine whether the relationships (path coefficients) between variables exhibit significant differences across the groups, which may indicate the presence of unobserved heterogeneity within the dataset [91]. Specifically, we evaluated whether the structural paths within the model differ among these countries. Our results suggest that there is no indication of heterogeneity across the four countries in this study, as the path coefficients remain generally consistent. In other words, the relationships between the variables influencing the adoption of Fintech services are similar across Ghana, Nigeria, Kenya, and South Africa (see Table 12). This finding implies that the model is robust and can be generalized across these Sub-Saharan African countries without concerns about country-specific variations affecting the overall results.

4.3. FSQCA analysis

In addition to the PLS-SEM results, FSQCA analysis was conducted to identify different combinations of conditions (antecedents) that are associated with high Fintech adoption. The FSQCA analysis was performed in accordance with the guidelines provided by Ref. [92]. First, the data was calibrated by converting it to fuzzy sets using threshold scores of 4, 3, and 2 for full membership, crossover membership, and non-full membership, respectively, are appropriate. The calibration process utilized the "calibrate function" in FSQCA version 4.0. The variables PFE, EFE, ECB, CVN, FRK, SRK, ORK, LRK, PVC, and AIT were calibrated and given new names as calPFE, calEFE, calECB, calCVN, calFRK, calSRK, calORK, calLRK, calPVC, and calAIT, respectively. The calibration process was followed by the truth table to examine complex, parsimonious, and intermediate solutions. In this study, the intermediate solution was considered superior to the other two solutions in management research [66]. Among the various configurations, those with a consistency of 0.9 and above and a minimum raw coverage value of 0.35 were considered. Nine configurations met these criteria and were selected for further analysis. The intermediate solution with the 9 configurations is presented in Tables 13 and 12. The results indicate that privacy concerns (PVC), economic benefit (ECB), legal risk (LRK), effort expectancy (EFE), performance expectancy (PFE), and convenience (CVN) are considered core antecedents as they are present in at least 70 % of the solutions. This finding aligns with the results obtained from the PLS-SEM, where ECB, LRK, EFE, and CVN were found to be important determinants of Fintech adoption. The results demonstrate that high Fintech adoption can be achieved by considering both risk and benefit factors, and that no single antecedent is sufficient to achieve high Fintech adoption (see Table 14).

5. Discussion

The PLS-SEM result demonstrates that benefit-related factors play a crucial role in driving Fintech adoption. Specifically, perceived economic benefit, performance expectancy, effort expectancy, and convenience are identified as important determinants of Fintech

Table 11
Robustness estimates.

Predictors	Outcomes	*R*-Square	*F*-square	*Q*-Square
EBN	AIT	0.506	0.085	0.542
EFE			0.039	
PFE			0.048	
CVN			0.125	
FRK			0.017	
SRK			0.098	
LRK			0.058	
ORK			0.190	
PVC			0.163	
TRS			0.230	
FRK	TRS	0.633	0.126	0.593
SRK			0.231	
LRK			0.102	
ORK			0.113	
PVC			0.230	

Table 12
Regression results of multi-country analysis.

Relationships	Ghana	Nigeria	Kenya	South Africa
PFE ➡ AIT	0.274** *(3.520)*	0.148*** *(3.170)*	0.458*** *(3.344)*	0.355*** *(3.243)*
EFE ➡ AIT	0.253** *(3.295)*	0.214** *(3.447)*	0.251** *(3.319)*	0.332*** *(2.985)*
EBN ➡ AIT	0.273** *(3.937)*	0.355*** *(3.691)*	0.239** *(1.995)*	0.411*** *(3.296)*
CVN ➡ AIT	0.301** *(5.754)*	0.118** *(2.877)*	0.349*** *(3.061)*	0.295** *(2.908)*
FRK ➡ AIT	−0.110 *(1.680)*	−0.225 *(1.811)*	−0.180 *(1.642)*	−0.240** *(2.609)*
SRK ➡ AIT	0.301** *(4.431)*	0.178** *(2.494)*	0.258** *(2.420)*	0.184** *(1.983)*
ORK ➡ AIT	−0.042 *(0.722)*	−0.329** *(4.002)*	−0.107 *(1.063)*	−0.042 *(0.575)*
LRK ➡ AIT	−0.238* *(2.128)*	0.043 *(0.286)*	−0.195** *(1.998)*	−0.322*** *(2.624)*
PVC ➡ AIT	−0.139* *(2.057)*	−0.005 *(0.062)*	−0.194** *(3.347)*	0.178*** *(3.476)*
TRS ➡ AIT	0.246** *(3.029)*	0.146** *(0.062)*	0.333*** *(2.755)*	0.199** *(2.782)*

**″ $p < 0.05$. ***$p < 0.01$.″ *“T values in parenthesis” PFE-Performance expectancy; EFE-Effort Expectancy; EBN-Economic Benefit; CVN-Convenience; ORK-Operational risk; LRK-Legal risk; FRK-Financial risk; SRK-Security risk; PVC-Privacy concerns; TRS-Trust; AIT-Adoption intentions.*

Table 13
Model: calADP = f(calPFE, calEFE, calECB, calCVN, calFRK, calLRK, calORK, calFRK, calSRK, calPVC).

Configurations	Raw consistency	Unique consistency	Consistency
calPFE*calEFE*calCVN*~calFRK*~calORK ~ calLRK ~ calPVC	0.352487	0.00733	0.9529
calPFE*~calEFE*calECB*~calFRK*~calSRK*~calLRK ~ calPVC	0.37336	0.00636	0.9665
calECB*calCVN*~calFRK*~calSRK*~calORK*~calLRK*~calPVC	0.40225	0.01147	0.97767
calPFE*calEFE*calECB*calCVN*~calSRK*~calLRK*calPVC	0.39979	0.02114	0.974574
calPFE*~calEFE*calCVN*calFRK*~calORK*~calLRK*~calPVC	0.36296	0.01871	0.980226
calPFE*calEFE*calECB*calSRK*~calORK*~calLRK*~calPVC	0.36130	0.01972	0.94516
calPFE*calEFE*calECB*calCVN*~calSRK*~calLRK*calPVC	0.45563	0.00907	0.98139
calPFE*calEFE*calECB*calCVN*~calFRK*~calLRK*calPVC	0.41954	0.01008	0.97731
calPFE*calEFE*calECB*calCVN*calFRK*calORK*calPVC	0.37226	0.00959	0.95089
Solution Coverage 0.809468			
Solution consistency 0.854173			

Note: calPFE-Caliberated Performance expectancy; calEFE-Caliberated Effort Expectancy; calEBN-Calibrated Economic Benefit; calCVN-Calibrated Convenience; calORK-Calibrated Operational risk; calLRK-Calibrated Legal risk; calFRK-Calibrated Financial risk; calSRK-Calibrated Security risk; calPVC-Calibrated Privacy concerns; calTRS-Calibrated Trust; calAIT-Calibrated Adoption intentions.

Table 14
Results of FSQCA to formulate high Fintech adoption.

	Solution								
	1	2	3	4	5	6	7	8	9
Performance Expectancy (PFE)	●	●		●	●	●	●	●	●
Effort Expectancy (EFE)	●	⊗		●	⊗	●	●	●	●
Economic Benefit (ECB)		●	●	●		●	●	●	●
Convenience (CVN)	●		●	●	●		●	●	●
Operational Risk (ORK)	⊗		⊗		⊗	⊗	⊗		●
Security Risk (SRK)	●	⊗	⊗	⊗		⊗	⊗		
Financial risk (FRK)	⊗	⊗	⊗		●			⊗	●
Legal Risk (LRK)	⊗	⊗	⊗	⊗	⊗	⊗	⊗	⊗	
Privacy Concern (PVC)	⊗	⊗	⊗	●	⊗	⊗	●	⊗	●
Raw Consistency	0.3524	0.3733	0.4022	0.3997	0.3629	0.3613	0.4556	0.4195	0.3722
Unique Coverage	0.0073	0.0063	0.0114	0.0211	0.0187	0.0197	0.0090	0.0100	0.0095
Consistency	0.9529	0.9665	0.9776	0.9745	0.9802	0.9451	0.9813	0.9773	0.9508
Consistency Coverage	0.854 0.809								

Note: “●” *indicate the presence of the antecedent.* “⊗” *denotes the absence of the antecedent. The blank cells denote “insignificance”.*

adoption in SSA. Our findings indicate that individuals are more likely to adopt Fintech services when they perceive tangible benefits in terms of efficiency, convenience, and financial gains. The result further revealed that perceived economic benefit is the strongest and most persuasive variable among the benefit-related factors. This aligns with the conclusions drawn by Ref. [40], who argue that perceived economic factors act as motivators for consumers to adopt technology-based financial services. Therefore, our results underscore the significance of perceived economic benefits, effort expectancy, and performance expectancy as key drivers in shaping consumers' intentions to adopt Fintech services.

We further observed that perceived risk factors, such as legal risk, privacy concerns, and security risk, have a detrimental impact on consumers' intentions to adopt Fintech in SSA. This implies that when Fintech consumers perceive a lack of legal protection, their trust in Fintech services may be weakened, as they cannot rely on legal safeguards in the event of financial losses. Similarly, privacy concerns are identified as a significant inhibitor of Fintech adoption, which is consistent with the findings of [93,94]. When consumers are uncertain about the confidentiality of their personal and financial information, they are less likely to adopt and utilize Fintech services. Therefore, these results suggest that perceived risk elements impose substantial barriers to Fintech adoption, as users may be apprehensive about potential financial losses, data breaches, and privacy violations associated with using Fintech services. This finding is in line with the previous findings of [27] who reported a significant negative effect of risk elements on Fintech adoption intentions. This result suggests that an increased perception of risk associated with Fintech services negatively impacts individuals' trust in these services. In simpler terms, when people perceive Fintech activities and products as risky or uncertain, they are more likely to have less trust in these services. These findings are consistent with the study by Ref. [18], which also concluded that heightened perceived risk adversely affects intentions to adopt Fintech.

Additionally, our results demonstrate that trust has a positive and significant influence on intentions to adopt Fintech services and acts as a significant mediator in the relationship between perceived risk and intentions to adopt Fintech services. This suggests that trust dampens the negative effect of perceived risk factors on Fintech adoption. Consequently, a higher level of trust can reduce concerns about risks and increase intentions to adopt Fintech services.

The results of our study lend support to the complexity theory, as we find that a single antecedent alone cannot predict high levels of Fintech adoption. Instead, a combination of two or more conditions is necessary to achieve high levels of Fintech adoption. Moreover, individual antecedents may have both positive and negative contributions to the outcome variable, depending on the presence or absence of other antecedents. This finding aligns with the proposal by Ref. [92]. In our study, we observe that variables such as perceived privacy concerns, effort expectancy, and financial risk play both positive and negative roles, depending on the presence or absence of other variables.

The use of various metrics such as, Cronbach's Alpha, Average Variance Extracted (AVE), Composite Reliability, Factor Loadings, the Heterotrait-Monotrait Ratio (HTMT), and the Fornell-Larcker criteria affirms the validity and reliability of the data and constructs employed in the study. Furthermore, robustness was established through the implementation of F-Square, Q-Square, R-Square, and Multi-Group Analysis (MGA). Collectively, these results provide comprehensive evidence that both the measurement and structural models are valid and reliable, making the findings of the study well-supported and generalizable.

6. Conclusion

This paper examined the risk and benefit factors that influence the adoption of Fintech services in Sub-Saharan Africa (SSA), utilizing the UTAUT model and other related theories using PLS-SEM and FSQCA techniques. The results of the PLS-SEM analysis reveal that benefit factors can promote Fintech adoption among consumers in SSA, while risk-related factors may hinder adoption. However, it was observed that consumers of Fintech products place more premium on the benefits derived from Fintech products and services compared to the associated risk. The study further revealed that contrary to conventional understanding, certain risk factors, such as financial and operational risks, have an insignificant effect on Fintech adoption intentions, suggesting that consumers' perceptions regarding Fintech risk are evolving in line with technological advancements. The FSQCA result indicates that there are multiple pathways to achieving higher Fintech adoption, supporting the equifinality theory espoused by Ref. [70]. It is worth noting that the findings of this study make important theoretical and practical contributions. Firstly, it contributes to the burgeoning area of Fintech by examining different components of perceived risk factors that affect the adoption of Fintech services in SSA. This enhances our understanding of the antecedents of Fintech adoption in SSA and contributes to the extension of the UTAUT model. Secondly, it provides insight into the complexity analysis of Fintech adoption intentions by establishing that different combinations or pathways of perceived risk and benefit factors interact to achieve high Fintech adoption. Furthermore, the study highlights the mediating role of trust in the relationship between risk-related factors and Fintech adoption intentions, a phenomenon that has not been extensively investigated in the existing literature. The practical implication of these findings is that policymakers, financial institutions, and Fintech firms can leverage them to shape their strategies, enhance consumer awareness, and design more tailored products for consumers. Therefore, the study offers comprehensive insights into the risk-benefit dynamics that can foster a more inclusive and technologically driven financial landscape, which is crucial in harnessing the full potential benefits of Fintech in SSA while addressing consumers' significant risk concerns.

7. Limitations and suggestions for future research

While this study successfully achieved its objective of developing a risk-benefit framework to understand the antecedents of Fintech adoption, it is important to acknowledge the limitations associated with it. These limitations do not in any way undermine the importance of the findings, but rather provide a context for interpreting and applying the results. Additionally, the limitations offer opportunities for future researchers to investigate related variables and areas that were not addressed in this research. Firstly, it is worth noting that this study sampled respondents from four SSA countries, and therefore the findings may not be representative of all other jurisdictions in SSA and other regions. Given the variation in consumer attitudes towards technology across different regions and jurisdictions, future researchers may consider including other regions in their study designs. Furthermore, there is a wide range of Fintech services currently available to consumers. However, this study focused only on the adoption of three platforms (mobile payment, crowdfunding, and peer-to-peer), which are the most common Fintech platforms in SSA. Future studies could explore other Fintech platforms to determine if there are variations in the findings. Additionally, the cross-sectional approach used in this study means that data was collected at a single point in time. Consequently, changes in consumers' Fintech adoption behaviour over time could not be observed. Moreover, there are various factors that could influence Fintech adoption, such as age, gender, educational background, and experience. These variables could potentially moderate the relationship between the identified risk-benefit variables and adoption intentions. However, this study did not consider these variables. Future researchers are encouraged to explore these and other social variables that may affect Fintech adoption.

CRediT authorship contribution statement

Thomas Appiah: Writing – review & editing, Writing – original draft, Project administration, Conceptualization. **Veronica Venyo Agblewornu:** Visualization, Software, Methodology, Formal analysis, Data curation.

Data availability statement

Data will be made available on request. For requesting data, please write to the corresponding author.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Choose one option for each question presented in the table below. Circle the number that represents your opinion. Indicate the extent to which you agree or disagree with the following statements.

Please be guided by the following: SD (1) = Strongly disagree; D (2) = Disagree; N=Neutral (3); A = Agree (4); SA=Strongly agree (5).

Category	Code	Statement	SD	D	N	A	SA
Effort Expectancy *(Venkatesh*et al.*, 2012)*	EFE1	I think the operation interface of Fintech is friendly understandable	**1**	**2**	**3**	**4**	**5**
	EFE2	It is easy to have the equipment to use Fintech services	**1**	**2**	**3**	**4**	**5**
Performance Expectancy *(Jain & Raman, 2022)*	PFE1	I expect Fintech to be useful for my financial needs	**1**	**2**	**3**	**4**	**5**
	PFE2	Fintech would enable me to accomplish my financial needs quickly	**1**	**2**	**3**	**4**	**5**
	PFE3	Fintech would improve my efficiency in accessing financial services	**1**	**2**	**3**	**4**	**5**
	PFE4	If I use Fintech services, it will increase my productivity	**1**	**2**	**3**	**4**	**5**
Economic Benefit *(Jain & Raman, 2022)*	EBN1	The use of Fintech platforms is cheaper than using traditional financial services	**1**	**2**	**3**	**4**	**5**
	EBN2	I can save money when I use Mobile Fintech	**1**	**2**	**3**	**4**	**5**
	EBN3	I can use various financial services with a low cost when I use Mobile Fintech	**1**	**2**	**3**	**4**	**5**
Convenience *(Jain & Raman, 2022)*	CVN1	I can access financial services quickly when I use Fintech platforms	**1**	**2**	**3**	**4**	**5**
	CVN2	I can access financial services anytime, anywhere when I use Fintech platforms	**1**	**2**	**3**	**4**	**5**
	CVN3	I can use financial services easily when I use Fintech	**1**	**2**	**3**	**4**	**5**
Financial Risk *(Jain & Raman, 2022)*	FRK1	Financial losses are more likely when I use Fintech services	**1**	**2**	**3**	**4**	**5**
	FRK2	Financial fraud or payment fraud are likely when I use Fintech services	**1**	**2**	**3**	**4**	**5**
	FRK3	Financial losses due to the lack of interoperability are possible when I use Fintech platforms	**1**	**2**	**3**	**4**	**5**
Security Risk *(Ryu, 2018a)*	SRK1	I worry about the abuse of my financial information when I use Fintech platforms	**1**	**2**	**3**	**4**	**5**
	SRK2	I worry that someone can access my financial information when I use Mobile Fintech	**1**	**2**	**3**	**4**	**5**
Legal Risk *(Ryu, 2018a)*	LRK1	My use of Fintech is uncertain due to unclear regulations.	**1**	**2**	**3**	**4**	**5**
	LRK2	It is not easy to use Fintech due to the government regulation	**1**	**2**	**3**	**4**	**5**
	LRK3	There is legal uncertainty for Fintech users	**1**	**2**	**3**	**4**	**5**
Operational Risk *(Ryu, 2018a)*	ORK1	I am worried about potential losses due to internal processes out of my field of control	**1**	**2**	**3**	**4**	**5**
	ORK2	I worry about the way Fintech companies respond to financial loss or financial information leakage	**1**	**2**	**3**	**4**	**5**
	ORK3	I am worried about the compensation of potential losses or information leakages	**1**	**2**	**3**	**4**	**5**
Privacy Concerns *(Featherman & Pavlou, 2003)*	PVC1	I am worried that my personal data may not be safe while using Fintech services	**1**	**2**	**3**	**4**	**5**
	PVC2	I am worried that Fintech firms may not be able to protect my information from unauthorized person	**1**	**2**	**3**	**4**	**5**

(*continued on next page*)

(*continued*)

Category	Code	Statement	SD	D	N	A	SA
	PVC3	I am worried that enough is not being done by Fintech firms to protect my data from unauthorized users	1	2	3	4	5
Trust (Kim et al., 2009)	TRS1	I trust Fintech systems to be reliable	1	2	3	4	5
	TRS2	Trust Fintech systems to be secure	1	2	3	4	5
	TRS3	Believe Fintech systems are trustworthy.	1	2	3	4	5
	TRS4	Trust Fintech systems	1	2	3	4	5
Adoption Intentions (*Jain & Raman, 2022)*	AIT1	I would positively consider Fintech in my choice set.	1	2	3	4	5
	AIT2	I intend to continue to use Fintech to access financial services	1	2	3	4	5
	AIT3	I would prefer Fintech.	1	2	3	4	5
	AIT4	I will use Fintech in the future	1	2	3	4	5

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