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Extending UTAUT2 with risk perception to explain Fintech adoption in an emerging market: evidence from Brazil

Ampliando a UTAUT2 com a percepção de risco para explicar a adoção de Fintech em um mercado emergente: evidências do Brasil

Ampliando UTAUT2 con la percepción del riesgo para explicar la adopción de Fintech en un mercado emergente: evidencia de Brasil

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Abstract
Financial technologies (FinTech) are rapidly transforming how financial services are delivered, particularly to unbanked and underbanked populations in emerging markets. Although there is evidence of intention to use FinTech services, actual use is disparate and follows no discernible pattern. This study extends the applicability of UTAUT2 to investigate the effect of perceived risk, as a behavioral inhibitor, on the actual use of a high-risk digital service. Unlike previous studies, which treat perceived risk as a predictor of behavioral intention, this study treats perceived risk as a direct inhibitor of actual use. A survey of 245 actual FinTech users from an emerging market economy is used to test the model. PLS SEM is employed for data analysis. revealing that behavioral intention and facilitating conditions were the best predictors of actual system use. The results also showed that hedonic motivation, price value, and habit influenced behavioral intention, but not actual system use. Perceived risk influenced actual system use but not intention. These results provide empirical evidence of an intention–behavior gap. The results also provide the basis for simple amendments to current technological acceptance models that can be applied in different contexts for high-risk digital services.

Keywords
FinTech Adoption, Perceived Risk, UTAUT2, Intention–Behavior Gap, Emerging Markets.

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Resumo
As tecnologias financeiras (FinTech) estão transformando rapidamente a forma como os serviços financeiros são prestados, especialmente para as populações não bancarizadas e subbancadas em mercados emergentes. Embora haja evidências de intenção de usar serviços FinTech, o uso real é desigual e não segue um padrão discernível. Este estudo amplia a aplicabilidade do UTAUT2 para investigar o efeito do risco percebido como inibidor comportamental no uso real de um serviço digital de alto risco. Ao contrário de estudos anteriores, que tratam o risco percebido como um preditor da intenção comportamental, neste estudo o risco percebido é tratado como um inibidor direto do uso real. Uma pesquisa com 245 usuários reais de FinTech de uma economia de mercado emergente é usada para testar o modelo. O PLS SEM é utilizado para análise de dados. revelando que a intenção comportamental e as condições facilitadoras eram os melhores preditores do uso real do sistema. Os resultados também mostraram que a motivação hedônica, o valor do preço e o hábito influenciaram a intenção comportamental, mas não o uso real do sistema. O risco percebido influenciou o uso real do sistema, mas não a intenção. Esses achados fornecem evidências empíricas de uma diferença entre intenção e comportamento. Os resultados também fornecem a base para emendas simples aos modelos atuais de aceitação tecnológica que podem ser aplicadas em diferentes contextos para serviços digitais de alto risco.
Palavras-chave
Adoção de FinTech, Risco Percebido, UTAUT2, Diferença entre Intenção e Comportamento, Mercados Emergentes.

Resumen
Las tecnologías financieras (FinTech) están transformando rápidamente la forma en que se prestan servicios financieros, especialmente a las poblaciones no bancarizadas y subbancarizadas en mercados emergentes. Aunque hay evidencia de intención de utilizar servicios FinTech, el uso real es dispar y no sigue un patrón discernible. Este estudio amplía la aplicabilidad de UTAUT2 para investigar el efecto del riesgo percibido como inhibidor conductual en el uso real de un servicio digital de alto riesgo. A diferencia de estudios anteriores que tratan el riesgo percibido como un predictor de la intención conductual, en este estudio el riesgo percibido se trata como un inhibidor directo del uso real. Se utiliza una encuesta a 245 usuarios reales de FinTech de una economía de mercado emergente para probar el modelo. El PLS SEM se emplea para el análisis de datos. revelar que la intención conductual y las condiciones facilitadoras eran los mejores predictores del uso real del sistema. Los resultados también mostraron que la motivación hedónica, el valor en precio y el hábito influyeron en la intención conductual, pero no en el uso real del sistema. El riesgo percibido influyó en el uso real del sistema, pero no en la intención. Estos hallazgos proporcionan evidencia empírica de una brecha entre intención y comportamiento. Los resultados también proporcionan la base para enmiendas sencillas a los modelos actuales de aceptación tecnológica que pueden aplicarse en diferentes contextos para servicios digitales de alto riesgo.
Palabras clave
Adopción de FinTech, Riesgo Percibido, UTAUT2, Brecha Intención–Comportamiento, Mercados Emergentes.

1. Introduction

Financial technologies (FinTech) have dramatically changed the way financial services are provided. This is especially pronounced in how payment systems, credit intermediaries, and investment services now operate. In emerging markets, a technology that once operated in the periphery of financial services has now become fundamental to the development and provision of financial services, at times even pushing traditional banking to the periphery (AlSharafi et al., 2025; Albuainain & Ashby, 2025). While FinTech has spread globally, important questions remain, especially regarding how FinTech services are perceived by consumers in emerging and advanced economies and how they are selected for adoption. There is a lack of in-depth insight into this “black box.”

The outcomes of FinTech adoption are studied by an increasing number of scholars, and the body of knowledge differs from consumer technology adoption studies in that, in the context of digital financial services, several financial, security, and institutional risks are involved. Our meta-analytical results indicate that factors enhancing the FinTech adoption outcomes include perceived value, convenience, and digital infrastructure. However, cybersecurity, fraud, privacy, and regulatory uncertainty concerns impede the adoption of FinTech services. These risks embedded in the services’ ecosystem call for reflection on whether the traditional TAM is sufficient to explain the behavioral intentions of FinTech service users.

Technology acceptance in information systems research is generally explained by intention-based frameworks such as TAM and UTAUT, and their consumer-oriented counterparts, e.g., UTAUT2. UTAUT2 is a consumer technology acceptance model that introduces cognitive, social, and behavioral factors, as well as moderating factors, that influence consumer technology acceptance and has been shown to have substantial explanatory power across numerous studies. It is no surprise that this framework has been applied in several studies on FinTech adoption (Firmansyah et al., 2023; Amnas et al., 2023).

Although initial applications of UTAUT2 to real-world phenomena have shown promise for predicting behavioral intentions regarding FinTech adoption, recent systematic reviews and meta-analyses have exposed cracks in the empirical performance of the theory’s core predictors. Even though the small number of reviews published to date continue to identify performance expectancy, effort expectancy, and social influence factors as the right predictors to include in acceptance models of FinTech adoption, recent results, especially in developed markets with high levels of digital experience, have established that these factors have a weak effect and do not reliably achieve statistical significance. The models for accepting low-risk technologies for consumer use are not yet sufficiently adapted to the higher risks, uncertainties, and severe consequences in financial services. Therefore, future research is needed to test the performance of alternative models that may better explain intentions to adopt FinTech.

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While perceived risk as a factor has already been incorporated into some FinTech adoption studies, it is typically treated as an antecedent of behavioral intention to adopt FinTech. Yet recent empirical and/or meta-analytical studies found that perceived risk exerts a greater effect on FinTech adoption's use intention and continuance intention than on behavioral intention (e.g., Neves et al., 2023; Wei et al., 2025). This seems to reveal an intention–behavior gap. Even when consumers intend to use FinTech services, they do not actually do so when it matters most due to risk perceptions about FinTech adoption.

In this work, perceived risk is not treated as a novel variable; instead, it is modeled as a factor that influences technology adoption behavior, affecting the digital service end user in high-risk situations. The work addresses a call for theory refinement rather than proliferation, maintaining model simplicity while incorporating realities of the new FinTech context to understand end-user behavior.

The present study extends UTAUT2 by examining the mediating role of behavioral intention in the relationship between psychosocial factors and the actual use of FinTech, from the perspectives of both customers and enterprise users in emerging markets. In addition, it examines whether including perceived risk can improve the model's predictive ability for behavioral intention and actual FinTech use. In doing so, the study gains deeper insights into technology acceptance models in the context of perceived risk.

2. Theoretical Framework and Hypotheses Development

2.1 Foundations of Technology Acceptance and Consumer Decision Making

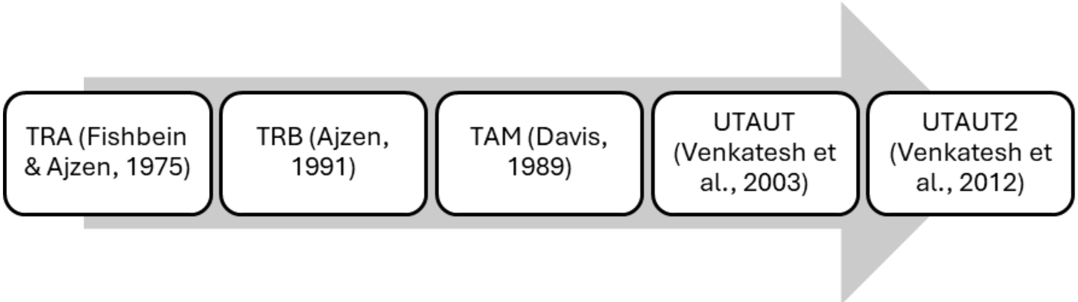
The acceptance of technology by individuals is studied using theories of human behavior and decision-making that originate in social psychology. In general, human behavior is predicted best by measuring behavioral intention, which in turn is predicted by attitudes, beliefs, and subjective norms (Fishbein & Ajzen, 1975; Ajzen, 1991). As a result, two prevailing models exist in the information systems literature, the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB), which both assert that behavioral intention is the best predictor of actual behavior.

Perspectives from diffusion and consumer behavior studies offered insights into the adoption process and its determinants (including benefits, complexity, compatibility, learning effects, and habits). These perspectives, in turn, influenced the development of information systems technology-oriented acceptance models. The most well-known of these models is the Technology Acceptance Model (TAM), which posits that adoption is influenced by two key beliefs: perceived usefulness and perceived ease of use (Davis, 1989).

TAM was a highly effective theory for predicting technology adoption. However, over time, a number of limitations were identified, leading to the development of more comprehensive theories, culminating in the Unified Theory of Acceptance and Use of Technology (UTAUT) and its extension to consumer technology acceptance behaviors, UTAUT2.For example:

Figure 1

Evolution of technology acceptance theories: from behavioral foundations (TRA/TPB) to integrative IS models (TAM, UTAUT, UTAUT2).



Source: Adapted from Fishbein and Ajzen (1975), Ajzen (1991), Davis (1989), Venkatesh et al. (2003), and Venkatesh et al. (2012).

2.2 UTAUT and UTAUT2 in Digital Financial Services

UTAUT2 is an extension of the basic UTAUT model. In addition to the original four antecedents, this model introduced three other factors: hedonic motivation, price value, and habit. This model has been used by many researchers in various studies. It can be used to explain consumers' behavior in adopting consumer technologies such as digital platforms and FinTech (Amnas et al., 2023; Firmansyah et al., 2023; Venkatesh et al., 2012).

Despite initial positive empirical results validating the UTAUT2 model, recent systematic literature reviews have uncovered considerable variability in the performance of UTAUT2's predictors when applied to FinTech services. The traditional predictors of performance expectancy, effort expectancy, and social influence factors may continue to explain consumers' intentions to engage in traditional financial services. However, preliminary results indicate that these factors have very low to no significance in the context of FinTech services, especially for tech-savvy customers.

However, constructs such as behavioral routinization (habit) and contextual enablement (facilitating conditions) have been found to explain variance in behavior better than other predictors in a number of studies. As FinTech services become more routine and normalized, instruments and social differences become less relevant, and evaluations are influenced by experience, behavior and

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contextual factors and factors. Table 1 synthesizes the core constructs of UTAUT and UTAUT2 and summarizes their empirical performance in recent FinTech adoption studies, highlighting the heterogeneous and context dependent nature of traditional acceptance predictors.

Table 1

Core constructs of UTAUT and UTAUT2 and their empirical performance in FinTech adoption studies.

Construct	Theoretical origin	Definition (UTAUT / UTAUT2)	Empirical performance in FinTech adoption literature
Performance Expectancy (PE)	UTAUT (Venkatesh et al., 2003)	Degree to which using technology provides benefits in performing certain activities	Mixed / Often non-significant. Recent reviews report weakening effects in mature FinTech environments, particularly among digitally experienced users, where usefulness becomes a baseline expectation.
Effort Expectancy (EE)	UTAUT (Venkatesh et al., 2003)	Degree of ease associated with the use of a technology	Frequently non-significant. SLRs indicate diminishing explanatory power as FinTech interfaces become standardized and intuitive.
Social Influence (SI)	UTAUT (Venkatesh et al., 2003)	Extent to which individuals perceive that important others believe they should use the technology	Context-dependent / Often weak. Evidence suggests reduced relevance once FinTech moves beyond early diffusion stages.
Facilitating Conditions (FC)	UTAUT (Venkatesh et al., 2003)	Degree to which individuals believe that technical and organizational infrastructure exists to support use	Consistently significant. Identified in recent reviews as one of the most robust predictors of both intention and actual use, especially in emerging markets.
Hedonic Motivation (HM)	UTAUT2 (Venkatesh et al., 2012)	Fun or pleasure derived from using the technology	Moderately significant. Appears relevant in mobile payments and app-based FinTech, capturing experiential quality rather than entertainment per se.
Price Value (PV)	UTAUT2 (Venkatesh et al., 2012)	Cognitive trade-off between perceived benefits and monetary/non-monetary costs	Significant in cost-sensitive contexts. Particularly relevant in emerging markets and competitive FinTech ecosystems.
Habit (HB)	UTAUT2 (Venkatesh et al., 2012)	Extent to which people tend to perform behaviors automatically due to learning	Highly significant. Frequently identified in recent studies and reviews as one of the strongest predictors of FinTech usage and continuance.
Perceived Risk (PR)	Consumer behavior & e-services literature (Bauer, 1960; Featherman & Pavlou, 2003)	Subjective expectation of potential losses (financial, security, privacy, performance)	Strong negative effect on actual use. Meta-analyses show risk impacts usage and continuance more than behavioral intention, highlighting an intention–behavior gap.

2.3 FinTech as a High-Risk Digital Service Context

There are many differences between FinTech and general consumer technologies. But the most important one is that, while consumer technologies can cost their users money, they generally do not pose the risk of financial losses, data fraud, security breaches, or institutional failure that FinTech does. Perceived risk at the consumer level is the perception of expected losses associated with a behavior under uncertainty (Bauer, 1960). Perceived risk with respect to electronic and information technologies in general and financial services in particular has been studied as a multi-dimensional construct encompassing financial risk and other types of risk, including security, privacy, and performance risk (Featherman & Pavlou, 2003). The same set of risk dimensions is relevant to FinTech. Perceived risk is found to be a significant antecedent of adoption and repurchase intention for digital financial services. Meta-analyses and systematic reviews show that risk perceptions are among the best predictors of adoption and continuance intentions for DFS. Importantly, the antecedents of the impact of perceived risk on adoption and repurchase intention in DFS differ qualitatively from traditional technology acceptance theory predictors.

2.4 Perceived Risk, Intention–Behavior Gap, and Model Extension

Traditional acceptance models view perceived risk as a predictor of behavioral intention. Recent research, however, finds that perceived risk has a stronger negative effect on actual use and continuance behavior than on intention. Despite an intention–behavior gap in FinTech adoption, results show that people are, to a large extent, symmetrically favorable towards FinTech services (intention), but reverse their behavior at adoption due to risk considerations. While recent reviews have suggested that perceived risk is one of the determinants of intentions to adopt FinTech (AlSharafi et al., 2025), results here suggest that it is a direct inhibitor of use behavior.

2.5 Hypotheses Development

This study hypothesizes, from the perspectives of TRA, TPB, and UTAUT, that behavioral intention is positively associated with the actual use of FinTech services among consumers. Whether the price for FinTech services is too high, customers will likely shy away. Importantly, perceptions of quality play an equally significant role in shaping the intention to use these services.

H1: Behavioral intention positively influences the use of FinTech services.

H2: Facilitating conditions positively influence the use of FinTech services.

H3: Facilitating conditions positively influence behavioral intention to use FinTech services.

Drawing on UTAUT2, hedonic motivation, price value, and habit are expected to shape behavioral intention, reflecting experiential evaluation, economic tradeoffs, and behavioral routinization.

H4: Hedonic motivation positively influences behavioral intention to use FinTech services.

H5: Price value positively influences behavioral intention to use FinTech services.

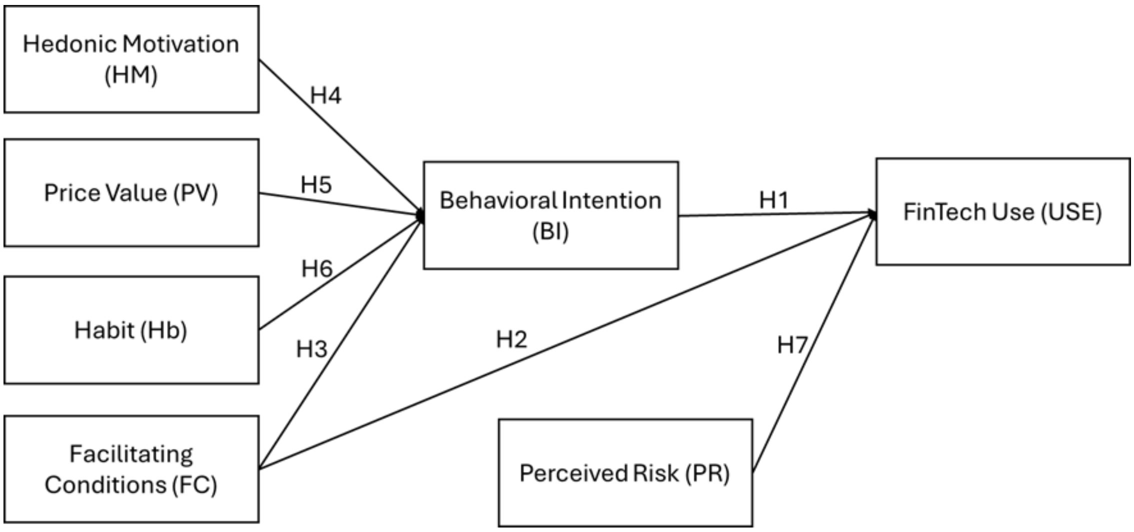
H6: Habit positively influences behavioral intention to use FinTech services.

Finally, based on perceived risk theory and recent meta-analytic evidence, perceived risk is expected to directly inhibit actual FinTech use.

H7: Perceived risk negatively influences the use of FinTech services

Figure 2

Proposed conceptual research model



3. Research Methodology

3.1 Research Design and Analytical Approach

This study applies a quantitative, explanatory approach to identify and assess the determinants of behavioral intention and actual FinTech adoption and usage in emerging markets. This study utilizes a quantitative survey-based approach to test theoretically developed relationships among underlying latent variables and to measure the relative explanatory power of the variables under study, thereby better understanding the complex factors at play.

Whilst numerous theories have been used to explain technology acceptance, their ability to account for variance in adoption intentions is generally limited. As such, rather than pursuing alternative theories, the focus should be on refining existing models in order to improve their

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predictive capability. Using a confirmatory–refinement methodology, this study initially examines the ability of the core determinants contained within UTAUT2 to predict behavior in a low-risk digital service context.

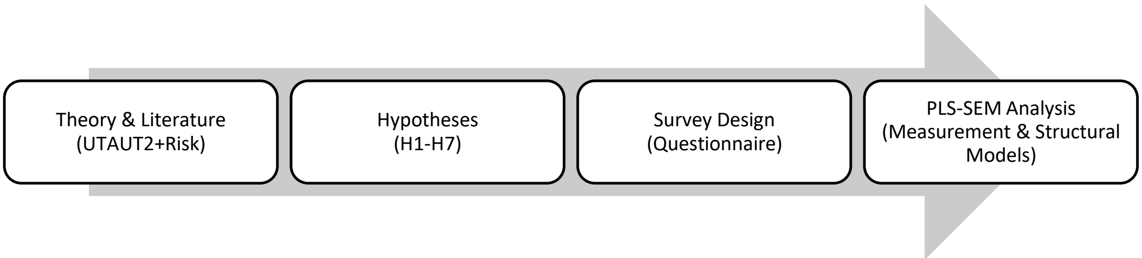
It examines attitudes and self-reported usage at a single point in time, an approach most recent meta-analyses on the adoption and use of digital financial services have followed (Neves et al., 2023). While cross-sectional data have limitations for establishing temporal causality, they are well-suited to test theoretical hypotheses about variables that are related in a theoretically meaningful way and to compare the relative predictive strength of alternative predictors of usage behavior in a fast-changing ecosystem where usage patterns stabilize rapidly.

To validate the research model developed for this study, PLS-SEM was used to test the hypotheses. PLS SEM was the appropriate research methodology for several reasons. Firstly, for the purposes of prediction and theory refinement, PLS-SEM is considered an appropriate methodology (Hair et al., 2019). In this study, our intent was to explain the variance in intention that went beyond the variables in the UTAUT2 model. Secondly, PLS SEM is suitable for moderate-sized samples and robust to complex models with many latent variables. Thirdly, PLS SEM imposes fewer distributional assumptions than covariance-based SEM and is typically used with self-reported survey data.

Our analytical approach followed a two-step approach, where in the first step we assessed the measurement model in terms of reliability and validity of the latent variables, and in the second step we assessed the structural model in terms of the path coefficients, the explained variance for all constructs, and hypothesis testing using bootstrapping techniques. These methods follow PLS SEM best practices and those employed in prior FinTech adoption studies.

Figure 3

Overall research design and analytical



3.2 Research Context and Unit of Analysis

This study investigates the consumers' risk propensities towards the usage of FinTech services in an emerging economy. The consumer FinTech market is characterized by high risk perception and uncertainty in a digital service context, where customers risk losing financial assets and sensitive information. The study focuses on actual users of FinTech services; that is, consumers who have prior experience of using at least one FinTech service. In the recent literature and meta-analytical studies on digital financial services, the distinction between potential adopters and actual users has been increasingly addressed (Neves et al., 2023; Wei et al., 2025).

3.3 Data Collection and Sample

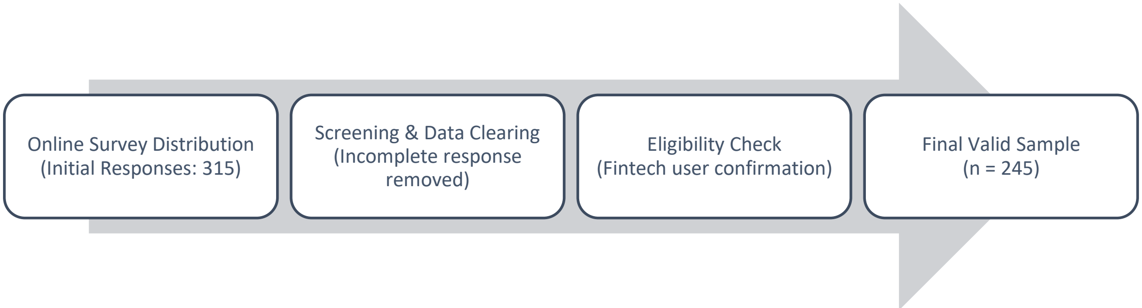
3.3.1 Data Collection Procedure

The survey uses an online questionnaire, as it is state-of-the-art for research on FinTech adoption. The sample consists of respondents who are active Internet users and users of platform-based financial services. Importantly, all surveyed individuals have already used at least one FinTech service, which distinguishes this study from those that measure adoption intentions rather than actual behavior.

This study recruited participants online and used a series of screener questions to pre-screen for prior FinTech experience. Participants were informed of the study's academic purpose and provided consent to participate in the survey before beginning. No Personally Identifiable Information (PII) was collected throughout the study.

Figure 4

Data collection and screening process.



3.3.2 Sampling Strategy

In total, 315 responses were collected for the study. After data cleaning (e.g., removing missing values and excluding participants with prior FinTech experience), a total of 245 valid cases were included in the study and used for the PLS SEM analysis. This is an adequate sample size for the study and comparable to other recent studies on FinTech adoption.

The study's samples were predominantly young and included experienced Internet users. Even though the samples were dominated by young people and cannot be generalized to the broader community, this is acceptable for a study of actual FinTech service users. Numerous studies have shown that active users of FinTech services are young (Firmansyah et al. 2023; Gupta et al. 2024).

Table 2

Demographic and usage profile of respondents

Variable	Category	Frequency	Percentage (%)
Gender	Male	149	60.8
	Female	96	39.2
Age group	19–29 years	159	64.9
	30 years or older	86	35.1
Education level	Undergraduate (incomplete)	120	49.0
	Undergraduate (complete)	36	14.7
	Postgraduate (MBA / MSc / PhD)	89	36.3
Smartphone ownership	Yes	221	90.2
	No	24	9.8
Use of FinTech services	Yes	203	82.9
	No	42	17.1

3.4 Measurement Instrument

The measurement instrument for this study was developed using several valid measures from previous technology acceptance studies and digital financial services studies. Perceived risk was measured by several items that described possible financial loss, security and privacy risks, and system reliability issues. The measure was multidimensional and was drawn from previous studies of electronic services (Featherman & Pavlou, 2003) and financial services (Martins et al., 2014). All studied constructs are modeled as reflective latent variables. Items for studied constructs were surveyed using a Likert scale with five levels of measurement, e.g., 1 (strongly disagree) and 5 (strongly agree).

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Table 3

Measurement constructs, indicators, and literature sources.

Construct	Code	Measurement item	Source
Behavioral Intention (BI)	BI1	I intend to continue using FinTech services in the future	Venkatesh et al. (2012)
	BI2	I plan to use FinTech services frequently	
	BI3	I will recommend FinTech services to others	
Facilitating Conditions (FC)	FC1	I have the resources necessary to use FinTech services	Venkatesh et al. (2012)
	FC2	I have the knowledge necessary to use FinTech services	
	FC3	FinTech services are compatible with other technologies I use	
Hedonic Motivation (HM)	HM1	Using FinTech services is enjoyable	Venkatesh et al. (2012)
	HM2	Using FinTech services is entertaining	
	HM3	I find using FinTech services to be pleasant	
Price Value (PV)	PV1	FinTech services offer good value for money	Venkatesh et al. (2012)
	PV2	FinTech services are reasonably priced	
	PV3	The benefits of FinTech services outweigh the costs	
Habit (HB)	HB1	Using FinTech services has become a habit for me	Venkatesh et al. (2012)
	HB2	I am addicted to using FinTech services	
	HB3	I use FinTech services automatically	
Perceived Risk (PR)	PR1	I am concerned about possible financial losses when using FinTech services	Featherman & Pavlou (2003); Martins et al. (2014)
	PR2	I am concerned about the security of my personal data when using FinTech	
	PR3	Using FinTech services involves significant risk	
Use Behavior (USE)	USE1	I frequently use FinTech services	Venkatesh et al. (2012)
	USE2	FinTech services are part of my daily routine	

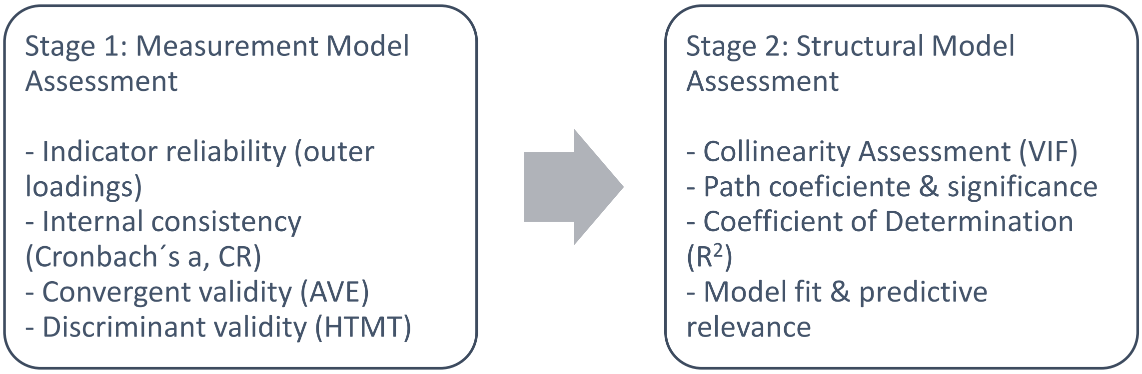
3.5 Data Analysis Technique

The proposed research model was analyzed using Partial Least Squares Structural Equation Modeling (PLS SEM). PLS SEM was chosen because the proposed research model is suited for so-called prediction-oriented or theory-refinement approaches. The chosen research purpose of this study calls for such an approach. Moreover, FinTech adoption is a current topic that warrants research; therefore, moderate sample sizes can be used. PLS SEM is well-suited for analyzing complex models comprising several latent constructs. Furthermore, it is well-suited for the analysis of so-called "soft data," such as self-reported survey data, because it imposes only moderate distributional assumptions, in contrast to traditional covariance-based SEM approaches.

For model validation, a two-stage approach is adopted. Firstly, the measurement model is validated to assess the indicator reliability, inner consistency, convergent validity, and discriminant validity. Secondly, the structural model is validated to assess collinearity among independent variables, estimate significant paths via bootstrapping, and evaluate the model's explanatory power. This is the conventional and best-practice approach in PLS SEM applications, as found in the literature and adopted in many FinTech adoption studies.

Figure 5

Two stage PLS SEM assessment process.



3.6 Common Method Bias

Given that our analysis is based on a single survey, we employ both procedural and statistical techniques to mitigate the risk of common method bias. Specifically, we guarantee respondents' anonymity and inform them that there are no right or wrong answers. According to methodological reviews of survey-based behavioral research, this is the best practice under the given circumstances.

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Post hoc statistical tests were used to determine whether small levels of common method variance threatened the validity of theoretical conclusions.

3.7 Ethical Considerations

This research was conducted in strict accordance with ethical protocols for human subject research. No personal identifiable information (PII) was collected during the survey process. All information collected during the survey will be maintained in strict confidence. If at any point the survey participant wants to withdraw from the survey, he or she can do so immediately.

4. Results

The paper follows an empirical analysis in two steps, following the common procedure for PLS SEM. In a first step, the measurement model is evaluated regarding reliability and validity. In a second step, the structural model is analyzed to test the hypotheses and assess the explanatory power of the research model, which explains how security and convenience features determine actual use behavior of mobile payment services. The variable of actual use behavior is a central component in current research on FinTech adoption.

4.1 Measurement Model Assessment

The measurement model was then evaluated for internal consistency reliability, convergent validity, and discriminant validity. Internal consistency reliability methods, i.e., Cronbach's alpha and composite reliability (CR), were used to test the internal consistency of the measures. The results indicated that all measures were reliable, as the alpha and CR values were above 0.70 and below 0.95, respectively.

Convergent validity was examined using Average Variance Extracted (AVE). The AVE results are reported in Table 6. The values of AVE for all constructs were higher than 0.50. The discriminant validity was assessed by calculating the Heterotrait–Monotrait (HTMT) ratio of constructs. The HTMT values for all combinations are depicted in Table 4. All values are below the conservative threshold of 0.90, supporting the notion that the latent factors under study are empirically distinct.

Table 4

Internal consistency reliability and convergent validity (Cronbach's alpha, CR, AVE)

Construct	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Behavioral Intention (BI)	0.910	0.944	0.848
Facilitating Conditions (FC)	0.829	0.897	0.743
Hedonic Motivation (HM)	0.836	0.904	0.760
Price Value (PV)	0.914	0.946	0.853
Habit (HB)	0.792	0.879	0.709
Perceived Risk (PR)	0.889	0.901	0.697

Table 5

Discriminant validity assessment using HTMT ratios

Construct	BI	FC	HM	PV	HB	PR
Behavioral Intention (BI)	—					
Facilitating Conditions (FC)	0.772	—				
Hedonic Motivation (HM)	0.856	0.808	—			
Price Value (PV)	0.810	0.778	0.827	—		
Habit (HB)	0.891	0.928	0.942	0.819	—	
Perceived Risk (PR)	0.158	0.248	0.167	0.248	0.185	—

4.2 Structural Model Assessment

First, the measurement model was validated, and then tests for multicollinearity and shared variance, and an assessment of goodness of fit, were conducted. Finally, the hypotheses were tested.

To assess collinearity among the independent constructs, the Variance Inflation Factor (VIF) was calculated for each construct. The results, which are below the threshold of 5.0, suggest no multicollinearity problems that could affect the estimation of the structural effects.

The explanatory power of the proposed model is evaluated by calculating the coefficient of determination (R^2) for the two factors of interest, behavioral intention and actual FinTech use.

Table 6

Variance Inflation Factor (VIF) values.

Endogenous construct	Predictor construct	VIF
Behavioral Intention (BI)	Hedonic Motivation (HM)	2.910
	Price Value (PV)	2.554
	Habit (HB)	3.503
	Facilitating Conditions (FC)	2.670
Use Behavior (USE)	Behavioral Intention (BI)	1.931
	Facilitating Conditions (FC)	1.933
	Perceived Risk (PR)	1.004

Table 7

Coefficient of determination (R^2) for endogenous constructs.

Endogenous construct	R^2	R^2 Adjusted	Interpretation of explained variance
Behavioral Intention (BI)	0.687	0.682	Moderate
Use Behavior (USE)	0.692	0.688	Moderate

4.3 Hypotheses Testing and Path Coefficients

Using the standardized coefficients from the model, the hypotheses are tested along the paths and their significance assessed using two-tailed t-tests and bootstrapping procedures. Results reveal a positive effect of behavioral intention on FinTech use as well as positive effects of facilitating conditions on behavioral intention and FinTech use.

Results revealed that hedonic motivation, price value, and habit positively influence users' behavioral intention to use FinTech services. Conversely, results also revealed that perceived risk negatively influences FinTech use but has no significant effect on behavioral intention.

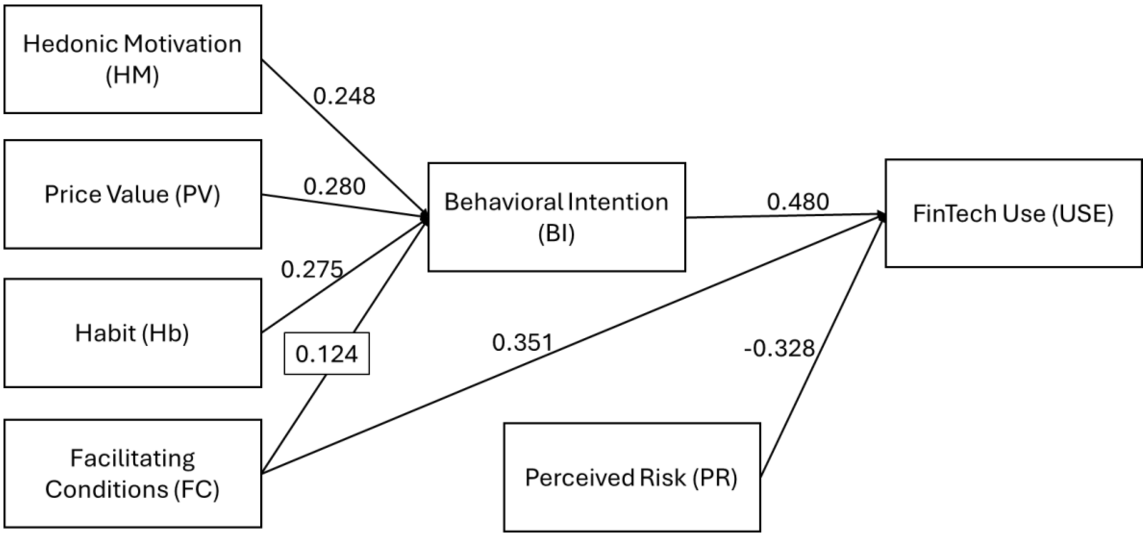
Table 8

Summary of hypotheses testing results (path coefficients, p values, and support status).

Hypothesis	Path	Path coefficient (β)	p-value	Support
H1	Behavioral Intention → Use	0.480	0.000	Supported
H2	Facilitating Conditions → Use	0.351	0.000	Supported
H3	Facilitating Conditions → Behavioral Intention	0.124	0.042	Supported
H4	Hedonic Motivation → Behavioral Intention	0.248	0.000	Supported
H5	Price Value → Behavioral Intention	0.280	0.000	Supported
H6	Habit → Behavioral Intention	0.275	0.000	Supported
H7	Perceived Risk → Use	-0.328	0.000	Supported

Figure 6

Final structural model with standardized path coefficients.



4.4 Model Fit and Predictive Adequacy

In addition to these individual fit indices, overall model adequacy, including global fit and predictive capability, was considered. For the Structural Model, the Standardized Root Mean Square Residual (SRMR) indicates that the correlation matrix is well approximated by the model-implied correlation matrix. Moreover, the model's strong explanatory power for behavioral intention and actual use generalizes well to lower-risk scenarios, such as FinTech adoption.

5. Discussion

This study investigates the impact of perceived risk on the determinants of behavior in a high-risk digital service context. The results indicate that perceived risk is a behavioral inhibitor that enhances UTAUT2's explanatory power in this context and contributes to both theory and practice. While behavioral intention to use FinTech remains a necessary and sufficient antecedent to behavior, individuals with more facilitating conditions are more likely to translate their intended use of FinTech into actual behavior. While behavioral intention to use FinTech remains a necessary and sufficient antecedent to behavior, individuals with more facilitating conditions are more likely to translate their intended use of FinTech into actual behavior. Consistent with foundational behavioral theories, behavioral intention to use FinTech remains a positive predictor of FinTech use behavior. However, results also suggest that facilitating conditions play a particular salience in predicting FinTech adoption in emerging markets, where institutional and technological heterogeneity generates greater friction between intentions and behavior.

However, it also emerges that the traditional predictors of UTAUT have diminishing explanatory power at advanced stages of FinTech adoption. The results suggest that in mature adoption stages, performance expectancy, effort expectancy, and social influence have become performance baselines. Recent systematic evidence supports these results and underpins a "less is more" approach when extending established acceptance models. Rather than continually adding peripheral predictors, models need to be refined to better explain technology acceptance across different contexts. A third set of mechanisms underlying behavioral intentions towards FinTech adoption comprises experiential, economic, and behavioral drivers, namely hedonic motivation, price value, and habit. We observe that consumers' adoption decisions are influenced not only by instrumental considerations and usage routines, but also by perceptions of economic trade-offs. Habit not only affects behavior but also stabilizes intentions over time, saving cognitive effort and reducing intentions' uncertainty.

This study is the first theoretical investigation of the impact of perceived risk on FinTech adoption. Our results show that whilst perceived risk negatively affects users' intention to use FinTech services, it does not affect their actual use. This asymmetric effect between perceived risk and behavior between intentions and behavior creates an intention–behavior gap for FinTech adoption. Although FinTech users are likely to favor digital financial services from a cognitive perspective, concerns about potential financial loss, privacy, and the security of sensitive personal information, as well as perceptions of financial service providers, impact their actual use of FinTech services. This study finds that perceived risk is a behaviorally relevant factor and challenges the conventional wisdom that perceived risk is an antecedent of behavioral intention. As such, perceived risk should no longer be treated as a separate predictor in existing technology acceptance models. The study further finds that the explanatory logic underlying UTAUT2 is service-specific and contingent on the service's risk profile. This underscores the need for context-aware technology acceptance models in digital financial services. Building on the existing literature, our results identify a key reason why intention-based models of FinTech adoption tend to overpredict actual adoption and offer a simple yet powerful fix to improve accuracy.

6. Conclusions, Implications, and Limitations

To understand the factors driving the acceptance and actual use of FinTech services in emerging markets, this study extends the UTAUT2 model by incorporating perceived risk. This practical and parsimonious approach addresses a significant theoretical gap in the current technology acceptance literature regarding high-risk digital services. The results of this study support three principal results. Firstly, the intention-based explanations for predicting FinTech usage intentions remain relevant, with behavioral intention and facilitating conditions among the most important predictors. Secondly, experiential or past-behavior factors (hedonic motivation, price value, and habit) explained a significant amount of variation in behavioral intentions for FinTech use. Thirdly, and most significantly, the results found that risk acts as a direct barrier to FinTech usage rather than a predictor of behavioral intentions. These results identify an 'intention–behavior gap' in the adoption of digital financial services.

The results of this research offer new theoretical insights into established knowledge of technology acceptance mechanisms and demonstrate that these mechanisms are not technology-generalizable. In FinTech, which is inherently high in financial, security, and institutional risk, perceived risk has a particular effect at the behavioral enactment stage of the model. Context-aware acceptance models that prioritize depth over breadth using the UTAUT2 framework are therefore most appropriate. The results of this study have relevant practical implications for increasing FinTech adoption. While perceived value, user experience, and habitual use are important precursors to intentions to adopt FinTech services, these intentions need to be translated into actual use. Strategies to reduce perceived risk, including cybersecurity, data privacy, and trust in institutions, should be present at various points throughout interactions with these services.

The study has some limitations. First, as a cross-sectional study, it cannot trace changes in risk perceptions and habit formation (the mediating variables) over time. Second, the study is based on a single emerging market. As such, it is subject to the limitations of a single-country study. Future studies should incorporate a longitudinal design, use more objective FinTech usage data, and investigate the moderating effects of financial literacy, institutional trust, and other variables that may affect the predictors of FinTech adoption behavior.

Moving beyond general technology acceptance theory explanations of FinTech adoption, we identify a more parsimonious yet context-aware set of explanations that incorporates behavioral risk. This research contributes to the theory and practice of digital financial services by illustrating the impact of perceived risk on FinTech usage behavior.

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