How Trust, Experience, and Expectations Drive Fintech Adoption through Technology Acceptance

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Abstract: While financial technology (fintech) reshapes the landscape of financial services, user adoption remains an elusive goal. This study unpacks the drivers of fintech uptake in China by extending the Technology Acceptance Model (TAM) to examine the roles of user experience, trust, and expectations. Drawing on partial least squares structural equation modeling (PLS-SEM), we analyzed survey data from 300 users to illuminate these intricate relationships. The results obtained reveal that user experience exerts a direct influence on adoption through TAM's mediating role, thereby underscoring the importance of cognitive processing in determining its functional benefits. Trust operates via dual pathways, directly boosting adoption intent and indirectly enhancing it through TAM, thus highlighting its pivotal role in alleviating risk and fostering confidence. User expectations shape adoption in both a direct and indirect manner, reflecting their nuanced influence on perceived performance and security. These findings position TAM as a critical bridge linking user experience to behavior, while trust and expectations enrich adoption dynamics through multi-path effects. This research contributes to fintech adoption theory and offers strategic insights for promoting fintech products in practice.

Keywords: Fintech; Experience; Trust; Expectations; Technology Acceptance Model; Partial Least Squares

1. Introduction

China stands at the forefront of financial technology (fintech), with platforms like Alipay and WeChat Pay transforming how millions transact daily. This digital shift, fueled by widespread mobile adoption, has redefined financial services, enhancing efficiency and accessibility in a market of unparalleled scale[1]. Yet, adoption remains uneven, as users grapple with concerns beyond functionality—privacy risks and financial stakes demand more than ease of use[2]. Unlike general technology, fintech's high-risk nature amplifies the roles of trust, experience, and expectations in shaping user behavior. Understanding these drivers is critical, particularly in China, where fintech's rapid growth underscores both its potential and the persistent barriers to full acceptance.

Despite this growth, the Technology Acceptance Model (TAM)[3-4] and its extensions (e.g., TAM2 [5], UTAUT [6]) fall short in fully explaining fintech adoption. While TAM excels at linking perceived usefulness and ease to uptake in IT contexts, its focus on single factors overlooks the joint effect of psychological dimensions critical to financial services. Existing studies rarely explore how trust, user experience, and expectations collectively influence adoption through technology acceptance, especially in risk-sensitive settings. This gap limits theoretical insight into fintech's unique dynamics, where trust mitigates privacy fears, experience builds reliance, and expectations frame value—elements insufficiently captured by traditional frameworks.

To address this, this study extends TAM to examine how trust, experience, and expectations jointly drive fintech adoption in China. Analyzing survey data from 300 users via Partial Least Squares Structural Equation Modeling (PLS-SEM), we uncover distinct pathways: trust influences adoption both directly and via acceptance, experience shapes it fully through acceptance, and expectations exert dual effects. These findings refine TAM for fintech's complexities, highlighting trust's pivotal role and acceptance's mediation of experience. Beyond enriching adoption theory, this research offers fintech firms' actionable strategies—prioritizing trust and streamlined experiences—to boost uptake in high-stakes markets like China.

2. Theoretical Framework and Research Hypotheses

2.1 Definition of Technology Acceptance

Technology acceptance (TA) has long been considered a reflection of users' assessments of technology functionality0 with ease of use and practicality at its core[3]. The definition provided serves as the groundwork for the Technology Acceptance Model (TAM), which underscores the role of technological attributes in shaping individuals' behavioral intentions and attitudes toward technology use [4]. However, in the field of financial technology, a purely functional perspective is no longer adequate to capture the complexity of user choice-making. The inherent uncertainty in financial services, coupled with the need for enhanced security, necessitates that Technology Adoption (TA) extend beyond conventional frameworks. It should incorporate a broader spectrum of psychological and behavioral factors to establish a more robust theoretical foundation for understanding the adoption process.

To this end, subsequent research has revealed the multidimensional nature of TA by expanding TAM. TAM2 revealed the importance of social influence on the basis of the original theory, indicating that users' technology acceptance is deeply driven by subjective norms and perceptions[5]. Subsequent integration of factors such as usage experience and age by UTAUT emphasised the role of individual background in the adoption process[6]. As research continued to deepen, TAM3 further refined the original model, elucidating the dynamic nature of user attitudes over time[7]. Based on these theoretical developments, this study defines TA as a multidimensional construct integrating functional cognition and psychological adaptation. It is not confined to technical attributes, but also encompasses the user's capacity to adapt to complex environments. This definition is of particular significance in the context of financial technology, and provides a robust theoretical foundation for subsequent analysis of the driving mechanisms of adoption behavior.

2.2 User Experience and Fintech Adoption

The concept of user experience (UX) emerged in the late 1980s, with Norman pioneering the definition of user experience as the sensory and emotional response of users when using a system, thereby establishing the theoretical foundation for the concept[8]. Empirical studies of Davis and his colleagues on technology acceptance models further show that perceived pleasure, as a key factor in user experience, plays a greater role in technology acceptance (TA) than perceived usability and easiness to use[9]. In addition, Partala and Saari further demonstrated that the extent to which users' emotional and psychological needs are met during the user experience significantly enhances their propensity to accept technology[10].

In the field of financial technology, Singh et al. have shown that the perceived utility and user-friendliness, fundamental components of user experience, directly influence users' decisions to accept financial technology[11]. Nugraha et al. also found that SME are more inclined to adopt financial technology solutions due to improved usability and practicality. This further supports the direct influence of user experience on adoption behavior[12]. Furthermore, Hu et al. highlighted the mediating effect of technology acceptance between user experience and adoption intention, extending the technology acceptance model to underscore its central role in the causal pathway[13].

Therefore, the subsequent hypotheses are advanced:

Hypothesis 1: User experience positively influences technology acceptance;

Hypothesis 2: User experience positively influences FinTech adoption;

Hypothesis 3: Technology acceptance serves as an intermediary factor that connects user experience with the adoption of financial technology.

2.3 User Trust and Fintech Adoption

In the field of financial technology, user trust (UT) is a pivotal factor influencing technology acceptance, given its implications for fund security and privacy protection. Hu et al. utilized an extended technology acceptance model (TAM) to ascertain that user trust in financial technology services substantially enhances technology acceptance, thereby underscoring the foundational role of trust in cognitive formation[13]. In a similar vein, the results of Albarayati et al. highlight the crucial influence of user trust, enhanced by government regulation and prior usage experience, in promoting the adoption of cryptocurrency and blockchain technologies[14]. A parallel study by Singh et al. illuminates the manner in which initial trust, stemming from system and information quality, amplifies users' propensity to embrace mobile payment technologies[11]. Luarn and Lin's findings concurred with this, demonstrating that trust can assist mobile banking users in surmounting initial resistance and, consequently, fostering technology acceptant[15].

The influence of trust is not confined to the realm of technology acceptance. Hamakhan's systematic analysis revealed that user trust directly fosters adoption behavior in e-banking services, underscoring its role as a conduit between personal characteristics and behavior[16]. In addition, Pathak and Bansal's research on AI digital agents also highlighted that user trust directly enhances willingness to adopt by improving perceptions of technology quality, especially in the field of banking services[17] Meanwhile, Malaquias and Hwang's study of mobile banking in developing countries found that user trust indirectly affects adoption behavior through technology acceptance, further verifying the central role of trust in this process[18].

Accordingly, the following hypotheses are put forward:

Hypothesis 4: User trust positively influences technology acceptance;

Hypothesis 5: User trust positively influences FinTech adoption;

Hypothesis 6: Technology acceptance serves as a mediator in the relationship between user trust and the adoption of financial technology.

2.4 User Expectations and Fintech Adoption

According to the Expectation Confirmation Theory (ECT) framework, Shiau et al. demonstrate that consumers' anticipations regarding fintech solutions' functionality, security measures, and operational simplicity substantially influence their disposition toward technology adoption[10] The ECT framework highlights how congruence between users' pre-use anticipations and actual experience influences their technological perception. Bhattacherjee's research further found that when users expectations of technology effectiveness and security are met, their acceptance of the technology also increases significantly, highlighting the driving role of expectations in the acceptance process[19]. In their technology acceptance framework, Davis and colleagues validated that preliminary user anticipations favorably impact adoption disposition through heightened perceptions of functionality benefits and operational simplicity[9].

In addition, the role of user expectations in FinTech adoption behavior should not be ignored. Albayati et al. found that high user expectations of blockchain technology security and performance directly promote their willingness to adopt, especially when security expectations are high[14]. Furthermore, Gupta et al. pointed out through an extended expectancy confirmation model that users' performance expectations before adopting mobile payments can promote consumption-driven confirmation, thereby enhancing their continued adoption behavior[20]. Idrees and Ullah also confirmed in a study of Pakistani consumers that performance expectations and effort expectations significantly promote the adoption of financial technology, further verifying the direct effect of user expectations[21]. Meanwhile, Venkatesh pointed out in the UTAUT model that technology acceptance mediates the relationship between user expectations and adoption behavior, further emphasizing the path by which user expectations indirectly influence adoption behavior through technology acceptance[6].

Based on the preceding literature, this study advances the following propositions:

Hypothesis 7: User expectations exert a favorable influence on technology acceptance;

Hypothesis 8: User expectations contribute positively to FinTech solution adoption;

Hypothesis 9: Technology acceptance functions as an intervening variable in the pathway connecting user expectations to FinTech solution adoption.

2.5 Technology Acceptance and Fintech Adoption

Research shows that user acceptance of financial technology directly affects their willingness and behavior to use it[4]. In particular, in the dynamic financial transaction environment, technology acceptance promotes adoption decisions by shaping users' positive attitudes towards services[11]. Furthermore, mitigating psychological resistance to novel technological platforms and strengthening users' confidence in their abilities can substantially facilitate financial technology implementation[22]. This connection between improved acceptance and increased adoption patterns leads to the following hypothesis: Technology acceptance positively influences FinTech adoption.

To conclude, the theoretical model with its interconnected variables is presented in Figure 1, offering a comprehensive visualization of the research constructs and their proposed associations examined throughout this study.

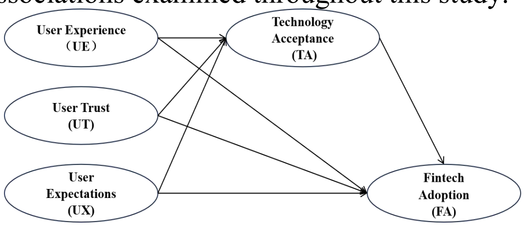

Figure 1. Explanation Framework

3. Research Design

3.1 Measurement Concept

This paper's measurement scale is based on a literature review of five dimensions: user experience, trust, expectations, acceptance and adoption. The measurement scales utilized in this investigation were sourced from established scholarly works and subsequently modified to align with the specific parameters of this empirical context. The user experience includes four measurement items that mainly measure the user's operational experience and satisfaction when using the fintech platform. User trust includes four measurement items that mainly assess the user's trust in the platform in terms of security and stability. User expectations include four items on platform functionality and security[19][23][24]. Technology acceptance includes six items on user perception[25]. The platform's technical features are accepted and mastered[4,6]. The financial technology acceptance construct comprises four evaluative criteria that examine users' assessments regarding platform innovativeness and operational congruence[26]. Respondents indicated their level of agreement with each statement using a five-point measurement scale ranging from complete disagreement (1) to complete agreement (5), enabling quantitative analysis of subjective evaluations. This methodological approach establishes a rigorous foundation for empirical hypothesis testing.

3.2 Data Acquisition

The empirical investigation employed structured survey instruments administered through digital and physical channels during the initial two months of 2024. Experts in related fields evaluated the content and conducted a pre-test. The questionnaire was revised based on feedback. Test items and reverse items in the scale were used as quality control indicators. 318 questionnaires were distributed, 308 were returned. Invalid questionnaires were eliminated during data cleaning based on the following criteria: incorrect answers, inconsistencies, the same option appearing more than 8 times, and the time taken to complete the questionnaire being too short. Following a rigorous data collection process, 300 complete and usable survey instruments were successfully recovered, yielding an effective return rate of 94.34% from the total distribution.

3.3 Methodology

Data analysis in this study was conducted using SPSS 27.0 and Smart PLS 4.0. SPSS 27.0 was employed for performing descriptive statistical analysis, whereas Smart PLS 4.0 was utilized for both exploratory and confirmatory factor analyses, as well as for testing the hypotheses through structural equation modeling.

4. Result

4.1 Statistical Profile Assessment

The quantitative examination of survey responses demonstrates an approximately equitable division between genders, with males comprising 50.7% and females representing 49.3% of participants. Regarding age demographics, the predominant cohort within the sample population falls within the 26-45year bracket, constituting 53% of all respondents. A significant proportion of respondents hold a Bachelor's degree (33.7%), with more than 51% possessing a Bachelor's degree or a higher qualification. People use an average of 2.46 financial technology platforms. Alipay and WeChat Pay have the highest usage rates at 80.0% and 77.3% respectively, making it the most important platform combination. Online investment platforms and digital banks have usage rates of 43.0% and 39.3% respectively, showing room to grow in investment and wealth management and digital banking services. The platform combination analysis shows that 24.0% of users only use the basic payment services of WeChat Pay and Alipay, while 34.7% use all three platforms (including investment platforms or digital banks), reflecting the growing demand for diversified financial technology services (see Table 1 for specific information).

Table 1. Demographic Information

category	indicator	frequency	pct (%)
gender	male	152	50.7
	female	148	49.3
age	18-25	58	19.3
	26-35	83	27.7
	36-45	76	25.3
	46-60	62	20.7
	over 60	21	7.0
platform pairing	Alipay & WeChat Pay	184	61.3
	WeChat Pay & Online Investment	89	29.7
	Alipay & digital banking	86	28.7
	Alipay & online investment	83	27.7
	WeChat Pay & Digital Banking	72	24.0
	Alipay & WeChat Pay	184	61.3
education level	high school diploma or lower	74	24.7
	College	73	24.3
	Bachelor degree	101	33.7
	Master degree	33	11.0
	Doctor degree	19	6.3
single platform usage	Alipay	240	80.0
	WeChat Pay	232	77.3
	digital bank	118	39.3
	online invest ment	129	43.0
	other	18	6.0

4.2 Confirmatory Factor Analysis

The validation of the measurement model was conducted through an assessment of both convergent and discriminant validity metrics. Table 2 illustrates that all item loadings for constructs in the present investigation range from 0.728 to 0.892, substantially surpassing the conventional minimum criterion of 0.7 that is widely recognized in empirical research literature Concurrently, the internal consistency assessment revealed that each latent construct demonstrated robust psychometric properties. Specifically, the Cronbach's alpha coefficients fell between 0.855 and 0.899, exceeding the recommended threshold of 0.8, while construct reliability indices (CR) were calculated between 0.902 and 0.923, surpassing the established benchmark of 0.7. These statistical parameters substantiate the methodological rigor and measurement fidelity of the instruments employed to operationalize the theoretical constructs under investigation [27]. Additionally, analysis of Average Variance Extracted (AVE) demonstrated substantive measurement adequacy across all theoretical constructs, with values distributed between 0.667 and 0.736. These coefficients universally surpass the methodologically prescribed minimum criterion of 0.5 [28], thus establishing compelling empirical support for the measurement model's convergent validity. Furthermore, the discriminant validity assessment is documented comprehensively in the subsequent statistical summary (Table 3), the discriminant validity values, assessed using the HTMT method, ranged from 0.305 to 0.675, well below the stringent threshold of 0.85. Additionally, the correlation coefficients between the variables (ranging from 0.261 to 0.602) are all lower than the square roots of their respective AVEs, thus meeting the Fornell-Larcker criterion. These results collectively confirm that the measurement scale demonstrates strong discriminant validity. In the preceding tabulation, diagonal elements (displayed in bold typeface) constitute the square root calculations of Average Variance Extracted (AVE) for each construct, whereas the numerical coefficients positioned in the upper triangular matrix denote the Heterotrait Monotrait (HTMT) correlation ratios between construct pairs.

Table 2. Reliability Evaluation and Convergent Validity

conception	indicator	factor load	Cronbach's α	composite reliability	AVE
user experience	UE1	0.873	0.86	0.905	0.705
	UE2	0.86			
	UE3	0.728			
	UE4	0.887			
user trust	UT1	0.845	0.855	0.902	0.697

	UT2	0.871			
	UT3	0.784			
	UT4	0.837			
user expectations	UX1	0.774	0.874	0.913	0.726
	UX2	0.877			
	UX3	0.887			
	UX4	0.865			
technology acceptance	TA1	0.865	0.899	0.923	0.667
	TA2	0.857			
	TA3	0.773			
	TA4	0.865			
	TA5	0.751			
	TA6	0.779			
fintech adoption	FA1	0.793	0.880	0.917	0.736
	FA2	0.871			
	FA3	0.892			
	FA4	0.871			

Table 3. Discriminant Validity Test

	AVE	UT	FA	TA	UE	UX
UT	0.697	**0.835**	0.55	0.492	0.305	0.478
FA	0.736	0.482	**0.858**	0.675	0.359	0.499
TA	0.667	0.434	0.602	**0.817**	0.471	0.524
UE	0.705	0.261	0.321	0.417	**0.840**	0.534
UX	0.726	0.424	0.441	0.467	0.463	**0.852**

4.3 Hypothesis Test

This study tested the hypotheses using the Smart PLS 4.0 bootstrapping method. The results are shown in Table 4 and Figure 2. The empirical findings establish that technological acceptance exerts a statistically significant positive influence on financial technology implementation behaviors (β = 0.431, t = 6.060, P < 0.001), as demonstrated through rigorous statistical analysis. that user trust has a significant positive impact on fintech adoption (β = 0.235, P < 0.001); that user expectations have a significant positive impact on fintech adoption (β = 0.131, P < 0.05); user experience has a significant positive impact on technology acceptance (β = 0.234, P < 0.001); user trust has a significant positive impact on technology acceptance (β = 0.269, P < 0.001); user expectations have a significant positive impact on technology acceptance (β = 0 .245, P < 0.001); while the direct impact of perceived user experience on fintech adoption is not significant (β = 0.019, P > 0.05). At the same time, the R^2 of the two variables of technology acceptance and fintech adoption in this study are $R^2_{TA} = 0.329$ and $R^2_{FA} = 0.437$, respectively, which have a moderate explanatory power [29]. In summary, the hypotheses H1, H4, H5, H7, H8, and H10 were supported, while H2 was not.

Table 4. Hypothesis Test Result

hypothesis	path	path coefficient	t value	P value	test result
H1	UE->TA	0.234	3.665	0.000***	Accept
H2	UE->FTA	0.019	0.296	0.768	Reject
H4	UT->TA	0.269	4.166	0.000***	Accept
H5	UT->FTA	0.235	3.507	0.000***	Accept
H7	UX->TA	0.245	3.598	0.000***	Accept
H8	UX->FTA	0.131	2.071	0.038*	Accept
H10	TA->FTA	0.431	6.060	0.000***	Accept

Note: *p<0.05, **p<0.01, ***p<0.001

This study tests the mediating effect through the ratio of indirect effect to total effect (VAF). As shown in Table 5, the indirect effects of user experience, user trust and user expectations on fintech adoption through technology acceptance do not include zero in the 95% confidence interval, and the mediating effects are all significant. Among these, technology acceptance partially mediates the relationship between user trust and fintech adoption (indirect effect value of 0.116, t = 3.505, P < 0.001), with a VAF value of 33.14%; technology acceptance partially mediates the relationship between user perception and fintech adoption (indirect effect value of 0.106, t = 3.089, P < 0.01), with a VAF of 44.73%. Since the direct effect of user experience on fintech adoption was not significant, technology acceptance fully mediated the relationship between user experience and fintech adoption (indirect effect value of 0.101, t = 3.130, P < 0.01), with a VAF of 84.17%.

The structural model assessment revealed favorable fit indices, with a Standardized Root Mean Square Residual (SRMR) of 0.048, falling beneath the methodological threshold of 0.08, thus confirming adequate empirical congruence. Comprehensive path coefficient examination through total effects analysis identified user trust as the predominant determinant of financial technology utilization (β = 0.350, t = 5.382, P < 0.001), with user expectations emerging as the secondary influential factor (β = 0.237, t = 3.351, P < 0.01). Notably, the cumulative impact of experiential variables demonstrated comparatively modest statistical significance (β = 0.120, t = 1.828, P < 0.10), suggesting a hierarchical structure of adoption antecedents.

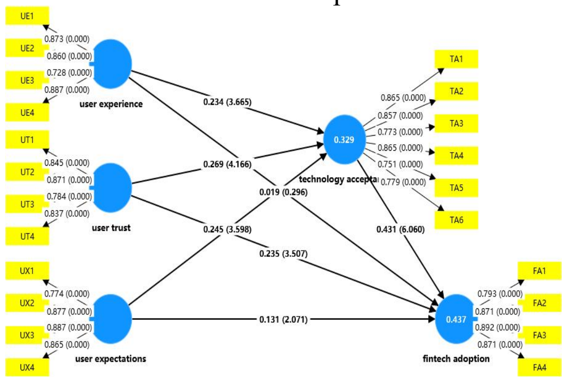

Figure 2. Empirical Results

Table 5. Mediating Effect

independent variable	mediator variable	dependent variable	direct effect	indirect effect	total effect	VAF (/%)	confidence interval	P value	test result
UE	TA	FTA	0.019 (0.296)	0.101 (3.130)	0.120 (1.828)	84.17	[0.043, 0.169]	0.002	full mediation
UT	TA	FTA	0.235 (3.507)	0.116 (3.505)	0.350 (5.382)	33.14	[0.056, 0.184]	0.000	partial mediation
UX	TA	FTA	0.131 (2.071)	0.106 (3.089)	0.237 (3.351)	44.73	[0.043, 0.179]	0.002	partial mediation

5. Discussion

This study reveals how user experience (UE), trust (UT) and expectations (UX) drive fintech adoption through technology acceptance (TA), providing key insights into user behavior in this high-risk area. Based on a structural equation model (PLS-SEM), the results not only validate the paths of the variables, but also provide rich insights into the theory and practice of fintech.

The influence of user experience (UE) on fintech adoption is entirely indirect through technology acceptance (TA) (β = 0.234, p < 0.001; H1 supported, H2 rejected), and the mediating effect is significant (VAF = 84.17%). This is consistent with the technology acceptance model (TAM), which states that perceived ease of use and usefulness must first be translated into acceptance in order to promote behavior. However, the specificity of the financial sector is that users not only rely on sensory appeal, but also pay more attention to the functional efficiency of the technology. In the actual environment, users' adoption decisions rely more on the performance of the technology in tasks than on the visual appeal of the interface. Specifically, Alipay's “one-click payment” function significantly improves TA rather than direct adoption by simplifying the transaction process and reducing the burden on users. This full mediation effect shows that UE acts more as a cornerstone of functional dependence, and its influence only extends to action after the technology is accepted. In the context of China's highly popular mobile payments, simplifying the KYC (Know Your Customer) process and other links can significantly increase users' intention to adopt, which will generate a greater return than visual beautification of the platform interface.

Second, trust exerts a dual influence on FinTech adoption: in one respect, trust directly enhances the intention to adopt technology by enhancing perceptions of FinTech security and privacy protection (β = 0.235, $p < 0.001$; H5 supported); in another respect, trust indirectly affects adoption behavior through technology acceptance (TA) (β = 0.269, $p < 0.001$; H6 supported), representing a partial mediation effect (VAF=33.14%). This finding confirms the important role of trust in adoption, especially by reducing users' concerns about data breaches or financial fraud and enhancing their evaluation of financial technologies and functions. This is also supported by Featherman and Pavlou's perceived risk theory, which suggests that trust increases willingness to use by making users believe that payment systems have strict security and privacy protection measures in place, which in turn makes them more inclined to trust the platform's services [30]. For example, WeChat Pay's transparent privacy policy simultaneously enhances both immediate usage intentions and long-term acceptance. This dual effect stems from the multidimensional nature of trust: cognitive trust ensures system reliability, while affective trust gives users a sense of security. This dual-path effect is particularly pronounced in the Chinese market, where privacy sensitivity is high, reflecting the centrality of trust in the adoption of high-risk technologies.

Meanwhile, expectations (UX) shape FinTech adoption behavior through a direct effect (β = 0.131, $p < 0.05$; H8 supported) and an indirect effect through technology acceptance (TA) (β = 0.245, $p < 0.001$; H9 supported), showing a significant partial mediating effect (VAF = 44.73%). According to the theory of expectation confirmation [19], users' prior expectations of fintech performance (e.g., transaction speed or security) primarily drive adoption through TA, and their direct effect is relatively weak. When users expect digital banks to provide efficient services, they are more inclined to accept the technology rather than adopt it immediately. Beyond this cognitive perspective, prospect theory further clarifies how users weigh expected benefits against perceived risks in their adoption decisions. This perspective explains the weak direct effect, as risk concerns may offset some of the expected benefits, complementing the mitigating effect of trust. Against the backdrop of users' increasingly pragmatic needs, the driving role of expectations is not only rooted in cognition, but also dynamically adjusted with technological evolution, providing new insights into the psychology dimension for future research.

6. Conclusion

6.1 Theoretical Contribution

This research expands the scholarly discourse on financial technology implementation through several theoretical enhancements.

Initially, our investigation broadens the conceptual architecture of the Technology Acceptance Model (TAM) via the integration of experiential dimensions, confidence mechanisms, and anticipatory constructs into the analytical framework. TAM focuses on ease of use and usefulness, but this study introduces expectations as a factor that complements these. It shows that these factors drive adoption behavior through technology acceptance. This extends TAM to explain high-risk scenarios, verifying its applicability in the context of fintech and providing a comprehensive perspective on user behavior. Trust's role in fintech adoption is twofold: it directly reduces users' risk concerns and promotes intentions to use the technology, and indirectly increases intentions by demonstrating its functionality. This dual effect highlights the importance of trust in fintech adoption, particularly in building user trust through technical guarantees and institutional transparency.

Fintech's unique risks highlight the complexity of adoption behavior. User experience, trust and expectations show that efficiency and security complement each other in driving adoption. This integration enhances the relevance of TAM in high-risk contexts and offers a robust structure for examining the acceptance behavior in other high-risk technological environments, thereby broadening the scope of technology adoption theory.

6.2 Limitations and Future Research

This paper's limitations suggest future research directions. The sample's geographical limitations may affect the conclusions' universality. The Chinese market is highly representative of the financial sector, but cultural and regulatory differences in countries/regions (Europe, the United States, Southeast Asia) may lead to changes in adoption behavior. For example, Chinese users have a higher tolerance for data privacy, while European and American users are more concerned about GDPR compliance. Future research should test the universality of the model through cross-cultural comparisons. These studies should explore the role played by cultural differences, legal environments and social norms in the application of financial technology in different markets. This study adopted a cross-sectional design, which is limited in its ability to infer causality due to the lack of a time dimension. Research could adopt a longitudinal design to track changes in user behavior and test causal mechanisms in the long-term evolution of fintech. This study did not consider some variables that may play an important moderating role between experience, trust and expectations. To improve the adoption model and reveal deeper differences in user behavior, these variables should be introduced. This study used a structural equation model (SEM) for quantitative analysis, but this method doesn't fully reveal the psychological motivations and behavioral mechanisms of users. Future research should explore the driving factors behind user behavior from multiple dimensions by combining quantitative and qualitative methods.

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