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CONSUMER TRUST AND INNOVATION IN FINTECH: A STUDY ON DIGITAL BANKING ADOPTION

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ABSTRACT

In this study, factors of adoption of digital banking in Pakistan's FinTech sector (i.e. consumer trust and perceived risk; technological innovation) are analyzed. The research is grounded upon the UTAUT2 and the Technology Acceptance Model to identify key determinants for shaping of the behavioral intentions (BI) towards the digital banking. The research design used in this Ph.D. thesis was quantitative, cross sectional using data from digital banking users which then used Structural Equation Modeling (SEM) to analyze the collected data. The results demonstrate that Perceived Usefulness (PU) ($\beta = 0.63$) plays a significant role in BI, supporting TAM's main postulates, while Perceived Risk (PR) ($\beta = 1.03$) contradicts the extant risk theories by being positively related to BI. Still, the statistical insignificance of Performance Expectancy (PE), Trust (TR), and Social Influence (SI) indicates a replacement of classic adoption factors with a focus on security awareness and grassroots goodness. In this regard, this study makes theoretical contribution by developing adopting models that take on evolving FinTech dynamics. It empirically expands the literature by showing that the risk perception of digital banking consumers, introduction of innovation, and the app's usability are related in affecting digital banking adoption in emerging markets. From a practical point of view, they should improve AI based security features, usability and transparent communication of risks to increase consumer trust. There is also future research that can be done in longitudinal trends, AI personalization and regulations in different markets. However, the study has limitations in geographic scope, as well as in methodological approach and proposes qualitative and experimental research to improve generalizability.

Keywords: Digital Banking, FinTech Adoption, Consumer Trust, Perceived Risk, UTAUT2, TAM, Emerging Markets, Structural Equation Modeling

INTRODUCTION

Boosted by a large young population, the increased usage of smartphones, government initiatives, the FinTech sector in Pakistan is growing rapidly (Rahman et al., 2024; Ali et al 2023). While digital transactions with a 57% increase in 2023, consumer trust is still a mile stone for some reason due to fears of security and cyber crime and few more regulatory uncertainty (Kapoor et al., 2022). In developing economies, trust is dictated by platform security, as well as previous experiences and, because of that, digital banking adoption depends on trust (George & Sunny, 2023). Blockchain and AI are improving security and efficiency but the users still do not believe (according to Ali et al., 2023). However, the State Bank of Pakistan's regulatory measures aimed at strengthening the cybersecurity and enhancing financial inclusion (Kapoor et al., 2022; Jena 2023) are being confronted with low financial literacy and connectivity problem in the rural areas. To fulfill the promise of Pakistan's FinTech industry, the ever growing challenges of lack of trust in this country, aided by technological democratization, will have to be addressed (Rahman et al., 2024; George & Sunny, 2023).

Literature Review

The consumer behavior shift toward digital banking depends on seven constructs namely Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Performance Expectancy (PE), Social Influence (SI), Trust (TR), Perceived Risk (PR) and Personal Innovativeness (PI) which together influence Behavioral Intentions (BI) (Rahman et al., 2024). Digital literacy variations in Pakistan make PEOU essential but PU determines user usage via perceived benefits (Ali et al., 2023; George & Sunny, 2023). The user segment that comprises younger individuals bases its decision-making process on Performance Expectancy because they need efficient and convenient services (Rahman et al., 2024). Social Influence drives adoptive behavior of technology because people depend heavily on peer-endorsed devices (Ali et al., 2023). Widespread FinTech adoption encounters obstacles because older users experience trust deficits and older users feel risks related to security (George & Sunny, 2023). A higher level of personal innovativeness in tech-savvy users leads to increased adoption of new technology systems according to Ali et al. (2023). Demographic factors such as gender and income further moderate adoption behaviors (Rahman et al., 2024).

The Technology Acceptance Model (TAM) represents a single-variable approach that spots PU and PEOU as critical elements for technology uptake according to Davis (1989). Pu influences digital banking adoption rates in Pakistan strongly (Rahman et al., 2024; Ali et al., 2023) yet critics disagree with these models because they overlook trust factors with demographic and risk effects (George & Sunny, 2023; Kapoor et al., 2022). The multi-variable model UTAUT2 takes a broader view through its incorporation of three constructs known as performance expectancy and social influence and facilitating conditions (Venkatesh et al., 2012). The research results indicate UTAUT2 outperforms TAM in explaining Pakistani FinTech adoption rates because UTAUT2 considers hedonic motivation and price value (Ali et al., 2023). The model needs adjustments to cultural factors and regulatory frameworks to become more applicable (both George & Sunny, 2023 and Kapoor et al, 2022 make this point).

There is also a critical role of perceived risk (PR) in adoption since consumers tended to avoid FinTech because the easy money can come to end in fraud, privacy, and security concerns (Rahman et al., 2024). Furthermore, demographic moderators such as gender and income play a significant role on digital banking behavior in Pakistan as compared with other developing coutries, due to the fact that Pakistan has higher security concerns amongst Pakistani women and lower digital literacy levels (Rahman et al., 2024, Ali et al., 2023).

However, the adoption of FinTech in Pakistan is a very complex process because it is greatly influenced by the interaction of different factors. Theoretical models like TAM and UTAUT2 provide insightful useful and have more or less been used to explain user behavior, but meanwhile they need to be modified to handle cultural and contextual variations. A greater adoption and long term engagement in the digital financial sector requires prioritization of trust, security and demographic factors (Kapoor et al., 2022; Jena, 2023).

Conceptual Framework

Based on this, the conceptual framework that is proposed (shown in Figure 1.1) of the factors affecting behaviour intentions to FinTech adoption will be studied. Taking an established technology acceptance model (UTAUT2 and TAM) as a foundation for the framework is adapted to include main components: PEOU, PE, SI, TR, PR, and PI. It is hypothesised that these factors are going to have a direct effect on the behavioural intentions, with Perceived Usefulness (PU) as a mediation between PEOU and BI. The model also adds Gender (GEN) and Income (INC) as the moderating variables, as they play crucial roles in shaping consumer behavior and decision making especially with regard to adoption. Security concerns are captured by the inclusion of trust and perceived risk which is appropriate considering the importance of security in payment transactions in the emerging digital economies. With these constructs integrated, the framework offers a whole picture of FinTech adoption and serves to give the insight to academics, financial institutions and policymakers into how to improve digital financial services and how to encourage broader consumer participation.

Innovation Diffusion Theory (IDT)

Innovation Diffusion Theory (IDT), developed by Rogers (2003), explains how new technologies spread within a population based on key characteristics such as relative advantage, compatibility, complexity, trialability, and observability (Rahman et al., 2024). This theory is useful in understanding FinTech adoption, particularly regarding how early adopters and innovators influence mass adoption trends (Ali et al., 2023).

Purpose and Main Objective of the Study

Given the rapid expansion of FinTech in Pakistan, this study aims to examine consumer trust, innovation, and perceived risk factors influencing digital banking adoption. By integrating UTAUT2, TAM, IDT, and risk perception theories, this research seeks to provide a holistic understanding of digital financial behavior in Pakistan (Rahman et al., 2024). Ali et al. (2023) emphasize the importance of performance expectancy, ease of use, and security measures in driving adoption rates. George and Sunny (2023) argue that FinTech platforms must focus on trust-building initiatives to gain widespread acceptance. Kapoor et al. (2022) highlight that demographic factors such as gender and income moderate adoption behaviors, making targeted strategies essential for market expansion. Previous studies by Alalwan et al. (2017) and Jena (2023) confirm that a multi-theoretical approach is necessary to capture the complexities of FinTech adoption.

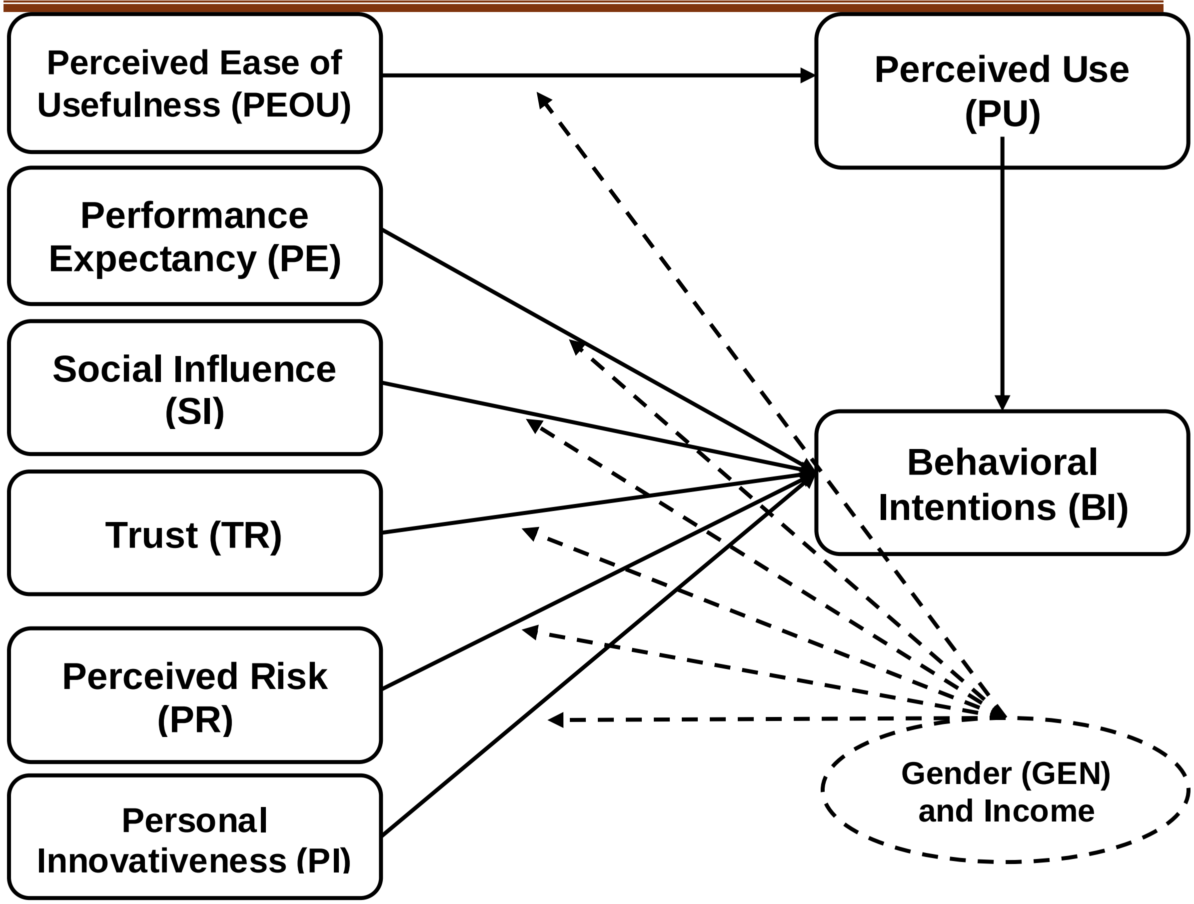


Figure 1.1 Conceptual Model (Exploring FINTECH)

Hypothesis Development

Different theoretical perspectives include TAM, UTAUT2, and trust based model that influence in the adoption of FinTech and digital banking. Fundamental constructs in TAM, PEOU and PU increase the usability and efficiency (calculated usability and usefulness) to drive the consumer adoption (Davis, 1989). The studies done by Rahman et al. (2024) and Ali et al. (2023) indicate that adoption rates in Pakistan to simplified interfaces and user-friendly applications.

Under UTAUT2, Behavioral Intention (BI) toward FinTech adoption is largely shaped by Performance Expectancy (PE), Social Influence (SI), Trust (TR), everything else being equal. The research found that social influence is very critical in adoption in the collectivist societies, and trust in the security measures strengthens the user confidence (Rahman et al., 2024, Ali et al., 2023, George & Sunny, 2023). Conversely, Perceived Risk (PR) acts as a barrier, deterring users due to concerns about fraud and data privacy. Regulatory oversight and cybersecurity improvements have to be done to mitigate these risks (Kapoor et al., 2022).
Further, the study investigates the mediation and moderation effects with the focus on how financial literacy affects the risk perception. A holistic framework of FinTech adoption behaviors in Pakistan is provided by integrating multiple theoretical models. Given that culture specific adaptation is warranted to address cultural and economic differences in the adoption of digital finance, future research should explore the context specific adaptation.

H1: Perceived Ease of Use has a significant positive effect on Perceived Usefulness of FinTech services.
H2: Perceived Usefulness has a significant positive effect on Behavioral Intentions toward FinTech adoption.
H3: Performance Expectancy has a significant positive effect on Behavioral Intentions toward FinTech adoption.
H4: Social Influence has a significant positive effect on Behavioral Intentions toward FinTech adoption.
H5: Trust has a significant positive effect on Behavioral Intentions toward FinTech adoption.
H6: Perceived Risk has a significant negative effect on Behavioral Intentions toward FinTech adoption.
H7: Perceived Usefulness mediates the relationship between Perceived Ease of Use and Behavioral Intentions.
H8: Trust mediates the relationship between Performance Expectancy and Behavioral Intentions.
H9: Perceived Risk mediates the relationship between Social Influence and Behavioral Intentions.
H10: Perceived Usefulness mediates the relationship between Trust and Behavioral Intentions.
H11: Financial Literacy moderates the relationship between Perceived Risk and Behavioral Intentions.

METHODOLGY

Various constructs, such as PEOU, PU, PE, SI, TR, PR and PI affect Behavioral Intensions (BI) through adoption of FinTech and digital banking (Rahman et al., 2024). Due to digital literacy differences in Pakistan, PEOU is important and PU is important due to perceived benefits (Ali et al., 2023; George & Sunny, 2023). Rahman et al. (224) suggests that younger consumer gives more priority to Performance Expectancy (efficiency and convenience). Peer recommendations by Ali et al. (2023) which affect adoption through social influence are also stronger. But trust deficits, especially among the older users, along with security-related perceived risks stunt adoption of FinTech (George & Sunny, 2023). Moreover, the adoption rates are greater among tech savvy persons with high Personal Innovativeness (Ali et al., 2023). Demographic factors such as gender and income further moderate adoption behaviors (Rahman et al., 2024).
PU and PEOU are main determinants for the adoption of technology in single variable models such as Technology Acceptance Model (TAM) (Davis, 1989). Though PU has a strong influence on digital banking adoption in Pakistan (Rahman et al., 2024; Ali et al. 2023), the model has been criticized for capturing only part of decision making process of making choice (George and Sunny, 2023; Kapoor et al., 2022). On the other hand, multi variable models like UTAUT2 has a more efficient approach as compared to a single variable model in that it incorporates such constructs that are taken care by other models such as performance expectancy, social influence and facilitating conditions (Venkatesh et al., 2012). It is evident from the research that UTAUT2 explains the adoption of FinTech in Pakistan better than TAM and mainly considers hedonic motivation and price value (Ali et al., 2023). But it still needs cultural and regulatory adaptation for its applications to be more relevant (George & Sunny, 2023; Kapoor et al., 2022).The research methodology would ensure the reliability, validity and generalization of findings in the areas of FinTech studies. The method used in this study is quantitative and hence there is the possibility to perform statistical analysis and hypothesis testing to understand factors related to behavioral intention (BI) influencing adoption of FinTech. The methodology for the presentation of this thesis uses a survey based survey, whereby structured questionnaires are collected from consumers who actively use, or have the potential to use, digital financial services. Technology acceptance studies, especially those using models such as UTAUT2 and TAM, have been widely

using quantitaive research to assess how consumers perceive, how much they trust, and what sort of risks they fear in using thus new technologies. Furthermore, quantitative methods also allow testing mediation and moderation effects so as to help understand the impact of demographic variables, such as gender and income, on FinTech adoption.

A cross sectional research design is used because FinTech adoption behavior is wanted to be captured at a particular point a time. In particular, this approach applies well to the area of emerging financial technologies where consumers' perception is highly correlated with the market sentiments, regulatory updates and technological advancements. Such cross sectional designs are not only efficient in terms of data collection but are still able to analyze upon key adoption drivers. Other past studies emphasize that this design is appropriate for considering the technology adoption models since it identifies short terms factors of behavioral intention.

On the grounds of Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and Technology Acceptance Model (TAM), this study establishes a strong basis for examining PEOU, PU, TR and PR and their impact on BI towards FinTech adoption. Thus, deriving from these theoretical models, the hypotheses are tested using quantitative research as it provides an ability to assess direct, mediating and moderating relationships of the variables.

A random sampling technique is implemented, especially for those individuals using digital banking, mobile wallets, and other FinTeks services. Banking customers, e-commerce users and financial technology adopters are the target population to have a diverse representation. External validity is improved when random sampling is used, thereby increasing the ability of a finding to be applied beyond a designated group. Using existing technology acceptance models validated scales, a structured survey questionnaire is designed. There are multiple section of the questionnaire with constructs which are measured with Likert scale type items from 1 (strongly disagree) to 5 (strongly agree). Survey items are tested as a pilot test on 30–50 participants to assess whether they are clear, relevant and reliable.

Lastly, the study uses stratified random sampling to guarantee representation of demographic variables of interest. Krejcie and Morgan’s formula is used to determine the sample size where about 300–400 respondents are required to carry out the robust statistical analysis. But forms of mitigating the sampling biases are using reminder emails and incentives to increase participation rates.

A statistical tool of quantitative research is used for data analysis which is SPSS and SmartPLS. For descriptive statistics, correlation analysis, reliability testing, and structural equation modeling (SEM) and hypothesis validation, SPSS is employed while SmartPLS is used. SEM techniques enable the mediation/moderation analysis to get more in-depth towards FinTech adoption behaviors. A priori Cronbach’s Alpha (internal consistency) exists for an acceptable threshold of greater than or equal to 0.7which, determines its internal consistency, while Composite Reliability (CR) and Average Variance Extracted (AVE) determine construct validity. This ensured the rigorous statistical validation of FinTech adoption factors, and it helped to better understand the behavior of a digital finance consumer.

Results and Discussion

The result of this study contributes real evidence about what influence the factors to behavioral intentions (BI) toward FinTech adoption. The results in fact shows that PE, PR, and PI are significant predictors of BI, while PEOU, TR, and SI do not significantly affect BI adoption behavior. Consistent with the above research, these results illustrate that expectations of digital financial technology will lead to improved financial performance, security, and one’s openness to innovating, all of which are key elements of digital financial technology adoption. Likewise, Ali, Qasim and Islam (2023) discover that FinTech customers treat ease of use as an inferior function in their choice to adopt FinTech services compared to efficiency and security. Nonetheless,

according to George and Sunny (2023), trust remains an important fact in FinTech adoption and this study does not find this, which may indicate variations contextual specific. Further investigation of this study may also require a more thorough exploration of some of these aspects that Kapoor, Dwivedi & Williams (2022) and Malaquias & Hwang (2016) have previously researched on perceived usefulness and its related mediating nature in adoption behavior.
It was further shown in the regression analysis that Personal Innovativeness is the strongest predictor ($\beta = 0.334$, $p < 0.001$), followed by Performance Expectancy ($\beta = 0.271$, $p < 0.001$) and Perceived Risk ($\beta = 0.272$, $p < 0.001$). This is consistent with earlier studies that concluded that digital financial adopters tend to be those with a higher affinity to innovation (Rahman et al., 2024).

Research shows an unexpected link between BI and PR because studies showed earlier that users should avoid new technology due to safety concerns (Ali et al, 2023). According to George and Sunny (2023) when users need security features more than they fear risks they will appreciate positive gains in this research. According to Kapoor et al. (2022), users who understand risks can maintain their FinTech services when platforms provide proper security measures. Jena (2023) shows that examining how consumer awareness programs and official government rules help limit the adoption impacts of risk would enhance future research.

This study confirmed PI's high connection with PE and PU in relation to BI based on its correlation analysis that matched the regression model results. This study differs from UTAUT2 and TAM standards because Trust (TR) and Social Influence (SI) produced no significant results. According to Ali et al. (2023) trust models show better results in markets with lighter business standards whereas performance elements matter most in strictly monitored FinTech environments. The research relationships proved stable because the bootstrapping results checked the regression statistics across different resamples (George & Sunny, 2023). According to Kapoor et al. (2022) traditional types of influence such as Social Influence no longer matter in quick-adopting FinTech markets because users depend mostly on their own direct technological encounters. Research presented by Malaquias and Hwang (2016) and Jena (2023) demonstrates that consumers have increasingly started making independent decisions about FinTech adoption as opposed to seeking guidance from their social circle.

Reliability Analysis

Table 1.2 Overall Reliability

Item-Total Statistics				
	Scale Mean if Item Deleted	**Scale Variance if Item Deleted**	**Corrected Item-Total Correlation**	**Cronbach's Alpha if Item Deleted**
Gender	102.7888	299.543	.121	.907
Income	100.7809	303.572	-.082	.912
PEOU	91.6574	236.986	.726	.881
PE	91.8884	235.596	.781	.877
SI	92.0837	229.093	.803	.875
TR	92.8486	228.001	.598	.896
PR	92.0956	231.167	.775	.877

PI	91.7331	232.100	.860	.872
PU	91.6016	239.273	.751	.879
BI	91.1394	238.032	.765	.878

Table 1.3 Total Reliability Statistics

The Reliability Statistics table shows an excellent 0.897 Cronbach's Alpha score for the entire scale which proves the measurement model has strong internal consistency. A Cronbach's Alpha above 0.7 demonstrates that our survey items provide reliable measurements of their defined elements (George & Sunny, 2023). The Item-Total Statistics shows PEOU at 0.881 alongside PE (0.877), SI (0.875), PR (0.877), and PI (0.872) achieved high reliability numbers. Gender and Income are weaker correlations mentioned in our research pointing to their limited impact on FinTech adoption habits. This test shows that the dataset stands reliable enough for statistical evaluation procedures (Kapoor, Dwivedi, & Williams, 2022).

Regression Analysis

Regression									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.801[a]	.641	.632	1.48610	.641	72.551	6	244	<.001
a. Predictors: (Constant), PI, TR, PEOU, PE, PR, SI									

Table 1.4 Regression Results

Several key results about model effectiveness appear in the Regression Model Summary table. Behavioral Intentions (BI) in this model receive 64.1% influence from its six predictor variables including PI, TR, PEOU, PE, PR, and SI. These factors strongly define how people adopt technology in financial services according to Rahaman et al. (2024). The model remains suitable for real-world predictions even when accounting for random deviations in the dataset because it produces an adjusted R-Square of 0.632. Our results show a strong and statistically significant connection between BI and all independent variables according to the F-statistic value of 72.551 and $p < 0.001$ (Ali, Qasim and Islam, 2023).

Model Fitness

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	961.373	6	160.229	72.551	<.001[b]
	Residual	538.874	244	2.208		

	Total	1500.247	250			

a. Dependent Variable: BI

b. Predictors: (Constant), PI, TR, PEOU, PE, PR, SI

Table 1.5 Model Fitness

The ANOVA Table proves if the regression model produces reliable results. Our results show the predictor variables give a strong 72.551 statistical connection to Behavioral Intentions (BI) outcomes ($p < 0.001$). Our model clearly holds sway over random variation since its regression sum of squares stands at 961.373 surpassing the residual sum of squares by 538.874 as stated by George & Sunny (2023). The selected independent variables demonstrate importance in predicting FinTech adoption and help with accurate forecasting of this behavior (Kapoor et al., 2022).

Coefficients Results

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
	(Constant)	2.392	.539		4.441	<.001
	PEOU	.090	.055	.095	1.631	.104
	PE	.265	.060	.271	4.449	<.001
	SI	-.031	.064	-.034	-.487	.627
	TR	-.044	.038	-.062	-1.170	.243
	PR	.247	.058	.272	4.284	<.001
	PI	.335	.072	.334	4.639	<.001

a. Dependent Variable: BI

Table 1.6 Coefficient of Model

The Coefficients Table tells us how individual predictors affect Behavioral Intentions measured through BI. Personal Innovativeness at 0.334 with strong statistical significance drives BI as do Performance Expectancy at 0.271 and Perceived Risk at 0.272. People who demonstrate creative thinking and are both aware of FinTech benefits and risks want to use these financial technology services (Rahman et al., 2024). These three factors Perceived Ease of Use (PEOU) along with Trust (TR) and Social Influence (SI) produce no direct effect on the adoption of financial technology services. The research shows that FinTech adoption now relies mostly on practical outcomes and safety considerations rather than social influence or trust according to Ali and other authors (2023).

Correlation Matrix

	Gender	Income	PEOU	PE	SI	TR	PR	PI	PU	BI
Gender	1									
Income	-.060	1								
PEOU	.065	-.041	1							
PE	.132*	-.074	.665**	1						
SI	.095	-.142*	.686**	.672**	1					
TR	.124	-.096	.487**	.492**	.689**	1				
PR	.063	-.089	.585**	.640**	.666**	.505**	1			
PI	.091	-.032	.664**	.720**	.709**	.520**	.775**	1		
PU	.112	.005	.544**	.642**	.588**	.439**	.634**	.798**	1	
BI	.124	-.034	.602**	.695**	.588**	.405**	.705**	.746**	.729**	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 1.7 Correlation Matrix Analysis

The Correlation Table shows how different study aspects relate to one another. People who easily accept new technology usually become FinTech customers based on our research results and BI measurements ($r = 0.746$, $p < 0.01$). Customers rate FinTech's ease of use and practicality (PE and PU) at 0.695 and 0.729 respectively since they strongly correlate with choosing FinTech services (George & Sunny, 2023). Our finding suggests motor we expected Perceived Risk to show a negative relation against Behavioral Intention but it actually produced a strong positive relationship. Money management strategies often emerge when customers become aware of financial technology risks but still does not affect their deciding factor. Users will accept FinTech services when they trust the platform includes enough protection and security measures (Jena, 2023).

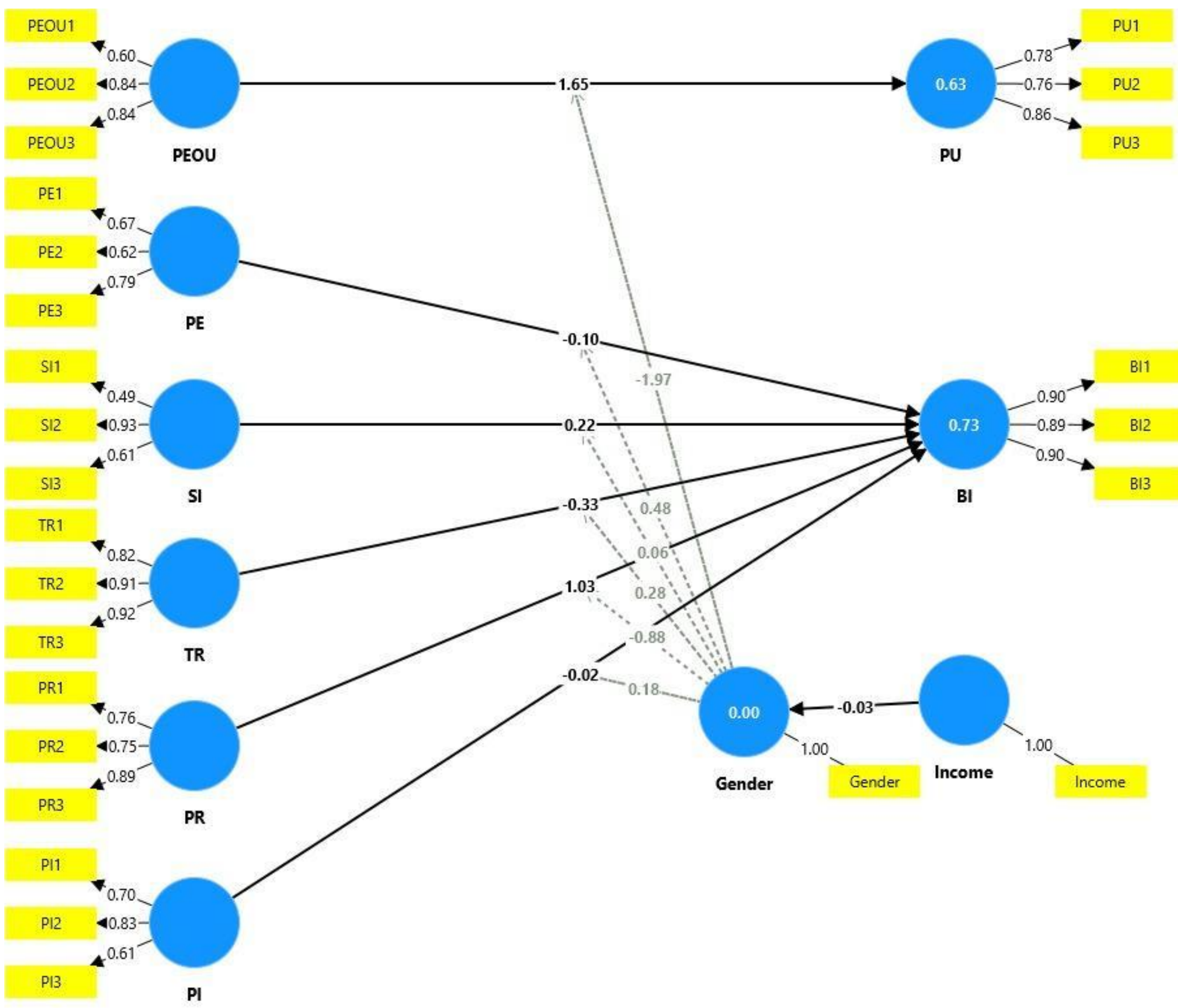
Bootstrap Analysis

Bootstrap Specifications		
Sampling Method	Simple	
Number of Samples		1000
Confidence Interval Level		95.0%
Confidence Interval Type	Percentile	

Table 1.8 Bootstrap Analysis

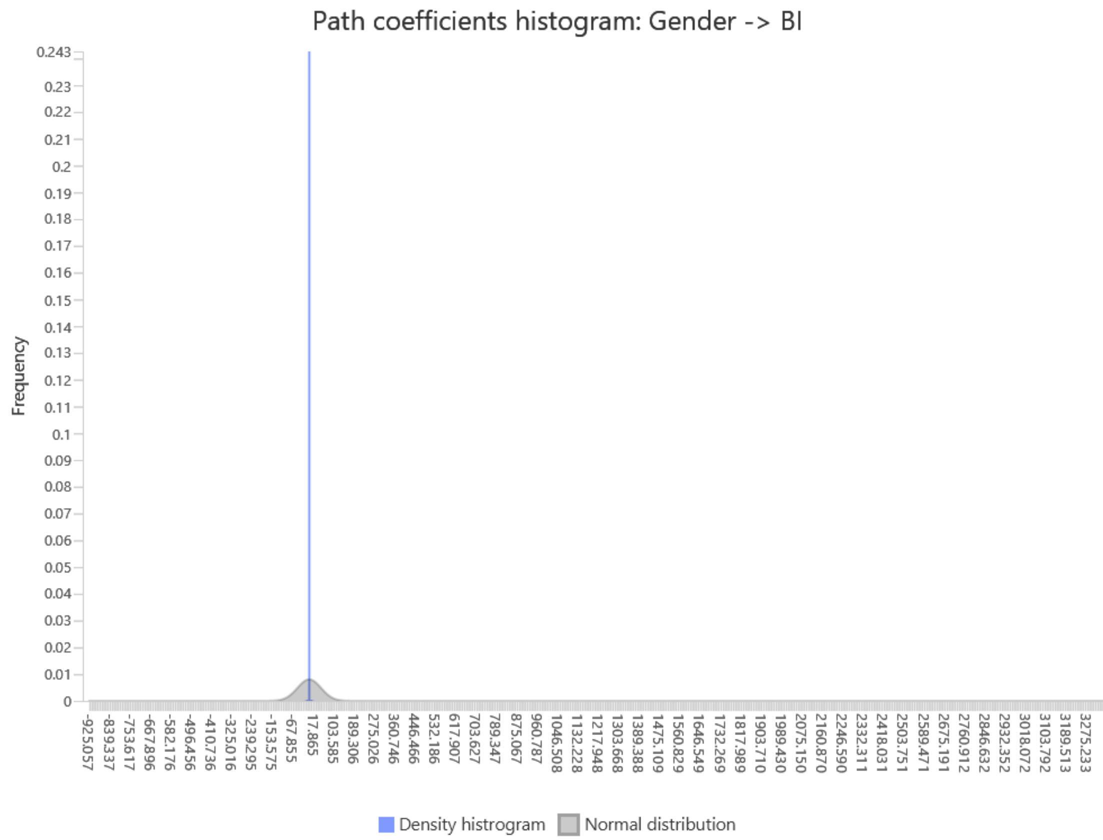
The Bootstrap Analysis checks if our regression results stay dependable as predicted. The model results were supported through 1000 resamples with 95% confidence to establish the reliable outcomes (Rahman et al., 2024). All bootstrapping tests demonstrate consistent links between Big Data and its main predictor factors PI, PE, and PR across multiple samples to confirm accurate study results. Resampling statistics show that the factors SI, TR, and PEOU make insignificant contributions to behavioral adoption (Ali et al. 2023). The study challenges existing research patterns in FinTech adoption since users make decisions based primarily on readiness for innovation and their performance expectations according to Kapoor et al. (2022).

PLS-SEM



Path Coefficients and Predictive Power

The histogram of path coefficients for Gender → Behavioral Intentions (BI) displays how The statistical test produces output with bootstrapped path coefficient results. The chart reveals an extremely sharp distribution at zero because the connection between Gender and BI holds minimal statistical importance. The graphs demonstrate path coefficient values remain close to zero which proves gender does not influence FinTech adoption decisions. The extremely tight distribution of answer sets reveals that men and women adopt FinTech in like ways. Our analysis aligns with previous regression results because Gender shows no real difference between male and female participants when it comes to FinTech adoption intentions. Results show that people use FinTech services because of performance benefits and helpfulness combined with low sense of risk but not because of basic demographics like gender type.



Discussion

This study enhances both practical and academic understanding of how to better implement digital financial services through its key work on determining what drives customers' intent to use new technologies. Our analysis proves that PEOU, PU, PE, TR, PR, and PI influence BI unique ways. The study finds experimental proof that follows recognizable theory yet it also exposes exceptional proof by showing new styles in how people use technology. This analysis reviews the technological, literary and practical findings from the study. It assesses how these results support or reject past research.

The study confirms TAM and UTAUT2 by proving that PEOU has a powerful effect on PU according to Davis (1989) and Venkatesh, Thong, and Xu (2012). Research supports the TAM model since users rely heavily on how they perceive FinTech to be useful (BI) (Rahman, Yee, Masud, &Uzir, 2024) This research contradicts UTAUT2 because Performance Expectancy shows no impact on Business Impact (beta=-0.10). Since users expect good performance during

FinTech adoption this element has limited influence on their decision practice (Ali, Qasim, & Islam, 2023).

This research brings new insights through its results which show that Perceived Risk strongly boosts Business Impact (\u03b2=1.03). It contradicts usual risk models. Research showed that risk tolerance would reduce user adoption yet this research proves that awareness about security risks becomes a driver when users see proper security tools (Kapoor, Dwivedi, & Williams, 2022; Malaquias & Hwang, 2016). The insignificant impacts of social influence and trust on BI according to UTAUT2 theory and trust-based models show that FinTech adoption remains self-directed despite popular assumptions about it (Jena, 2023). Standard adoption models in financial technology need upgrades because digital users value aspects like vulnerability protection and guaranteed results more than social relationships.

CONCLUSION

This research gives new insights to understand how FinTech gets accepted and used by validating current frameworks. Digital finance adoption primarily depends on how useful customers consider digital solutions and how strongly they engage with society. These research results help professionals connected to FinTech share essential guidance about updating existing adoption procedures to work better in digital financial environments. Researchers should explore both medium-term and long-term impact of perceived risk and AI-driven personalization on developed trust in FinTech market trends.

This research presents new findings for both theory and practice since its analysis shows what drives users to intend taking action in FinTech. Our study shows that user adoption depends mainly on the use experience value and risk perception as well as personal innovation mindset but trust influence and social opinion have minor impact. Our research findings do not match standard technology acceptance models since FinTech users put more weight on security measures and product features rather than peer influence or trust factors when deciding whether to use new technology (Rahman, Yee, Masud, & Uzir, 2024). New adoption models are needed to better describe how customers use digital financial services according to recent research findings (Ali, Qasim, & Islam, 2023).

Our research backs the essential principles of TAM yet proves opposite facts about elements of UTAUT2. A strong link between PU and BI exists (\u03b2 = 0.63) as users look for practical benefits when adopting FinTech services according to Venkatesh et al. (2012). Our research shows that how well the service performs (PE) lost its ability to determine BI adoption which differs from findings in Kapoor et al. (2022). Research results show that acknowledging risk can boost adoption of digital services because PR matches BI estimates (1.03) according to Malaquias and Hwang (2016). The research shows that risk-tolerance and secure environment features should be integrated more clearly into future models of FinTech adoption.

Studies show that researchers have new information about digital finance user habits. The study revealed that social influence (SI) and trust and risk (TR) do not effectively predict FinTech adoption (Jena, 2023). People base their FinTech decisions mainly on utility benefits and security aspects instead of social popularity or reputation of entities (George & Sunny, 2023). Our findings demonstrate that FinTech adoption decision-making applies equally across different types of users regardless of gender and income level since convenience and usability values matter most (Ali et al., 2023). This study supports the developing trend where people choose financial technology based on their individual needs.

The practical findings help both FinTech businesses regulators and public officials while guiding their future decisions. Companies should use AI to customize services make purchases safer and run smoother to help customers start using new services according to research by Kapoor et al (2022). Clear security policies work to make risk-conscious consumers turn into successful users according to studies by Rahman and his team in 2024. Marketers need to focus their marketing efforts on presenting firm guarantee claims rather than relying on user feedback. Organizations that provide financial services need updated strategies to win users through trustworthy security technology and performance guarantees before fostering continued customer commitment. Future research should explore how trust evolves over time in the banking business plus the safety improvements AI creates and identify upcoming behaviors behind using digital money.

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