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Drivers Influencing The Adoption Intention Towards Mobile Fintech Services In The Emerging Pakistani Market

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Abstract

The adoption and diffusion of MFS in Pakistan, there is not a straightforward or homogeneous process. It is influenced by many factors, both internal and external, that affect the perceptions, attitudes, and behaviors of potential and existing users of MFS. Understanding these factors and their impacts is crucial for MFS providers and policymakers to design and implement effective strategies and interventions to enhance the adoption and usage of MFS in Pakistan, and to achieve the desired outcomes and benefits of MFS for the economy and society. The main objective of this article is to explore and analyze the drivers influencing the adoption intention of consumers towards MFS in Pakistan, using a comprehensive and robust research model. The research model that we have developed and tested is based on the integration of several established theories and frameworks in the literature, such as the technology acceptance model (TAM), the unified theory of acceptance and use of technology (UTAUT), the theory of planned behavior (TPB), and the trust-risk-benefit framework. The model consists of five main factors that influence the intention to adopt fintech (IAF) of consumers: perceived trust (PT), perceived benefit (PB), effort expectancy (EE), perceived risk (PR), and social influence (SI). The model also includes several sub-factors under each main factor. We have collected and analyzed data from a sample of 218 respondents in Pakistan, using a structured questionnaire and structural [1]equation modeling (SEM) technique. The results and findings of our analysis reveal the significant and positive effects of PT, PB, EE, and SI on IAF, as well as the negative effect of PR on IAF. The results also show the mediating and moderating roles of some sub-factors, such as perceived security, perceived privacy, perceived usefulness, and perceived ease of use, on the relationships between the main factors and IAF. The results and findings of this article contribute to the existing literature and knowledge on MFS adoption in Pakistan and other similar markets, and provide useful implications and recommendations for MFS providers and policymakers.

Keywords: *Intention to Adopt FinTech; perceived trust, perceived benefit, perceived expectancy and perceived risk.*

Introduction:

Financial transaction systems are the mechanisms and processes that enable the exchange and transfer of money and other financial assets among individuals, businesses, and institutions. Financial transaction systems are essential for the functioning and development of any

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economy, as they facilitate trade, commerce, investment, saving, and consumption. The modernization of financial transaction systems refers to the adoption and diffusion of digital and innovative technologies and practices that enhance the efficiency, security, accessibility, and inclusivity of financial transaction systems. Modernization of financial transaction systems can bring significant benefits to the economy and society, such as reducing transaction costs, increasing financial inclusion, improving transparency and accountability, and fostering economic growth and stability. Mobile financial technology (fintech) services are digital platforms that enable users to access and manage various financial transactions and activities through their mobile devices, such as smartphones and tablets. Mobile fintech services (MFS) include mobile banking, mobile payments, mobile money, mobile wallets, and mobile lending, among others. MFS have emerged as a disruptive and innovative force in the financial sector, offering convenience, efficiency, affordability, and inclusivity to consumers and businesses, especially in developing and emerging markets Pakistan.

Pakistan is one of the fastest-growing and most promising markets for MFS in the world, with a population of over 241.49 million, of which 192.27 million are mobile subscribers, and 87.35 million are mobile internet users. Only 37% of the adult population in Pakistan have formal bank accounts, and only 9% have access to credit. This indicates a huge potential and demand for MFS in Pakistan, as well as a significant challenge and opportunity for MFS providers and regulators. The adoption and diffusion of MFS in Pakistan, there is not a straightforward or homogeneous process. It is influenced by a myriad of factors, both internal and external, that affect the perceptions, attitudes, and behaviors of potential and existing users of MFS. Understanding these factors and their impacts is crucial for MFS providers and policymakers to design and implement effective strategies and interventions to enhance the adoption and usage of MFS in Pakistan, and to achieve the desired outcomes and benefits of MFS for the economy and society.

Unraveling the drivers of adoption intention towards mobile fintech services in Pakistan. In the emerging Pakistani market, the intention to adopt FinTech is influenced by a many of factors. This article delves into an analytical exploration of these drivers, focusing on perceived trust, perceived benefit, effort expectancy, and perceived risk. Perceived trust are pivotal elements underlining the role of trust in adopting mobile FinTech services. The credibility and reliability of these services are paramount for users to consider integrating them into their daily financial transactions. Perceived Benefit encapsulate the tangible and intangible gains users anticipate from utilizing mobile FinTech services. These benefits range from convenience and efficiency to cost-effectiveness. Effort Expectancy emphasize the ease of use associated with mobile FinTech applications. The user-friendly interface and seamless navigation significantly influence adoption intention. Perceived Risk underscore potential risks that users might associate with mobile FinTech services. Security concerns and data privacy are central themes that can potentially deter users from adopting these platforms. Intention to Adopt FinTech represent the culmination of influences from perceived trust, benefit, effort expectancy, and risk on users' intentions to embrace mobile FinTech services in Pakistan. There are several studies available on the factors influencing the adoption of FinTech in Pakistan, including mobile payment systems. The present study has incorporated the Unified Theory of Acceptance and Use of Technology (UTAUT) model to assess the behavioral intention of mobile payment adoption in Pakistan. The UTAUT framework with additional trust, anxiety, personal innovativeness, and grievance redressal to explore consumers' choices of mobile payments in Pakistan. The main objective of this article is to explore and analyze the drivers influencing the adoption intention of consumers towards MFS in Pakistan, using a comprehensive and robust research model. The research question that guides this article is:

What are the factors that affect the intention of consumers to adopt and use MFS in Pakistan, and how do they interact and influence each other?

2. Literature Review

FinTech, refers to the use of technology to improve and automate traditional forms of finance. FinTech includes a wide range of applications, from mobile payment apps to complex blockchain systems. Some of the technologies that power FinTech include artificial intelligence, big data, and cloud computing. According to Giglio (2021), FinTech products and services comprise asset management, financing, payments, and other business models. Mobile fintech services (MFS) are a subset of financial technology (fintech), which refers to the application of new technologies to financial services and processes. Fintech covers a wide range of products and services, from mobile banking and insurance to cryptocurrency and investment apps. Fintech aims to improve and automate the delivery and use of financial services, and to enhance the efficiency, security, accessibility, and inclusivity of the financial sector. MFS are specifically designed for mobile devices, such as smartphones and tablets, and rely on mobile networks, such as 3G, 4G, or 5G, to enable users to access and manage various financial transactions and activities (Elsaid, 2023).

Butler, Herman and Initiative (2023) stated that Fintech's Digital Assets market worldwide is projected to grow by 5.13% (2024-2028) resulting in a market volume of US$3409.00bn in 2028. The global Fintech market is worth approximately $167.54 billion, and it is projected to grow to $514.9 billion by 2028 at a compound annual growth rate (CAGR) of 25.18% (Jalal, Al Mubarak, & Durani, 2023). A third report estimates that the global Fintech market is valued at USD 133.84 Billion in the year 2022 and is projected to reach a value of USD 556.58 Billion by the year 2030 (Kowalewski & Pisany, 2023).

Balsinhas (2023) stated that the North America Fintech Market size in terms of transaction value is expected to grow from USD 4.93 trillion in 2023 to USD 9.52 trillion by 2028, at a CAGR of 14.07% during the forecast period (2023-2028). The United States dominates the North American fintech market, accounting for over 80% of the total fintech investment in the region. The market is being primarily driven by the increasing adoption of e-commerce and the rising usage of blockchain technology, particularly in segments such as cross-border payments and digital currencies. The North American Fintech market is also witnessing the emergence of a large number of fintech startups, which are contributing to the market's growth. The market is expected to continue its expansion, supported by a strong foundation for fintech innovation and growth, as well as access to large pools of capital and talent (Elia, Stefanelli, & Ferilli, 2023).

Ali et al. (2021) explores the factors that influence the adoption of Fintech in Islamic finance. The study focuses on the perceived risk, benefit, and trust of users in Fintech adoption. The authors conducted a survey of 400 respondents in Malaysia and used structural equation modeling to analyze the data. The results show that perceived benefit and trust have a positive impact on Fintech adoption, while perceived risk has a negative impact. The study provides insights for policymakers and practitioners in the Islamic finance industry to enhance Fintech adoption. Overall, the article contributes to the literature on Fintech adoption and Islamic finance. Vasenska et al. (2021) presents a survey analysis of Fintech utilization by individual customers before and after the COVID-19 crisis in Bulgaria. The study identifies problems related to Fintech transactions during the pandemic, such as the lack of trust in Fintech providers and the need for better cybersecurity measures. The authors suggest that the utilization of Fintech financial transactions leads to a risk-reduction approach when in contact with other people. The article contributes to the literature on Fintech adoption and its implications during the COVID-19 crisis.

Hassan et al. (2022) investigates the factors that influence the adoption intention of mobile Fintech services in Bangladesh. The study identifies seven drivers that impact the adoption intention, including behavioral intention, perceived trust, perceived risk, perceived benefit, social influence, facilitating conditions, and effort expectancy. The authors conducted a survey of 400 respondents in Bangladesh and used structural equation modeling to analyze the data. The results show that perceived benefit, perceived trust, and facilitating conditions have a positive impact on the adoption intention, while perceived risk has a negative impact. The study provides insights for policymakers and practitioners in the Fintech industry to enhance Fintech adoption in Bangladesh. Overall, the article contributes to the literature on Fintech adoption in emerging markets.

Dianty and Faturohman (2023) integrates several established theories and frameworks in the literature, such as the technology acceptance model (TAM), the unified theory of acceptance and use of technology (UTAUT), the theory of planned behavior (TPB), and the trust-risk-benefit framework. Putri, Widagdo and Setiawan (2023) the research model consists of five main factors that influence the intention to adopt fintech (IAF) of consumers: perceived trust (PT), perceived benefit (PB), effort expectancy (EE), perceived risk (PR), and social influence (SI). The research model also includes several sub-factors under each main factor. Kumar and Siddiqui (2023) provide a comprehensive and updated overview of the existing literature on MFS adoption in Pakistan and other similar markets, and identify the main themes, gaps, controversies, and directions for future research.

Ahmad et al. (2023) stated that mobile banking refers to the use of mobile devices to access and perform banking services, such as checking account balance, transferring money, paying bills, depositing checks, and applying for loans. In Pakistan mobile banking can be offered by traditional banks, such as Habib Bank Limited (HBL) and Meezan Bank, or by digital-only banks, such as Telenor Bank and U Microfinance Bank, which operate without physical branches or ATMs. Mobile banking can also be offered by mobile network operators (MNOs), such as Jazz and Zong, or by third-party providers, such as Easypaisa and JazzCash, which partner with banks or MNOs to provide mobile banking services. Mobile banking can be accessed through different channels, such as mobile applications, mobile web browsers, or unstructured supplementary service data (USSD) codes. Mobile banking offers convenience, speed, and cost-effectiveness to users, as well as the opportunity to reach the unbanked and underbanked segments of the population, who lack access to formal financial services (Majeed et al., 2024).

Khan et al. (2023) explored that the mobile payments refer to the use of mobile devices to make or receive payments for goods and services, either online or offline. Mobile payments can be classified into two main types: mobile proximity payments and mobile remote payments. Mobile money refers to the use of mobile devices to store and transfer money electronically, without the need for a bank account. Mobile money is a type of mobile payment that is based on a stored-value account (SVA) that is linked to a mobile phone number. Mobile wallets refer to the use of mobile devices to store and manage various types of digital assets, such as money, cards, coupons, tickets, or loyalty points. Mobile wallets are a type of mobile payment that is based on a digital representation of a physical wallet, which can be accessed through a mobile application or a mobile web browser.

Khan et al. (2023) stated that proliferation of mobile fintech services in Pakistan is evident from the significant growth of mobile financial services (MFS) in the country. The first fintech service in Pakistan was introduced in 2009 by the telecom company Easypaisa, and since then, Pakistan has seen a wide range of MFS, making it the first fintech platform in the country. These services, which do not rely on physical banks but instead on agents (vendors) nationwide, have gained substantial usage due to their convenience and essential financial offerings, such as money transfers and mobile apps for various financial services. Despite challenges such as a mixed cash-based economic system and certain unfriendly government policies, the State Bank of Pakistan has been actively working to improve the fintech sector in the country. Furthermore, local financial technology startups are eager to tap into the growing market, and collaborations with global companies like Mastercard are revolutionizing digital payments in Pakistan, aiming to foster financial inclusion and digitize the economy.

The model illustrates a complex interplay between these factors that collectively shape user behavior towards mobile financial technology applications. In-depth understanding of each driver is essential for service providers aiming at enhancing adoption rates amidst a rapidly evolving digital landscape in Pakistan's economy. The image depicts a model illustrating various factors influencing the intention to adopt Fintech.

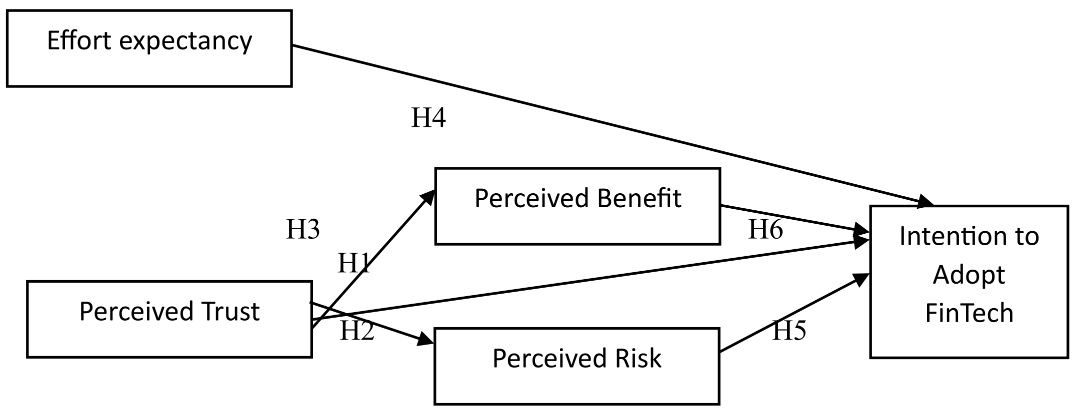

Figure 1. Research framework.

2.1 Intention to Adopt FinTech

According to Hu et al. (2019) the intention to adopt fintech operations refers to the likelihood that individuals or organizations will use fintech services, such as mobile banking, digital wallets, and peer-to-peer lending platforms. The adoption intention of fintech services can be influenced by various factors, including user innovativeness, attitude, and perceived usefulness and ease of use. The attitude towards using fintech services can influence the intention to adopt them. A positive attitude towards fintech services can increase the likelihood of adoption (Alshari & Lokhande, 2022). These factors are determinants of the attitude towards using technology. If individuals perceive fintech services as useful and easy to use, they are more likely to adopt them (Almashhadani et al., 2023). Social norms and attitudes can play a mediator role in the adoption of fintech services. Understanding the influence of these factors can help predict the pace of fintech adoption (Bajunaied, Hussin, & Kamarudin, 2023). Privacy enablers and inhibitors: Privacy concerns can influence the intention to adopt fintech services. Extending the unified theory of acceptance and use of technology by adding privacy enablers and inhibitors can provide a more comprehensive understanding of fintech adoption (Roh, Park, & Xiao, 2023).

2.2 Perceived Trust

Perceived trust refers to the degree of willingness to believe that expectations will be met during online transactions (Dawood, Liew, & Lau, 2021). It is a mental state of positive expectancy that an individual has in another entity to perform expected activities without taking advantage. Perceived trust is a crucial factor in the adoption of fintech services, as it influences the intention to use them (Liew, Lau, & Dawood, 2021). It has been studied from the perspective of manager-subordinate relationships, focusing on the impact on employees when they trust managers. Perceived trust is also a concept related to the perception of reliability, credibility, and dependability towards a particular entity or organization. In the context of online trading systems, perceived trust, usefulness, and ease of use are important issues. Understanding perceived trust is important for the overall trust dynamic and can contribute to promoting the adoption of fintech services (Shin, 2021). Perceived trust is one of the factors that contribute to customer intention towards embracing fintech products and services. It plays a role in the connection between the perception of security, risk, and the intention to adopt fintech services (Chawla et al., 2023).

H1: Perceived Trust (PT) positively influences the Intention to Adopt FinTech.

2.3 Perceived Risk

Perceived risk is a subjective judgement of an individual that combines factors such as emotion, contextual factors, and personal experiences (Thompson & Pescaroli, 2023). It is different from actual risk, which refers to the quantifiable aspects of risk, including the likelihood, impact, and severity of the risk. Perceived risk is influenced by various factors, such as risk tolerance, cultural factors, and the presence of positive safety culture and buy-in from leadership. In the context of fintech services, perceived risk can be summarized as the difference between risk tolerance and expected loss (Freudenstein et al., 2023). Higher risk tolerance will lead to more risk behavior, as the difference between tolerance and expected loss is larger. Perceived risk is a crucial factor in the adoption of fintech services, as it influences the intention to use them (Freudenstein et al., 2023). The level of trust an individual has in a particular entity or organization performing expected activities without taking advantage positively affects the subjective evaluation of risk associated with adopting fintech services (Falchetta et al., 2021). Perceived Trust (PT) positively influences Perceived Benefit (PB) suggests that the level of trust an individual has in a particular entity or organization performing expected activities without taking advantage positively affects the perceived benefits associated with adopting fintech services (Ribeiro, Gursoy, & Chi, 2022).

H2: Perceived Trust (PT) positively influences the Perceived Risk (PR).

H3: Perceived Risk (PR) negatively influences Intention to Adopt FinTech.

2.3 Perceived Benefit

Perceived Benefit (PB) is defined as an individual's belief that specific positive outcomes will result from a specific behavior (Hassan et al., 2022). It is a construct that is most often applied to health behaviors and is specific to the behavior in question. Perceived benefits are beliefs about the positive outcomes associated with a behavior in response to a real or perceived threat. In the context of fintech services, perceived benefit refers to the perception of the positive consequences that are caused by adopting fintech services(Saxena, Baber, & Kumar, 2021). Perceived benefit is an important factor in the adoption of fintech services, as it influences the intention to use them (Kanwal et al., 2020). The impact of perceived trust and perceived risk on individual user acceptance of cloud computing demonstrated that trust has a significant positive effect on perceived benefit, explaining a portion of the variance in perceived benefit (Ha et al., 2020). The impact of perceived trust and perceived risk on individual user acceptance of cloud computing demonstrated that perceived benefit has a significant positive effect on the intention to adopt fintech services (Ha et al., 2020).

H4: Perceived Trust (PT) positively influences Perceived Benefit (PB).

H5: Perceived Benefit (PB) positively influences Intention to Adopt FinTech.

2.4 Perceived Expectancy

Perceived Expectancy is a construct that refers to an individual's expectations or predictions about the attributes or characteristics of a product, service, or technology artifact, and how these expectations influence their perceptions of performance and satisfaction (Shaikh & Amin, 2024). Perceived Expectancy is a key factor in the Expectation Confirmation Theory, which posits that pre-purchase or pre-adoption expectations form the basis of comparison against which the product, service, or technology artifact is ultimately judged. "Perceived Expectancy" in the context of fintech services, the concept of perceived benefit can be related to perceived expectancy. Perceived benefit is defined as an individual's belief that specific positive outcomes will result from a specific behavior (Jena, 2022). The determinants of intention to use fintech services by accounting students showed that effort expectancy is positively associated with the intention to use fintech services (Frare et al., 2023).

H6: Effort Expectancy (EE) positively influences Intention to Adopt FinTech.

3. Methodology

The purpose of the current study is to analyze the drivers influencing the adoption intention towards mobile fintech services in the emerging Pakistani market. The drivers influencing the adoption intention regarding the fintech adoption is being analyzed by considering the different parameters like perceived trust, perceived benefit, perceived expectancy and perceived risk. This study was quantitative and cross-sectional. Purposive sampling techniques was used in this research, questionnaires were distributed in person and online (Goggle Form) in order to collect as many replies.

3.1. Data Collection

the data collection, research questionnaire instrument is being developed in line with the previous studies to get the reliable responses. The data collection was done with questionnaire. The questionnaire distribution done by personal distribution as well as the distribution using online (google form) because many of the consumers do not have time to response the questionnaire physically. The questionnaire draws inspiration from previous studies in the field, adapting their proven constructs to the specific context of FinTech adoption within Pakistan's banking sector. The questionnaire has been tailored to encapsulate key dimensions such as consumer perceptions of risk, benefits, trust, and various expectations associated with FinTech usage. The distribution of the questionnaire has been strategically devised to maximize participation and gather insights from a diverse spectrum of respondents. Two primary distribution methods were employed: personal distribution and online distribution via Google Forms. The questionnaire instrument is divided in to different sections. One of the sections includes the cover letter which describe briefly the research and its purpose while the other section includes the respondent's demographical information and the final section includes the questions to be responded for the purpose of the analysis. Likert scale is being used in the questionnaire where value 1 is counted for strongly agree through value 5 depicting strongly disagree for any of the questions. The questions in the instruments are closed ended and one last question is open ended to describe the views of the respondents towards the Fintech adoption. Before conducting the actual survey, a pilot testing phase was carried out to ensure the validity and reliability of the questionnaire. The pilot test involved a small sample of respondents (around 30) who were similar to the target population. The purpose of the pilot test was to identify any potential issues with the questionnaire, such as unclear or ambiguous questions, and to assess the overall feasibility of the survey.

3.2. Data Analysis

Partial Least Squares Structural Equation Modeling, a second-generation method from the Statistical Package for Social Science (SPSS) version 25, was used to evaluate the data for this study (PLS-SEM). The first step in the statistical analysis is to assess the sample characteristics using descriptive statistics. This involves calculating means, standard deviations, and frequencies of the variables to provide a clear overview of the data. Next, the relationships between the constructs are examined using PLS-SEM. The research model, consisting of the constructs and their hypothesized relationships, is tested for validity and reliability. Validity is assessed through measures such as convergent validity and discriminant validity, which ensure that the constructs and items are measuring what they are intended to measure. Reliability is evaluated using measures such as internal consistency reliability (e.g., Cronbach's alpha) to assess the consistency of responses. After confirming the validity and reliability of the measurement model, the structural model is analyzed to test the research hypotheses.

4. Results and Findings

Table 1. Demographic Information of Respondent

Variable	N	%
Gender		
Male	285	74.4%
Female	98	25.6%
Age		
Up to 25	133	34.7%
26-45	218	56.9%
46-55	20	5.2%
56+	12	3.1%
Education		
Bachelor’s	93	24.3%
Master’s	112	29.2%
MPhil	134	35.0%
Other	43	11.2%
Bachelor’s	1	0.3%
Using Bank Account Since		
Up to 1 year	178	46.5%
2-5 year	102	26.6%
5-10 year	70	18.3%
10 years +	33	8.6%
Using FinTech Since		
Up to 1 year	167	43.6%
2-5 year	133	34.7%
5-10 year	59	15.4%
10 years +	24	6.3%

The demographic information of the respondents reveals a predominantly male representation at 74.4%, with females comprising the remaining 25.6%. In terms of age, the majority falls within the 26-45 age range (56.9%), followed by those up to 25 years old (34.7%). Education-wise, a significant portion holds an MPhil degree (35.0%), while others have Master's (29.2%)

and Bachelor's (24.3%) degrees. Regarding banking and FinTech usage, a notable proportion has been using their bank account and FinTech services for up to 1 year (46.5% and 43.6%, respectively), indicating a relatively recent adoption, while smaller percentages have longer usage durations, providing a comprehensive snapshot of the respondent demographics in the study.

4.1. Measurement Model

The measurement model assessment involves several steps to ensure the reliability and validity of the model. The first step is to create a research framework and extract data from the excel file. After constructing the path model, the path analysis is conducted to check the reliability and validity of the model. The recommended value for the indicator loadings should be more than 0.708, and the recommended value for the constructs is 0.70. The next phase is to check the convergent validity, and the average variance extracted is the indicator used to verify the validity (Singh, Sahni, & Kovid, 2020). The construct score should be more than 0.50 to meet the requirements. The final phase is to check the discriminant validity, and three different techniques are used to verify the discriminant validity, including the Fornell–Larcker criterion, cross-loading, and heterotrait–monotrait (HTMT) ratio (Piyananda & Aluthge, 2022). The Fornell–Lacker criterion explains whether the square root of the AVE of a particular construct is greater than other constructs. For cross–loadings, a construct's own parent construct should have higher loadings than with other constructs. In addition, Shiau et al. (2020) suggested that the threshold value for conceptually related constructs in structural models is 0.90, while 0.85 is the suggested threshold for conceptually separate constructs. A higher value indicates a lack of discriminant validity.

Table 2. Construct reliability and validity values.

	Cronbach's Alpha	**rho_A**	**Composite Reliability**	**Average Variance Extracted (AVE)**
EE	0.752	0.761	0.863	0.682
IAF	0.742	0.755	0.854	0.663
PB	0.496	0.803	0.724	0.555
PR	0.647	0.682	0.815	0.602
PT	0.646	0.656	0.812	0.593

Table 2 presents the reliability and validity values for key constructs in the study. The internal consistency, as measured by Cronbach's Alpha, is generally acceptable, ranging from 0.496 to 0.752. The constructs demonstrate good reliability, as indicated by rho_A values ranging from 0.656 to 0.803. Composite Reliability scores, measuring the consistency of latent constructs, are robust, ranging from 0.724 to 0.863. The constructs also exhibit satisfactory convergent validity, with Average Variance Extracted (AVE) values ranging from 0.555 to 0.682, surpassing the recommended threshold of 0.5. These findings suggest that the measurement instruments are reliable, consistent, and valid, providing a solid foundation for assessing the relationships between variables in the study. The lower Cronbach's Alpha for "Perceived Benefit" may warrant further investigation into the scale's reliability, while the high rho_A and Composite Reliability values across constructs enhance the overall confidence in the measurement model.

Table 3. Discriminant Validity and Fornell-Lacker Criteria Average Variance Extracted (AVE).

	EE	IAF	PB	PR	PT
EE	0.826				
IAF	0.605	0.814			
PB	0.497	0.523	0.745		
PR	0.536	0.507	0.416	0.776	
PT	0.238	0.314	0.269	0.059	0.77

Table 4. Discriminant validity and het erotrait–monotra it (HTMT) value

	EE	IAF	PB	PR	PT
EE					
IAF	0.814				
PB	0.823	0.779			
PR	0.778	0.727	0.724		
PT	0.345	0.468	0.444	0.206	

4.2 The structural model Assessment

The structural model assessment in partial least squares structural equation modeling (PLS-SEM) involves evaluating the significance and relevance of path coefficients, as well as assessing multicollinearity among the constructs. The Variance Inflation Factor (VIF) is used to evaluate multicollinearity, with a common threshold being that VIF values should be less than 5 to indicate no multicollinearity (Dianty & Faturohman, 2023). VIF measures the amount of multicollinearity in a set of multiple regression variables, and a VIF greater than 10 is considered a sign of significant multicollinearity that needs to be addressed (Piyananda & Aluthge, 2022). The path coefficients in a structural equation model are interpreted as the strength and sign of the effect from a causal variable to an endogenous or outcome variable. Therefore, the VIF values being less than 5, as indicated in Table 5, suggest that there is no significant multicollinearity among the constructs in the structural model used in the study.

Table 5. Values of variance information (VIF).

	VIF
EE	1.654
PB	1.444
PR	1.488
PT	1.112

4.2. Structural Model Assessment

The structural model assessment in partial least squares structural equation modeling (PLS-SEM) involves evaluating the significance and relevance of path coefficients, as well as assessing multicollinearity among the constructs. The Variance Inflation Factor (VIF) is used to evaluate multicollinearity, with a common threshold being that VIF values should be less than 5 to indicate no multicollinearity. VIF measures the amount of multicollinearity in a set of multiple regression variables, and a VIF greater than 10 is considered a sign of significant multicollinearity that needs to be addressed. The path coefficients in a structural equation model are interpreted as the strength and sign of the effect from a causal variable to an endogenous or outcome variable. Therefore, the VIF values being less than 5, as indicated in

Table 5, suggest that there is no significant multicollinearity among the constructs in the structural model used in the study. The proliferation of mobile fintech services in Pakistan is evident from the significant growth of mobile financial services (MFS) in the country.

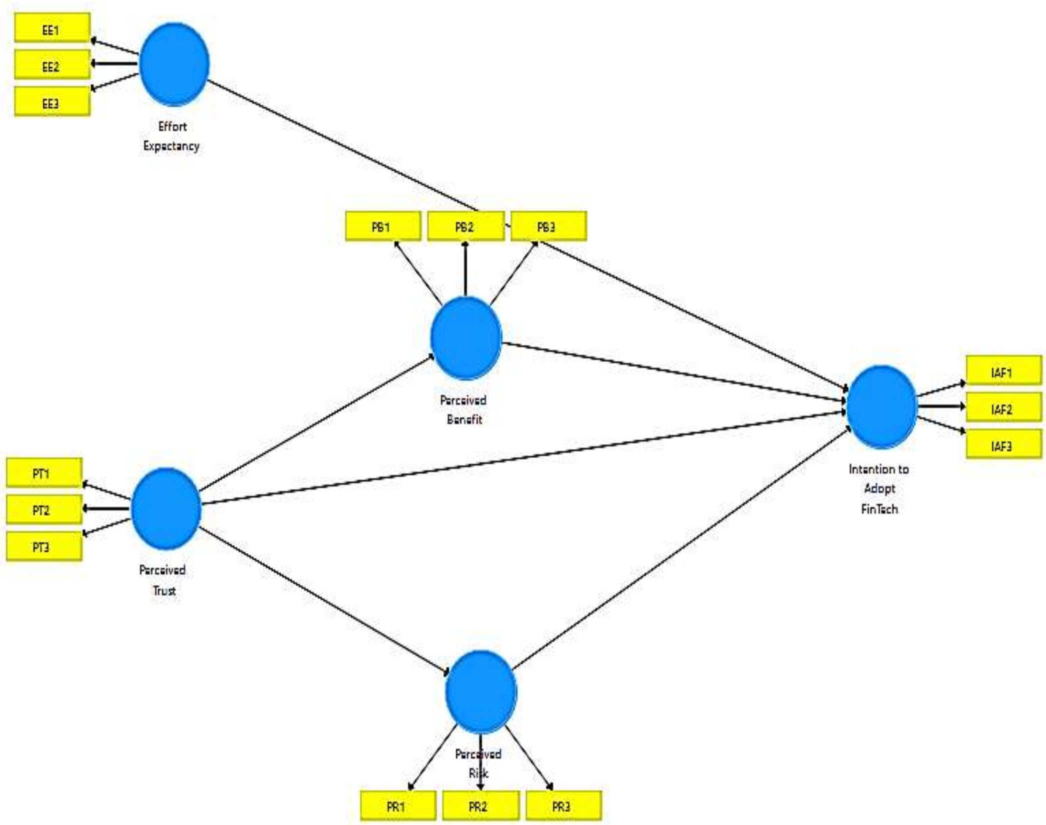

Figure 2. Path coefficient (T-values) results from SmartPLS.

Table 6. Path coefficient values.

	Original Sample (O)	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	**P Values**
EE -> IAF	0.338	0.335	0.061	5.555	0
PB -> IAF	0.217	0.218	0.069	3.168	0.002
PR -> IAF	0.226	0.229	0.05	4.54	0
PT -> IAF	0.162	0.163	0.047	3.404	0.001

4.3. Post Hoc Analysis

Table 6 presents the path coefficient values for the relationships between key constructs in the study. The path coefficients represent the strength and direction of the relationships in the structural model. In the original sample, "Effort Expectancy" exhibits a significant positive influence on "Intention to Adopt FinTech" with a path coefficient of 0.338, indicating that as users perceive FinTech to be less effortful, their intention to adopt it increases. Similarly, "Perceived Benefit," "Perceived Risk," and "Perceived Trust" also significantly impact "Intention to Adopt FinTech" with path coefficients of 0.217, 0.226, and 0.162, respectively. These findings suggest that individuals are more likely to adopt FinTech if they perceive it as beneficial, low in risk, and trustworthy. The T Statistics values, which are considerably larger than 2 (the conventional threshold for statistical significance), and the corresponding P values (all being less than 0.05) further support the statistical significance of these relationships. The results underscore the importance of user perceptions in shaping intentions to adopt FinTech, providing valuable insights for both researchers and practitioners in the financial technology domain.

Table7. Indirect Hypothesis

	Original Sample (O)	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	**p Values**
PT -> PR-> IAF	0.013	0.014	0.013	1.062	0.289
PT -> PB-> IAF	0.058	0.06	0.021	2.81	0.005

Table 7 presents the results of the indirect hypotheses testing, examining the mediating effects of perceived risk and perceived benefit on the relationship between perceived trust and intention to adopt FinTech. In the first indirect hypothesis, the path through perceived risk shows a non-significant indirect effect (0.013) on the relationship between perceived trust and intention to adopt FinTech. Conversely, the second indirect hypothesis through perceived benefit reveals a significant indirect effect (0.058), indicating that the relationship between perceived trust and intention to adopt FinTech is partially mediated by the perceived benefit. The T Statistics values (1.062 for the first hypothesis and 2.81 for the second hypothesis) provide insights into the significance of these indirect effects. The corresponding P values (0.289 for the first hypothesis and 0.005 for the second hypothesis) further confirm the significance of the mediated effect through perceived benefit. These findings suggest that while perceived trust may influence intention to adopt FinTech indirectly through perceived benefit, the mediation effect via perceived risk is not statistically supported. These results contribute to a nuanced understanding of the factors influencing FinTech adoption and offer practical implications for designing interventions to enhance trust and perceived benefit in financial technology contexts.

Table 8. Summary of hypotheses results.

	Hypothesis	**Results**
H1	Perceived Trust (PT) positively influences the Intention to Adopt FinTech.	Supported

H2	Perceived Trust (PT) positively influences the Perceived Risk (PR).	Supported
H3	Perceived Risk (PR) negatively influences Intention to Adopt FinTech.	Supported
H4	Perceived Trust (PT) positively influences Perceived Benefit (PB).	Supported
H5	Perceived Benefit (PB) positively influences Intention to Adopt FinTech.	Supported
H6	Effort Expectancy (EE) positively influences Intention to Adopt FinTech.	Supported

References

1. Ahmad, S., Ghazi, S., Shahzad, R. F., Ali, I., Iqbal, S., Akram, S., Qureshi, M. A., Awan, U. H., Khan, I., & Ahmad, G. (2023). Forced Regressive Wedge of the Early Cretaceous Sembar Formation, the Potential Reservoir Body Encased Within Outershelf Sediments; Lower Indus Basin, Pakistan. Abu Dhabi International Petroleum Exhibition and Conference,
2. Ali, M., Raza, S. A., Khamis, B., Puah, C. H., & Amin, H. (2021). How perceived risk, benefit and trust determine user Fintech adoption: a new dimension for Islamic finance. foresight, 23(4), 403-420.
3. Almashhadani, I. S., Abuhashesh, M., Bany Mohammad, A., Masa'deh, R. e., & Al-Khasawneh, M. (2023). Exploring the determinants of FinTech adoption and intention to use in Jordan: The impact of COVID-19. Cogent Social Sciences, 9(2), 2256536.
4. Alshari, H. A., & Lokhande, M. (2022). The impact of demographic factors of clients' attitudes and their intentions to use FinTech services on the banking sector in the least developed countries. Cogent Business & Management, 9(1), 2114305.
5. Bajunaied, K., Hussin, N., & Kamarudin, S. (2023). Behavioral intention to adopt FinTech services: An extension of unified theory of acceptance and use of technology. Journal of Open Innovation: Technology, Market, and Complexity, 9(1), 100010.
6. Balsinhas, G. N. F. (2023). Equity valuation of Nike, Inc
7. Butler, A. W., Herman, A., & Initiative, Q. A. (2023). Prosperity at Risk: The Quantum Computer Threat to the US Financial System.
8. Chawla, U., Mohnot, R., Singh, H. V., & Banerjee, A. (2023). The Mediating Effect of Perceived Trust in the Adoption of Cutting-Edge Financial Technology among Digital Natives in the Post-COVID-19 Era. Economies, 11(12), 286.
9. Dawood, H. M., Liew, C. Y., & Lau, T. C. (2021). Mobile perceived trust mediation on the intention and adoption of FinTech innovations using mobile technology: A systematic literature review. F1000Research, 10.
10. Dianty, M. A., & Faturohman, T. (2023). Factors influencing the acceptance of Fintech lending platform in Indonesia: an adoption of technology acceptance model. International Journal of Monetary Economics and Finance, 16(3-4), 222-230.
11. Elia, G., Stefanelli, V., & Ferilli, G. B. (2023). Investigating the role of Fintech in the banking industry: what do we know? European Journal of Innovation Management, 26(5), 1365-1393.
12. Elsaid, H. M. (2023). A review of literature directions regarding the impact of fintech firms on the banking industry. Qualitative Research in Financial Markets, 15(5), 693-711.
13. Falchetta, G., Dagnachew, A. G., Hof, A. F., & Milne, D. J. (2021). The role of regulatory, market and governance risk for electricity access investment in sub-Saharan Africa. Energy for Sustainable Development, 62, 136-150.
14. Frare, A. B., Fernandes, C. M. G., Santos, M. C. d., & Quintana, A. C. (2023). Determinantes da intenção de uso de serviços de FinTechs por estudantes de Ciências Contábeis: uma abordagem de métodos mistos. BBR. Brazilian Business Review, 20, 580-599.
15. Freudenstein, F., Boerner, F., Croft, R., Leung, R., Loughran, S., & Wiedemann, P. (2023). Effects of generalization descriptions on risk perception. Environmental research, 223, 115422.
16. Giglio, F. (2021). Fintech: A literature review. European Research Studies Journal, 24(2B), 600-627.

17. Ha, T., Kim, S., Seo, D., & Lee, S. (2020). Effects of explanation types and perceived risk on trust in autonomous vehicles. Transportation research part F: traffic psychology and behaviour, 73, 271-280.
18. Hassan, M. S., Islam, M. A., Sobhani, F. A., Nasir, H., Mahmud, I., & Zahra, F. T. (2022). Drivers influencing the adoption intention towards mobile fintech services: a study on the emerging Bangladesh market. Information, 13(7), 349.
19. Hu, Z., Ding, S., Li, S., Chen, L., & Yang, S. (2019). Adoption intention of fintech services for bank users: An empirical examination with an extended technology acceptance model. Symmetry, 11(3), 340.
20. Jalal, A., Al Mubarak, M., & Durani, F. (2023). Financial technology (fintech). In Artificial Intelligence and Transforming Digital Marketing (pp. 525-536). Springer.
21. Jena, R. K. (2022). Examining the factors affecting the adoption of blockchain technology in the banking sector: An extended UTAUT model. International Journal of Financial Studies, 10(4), 90.
22. Kanwal, S., Rasheed, M. I., Pitafi, A. H., Pitafi, A., & Ren, M. (2020). Road and transport infrastructure development and community support for tourism: The role of perceived benefits, and community satisfaction. Tourism Management, 77, 104014.
23. Khan, S., Khan, S. U., Khan, I. U., Khan, S. Z., & Khan, R. U. (2023). Understanding consumer adoption of mobile payment in Pakistan. Journal of Science and Technology Policy Management.
24. Kowalewski, O., & Pisany, P. (2023). The rise of fintech: a cross-country perspective. Technovation, 122, 102642.
25. Kumar, A., & Siddiqui, D. A. (2023). Financial Services in Pakistan using Mobile: Rural and Urban Perspective with Gender as a Moderator. Available at SSRN.
26. Liew, C. Y., Lau, T. C., & Dawood, H. (2021). Mobile perceived trust mediation on the intention and adoption of FinTech innovations using mobile technology: A systematic literature review.
27. Majeed, K. U., Ali, S. K., Ali, S. U., Haris, M., Ahmad, R. Q., Khan, B. A., Jamil, A., & Nazir, N. (2024). Facies architecture and sequence stratigraphy of Kungurian Amb Formation, western Salt Range, Pakistan. Kuwait Journal of Science, 51(1), 100167.
28. Piyananda, D., & Aluthge, C. (2022). Factors Affecting Fintech Acceptance in Sri Lanka. INTERNATIONAL JOURNAL OF CONTEMPORARY BUSINESS RESEARCH, 100.
29. Putri, G. A., Widagdo, A. K., & Setiawan, D. (2023). Analysis of financial technology acceptance of peer to peer lending (P2P lending) using extended technology acceptance model (TAM). Journal of Open Innovation: Technology, Market, and Complexity, 9(1), 100027.
30. Ribeiro, M. A., Gursoy, D., & Chi, O. H. (2022). Customer acceptance of autonomous vehicles in travel and tourism. Journal of Travel Research, 61(3), 620-636.
31. Roh, T., Park, B. I., & Xiao, S. S. (2023). Adoption of AI-enabled Robo-advisors in Fintech: Simultaneous Employment of UTAUT and the Theory of Reasoned Action. Journal of Electronic Commerce Research, 24(1), 29-47.
32. Saxena, C., Baber, H., & Kumar, P. (2021). Examining the moderating effect of perceived benefits of maintaining social distance on e-learning quality during COVID-19 pandemic. Journal of Educational Technology Systems, 49(4), 532-554.
33. Shaikh, I. M., & Amin, H. (2024). Consumers' innovativeness and acceptance towards use of financial technology in Pakistan: extension of the UTAUT model. Information Discovery and Delivery, 52(1), 114-122.
34. Shiau, W.-L., Yuan, Y., Pu, X., Ray, S., & Chen, C. C. (2020). Understanding fintech continuance: perspectives from self-efficacy and ECT-IS theories. Industrial Management & Data Systems, 120(9), 1659-1689.
35. Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. International Journal of Human-Computer Studies, 146, 102551.
36. Singh, S., Sahni, M. M., & Kovid, R. K. (2020). What drives FinTech adoption? A multi-method evaluation using an adapted technology acceptance model. Management decision, 58(8), 1675-1697.
37. Thompson, D., & Pescaroli, G. (2023). Buying electricity resilience: using backup generator sales in the United States to understand the role of the private market in resilience. Journal of Infrastructure Preservation and Resilience, 4(1), 1-14.
38. Vasenska, I., Dimitrov, P., Koyundzhiyska-Davidkova, B., Krastev, V., Durana, P., & Poulaki, I. (2021). Financial transactions using fintech during the COVID-19 crisis in Bulgaria. Risks, 9(3), 48.