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Perceived Benefits and Risks Influencing Consumer Adoption of Digital Finance in India: A PLS-SEM Approach

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Abstract
Digital finance has had a significant impact on the provision and utilization of financial services in India and is rapidly transforming the landscape of financial services in India. Digital platforms such as mobile banking, online banking, digital wallets and mobile payments via UPI have contributed to better access, convenience and transaction efficiency. Nonetheless, in spite of the increasing use of digital money, consumers persist in expressing apprehensions about security, efficacy, and financial risk. This study examines the effects of perceived benefits and perceived threats on acceptance of digital banking. Convenience, ease of transactions, and economic gain are seen as elements of perceived benefits, whereas security risk, performance risk, and financial risk are considered as elements of perceived dangers. The method used for this research was quantitative research and the data was collected with the constructed questionnaire, consisting of 9 dimensions with 29 questions. The analysis of the data was conducted with SPSS v25 and Partial Least Squares Structural Equation Modeling. The examination comprised reliability, common method bias, validity of the measurement model, and the linkages along the structural model. These findings clearly indicate that perceived benefits are significantly improved by simplicity, ease of transaction and financial gain, which in turn positively impact digital banking adoption. Perceived risk is significantly affected by security and performance risks, but not by financial risk. The perception of risk adversely influences the adoption of digital banking. The study highlights the need to enhance user-friendliness, transaction flow, cost-effectiveness, trust, security, and service reliability to encourage the adoption of digital banking.
Keywords: *Digital finance; digital payment adoption; perceived benefit; perceived risk; consumer behaviour; PLS-SEM; financial technology; digital banking; India*

I. Introduction

A domino effect will spread across all sectors as a result of India's economic digital transformation. Consumers are being enticed by a range of digital offerings, which has led to the adoption of new and emerging technologies taking center stage. In the middle of this upheaval, the banking sector embraced the new normal and developed digital banking. To achieve economic progress, digital finance is foundational. Businesses and consumers are able to invest, save, and pay using digital platforms, thanks to digital finance. It's the lifeblood for economic improvement. Two million individuals in the developing world do not have access to a bank, according to McKinsey Global Institute (2016) (Manyika et al., 2016).

According to Demirgüç-Kunt et al. (2018), India has the second-highest number of unbanked individuals globally, with over 50% of its population being either financially excluded or underserved. Since banks play an essential role in protecting Indians from cash-related hazards, they are an important part of Indian culture that discourages risk-taking. Due to technology advancements, the banking sector was able to substitute a versatile and inexpensive payment mechanism for actual cash. There has been a meteoric rise in the use of IT in the financial sector. To keep up with the rapidly evolving business and economic landscape, it is essential to adapt and embrace these changes (Gomber et al., 2017).

While digital finance and e-finance emerged in the 2000s, financial technology was first used to describe online financial services in the 1990s. Technology in the financial sector has come a long way since the days of ATMs, credit cards, and smartphones (Gomber, Koch, & Siering, 2017). Demonetization in 2016 hastened the shift to digital payment methods in India due to the country's decreased reliance on physical currency (Pazarbasioglu et al., 2020). According to Arner et al. (2020), the Covid-19 further bolstered the financial sector's embrace of digitalization. The COVID-19 pandemic is different from the financial crisis of 2008 in that it affects the banking industry and, therefore, the economy. Digital wallets and other digital financial services allowed for the distribution of funds to those in need (Arner et al., 2020). Digital financial services have become more well-known as a result of the increasing social distance caused by the COVID-19 pandemic (Agur, Peria, & Rochon, 2020).

Nowadays, people are looking for an easy and inexpensive way to get their hands-on financial services. Younger generations' inclination to embrace technology—including the internet and digital platforms—is driving consumers toward digital finance. Consumers continue to be wary about sharing sensitive financial and personal information online. According to two sources, the success of digitalization implementation will be determined by two factors (Chawla & Joshi, 2019; Singh et al., 2020). First, the digital solutions used by the low-income sector group, which is affected by factors such as digital literacy, access to and usage of mobile devices, credit, and financial services. Secondly, consumers' propensity to stick with digital finance for future monetary transactions, equipped with full awareness of all the options.

After China, India, Pakistan, and Indonesia in terms of the world's biggest unbanked populations, we find China with 190 million, Pakistan with 100 million, and Indonesia with 95 million. Not only do these four countries have unbanked populations, but so do Bangladesh, Nigeria, and Mexico (Demirgüç-Kunt et al., 2018).

Credit, savings, insurance, and payment processing are all part of these services. Internet access, mobile phones, point-of-sale terminals, automated teller machines, tablets, and electronic cards are all part of the digital channels. Consequently, "digital financial services" describe the conveyance of these monetary goods and services via electronic means. One recent addition to the concept of digital finance is the inclusion of mobile financial services (Pazarbasioglu et al., 2020).

II. Literature review

The literature on digital finance adoption shows that digital platforms have moved financial services from branch-based delivery to app-based, internet-enabled and payment-infrastructure-driven delivery. Manyika et al. (2016), Demirgüç-Kunt et al. (2018), Pazarbasioglu et al. (2020), Ozili (2018), Asif et al. (2023), Amnas et al. (2024), and Jena (2025) have highlighted that digital finance improves access, lowers transaction costs, supports financial inclusion, and extends formal financial services to underserved users. Rogers (2003) also explained that adoption of innovations depends on perceived advantage, compatibility, complexity and diffusion through social systems. Therefore, the adoption of digital finance is not merely a technological decision but also a social, economic and institutional decision.

Technology-adoption theories provide a strong base for understanding why consumers accept or avoid digital financial services. Davis (1989) has studied perceived usefulness and perceived ease of use as the core determinants of technology acceptance, whereas Ajzen (1991) has explained the role of attitude, subjective norms and perceived behavioural control in behavioural intention. Venkatesh et al. (2003) and Venkatesh et al. (2012) later integrated performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit and price value in UTAUT and UTAUT2. Agarwal and Prasad (1999), Bhattacherjee (2001), Baptista and Oliveira (2015), and Alalwan et al. (2017) further demonstrated that individual differences, continuance intention, culture, trust and facilitating conditions significantly shape technology usage behaviour.

Convenience, ease of use, speed of adoption, usefulness, trust, transaction efficiency etc. have been cited as important factors influencing the adoption of mobile payments, mobile banking and e-wallets in several studies conducted so far. Various digital payment context studies have been conducted by researchers like Chen (2008), Schierz et al. (2010), Shin (2009), Oliveira et al. (2016), Madan and Yadav (2016), Chawla and Joshi (2019), Singh et al. (2020), Padma Kiran and Vedala (2025), and Wei et al. (2025), who have found that consumers use digital finance when payment is facilitated, time is reduced, perceived value is added, and confidence is built through the completion of transactions. Other studies, such as those by Liébana-Cabanillas et al. (2014), Limayem et al. (2007) and Junadi and Sfenrianto (2015) have also found that habit, age, platform familiarity and payment-system design have an impact on digital payment intention.

Perceived benefit is one of the main constructs influencing digital finance adoption as users assess digital financial services based on the potential benefits relative to the effort required and to any losses incurred. Perceived value, usefulness, promotional benefit, convenience and service performance have been found to have a positive relationship with better behavioural intention by Ryu (2018), Abdul-Rahim et al. (2022), Wei et al. (2025), Kaur et al. (2020), Bailey et al. (2017), Al-Saedi et al. (2020) and Gupta and Arora (2020). These findings support the present model in which convenience, seamless transaction and economic benefit are seen as dimensions of perceived benefit that have a formative influence.

Perceived risk is equally important because financial transactions involve money, personal data, authentication and service reliability. Featherman and Pavlou (2003) have studied perceived risk facets in e-service adoption, while Kim et al. (2008) and Gefen et al. (2003) have shown that trust reduces perceived uncertainty in online transactions. Lee (2009), Roca et al. (2009), Baganzi and Lau (2017), Luo et al. (2010), Bamasak (2011), and Pal et al. (2021) have further established that security risk, privacy risk, financial risk, performance risk and trust concerns affect the acceptance of internet banking, mobile money and mobile banking services. Therefore, security risk, performance risk and financial risk are appropriate determinants of perceived risk in digital finance adoption research.

A large body of digital banking and mobile-banking literature also supports the relationship between user experience and adoption intention. Pikkarainen et al. (2004), Chitungo and Munongo (2013), Chong et al. (2010), Koksal (2016), Laukkanen (2016), Shaikh and Karjaluoto (2015), Kaur et al. (2020), and Kapoor et al. (2022) have reported that perceived usefulness, perceived ease of use, service availability, trust, cost, risk reduction and crisis-driven digital habits influence adoption and continuance. These studies are directly relevant to the Indian digital finance context because consumers use mobile banking, internet banking, digital wallets and UPI for similar purposes such as fund transfer, bill payment, shopping and account management.

The methodological foundation of the present study is also supported by established measurement and structural-equation modelling literature. Cronbach (1951), Nunnally (1978), and Cortina (1993) have discussed internal consistency reliability, whereas Jöreskog (1971), Bagozzi and Yi (1988), Fornell and Larcker (1981), and Henseler et al. (2015) have provided standards for factor analysis, convergent validity and discriminant validity. Hair et al. (2017), Hair et al. (2019), Hair et al. (2022), Hulland (1999), Tenenhaus et al. (2005), Schuberth et al. (2018), Schuberth and Henseler (2021), Podsakoff et al. (2003), and Akter et al. (2011) support the use of PLS-SEM, reliability testing, common method bias checks, model-fit diagnostics and predictive relevance assessment.

The reviewed literature indicates that digital finance adoption is shaped by a benefit-risk evaluation. Consumers are more likely to adopt digital finance when platforms are convenient, economical, reliable, fast and easy to use. However, adoption weakens when security, privacy, financial loss, transaction failure and system-performance concerns are high. The present study therefore integrates perceived benefit and perceived risk into a PLS-SEM framework to examine adoption of digital finance in India. The model is consistent with prior research on digital finance, internet banking, mobile banking, e-wallets, UPI, technology acceptance and behavioural decision-making.

III. Methodology

The present study adopted a quantitative research design to examine the factors influencing the adoption of digital finance among users. The study was based on a structured research model in which perceived benefit and perceived risk were considered as important determinants of adoption of digital finance. Perceived benefit was examined through convenience, seamless transaction, and economic benefit, whereas perceived risk was examined through security risk, performance risk, and financial risk. Adoption of digital finance was treated as the final dependent construct of the study.

The primary data were gathered through a structured questionnaire which was designed based on previous research on the topic of digital finance, digital payment adoption, technology acceptance, perceived benefit, and perceived risk. The questionnaire was divided into nine constructs: economic benefit, seamless transaction, convenience, perceived benefit, and security risk, performance risk, financial risk, perceived risk, and adoption of digital finance. A total of 29 measurement items were included in the questionnaire. The answers were given on a Likert scale to enable statistical analysis of the perception and behavioural intention of the respondents towards the digital finance.

The study targeted the users of digital financial service including digital wallet, mobile banking, internet banking, UPI based payment and other electronic financial platforms. The respondents were chosen from users who had some exposure to digital financial transactions. A survey method was deemed to be suitable as the study was designed to get insight into the perception of the benefits, risks, and adoption of digital finance. The received responses were then screened for missing responses, inconsistent responses and for suitability of statistical analysis.

The collected data were analysed in two major stages. In the first stage, preliminary statistical tests were performed using SPSS version 25. The normality of the data was examined through the Kolmogorov-Smirnov test. Since the significance values of the variables were found to be below the accepted threshold, the data were considered non-normal. This supported the use of Partial Least Squares Structural Equation Modelling because PLS-SEM is suitable for analysing complex models and does not require strict normality assumptions.

Reliability of the research instrument was examined through Cronbach's alpha. The internal consistency of the overall scale was assessed to ensure that the items used in the questionnaire were reliable for measuring the selected constructs. After establishing reliability, common method bias was examined because the data were collected from a single source through a self-reported questionnaire. Principal axis component analysis was applied to determine whether a single factor explained the majority of variance. The result indicated that common method bias was not a serious concern in the study.

In the second stage, the proposed research model was analysed using Partial Least Squares Structural Equation Modelling. The measurement model was first assessed to confirm the reliability and validity of the constructs. Indicator reliability was examined through outer loadings. Items with weak loading values were reviewed, and the item FR4 was removed because its loading was below the prescribed acceptable limit. After removing the weak item, the remaining indicators were retained for further analysis.

Cronbach's alpha, rho alpha and composite reliability were used to test the internal consistency reliability of constructs. These measures were employed to ensure the consistency of representation of the items within their respective constructs. Convergent validity was tested in the form of Average Variance Extracted value. Constructs were judged to be acceptable if reliability and validity values were greater than the recommended cutoff values. This validated the measurement model and justified for proceeding with the structural analysis.
After validating the measurement model, the structural model was assessed to test the hypothesised relationships among the constructs. The relationship of convenience, seamless transaction, economic benefit and perceived benefit was explored. The relationships between security risk and performance risk, financial risk and perceived risk were also analysed. Last, the impact of perceived benefit and perceived risk on the digital finance adoption was assessed. The significance of path coefficients, t statistics, and p values were estimated using the bootstrapping method.
The coefficient of determination was used to evaluate the explanatory power of the structural model. This enabled the authors to gain insight into how much perceived benefit and perceived risk accounted for digital finance adoption. The validity of the model for predicting was explored by the blindfolding method based on cross-validated communality and redundancy values. Furthermore, model fit was evaluated overall using the Standardized Root Mean Square Residual value. These procedures made the proposed model statistically reliable, valid and appropriate to explain adoption behavior toward digital finance.

IV. Results and Discussion

4.1 Data Normality Assessment

The data of variables which constituted research model 1 was first tested for data normality through Kolmogorov-Smirnov test of normality. The p value obtained for each variable was observed below at $\alpha = 0.00$, which was below $\alpha = 0.05$ indicating that the data is not normally distributed.

4.2 Cronbach's Alpha

Table 1 Reliability Statistics

Cronbach Alpha	No. of items
0.818	29

4.3 Common Method Biasness

Before moving further with the PLS-SEM analysis, the data needs to be checked for common method biasness as recommended by (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Thus, SPSSv25 was used for analysing the absence of common method bias via principal axis component analysis. According to (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003), the total variance in a single factor should not account for more than 50% to confirm the absence of common method biasness. The value obtained was 38.515%, which ensures elimination of the biasness.

4.4 Assessment of Reflective Measurement Model

The reflective measurement model has been displayed in Figure 1 following the guidelines and suggestions of (Hair et al., 2017; Hair et al., 2019).

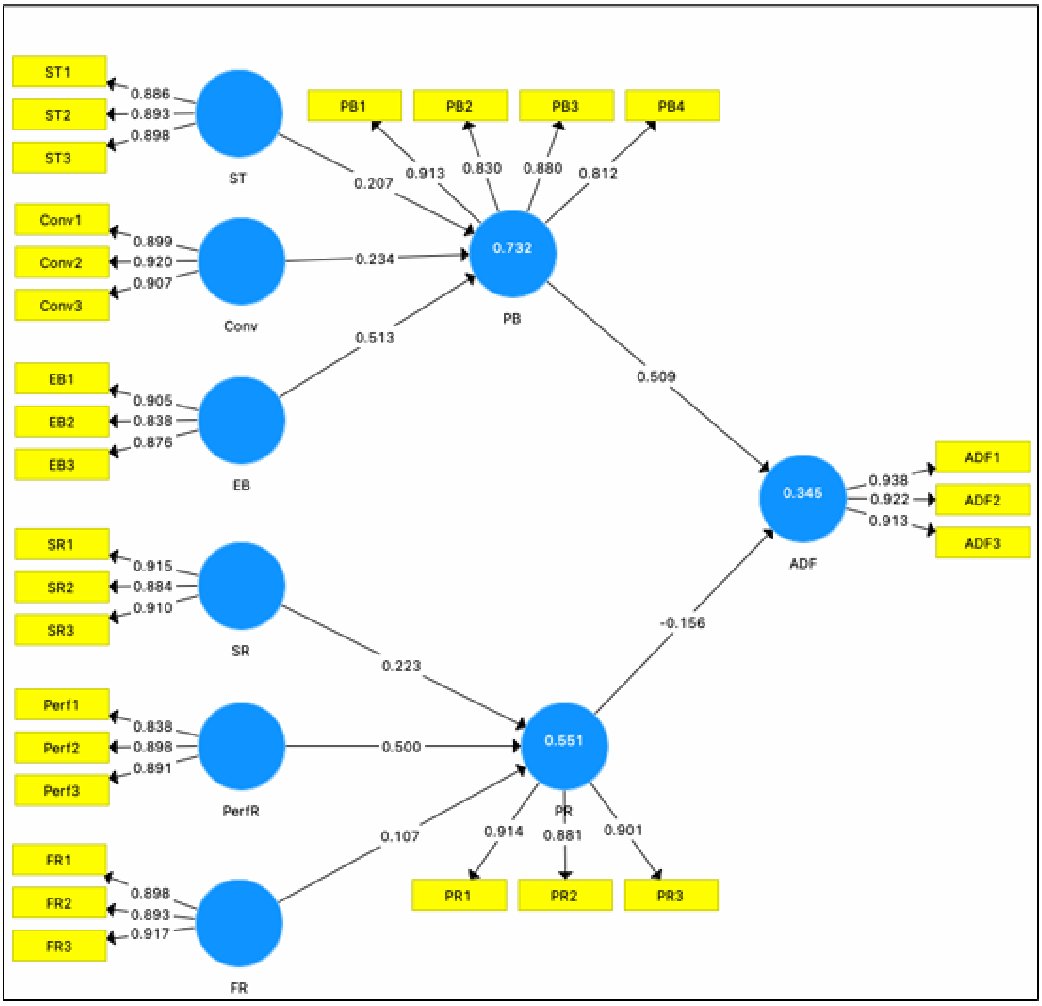

Figure 1 Reflective Measurement Model

Computing the outer loadings of each indicator variable was the first step in evaluating the measurement model and confirming the dependability of the indicators. In order to keep the measurement model adequate and reliable, the value for indicator FR4 was eliminated since it was determined to be below the specified level of 0.4 (Hair et al., 2017). (Hulland, 1999). Reliability of the remaining build pieces as indicators was confirmed. Through the tripartite features of Cronbach Alpha (α), Composite Reliability (CR), and Rho Alpha, the internal consistency of the data was determined. In order to guarantee the internal consistency dependability, the values of the aforementioned criteria were determined to be more than the specified limit of 0.708 (Cronbach, 1951; Hair, Risher, Sarstedt, & Ringle, 2019; Jöreskog, 1971). Additionally, the convergent validity was taken into consideration by looking at the AVE values. For a model to be deemed acceptable, the values of AVE should be more than 0.5, as stated by Bagozzi and Yi (1988). The correctness of convergent computation was verified.

Table 2 Indicator Reliability, Internal Consistency, and Convergent Validity of Reflective Measurement Model

Constructs	Items	Outer Loadings	Cronbach's Alpha	Rho Alpha	Composite Reliability	AVE
ADF	ADF1	0.938	0.916	0.925	0.947	0.855
	ADF2	0.922				
	ADF3	0.913				
Conv	Conv1	0.899	0.894	0.896	0.934	0.825
	Conv2	0.92				

	Conv3	0.907				
EB	EB1	0.905	0.844	0.847	0.906	0.763
	EB2	0.838				
	EB3	0.876				
FR	FR1	0.898	0.887	0.888	0.93	0.815
	FR2	0.893				
	FR3	0.917				
PB	PB1	0.913	0.882	0.889	0.919	0.739
	PB2	0.83				
	PB3	0.88				
	PB4	0.812				
PR	PR1	0.914	0.881	0.882	0.926	0.807
	PR2	0.881				
	PR3	0.901				
PerfR	PerfR1	0.838	0.851	0.883	0.908	0.767
	PerfR2	0.898				
	PerfR3	0.891				
SR	SR1	0.915	0.887	0.888	0.93	0.815
	SR2	0.884				
	SR3	0.91				
ST	ST1	0.886	0.873	0.879	0.921	0.796
	ST2	0.893				
	ST3	0.898				

Table 3 Outer Weights Testing

	Original Sample (O)	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**
ADF1 <- ADF	0.351	0.008	43.522
ADF2 <- ADF	0.402	0.012	32.368
ADF3 <- ADF	0.328	0.01	33.26
Conv1 <- Conv	0.352	0.008	42.424
Conv2 <- Conv	0.384	0.008	46.886
Conv3 <- Conv	0.365	0.008	43.222
EB1 <- EB	0.395	0.01	37.695

EB2 <- EB	0.364	0.01	36.884
EB3 <- EB	0.385	0.012	30.916
FR1 <- FR	0.353	0.01	35.538
FR2 <- FR	0.382	0.012	32.291
FR3 <- FR	0.373	0.009	39.381
PB1 <- PB	0.319	0.008	39.847
PB2 <- PB	0.245	0.008	29.434
PB3 <- PB	0.296	0.007	42.655
PB4 <- PB	0.302	0.009	33.851
PR1 <- PR	0.385	0.009	42.47
PR2 <- PR	0.378	0.009	42.595
PR3 <- PR	0.35	0.008	41.668
Perf1 <- PerfR	0.325	0.011	30.813
Perf2 <- PerfR	0.464	0.014	33.954
Perf3 <- PerfR	0.349	0.009	38.943
SR1 <- SR	0.348	0.01	33.743
SR2 <- SR	0.38	0.014	27.977
SR3 <- SR	0.38	0.011	35.624
ST1 <- ST	0.349	0.009	38.343
ST2 <- ST	0.414	0.011	37.886
ST3 <- ST	0.358	0.009	38.5

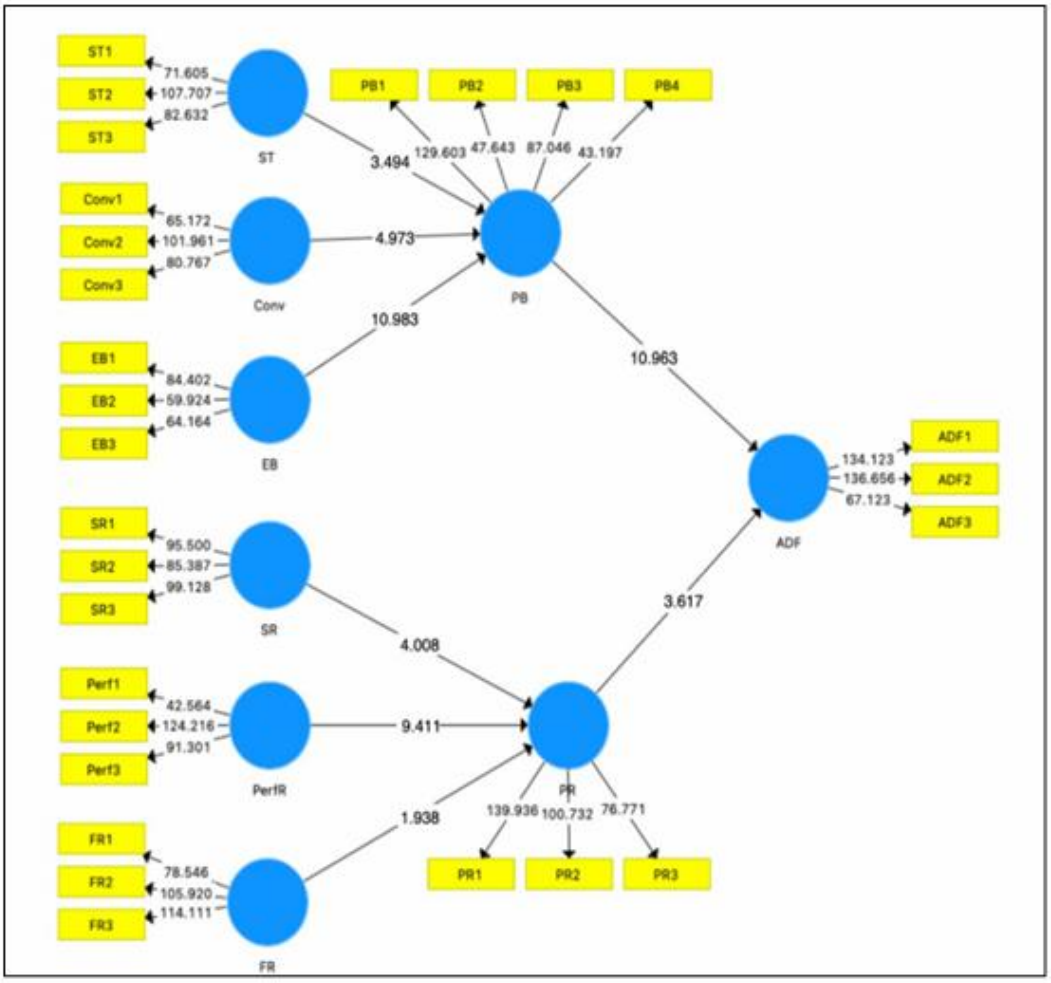

Figure 2 Structural Model

The path coefficients shown in figure 2 were used to examine the importance of the relationship between exogenous (PR: FR, PerfR, SR, PB: Conv, ST, EB) and endogenous (ADF) variables as displayed in Table 4. Between the relationships formed among exogeneous and endogenous constructs, a positive relationship existed between PB [Conv ($\beta = 0.23$, $t = 4.97$), EB ($\beta = 0.51$, $t = 10.98$), ST ($\beta = 0.21$, $t = 3.49$)], PB ($\beta = 0.51$, $t = 10.96$)] and ADF at p =0.05, t = 1.96. Further, a significant positive relationship was also established between PR and its constructs [PerfR ($\beta = 0.5$, $t = 9.411$), SR ($\beta = 0.22$, $t = 4.01$)]. However, no significant relationship was predicted between FR ($\beta = 0.11$, $t = 1.938$) and PR. Furthermore, a negative relationship exists between PR ($\beta = -0.16$, $t = 3.62$) and ADF at p=0.05, t = 1.96.

Table 4. Path Coefficients

	Original Sample (O)	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	**P Values**	**Decision**
Conv -> PB	0.234	0.047	4.973	0.00	Supported
EB -> PB	0.513	0.047	10.983	0.00	Supported
FR -> PR	0.107	0.055	1.938	0.053	Not Supported
PB -> ADF	0.509	0.046	10.963	0.00	Supported
PR -> ADF	-0.156	0.043	3.617	0.00	Supported
PerfR -> PR	0.5	0.053	9.411	0.00	Supported

SR -> PR	0.223	0.056	4.008	0.00	Supported
ST -> PB	0.207	0.059	3.494	0.00	Supported

The coefficient of determination (R^2 value) and predictive relevance were used to assess the model's final validity (Q^2 value). The blindfolding procedure was used to generate the Q^2 value (cross validated communality and redundancy) using an omission distance of D = 7. Tables 4.9, 4.10 illustrate the outcomes.

Table 5 Coefficient of Determination

Constructs	Coefficient of Determination (R^2)
ADF	0.345
PB	0.732
PR	0.551

Table 6 Predictive Relevance

Endogenous Variable	**Q^2 Value**		**Strength of Explanatory Power**
	Cross Validated Communality	**Cross Validated Redundancy**	
ADF	0.664	0.288	Acceptable, Medium
PB	0.554	0.533	Acceptable, Large
PR	0.581	0.438	Acceptable, Large

4.5 Goodness of Fit Index

The overall predictive power of SEM model is evaluated and analysed through Goodness of Fit Index (GoF) by comprehending both model parameters - measurement and structural (Tenenhaus, Vinzi, Chatelin, & Lauro, 2005). Table 6 shows the GoF index of the research model indicating that the model data is a very good fit for universal validation (Akter, D'Ambra, & Ray, 2011).

Table 6 Goodness of Fit Index

Endogenous Variable	GoF Value	Strength
ADF	0.48	Large
PB	0.64	Large
PR	0.57	Large

4.6 Standardized Root Mean Square Residual

However, (Hair et al., 2022; Schuberth et al., 2018; Schuberth & Henseler, 2021) argued the use of GoF for establishing the overall predictive power of the SEM Mode. Therefore, the Standardised Root Mean Square Residual (SRMR) has also been used for evaluating the fitness of the proposed model. The value of SRMR is reported at 0.065 which is <0.08.

V. Conclusion

According to the present study, perceived benefits and perceived risks are important influencing factors for digital finance adoption. This finding is consistent with the results that indicate convenience, seamless transaction and economic benefit are influencing factors in user's perceived benefits of digital finance. Of these, economic benefit proves to be a good contributor, meaning customers are more likely to accept digital finance when they feel they can save money, save time and make their finances more efficient. The positive correlation between perceived benefit and uptake of digital finance confirms that the people using digital finance like them more when they believe they are useful and convenient, are quick, and are cost-effective.

The study further shows that perceived risk is a key factor in the adoption of digital finance. Perceived risk is significantly affected by security risk and performance risk, indicating that users continue to be worried about the security of transactions, privacy, system failure, and service reliability. In the current model, however, a significant relationship between financial risk and perceived risk is not shown. The negative sign for the relationship between perceived risk and adoption of digital finance suggests that increased perceived risk made the user less likely to take up the digital financial services.

The findings, overall, indicate that there is a need to boost adoption of digital finance by building users' confidence and mitigating perceived uncertainties. Secure transaction systems, user friendly platforms, transparent grievance redressal mechanisms, and awareness programmes on safe digital transactions should be the focal points of attention for banks, fintech firms and policy makers. Enhancing security, making services more reliable and conveying user benefits of digital finance in economic and functional terms can help to promote broad acceptance of digital finance. The study advances the knowledge on the adoption of digital finance by incorporating the perceived benefit and perceived risk dimensions in a structural equation model.

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