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EXPLORING THE ADOPTION OF DIGITAL FINANCE IN SAMBALPUR CITY: A BEHAVIORAL ECONOMICS PERSPECTIVE

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Abstract
Digital finance has emerged as a key driver of financial inclusion and innovation in India, especially in the wake of the COVID-19 pandemic. However, there is a lack of research on how digital finance affects the financial behaviour and well-being of consumers, how it promotes financial literacy and education among consumers, and what are the obstacles and possibilities of digital finance for financial innovation and inclusion in the post-pandemic scenario. This paper explores the factors affecting the adoption of digital finance in Sambalpur City, with a particular focus on perceived benefits and perceived risks. The study employs a quantitative approach, utilizing a structured questionnaire administered to participants across various regions in Sambalpur city. The findings reveal that perceived benefits outweigh perceived risks, indicating a general movement towards digital finance adoption. The study offers valuable insights for financial managers and digital finance service providers, enabling them to efficiently allocate resources and improve their services to grow the adoption of digital finance. The paper concludes by highlighting the ability of digital finance to drive financial inclusion and economic growth in India, and the need for a more inclusive and secure digital financial future.
Keywords: Digital finance; Financial behaviour; Financial literacy; Financial innovation

Introduction

In the rapidly changing digital environment of today, the significance of embracing digital finance has grown, playing a crucial role in advancing financial inclusion and fostering economic growth. Notably, digital financial services have emerged as a catalyst for broadening access to financial resources and services. A study investigating the impact of FinTech on enhancing financial inclusion reveals that digital finance holds the capability to offer cost-effective services to diverse population segments, effectively closing the gap between those without access to banking and the conventional banking system. Insufficient attention has been given to the social, economic, and cultural contexts within which these systems are employed (Goswami et al., 2022). Furthermore, there is a shortage of empirical research in India that identifies the crucial success elements for using technology to increase financial services. This research aims to address a gap in the existing literature by emphasizing the significance of studies focused on the inclusion and empowerment of marginalized populations. Digital finance involves leveraging technology, especially mobile devices and the internet, to deliver financial services, including mobile banking, digital payments, and online loans.

The Government of India and the central bank have implemented various policy measures to promote digital finance and ensure its accessibility to all sections of society, especially those who .have traditionally been excluded from formal financial systems. Initiatives like Aadhaar, the national digital identity program, and UPI, the unified payments interface, have significantly reduced barriers to entry and boosted adoption among underserved communities. However, challenges remain. Lack of digital literacy, limited internet access in rural areas, and concerns around data privacy continue to deter a significant portion of the population from fully embracing digital finance.

This research aims to shed light on these nuances by conducting a thorough analysis of the social, economic, and cultural contexts surrounding the implementation of digital finance in India. By delving into regional disparities, language barriers, gender-based disparities, and traditional financial practices, we seek to identify the critical success factors that can lead to inclusive and sustainable financial empowerment for all. The adoption of digital finance has become increasingly crucial in today's economy, offering numerous benefits such as easy access to financial records, reduced circulation of counterfeit currency, and contributions to the overall gross domestic product. However, despite the awareness of available financial services through digital platforms, there remains a level of resistance among potential users due to perceived risks and hesitations associated with the adoption of this technology. Previous research has recognised the importance of perceived benefits and risks in driving the adoption of various financial services. However, there is a limited understanding of how these characteristics explicitly influence the desire to use digital finance, particularly in the setting of Sambalpur, Odisha. This study seeks to bridge this gap by explicitly integrating both positive (perceived benefits) and negative (perceived risks) aspects to evaluate their influence on the adoption of digital finance.

Furthermore, to persist and flourish in the local economy, the fintech business must first comprehend and work on a risk-free transaction environment. By addressing the factors of perceived risk and perceived benefits, this study seeks to provide valuable insights for financial managers and digital finance service providers, enabling them to efficiently allocate resources and improve their services to increase the adoption of digital finance. In light of the above, this research aims to investigate the specific factors influencing the adoption of digital finance in Sambalpur with a focus on perceived benefits and perceived risks. By addressing this research gap, the study endeavors to contribute to the understanding of individuals' behavior towards digital finance adoption and provide practical implications for industry stakeholders.

Literature Review

Digital Finance

Digital finance revolutionizes the financial landscape by harnessing digital technologies to deliver services. From credit cards and internet banking to mobile payments and online loans, this transformation extends beyond simply offering products. It encompasses innovative businesses, software solutions, and customer interaction methods, primarily through FinTech companies and service providers (Gomber et al., 2017).

This shift necessitates a multi-layered ecosystem – digital platforms, retail agents, and accessible devices (CGAP, 2015). Users typically require active bank accounts and internet connectivity to transact via mobile phones or computers (Ozili, 2018).

Digital finance shines as a powerful tool for swift and targeted resource delivery, especially during crises (Arner et al., 2016, 2020). However, it also introduces novel risks, most notably the growing threat of digital crime (Buckley et al., 2020).
The COVID-19 pandemic accelerated the adoption of digital financial services, integrating them into the online commerce fabric (Arner et al., 2020). This holds immense potential for financial inclusion, particularly in underdeveloped regions or rural areas with limited access to traditional banking (Finau et al., 2016).
Several advantages fuel the rise of digital finance:

- Financial inclusion: Extending services to previously marginalized individuals.
- Convenience and affordability: Simplifying banking and facilitating the transition to a cashless economy.
- Product diversification: Broadening options and potentially boosting GDP growth.
- Reduced counterfeiting: Minimizing the circulation of fake currency.
- Empowerment: Enabling faster financial decisions, personal record control, and instant mobile transactions.

Despite these benefits, challenges remain:

- Accessibility: Digital devices and bank accounts are essential but not universally available.
- Data security: Breaches can erode trust and hinder adoption.
- Affordability: Fees might exclude low-income earners from fully benefiting.

Research underscores the complexities of user behavior in this evolving landscape. Studies by Featherman and Pavlou (2003), Gerlach et al. (2019), Aisaiti et al. (2019), and Finau et al. (2016) highlight the interplay of perceived risks and benefits, along with factors like ease of use, social influence, and financial expertise.
Understanding these dynamics is crucial for guiding future advancements and ensuring that digital finance truly unlocks its potential for a more inclusive and empowered financial future.

Risk–benefit framework

Understanding the interplay of risk and benefit is crucial when analyzing adoption behavior, particularly in the context of digital financial services. Previous research has established an inverse relationship between perceived risk and perceived benefit, suggesting that individuals are more likely to adopt a new technology when they perceive it as beneficial and less risky (Alhakami and Slovic, 1994). Based on this understanding, Peter and Tarpey (1975) introduced a net-valence framework, suggesting that individuals embrace innovations only when the perceived benefits surpass the perceived risks.
Further understanding this dynamic requires integrating existing theoretical frameworks. The present research combines the Theory of Reasoned Action (TRA) with the net-valence framework. TRA posits that individuals' behaviors are guided by their attitudes, subjective norms, and

perceived behavioral control (Ajzen and Fishbein, 1977; Staats, 2004). In the context of digital finance adoption, this suggests that risk and benefit perceptions directly influence individual intentions to utilize these services (Jurison, 1995).

Empirical research on the specific factors influencing digital finance adoption through the lens of a risk-benefit framework is limited, but existing studies offer valuable insights (Ryu, 2018; Abramova and Böhme, 2016; Liu et al., 2012; Lee, 2009). These studies consistently identify both perceived risks and perceived benefits as multifaceted constructs.

For example, Ryu (2018) investigated user willingness and reluctance towards financial technology, categorizing perceived benefits into economic gain, seamless transactions, and convenience, and perceived risks into legal, financial, security, and operational categories. Furthermore, the study identified legal risks as a significant barrier to adoption, while convenience consistently shaped perceived benefits. Significantly, variations in the perceived advantages and drawbacks were observed to affect individuals who embraced a new concept or technology early on, as well as those who adopted it later.

Similarly, Abramova and Böhme (2016) integrated perceived risks and benefits into the utilizing the technology acceptance model to elucidate the acceptance of Bitcoin adoption. They defined perceived benefits as encompassing convenience, security, and decentralization, while perceived risks included financial losses, legal issues, operational disruptions, and challenges due to early adoption.

Emphasizing the distinct elements influencing the adoption of mobile payments, Liu et al. (2012) pinpointed financial risk, privacy risk, and psychological risk as integral components of perceived risk, while treating perceived benefits and perceived value as single-dimensional constructs. Notably, their study found financial risk to be the most significant barrier to mobile payment adoption.

Finally, Lee (2009) proposed a comprehensive model of user intentions regarding internet banking adoption, integrating perceived risks and benefits with both the model of technology acceptance and the planned behavior theory. Perceived risk was categorized into financial, security/privacy, performance, social, and time dimensions, while perceived benefit was treated as a unified construct. This study identified security risk as the primary influencer of online banking adoption, while perceived benefit emerged as the most positive influence on user intentions.

These studies collectively demonstrate the importance of considering both perceived risks and perceived benefits when analyzing digital finance adoption behavior. By integrating existing theoretical frameworks and drawing from empirical research, we can enhance our comprehension of the complex factors influencing individuals' decisions to embrace or reject these innovative technologies.

Perceived Risk and Its Determinants

Consumer anxieties surrounding potential drawbacks and uncertainties, known as perceived risk, play a crucial role in their decisions to adopt new services, particularly in the realm of financial technology (Featherman & Pavlou, 2003). This phenomenon, characterized by a mix of uncertainty and the potential severity of negative outcomes (Bauer, 1967), has been investigated extensively within the realm of electronic finance and online services adoption (Alalwan et al., 2018; Martins et al., 2014; Safeena et al., 2011).

Although the influence of perceived risk on adoption is a complex subject, research findings paint a diverse picture. For instance, Fernando (2019) found that trust, rather than risk, significantly influences fintech adoption, highlighting the importance of establishing a secure and reliable image.

Conversely, studies like Yang et al. (2015) emphasize the resistance triggered by uncertainties and risks in online transactions. Their categorization of perceived risk into systematic (e.g., platform stability) and transactional (e.g., fraud) dimensions provides valuable insights into how specific concerns shape trust and influence adoption.

Further complexity is introduced by the moderating role of various factors. Im et al. (2008) demonstrated that perceived risk, user experience, gender, and technology type all significantly moderate an individual's behavioral intention. This underscores the need for a multi-faceted approach to understanding adoption behavior.

Recognizing the multifaceted nature of perceived risk, Cunningham (1967) proposed a comprehensive classification encompassing six distinct categories: financial, performance, safety, social, psychological, and time risk. Drawing upon this framework and existing research, the present study focuses on three specific types of perceived risk particularly relevant to fintech adoption: financial (potential loss), security (fraud, data breaches), and performance (transaction disruptions).

Perceived Benefts and Its Determinants

Understanding the potential advantages that users anticipate, or perceived benefits, is crucial for analyzing their adoption of new technologies. These positive outcomes can act as counterpoints to perceived threats, potentially driving individuals to embrace an innovation (Chandon et al., 2000).

A prime example of this interplay is M-payment adoption during the pandemic. Zhao and Bacao (2021) investigated factors influencing Chinese consumers' intentions, highlighting the positive roles of perceived benefits, social influence, and trust. Their research established a causal chain where trust and social influence directly enhanced perceived benefits, which in turn boosted adoption. Notably, trust and effort expectancy also influenced users' performance expectations, providing further insight into the adoption process.

Similarly, studies like Wong et al. (2021) explore how perceived benefits and harms interact with social demographics. Their research on family well-being during the pandemic found that both benefits and harms, with a higher degree of variability observed in benefits across demographics, affected families to varying degrees.

Beyond pandemic-specific contexts, research like Okazaki and Mendez (2013) delves into factors influencing mobile commerce adoption. Their study identified three key elements of perceived benefits: seamless transactions, convenience, and economic gains. These encompass the ease and speed of financial interactions (Chishti, 2016), the flexibility of time and location (Kim et al., 2010), and potential cost savings or financial advantages (Ryu, 2018). Notably, their research also reveals how factors like gender can moderate the impact of specific benefits, highlighting the need for a multifaceted approach to understanding adoption behavior.

Research Methodology

Data collection and sample design

This study employs a quantitative approach to explore the elements that impact the adoption of digital finance in India, with a particular focus on perceived benefits and perceived risks. Data collection for this research utilized a structured questionnaire administered to participants across various regions in Sambalpur city.

Sampling:

A Stratified Random technique was employed to select participants from the following branchs of UCO bank Sambalpur: Golebazar, Budharaja, Hirakud, MCL, Jyoti Vihar, Bajamunda, and Godbhaga. This targeted approach aimed to capture diverse perspectives from geographically distinct areas. A total of 400 questionnaires were distributed, and 333 responses were received. After accounting for incomplete or outlier responses, 311 responses were deemed suitable for the final analysis, resulting in an acceptable response rate as per Nutty (2008).

Data Collection:

Data is collected with the help of the questionnaire of Jain (2022) as the author has already tested the reliability of the questionnaire. Questionarie was made on google form and share with selected user for data collection. The questionnaire, using a five-point Likert scale, measured the constructs of perceived benefits, perceived risks, and intention to adopt digital finance.

Data Analysis:

The analysis employed a combination of quantitative techniques to guarantee the strength and credibility of the study findings:

- Variance Inflation Factors (VIF): Identified multicollinearity among the constructs.
- Standardized Root Mean Square Residual (SRMR), RMS Theta: Evaluated the goodness-of-fit of the model Normed Fit Index (NFI),

These methods provided a comprehensive understanding of the relationships between perceived benefits, perceived risks, and the objective to adopt digital finance in the context of Northern India.

Hypotheses Formulation:

Perceived Risks and Adoption:

This study draws on established research indicating that perceived risks act as a significant barrier to digital finance adoption (Abramova & Böhme, 2016; Ryu, 2018; Benlian & Hess, 2011). Therefore, we hypothesize:

- H1: Perceived risks negatively influence digital finance adoption.

Perceived Benefits and Adoption:

Conversely, the literature consistently highlights perceived benefits as a driving force for IT service adoption (Abramova & Böhme, 2016; Ryu, 2018; Benlian & Hess, 2011). Building on this evidence, we propose:

- H2: Perceived benefits positively influence digital finance adoption.

Unpacking Perceived Risks and Benefits:
To gain deeper insights, we further dissect both constructs.
Perceived Risks:

- H3: Financial risk is associated with increased perceived risk (Melewar et al., 2013).
- H4: Security risk is associated with increased perceived risk (Ryu, 2018).
- H5: Performance risk is associated with increased perceived risk (Lee, 2009).

Perceived Benefits:

- H6: Economic benefit is associated with increased perceived benefit (Mackenzie, 2015).
- H7: Seamless transaction is associated with increased perceived benefit (Chishti, 2016).
- H8: Convenience is associated with increased perceived benefit (Kim et al., 2010).

Model Development and Data Analysis:
This study employed a nine-variable model adapted from established research in the field. While drawing heavily on prior works, the specific items were carefully modified to align with the study's unique objectives. A five-point Likert scale structured questionnaire served as the data collection instrument, with responses analyzed using partial least squares-structural equation modeling (PLS-SEM). SmartPLSv2.0 software provided the platform for investigating the relationships between variables.
PLS-SEM, identified as a second-generation exploratory technique, proved to be well-suited for unveiling the impact of exogenous variables on the targeted endogenous variable (Hair et al., 2012, 2019; Reinartz et al., 2009). The design of the survey was meticulously shaped by an extensive literature review. Constructs such as perceived risk were inspired by Yang et al. (2015) and (Meyliana and Fernando, 2019) and perceived benefit were inspired by the works of Lee (2009) and (Zheng et al., 2006), while economic benefit from Featherman and Pavlou (2003) and Lee (2009), financial risk from (Bettman, 1973),and Lee (2009), and security risk were drawn from the studies of Jacoby and Kaplan (1972) and Littlerand Melanthiou (2006). Additional variables, such as performance risk (Kuisma et al., 2007) and Yiu et al.(2007), seamless transaction (Ryu, 2018), and convenience (Bilgihan et al., 2016), were similarly derived from pertinent literature. The dependent variable, Adoption of Digital Finance, was adapted from Cheng et al. (2006) and Ryu, 2018b. It is worth noting that Gerlach et al. (2019) provided a foundational framework for integrating key independent variables like financial risk, security risk, perceived benefit, and convenience into the research model. Table 1 succinctly presents the components of the model along with their respective origins in the literature.

Table1: Construct and their sources

Constructs	No. of Items	Source
Perceived Risk	3	Yang et al. (2015) and (Meyliana and Fernando, 2019)
Financial Risk	3	(Bettman, 1973),and Lee (2009)
Security Risk	4	Jacoby and Kaplan (1972) and Littlerand Melanthiou (2006)
Performance Risk	3	(Kuisma et al., 2007) and Yiu et al.(2007)
Perceived Benefit	4	Lee (2009) and (Zheng et al., 2006)
Economic Benefit	3	Featherman and Pavlou (2003) and Lee (2009)
Seamless Transaction	3	Ryu, 2018
Convenience	3	Bilgihan et al., 2016
Adoption of Digital Finance	3	Cheng et al. (2006) and Ryu, 2018b
Constructs	**No. of Items**	**Source**
Perceived Risk	3	Kim et al. (2008) and Benlian and Hess (2011)
Financial Risk	3	Featherman and Pavlou (2003) and Lee (2009)
Security Risk	3	Featherman and Pavlou (2003) and Lee (2009)
Performance Risk	3	Featherman and Pavlou (2003) and Lee (2009)
Perceived Benefit	4	Kim et al. (2008) and Benlian and Hess (2011)
Economic Benefit	3	Featherman and Pavlou (2003) and Lee (2009)
Seamless Transaction	3	Chishti (2016)
Convenience	3	Okazaki and Mendez (2013)
Adoption of Digital Finance	3	Cheng et al. (2006) and Lee (2009)

Table 2: Demographic Evidence

Characteristics	Frequency	Percentage (%)
Gender		
Male	168	54.3
Female	143	45.7
Age		
18–25 years	9	2.9
25–35 years	106	34.1
35–45 years	75	24.3
45–55 years	88	28
Above 55 years	33	10.7
Educational Qualifcation		
High School	11	3.4
Diploma	53	17
Graduate	125	40.1

Post-graduate	98	31.4
PhD	24	8
Most Digital Financial services used		
Internet Banking	90	28.7
Mobile Banking	89	28.5
Mobile Wallets	29	9.5
Credit Cards	29	9.2
Debit Cards	74	24.1

Table 2 offers a rich tapestry of demographic insights gleaned from our study on digital financial services (DFS) adoption in India. Let's dissect its threads to unveil the intricate patterns woven within.

Demographic Composition:

- Gender Dynamics: Our sample exhibits a slight male skew, with 54.3% identifying as male and 45.7% as female. This aligns with broader national trends regarding digital finance user demographics.
- Age Spectrum: The data reveals a clustering within the 25-35 age group (34.1%), suggesting targeted outreach opportunities for this demo. Further segments include the 45-55 age group (28%), 35-45 age group (24.3%), and smaller proportions in younger and older cohorts.
- Educational Landscape: A significant majority (71.5%) possess graduate or postgraduate qualifications, highlighting the potential influence of educational attainment on DFS adoption.

Digital Finance Preferences:

- Internet Ascendant: As the most frequently used tool (28.7%), internet banking emerges as the clear frontrunner in this sample's DFS repertoire. This resonates with existing research on its perceived convenience and security.
- Mobile Momentum: Mobile banking follows closely behind at 28.5%, underscoring its increasing ubiquity and user acceptance. This trend presents valuable avenues for further innovation and expansion.
- Varied Adoption: Mobile wallets, credit cards, and debit cards exhibit diverse usage levels, highlighting the interplay of specific needs, access, and preferences among users. Notably, credit cards appear to be the least favored option, warranting further investigation.

Data Analysis Nuances:

- Normality Check: The data exhibited non-normality, prompting the choice of PLS-SEM as a robust analytical technique for uncovering latent variable relationships.

- Bias Control: Common method bias assessment confirmed its absence, ensuring the integrity of our findings.

Table 2 paints a vivid picture of a population embracing internet and mobile banking as preferred DFS tools. The dominance of younger and more educated demographics suggests a potential nexus between age, education, and DFS adoption. Further research can delve deeper into these relationships and explore the underlying motivations and barriers to DFS use across diverse segments.

Table 3: Reliability of indicators, internal coherence, and convergent validity of the measurement model.

Constructs	**Items**	**Outer loadings**	**Cronbach alpha**	**RHO alpha**	**CR**	**AVE**
ADF	ADF1	0.945	0.929	0.939	0.955	0.874
	ADF2	0.918				
	ADF3	0.926				
CONV	Conv1	0.908	0.908	0.908	0.939	0.841
	Conv2	0.927				
	Conv3	0.909				
EB	EB1	0.927	0.859	0.869	0.919	0.789
	EB2	0.828				
	EB3	0.902				
ST	ST1	0.901	0.869	0.889	0.924	0.789
	ST2	0.889				
	ST3	0.887				
PB	PB1	0.904	0.868	0.880	0.910	0.719
	PB2	0.809				
	PB3	0.858				
	PB4	0.819				
FR	FR1	0.909	0.904	0.909	0.940	0.839
	FR2	0.903				
	FR3	0.926				
SR	SR1	0.937	0.910	0.912	0.944	0.849
	SR2	0.901				
	SR3	0.929				
PERFR	PERFR1	0.881	0.889	0.914	0.919	0.799
	PERFR2	0.910				
	PERFR3	0.901				
PR	PR1	0.919	0.904	0.903	0.939	0.837
	PR2	0.890				

	PR3	0.939				

Model Assessment and Validation:

A comprehensive evaluation of the reflective measurement model's strength involved rigorous assessments of three essential parameters: indicator reliability, convergent validity, and discriminant validity (Coltman et al., 2008; Hair et al., 2011).

Reliability of Indicators:

Analyzing the outer loadings in Table 3, with all exceeding 0.7, provided compelling evidence for strong indicator reliability. This suggests that each indicator effectively captures the corresponding latent construct it represents.

Convergent Validity:

The model's convergent validity was evaluated through a multi-pronged approach encompassing internal consistency, composite reliability and average variance extracted (AVE) (Barclay et al., 1995) were assessed. Cronbach's alpha and rho alpha values, both surpassing 0.7 (Nunnally & Bernstein, 1994; Henseler et al., 2015), confirmed satisfactory internal consistency. Similarly, composite reliability values exceeding 0.7 and AVE values surpassing 0.5 (Bagozzi & Yi, 1988) collectively confirmed the model's convergent validity.

Table 4: Discriminant validity

	ADF	**Conv**	**EB**	**FR**	**PB**	**PR**	**Perf R**	**SR**	**ST**
ADF	0.929								
Conv	0.569	0.919							
EB	0.483	0.601	0.890						
FR	-0.511	-0.489	-0.458	0.909					
PB	0.549	0.669	0.826	-0.528	0.849				
PR	-0.479	-0.528	-0.489	0.627	-0.548	0.910			
Perf R	-0.329	-0.438	-0.458	0.719	-0.541	0.712	0.890		
SR	-0.519	-0.439	-0.458	0.715	-0.510	0.618	0.590	0.918	
ST	0.659	0.769	0.678	0.516	0.712	-0.548	-0.437	-0.487	0.889

Discriminant validity was established through two complementary approaches. Firstly, Fornell and Larcker's (1981) method was employed, comparing comparing the square root of AVE values (diagonal elements in Table 4) with the inter-construct correlations (off-diagonal elements), specifically considering the square root of AVE consistently exceeded the corresponding inter-construct correlations, discriminant validity was upheld. However, acknowledging the potential limitations of this method (Henseler et al., 2015), the analysis was further strengthened by calculating the Heterotrait-Monotrait ratio (HTMT), as indicated in Table 5, demonstrated that all HTMT values remained below the suggested threshold of 0.85, as recommended by (Henseler et al., 2015), providing additional support for discriminant validity.

Table 5: HTMT ratio

	Conv	DF	EB	FR	PB	PR	PerfR	SR	ST
Conv									
DF	0.624								
EB	0.679	0.524							
FR	0.538	0.548	0.514						
PB	0.739	0.590	0.760	0.579					
PR	0.590	0.518	0.549	0.701	0.618				
PerfR	0.478	0.360	0.524	0.803	0.609	0.783			
SR	0.530	0.560	0.524	0.789	0.559	0.678	0.650		
ST	0.771	0.734	0.770	0.579	0.798	0.614	0.490	0.538	

Structural Model: A Rigorous Assessment

The study delved deeper into the intricacies of the structural model through a meticulous three-pronged approach: assessing collinearity, evaluating the significance of relationships, and examining model fit.

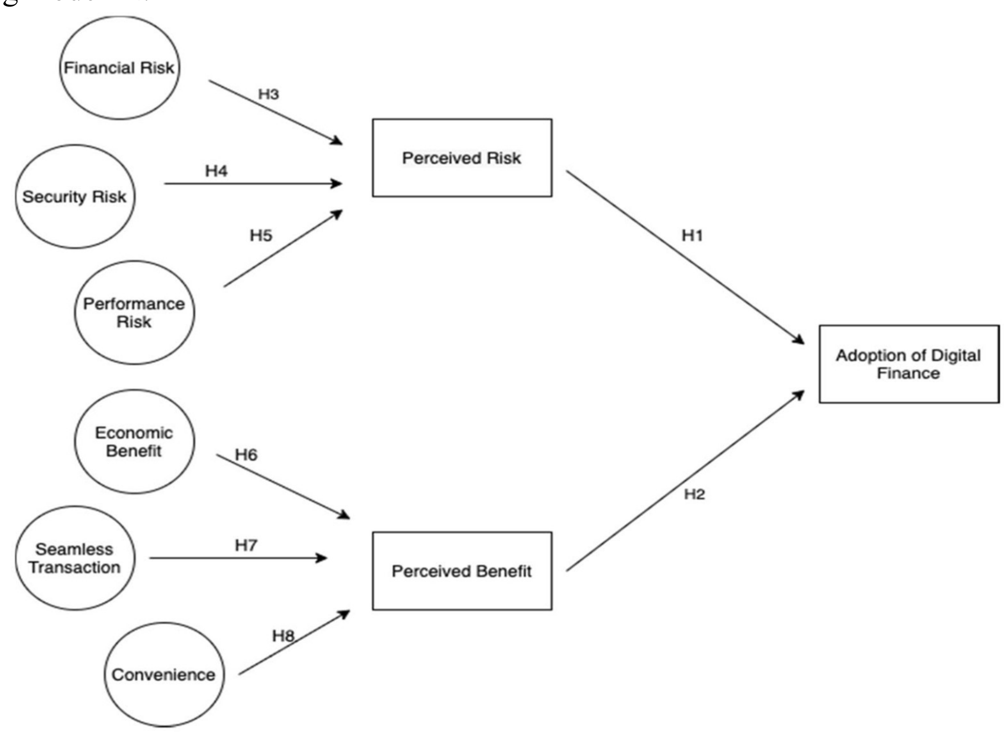

Fig 1: Research Model

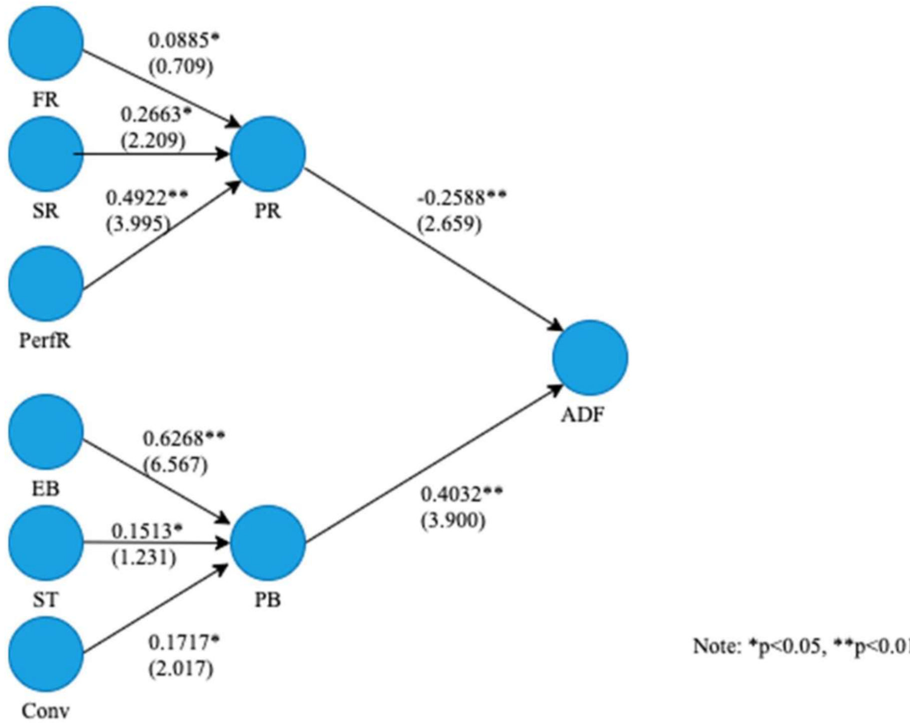

Fig. 2 Path coefficients and structural model

Collinearity:

To ensure meaningful interpretation, we first tackled the potential of multicollinearity, a hidden foe that can distort relationships. Employing Variance Inflation Factors (VIF) calculated through SPSSv25 with scores of latent variables (Henseler et al., 2009; Hair et al., 2012), we analyzed each construct. As showcased in Table 6, each VIF value comfortably remained below the critical threshold of 5 (Hair et al., 2012), confidently banishing this threat and paving the way for reliable analysis.

Table 6: Multicollinearity examination

Constructs	**VIF values**
CONV	2.711
EB	3.470
FR	2.990
PB	4.159
PR	2.566
PERF	2.774
SR	2.342
ST	3.213

Unveiling Significance:

Next, we sought to unveil the significance of relationships within the model. The powerful PLS-SEM bootstrapping algorithm (Henseler et al., 2009; Hair et al., 2012) came to our aid, generating

5000 random samples from the original dataset to rigorously scrutinize each relationship. Table 7 proudly displays the results, with each relationship standing tall with statistical significance.

Gauging Model Fit:

Beyond significance and explanation, ensuring a good model fit was paramount. We employed established criteria, examining the SRMR (Standardized Root Mean Square Residual).Top of Form Nestled comfortably below the recommended limit of 0.08 (Henseler et al., 2014; Hair et al., 2020), this value in Table 7 underscores the model's close alignment with reality. Moreover, the Normed Fit Index (NFI) recorded a value of 0.844 and RMS theta of 0.133 (Mardia, 1970) provided additional confidence in the model's suitability for interpreting the hypothesized relationships.

Table 7: Testing hypotheses

Hypothesis	Path coefficients	T Statistics	P-value	Decision
Conv → PB	0.1701	2.020	0.05	supported
EB → PB	0.6303	6.571	0.05	supported
FR → PR	0.090	0.712	0.05	not supported
PB → ADF	0.404	3.900	0.05	supported
PR → ADF	-0.260	2.660	0.05	supported
Perf R → PR	0.490	4.000	0.05	supported
SR → PR	0.270	2.211	0.05	Supported
ST → PB	0.151	1.232	0.05	Not Supported

Quantifying Explained Variance:

Moving beyond significance, we delved into the model's explanatory power by calculating the coefficient of determination (R2) (Cohen, 1988). As evidenced in Table 8, the achieved R2 value met established standards, further bolstering the model's credibility.

Table 8: R^2 value

Variables	Coefcient of Determination (R2)
PB	0.73
PR	0.56
ADF	0.34

Discussion

This analysis, employing PLS-SEM and bootstrapping, ventured into the labyrinthine pathways influencing digital finance adoption. Our journey uncovered two key pillars shaping users' decisions: perceived risks and perceived benefits.

Deciphering Risk and its Facets:

As hypothesized, perceived risk served as a formidable deterrent to embracing digital finance (H1, supported). Delving deeper, we discovered that performance and security concerns significantly contributed to this apprehension (H4, H5 supported), while financial anxiety remained unlinked

(H3 rejected). Interestingly, these factors collectively explained over half (57%) of the perceived risk variance, highlighting their crucial role in users' minds.

Unpacking the Allure of Benefits:

On the flip side, perceived benefits emerged as a powerful magnet drawing users towards digital finance (H2 supported). Convenience and economic advantages proved to be the major contributors (H6, H8 supported), collectively explaining a substantial 74% of the perceived benefit variance. This aligns with Gerlach et al. (2019), suggesting that users value practicality and financial gain when considering digital platforms. However, seamless transactions surprisingly failed to resonate with users (H7 rejected), implying that other factors may hold greater sway in shaping perceptions of convenience.

Navigating the Landscape of Existing Research:

Our findings paint a nuanced picture, both confirming and challenging existing knowledge. The significant influence of performance and security risks on perceived risk aligns with Liu et al. (2012), Luo et al. (2010), and Abramova and Böhme (2016). However, the weak association between financial risk and perceived risk seems to diverge from their conclusions. This intriguing discrepancy warrants further exploration in future research.

Beyond Theory: Practical Implications and Future Directions:

This study's insights hold valuable implications for stakeholders. Policymakers can leverage user concerns about performance and security to implement robust regulations and educate users about risk mitigation strategies. Financial institutions must prioritize transparent communication and user-friendly interfaces to address performance anxieties. Technology developers should focus on enhancing efficiency and reliability to solidify trust and attract users.

Unveiling the true drivers of digital finance adoption remains an ongoing quest. Further research could examine the influence of user demographics, cultural contexts, and individual technology experiences on risk and benefit perceptions. By continuously refining our understanding, we can pave the way for a more inclusive and secure digital financial landscape for all.

Conclusion

In the dynamic world of finance, information technology has become a vital engine for growth, particularly in India. Embracing digital finance isn't just about convenience and personal financial record accessibility; it holds immense potential to boost the nation's GDP by curbing black money circulation. Yet, while awareness of these benefits exists, hesitation and perceived risks impede widespread adoption. This study delves into both sides of the coin, analyzing both perceived risks and benefits associated with digital finance.

While some resistance lingers, our findings reveal that perceived benefits outweigh perceived risks, indicating a general movement towards digital finance adoption. To acquire a more profound insight into user perceptions, the study categorized perceived risks (financial, performance, security) and benefits (convenience, economic, seamless transaction), offering a richer picture of the decision-making process. For the fintech industry, this research illuminates crucial pathways for sustainable growth in the Indian economy. Building a risk-free transaction environment should be a top priority, fostering trust and encouraging potential users to take the leap. Financial managers, armed with these insights, can tailor their marketing strategies, emphasizing specific benefits and addressing lingering concerns about risks. This targeted approach ensures efficient resource allocation for service improvement and customer base expansion.

Digital finance service providers have a dual responsibility: reducing risks and creating a stable, user-friendly environment. Understanding their target audience, their anxieties, and their needs is key to designing products and services that mitigate risks and maximize benefits. This study serves as a foundation for further exploration in the realm of digital finance. By introducing additional factors influencing individual adoption behavior, future research can deepen our understanding of this vital phenomenon and pave the way for a more inclusive and secure digital financial future for India.

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