Analyzing the Dissemination of Artificial Intelligence in Digital Banking: A Mixed-Methods Study of FinTech Adoption Behavior

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ABSTRACT

This study purposefully addresses the FinTech and digital banking literature by examining the diffusion of artificial intelligence (AI) across technological, organisational, and consumer dimensions through a mixed-methods approach, with a particular focus on semi-urban and developing market contexts. The qualitative phase comprised semi-structured interviews with representatives from two nationalised and four private Indian banks, chosen for their strong reputations, extensive user bases, and early FinTech adoption in semi-urban areas, and subsequently tested through a cross-sectional quantitative survey of semi-urban consumers using a structured questionnaire. Quantitatively, 547 valid stratified-random responses were analysed using validated five-point Likert measures. The measurement model has a high level of reliability and validity, and a high level of internal consistency, convergent and discriminant validity, and lack of multicollinearity, which proves the applicability of the measurement model to structural analysis. The structural findings demonstrate that the digital literacy is the strongest contributor to trust, the satisfaction leads to loyalty, the organisational agility has a positive impact on satisfaction and trust, and the perceived usefulness has a relatively small impact. The findings of mediation and moderation indicate that trust and satisfaction are able to transfer the important effects on loyalty together but a greater perceived risk has the capability of eroding the trust-loyalty relationship. By offering practical insights, this research provides valuable guidance for policymakers and financial institutions seeking to balance innovation with consumer protection in the evolving AI-enabled digital banking ecosystem.

Keywords: AI-diffusion, Developing economies, Organisational agility, Trust; satisfaction;,loyalty, Digital literacy, Risk
Jel Code: G21; G28; D82; K14

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1. INTRODUCTION

The meteoric ascension of artificial intelligence (AI) within the realms of digital banking and FinTech is profoundly transfiguring the global financial firmament. It is transforming the banking institutions and the delivery models using AI-based tools, attempting to automate credit score, fraud detection, robo-advisory, algorithm robots to create investment options, compliance robots, and personalised customer services (Arner et al., 2017; Chen et al., 2019; Mhlanga, 2020). Artificial intelligence is harnessed in digital banking to orchestrate instantaneous decisions, prescient analytics, bespoke personalisation, and vanguard advancements in fraud deterrence—thereby elevating operational efficiency and customer delight to unparalleled echelons (Bussmann et al., 2021; Dwivedi et al., 2021; Demirel, 2024; Gyau, 2024). Financial institutions increasingly adopt AI to improve competitiveness, service quality, and scalability, while consumers embrace technology-driven financial services prioritising convenience and reliability (Gomber et al., 2017). Moreover, in emerging and digitally evolving economies, disparities in digital literacy, institutional trust, and technological readiness further complicate AI diffusion and equitable FinTech adoption (Tornatzky & Fleischer, 1990; Oliveira & Martins, 2011; Demirgüç-Kunt et al., 2018; Ozili, 2018). However, AI diffusion remains uneven across regions and contexts (Bons et al., 2020), constrained by organisational readiness, skills gaps, regulatory ambiguity, transparency concerns, and systemic risk (Bisschoff, 2020; Reuters, 2024; Vuković, 2025; BIS, 2025), particularly in semi-urban and developing markets (Ozili, 2018; Mhlanga, 2020; Gyau, 2024).Trust, perceived usefulness, and perceived risk are factors that influence the adoption behaviour of the consumer (Davis, 1989; Gefen et al., 2003). Although AI increases personalisation and efficiency of services, issues with privacy, algorithm bias, transparency, and responsibility influence behavioural intentions to a substantial degree (Goodman & Flaxman, 2017; Glas & Pelzer, 2019). Opaque algorithm systems also decrease the development of trust, especially in developing economies with weak institutional trust (Siau & Wang, 2018; Castelo et al., 2019; Shin, 2021). Risks of cybersecurity, data privacy, financial loss, and algorithmic discrimination, among others, are among the key obstacles to the adoption of AI (Featherman & Pavlou, 2003; Dinev et al., 2015) and perceived vulnerability to these risks is a significant factor in breaking trust -loyalty links in high-risk digital settings (Rogers, 1983; Li & Huang, 2020; Kaur et al., 2022).

2. LITERATURE REVIEW

Albeit under-theorised, digital literacy can be crucial in the adoption of AI by improving user confidence and trust, but it is not considered one of the primary drivers (Eshet-Alkalai, 2004; Ng, 2012; Chawla & Joshi, 2021). The existing patterns of technology acceptance, e.g., the Theory of Planned Behaviour (Ajzen, 1991) and UTAUT (Venkatesh et al., 2003), are not sufficiently effective at explaining technology acceptance since they cannot define the socio-technical intricacy of AI diffusion in semi-urban and developing market settings (Ozili, 2018; Daqar et al.,2020). As indicated by literature, technology acceptance, innovation diffusion, and behavioural intention are the primary factors that drive AI diffusion in digital banking, and the perceived usefulness, ease of use, trust, and risk largely impact the adoption of FinTech (Davis, 1989; Featherman and Pavlou, 2003; Gefen et al., 2003; Rogers, 2003; Venkatesh et al., 2003; Kim et al., 2009; Venkatesh et al., 2012). Research also supports the notion that AI-facilitated personalisation, quality of service, security, and perception of customer value contribute to satisfaction, loyalty, and further use, especially in the case of digitally transforming banking ecosystems (Rai et al., 2019; Shankar & Jebarakirthy, 2019; Glikson & Woolley, 2020; Huang & Rust, 2021; Verhoef et al., 2021). Digital literacy, organisational readiness, innovation capability, regulatory environment, and ethical AI governance collaboratively influence adoption behaviour in emerging and FinTech-driven settings, supporting integrated mixed-methods inquiry (Tornatzky & Fleischer, 1990; Oliveira & Martins, 2011; Arner et al., 2016; Demirguc-Kunt et al., 2018; Ozili, 2018; Gomber et al., 2018; Dwivedi et al., 2021).

Some persistent gaps remain- limited empirical evidence on AI diffusion mechanisms (Manta et al., 2025); dominance of single-method research designs (Gomber et al., 2017; Chen et al., 2019; Bons et al., 2020; Mhlanga, 2020) and strong urban and developed-market bias marginalising semi-urban populations (Gyau, 2024). These gaps underscore the need for a holistic framework integrating technological, organisational, and consumer dimensions, with trust and satisfaction as mediators and perceived risk as a moderator (Creswell & Plano Clark, 2017; Chen et al., 2019; Bons et al., 2020). Accordingly, this study examined AI-enabled FinTech diffusion in digital banking through a mixed-method design, offering insights for sustainable innovation, consumer trust, and regulatory alignment.

Literature acknowledge the increased FinTech/digital banking integration, but AI-based innovation has not been theorised, distributed, and analysed thoroughly, which is why the mixed-method research design should be used to investigate the inclusion of AI across a range of organisational agility, cross-sectoral dynamics, and semi-urban/developing market landscapes with structural limitations (Zhang et al., 2022; Rahman et al., 2023; Garg, 2024; Gyau, 2024; Lazo & Ebardo, 2024).

2.1 OBJECTIVES OF THE STUDY

This study investigated the diffusion of AI-enabled FinTech within digital banking ecosystems through a rigorous mixed-method research design, elucidating organisational-consumer dynamics while offering strategic and practical insights to support banks, policymakers, and regulators in advancing trusted, compliant, and sustainable AI-driven innovation.

2.2 DEVELOPMENT OF HYPOTHESIS

Technology Readiness recommends adoption, based on optimism, innovativeness and security (Parasuraman, 2000). In digital banking with AI, acceptance, confidence and satisfaction are enhanced by trust that is backed by Technology Acceptance Model (TAM) wherein digital competence, perceived ease of use and usefulness promote trust and continuance (Davis, 1989). Technological readiness and perceived risk reduction is enhanced by organisational agility as well as digital literacy (Becker, 1993; Teece et al., 1997). Expectation-Confirmation and Commitment-Trust theories associate loyalty and sustainability to trust and satisfaction (Oliver, 1980, 1999; Morgan & Hunt, 1994). Consumer Trust leads to Satisfaction and directly to the Consumer Loyalty (H6-H8), whereas the perceived risk undermines the trust and loyalty (Bauer, 1960; Bhattacharjee, 2001; Featherman & Pavlou, 2003).

The following hypotheses were formulated for the purpose of this study:

H_{1A}: **Consumer Trust (CT) is positively influenced by Technology Readiness (TR).**

H_{1B}: **Consumer Satisfaction (CS) is positively impacted by Technology Readiness (TR).**

H_{2A}: **Perceived Ease of Use (PEOU) positively impacts Consumer Trust (CT).**

H_{2B}: **Perceived Ease of Use (PEOU) positively influences Consumer Satisfaction (CS).**

H_{3A}: **Perceived Usefulness (PU) positively affects Consumer Trust (CT).**

H_{3B}: **Perceived Usefulness (PU) positively impacts Consumer Satisfaction (CS).**

H_{4A}: **Organisational Agility (OR) enhances the level of Consumer Trust (CT).**

H_{4B}: Organizational Agility (OR) positively impacts Consumer Satisfaction (CS).

H_{5A}: Consumer Trust (CT) is positively affected by Digital Literacy (DL).

H_{5B}: Digital Literacy (DL) positively influences Consumer Satisfaction (CS).

H_6: Consumer Trust (CT) positively influences Consumer Satisfaction (CS).

H_7: Consumer Trust (CT) positively influences Consumer Loyalty & Sustainability (CL).

H_8: Consumer Satisfaction (CS) positively influences Consumer Loyalty and Sustainability (CL).

H_9: Perceived Risk (PR) moderates the relationship between Consumer Trust (CT) and Consumer Loyalty and Sustainability (CL).

A conceptual model was devised for the purpose of this study and the hypotheses are indicated on the depiction in Figure 1

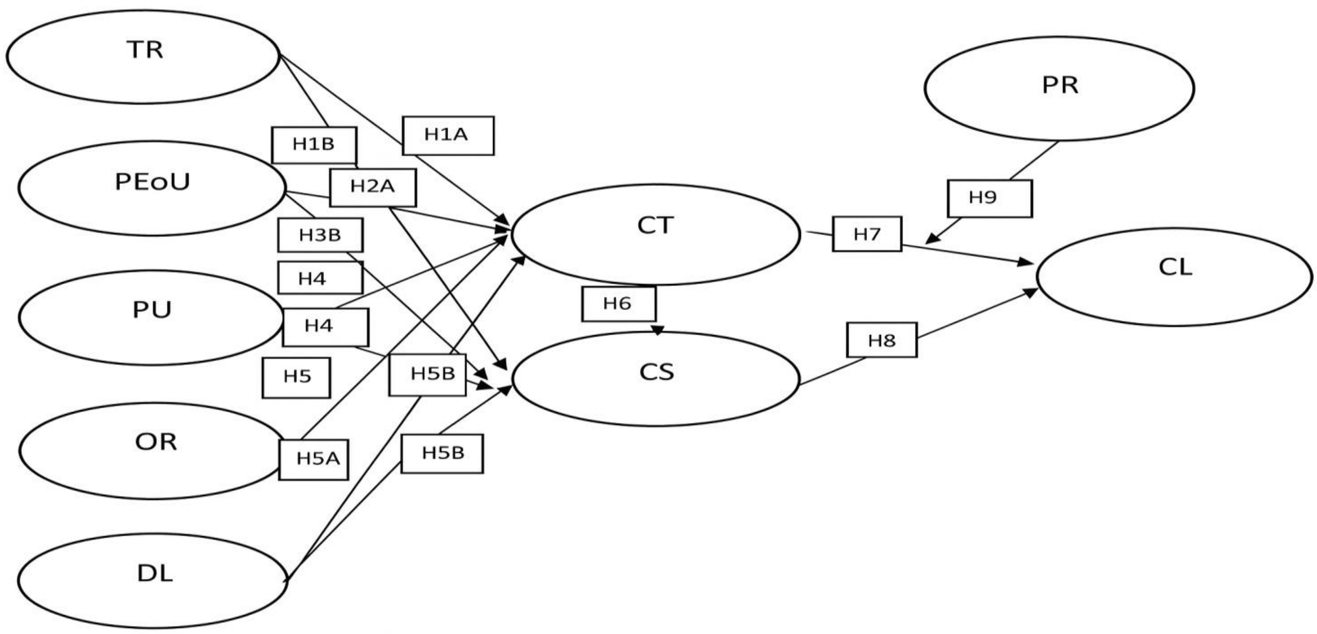

FIGURE 1: CONCEPTUAL MODEL

Figure 1 shows the conceptual framework of the study, with the relationships between the study variables, including Customer Trust (CT), Customer Satisfaction (CS), Trust (TR), Perceived Ease of Use (PEoU), Perceived Usefulness (PU), Operational Risk (OR), and Digital Literacy (DL) explained by the proposed hypotheses (H1–H6). In addition, Customer Trust (CT) and Customer Satisfaction (CS) are hypothesized to influence Customer Loyalty (CL) (H7–H8), and Perceived Risk (PR) is hypothesized to moderate the influence of Customer Trust on Customer Loyalty (H9).

3. METHODOLOGY

An exploratory sequential mixed-method design was adopted for the purpose of this study to examine FinTech adoption among semi-urban, vulnerable, and less-educated Indian populations, enabling a holistic understanding through methodological triangulation (Creswell & Creswell, 2018). The qualitative phase identified context-specific barriers—particularly trust, perceived risk, and digital literacy—and developed and merged salient constructs which has been developed in the earlier context and subsequently validated quantitatively to strengthen reliability and validity (Bryman, 2016; Venkatesh et al., 2013). This triple-corroboration approach integrated qualitative depth with quantitative precision, enhancing theoretical rigor, policy relevance, and inclusive digital banking research (Creswell & Clark, 2017; Rahman et al., 2023).

3.1 PHASE ONE: QUALITATIVE STUDY

Semi-structured interviews were conducted with representatives from two leading commercial nationalised banks and four leading private commercial banks with strong retail, corporate, and digital banking presence, selected for early FinTech adoption and strong semi-urban presence (Yin, 2017). After informed consent and anonymity assurance, purposive sampling achieved theoretical saturation with twelve respondents (Creswell & Poth, 2018; Yin, 2017). Participation was entirely voluntary, within informed consent obtained, anonymity strictly preserved through de-identification, and impartiality maintained by neutral, non-leading questioning and unbiased data handling. Data were analysed inductively using NVivo 11, generating hierarchical themes and a robust conceptual framework (Braun et al., 2012).

3.2 PHASE TWO: QUANTITATIVE STUDY

Phase two of the study involved a cross-sectional survey conducted on semi-urban consumers. The PLS-SEM was used to analyse the data in SmartPLS 4.1, after the thorough evaluation of the measurement and structural models (Hair et al., 2021). The final sample size of 547 was extracted from 558 responses selected through stratified-random sampling. Items were measured based on validated scale and administered in terms of five-point Likert scale. (Brislin, 1986; Hair et al., 2019). The content validity was ensured by expert review and satisfactory reliability was established in a pilot test (n = 30). The data were gathered in the period between April and June 2025 in various socio-economic groups in the semi-urban segment of adjacent Kolkata metropolitan area to increase representativeness and external validity.

4. ANALYSIS AND RESULT:

4.1 PHASE ONE: QUALITATIVE DATA ANALYSIS AND FINDINGS

This research involved carefully constructed semi-structured interviews with twelve prominent banking personnel, and the anonymity of the participants was ensured through the use of sequential identification numbers (Res1-12) and informants were selected based on their position, their professional experience and their subject matter expertise, pertaining to the thematic focus of this research (see Table 1).

TABLE 1: RESPONDENTS' PROFILE

Respondent No.	Bank	Semi-Urban Location	Current Position	Site	Work Experience
1	ICICI	Sodepur	Deputy Manager	Branch	11 years
2	ICICI	Belghoria	Branch Manager	Branch	15 years
3	HDFC	Uttarpara	Chief Manager – Operations	Branch	13 years
4	HDFC	Belghoria	Branch Manager	Branch	10 years
5	AXIS	Panihati	Branch Manager	Branch	14 years
6	AXIS	Khardaha	Deputy Manager	Branch	8 years
7	Bandhan	Belghoria	Branch Manager	Branch	10 years
8	Bandhan	Madhyamgram	Deputy Branch Manager	Branch	7 years
9	Union	Panihati	Sr. Operation Manager	Branch	15 years
10	Union	Khardaha	Branch Manager	Branch	9 years
11	SBI	Belghoria	Sr. Manager	Branch	18 years
12	SBI	Birati	Deputy Manager	Branch	10 years

Source: Researchers and Field Survey

The sample population included 12 professionals, who have worked in banks for a long time and are well spread across six banks, namely ICICI, HDFC, AXIS, Bandhan, Union, and SBI, so that there is an equal distribution of the institutions. The respondents, all of them semi-urban branch operations, volunteered and gave informed consent, bringing the ground-level information needed for this study. The sample is mostly managerial as 50% of the sample are the Branch Managers with senior and deputy-level officers to provide a strategic and an operational view. The respondents are highly knowledgeable with regard to institutions and are very mature in their professional life as they have an average of 12 years of experience and 75 percent of them have more than a decade of working experience. In general, the dataset includes representatives of experienced decision-makers in developing semi-urban banking environments, which are appropriate to examine managerial behaviour, operational dynamics, and adoption of digital banking.

The major themes and sub-themes, which arose during the qualitative investigation, are summarized in Table 2. The frequency of responses and density analysis reveal key factors that contribute to digital banking adoption and customer behaviour.

TABLE 2: OVERVIEW OF THE RESULTS FROM THE QUALITATIVE PHASE

		Responses													
Themes	Sub-Themes Extracted	Res 1	Res 2	Res 3	Res 4	Res 5	Res 6	Res 7	Res 8	Res 9	Res 10	Res 11	Res 12	Extracted Constructs	DensityAnalysis
Technological Drivers	AI capabilities,	√	√	√	√		√	√	√	√	√	√	√	Technology Readiness	0.91
	FinTech innovations,	√	√		√	√	√	√	√	√	√	√	√	Perceived Usefulness,	0.91
	Infrastructure readiness	√	√	√	√	√	√	√	√	√	√			Perceived Ease of Use	0.83
Dynamics of organisational adoption	Top Management Support		√		√	√	√							Top management support,	0.33
	Resource Availability	√	√	√	√		√		√		√	√	√	Organizational Agility	0.75
Consumer-centric Perspective	Trust	√	√	√	√	√	√	√	√	√	√	√	√	Trust	1.00
	Digital Literacy	√	√	√	√	√	√	√	√	√	√	√	√	Digital Literacy	1.00
	Risk Proposition	√	√	√	√	√	√	√	√	√	√	√	√	Perceived Risk	1.00
	Adoption within banks	√	√	√	√									Intention to use	0.33
Diffusion and Performance Outcomes	operational efficiency	√	√	√	√	√		√						Operational Efficiency	0.50
	customer satisfaction and loyalty	√	√	√	√	√	√	√	√	√	√	√	√	Customer Satisfaction and Loyalty	1.00
	Competitive advantage & market expansion	√	√	√	√									Competitive Priority	0.33

The qualitative analysis condensed into four integrative thematic domains Technology Drivers, Organisational Adoption Dynamics, Consumer-Centric Perspective and Diffusion and Performance Outcomes, and the density analysis (0.75 as a threshold) kept the following high-salience constructs: Technology Readiness (0.91), Perceived Usefulness and Ease of Use (0.83), Organisational Agility (0.75), Trust (1.00), Digital Literacy (1.00), Perceived Risk (1.00), and Customer Satisfaction (1.00). As confirmatory variables, lower-density variables were eliminated during the initial stage of the study.

4.2 PHASE TWO: QUANTITATIVE DATA ANALYSIS

The measurement model table below presents the evaluation of the reliability and validity of the study constructs, operationalised through organisational agility and customer-driven service orientation using established scales (Sambamurthy et al., 2003; Lu & Ramamurthy, 2011).

TABLE 3: MEASUREMENT MODEL

Antecedents & Consequents	Indicator Variables	VIF	Factor Loading	Alpha	CR (rho_a)	CR (rho_c)	AVE
Technology Agility [TR]	(adopted from **Parasuraman, 2000**)			0.776	0.778	0.857	0.600
	TR1- New technologies contribute to a better quality of life	1.769	0.794				
	TR2 - Technology gives me more freedom of mobility	1.450	0.718				
	TR3 – I like to experiment with new technology	1.941	0.843				
	TR4 - In general, I am the pioneer to try out new technology	1.498	0.738				
Perceived Ease of Use [PEoU]	(adapted from **Gefen et al., 2003**)			0.729	0.735	0.847	0.649
	PEOU1: Learning to use the bank's AI features is easy for me	1.461	0.802				
	PEOU2: Interacting with the AI assistant is clear and understandable	1.364	0.773				
	PEOU3: I find AI-based FinTech tools easy to navigate for my banking transactions.	1.522	0.841				
Perceived Usefulness [PU]	(adapted from **Venkatesh, & Davis, 2000**)			0.804	0.806	0.884	0.718
	PU1- Using AI-driven FinTech services improves the efficiency of my banking activities.	1.769	0.858				
	PU2- AI-driven services save me time in managing banking and financial tasks	1.609	0.820				
	PU3- AI features help me complete banking tasks more quickly	1.905	0.864				
CL [Customer Loyalty]	(adapted from **Mariani et al., 2021**)			0.774	0.776	0.869	0.689
	CL1- I intend to continue using AI-driven FinTech services from my bank in the future.	1.699	0.853				
	CL2 - I would recommend my bank's AI-powered financial services to others.	1.593	0.833				
	CL3 - I will remain loyal to my bank because of its AI-powered innovations.	1.519	0.804				
Digital Literacy [DL]	(adapted from **Ng, 2012**)			0.810	0.811	0.887	0.724
	DL1 - I have the necessary skills to use AI-powered digital banking applications	1.677	0.841				
	DL2 - I can evaluate the reliability of information provided by AI-driven financial tools.	1.766	0.853				
	DL3 - I can adapt to new AI-driven banking technologies without difficulty	1.918	0.859				
Customer Trust [CT]	(adapted from **Reddy et al., 2023**)			0.840	0.841	0.893	0.676
	CT1- I trust the bank's AI to act in my best interest.	2.193	0.841				
	CT2- I believe the AI provides reliable and accurate information	1.851	0.803				
	CT3- I feel comfortable relying on AI for routine banking tasks	2.005	0.810				
	CT4 - Overall, I trust my bank's AI-powered FinTech services	2.039	0.834				
Organizational Agility (OR)	(adapted from **Lu, Y., & Ramamurthy, 2011)**			0.851	0.851	0.900	0.693
	OR1 -AI-powered services make my banking interactions faster and more convenient compared to traditional methods.	1.918	0.874				
	OR2 -My bank quickly adapts its AI-enabled services to meet my changing financial needs.	1.527	0.768				
	OR3 -The bank responds promptly to customer feedback by upgrading AI-based digital features	1.818	0.819				
	OR4 -The bank's AI-driven services adjust to my individual preferences, making me feel valued as a customer.	2.696	0.864				
Customer Satisfaction [CS]	(adopted from **Lee, & Lee, 2020**)			0.730	0.732	0.848	0.650
	CS1- AI-powered financial tools in banking meet my expectations.	1.458	0.793				
	CS2- Compared to traditional banking, I am more satisfied with AI-powered services.	1.360	0.768				
	CS3- I am satisfied with the overall experience of using AI-driven FinTech services in banking.	1.688	0.856				

Antecedents & Consequents	Indicator Variables	VIF	Factor Loading	Alpha	CR (rho_a)	CR (rho_c)	AVE
Perceived Risk	(adopted from **Gai et al., 2018**)			0.716	0.728	0.840	0.638
	PR1 – AI-drive n banking applications may not work as expected.	1.430	0.814				
	PR2 – I fear system errors or technical failures when using AI-powered financial services.	1.519	0.841				
	PR3 – Using AI-driven FinTech services in banking could lead to financial loss	1.322	0.738				

Source: Researchers and smart PLS 4.1

Factor loadings exceeding 0.70 indicate strong indicator reliability (Hair et al., 2019). Internal consistency is confirmed through Cronbach's Alpha and Composite Reliability values ≥0.70 (Fornell & Larcker, 1981; Nunnally & Bernstein, 1994). Convergent validity is supported by AVE values ≥0.50 (Fornell & Larcker, 1981), while VIF scores <3.33 indicate acceptable multicollinearity (Hair et al., 2019). These results confirm statistically robust construct reliability and validity, justifying progression to structural model analysis (Tallon & Pinsonneault, 2011; Teece et al., 2016).

4.2.1 Discriminant Validity:

Discriminant validity was assessed using the Fornell–Larcker criterion to examine the distinctiveness of the study constructs. Table 4 depicts the Fornell-Larcker criteria.

TABLE 4: FORNELL AND LARCKER CRITERIA

	CL	CS	CT	DL	OR	PEoU	PR	PU	TR
CL	**0.830**								
CS	0.454	**0.806**							
CT	0.330	0.316	**0.822**						
DL	0.379	0.334	0.311	**0.851**					
OR	0.380	0.241	0.372	0.293	**0.832**				
PEoU	0.298	0.263	0.472	0.379	0.328	**0.805**			
PR	0.253	0.206	0.404	0.335	0.275	0.302	**0.799**		
PU	0.330	0.207	0.490	0.332	0.352	0.397	0.309	**0.847**	
TR	0.260	0.346	0.529	0.363	0.394	0.214	0.352	0.367	**0.775**

Table 4 indicates the discriminant validity using the Fornell–Larcker criterion, where the square root of AVE (diagonal values) exceeds inter-construct correlations, confirming construct distinctiveness (Fornell & Larcker, 1981). This demonstrates adequate conceptual separation and validates the robustness of the measurement and structural models (Henseler et al., 2015; Hair et al., 2019).

4.2.2 Common Method Bias [CMB]

Independent and dependent elements were both measured by seeking responses of the same respondents which can lead to the occurrence of common method bias (CMB). Thus, the one-factor test by Harman was applied to analyse the CMB (Fuller et al., 2016). The percentage of variance explained was 32.92 which is less than half. Since all the VIF values are less than 3.33 in this perspective, hence it can be stated that there is no significant CMB.

4.2.3 Structural Model Analysis

After testing the measurement model, the structural model was tested to determine the hypothesized relationships between the constructs. Analysis reveals the importance, direction and strength of the proposed paths, and identifies how well the model explains and predicts.

TABLE 5: PATH CO-EFFICIENT

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	p- values	f^2	VIF
H8: CS -> CL	0.364	0.363	0.040	9.179	0.000	0.21	3.104
H7: CT -> CL	0.219	0.220	0.039	5.693	0.000	0.07	2.739
H6: CT -> CS	0.166	0.165	0.049	3.427	0.001	0.12	2.624
H5B: DL -> CS	0.150	0.150	0.056	2.650	0.008	0.32	1.417
H5A: DL -> CT	0.640	0.639	0.049	13.024	0.000	0.48	1.705
H4B: OR -> CS	0.142	0.143	0.063	2.237	0.025	0.25	2.249
H4A: OR -> CT	0.241	0.241	0.049	4.865	0.000	0.19	2.866
H2B: PEoU -> CS	0.061	0.061	0.037	1.629	0.103	0.21	1.695
H2A: PEoU -> CT	0.083	0.083	0.031	2.655	0.008	0.11	2.650
PR -> CL	0.345	0.345	0.038	9.120	0.000	0.18	2.668
H3B: PU -> CS	0.129	0.129	0.045	2.861	0.004	0.12	2.942
H3A:PU -> CT	-0.034	-0.034	0.038	0.882	0.378	0.13	2.934
H1B:TR -> CS	0.291	0.292	0.051	5.658	0.000	0.05	2.760
H1A:TR -> CT	0.023	0.023	0.041	0.559	0.577	0.11	2.756

Table 5 reports on the significant and substantive relationships among key constructs. Digital Literacy strongly predicts Customer Trust, highlighting the central role of digital competence in AI-enabled digital banking. Customer Satisfaction significantly drives Loyalty, while Organisational Agility influences both Satisfaction and Trust. Perceived Usefulness shows a small–moderate effect on Satisfaction (Davis, 1989). Non-significant paths (e.g., PEoU→CS, PR→CL, TR→CT) suggest indirect or conditional effects (Henseler et al., 2009). The VIF values indicate no multicollinearity (Hair et al., 2019).

The endogenous constructs in the structural model have the coefficient of determination (R2) and adjusted R2 values shown in Table X. The statistics show how much variance in Customer Loyalty (CL), Customer Satisfaction (CS), and Customer Trust (CT) is explained by the model, based on the proposed predictors.

TABLE 6: R2 VALUE

	R-square	R-square adjusted
CL	0.826	0.825
CS	0.777	0.774
CT	0.849	0.848

The model (Figure 2) demonstrates strong explanatory power: consumer loyalty (CL), satisfaction (CS), and trust (CT), indicating substantial variance explained. Robustness is confirmed by high adjusted R^2 values (Henseler et al., 2009; Hair et al., 2019).

4.2.4 Mediation Analysis

The results of the mediation analysis are reported in Table 7, which answers the question of whether the effect of the independent variables on the dependent variable is mediated by the proposed mediator(s). The table allows readers to evaluate the importance and size of indirect effects, which helps them to identify and understand the nature of mediation in the model.

TABLE 7: MEDIATION ANALYSIS

direct impact	indirect impact	remarks
TR→CS: 0.295**	TR→CT→CS: 0.004(ns)	No Mediation
PEOU→CS: 0.014*	PEOU→CT→CS: 0.075*	Partial Mediation
PU→CS: 0.123**	PU→CT→CS: 0.006 (ns)	No Mediation
OR→CS: 0.182**	OR→CT→CS:0.040**	Partial Mediation
DL→CS:0.256**	OR→CT→CS: 0.107**	Partial Mediation
CT→CL: 0.280**	CT→CS→CL: 0.061**	Partial Mediation
PU→CL: 0.037(ns)	PU -> CT -> CS -> CL :0.002(ns)	No Serial Mediation
TR→CL: 0.112**	TR -> CT -> CS -> CL :0.001(ns)	No Serial Mediation
PEOU→CL: 0.045**	PEoU -> CT -> CS -> CL: 0.005*	Partial Serial Mediation
OR→CL: 0.119**	OR -> CT -> CS -> CL :0.015**	Partial Serial Mediation
DL→CL: 0.233**	DL -> CT -> CS -> CL: 0.039**	Partial Serial Mediation

The Mediation analysis using Baron and Kenny's (1986) approach shows that Technology Readiness (TR) and Perceived Usefulness (PU) exert direct effects on satisfaction (CS) and loyalty (CL) without mediation via consumer trust (CT). In contrast, Perceived Ease of Use (PEoU), Organisational Agility (OR), and Digital Literacy (DL) partially influence satisfaction through CT, confirming trust as a key mediating mechanism. CT further drives loyalty, establishing trust and satisfaction as central pathways converting organisational and individual factors into sustained loyalty in AI-based FinTech ecosystems (Baron & Kenny, 1986; Henseler et al., 2009; Hair et al., 2019).

4.2.5 Moderation Analysis

Table 8 below shows the findings on moderation analysis which tested whether there was any difference in the strength or direction of the relationship between the study constructs at different levels of the moderating variable. The significance and impact of the interaction effects can be judged from the table and hence to conclude whether there is a moderation in the proposed model.

TABLE 8: MODERATION ANALYSIS

INTERACTION EFFECT	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	*p*-value	Remarks
H_9: PR x CT → CL	-0.090	-0.089	0.027	3.264	0.001	SUPPORTED

Source: Researchers and smart PLS 4.1

The Moderation analysis shows a significant negative interaction between perceived risk (PR) and consumer trust (CT) on loyalty (CL), indicating that higher risk weakens trust-driven loyalty. This effect is statistically robust and consistent with prior evidence on risk-constrained digital adoption (Featherman & Pavlou, 2003; Kim et al., 2008; Hair et al., 2019).

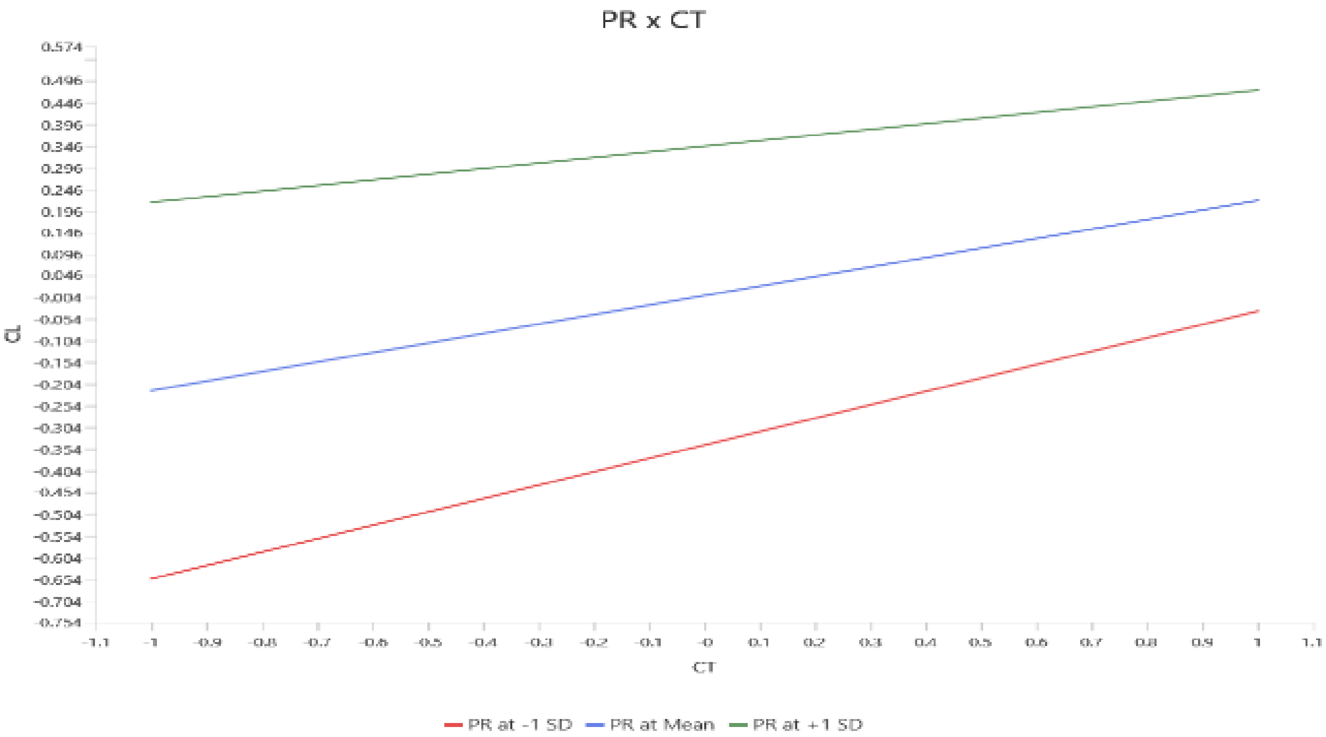

FIGURE 2: SIMPLE SLOPE MODERATION EFFECT DIAGRAM

4.2.6 Statistically Proven Model

Figure 2 shows the result of the structural model analysis that includes the measurement and structural components of the proposed research framework. The standardized path coefficients, factor loadings, significance of hypothesized relationships, and R^2 values are shown to help readers assess the strength and significance of the hypothesized relationships among constructs. Moreover, it allows insights to be gained on the explanatory power of the model and the influence of the independent variables on Customer Trust (CT), Customer Satisfaction (CS) and Customer Loyalty (CL), as well as the moderating effect of Perceived Risk (PR).

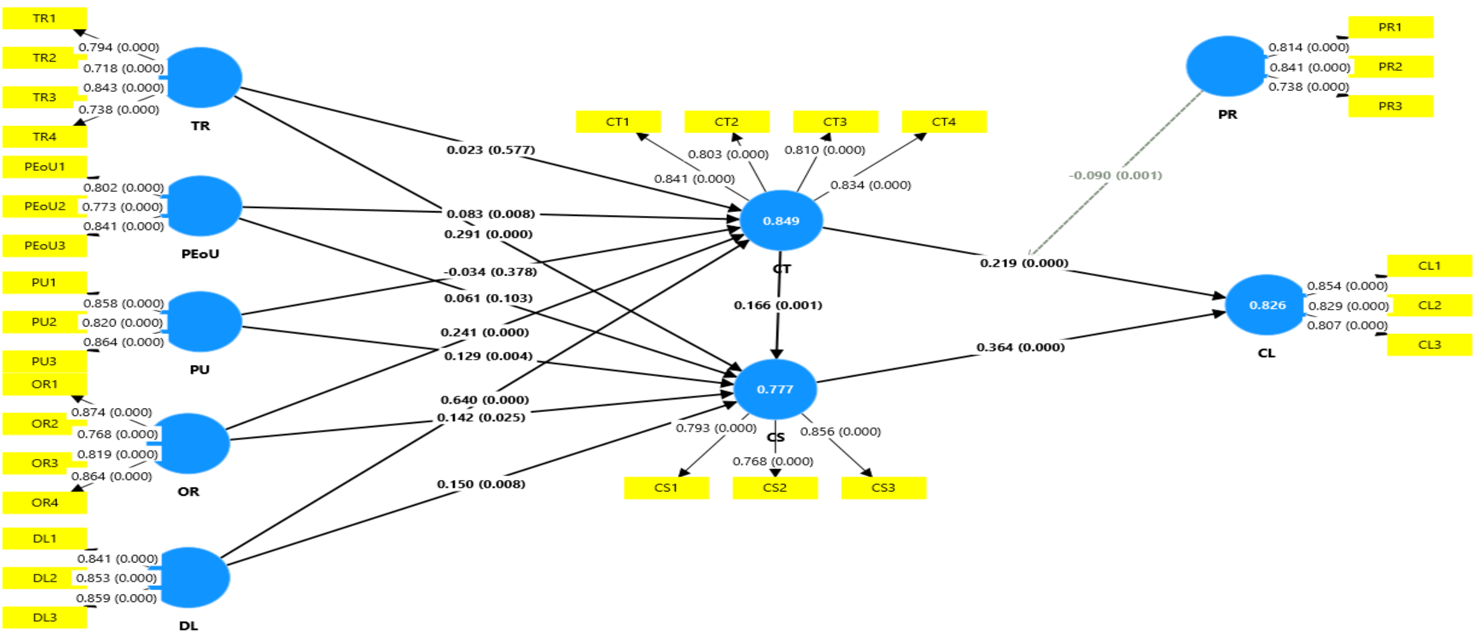

FIGURE 3: STATISTICALLY PROVEN MODEL

5. DISCUSSION:

The results of the study show a consistent but unique trend in the use of AI in digital banking. The outcomes of moderation indicate that the perceived risk is a key factor undermining the relationship between trust and loyalty, which confirms the risk-constrained character of the digital interaction (Featherman & Pavlou, 2003; Kim et al., 2008; Hair et al., 2019). The structural model shows that the readiness to technology increases satisfaction but not trust (Parasuraman, 2000; Lin et al., 2007), perceived ease of use promotes trust (Gefen et al., 2003) and perceived usefulness leads to satisfaction (Venkatesh & Davis, 2000), whereas organisational agility and digital literacy are strong predictors of trust and satisfaction (Zhu et al., 2006; Teo et al., 2009). The findings of mediation indicate selective and serial effects in which perceived ease of use mediates its effect on loyalty by organisational agility and digital literacy, but technology readiness and usefulness do not mediate, defying the classical TAM hypothesis (Davis, 1989; Venkatesh & Davis, 2000). In general, the research is an addition to TRI-TAM literature that reveals that consumer loyalty in the context of AI-driven FinTech banking is more dependent on organisational credibility, digital competence, and effective risk prevention than perceived usefulness or personal readiness (Zhou, 2013; Rahi et al., 2021).

The main novelty of this study is the disclosure of the consumer loyalty to AI-powered digital banking being more organisation- and capability-based than the perception of traditional technologies. To begin with, it indicates that technology readiness does not substantially foster the creation of trust, which refutes classical assumptions about the formation of the TRI-TAM model but suggests that the development of trust is more influenced by organisational credibility and security assurance than individual readiness (Parasuraman, 2000; Lin et al., 2007). Secondly, this research revealed a selective and serial mediatory route, in which perceived ease of use indirectly affects loyalty via organisational agility and digital literacy, which underlines a capability-based mechanism that remained undetected in previous TAM studies (Davis, 1989; Teo et al., 2009; Al-Omoush et al., 2021). Thirdly, perceived risk surfaced in this research as a significant unfavourable moderator that undermines the relationship of trust and loyalty, and it is proved that even trust is not enough to maintain a relationship of loyalty unless such risks are mitigated in AI-based FinTech settings (Featherman & Pavlou, 2003; Kim et al., 2008; Zhou, 2013). This study aimed to combine TRI, TAM, dynamic capability, and risk perspectives and suggests a capability-risk-trust framework, which contributes to the existing usefulness-ease of use models (Rahi et al., 2021).

6. CONCLUSION

This paper combined technology acceptance, technology readiness, and trust-risk perspectives to elucidate consumer adoption of AI-based digital banking and shows that trust and satisfaction (rather than perceived usefulness and ease of use) are the fundamental psychological processes whereby digital literacy, organisational agility, and technological competencies are converted into long-term loyalty and perceived risk undermines the relationship. This study, based on relationship marketing, institutional theory, and risk-trust theories, goes past the adoption models based on TAM, TRI, and trust-risk logics by integrating each of these theories into a cohesive analytical framework. The results build on the technology acceptance and trust theory by independently defining psychological confidence as the basis of sustainable digital loyalty, proving that technological efficiency in itself is not enough. Rather, long-term loyalty will be a result of the combination of digital proficiency, organisational readiness, understandable and explicable AI systems, reputation-building structures, and proactive risk management. In practise, the findings can provide a strategic direction to banks and FinTech companies that want to strike a balance between innovation and consumer protection and regulatory conformity in AI-based financial systems.

Further studies are needed to explore the framework in a variety of cultural and regulatory settings, using longitudinal designs to measure the dynamics of trust, and add supply-side factors when experimenting with new constructs, including algorithmic transparency, ethical AI, and data privacy as foundations of sustainable digital trust and loyalty.

7. RECOMMENDATIONS

Based on the different findings it is recommended that digital literacy should be a priority of banks and FinTech companies as the main infrastructure of trust-building by providing specific education, in-app instructions, and AI transparency products because it is a direct predictor of trust and satisfaction. At the same time, organisational agility should be increased to higher levels than technology implementation through creating responsive service design, adaptive IT systems, and agile governance structures by institutionalisation of trust. The AI trust-building strategies need to shift to security assurances, explainable AI, institutional credibility, and ethical governance as opposed to usability and functional effectiveness. Lastly, digital banking plans need to incorporate sound risk governance with visible risk-reduction measures, which would promote the continuation of trust founded on the perceived safety, transparency, and information security, and not just convenience.

CONFLICT OF INTEREST:

The authors declare that they have no known financial or non-financial conflicts of interest that could have influenced the research, authorship, or publication of this article. The authors declare that they have no conflicts of interest concerning the research, authorship, or publication of this article.

INFORMED CONSENT:

All participants provided informed consent prior to their inclusion in the study. The procedures adhered to the ethical standards of the institutional research committee and complied with the 1964 Helsinki Declaration and its subsequent amendments.

The research involving all human participants was carried out in accordance with the established ethical standards. The non-intervention of the researcher, the neutrality of the participant selection criteria, and the use of standardised data collection tools ensured impartiality. The protection of anonymity was ensured with the highest level of strictness; all personally identifiable information was removed, coded identifiers were used, and findings were reported in aggregate. All participants received informed consent before data collection was done through a clear consent process [in qualitative research] that clarified purpose of the study, voluntary participation and the freedom to withdraw at any point without consequence. Anonymity protection, secure data storage protocols, and the sole use of their data in academic research were specifically explained to the participants, which guaranteed transparency, autonomy, and integrity of ethics in the research process.

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