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The Role of Artificial Intelligence on Behavioural Intention to Adopt Fintech: Examining Mediating and Moderating Effects

Kesha Joshi[1] | Dr. Sourabh Jain[2*] | Sonalee Telang[3]

[1]BBA-6th Semester, ITM SLS Baroda University, Vadodara, Gujarat.
[2]Assistant Professor, School of Business, ITM SLS Baroda University, Vadodara, Gujarat.
[3]Research Scholar, School of Business, ITM SLS Baroda University, Vadodara, Gujarat.

[*]Corresponding Author: sourabhjain2010@gmail.com

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ABSTRACT

The rapid growth of Artificial Intelligence (AI) has reshaped the FinTech industries by enhancing personalization, automation, and decision-making efficiency. This study investigates how Artificial Intelligence influences the intention of the users' behavioural to adopt FinTech services, while exploring mediating roles of Perceived Value (i.e. Perceived Risk and Perceived Usefulness) and the moderating effects of Perceived Assurance (i.e. Trust and Service Quality). The research aims to bridge theoretical and practical gaps by integrating technological, ethical, and behavioural dimensions into a unified framework. Data were collected from 123 respondents in Vadodara, Gujarat, encompassing retail and IT professionals who actively engage with FinTech applications. The convenient sampling technique used for the collection of data. Structural Equation Modelling (SEM) and ANOVA were used for the testing of hypothesis. This research provides valuable insights for financial institutions, policymakers, and AI developers to design responsible, user-centric, and trustworthy FinTech ecosystems that balance innovation with data privacy and regulatory compliance.

***Keywords**: Artificial Intelligence (AI), FinTech Adoption, Behavioural Intention, Perceived Value, Perceived Risk.*

Introduction

This study explores how Artificial Intelligence (AI) influences consumer behavioural intention to adopt FinTech, focusing on direct, mediating, and moderating relationships between key constructs. The purpose is to understand how AI impacts consumer decisions to engage with financial technologies such as digital wallets, mobile banking, and robo-advisory systems, while accounting for the psychological and contextual factors that drive these choices. AI, defined as computational systems performing tasks requiring human intelligence, incorporates advanced technologies such as machine learning and natural language processing. FinTech refers to technology-driven financial services that combine innovation and accessibility, while behavioural intention represents an individual's motivation and likelihood to use these technologies. The study identifies a critical gap in existing research – the absence of integrated frameworks that align AI's technical benefits with ethical, cultural, and regulatory dimensions. Despite AI's capacity to enhance efficiency and personalization, concerns about trust, data privacy, and fairness persist. This research addresses these gaps by proposing a holistic empirical model that integrates ethical governance, regulatory awareness, and user perception into the AI – FinTech adoption framework.

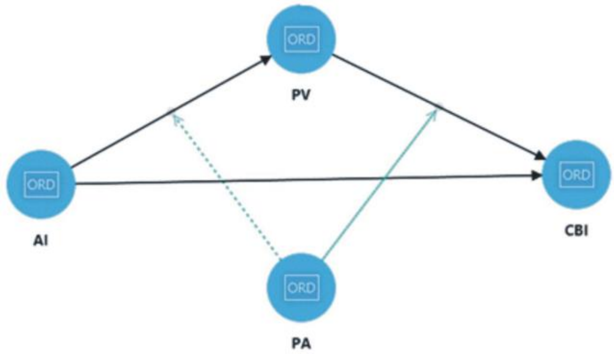

Fig. 1: Suggested Model. ***Source*****: Based on author's computation**

This study is intentionally situated in Vadodar Gujarat, a rapidly developing Tier-II Indian city with growing FinTech penetration, rising digital literacy, and active use of AI-enabled financial applications. Unlike metropolitan cities, Tier-II cities represent an emerging adoption context where trust, perceived value, and assurance mechanisms play a more critical role in shaping behavioural intention. By focusing on this setting, the study provides context-sensitive insights into AI-driven FinTech adoption in emerging urban markets, which remain underexplored in existing literature largely dominated by metro-centric or cross-country analyses.

Objective

- To explore the direct association between the adoption of Artificial Intelligence (AI) and users' behavioral intentions.
- To assess the mediating influence of perceived value—encompassing perceived usefulness and perceived risk—on the linkage between AI adoption and behavioral intention.
- To examine the moderating role of perceived assurance—comprising perceived service quality and trust—within the relationship between AI adoption and behavioral intention.
- To investigate the impact of demographic factors, including income, educational level, and digital literacy, on the association between AI adoption and behavioral intention.
- To propose actionable strategies aimed at strengthening user trust and acceptance of AI technologies through effective communication of value and assurance in service delivery.

Literature Review

The research conducted an extensive review of the literature and collected insights on various dimensions of Artificial Intelligence.

Author	Year	Title of Research	Dimensions
Tan, J.	2025	Role of AI in FinTech and Consumer Trust	Consumer trust, regulation, transparency
Pazouki, S., Jamshidi, M., Jalali, M., & Tafreshi, A.	2025	Transformative Impact of AI and Digital Technologies on FinTech	AI adoption, productivity, personalization, ethical issues
Yaseen, H., & AL-Amarneh, A.	2025	AI-driven Fraud Detection in Banking	Transparency, fairness, explainable AI
Appiah, T., &Agblewornu, V.V.	2025	Perceived Benefit, Risk, and Trust in FinTech Adoption	Trust as mediator, UTAUT model
Basariya, S.R., & Mishra, P.K.	2025	Role of Personalization in Digital Retail	AI personalization, data privacy
Patil, D.	2024	AI in Retail and E-commerce	Predictive analytics, personalization, customer engagement
Yadav, A.K.	2024	Data Protection and Artificial Intelligence	Privacy, consent, algorithmic transparency
Banerjee, S., Whig, P., & Parisa, S.K.	2024	AI for Personalization and Cybersecurity in Retail	Data privacy, GDPR, explainable AI

Joshi, N.K.	2024	AI in Enhancing Customer Service in Retail	Chatbots, automation, customer engagement
Daiya, H.	2024	AI-driven Risk Management in FinTech	Fraud Detection, credit risk, efficiency
Blumenstock, J.E., & Kohli, N.	2023	Big Data Privacy in Emerging Market FinTech	Data Protection, privacy policies
Chawla, U.	2023	Perceived Trust in Post-COVID FinTech Adoption	Trust as mediator, risk perception
Igwesi, C.	2023	Authentication and Fraud Detection in FinTech	Cybersecurity, biometrics, blockchain
Zhang, W.	2023	Data Security and Customer Trust in FinTech Services	Perceived usefulness, data security, ease of use
Khan, W.A., & Abideen, Z.U.	2023	Behavioural Intention and Digital Wallet Use	Trust, perceived risk, service quality
Tsai, S. –C.	2022	Transaction Security and Mobile Payments	Security, ease of use, perceived usefulness
Ramadugu, R., &Doddipatla, L.	2022	AI-based Security Systems in FinTech	Security, engagement, personalization
Ojika, F.U.	2021	AI-driven Digital Transformation in Retail	NLP, machine learning, automation
Olutimehin, D.O.	2021	Framework for Digital Transformation in Banking	AI, IoT, big data, blockchain
Nashold, D.B. Jr	2020	Trust in AI-driven Virtual Finance Assistants	Technology Acceptance, trust dimensions

Theoretical Background

Model	Core Concept & Application to AI/ FinTech	Key Hypothesis Included
Technology Acceptance Model (TAM)	States that a user's intention to adopt a technology is driven by Perceived Usefulness (PU) (enhancement of performance) and Perceived Ease of Use (PEOU) (being free of effort).	H1:The adoption of artificial intelligence (AI) has a significant and positive impact on consumers' behavioral intentions within the FinTech sector
Extended TAM (TAM2 or TAM3)	Extensions of TAM incorporating factors like subjective norms, job relevance, and computer self-efficiency. AI's contribution via personalization and automation enhances PU, thereby influencing adoption intention.	H_{2a}:Perceived usefulness serves as a mediating variable in the relationship between artificial intelligence and consumers' behavioral intentions
Perceived Risk Theory	Focuses on a consumer's subjective fear of potential negative consequences, such as financial loss, privacy risk, and security risk. AI has a dual role: it can reduce risk (e.g., fraud detection) or increase perceived risk (e.g., data misuse concerns).	H_{2b}:Perceived risk functions as a mediator in the relationship between artificial intelligence and consumers' behavioral intentions
Trust-Based Technology Acceptance Model	The moderating role of perceived trust is grounded in the Trust-Based Technology Acceptance Model**,** which posits that trust reduces uncertainty and amplifies technology acceptance under conditions of perceived risk.	H_{3a}:The association between artificial intelligence and consumers' behavioral intentions is moderated by perceived trust.
SERVQUAL Model	Perceived service quality is anchored in the SERVQUAL framework**,** suggesting that consistent and reliable service delivery shapes users' evaluative judgments of technology usefulness. Accordingly, trust and service quality are theoretically positioned as moderators rather than direct antecedents.	H_{3b}:The relationship between artificial intelligence and consumers' behavioral intentions is moderated by perceived service quality

Note: Analysis of the PaySmart case study indicates that all hypotheses are supported.

Construct Definitions

Construct	Definition	Source
Artificial Intelligence	User perception of AI-driven personalization, automation, security, and compliance in FinTech platforms	Pazouki, S., Jamshidi, M., Jalali, M., & Tafreshi, A. (2025)
Perceived Usefulness	Degree to which AI improves efficiency and decision quality	Zhang, W. (2023)
Perceived Risk	User perception of financial, privacy and security risk	Khan, W.A., & Abideen, Z.U. (2023)
Perceived Trust	Confidence in AI systems' reliability and fairness	Nashold, D.B. Jr
Service Quality	Reliability, responsiveness, and assurance of AI-enabled services	SERVQUAL

Research Gap

The literature highlights Artificial Intelligence (AI) as both an enabler and a challenge in FinTech adoption. AI enhances automation, decision-making, and personalization, improving efficiency and financial inclusion through predictive analytics and fraud detection. However, ethical and regulatory issues, guided by frameworks like the GDPR (2023) and Corporate Digital Responsibility (CDR), stress the importance of transparency, fairness, and accountability.

Trust and security remain key drivers of behavioral intention, supported by technologies such as blockchain, biometrics, and big data. Additionally, user characteristics—especially income, education, and digital literacy—significantly influence adoption. Overall, AI's dual role demands a balanced approach that combines innovation with responsible and human-centered practices to sustain trust and inclusion in FinTech.

Hypotheses

H1: The adoption of artificial intelligence (AI) has a significant and positive impact on consumers' behavioral intentions within the FinTech sector.

H2a: Perceived usefulness serves as a mediating variable in the relationship between artificial intelligence and consumers' behavioral intentions.

H2b: Perceived risk functions as a mediator in the relationship between artificial intelligence and consumers' behavioral intentions.

H3a: The association between artificial intelligence and consumers' behavioral intentions is moderated by perceived trust.

H3b: The relationship between artificial intelligence and consumers' behavioral intentions is moderated by perceived service quality.

H4: Users' income levels significantly influence the relationship between AI adoption and behavioral intention.

H5: Users' educational attainment significantly moderates the relationship between AI adoption and behavioral intention.

H6: Users' level of digital literacy significantly affects the relationship between AI adoption and behavioral intention.

Conceptual Model

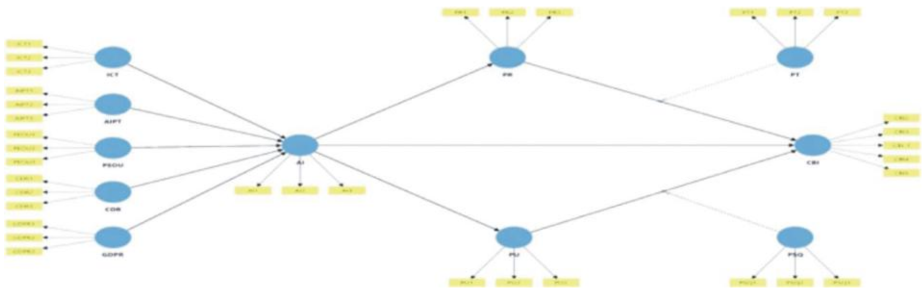

Fig. 2: Conceptual framework. *Source*: author's proposed model

Research Methodology

Area of Study	Respondents are taken from Vadodara, Gujarat, retail and IT professionals, FinTech users.
Research Design	Causal Research Design is preferred
Sample Size	123 (384 is the standard sample size according to Cochran at 95% Confidence Level).The nature of the study and the inclusion of mediation and moderation effects, PLS-SEM using SmartPLS was employed. This technique is well suited for prediction-oriented research with small to medium samples and complex models, and prior studies support its robustness with sample sizes of 100–150. Accordingly, the sample size of 123 respondents is methodologically adequate for this analysis.
Sampling Technique	This research adopts a contextualized sampling approach focusing on retail and IT professionals in Vadodara**,** who actively use FinTech applications. Convenience sampling is frequently employed to capture early adopters and digitally informed users, who play a pivotal role in shaping technology diffusion. Rather than aiming for universal statistical generalization, the study emphasizes analytical generalization, allowing the findings to inform theory and practice in India.
Data collection	Primary data are collected through a structured questionnaire. Researcher have used the Likert Scale to conduct the survey. Secondary data are collected through various sources such as journals, web references and articles.
Tools used for analysis	Structural Equation Modelling (SEM) & ANOVA Analysis

Further, In this study Artificial Intelligence (AI) is conceptualized as a second-order formative construct comprising key functional dimensions such as personalization, automation, decision support, data security, and regulatory alignment, capturing the functional diversity of AI in FinTech.

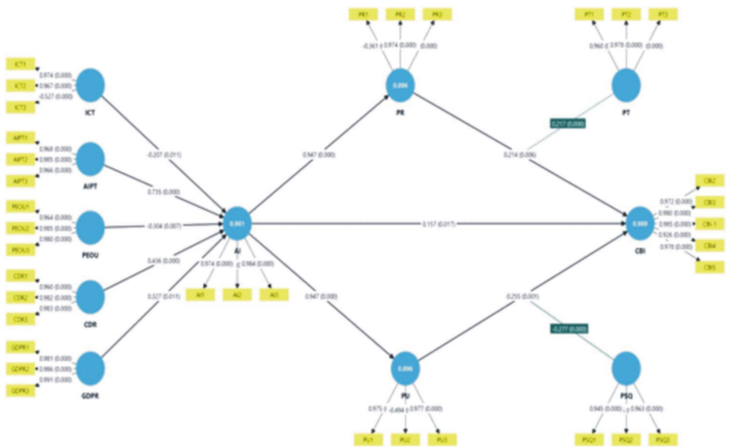

Fig.3: Measurement Model. ***Source:*** **Based on author's computation**

The measurement model was evaluated using indicator reliability, internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity (AVE), and discriminant validity (Fornell–Larcker criterion). Moderation effects were tested using interaction terms in PLS-SEM with bootstrapping (5,000 resamples), consistent with prior FinTech adoption studies.

Data Analysis

Table 1: Descriptive Analysis

Items	Mean	SD
Information and Communication Technology	4.48	0.87
AI Personalization Tools	4.54	0.79
Perceived Ease of Use	4.47	0.81

General Data Protection Regulation	4.52	0.78
Corporate Digital Responsibility	4.52	0.87
Artificial Intelligence	4.57	0.81
Perceived Usefulness	4.49	0.86
Perceived Risk	4.61	0.71
Perceived Trust	4.55	0.80
Perceived Service Quality	4.53	0.78
Customer Behavioural Intention	4.47	0.86

Note: Represents descriptive statistics for various constructs

Table 2: Construct Reliability and Validity

Items	No. of items	Outer loadings	Cronbach Alpha	CR	AVE
ICT	03	[ICT1] – 0.974 [ICT2] – 0.967 [ICT3] - (-0.527)	0.981	0.981	0.963
AIPT	03	[AIPT1] – 0.968 [AIPT2] – 0.985 [AIPT3] – 0.966	0.972	0.973	0.947
PEOU	03	[PEOU1] – 0.640 [PEOU2] – 0.985 [PEOU3] – 0.980	0.976	0.977	0.953
CDR	03	[CDR1] – 0.960 [CDR2] – 0.982 [CDR3] – 0.983	0.974	0.975	0.951
GDPR	03	[GDPR1] – 0.981 [GDPR2] – 0.986 [GDPR3] – 0.991	0.986	0.986	0.972
AI	03	[AI1] – 0.974 [AI2] – 0.980 [AI3] – 0.984	0.979	0.979	0.959
PU	03	[PU1] – 0.975 [PU2] –(-0.494) [PU3] – 0.977	0.985	0.985	0.971
PR	03	[PR1] –(-0.361) [PR2] – 0.974 [PR3] – 0.973	0.949	0.951	0.908
PT	03	[PT1] – 0.960 [PT2] – 0.978 [PT3] – 0.943	0.958	0.959	0.922
PSQ	03	[PSQ1] – 0.945 [PSQ2] –(-0.455) [PSQ3] – 0.963	0.964	0.964	0.933
CBI	05	[CBI1] – 0.985 [CBI2] – 0.972 [CBI3] – 0.980 [CBI4] – 0.926 [CBI5] – 0.978	0.983	0.984	0.938

Note: Cronbach's Alpha measured is above 0.90 for all the variables.

Table 1 The mean and standard deviation values show that all variables have high mean scores, ranging from **4.47 to 4.61**, indicating that respondents generally agreed with the statements related to each construct.

Among the variables, **Perceived Risk** recorded the highest mean (M = 4.61, SD = 0.71), suggesting that participants have strong awareness or concern about potential risks related to AI in the FinTech sector. **Artificial Intelligence (M = 4.57, SD = 0.81)** and **Perceived Trust (M = 4.55, SD = 0.80)** also show high mean values, reflecting positive attitudes toward AI and trust in its application.Other factors such as **AI Personalization Tools (M = 4.54)**, **Perceived Service Quality (M = 4.53)**, and

General Data Protection Regulation (M = 4.52) also have high mean values, indicating that these dimensions are viewed favorably by respondents.The **standard deviation (SD)** values range from **0.71 to 0.87**, showing moderate variability in responses, which means participants' opinions were mostly consistent.

Table 2 presents the reliability and validity outcomes for all constructs used in the study. All constructs show **high outer loadings** for most items, confirming strong indicator reliability. However, a few items (e.g., *ICT3, PU2, PR1, PSQ2*) have **negative or low loadings**, suggesting they may not contribute effectively to their respective constructs and could be considered for removal in future analyses. The **Cronbach's Alpha (α)** values range from **0.949 to 0.986**, indicating excellent internal consistency across all variables. Similarly, the **Composite Reliability (CR)** values, ranging between **0.951 and 0.986**, further confirm that the measurement model has strong construct reliability. The **Average Variance Extracted (AVE)** values are all above the recommended threshold of **0.50**, with values between **0.908 and 0.972**. This shows that each construct captures a large portion of variance from its indicators, confirming **convergent validity**.

Table 3. Discriminant Validity

	AI	AIPT	CBI	CDR	GDPR	ICT	PEOU	PR	PSQ	PT	PU
AI											
AIPT	**0.704**										
CBI	0.785	**0.814**									
CDR	0.776	0.677	**0.640**								
GDPR	0.732	0.729	0.776	**0.670**							
ICT	0.750	0.666	0.618	0.622	**0.621**						
PEOU	0.756	0.673	0.671	0.695	0.629	**0.809**					
PR	0.752	0.817	0.740	0.711	0.777	0.729	**0.724**				
PSQ	0.663	0.776	0.784	0.777	0.784	0.706	0.710	**0.754**			
PT	0.780	0.686	0.567	0.729	0.609	0.650	0.623	0.783	**0.686**		
PU	0.723	0.723	0.548	0.768	0.644	0.686	0.651	0.801	0.746	**0.789**	

Source: Based on author's computation

Table 4: Coefficient of Determination R^2Result

	R-square	Adjusted R^2
AI	0.981	0.981
PR	0.896	0.896
PU	0.896	0.895

Source: Based on author's computation

Table 5: Path coefficient

	Original sample	T values	P values
AI -> CBI	0.157	2.396	0.017
AI -> PR	0.947	52.251	0.000
AI -> PU	0.947	114.737	0.000
AIPT -> AI	0.735	3.652	0.000
CDR -> AI	0.436	4.022	0.000
GDPR -> AI	0.327	2.538	0.011
ICT -> AI	-0.207	2.546	0.011
PEOU -> AI	-0.304	2.715	0.007
PR -> CBI	0.214	2.759	0.006
PSQ -> CBI	-0.060	0.941	0.347
PSQ x PU -> CBI	-0.277	6.076	0.000
PT -> CBI	0.400	4.004	0.000
PT x PR -> CBI	0.217	5.119	0.000
PU -> CBI	0.255	3.332	0.001

Source: Based on author's computation

Table 6: Direct Effect

H_1: The adoption of artificial intelligence (AI) has a significant and positive impact on consumers' behavioral intentions within the FinTech sector.

	Original Sample	T Statistics	P values	Hypothesis	Interpretation
AI -> CBI	0.601	7.379	0.000	H_1 (Supported)	Strong & Positive

Source: Based on author's computation

Table 7: Mediation Analysis

$H2_a$: Perceived usefulness serves as a mediating variable in the relationship between artificial intelligence and consumers' behavioral intentions.

$H2_b$: Perceived risk functions as a mediator in the relationship between artificial intelligence and consumers' behavioral intentions.

	Original sample	T statistics	P values	Hypothesis & Result	Interpretation
AI -> PU -> CBI	0.241	3.349	0.001	H_{2a} (Supported)	Strong Positive Mediation
AI -> PR -> CBI	0.203	2.743	0.006	H_{2b} (Supported)	Moderate Mediation

Source: Based on author's computation

Table 8: Moderation Analysis

H3a: The association between artificial intelligence and consumers' behavioral intentions is moderated by perceived trust.

H3b: The relationship between artificial intelligence and consumers' behavioral intentions is moderated by perceived service quality.

	Original Sample	T Statistics	P Values	Director	Hypothesis & Result	Interpretation
PT x PR -> CBI	0.217	5.119	0.000	Positive	H3a (Supported)	Strong and Favourable Moderation
PSQ x PU -> CBI	-0.277	6.076	0.000	Negative	H3b (Supported)	Strong but Unfavourable Moderation

Source: Based on author's computation

Table 3 establishes discriminant validity The discriminant validity test was conducted using the Fornell–Larcker criterion. The findings show that the square root of the AVE for each construct is higher than its correlations with other constructs. This confirms that all variables in the study are distinct from each other. For instance, the values for AI, PU, PR, PSQ, PT, and other constructs are greater on the diagonal than the related correlation values. Hence, the results indicate that the model has acceptable discriminant validity, and each construct measures a separate concept.

Table 4 The R^2 values show how well the independent variables explain the variation in the dependent variables. As presented in the table, AI has an R^2 value of 0.981, indicating that 98.1% of its variance is explained by the model. Similarly, PR and PU have R^2 values of 0.896 and 0.896 respectively, showing that 89.6% of their variance is also explained by the predictors.

Since all R^2 and adjusted R^2 values are very high, the model demonstrates strong explanatory power, meaning the independent variables effectively predict the dependent variables.

Table 5 The results show that Artificial Intelligence (AI) has a positive and significant impact on Consumer Behavioral Intention (CBI) ($\beta = 0.157$, $p = 0.017$). AI also shows a very strong and significant influence on both Perceived Risk (PR) and Perceived Usefulness (PU) ($\beta = 0.947$, $p < 0.001$).Among the factors affecting AI, AIPT ($\beta = 0.735$, $p < 0.001$), CDR ($\beta = 0.436$, $p < 0.001$), and GDPR ($\beta = 0.327$, $p = 0.011$) have significant positive effects, while ICT ($\beta = -0.207$, $p = 0.011$) and PEOU ($\beta = -0.304$, $p = 0.007$) have significant negative effects. This means some factors promote AI adoption, while others reduce it.For CBI, PR ($\beta = 0.214$, $p = 0.006$), PU ($\beta = 0.255$, $p = 0.001$), and PT ($\beta = 0.400$, $p < 0.001$) have significant positive effects, while PSQ ($\beta = -0.060$, $p = 0.347$) has no significant effect.

In terms of moderation, PSQ × PU (β = -0.277, p < 0.001) shows a significant negative effect, meaning high service quality weakens the effect of usefulness on behavioral intention. PT × PR (β = 0.217, p < 0.001) shows a significant positive effect, indicating that higher trust reduces the negative influence of risk on behavioral intention.

Table 6 provides a specific summary of the Artificial Intelligence (AI) has a strong and positive direct influence on Consumer Behavioral Intention (CBI) (β = 0.601, t = 7.379, p < 0.001). This indicates that consumers' intention to use or engage with AI-based services increases significantly as their perception of AI improves. In essence, a higher level of acceptance and understanding of AI directly contributes to stronger behavioral intentions among consumers.

Table 7 confirms the mediation analysis indicated that both Perceived Usefulness (PU) and Perceived Risk (PR) play significant roles in linking Artificial Intelligence (AI) with Consumer Behavioral Intention (CBI). The indirect path through PU (β = 0.241, p = 0.001) demonstrates a strong and positive mediating effect, showing that when consumers find AI useful, their intention to adopt or engage with it increases. In contrast, the mediation through PR (β = 0.203, p = 0.006) is also statistically significant but comparatively moderate, implying that AI impacts behavioral intention by shaping how consumers perceive and evaluate potential risks.

Table 8 The moderation analysis examined the interaction effects of Perceived Service Quality (PSQ) and Perceived Trust (PT) on the relationships between Perceived Usefulness (PU), Perceived Risk (PR), and Consumer Behavioral Intention (CBI).

The interaction between PT and PR demonstrated a significant positive moderation effect on CBI (β = 0.217, t = 5.119, p < 0.001). This implies that perceived trust enhances the relationship between perceived risk and consumer behavioral intention. Specifically, when consumers' trust levels are high, the negative impact of perceived risk on behavioral intention is reduced. Therefore, trust acts as a **positive and beneficial moderator**, strengthening consumers' willingness to engage despite potential risks associated with artificial intelligence in finance.

On the other hand The interaction term between PSQ and PU showed a significant negative effect on CBI (β = -0.277, t = 6.076, p < 0.001). This indicates that PSQ significantly moderates the relationship between PU and CBI. However, the negative coefficient suggests that when service quality is high, the positive influence of perceived usefulness on consumer behavioral intention becomes weaker. In other words, consumers who already experience a high level of service quality may rely less on the perceived usefulness of artificial intelligence when forming their behavioral intentions. This represents a **strong but inverse moderating effect**.

ANOVA Analysis

H4: Users' income levels significantly influence the relationship between AI adoption and behavioral intention.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	88.162	4	22.040	242.000	.000
Within Groups	10.838	119	.091		
Total	99.000	123			

Source: Based on author's computation

The significant F-value and p-value show that consumers' behavioral intentions toward AI adoption vary depending on their income levels. Alternative Hypothesis supported; users' income levels have a significant impact on the AI adoption–behavioral intention relationship.

H5: Users' educational attainment significantly moderates the relationship between AI adoption and behavioral intention.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	87.147	4	21.787	218.741	.000
Within Groups	11.853	119	.100		
Total	99.000	123			

Source: Based on author's computation

The high F-value and the p-value of 0.000 show that there are **significant differences between the groups**. This indicates that the factor under study has a strong effect on the dependent variable.

Alternative Hypothesis Supported that educational attainment significantly moderates the relationship between AI adoption and behavioral intention.

H6: Users' level of digital literacy significantly affects the relationship between AI adoption and behavioral intention

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	89.233	4	22.308	271.811	.000
Within Groups	9.767	119	.082		
Total	99.000	123			

Source: Based on author's computation

The high F-value and the very low significance level (p = 0.000) indicate that users' digital literacy levels have a **strong and significant impact** on how AI adoption influences their behavioral intentions. Alternative Hypothesis is **supported**, confirming that digital literacy plays an important moderating role in the relationship between AI adoption and behavioral intention.

Findings and Conclusion

Statistical analysis revealed that income, education, and digital literacy had significant effects on behavioural intention, with digital literacy showing the strongest influence. Structural Equation Modeling confirmed multiple direct and mediated relationships among the constructs. AI demonstrated a strong positive direct effect on behavioural intention. Perceived usefulness and perceived risk served as significant mediators: AI improved perceived usefulness while simultaneously reducing perceived risk, leading to stronger behavioural intention. The results collectively demonstrate that AI acts as both a technological and psychological enabler of FinTech adoption by enhancing perceived value and trust.

The study concludes that Artificial Intelligence is a pivotal factor influencing consumers' behavioural intention to adopt FinTech. Technology alone does not ensure adoption; user perception, trust, and assurance play defining roles in shaping the success of digital financial innovations. Firms are advised to invest in AI-driven personalization, strengthen Corporate Digital Responsibility practices, and adopt transparent data-handling policies. Enhancing service quality, implementing feedback loops, and promoting awareness campaigns are practical strategies to improve user confidence.

The findings demonstrate that in a Tier-II Indian urban context such as Vadodara, Artificial Intelligence influences FinTech adoption not merely through technological capability, but through users' perceived value and assurance mechanisms. Trust and service quality emerge as critical contextual moderators, highlighting the importance of responsible AI deployment in emerging markets. By grounding the analysis in a real-world urban setting, the study contributes place-based evidence to the AI–FinTech adoption literature and offers actionable insights for financial institutions targeting similar cities across India and other developing economies.

Limitations of the Study

This study employed convenience sampling from a single urban location (Vadodara, Gujarat), which may limit the generalizability of the findings. However, the objective of this research was not statistical generalization but theoretical explanation and model validation within a FinTech-active population. Similar methodological approaches have been widely accepted in FinTech and AI adoption research. Future studies should employ multi-city, cross-cultural, and longitudinal designs to enhance external validity.

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