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Determinants of Customer Adoption of Generative AI-Enabled Banking Services in India: An Empirical Study

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Abstract

While GenAI is transforming the customer interface in banking, there is limited empirical evidence that offers insights into why customers in India may or may not embrace GenAI. This study explores the effects of perceived usefulness (PU), perceived ease of use (PEOU), security and privacy (SP) and perceived risk (PR) on customers' intentions to use GenAI capabilities in Indian banking, examines trust in GenAI as a mediator between the two, and examines differences in intention across groups of respondents. A structured online questionnaire (five-point Likert scale) was used to gather data, which was subsequently analysed in MS Excel using descriptive statistics, Cronbach's alpha, chi-square tests of independence, one-way ANOVA and regression-based mediation (Sobel test) and moderation (interaction terms) models. Together, the four perceived characteristics accounted for 34.2% of the variance in adoption intention ($F(4, 126) = 16.35$, $p < .001$); and, when examined individually, only perceived usefulness was found to be a statistically significant predictor ($B = 0.226$, $p = .017$). All four characteristics were robust predictors of trust in GenAI ($R^2 = .739$) but failed to mediate the influence of the four on the adoption intention (all Sobel $p > .42$). There were four significant moderation effects (interaction $p < .05$) for digital literacy. In the chi-square tests, intention was not significantly different across gender or prior use or frequency of use of the AI features, and in the ANOVA, intention was significantly different across usage frequencies ($F(4, 126) = 4.68$, $p = .001$), and was linked to age group. The study provides a preliminary evidence basis for banks and policymakers in India around the adoption of GenAI by customers.

Keywords: *Generative AI; GenAI-enabled banking; customer adoption intention; perceived usefulness; perceived risk; trust; digital literacy; India*

1. Introduction

The banking sector has experienced a huge transformation along with the rapid development of digital technologies and Artificial Intelligence (AI). The success of technological innovations is also heavily reliant on customer adoption: the value of a new banking service relies heavily on customers' acceptance and use of the innovation. Usefulness, ease of use, trust, security, privacy, perceived risk and customers' ability to use digital technologies can affect the uptake of innovative banking products.

Generative Artificial Intelligence (GenAI) is a recent innovation in AI that is capable of creating human-like text, responses, recommendations, and other types of content from user input. Unlike the rule-based systems, GenAI can comprehend conversational queries and produce context-based answers. These functions have provided banks with opportunities to improve their contact with customers, automate information processing, facilitate decision making, and deliver more tailored services.

Lee et al. (2024) highlight the increased use of Generative AI in banking, and how it can enhance financial analytics, decision-making and service provisioning. As financial services become more and more dependent on GenAI, questions about reliability, privacy, security, regulation, and responsible use become pertinent.

From the customers' point of view, the adoption of GenAI-powered banking services is pivotal. While banks can adopt highly advanced AI tools, user-centric elements like usefulness, convenience, security, trustworthiness, and alignment with the customer's banking requirements are all crucial factors for the successful deployment of these tools. Perceived

usefulness means that the customers feel that using GenAI-powered banking services could reduce their time and effort in making banking transactions, make them more efficient and easier to complete. Likewise, perceived ease of use is the customers' opinion of the ease of learning and using the services.

Security and privacy are also important factors to consider as banking services involve sensitive personal and financial information. When users are not sure how their data is being used, processed, stored, and protected, they may be hesitant to engage with GenAI systems. Additional factors that could hinder adoption include concern about inaccurate information generated by AI, data privacy issues, security vulnerabilities, or the use of AI-generated answers to make financial decisions that may not align with what customers are looking for. While GenAI holds great promise for banking, it has also been identified as a challenge due to privacy, regulatory compliance, reliability, **and responsible implementation** (Moharrak & Mogaji, 2024).

Trust in GenAI is another key consideration that will impact customer uptake. When customers think the GenAI can deliver reliable and accurate answers, and that banks can do so responsibly, they're more inclined to want to use the technology in banking. Thus, it is possible that such perceptions of the nature of GenAI-embarked banking services mediate on the intentions to use these services, making it more probable that trust explains this linkages. Past banking work finds that adoption of GenAI for customer interaction is limited by issues like privacy and regulation, despite its potential to create operational and customer-service value (Ek & Arnarp, 2024).

Digital literacy can also influence customers' reactions to the banking services they get through GenAI. Customers who feel comfortable with learning new technologies, using digital banking products and services, and addressing basic digital issues and evaluating digitally delivered information could react differently to GenAI services than customers with less digital literacy. Therefore, it is essential to have knowledge about digital literacy when analyzing the adoption of digital customers in the current technology-driven banking environment.

Existing literature on GenAI in finance and banking has largely concentrated on technological applications, operational efficiency, organisational implementation, risk management, regulatory issues, and potential opportunities and threats. Ostrowska (2025), for example, identifies opportunities for large language models in customer service and internal banking operations while also highlighting legal, ethical, and customer-acceptance concerns. But there is not much empirical work that has studied customer level adoption of GenAI supported banking services, especially in Indian banking context. However, the interaction of perceived usefulness, perceived ease of use, security and privacy, perceived risk, and the factors of trust and digital literacy need to be further explored via an empirical lens.

In this context, the present study, entitled, “Determinants of Customer Adoption of Generative AI-Enabled Banking Services in India: An Empirical Study”, has investigated the factors that influence customers' intention to use the GenAI-enabled banking services in India. Specifically, the study examines perceived usefulness, perceived ease of use, security and privacy, and perceived risk as factors influencing an intention to adopt. It also explores the mediating role of trust in GenAI and the moderating role of digital literacy, aiming for the creation of an empirical framework that better illuminates the path for customers' adoption of banking services through GenAI.

2. Review of Literature

Lee, D. K. C., Guan, C., Yu, Y., and Ding, Q. (2024) reviewed the applications of Generative AI in finance using the BERTopic method to identify major research themes. The study highlights GenAI’s potential to improve financial analytics, decision-making, and synthetic data generation, while emphasizing the need for stronger regulation and more empirical research on practical implementation and adoption.

Thuraisamy, K. S., Baig, Z., and Zeadally, S. (2025) examined the economic benefits, institutional challenges, regulatory issues, and cyberthreats associated with Generative AI in financial services. The study highlights GenAI’s

potential to improve productivity and operational efficiency while emphasizing the need for robust cybersecurity safeguards and risk management frameworks to address privacy, ethical, and systemic financial risks.

Moharrak, M., and Mogaji, E. (2024) examined the integration of Generative AI in banking, focusing on managerial readiness, regulatory compliance, and operational effectiveness. The study identified five key factors influencing adoption: Recognition, Requirement, Reliability, Regulatory, and Responsiveness, and recommended large-scale quantitative research across multiple countries and banking institutions.

Chua, X. J., Tan, J. M. L., Tan, J. X., Poh, S. C., Goh, Y. X., Choong, D. H. T., Foong, C. M., Yang, S. J., and Chan, C. S. (2025) introduced Ryt AI, a regulator-approved, LLM-based banking system that enables customers to perform financial transactions through natural language conversations. The study demonstrates the potential of conversational AI to improve banking efficiency and user experience while maintaining security and regulatory compliance, highlighting the need for further validation across banks, countries, and customer populations.

Chen, Y., Yan, S., Jin, Y., Li, J., Jin, X., and Jin, Y. (2025) systematically reviewed the applications, opportunities, and challenges of Generative AI in finance and proposed a future research agenda. The study highlights GenAI's potential to improve financial innovation, forecasting, customer service, and compliance while emphasizing the need to address technical, ethical, regulatory, and operational risks.

Raju, R. (2025) examined the adoption of Generative AI in Indian financial services, focusing on regulatory challenges, ethical considerations, and strategic implementation. The study highlights GenAI's potential to improve multilingual customer support, automation, financial inclusion, and operational efficiency while emphasizing the need for responsible governance and further empirical research on implementation and customer adoption in India.

Fan, M. (2024) examined the applications, challenges, and implementation strategies of Large Language Models (LLMs) in the banking sector, focusing on customer experience, operational efficiency, risk management, and compliance. The study highlights the potential of LLMs to improve automation, decision-making, and customer engagement while identifying privacy, bias, interpretability, and integration challenges.

Ek, L., and Arnarp, E. (2024) examined the use of Generative AI in traditional banks, focusing on its applications, value creation, challenges, and strategic facilitators. The study found that banks primarily use GenAI internally to automate repetitive tasks and improve productivity, while customer-facing adoption remains limited due to privacy and regulatory concerns.

Gehrmann, S., et al. (2025) examined the risks of Generative AI in financial services, developed a domain-specific AI content risk taxonomy, and evaluated existing AI safety guardrails. The study found that general-purpose guardrails often fail to detect financial risks, highlighting the need for specialized safety frameworks and improved guardrails for financial institutions.

Ostrowska, A. (2025) examined the applications, opportunities, and threats of Large Language Models (LLMs) in the banking sector, considering the perspectives of both banks and customers. The study highlights the benefits of LLMs in customer service and internal operations while identifying legal, ethical, and customer acceptance concerns that require further empirical research.

2.1 Research Gap

The current research about Generative AI in finance and banking has primarily addressed the technological applications, efficiency, risk management, regulatory issues, privacy and security, and organizational adoption. While a few studies acknowledge customer acceptance as an important issue, few empirical studies have investigated customer-level adoption of GenAI in banking services. More specifically, the effect of the factors perceived usefulness, perceived ease of use, security and privacy, and perceived risk on the adoption intention of the customer has not been adequately studied. Existing literature does not sufficiently examine the role of trust as a mediator and that of digital literacy as a moderator for GenAI. Moreover, although the potential and problems of GenAI in the financial services sector have been discussed

in Indian studies, empirical data specifically for Indian banking clients' adoption of GenAI is scarce. Thus, this research work will fill in this gap, as it will empirically study the determinants which influence customer adoption of GenAI banking services in India.

2.2 Problem Statement

Financial and banking services are rapidly evolving with Generative AI, allowing them to offer personalised services, enhance customer support, process information efficiently, and create better banking experiences. The intention to adopt GenAI-enabled banking services in relation to usefulness, ease of use, security, trust, privacy, and risk factors has not yet been clearly established among customers.Previous studies have been very much concerned with technology applications, operational efficiency, organisational uptake, and regulatory issues, and few empirical studies have examined customer-level uptake. Furthermore, the contribution of trust to customers' adoption intentions in the context of GenAI has not been sufficiently explored, nor has digital literacy been extensively investigated as a factor driving customers' intentions to adopt GenAI. Empirical evidence on these determinants of customers in the Indian banking context is especially scarce. Thus, empirical analysis of factors affecting customer adoption intention of GenAI services in banking and building a framework to understand their adoption behaviour is in need.

2.3 Research Questions

RQ1. How does perceived usefulness, perceived ease of use, security and privacy, and perceived risk affect customers' willingness to consider using GenAI tools in their banking services in India?
RQ2. Does trust in GenAI have a mediating effect between perceived characteristics of GenAI enabled banking service and the customer intention to adopt GenAI?
RQ3. Does digital literacy act as a moderating variable between the perceived characteristics of GenAI backed banking services and the customer intention to adopt GenAI?
RQ4. Which are the most significant factors influencing customers' intent to use GenAI-enabled banking services in India?

3. Research Objectives

RO1. To examine how perceived usefulness, perceived ease of use, security and privacy and perceived risk affect the intention to adopt the GenAI-enabled banking services by Indian customers.

RO2. To test the mediating effect of trust in GenAI in the link between the perceived features of GenAI enabled banking services and customer intention to adopt.

RO3. To investigate if digital literacy acts as a moderating effect between the perceived characteristics of GenAI-enabled banking service and customer intention on its adoption.

RO4. To compare the differences in adoption intention among respondent groups (gender, age group, prior use of features of AI with digital banking, and frequency of use of digital banking).

RO5. To build an empirical framework to understand customer adoption of the GenAI-enabled banking services in India.

4. Conceptual Framework and Hypotheses

The framework is based on the Technology Acceptance Model (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) that both indicate perceived usefulness and perceived ease of use as important factors in the acceptance of technology. It builds on these models with two factors that are particularly relevant for the application of AI in banking – security and privacy as well as perceived risk – reflecting the concern of the customers regarding sensitive financial information – and as a mediating mechanism, trust in GenAI. The

introduction of Digital Literacy as a boundary condition, which could affect the strength of the customer's perception to intention. The dependent variable is the intention of customers to adopt.

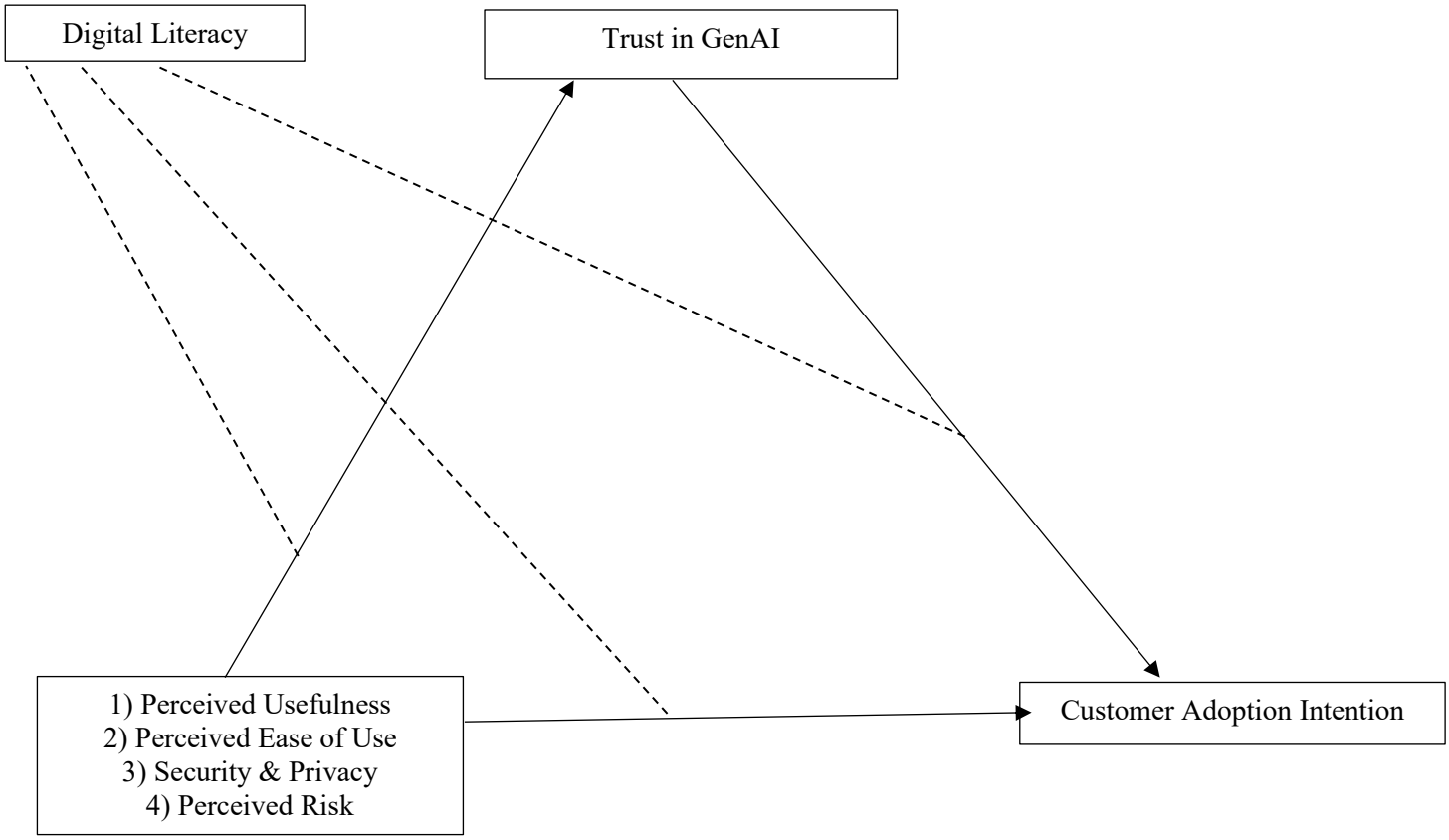


Figure 1. Conceptual framework of the study

4.1 Research Hypotheses

H_{01}: There is no significant relationship between the levels of perceived usefulness, perceived ease of use, security and privacy, and perceived risk on the customer's adoption intention of using GenAI-based banking services in India.

H_{11}: Perceived usefulness, perceived ease of use, security and privacy, and perceived risk have a significant influence on customer adoption intention of GenAI-enabled banking services in India.

H_{02}: The relationship between the perceived characteristics of GenAI-enabled banking services and the intention to adopt it is not significantly mediated by trust in GenAI.

H_{12}: Trust in GenAI is a significant mediator between perceived characteristics of GenAI-enabled banking services and customer adoption intention.

H_{03}: There is no significant moderating effect between perceived features of GenAI-enabled banking services and intention to adopt by customers.

H_{13}: Digital literacy can serve as a crucial moderating role between the perceived features of GenAI-assisted banking services and customer adoption intention.

H_{04}: There is no significant difference between the adoption intention of customers and the variables gender, age group, prior use of the AI-features, and the frequency of the use of digital banking (χ^2 tests).

H_{14}: Customer adoption intention correlates with at least one of the following: gender, age group, previous use of AI-feature or previous digital banking usage frequency.

H_{05}: The mean adoption intention for the groups of digital banking use frequency and prior use of digital banking features or income is not significantly different (ANOVA).

H_{15}: A significant difference in mean adoption intention is found across at least one grouping of usage frequency or prior use of AI-features or income.

5. Research Methodology

5.1 Research Design and Data Collection

The study is quantitative and of the cross-sectional survey design. The primary data were gathered through a structured online questionnaire from 18th to 30th September 2026. This was a convenience sampling and 131 respondents provided responses which were analysed.

5.2 Research Instrument

There were two sections of the questionnaire. Section A contained seven demographic and usage items such as age group, gender, education, occupation, monthly income, frequency of digital banking usage, and prior usage of AI-powered features in banking. In Section B, there were 20 statements to be rated using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). The items that were assigned to the study constructs are listed in Table 1. 1 item was used to measure perceived ease of use, security and privacy, while the remaining constructs were measured with the mean of their corresponding items. The variable "perceived risk" was not reverse scored and higher scores reflect increased risk. The relationships between constructs or overall views are reported descriptively in the items Q8 – Q10, Q13 – Q15, Q19 and Q20.

Table 1. Constructs and questionnaire items

Construct	Items	Sample statement
Perceived usefulness (PU)	Q1–Q2	GenAI-enabled banking services would make my banking activities more convenient.
Perceived ease of use (PEOU)	Q3	I believe GenAI-enabled banking services would be easy for me to use.
Security and privacy (SP)	Q4	I believe my personal and financial information would be secure.
Perceived risk (PR)	Q5	I would be concerned about the risks involved in using GenAI-enabled banking services.
Trust in GenAI (TR)	Q6–Q7	I would trust GenAI to provide reliable information through banking services.
Digital literacy (DL)	Q11–Q12	I am comfortable learning and using new digital technologies.
Adoption intention (ADOPT)	Q16–Q18	I intend to use GenAI-enabled banking services if they are offered by my bank.

Source: Survey instrument; construct assignment by the researcher.

5.3 Statistical Tools

The data was analysed using worksheet formula in Microsoft Excel (AVERAGE, STDEV, CORREL, CHIDIST, FDIST, LINEST and TDIST). The following techniques were used:

- Descriptive statistics and Cronbach's alpha for profiling respondents and testing the internal consistency.

- Chi-square tests for independence were conducted between the demographic variables and the adoption intention (categorised as High (mean of Q16–Q18 ≥ 4.0) and Lower), and usage variables and adoption intention (High and Lower). Effect size is presented as the value of the Cramér's V.
- One-way ANOVA comparing mean adoption intention across usage-frequency, prior-AI-use and income groups. Effect size is reported as eta squared.
- Multiple linear regression (ordinary least squares) of the intention to adopt on PU, PEOU and SP and PR; the multicollinearity was checked by the variance inflation factors.
- Regression-based mediation (Baron & Kenny, 1986) with the (Sobel 1982) test, and moderation (mean-centred predictors and product terms) with digital literacy.

Throughout the tests, a 5% level of significance was used.

6. Data Analysis and Results

6.1 Respondent Profile

Table 2 profiles the 131 respondents. All were students, 97% were undergraduates and 90% were aged 18–25. Women formed 74.8% of the sample. Nearly half (48.1%) used digital banking daily, and 48.1% had already used AI features in banking. Most respondents (80.9%) reported no income, which is consistent with a student sample.

Table 2. Respondent profile (N = 131)

Variable	Category	Frequency	Percent
Age	Below 18	13	9.9
	18–25	118	90.1
Gender	Female	98	74.8
	Male	33	25.2
Education	Undergraduate	127	96.9
	Postgraduate	4	3.1
Occupation	Student	131	100.0
Monthly income	No income	106	80.9
	Below ₹25,000	9	6.9
	₹25,001–₹50,000	12	9.2
	Above ₹75,000	4	3.1
Digital banking frequency	Daily	63	48.1
	Several times a week	37	28.2
	Once a week	8	6.1
	Occasionally	14	10.7
	Rarely	9	6.9
Prior use of AI features in banking	Yes	63	48.1
	No	52	39.7
	Not sure	16	12.2

Source: Survey data (Descriptives sheet of the accompanying workbook).

6.2 Descriptive Statistics and Reliability

Mean construct scores ranged from 3.44 (perceived usefulness) to 3.95 (digital literacy), all above the scale mid-point of 3. Adoption intention averaged 3.83. Cronbach's alpha exceeded .70 for every multi-item construct (Table 3), which is acceptable for research of this kind. Alpha for digital literacy (.701) is at the lower bound, and alpha cannot be computed for single-item measures.

Table 3. Descriptive statistics and reliability of constructs

Construct	Items	Mean	SD	Cronbach's α
Perceived usefulness (PU)	2	3.44	1.01	.842
Perceived ease of use (PEOU)	1	3.75	0.91	n/a
Security and privacy (SP)	1	3.56	0.95	n/a
Perceived risk (PR)	1	3.53	1.02	n/a
Trust in GenAI (TR)	2	3.58	0.93	.847
Digital literacy (DL)	2	3.95	0.81	.701
Adoption intention (ADOPT)	3	3.83	0.82	.851

Note: n/a = single-item measure.

6.3 Correlation Analysis

All construct pairs were positively correlated (Table 4). Adoption intention correlated most strongly with digital literacy (r = .76) and then with PEOU (.54), PU (.53) and trust (.50). Perceived usefulness and ease of use were highly intercorrelated (r = .78), and trust correlated .78 with ease of use. Perceived risk correlated positively with adoption intention (r = .34), the opposite of the sign theory would predict if risk were a deterrent; this is considered in the discussion. Critical |r| at the 5% level is approximately .17.

Table 4. Pearson correlations among constructs

	PU	PEOU	SP	PR	TR	DL	ADOPT
PU	1	.78	.40	.36	.72	.38	.53
PEOU	.78	1	.55	.45	.78	.36	.54
SP	.40	.55	1	.37	.64	.22	.39
PR	.36	.45	.37	1	.25	.05	.34
TR	.72	.78	.64	.25	1	.39	.50
DL	.38	.36	.22	.05	.39	1	.76
ADOPT	.53	.54	.39	.34	.50	.76	1

Note: all coefficients except PR–DL (.05) are significant at the 5% level.

6.4 Chi-Square Tests of Independence

Adoption intention was split into High (mean ≥ 4.0; n = 72, 55.0%) and Lower (n = 59). Table 5 reports the tests. No expected cell count fell below 5 in any test. Gender, prior AI-feature use and digital banking usage frequency were not significantly associated with intention, so H_{04} is retained for these variables. Age group was significantly associated with intention, $\chi^2(1) = 17.61$, $p < .001$, with a medium-to-large effect (Cramér's V = .37): none of the 13 respondents below 18 fell in the High group, compared with 61.0% of those aged 18–25. With only 13 respondents under 18, this result should be interpreted cautiously.

Table 5. Chi-square tests of independence with adoption intention

Variable	High intention (%) by category	χ^2	df	p	Cramér's V
Gender	Female 52.0; Male 63.6	1.341	1	.247	.101
Age group	Below 18: 0.0; 18–25: 61.0	17.612	1	< .001	.367
Prior AI-feature use	Yes: 54.0; No: 50.0; Not sure: 75.0	3.138	2	.208	.155
Digital banking frequency	Daily: 60.3; Several times a week: 56.8; Weekly or less: 41.9	2.903	2	.234	.149

Note: "Weekly or less" combines once a week, occasionally and rarely to avoid sparse cells.

6.5 One-Way ANOVA

Table 6 compares mean adoption intention across groups. Intention differed significantly by digital banking usage frequency, $F(4, 126) = 4.68$, $p = .001$, $\eta^2 = .13$ (a medium-to-large effect). The lowest means were among respondents who used digital banking once a week (3.17, n = 8) and rarely (3.00, n = 9), compared with about 3.9–4.0 for daily, several-times-a-week and occasional users. The "rarely" group had zero variance, which departs from the equal-variance assumption, so group sizes and variances should be considered before drawing conclusions. Intention did not differ significantly by prior AI-feature use, $F(2, 128) = 2.25$, $p = .110$. The income comparison was significant, $F(3, 127) = 31.09$, $p < .001$, $\eta^2 = .42$, but it is exploratory: it rests on very small groups (n = 4, 9 and 12), two of which have zero variance, and no respondent reported ₹50,001–₹75,000, so it is not interpreted substantively.

Table 6. One-way ANOVA of adoption intention

Factor	Group means (n)	F	df	p	η^2
Digital banking frequency	Daily: 3.97 (63); Several times a week: 3.89 (37); Once a week: 3.17 (8); Occasionally: 3.95 (14); Rarely: 3.00 (9)	4.682	4, 126	.001	.129
Prior AI-feature use	Yes: 3.94 (63); No: 3.65 (52); Not sure: 4.00 (16)	2.249	2, 128	.110	.034
Monthly income (exploratory)	No income: 3.85 (106); Below ₹25,000: 2.93 (9); ₹25,001–₹50,000: 5.00 (12); Above ₹75,000: 2.00 (4)	31.092	3, 127	< .001	.423

6.6 Multiple Linear Regression (H1)

Model 1 regressed adoption intention on PU, PEOU, SP and PR. The model was significant, $F(4, 126) = 16.35$, $p < .001$, and explained 34.2% of the variance (adjusted $R^2 = .321$; standard error of estimate = 0.68). Variance inflation factors were below 3.2, so multicollinearity was not a concern despite the high PU–PEOU correlation. Perceived usefulness was the only individually significant predictor ($B = 0.226$, $\beta = .28$, $p = .017$). Ease of use ($p = .105$), security and privacy ($p = .158$) and perceived risk ($p = .223$) were positive but not significant. Perceived risk therefore did not deter intention in this sample. H_{11} is partially supported: the set of perceived characteristics significantly predicts intention, driven mainly by perceived usefulness.

Table 7. Regression of adoption intention on perceived characteristics (Model 1)

Predictor	B	SE	β	t	p	VIF
(Constant)	1.672	0.290		5.771	< .001	
Perceived usefulness	0.226	0.093	.278	2.424	.017	2.52
Perceived ease of use	0.190	0.116	.209	1.631	.105	3.14
Security and privacy	0.108	0.076	.124	1.419	.158	1.46
Perceived risk	0.081	0.066	.101	1.225	.223	1.29

Note: R^2 = .342, adjusted R^2 = .321, $F(4, 126) = 16.354$, $p < .001$, $n = 131$. Dependent variable: adoption intention.

6.7 Mediation by Trust in GenAI (H2)

Following Baron and Kenny (1986), Trust was regressed on the four predictors (Model 2) and adoption intention was regressed on the predictors plus Trust (Model 3). All four predictors strongly influenced trust (R^2 = .739; PU B = 0.276, PEOU B = 0.467, SP B = 0.336, PR B = −0.177; all $p < .001$). However, trust did not significantly predict adoption intention once the predictors were controlled (B = 0.100, SE = 0.125, p = .425), and the Sobel test was not significant for any predictor (Table 8). H_{02} is therefore not rejected. The direct effect of perceived usefulness remained marginally significant (p = .048). The high correlations between trust and ease of use (.78) and usefulness (.72) suggest that trust and the perceived characteristics overlap empirically, which may limit the ability to detect mediation.

Table 8. Mediation analysis with Trust as mediator

Predictor	Total effect c	a (X→TR)	b (TR→ADOPT)	Direct c′ (p)	Indirect a×b	Sobel z	Sobel p
PU	0.226	0.276	0.100	0.199 (.048)	0.028	0.786	.432
PEOU	0.190	0.467	0.100	0.143 (.274)	0.047	0.793	.428
SP	0.108	0.336	0.100	0.074 (.394)	0.034	0.794	.427
PR	0.081	−0.177	0.100	0.099 (.160)	−0.018	−0.783	.434

Note: unstandardised coefficients. Model 2 R^2 = .739; Model 3 R^2 = .345.

6.8 Moderation by Digital Literacy (H3)

Model 4 added mean-centred digital literacy and its product terms with each predictor. The model was significant, $F(9, 121) = 60.51$, $p < .001$, and explained 81.8% of the variance (adjusted R^2 = .805). Digital literacy had a strong main effect (B = 0.465, $p < .001$), and all four interaction terms were significant: PU × DL (B = −0.255, p = .006), PEOU × DL (B = −0.181, p = .039), SP × DL (B = 0.385, $p < .001$) and PR × DL (B = −0.318, $p < .001$). H_{03} is rejected. The negative PU and PEOU interactions indicate that the effect of usefulness and ease of use on intention is weaker for more digitally literate respondents, whereas security and privacy matters more as digital literacy rises. The large increase in R^2 over Model 1 reflects mainly the main effect of digital literacy rather than the interactions alone; the main effects of PR (B = 0.337) and SP in this model should be read at the mean of digital literacy.

Table 9. Moderated regression with digital literacy (Model 4)

Predictor	B	SE	t	p
(Constant)	3.909	0.035	110.759	< .001
PU (centred)	0.054	0.057	0.943	.348
PEOU (centred)	0.131	0.070	1.863	.065
SP (centred)	0.156	0.048	3.285	.001
PR (centred)	0.337	0.044	7.678	< .001

Predictor	B	SE	t	p
DL (centred)	0.465	0.059	7.844	< .001
PU × DL	−0.255	0.092	−2.778	.006
PEOU × DL	−0.181	0.087	−2.086	.039
SP × DL	0.385	0.076	5.042	< .001
PR × DL	−0.318	0.045	−7.155	< .001

Note: R^2 = .818, adjusted R^2 = .805, $F(9, 121) = 60.506$, $p < .001$, $n = 131$.

6.9 Robustness Check on Distinct Response Patterns

Model 1 was re-estimated on the 31 distinct response patterns. The overall model remained significant, $F(4, 26) = 3.26$, $p = .027$, with $R^2 = .334$, close to the full-sample value. However, no individual predictor was significant (PU B = 0.190, p = .377; PEOU B = 0.228, p = .387; SP B = 0.124, p = .467; PR B = 0.049, p = .741). The significant effect of perceived usefulness in the full sample therefore does not survive the removal of repeated rows, and individual-predictor findings should be treated as tentative until the data source is verified. The chi-square, ANOVA, mediation and moderation analyses were not repeated on the 31 distinct patterns.

6.10 Summary of Hypothesis Tests

Table 10. Summary of hypothesis testing

Hypothesis	Test	Result
H1: PU, PEOU, SP, PR influence adoption intention	Multiple regression	$F(4, 126) = 16.35$, $p < .001$; only PU significant
H2: Trust mediates	Baron–Kenny with Sobel	Sobel p > .42 for all predictors
H3: Digital literacy moderates	Moderated regression	All four interactions p < .05
H4: Intention associated with gender, age, AI use, frequency	Chi-square	Only age group significant (p < .001)
H5: Mean intention differs across groups	One-way ANOVA	Frequency (p = .001) and income (p < .001, exploratory) significant; prior AI use not (p = .110)

Note: results are based on all 131 responses; see Section 6.9 for the robustness check.

7. Discussion

The results support in part the TAM framework for the adoption of GenAI in banking in India. In general, it appears that respondents were positive, with a mean intention of 3.83 out of 5. The direct relationship between perceived usefulness and intention was the most evident, and was similar to the central thrust of technology acceptance research (Davis 1989; Venkatesh et al. 2003). Once usefulness was held constant, ease of use and security/privacy were positively but not significantly related to intention, in part because of their high inter-correlation (and with usefulness).

Perceived risk positively and not negatively correlated with intention. This is counter-intuitive, as the question is about 'concern for risk'; it may be because respondents who are positive about GenAI are also positive about most of the statements or because people who know about the risks are nonetheless planning to use the services. It might also be sampling error as a result of the sample. More research is needed with multi-item risk scales and with reverse-worded items.

The influence of usefulness and ease of use, as well as security and (negatively) risk, was also influential on trust in line with literature on privacy and reliability concerns regarding GenAI banking (Moharrak & Mogaji, 2024; Ek & Arnarp,

2024). However, the mediation hypothesis was not confirmed as these changes did not transfer to intention. The explanation is more likely to be that there is no empirical distinction between trust and the perceived characteristics within the two-item measure than there is that trust is unimportant.

The strongest correlate of intention and the mediator of all relationships was digital literacy. A smaller effect on intention was found for more digitally literate customers, implying that such customers place less weight on the perceived benefits, and more on the perceived self-efficacy, while security and privacy were more important. This aligns with the perspective that digital skills enable customers to assess benefits and risks of GenAI services. As the moderation model is also sensitive to the sample issue described above, it should be replicated.

There was minimal difference observed in intention between groups based on gender or previous exposure to AI features in banking. The decrease in weekly and infrequent digital banking for respondents and those under 18 is possible but based on small numbers.

8. Implications

8.1 Theoretical Implications

This study introduced perceived risk and trust and digital literacy together in a single framework to the already established models of TAM and UTAUT and found that digital literacy influences the relationship between perceptions and intention for customer-facing GenAI banking in India. In addition, it demonstrates that for a short form survey, trust can be difficult to disentangle from perceived attributes.

8.2 Managerial and Policy Implications

- Concrete usefulness of GenAI features, including time savings and ease in repetitive work, as the most consistent direct driver, should be communicated by banks.
- Since digital literacy affects customer reactions, banks can combine GenAI rollout with guided onboarding and education, especially for customers who do not have a high frequency of digital banking.
- Security and privacy statements should be easily seen and clearly stated, as this was important for digitally literate customers and had a significant impact on trust.
- It is important that GenAI is governed by regulators and banks in a transparent manner, allowing for the establishment of trust based on reliability.

9. Limitations and Future Research

The sample consists of undergraduate students, predominantly female, which is a convenience sample and results may not be extrapolated to all Indian bank customers. Second, some measures contained only a single or two items, resulting in low reliability and perhaps account for the low distinction between trust and the measures of perceived characteristics. Third, the other income groups (those with less than $240/month or more than $1,200/month) were very small, with most respondents reporting no income. Fourth, Cross-sectional design does not measure actual behavior. Future studies should employ larger and more diverse and verified samples, scales that have multiple items and can be validated, structural equation modelling to test mediation and moderation together, and behavioural data.

10. Conclusion

This research explores the factors influencing customers' decision to embrace GenAI-powered banking products in India. Taken together, perceived usefulness, ease of use, security and privacy and perceived risk accounted for nearly one-third of the variance in adoption intention, with perceived usefulness being the primary individual predictor for the overall sample. These did not go through trust, and digital literacy significantly moderated all four relations. Prior use of AI-features and intention were largely independent of each other and gender. It is important to note that the data are numerous and repeated responses, and are obtained from a student sample, so should be viewed as tentative evidence, subject to further investigation with a larger, verified and more diverse sample.

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