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Drivers of AI Adoption of Banks in Bangladesh: Moderating Role of Technology Readiness

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Abstract*:* The main focus of this study is to examine the key factors contributing to consumers' inclination towards embracing AI within banking services. It further discusses the moderating role of technology readiness in determining the effect of perceived usefulness, perceived ease of use, user innovativeness, and perceived trust on the intention to use AI applications in the banking services. The research gathered data using a structured questionnaire and non-probability random sampling methods. Data were collected from 300 private bank customers residing in two urban cities (Dhaka and Chattogram) in Bangladesh. The study found that perceived usefulness, perceived ease of use, user innovativeness, and perceived trust are significantly correlated with behavioral intentions to adopt AI-based banking services. Simultaneously, technology readiness moderates the interaction between perceived usefulness and perceived ease of use and intentions to adopt AI services in banking transactions. The originality of this study lies in its investigation of AI adoption in Bangladeshi banks by integrating TAM constructs with user innovativeness and trust, while uniquely examining technology readiness as a moderator influencing adoption intentions.

Keywords: AI Adoption, ETAM, Technology Readiness and Banks.

Introduction

Artificial Intelligence (AI) has been widely recognized as a transformative technology capable of reshaping industries worldwide. Andrew Ng famously compared its impact to electricity, emphasizing its potential to revolutionize all sectors (Lynch, 2017). Banking, as a data-intensive and service-oriented sector, has been at the forefront of adopting digital technologies to improve efficiency, customer service, and risk management. In both developed and emerging economies, banks are leveraging AI applications for fraud detection, credit scoring, customer engagement, and operational efficiency (Arora & Kaur, 2020; Fares et al., 2022; Hoque et al, 2024). However, while developed countries have achieved significant progress in AI adoption, banks in emerging economies face several structural, regulatory, and technological barriers. that constrain full implementation. This uneven adoption raises critical questions about the drivers influencing AI implementation and the role of technology readiness in shaping its outcomes.

Although global evidence suggests AI significantly enhances banking performance, findings across contexts are fragmented. For example, Guang-Wen & Siddik (2022) and Meraj et al. (2025) highlighted AI and related technologies as enablers of sustainability and efficiency in Bangladesh and India, while Rahman et al. (2023) revealed that consumers' trust, perceived risk, and attitudes are major predictors of AI adoption in Malaysia's banking sector. Similarly, Pahari et al. (2023) showed that although Indian banks use AI to automate operations and prevent fraud, they struggle with issues of maturity and implementation. Evidence from Eastern Europe (Adamyk et al., 2024) and Saudi Arabia (Eskandarany, 2024) further reveals barriers, including costs, limited strategies, and ethical concerns, despite a readiness to adopt AI/ML technologies. These studies collectively confirm AI's transformative role but also underscore inconsistent adoption patterns shaped by institutional, technological, and cultural contexts.

Within the local context of Bangladesh, AI adoption in banking remains relatively low. A survey by the Bangladesh Institute of Bank Management (BIBM) indicated that only 29% of banks have introduced AI-based solutions, primarily in limited areas such as cash counting, KYC assessment, and vault management. This underutilization exists despite Bangladesh Bank's 2020 directive on AI in banking and the government's release of a draft national AI strategy. The barriers include lack of infrastructure, insufficient technical expertise, regulatory uncertainties, and cultural resistance (DBR, 2019; Rahman et al., 2023). While some banks experiment with chatbots or fraud detection tools, the comprehensive integration of AI into strategic operations is still in its early stages. This highlights the importance of exploring not only the drivers of AI adoption (e.g., perceived usefulness, trust, cost reduction, regulatory pressure) but also the moderating role of technology readiness, which determines whether banks can effectively integrate and scale AI initiatives.

Despite growing literature, significant research gaps remain. First, while prior studies have examined AI adoption factors from organizational or consumer perspectives (Lazo & Ebardo, 2023; Manoharan, 2024), fewer studies have analyzed how technology readiness conditions the success of AI adoption in emerging economies. Second, much of the empirical evidence comes from developed markets, with limited focus on South Asia, particularly Bangladesh, where structural and cultural constraints may differ substantially. Finally, most studies emphasize either customer-centric adoption or regulatory challenges, overlooking the interplay between internal drivers and contextual enablers. Addressing these gaps, the present study aims to identify the drivers of AI adoption in banks in emerging economies and examine the moderating effect of technology readiness. The findings will provide theoretical contributions by extending adoption models to banking in developing contexts and offer practical insights for policymakers, regulators, and bank managers seeking to accelerate AI integration for sustainable competitiveness.

Theoretical Background and Hypothesis Development

The Extended Technology Acceptance Model (ETAM) provides a strong foundation for understanding the drivers of AI adoption in the banking sector, particularly in emerging economies like Bangladesh. Prior studies highlight the importance of perceived usefulness, trust, subjective norms, and awareness in shaping adoption intention (Lim et al., 2025; Rahman et al., 2023). Other research emphasizes effort expectancy, hedonic motivation, and organizational factors such as top management support and competitive pressure (Papathomas et al., 2025; Kumar et al., 2025). Moreover, consumer attitudes and perceptions of risk significantly mediate the relationship between usefulness and adoption (Rahman et al., 2023). The inclusion of technology readiness as a moderator is crucial, as studies show that technological literacy and readiness strengthen the relationship between performance expectations and user behavior (Mei et al., 2024). Thus, ETAM, enriched with technology readiness, offers a comprehensive model to capture both individual and contextual drivers of AI adoption in Bangladeshi banks**.** Based on the ETAM, the following conceptual framework has been proposed in this study.

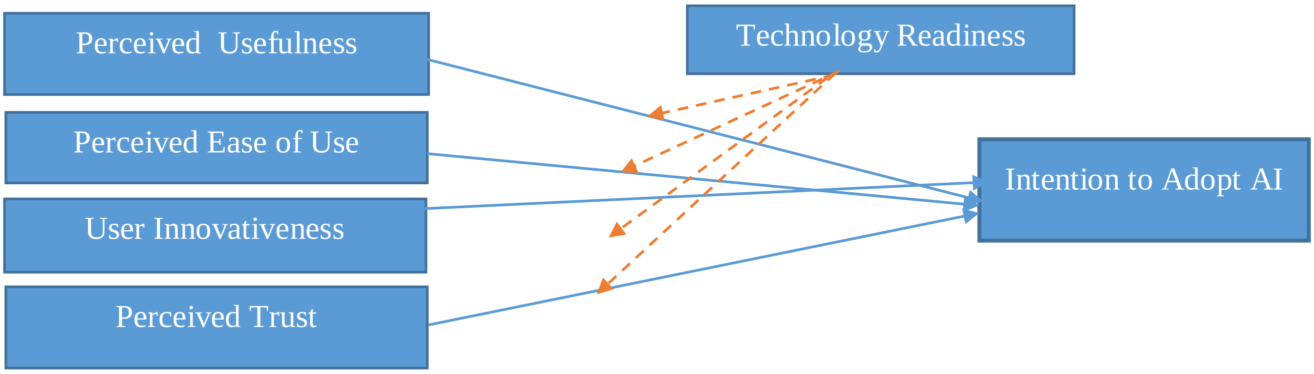

Figure 1: Conceptual Framework

Hypothesis Development

Perceived Usefulness

Perceived usefulness (PU) is consistently validated as a critical determinant of AI adoption across various contexts, supporting its relevance to banking. Kim et al. (2025) highlight that PU positively shapes attitudes and usage intentions toward AI-powered coding assistants, demonstrating its pivotal role in professional adoption decisions. Similarly, Khan et al. (2024) found that PU strongly mediates the effects of performance expectancy, facilitating conditions, and attitudes on the behavioral intention to adopt AI image generators, emphasizing its central influence in shaping adoption. In education, Aldraiweesh et al. (2025) report that PU is the strongest predictor of attitudes toward AI, which directly affect intentions to use, while Hosseini (2025) also confirms PU's predictive relationship with readiness to adopt AI tools. These findings collectively affirm that when users perceive AI as applicable, they are more likely to adopt it. Thus, the following hypothesis is proposed:

H_1 : Perceived usefulness significantly influences AI adoption in banks.

Perceived Ease of Use:

Perceived Ease of Use (PEOU) is a central determinant in the Technology Acceptance Model (TAM) that explains technology adoption. Several studies confirm its significance in shaping attitudes and behavioral intentions. Vidarshika et al. (2025) demonstrated that PEOU positively impacts attitudes toward ChatGPT usage, which in turn drives adoption in higher education. Similarly, Talha et al. (2025) found that teachers are more likely to adopt AI tools when they perceive them as user-friendly and straightforward. AlAjmi et al. (2024) also highlighted that PEOU has a direct effect on individual impact, which subsequently links to intention to use AI. From an organizational perspective, Park et al. (2025) showed that AI readiness and agility enhance PEOU, reinforcing its role in fostering adoption intention. Furthermore, Abulail et al. (2025) emphasized PEOU as a significant factor influencing AI adoption in higher education institutions. Thus, based on these findings, it is sensible to hypothesize that PEOU will significantly influence AI adoption in the banking sector. Hence, the following hypothesis is proposed:

H_2 : Perceived ease of use significantly influences AI adoption in banks.

User Innovativeness:

User innovativeness plays a critical role in shaping behavioral intentions toward adopting new technologies, including artificial intelligence (AI) in the banking sector. Prior research consistently demonstrates that innovative individuals are more willing to experiment with emerging technologies and perceive greater value in their use. For example, Zhang et al. (2025) found that personal innovativeness moderated the influence of social factors on perceived ease of use in AI adoption. Similarly, Setiawan et al. (2025) confirmed that although user innovativeness was less influential compared to other factors, it still contributed to adoption decisions in higher education AI tools. Chauhan and Jishtu (2025) highlighted that consumer innovativeness enhanced favorable attitudes and indirectly promoted behavioral intentions toward AI-powered travel tools. Xu et al. (2025) further emphasized that innovativeness positively influenced attitudes toward AR adoption in tourism contexts. Likewise, Kumar et al. (2024) reported that personal innovativeness has a significant impact on attitudes and behavioral intentions toward ChatGPT adoption. Therefore, based on these empirical insights, the following hypothesis is proposed in this study:

H_3 : User Innovativeness significantly influences AI adoption in banks.

Perceived Trust:

Perceived trust plays a crucial role in shaping individuals' willingness to adopt Artificial Intelligence (AI) technologies, including in the banking sector. Prior research highlights trust as a central determinant of AI acceptance. For instance, Alzyoud et al. (2024) found that perceived trust has a positive influence on students' willingness to adopt AI in education, underscoring its importance in environments where reliability and security are critical. Similarly, Chen et al. (2025) demonstrated that perceived trust significantly moderated the relationship between personalization of ESG portfolios and investors' behavioral intention to adopt green FinTech solutions, highlighting trust as a condition for user engagement in financial contexts. Furthermore, Jridi (2025) emphasized that trust, alongside perceived humanness and satisfaction, drives intentions to use AI-based conversational agents for ecological purposes. Additionally, Devi and Shunmugasundaram (2025) showed perceived trust as a significant determinant of FinTech adoption and satisfaction among startup entrepreneurs. Collectively, these findings justify that in banking, where security and credibility are paramount, perceived trust significantly influences AI adoption. Thus, proposed the following hypothesis.

H_4 : Perceived trust significantly influences AI adoption in banks.

Moderating role of technology-readiness

Technology readiness (TR) is a critical factor influencing how individuals adopt emerging technologies, including AI services in banking. TR reflects users' psychological preparedness to embrace technological innovations (Leung & Cheung, 2025). Prior studies show that students with high TR more effectively translate perceived usefulness into actual adoption intentions, while those with low TR may acknowledge usefulness but hesitate to adopt (Ma et al., 2025). Similarly, TR enhances the effect of perceived ease of use, as users with strong readiness are more comfortable and confident in adopting user-friendly technologies (Can & Nguyen, 2025). Moreover, TR interacts with user innovativeness, where individuals with higher readiness and innovative tendencies are more likely to explore and adopt new technologies. In comparison, those with lower readiness may resist despite their innovativeness (Abuadas & Albikawi, 2025). Finally, TR significantly strengthens the effect of perceived trust on adoption, as trust in AI is more impactful when users are mentally prepared to engage with new technologies (Chen et al., 2025). Thus, TR moderates these relationships, making it central to AI adoption in banking, and proposed the following hypothesis.

$H_{5\text{-}8}$: Technology-readiness moderates the effect of perceived usefulness, perceived ease of use, user innovativeness, and perceived trust on AI services adoption in Banks.

Methodology

Study variables and questionnaire design

To apply the ETAM model in this study, relevant measures and items were adapted from prior literature on AI adoption in the banking sector. The items were refined with input from three psychometric scale development experts, who suggested minor revisions in language and wording. A pilot study with 30 participants, representing the target user group, was conducted before the primary survey. Participants reviewed the questionnaire and provided feedback on unclear or confusing items. Based on their input, further adjustments were made to improve clarity. The final survey used a five-point Likert scale ranging from “strongly disagree” (1) to “strongly agree” (5) to measure all constructs, ensuring suitability for assessing AI adoption among Bangladeshi bank consumers.

Sample and data collection

A non-probability random sampling method was used to administer the questionnaires, ensuring that the participants were within the scope of being engaged in tertiary education. Two urban cities (Dhaka and Chattogram) in Bangladesh were included as study areas. According to the Quarterly Scheduled Bank Statistics of Bangladesh Bank, September 2024, 82.73 percent of bank deposits in Bangladesh are contributed by two divisions: Dhaka and Chattogram, and 56.72 percent of bank branches in Bangladesh are situated in these divisions. For this reason, the three urban cities of Dhaka and the Chattogram division were taken as study areas.

Data analysis

This study employed the Partial Least Squares (PLS) - Structural Equation Modeling (SEM) technique to certify the research model. The PLS-SEM has many benefits, including the ability to analyze data that is non-normally distributed, imposing no stringent sample size requirements, and producing reliable outcomes (Hair et al., 2017). This study followed a two-step SEM process, as recommended by Hair et al. (2020). In the first step, the study analyzed the reliability of the scales by computing their Cronbach's alpha (CA), average variance extracted (AVE), composite reliability (CR), and individual item factor loadings (RL). This study's nine hypotheses were tested using the structural model in the second step (Hair et al., 2020). More information about these steps is provided in the following sections.

Results and Discussion

Demographic Information

The following table presents the demographic characteristics of the 300 respondents who participated in this study. The majority of respondents were male (70%), while females accounted for 30%. In terms of age, most participants were between 21 and 30 years (38.4%), followed by 31 and 40 years (27.2%), indicating that the sample was primarily composed of young and middle-aged adults, who are typically more exposed to technological innovations. Regarding education, a significant proportion held a master's degree (42.3%), while 30.4% completed a bachelor's degree, reflecting a relatively well-educated sample suitable for understanding AI-based banking applications. Professionally, the highest proportion was engaged in private service (23.8%) and business (20.4%), followed by housewives (16.0%). Income distribution shows that 31.6% earned less than BDT 30,000, while 22.2% earned above BDT 90,000, indicating a balanced mix of low- and high-income respondents. Awareness of AI services varied: 39.8% seemed familiar with such services, 30.6% had a better understanding, while 15% had never heard of them. Banks (33.2%) and other account holders (27.2%) emerged as the primary sources of information, followed by media (17.6%). These findings suggest that the respondents represent a diverse group in terms of demographics, education, and income, offering valuable insights into AI adoption in the Bangladeshi banking sector. The details of the demographic profile are described in Table 1**.**

Table 1: Demographic Profile of the Respondents

Demographics	Categories	Frequency	Percentage (%)
Gender	Male	210	70.0
	Female	90	30.0
Age Range	Less than 20 years	37	12.4
	21-30 years	115	38.4
	31 to 40 years	82	27.2
	41 to 50 years	43	14.4
	51 to 60 years	16	5.2
	Above 60 years	7	2.4
Education	Secondary	25	8.2
	Higher Secondary	32	10.6
	Bachelor's Degree	91	30.4
	Master's Degree	127	42.33
	Others	25	8.2
Profession	Govt Service	35	11.8
	Private Service	72	23.8
	Business	61	20.4
	Housewife	48	16.0
	Self Employed	39	13.0
	Others	45	15.0
Monthly Income	Less than BDT 30,000	94	31.6
	BDT 30001-60000	79	26.2
	BDT 60001-90000	60	20.0
	More than 90000	67	22.2
Understanding of AI Services	Never heard of that	45	15.0
	Seems Familiar	119	39.8
	A Little Understanding	44	14.8

	Better Understanding	92	30.6
Source of AI Services Information	Media	53	17.6
	Through a friend	32	10.8
	From the neighbour	34	11.2
	From another account holder	82	27.2
	From the bank	99	33.2

Measurement Model Analysis

The measurement model was assessed to determine the reliability and validity of the constructs used in this study **(**Table 2**).** The factor loadings for all items ranged between 0.714 and 0.829, exceeding the recommended cut-off value of 0.70 (Hair et al., 2019), confirming that each item appropriately represents its construct. No items were dropped, as all demonstrated acceptable loadings. To establish convergent validity, both Composite Reliability (CR) and Average Variance Extracted (AVE) were examined. The CR values ranged from 0.844 to 0.894, well above the minimum threshold of 0.70, confirming internal consistency and construct reliability. Similarly, AVE values ranged from 0.576 to 0.629, indicating that each construct captures a sufficient amount of variance from its indicators (Hair et al., 2019). The Cronbach's Alpha (CA) values for all constructs were also above the 0.70 threshold, further supporting reliability. After confirming convergent validity, discriminant validity was assessed. Using Fornell and Larcker's (1981) criterion and HTMT ratios, all values were found below the critical cut-off of 0.90 (Franke & Sarstedt, 2019), confirming that the constructs are distinct and non-overlapping. Overall, the measurement model demonstrates strong reliability, convergent validity, and discriminant validity, justifying its suitability for further analysis.

Table 2: Factor loadings, construct reliability and validity

Constructs	**Items**	**Factor Loadings (FL)**	**Cronbach's Alpha (CA)**	**Composite Reliability (CR)**	**Average Variance Extracted (AVE)**
Perceived Usefulness	PU01	0.825	0.852	0.894	0.629
	PU02	0.816			
	PU03	0.759			
	PU04	0.829			
	PU05	0.732			
Perceived Ease of Use	PEU01	0.786	0.759	0.844	0.576
	PEU02	0.720			
	PEU03	0.774			
	PEU04	0.753			
User Innovativeness	UI01	0.777	0.850	0.892	0.623
	UI02	0.791			
	UI03	0.792			
	UI04	0.807			
	UI05	0.780			
Perceived Trust	PT01	0.714	0.766	0.850	0.587
	PT02	0.742			

	PT03	0.795			
	PT04	0.810			
Intention to Adopt AI	AIA01	0.747	0.831	0.881	0.597
	AIA02	0.805			
	AIA03	0.793			
	AIA04	0.782			
	AIA05	0.734			

After confirming convergent validity, the next step was to assess discriminant validity, which ensures that the constructs are distinct from one another. According to Fornell and Larcker (1981), discriminant validity is achieved when the square root of the Average Variance Extracted (AVE) of each construct, shown on the diagonal, is greater than its correlations with other constructs. As presented in the table, the diagonal values (ranging from 0.759 to 0.793) are all higher than their corresponding inter-construct correlations, confirming discriminant validity. Furthermore, following Franke and Sarstedt (2019), the HTMT values were also examined and found to be below the 0.90 threshold **(**Table 3). These results demonstrate that the constructs are not overlapping and are statistically distinct, ensuring validity.

Table 3: Discriminant validity (Fornell–Larcker criterion)

	PU	PEU	UI	PT	AIA
Perceived Usefulness	0.793				
Perceived Ease of Use	0.469	0.759			
User Innovativeness	0.629	0.508	0.790		
Perceived Trust	0.457	0.491	0.662	0.766	
Intention to Adopt AI	0.573	0.569	0.767	0.669	0.773

Structural Model

The figure illustrates the structural model results for AI adoption in banks, showing the relationships among the constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEU), User Innovativeness (UI), Perceived Trust (PT), and Intention to Adopt AI (AIA). Each construct is represented as a blue oval, while the measurement items (PU01–PU05, PEU01–PEU04, UI01–UI05, PT01–PT04, AIA01–AIA05) are shown in yellow boxes. The arrows from items to constructs indicate factor loadings, all above the acceptable threshold, confirming measurement reliability. The structural paths from PU, PEU, UI, and PT to AIA indicate the strength of relationships. The path coefficients are displayed: PU → AIA (2.091), PEU → AIA (3.261), UI → AIA (7.883), PT → AIA (4.451). These values suggest that User Innovativeness (UI) has the most decisive influence on Intention to Adopt AI, followed by Perceived Trust (PT), Perceived Ease of Use (PEU), and Perceived Usefulness (PU). Overall, the model demonstrates that both technological perceptions and individual innovativeness significantly contribute to consumers' intention to adopt AI services in the banking sector, highlighting the importance of trust and innovativeness in driving adoption.

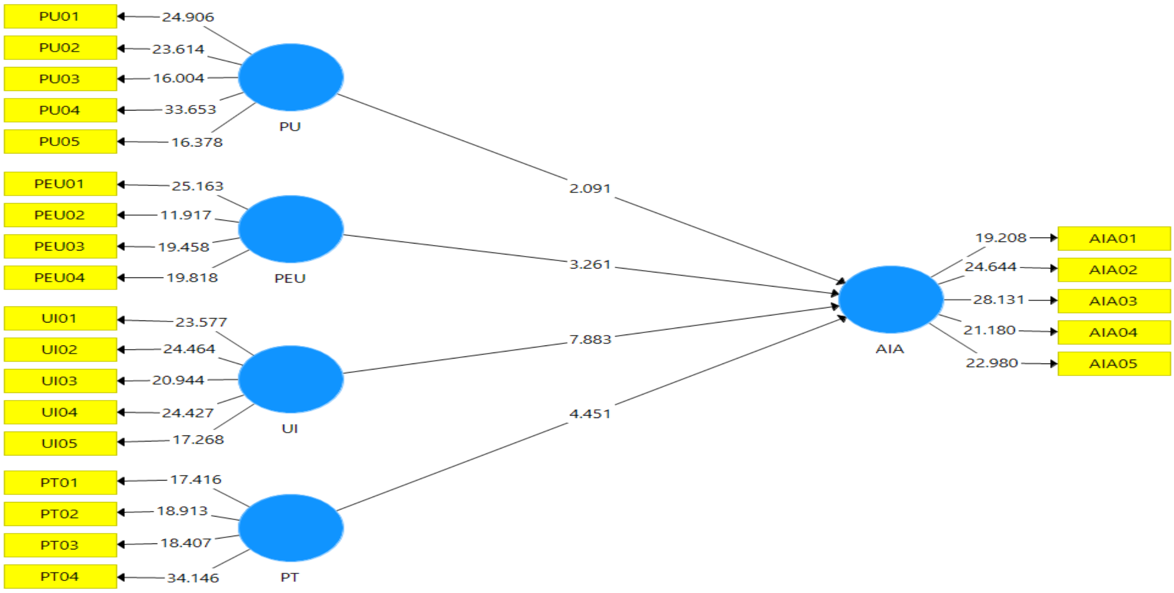

Figure 2: Structural Model

Structural Model: Coefficient of Determination (R^2), Predictive Relevance (Q^2), and Effect Size (f^2) of the Structural Model

Table 4 presents the values of R^2, Q^2, and f^2 to evaluate the explanatory power, predictive relevance, and effect size of the independent constructs on the intention to adopt AI (AIA). The R^2 value of 0.665 indicates that 66.5% of the variance in AIA is explained by perceived usefulness, perceived ease of use, user innovativeness, and perceived trust. The adjusted R^2 (0.661) confirms the robustness of this explanatory power. The Q^2 value of 0.386 demonstrates strong predictive relevance of the model. Regarding effect sizes, user innovativeness ($f^2 = 0.273$) has the most significant contribution to AIA, followed by perceived trust (0.084) and perceived ease of use (0.062), while perceived usefulness (0.014) shows only a weak effect. These results indicate that innovativeness and trust are the most influential drivers of AI adoption in the banking context.

Table: 4

Independent Constructs	Q2	R Square	R Square Adjusted	f^2
Perceived Usefulness				0.014
Perceived Ease of Use				0.062
User Innovativeness				0.273
Perceived Trust				0.084
Intention to Adopt AI (AIA)	0.386	0.665	0.661	

Path Coefficient

Table 5 presents the direct effects of the independent variables on the intention to adopt AI (AIA). All four constructs show significant positive relationships. Among them, User Innovativeness (β = 0.468, p < 0.001) is the strongest predictor, followed by Perceived Trust (β = 0.231, p < 0.001), Perceived Ease of Use (β = 0.176, p = 0.001), and Perceived Usefulness (β = 0.090, p = 0.037). These results indicate that consumers' innovativeness and their trust in AI technologies play a crucial role in shaping adoption intentions.

Table 5: Path coefficient (Direct Effect)

Relationship	β	SD	T Values	P Values	Comment
PU -> AIA	0.090	0.043	2.091	0.037	Significant
PEU -> AIA	0.176	0.054	3.261	0.001	Significant
UI -> AIA	0.468	0.059	7.883	0.000	Significant
PT -> AIA	0.231	0.052	4.451	0.000	Significant

Table 6 examines the moderating effect of Technology Readiness (TR). The interaction terms reveal that TR significantly moderates the relationships between Perceived Usefulness and AIA (β = -0.142, p = 0.003) and User Innovativeness and AIA (β = -0.072, p = 0.012), but not the effects of Perceived Ease of Use or Perceived Trust. Interestingly, the negative coefficients suggest that when technology readiness is high, the influence of usefulness and innovativeness weakens.

Table 6: Moderating Effect (Technology Readiness)

Moderating Relationship	Original Sample (O)	Sample Mean (M)	(STDEV)	T Statistics (|O/STDEV|)	P Values	Comment
TR*PU -> AIA	-0.142	-0.135	0.048	2.972	0.003	Significant
TR*PEU -> AIA	-0.050	-0.042	0.062	0.807	0.420	Not Sig.
TR*UI -> AIA	-0.072	-0.065	0.028	2.524	0.012	Significant
TR*PT -> AIA	-0.082	-0.076	0.043	1.898	0.058	Not. Sig.

Figure 3 illustrates these moderation effects, showing differences in AI chatbot usage between respondents with low versus high technology readiness, thereby confirming the nuanced role of TR in AI adoption.

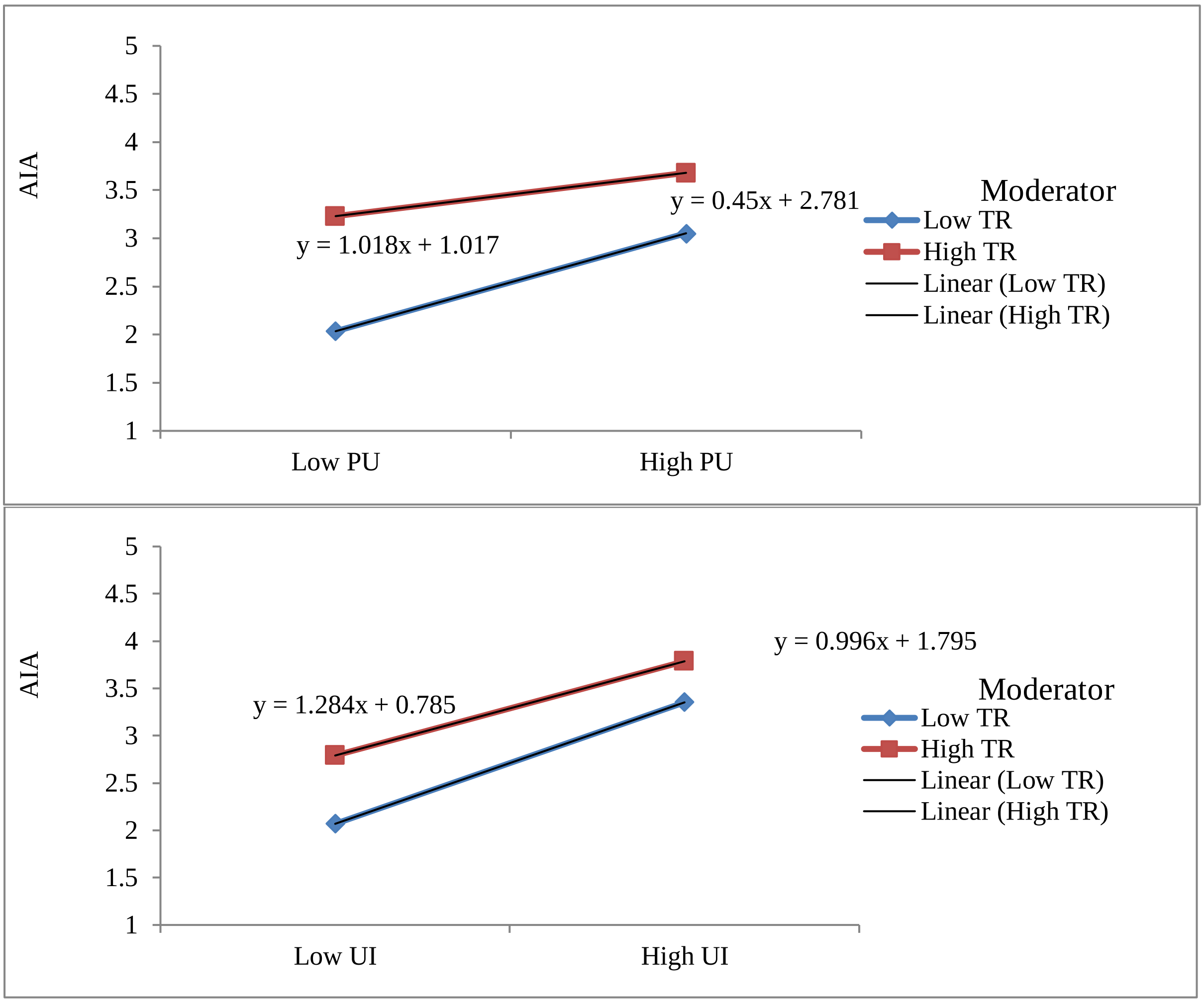

Figure 3: Interaction Effects of Tech Readiness on Intention to AI Adoption
Sources: Author`s own work

Discussion of the Results

The findings in Table 5 suggest that all four direct effects on AI adoption intention (i.e., perceived usefulness, perceived ease of use, user innovativeness, and perceived trust) have a statistically significant influence. Of these predictors, user innovativeness ($\beta = 0.468$, $p < 0.001$) is found to have the most substantial positive impact, suggesting that individuals with high innovativeness are much more likely to use AI services. This result aligns with that of Abuadas and Albikawi (2025), who posited innovativeness as a primary antecedent of digital adoption, particularly when new technologies necessitate experimentation and flexibility. In other words, innovative individuals are more likely to see AI as an opportunity rather than a threat, which leads them to have a high intention of using it. The second most significant factor determining adoption is perceived trust ($\beta = 0.231$, $p < 0.001$), which confirms the importance of credibility, reliability, and the perception of security on users' motivations. This finding is consistent with previous literature by Jridi (25) and Chen et al. (2025), who underscore the importance of trust in AI-enabled services, particularly in sustainability and financial contexts where perceived risks may deter users. Therefore, trust is crucial in minimizing such uncertainties and fostering confidence in technology-based systems.

In addition, perceived ease of use (β = 0.176, $p < 0.001$) significantly affects adoption intention, indicating that people are more likely to adopt AI services when they perceive them as being straightforward and uncomplicated to use. This finding provides strong support for the Technology Acceptance Model (TAM), which has long emphasized the critical role of usability in technology adoption. In addition, perceived usefulness (β = 0.090, $p < 0.05$) is found to be a weak but significant predictor of intention to use likewise. This is consistent with the observation that people become motivated to use AI when they realize it can provide some value or improve their task performance. The results of both PEU and PU are consistent with those of Jahan et al. (2024) and Lim et al. (2025), indicating that usability and utility remain core factors in technology adoption for emerging markets. The moderating effects of technology readiness (TR), as shown in Table 6 and Figure 2, provide further insights into the adoption process. TR significantly strengthens the relationship between PU and AIA (β = 0.142, $p = 0.003$), as well as between UI and AIA (β = 0.072, $p = 0.012$). This suggests that individuals with higher TR are more capable of translating their perceptions of usefulness and innovativeness into actual adoption intentions. However, the interactions of TR with PEU and PT were found to be insignificant, implying that readiness does not necessarily enhance the effects of perceived simplicity or trust on adoption. These results complement those of Ma et al. (2025) and Rahman et al. (2023), who introduced TR as a crucial moderator that explains how individuals' perceptions influence their adoption behavior. Finally, our findings emphasize that although innovativeness and trust have a substantial direct impact on AI adoption, the existence of high technology readiness enhances the roles of usefulness and innovativeness. This also lends credibility to the notion that nurturing personal AI confidence and readiness through awareness, training, and exposure to digital technology is essential.

Implications of the Study

This study contributes to the growing body of literature on AI adoption by extending the Technology Acceptance Model (TAM) through the inclusion of user innovativeness and perceived trust. By integrating these constructs, the research highlights the multidimensional nature of AI adoption in banking services. Furthermore, the introduction of technology readiness as a moderating variable enriches theoretical understanding by demonstrating how personal readiness to embrace technology influences the relationship between core TAM factors and adoption intentions. This provides a more nuanced explanation of consumer behavior in emerging economies. For banking practitioners, the findings suggest that enhancing perceived ease of use, usefulness, and trust in AI-based services can significantly foster adoption. Banks should also identify and engage innovative customers as early adopters to encourage broader acceptance. Moreover, strategies that improve customers' technological readiness through awareness, training, and user-friendly interfaces- can further strengthen adoption, ensuring smooth integration of AI into banking services.

Limitations and Suggestions for Future Research Studies

This study is limited by its reliance on non-probability sampling and data collected only from two urban cities, which may restrict the generalizability of the findings to all banking customers in Bangladesh. Moreover, the cross-sectional design captures customer perceptions at a single point in time, preventing causal inferences about AI adoption behavior. Future research should employ longitudinal approaches to observe changes in adoption intentions over time and include diverse geographic regions, including rural areas, to improve representativeness. Additionally, incorporating other relevant factors such as perceived risk, cultural influences, or regulatory frameworks may provide deeper insights. Comparative studies across countries or financial sectors could also enrich the understanding of AI adoption in different contexts.

Conclusion

This study contributes to understanding the drivers of AI adoption in the banking sector of Bangladesh by integrating key constructs of the Technology Acceptance Model with user innovativeness and perceived trust. The findings reveal that perceived usefulness, perceived ease of use, innovativeness, and trust all significantly shape customers' behavioral intentions to adopt AI-enabled banking services. Among these, user innovativeness emerged as the strongest determinant, highlighting the importance of individual traits in shaping adoption decisions. Furthermore, the moderating analysis underscores the role of technology readiness in strengthening the relationships between perceived usefulness, ease of use, and adoption intentions, suggesting that customers who are technologically prepared are more inclined to embrace AI applications. These insights confirm the relevance of TAM in the context of emerging technologies, while extending it with additional constructs. Overall, the study emphasizes that both technological perceptions and individual readiness factors are critical for fostering AI adoption in banking.

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Data Availability: The author has all the data employed in this research and is open to sharing it upon reasonable request.

References

Abuadas, M., & Albikawi, Z. (2025). Predicting nursing students' behavioral intentions to use AI: the interplay of ethical awareness, digital literacy, moral sensitivity, attitude, self-efficacy, anxiety, and social influence. Journal of Human Behavior in the Social Environment, 1-21.

Abulail, R. N., Badran, O. N., Shkoukani, M. A., & Omeish, F. (2025). Exploring the Factors Influencing AI Adoption Intentions in Higher Education: An Integrated Model of DOI, TOE, and TAM. Computers, 14(6), 230.

Adamyk, B., Benson, V., Adamyk, O., Fraczek, B., & Chinnaswamy, A. (2024, September). Barriers to Trust in AI: a Study of the Explainability Technologies Adoption in Banks. In 2024 14th International Conference on Advanced Computer Information Technologies (ACIT) (pp. 230-234). IEEE.

AlAjmi, Q., AlRoshdi, Y., & Rostaq, A. (2024, December). Impact of Perceived Ease of Use and Usefulness, with Trust and Individual Impact as Mediators on AI Adoption Intentions among IT Students at UTAS-Muscat. In The International Conference of Advanced Computing and Informatics (pp. 173-184). Cham: Springer Nature Switzerland.

Aldraiweesh, A. A., & Alturki, U. (2025). The Influence of Social Support Theory on AI Acceptance: Examining Educational Support and Perceived Usefulness using SEM analysis. IEEE Access.

Alzyoud, M., Al-Shanableh, N., Alomar, S., As' adAlnaser, A. A. M., Mustafa, A., Al-Momani, A., & Al-Hawary, S. I. S. (2024). Artificial intelligence in Jordanian education: Assessing acceptance via perceived cybersecurity, novelty value, and perceived trust. International Journal of Data & Network Science, 8(2).

Arora, N., & Kaur, P. D. (2020, June). Augmenting banking and FinTech with intelligent Internet of Things Technology. In 2020 8th International conference on reliability, Infocom technologies and optimization (Trends and Future Directions) (ICRITO) (pp. 648-653). IEEE.

Can, V. D., & Nguyen, V. H. (2025). The relationship between perceived usability and perceived credibility of Middle school teachers in using AI chatbots. Cogent Education, 12(1), 2473851.

Chauhan, R., & Jishtu, H. (2025). AI-powered travel planning: exploring anthropomorphism, innovativeness and privacy concerns. Journal of Hospitality and Tourism Insights, 1-18.

Chen, A., Wang, S., Mehta, A. M., Asif, M., Xu, S., & Shahzad, M. F. (2025). FinTech adoption for ESG integration through robo advisors, personalization, and perceived trust. Scientific Reports, 15(1), 31125.

Chen, R., Lee, V. R., & G Lee, M. (2025). A cross-sectional look at teacher reactions, worries, and professional development needs related to generative AI in an urban school district. Education and Information Technologies, 1-38.

Devi, P., & Shunmugasundaram, V. (2025). Understanding adoption intention and perceived satisfaction of startup entrepreneurs towards FinTech services. Journal of Modelling in Management.

Eskandarany, A. (2024). Adoption of artificial intelligence and machine learning in banking systems: a qualitative survey of board of directors. Frontiers in Artificial Intelligence, 7, 1440051.

Fares, Omar H., Irfan Butt, and Seung Hwan Mark Lee. "Utilization of artificial intelligence in the banking sector: a systematic literature review." Journal of Financial Services Marketing 28.4 (2023): 835-852.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of marketing research, 18(1), 39-50.

Franke, G., & Sarstedt, M. (2019). Heuristics versus statistics in discriminant validity testing: a comparison of four procedures. Internet research, 29(3), 430-447.

Guang-Wen, Z., & Siddik, A. B. (2023). The effect of Fintech adoption on green finance and environmental performance of banking institutions during the COVID-19 pandemic: the role of green innovation. Environmental Science and Pollution Research, 30(10), 25959-25971.

Hair Jr, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. Journal of business research, 109, 101-110.

Hair Jr, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. International Journal of Multivariate Data Analysis, 1(2), 107-123.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European business review, 31(1), 2-24.

Hoque, M. A., Jahan, F., & Begum, F. (2024). Exploring the Nexus of ATM Service Quality, Customer Satisfaction, and Loyalty in the Private Banking Sector in Bangladesh. Pakistan Journal of Life & Social Sciences, 22(1). https://doi.org/10.57239/PJLSS-2024-22.1.0074

Hosseini, N. (2025). The Effect of AI Self-Efficacy on Teachers' Behavioral Intention to Use AI in Education: The Mediating Role of Perceived Usefulness and Perceived Ease of Use. Research and Innovation in Primary Education, (Articles in Press).

Jahan, F., Chowdhury, S., Hoque, M. (2024): The effect of AI adoption and green leadership on organizational environmental performance in SMEs. Int. J. Relig. 5(11), 2207–2222; DOI: 10.61707/j9a56362

Jridi, S. (2025). From Perception to Action: The Role of Trust, Satisfaction, and Perceived Humanness in Ecological Chatbot Adoption. International Journal of Research and Innovation in Social Science, 9(6), 3495-3503.

Khan, T., & Emon, M. M. H. (2024, November). Determinants of AI Image Generator Adoption Among Marketing Agencies: The Mediating Effects of Perceived Usefulness. In 2024 IEEE 3rd International Conference on Robotics, Automation, Artificial-Intelligence and Internet-of-Things (RAAICON) (pp. 177-182). IEEE.

Kim, Y. W., Cha, M. C., Yoon, S. H., & Lee, S. C. (2025). Not merely useful but also amusing: Impact of perceived usefulness and perceived enjoyment on the adoption of AI-powered coding assistant. International Journal of Human–Computer Interaction, 41(10), 6210-6222.

Kumar, J., Rani, M., Rani, G., & Rani, V. (2024). Human-machine dialogues unveiled: an in-depth exploration of individual attitudes and adoption patterns toward AI-powered ChatGPT systems. Digital Policy, Regulation and Governance, 26(4), 435-449.

Kumar, J., Rani, M., Rani, G., & Rani, V. (2025). Unveiling employee readiness for artificial intelligence adoption: empirical insight from the perspective of the banking sector. Journal of Science and Technology Policy Management.

Lazo, M., & Ebardo, R. (2023). Artificial intelligence adoption in the banking industry: Current state and future prospect. Journal of Innovation Management, 11(3), 54-74.

Leung, L., & Cheung, M. (2025). The effects of technology readiness, risks, and benefits on smart home technology adoption: extending the Theory of Planned Behavior model. Media Asia, 52(1), 80-101.

Lim, K. B., Lau, K. H., Yeo, S. F., & Tan, C. L. (2025). Factors Influencing Generation Z's Adoption of AI in Banking: An Extended Technology Acceptance Model Approach. Journal of Logistics, Informatics and Service Science.

Lynch, Clifford. "Stewardship in the" Age of Algorithms"." First Monday (2017).

Ma, J., Wang, P., Li, B., Wang, T., Pang, X. S., & Wang, D. (2025). Exploring user adoption of ChatGPT: A technology acceptance model perspective. International Journal of Human–Computer Interaction, 41(2), 1431-1445.

Manoharan, G. (2024). Bridging the AI Gap: Adoption Strategies for Small and Medium-sized Banks in a Digital Era. International Journal of Advanced Research and Emerging Trends, 1(2), 86-92.

Mei, H., Bodog, S. A., & Badulescu, D. (2024). Artificial intelligence adoption in sustainable banking services: the critical role of technological literacy. Sustainability, 16(20), 8934.

Meraj, M., Ishrat, I., & Kaur, M. (2025). FinTech adoption in the UAE: total interpretive structural modeling of drivers and challenges. Qualitative Research in Financial Markets.

Pahari, S., Polisetty, A., Sharma, S., Jha, R., & Chakraborty, D. (2023). Adoption of AI in the banking industry: A case study on Indian banks. Indian Journal of Marketing, 53(3), 26-41.

Papathomas, A., Konteos, G., & Avlogiaris, G. (2025). Behavioral drivers of AI adoption in banking in a Semi-Mature digital economy: a TAM and UTAUT-2 analysis of stakeholder perspectives. Information, 16(2), 137.

Park, D. H., Jiang, Q., Ko, E., Son, S. C., & Kim, K. H. (2025). AI transformation and AI adoption intention in B2B environment. Journal of Global Scholars of Marketing Science, 1-19.

Rahman, M., Ming, T. H., Baigh, T. A., & Sarker, M. (2023). Adoption of artificial intelligence in banking services: an empirical analysis. International Journal of Emerging Markets, 18(10), 4270-4300.

Setiawan, R. J., & Ma'ruf, K. (2025). Determining Factors Influencing Indonesian Higher Education Students' Intention to Adopt Artificial Intelligence Tools for Self-Directed Learning Management. European Journal of Educational Research, 14(3), 805-828.

Talha, M., Nasreen, F., Farooq, L., & Fatima, D. (2025). Evaluating The Perceived Usefulness And Ease Of Adoption Of Artificial Intelligence Tools In Teaching. Journal of Social Signs Review, 3(05), 340-352.

Vidarshika, W., Dayapathirana, N., & Ranasinghe, A. (2025, April). Understanding AI Chatbot Adoption in Education: The Role of Perceived Usefulness, Ease of Use, and Anthropomorphic Tendencies. In 2025 International Research Conference on Smart Computing and Systems Engineering (SCSE) (pp. 1-6). IEEE.

Xu, W., Ismail, M., Shahruddin, S., Quan, W., & Li, Y. (2025). Exploring Tourists' Intentions to Adopt Augmented Reality in Cultural Heritage Museums: Insights From a Modified Technology Acceptance Model. SAGE Open, 15(2), 21582440251339936.

Zhang, H., Li, B., Hu, B., & Ai, P. (2025). Exploring the Role of Personal Innovativeness on Purchase Intention of Artificial Intelligence Products: An Investigation Using Social Influence Theory and Value-Based Adoption Model. International Journal of Human–Computer Interaction, 1-15.