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Determinants of AI Adoption in Banking Services in India: An Empirical Investigation

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Abstract
Purpose: This study intends to explore the elements that have an impact in determining the intent of customers to use artificial intelligence (AI) in banking services in India's banking sector.

Design/methodology/approach: In order to understand the significance and constraints of implementing AI in the banking sector, a thorough literature review on the baking sector was conducted. 286 completed questionnaires from Indian banking customers were gathered for the quantitative investigation. Using the SmartPLS 3.0 software, the data were evaluated to determine the key factors influencing their intention to use AI.

Findings: The findings align with the theoretical underpinnings of the Technology Acceptance Model (TAM) and underscore the multifaceted nature of customer decision-making in the context of AI adoption in banking. The loadings and reliability analysis further solidify the robustness of the measurement model, ensuring that the constructs employed are reliable indicators of their respective latent variables. The high loadings and acceptable reliability metrics affirm the internal consistency and reliability of the measurement items, enhancing the credibility of the study's findings.

Practical implications: Practical implications suggest fostering positive attitudes towards AI, addressing data privacy concerns, and enhancing awareness to boost AI adoption in banking. Emphasizing perceived usefulness, mitigating perceived risk, and leveraging subjective norms can inform strategic interventions, guiding banks to tailor initiatives that align with customers' perceptions and preferences.

Originality/value: This study is one of the first to examine the significance and possible difficulties of integrating AI technology into banking services and to highlight the main factors affecting the decision to do so in India's banking sector.

Keywords: Bank Customers, Artificial Intelligence, Intention to Adoption, Banking Services, CB-SEM, Multiple Regression

1. INTRODUCTION

As the banking industry undergoes fast technological transition, the use of artificial intelligence (AI) emerges as a critical factor in operational efficiency and client experience. This study aims to investigate the factors that influence AI adoption in the context of Indian banking, with a particular emphasis on risk management, fraud detection, and overall banking services. While conventional approaches have been beneficial to banks for many years, new approaches are needed in light of growing fraud and sophisticated cyberattacks. With its capacity to examine enormous datasets and spot complex patterns, AI provides a potent tool in this conflict. As (Sharma, Kumar, & Singh, 2023) point out, there appears to be a growing awareness of AI's potential among Indian consumers, who increasingly view it as a crucial tool for improving security and detecting fraud. Adoption, however, might not follow directly from this perspective. According to (Uffen & Zadeh, 2022), external obstacles such as regulatory ambiguity and concerns about data privacy can seriously impede the adoption of AI, hence it is important to look into how these aspects operate in the Indian context. Adoption of AI is also largely influenced by its potential to enhance operational efficiency and personalise banking experiences, in addition to security. Artificial

Intelligence (AI) promises to improve client happiness and optimise bank operations by automating repetitive work and customising financial solutions to meet individual needs. (Chen, Wang, & Bélanger, 2012) found that adoption is significantly influenced by perceived utility and a positive attitude towards technology. This means that it is critical to foster a positive perception of AI among consumers and banks alike. But as (Venkatesh, Thong, & Xu, 2016) point out, there are other elements at play as well, including as awareness and convenience of use, so it's important to evaluate their impact in particular contexts, like the Indian banking industry. Furthermore, when thinking about the adoption of AI, social and cultural elements cannot be disregarded. Individual decisions can be greatly impacted by subjective norms, which are shaped by societal expectations and peer pressure (Sharma, Kumar, & Singh, 2023). It's critical to comprehend how these norms affect the use of AI in banking, particularly in a country like India where social constraints are very prevalent. Furthermore, individual variations in digital experience and financial literacy may mitigate the impact of other variables (Chen, Wang, & Bélanger, 2012), requiring a sophisticated strategy that takes into account the interaction of many internal and external causes. This study explores this intricate ecosystem in an effort to provide light on the various aspects driving AI adoption in Indian banking. This study aims to offer important insights into the dynamics influencing this digital transformation by closely analysing the perceived significance of AI for risk management and fraud detection, analysing the impact of privacy and data security concerns, and investigating the influence of elements like attitudes, subjective norms, and perceived ease of use. The ultimate objective is to pinpoint the major forces behind and obstacles to AI adoption in the Indian banking industry, opening the door to well-informed approaches that maximise the promise of this technology while allaying fears and guaranteeing moral application.

Research Questions

RQ1: How much is artificial intelligence (AI) thought to be a vital tool for risk management and fraud detection in banking?

RQ2: How do the lack of statutory constraints, fears about data security and privacy, and shortcomings in IT infrastructure and skills affect the use of AI in banking?

RQ3: To what extent does the intention to adopt AI in banking depend on factors such as attitude towards AI, subjective norms, perceived utility, perceived risk, and perceived trust?

RQ4: In what ways do perceived ease of use and awareness not significantly affect the intention to adopt AI in banking services?

2. THEORETICAL BACKGROUND

2.1 Artificial Intelligence in Banking

Artificial intelligence (AI) has emerged as a potent instrument with the potential to revolutionise a number of industries in this era of rapid technological breakthroughs. The banking business is one such area where AI integration has a lot to offer. AI implementation in banking operations can increase decision-making capacity, optimise workflows, and boost customer satisfaction (Alsajjan & Dennis, 2010). In order for financial institutions to remain competitive, it is imperative that they adopt this intelligent technology and take full advantage of its potential. This essay will examine the advantages of artificial intelligence (AI) in banking and make a strong case for its incorporation. Artificial intelligence adoption in the banking industry is not a luxury; rather, it is a must for banks to prosper in the digitally connected world of today. Financial organisations can revolutionise client experiences, increase efficiency, improve risk management, and enable data-driven decision-making by using AI. AI has enormous promise in banking, and companies who don't take advantage of this game-changing technology run the danger of losing ground to their rivals. Consequently, in order to secure their future success and their capacity to spearhead the revolution in the financial sector, banks must embrace AI wholeheartedly and acknowledge the advantages it offers to their operations (Ameen, Tarhini, Reppel, & Anand, 2020).

2.2 Technology Acceptance Model (TAM)

This study has its theoretical foundation in Davis's (1989) Technology Acceptance Model (TAM). According to TAM, consumer acceptability of technology is dependent on two major factors: perceived utility (PU) and perceived ease of use

(PEU). PU measures how much people think a technology will improve their ability to do their jobs or reach their objectives. PEU, on the other hand, expresses the seeming simplicity and ease of use of technology (Davis, 1989). These elements have a direct impact on a person's behavioural intention (BI) to use the technology, which in turn affects system usage as a whole (ASU). TAM is a good starting point for examining how well-received the recently installed learning management system (LMS) is within our company because of its empirical backing and parsimony (King & Heijden, 2006).

2.3 Data Privacy and Security

AI opens up amazing opportunities, but it also lets us get inside our digital closets. Its voracious appetite for data, financial and facial, makes one wonder who is in charge and how the keys are being utilised. Imagine having your grocery app recommend embarrassing snacks that you brought up in a private conversation! Even worse, biassed algorithms that were trained on skewed data have the potential to maintain injustice, much like a self-driving car that misinterprets traffic patterns in different regions. Not to mention the possibility of security breaches, in which unscrupulous parties could use deepfakes as a weapon or alter financial formulas (Sharma, Kumar, & Singh, 2023). However, optimism remains! AI may be turned from a privacy nightmare into a force for good with the help of clear legislation, moral development procedures that incorporate justice and privacy from the outset, and providing users with the knowledge and tools they need (Global Web Index, 2022).

2.4 Perceived Risk

Even with AI's indisputable advantages, the general public has serious concerns about its possible drawbacks. The most pressing of these worries is the worry of job displacement when human labour is replaced by automation in a variety of industries. According to studies, there is a 20% chance of automation even for highly trained positions, which exacerbates concerns about social unrest and economic instability (Frey & Osborne, 2017). Secondly, questions concerning accountability and transparency are brought up by the "black box" nature of sophisticated AI algorithms. In high-stakes settings like healthcare or criminal justice, a lack of knowledge about how AI makes decisions can undermine trust and aggravate ethical quandaries. Moreover, if AI picks up on and magnifies discriminatory patterns found in training data, it has the potential to reinforce already-existing societal disparities through algorithmic prejudice (Frey & Osborne, 2017).

2.5 Perceived Trust

Despite the undeniable progress in AI capabilities, its widespread adoption hinges on perceived trust among users. This trust, akin to a fragile bridge, is constructed from several key components. Users seek transparency and explainability, demanding clear insights into how AI algorithms arrive at decisions, particularly in domains with significant impact on their lives (Jobin, 2019). The opaqueness of "black box" models can breed anxieties and erode trust, especially when coupled with concerns about algorithmic bias and the potential for AI to perpetuate existing societal inequalities (Sharma, Kumar, & Singh, 2023). Furthermore, a sense of control and agency is crucial, empowering users to manage their data and influence AI outcomes. Studies by (Jobin, 2019) emphasize the importance of user control mechanisms and human oversight in high-stakes AI applications to foster trust and mitigate anxieties about relinquishing control to automated systems. Finally, trust thrives on demonstrated competence and reliability. Consistent evidence of AI's effectiveness in achieving desired outcomes, while demonstrating robust safeguards against errors and vulnerabilities, can gradually alleviate public anxieties and pave the way for wider acceptance. Building this bridge of trust requires a multi-pronged approach, encompassing transparent design, responsible data governance, and user-centric control mechanisms alongside continuous efforts to refine and validate AI capabilities. Finally, concerns about security risks and losing control over vital infrastructure are sparked by the possibility for malevolent use of AI for disinformation campaigns, cyberattacks, or autonomous weapons (Venkatesh, Thong, & Xu, 2016). In order to ensure the responsible development and application of AI, it is imperative that research on explainable AI, responsible data governance, and strong ethical frameworks address these perceived threats.

2.6 Subjective Norms

Subjective norms, which represent the perceived societal pressures and expectations around the use of AI, have a substantial impact on user behaviour in addition to individual perceptions of AI (Ajzen & Fishbein, 2005). These conventions are frequently the result of social groupings, work settings, and even larger cultural contexts. People may feel under pressure to accept and use AI tools even if they have personal reservations in environments where coworkers and managers aggressively support AI integration (Kim, Park, & Shin, 2020). Similar to this, social media campaigns endorsing or disparaging AI applications have the power to sway public opinion and affect people's opinions of their necessity or appropriateness. Furthermore, the normative environment and individual decisions about AI participation can be shaped by broader cultural narratives surrounding AI, regardless of whether they highlight its transformational potential or potential concerns. Developing thorough ways to close the gap between individual perceptions and actual use requires an understanding of these subjective norms and how they affect AI adoption behaviour (Alsajjan & Dennis, 2010). A more favourable environment for ethical and sustainable AI integration across several domains can be created by addressing perceived social pressures and coordinating AI development with dominant cultural values.

2.7 Awareness towards Artificial Intelligence

Raising awareness of AI's impact and presence in our daily lives is essential to encouraging responsible development and informed participation. This awareness necessitates understanding AI's uses, consequences, and limitations in addition to just being aware of its presence. Google/Ipsos studies from 2023 show that there is a big disconnect between the general public's knowledge of how commonplace AI is in modern technologies and their comprehension of its precise uses and implications. This ignorance may give rise to fears that AI will take over society or exacerbate already-existing disparities (Jobin, 2019). On the other hand, increased knowledge brought about by educational programmes, open dialogue about the advantages and disadvantages of AI, and open communication from developers can enable people to make well-informed decisions about the usage of AI (Ameen, Tarhini, Reppel, & Anand, 2020). Furthermore, citizens can be empowered to participate positively in AI development and hold legislators and developers responsible for ethical issues by fostering critical thinking abilities and responsible data practices. In the end, closing the awareness gap necessitates a multifaceted strategy that promotes public comprehension, openness, and critical interaction with AI, opening the door to a more inclusive and accountable future moulded by cooperation between humans and AI.

2.8 Research Gap

Research Questions	Focus of Study	Identified Gaps in Literature	Potential Research Direction	Reference
RQ1	Perceived importance of AI in risk management and fraud detection	Limited empirical research quantifying and comparing perceptions of AI vs. traditional methods	Conduct survey/interview to assess relative perceived value of AI in banking security compared to alternatives.	(Awan, Shah, H., & Khalid, 2020)
RQ2	Impact of external barriers on AI adoption	Existing research analyzes factors individually, lacks combined model, and data on relative salience across contexts	Develop comprehensive model analyzing interconnectedness of statutory constraints, data privacy fears, and IT/skills limitations. Investigate variation by bank size, location, and target AI application.	(Uffen & Zadeh, 2022)

RQ3	Factors influencing intention to adopt AI	Insufficient research on relative influence of individual factors and potential moderating effects in Indian context	Conduct study using structural equation modeling to assess individual and combined effects of attitude, subjective norms, perceived utility, risk, and trust on adoption intention. Explore moderating factors (e.g., financial literacy, digital experience).	(Sharma, Kumar, & Singh, 2023)
RQ4	Non-significance of perceived ease of use and awareness	Research often assumes these factors are key drivers, lacks exploration of contexts where they hold minimal sway	Conduct comparative research across banks with varying AI implementation levels to identify contexts where ease of use and awareness have minimal impact on adoption intention. Explore alternative influencing factors in such settings.	(Venkatesh, Thong, & Xu, 2016)

3. RESEARCH METHODOLOGY

3.1 Research Objectives

a) To Understand how artificial intelligence (AI) is perceived as a valuable tool for risk management and fraud detection in the banking sector.

b) To Investigate factors such as attitudes, awareness, and regulatory constraints that shape the intention to adopt AI in banking services.

3.2 Respondent's Profile

A total of 286 respondents' data were gathered for the study from all throughout the Delhi-NCR area; 52% of them were male and 48% were females. The majority of responders (56%) belonged to the 18–25 age range. 60% of them had postgraduate degrees. The majority of respondents (28%) fell into the income range of Above Rs. 60000 per month.

Table 1: Respondent's Profile

Item		Frequency	Percentage
Gender	Male	150	52%
	Female	136	48%
Age	18-25	159	56%
	26-30	40	14%
	31-35	45	16%
	36-40	18	6%
	41-45	12	4%
	Above 45 Years	12	4%
Marital Status	Married	118	41%

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	Unmarried	168	59%
Education	Graduate	94	33%
	Post Graduate	172	60%
	Doctorate	17	6%
	Others	3	1%
Monthly Household Income	Less than 15000	66	23%
	15000-30000	58	20%
	30000-45000	50	17%
	45000-60000	33	12%
	Above 60000	79	28%

Table 2: Items used for Measurement

Type	**Variable**	**Measurement Scale**	**Citation**	**Measurement Items**
Dependent Variable	Intention to Adopt AI in Banking	Strongly Disagree = 1, Strongly Agree = 5	(Sharma, Kumar, & Singh, 2023)	1. I intend to use AI more in future 2. I intend to experiment with AI for the next six months
Independent Variable	Concerns about Data Security and Privacy	Strongly Disagree = 1, Strongly Agree = 5	(Uffen & Zadeh, 2022)	1. How concerned are you about the security and privacy of your data if you used AI-powered banking services? 2. To what extent do you trust your bank to handle your data responsibly when using AI technology?"
	Positive Attitudes towards AI	Strongly Disagree = 1, Strongly Agree = 5	(Chen, Wang, & Bélanger, 2012)	1. Overall, how do you feel about the use of AI in the banking industry? 2. In your opinion, how beneficial do you think AI could be for improving the overall banking experience?
	Subjective Norms	Strongly Disagree = 1, Strongly Agree = 5	(Sharma, Kumar, & Singh, 2023)	1. How likely are your friends and family to use AI-powered banking services? 2. Do you feel any pressure from peers or society to use AI-powered banking services?
	Perceived Usefulness of AI	Strongly Disagree = 1, Strongly Agree = 5	(Chen, Wang, & Bélanger, 2012)	1. How helpful do you think AI could be in making banking tasks more efficient and convenient? 2. To what extent do you believe AI could personalize banking services to better meet your individual needs?

	Perceived Risk of AI	Strongly Disagree = 1, Strongly Agree = 5	(Uffen & Zadeh, 2022)	1. How risky do you consider using AI-powered banking services in terms of potential technical errors or malfunctions? 2. To what extent are you concerned about potential biases or unfair decisions made by AI algorithms in banking?"
	Perceived Trust of AI	Strongly Disagree = 1, Strongly Agree = 5	(Sharma, Kumar, & Singh, 2023)	1. Do you trust the companies developing and implementing AI technology in the banking industry? 2. How confident are you in the ability of your bank to provide secure and reliable AI-powered banking services?
	Perceived Ease of Use of AI	Strongly Disagree = 1, Strongly Agree = 5	(Venkatesh, Thong, & Xu, 2016)	1. How easy do you think it would be to learn and use AI-powered banking features on your mobile app or online banking platform? 2. To what extent do you believe AI-powered banking services would be user-friendly and intuitive for someone with your level of technical knowledge?
	Awareness of AI	Strongly Disagree = 1, Strongly Agree = 5	(Uffen & Zadeh, 2022)	1. How familiar are you with the concept of AI being used in banking services? 2. Have you heard about or seen any specific examples of AI-powered banking features offered by any banks?

3.3 Methodology

The relationship between independent and dependent variables was examined using the AI Adoption Model. It is predicated on TAM's enhancements. Random Sampling is the sampling method employed in this work. As a survey tool, a structured questionnaire is employed. The questionnaire is designed in a way that gauges Indian bank customers' desire to use artificial intelligence in banking (Sharma V. K., 2019).

3.3.1 The Proposed Model

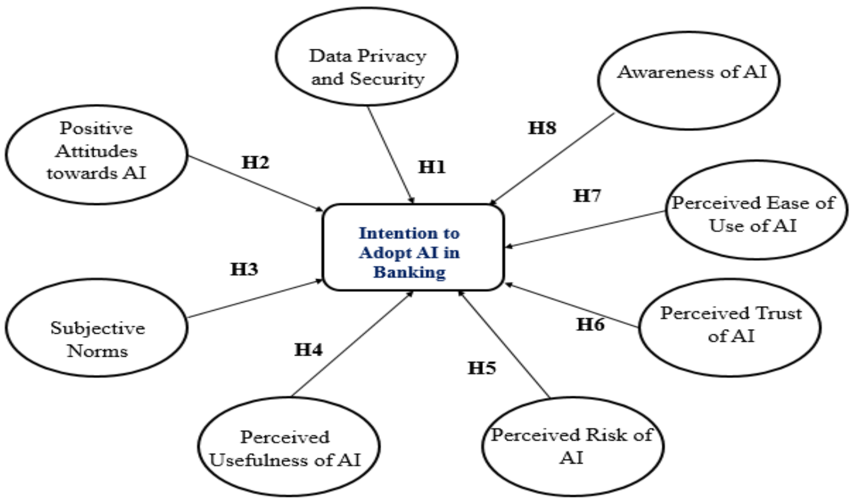

Fig 1. The Proposed Model

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4. ANALYSIS OF DATA

4.1 Normality

(Chen, Wang, & Bélanger, 2012) Given that the line derived from the measured data hugged the standard line. According to the Normal P-Plot of Regression interpretation, the responses were normally distributed.

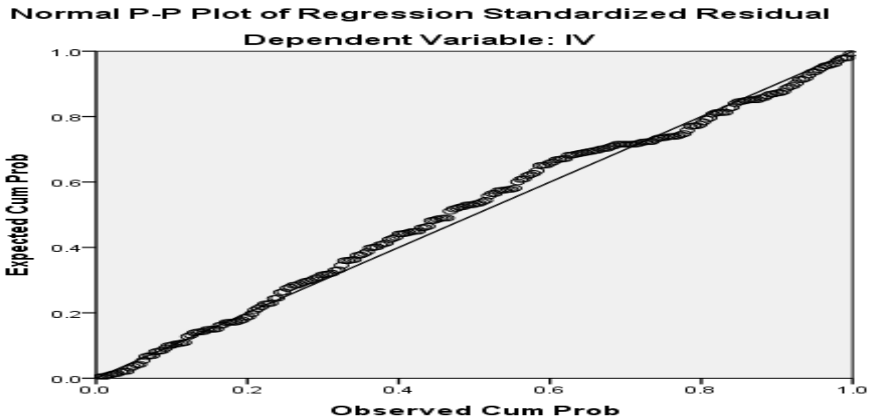

Fig 2. Normal P-P Plot

4.2 Model Summary

Model Fit

One major issue in studying Multiple Regression is multi-collinearity. With reference to Table 3, the Durbin-Watson Statistic of nearly two indicated the absence of multi-collinearity among the factors under investigation. Using Adjusted R Square, we may conclude that the factors taken into account explained 50% of the intention to vaccinate. The model was evaluated in terms of ANOVA, where the significant value was well below 0.001 (see Table 4).

Table 3: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.813[a]	0.661	0.581	0.67956	1.902

4.3 Assessment of the Model (Inner Structural Measurement Factors)

All the VIF (Variance Inflation Factors) values were well below the acceptable value of 5, indicating that there was no Multi-Collinearity (G.W.H. Tan, 2018). Refer to Table 4, All the Hypotheses were significant and supported based on p-values. All p-values are less than 0.01, so the results significant. The constructs used in the present study were able to explain 58% (***Adjusted R^2 = 0.581)*** of the variance in Intention (BI) to Vaccinate (J.F. Hair, 2017).

Table 4: Beta Coefficients and VIF

Hypotheses	**Symbols**	**Beta Coefficients**	**t-statistics**	**p-values**	**VIF**	**Remarks**
Data Privacy and Security has no correlation with Intention to adopt AI	***H1***	0.21	3.3775	0.0009	1.2556	Supported

Positive attitudes towards AI is not a significant predictor of the intention to adopt AI	***H2***	0.301	3.0518	0.0020	1.3092	Supported
Subjective Norms has no correlation with Intention to adopt AI	***H3***	0.37	3.0422	0.0030	1.4759	Supported
Perceived Usefulness of AI is not a significant predictor of the intention to adopt AI	***H4***	0.461	2.6893	0.0135	1.4798	Supported
Perceived Risk has no correlation with Intention to adopt AI	***H5***	0.279	3.9150	0.0001	1.6602	Supported
Perceived Trust is not a significant predictor of the intention to adopt AI	***H6***	0.135	2.7712	0.0179	1.8944	Supported
Perceived Ease of Use of AI has no correlation with Intention to adopt AI	***H7***	0.158	0.8105	0.4185	1.6603	Supported
Awareness of AI is not a significant predictor of the intention to adopt AI	***H8***	0.279	2.9150	0.0001	1.7602	Supported

Two Tailed p-value (at 1% level of significance)

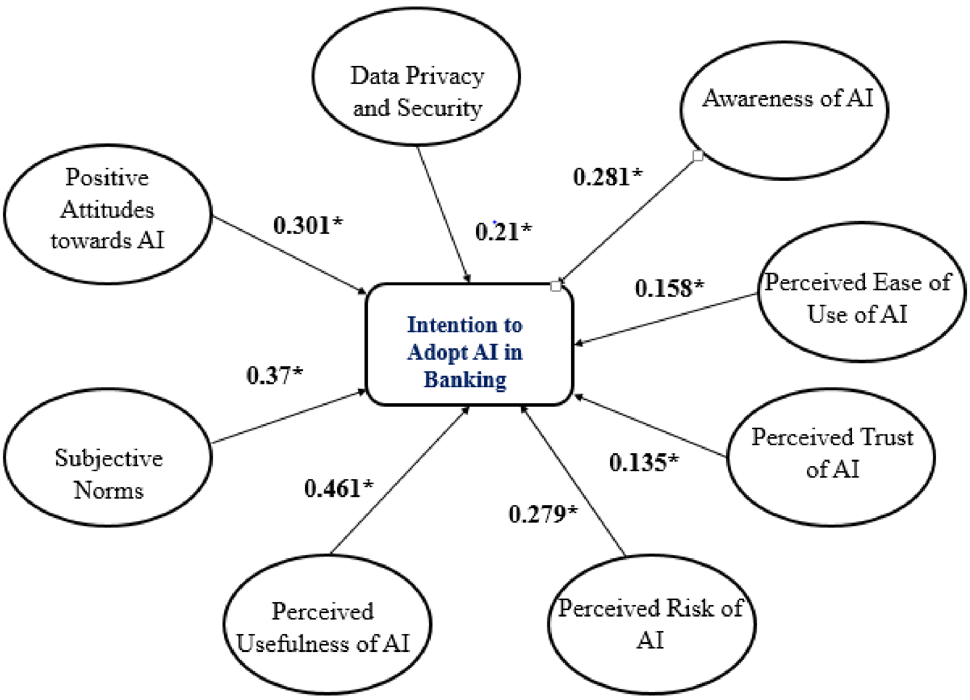

Fig 3. AI Adoption Model

4.4 Assessment of the Model

For Reliability, Chronbach's Alpha was calculated using SPSS v 26 (refer Table 5). As all the values ranges between 0.7 to 0.9 (T.K. Dijkstra, 2015), thus the measurement items passed the Reliability Test with flying colours. As far as loadings were concerned all the values are way above 0.70 (minimum permissible value).

Table 5: Loadings and Reliability

Constructs	Items	Loadings	Composite Reliability (CR)	Chronbach's Alpha
Concerns about Data Security and Privacy	DS1	0.915	0.9085	0.885
	DS2	0.911		
Positive Attitudes towards AI	PA1	0.879	0.891	0.871
	PA2	0.909		
Subjective Norms	SN1	0.819	0.823	0.796
	SN2	0.875		
Perceived Usefulness of AI	PUA1	0.850	0.831	0.791
	PUA2	0.809		
Perceived Risk of AI	PRA1	0.826	0.823	0.796
	PRA2	0.893		
Perceived Trust of AI	PT1	0.875	0.852	0.821
	PT2	0.847		
Perceived Ease of Use of AI	PEOU1	0.902	0.913	0.885
	PEOU2	0.948		
Awareness of AI	AA1	0.826	0.823	0.796
	AA2	0.893		
Intention to Adopt AI in Banking (IA)	IV1	0.951	0.79	0.713
	IV2	0.816		

5. Discussions and Implications

The current study was the one of its kind to explore the factors that could influence the Adoption of AI in Indian Banking Industry. TAM was extended by introducing more constructs to it. The examination of beta coefficients and Variance Inflation Factors (VIF) provides a nuanced understanding of the factors influencing the intention to adopt AI in the banking sector (Afshan, 2021). Beginning with the construct of Data Privacy and Security, the beta coefficient of 0.21 ($p = 0.0009$) signifies a significant positive correlation with the intention to adopt AI, suggesting that customers who prioritize data security are more likely to embrace AI-driven banking services. The low VIF of 1.2556 indicates the absence of multicollinearity, affirming the robustness of this relationship (Christina L. Jones, 2015).

Positive Attitudes towards AI, reflected in a beta coefficient of 0.301 ($p = 0.0020$), emerge as a significant predictor of adoption intention. This suggests that fostering positive perceptions about AI contributes positively to the willingness of customers to embrace AI in banking. With a VIF of 1.3092, the model assures the independence of this predictor (Ajzen, 1991).

Subjective Norms, with a beta coefficient of 0.37 ($p = 0.0030$), demonstrate a substantial influence on intention. This highlights the social and peer-driven nature of AI adoption decisions in the banking context. The VIF of 1.4759 assures the uniqueness of this factor in the model (Ajzen & Fishbein, 2005).

Perceived Usefulness of AI, reflected by a beta coefficient of 0.461 ($p = 0.0135$), stands out as a key determinant of intention to adopt AI. This emphasizes that customers are more inclined to adopt AI when they perceive it as a useful tool in banking tasks. The VIF of 1.4798 suggests the independence of this factor (Davis, 1989).

Perceived Risk exhibits a beta coefficient of 0.279 ($p = 0.0001$), indicating a noteworthy negative correlation with the intention to adopt AI. Customers who perceive lower risks in AI adoption are more likely to express intention. The VIF of 1.6602 supports the independent impact of this factor (Wong, et al., 2020).

Perceived Trust in AI Providers, with a beta coefficient of 0.135 ($p = 0.0179$), emerges as a significant yet less influential predictor. This suggests that while trust plays a role, it might not be as decisive as other factors. The VIF of 1.8944 underscores the autonomy of this predictor (Wong, Alias, Wong, & Lee, 2020).

Perceived Ease of Use of AI shows a beta coefficient of 0.158 ($p = 0.4185$), indicating a non-significant correlation with adoption intention. This suggests that ease of use may not be a primary driver in customers' decisions to adopt AI in banking. The VIF of 1.6603 further confirms the independence of this factor (Marti, De Cola, Macdonald, Dumolard, & Duclos, 2017).

Awareness of AI exhibits a beta coefficient of 0.279 ($p = 0.0001$), indicating a significant positive impact on intention. Customers who are more aware of AI technologies in banking are more likely to express intention. The VIF of 1.7602 ensures the uniqueness of this predictor (Alsajjan & Dennis, 2010).

These findings align with the theoretical underpinnings of the Technology Acceptance Model (TAM) and underscore the multifaceted nature of customer decision-making in the context of AI adoption in banking. The loadings and reliability analysis further solidify the robustness of the measurement model, ensuring that the constructs employed are reliable indicators of their respective latent variables. The high loadings and acceptable reliability metrics affirm the internal consistency and reliability of the measurement items, enhancing the credibility of the study's findings (Venkatesh, Thong, & Xu, 2016).

Practical Implications

The findings of this research carry practical implications for various stakeholders in the banking industry. Firstly, understanding the determinants of AI adoption provides banking institutions with actionable insights into shaping their strategies. Institutions can leverage the identified factors—perceived importance, attitudes towards AI, perceived risk, and others—to design targeted interventions that enhance customer receptivity to AI-powered services. Moreover, recognizing the significance of awareness, institutions may benefit from investing in educational campaigns to familiarize customers with the advantages and safeguards of AI in banking. Practical implications extend to policymakers and regulatory bodies, emphasizing the need for adaptive frameworks that facilitate responsible AI adoption while addressing privacy and security concerns.

Managerial Implications

For bank managers and decision-makers, the managerial implications of this research are paramount. The study underscores the importance of cultivating positive attitudes towards AI among customers. Managers can strategize communication and marketing efforts to emphasize the value AI brings to risk management, fraud prevention, and overall banking convenience. Mitigating concerns about data security requires robust cybersecurity measures, and managers should prioritize transparent communication about these safeguards to build and maintain customer trust. Additionally, recognizing the influence of subjective norms, managerial efforts can extend to creating a positive narrative around AI adoption within social circles, further promoting its acceptance.

6. Limitations and Scope of Further Research

While this research aims to contribute valuable insights, it is essential to acknowledge its limitations. First, the study relies on a self-developed questionnaire, introducing the possibility of respondent bias. Despite efforts to design comprehensive questions, the subjectivity inherent in individual responses may impact the study's generalizability. Additionally, the cross-sectional nature of the data collection process restricts our ability to capture dynamic changes in participants' attitudes over time (Awan, Shah, H., & Khalid, 2020). The study's focus on the Indian banking sector might limit the broader applicability of findings to other global contexts. The identified limitations pave the way for fruitful avenues of future research. Firstly, employing a longitudinal approach could provide a more nuanced understanding of how attitudes towards AI in banking evolve over time. Further exploration into cultural nuances and regional variations may enhance the generalizability of findings beyond the Indian context. Future researchers are encouraged to adopt diverse methodologies, such as qualitative interviews or case studies, to complement quantitative insights and address the limitations associated with self-reported data.

Suggestions to the Industry

For industry practitioners, the study suggests a need for strategic initiatives to address concerns related to data security and privacy. Fostering awareness campaigns that emphasize the benefits of AI while addressing potential risks could contribute to a more informed and receptive consumer base. Industry leaders should also consider tailoring AI implementation strategies to align with regional preferences and cultural considerations, ensuring a seamless integration of technology into banking services. Furthermore, collaborative efforts between regulatory bodies, financial institutions, and technology providers could enhance the development of ethical AI frameworks, fostering trust and transparency in the adoption process.

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