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Customer Trust in Era of AI: Examining the Adoption of Artificial Intelligence in Public and Private Sector Banking

Abstract

Purpose – This research throws light on the factors creating customer trust in AI in Indian banking sphere of public and private banks. It examines the ways in which usefulness, ease of use, security, and awareness of AI shape customer attitudes and intentions toward AI adoption, which contribute to their trust in AI. The mediating effects of attitude and behavioural intention between these perceptions and trust formation are also contemplated in investigation.

Design/methodology/approach – In an attempt to confirm the model, data were gathered from 453 Indian bank customers via a structured questionnaire. PLS-SEM was administered for the evaluation of the proposed conceptual model, while MGA was conducted for comparing the responses of public sector versus private sector bank users.

Findings – Perceived security turns out to be the strongest factor influencing attitude toward AI and intention to use AI, followed by ease of use and usefulness. Attitude and intention are significant mediators between technological perceptions and customer trust. Contrary to expectations, AI knowledge had no influence on trust, neither directly nor indirectly. Another set of results relates to the sectorial differences of those customers: customers in public sector emphasized security all the more.

Research Limitations/Implications – The cross-sectional nature of this study constrains analysis over time, and the results may not be generalized to the population beyond digitally literate respondents in India. Future works can follow the longitudinal and qualitative approach, including more constructs like algorithmic transparency, and extending the model to other service industries.

Originality/Value – The research investigates an extension of the Technology Acceptance Model through more trust-related variables concerning AI in banking. It provides practical as well as theoretical contributions by unravelling psychological and perceptual factors underlying AI trust, particularly in an emerging economy. The insights give bank managers and policymakers a conscious starting point for promoting responsible and inclusive AI adoption.

Keywords: Artificial Intelligence, Customer Trust, Banking Services, Technology Acceptance Model, PLS-SEM, India, Digital Banking, AI Adoption

1. Introduction

There has been a radical change in delivery and experiences of financial services in digital era owing to the rapid technological advancement brought about by AI in financial sector **(Peltier, Dahl and Schibrowsky, 2024)**. The provision of quality services, efficiency, and interaction with customers by implementing AI technologies are areas in which the banking industry is pressured to perform well in digital economy **(Tam and Oliveira, 2017).** AI in banking is all about smarter and quick operations, including uses such as chatbots, fraud detection mechanisms, predictive analysis, and tailored financial advice **(Kou *et al.*, 2021; Marr, 2019)**. However, while undoubtedly being transformative, customer trust remains a key issue in acceptance and sustained use of AI-laden banking services **(Lankton, McKnight and Tripp, 2015**; **Merhi and Harfouche, 2024).**

Trust in digital systems, especially in sensitive sectors like banking, is basically determined by customers' perceived usefulness or ease of use of AI systems **(Rahman *et al.*, 2023; Noreen *et al.*, 2023)**. Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), as delineated by the Technology Acceptance Model (TAM), are instrumental in determining the attitude shown by customers toward a technological innovation **(Abdullah, Ward and Ahmed, 2016)**. In banking, Perceived Usefulness and Perceived Ease of Use have become the central constructs inseparably influencing Attitudes Toward AI (ATA), which in turn affect the behavioural intention and trust of customers **(Yoon and Steege, 2013; Shin, 2021)**.

Attitude toward AI entails customers' affective and cognitive evaluations that further serve as mediating factors between perceived technological characteristics and their behavioural responses **(Della Corte *et al.*, 2023)**. Moreover, Intention to Use AI (ITUA) is predicated on various factors through which customers perceive its transparency, security, and reliability as being the foremost attributes that engender the trust of automated services **(Bock, Wolter and Ferrell, 2020**; **Makarius *et al.*, 2020)**. It is then imperative for both public and private sector banks to cultivate a positive attitude in customers toward AI, further fortifying their intention to use AI-centered solutions and sustain mutual relations of trust.

Though there have been ample investigations on various technical and operational dimensions of AI in banking **(Dwivedi and Kochhar, 2023)**, until now, few studies have paid attention to understanding the psychological and perceptual antecedents affecting trust along attitudinal and intentional pathways. This gap becomes ever more visible in comparative scenario of public and private sector banks in emerging economy like India, where dissimilarities in customer experience, technological infrastructural development, and service expectations could give rise to divergent trust-related outcomes (Sholevar and Bachmann, 2025).

Hence, this study attempts to understand the processes of customers perceiving and adopting AI-based services in banking industry and how such perception of AI service affects trust through attitude and behaviour. The aim, thus, is to pinpoint how Attitudes Toward AI and Intention to Use AI mediate the transformation of technological perceptions into trust outcomes.

Research Questions

RQ1. What is the influence of Perceived Usefulness (PU) on customers' Attitudes Toward AI (ATA) in online banking?

RQ2. How does Perceived Ease of Use (PEOU) affect Attitudes Toward AI (ATA) in context of banking services?

RQ3. What is the impact of Attitudes Toward AI (ATA) on the Intention to Use AI (ITUA)?

RQ4. How does Intention to Use AI (ITUA) influence Customer Trust (CT) in online banking services?

RQ5. What is the mediating role of Attitudes Toward AI (ATA) and Intention to Use AI (ITUA) in relationship between technological perceptions (PU, PEOU, KAAT, PS) and Customer Trust (CT)?

Research Objectives

1. To examine the influence of Perceived Usefulness (PU) on Attitudes Toward AI (ATA) in online banking services.

2. To assess the impact of Perceived Ease of Use (PEOU) on customers' Attitudes Toward AI (ATA).

3. To determine how Attitudes Toward AI (ATA) affect the Intention to Use AI (ITUA) in online banking.

4. To evaluate the influence of the Intention to Use AI (ITUA) on Customer Trust (CT) in banking services.

5. To identify the mediating role of Attitudes Toward AI (ATA) and Intention to Use AI (ITUA) in relationship between technological perceptions (PU, PEOU, KAAT, PS) and Customer Trust (CT).

The structure of this research paper is organized in five sections. The first section presents the introduction, gaps of research, and research questions that drive the study. The second section looks into the literature to frame the conceptual model and hypotheses. The third section pertains to outline the methodology of research and the method of data collection. The fourth section is concerned with the analysis of data and interpretations of findings. The fifth section concludes with the discussions, theoretical and managerial implications, limitations of the study, and directions to pursue in future research.

2. Literature Review

2.1 Theoretic Groundworks

Artificial Intelligence (AI) is the heart of recent innovations in financial services that improve customer relationships and fraud detection, loan processing, or predictive analytics **(Aziz and Andriansyah, 2023; Johora *et al.*, 2024)**. Building on the notions of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as major antecedents to forming attitudes and behavioural intentions towards new technologies introduced in Technology Acceptance Model (TAM) by **(Davis, 1989)**, the current research proceeds with these two dimensions **(Nguyen *et al.*, 2024)**. Hence, the implications of this theoretical foundation have been widely leveraged in banking to understand digital adoption **(Alalwan *et al.*, 2016)**.

Further, the Trust Theory extends into this study, bringing forth the necessity of implementing Trust Theory in AI systems **(Lukyanenko, Maass and Storey, 2022)**. Customer trust in AI systems stems from transparency, perceived fairness, and system reliability-all crucial for banking environments, which are high risk and sensitive to information **(Wong *et al.*, 2024**; **Wang and Siau, 2019)**. Consumers mostly assess AI systems from a rational-based perspective (performance-based: reasoning) versus an emotional trust-based perspective (security-based: intuition), positioning trust as a mediator of adoption decisions **(McKnight, Choudhury and Kacmar, 2002)**. Hence, the integration of TAM with trust-related constructs offers a more complete realization of AI adoption in private and public-sector banking banks.

2.1.1 Perceived Usefulness and Attitudes Toward AI

Perceived Usefulness (PU) means the user's belief that using a system will improve job performance **(Rawashdeh *et al.*, 2021)**. In banking, PU would mean faster processing of transactions, reduced errors, and better decision-making resulting from AI interventions **(Gupta and Agarwal, 2024; Oliveira *et al.*, 2014)**. It has been observed that customer attitudes change positively when AI programs such as chatbots or robo-advisors are deemed to be useful **(Belanche, Casaló and Flavián, 2019)**. **Brougham and Haar (2018)** noted that, in particular contexts such as digital banking where personalization and speed of service are highly desired, the perception of usefulness is more important. Therefore, PU has a significant effect on shaping the Attitudes Toward AI (ATA), opening the first link of the chain of acceptance of technology **(Papathomas, Konteos and Avlogiaris, 2025).**

2.1.2 Perceived Ease of Use and Attitudes Toward AI

Perceived Ease of Use (PEOU) is a person's expectancy that employing a particular system would be free of effort (Venkatesh & Bala, 2008). A system with easy-to-use interfaces, quick onboarding, and minimum learning efforts directly impacts customers' trust and confidence in using AI tools **(Baabdullah *et al.*, 2019).** A higher PEOU level positively affects customers' satisfaction and attitudes toward AI applications in digital banking platform **(Wang *et al.*, 2021)**. This is pertinent mostly towards customers with low levels of digital literacy, more-so being elderly, for whom the usability works either as an impediment or encouragement toward adoption of the technology **(Sørensen and Houmann, 2020)**. Designing AI systems to be super usable, therefore, improves accordance and lessens the emotional readiness of engaging with AI by customers **(Gao *et al.*, 2023)**.

2.1.3 Attitude Toward AI and Intention to Use AI

Attitudes Toward AI (ATA) result from beliefs, feelings, and experiences users hold in relation to intelligent technologies **(Lichtenthaler, 2020)**. When formed, favourable attitudes encourage a stronger Intention to Use AI (ITUA), which in turn may lead to adoption behaviour **(Emon and Khan, 2025)**. A sincere positive emotional association with AI that involves convenience, control, and safety becomes important in bridging attitudes into intentions **(Ahmed *et al.*, 2025)**. From a banking perspective, AI sits at the interface of trust, enmeshed in concerns regarding privacy, error, and accountability, and these will endow attitudes with the ability to connect technical competencies and customer behaviour **(Fundira, Edoun and**

Pradhan, 2024). This dynamic relationship of ATA and ITUA becomes the heart of analyzing AI adoption from a psychological and behavioural perspective.

2.1.4 Building Customer Trust through Mediating Mechanisms

Customer Trust (CT) in AI entails a belief in integrity, ability, and goodwill of the technology and those who deploy it **(Yang and Wibowo, 2022)**. Trust becomes central in case of banking, owing to the high-stake nature of financial transactions and absence of human supervision over AI systems **(Darangwa, 2021).** ATA and ITUA are mediators between PU, PEOU, and CT, enabling customers to translate their cognitive and emotional appraisal into trusting behaviours **(Fatokun, 2023)**. The need for this mediation mechanism is even more obvious when distinguishing between public and private sector banks, where the trust bestowed on technology could be filtered through the prism of brand image, past experiences in customer service, and regulatory opinions **(Kaushik and Rahman, 2015)**. A seasoned appreciation of these mediating constructs would allow the banks to devise solutions that, while promoting adoption, nurture sustained trust in AI-enabled service delivery.

2.2 Conceptual Framework

2.2.1 Constructs of Technology Perception and Attitude Toward AI

In a digital banking set-up, AI's success can be ensured depending on customers' technology perception and the resultant behaviour toward the technology. The present study includes the basic technology acceptance model constructs (Perceived Usefulness and Perceived Ease of Use) for customers to assess AI-enabled services. PU is defined as a customer's perception that AI may actually improve their efficiency; for example, by allowing quick services, reducing manual errors, and giving personalized recommendations **(Davis, 1989; Oliveira *et al.*, 2014)**. Studies have shown that higher PU would cause more favourable attitudes toward technology **(Lau and Woods, 2008; Porter and Donthu, 2006)**.

PEOU is another factor affecting users' comfort and the confidence of using digital services with minimal effort. Moreover, ease of use becomes very important in banking where the customer interacts with multiple applications and digital tools affecting the level of satisfaction and attitude **(Lean *et al.*, 2009; Prastiawan, Aisjah and Rofiaty, 2021)**.

Two additional constructs have been introduced to extend the TAM framework to the AI context: Knowledge About AI Technology (KAAT) and Perceived Security (PS). KAAT means an extent to which customers understand how AI works in banking system that can quell the fear of the unknown and become more open to adoption (Pelote, 2022). PS on the other hand refers to the extent to which customers feel safe that their personal and financial data are protected by the AI systems, something that is a huge concern when it comes to trust in domains such as banking **(Stewart and Jürjens, 2018)**.

Based on the above discussion, we put forth the hypotheses:

H1: Perceived Usefulness (PU) has a positive effect on Attitude Toward AI (ATA).

H2: Perceived Ease of Use (PEOU) has a positive effect on Attitude Toward AI (ATA).

H3: Knowledge About AI Technology (KAAT) has a positive effect on Attitude Toward AI (ATA).

2.2.2 Intention to Use AI, Attitude Toward AI

Attitude Toward AI (ATA) is an intermediate variable and represents a customer's affective and evaluative orientation toward using AI for banking. ITUA can be strongly predicted by positive attitudes, especially when they evaluate AI to be useful, secure, and easy to use **(Hidas, 2024; Pawaskar and Nattuvathuckal, 2024)**. Intention to use has been described as a conscious willingness of a customer to regularly engage with AI-driven services.

In a high-trust industry such as banking, intention is seen as the antecedent of behavioural adoption and sustained use. A stronger intention will have more chances of evolving into a trustful engagement with AI technologies **(Choung, David and Ross, 2023)**; hence, the study proposes the following hypotheses:

H4: Attitude Toward AI (ATA) has a positive effect on Intention to Use AI (ITUA).

H5: Knowledge About AI Technology (KAAT) has a positive effect on Intention to Use AI (ITUA).

H6: Perceived Security (PS) has a positive effect on Intention to Use AI (ITUA).

2.2.3 Customer Trust in AI-Enabled Banking Services

Customer Trust (CT) is the foundation for adopting AI within banking arena, especially where sensitive personal and financial information is involved. Trust in AI is influenced by a system's perceived integrity, dependability, and competence **(Ryan, 2020; Qin, Li and Yan, 2020)**. In this research, trust is modeled as an outcome of intention and attitude and is also considered an end-goal for technology-driven service relationships.

Attitudes and intentions come first and serve to mediate trust-building efforts. For example, customers with a positive attitude and high intention to use AI will proceed to trust AI-enabled systems and institutions that deploy them **(Muthuswamy and Dilip, 2024, 2015; Ostrom, Fotheringham and Bitner, 2019)**. Hence, the following hypotheses are proposed:

H7: Attitude Toward AI (ATA) positively influences Customer Trust (CT).

H8: Intention to Use AI (ITUA) positively influences Customer Trust (CT).

2.2.4 Mediating Role of Attitude and Intention

Attitude Toward AI (ATA) and Intention to Use AI (ITUA) mediate the relationship between technology perceptions (PU, PEOU, KAAT, PS), and Customer Trust (CT). Mediation would imply that PU, PEOU, KAAT, and PS influence trust indirectly by affecting attitude and/or intention. This is true as several past studies confirm that trust in digital services rarely evolves directly from technical features but rather from positive psychological reactions such as confidence, understanding, and intentional habits **(Kelton, Fleischmann and Wallace, 2008; Glikson and Woolley, 2020)**.

Hence, these are the mediating hypotheses to be tested:

H9: Attitude Toward AI (ATA) mediates the relationship between PU, PEOU, KAAT, and Customer Trust (CT).

H10: Intention to Use AI (ITUA) mediates the relationship between KAAT, PS, ATA, and Customer Trust (CT).

2.2.5 Proposed Conceptual Model

On the basis of an extensive amount of theoretical and empirical literature, a conceptual model has been formulated. It attempts to demonstrate the multiple-path interrelationships between technology perceptions, attitude, intention, and trust focusing on mediation effects in AI-based banking contexts. Representation of the empirical structural model used in hypothesis validation is given in figure 1.

3.1 Research Design

A structured questionnaire was administered to 600 bank customers belonging to public and private sector banks in India. The respondents are selected, taking care to provide equal representation to those actively engaged in online banking. Here the focus was on understanding the effect of several technological and perceptual constructs, like perceived usefulness, ease of use, knowledge of AI, and perceived security, on their trust in AI-enabled banking services. The questionnaire contained closed-ended statements rated on a five-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree". No monetary or any kind of gifts were considered for the respondents.

The data were collected by a cross-sectional survey during purposive sampling, wherein people with varied levels of banking and digital sciences were considered. Only 453 valid responses were retained after excluding incomplete or inconsistent ones. The research followed the descriptive research design with a strategic goal pertaining to the study of attitudes and behaviours of customers to AI-enabled banking.

Pilot testing on a convenient sample of 50 respondents ensured the reliability and clarity of item statements in questionnaire. Informal permissions were obtained from the local bank branches, as typically Indian banking institutions do not have such formal institutional review boards for market research. The sample size was calculated by means of G*Power software, which calculated a minimum sample size of 159 for a power level of 0.80 and a significance level of 0.05 **(Bartlett, 2019)**. The overall sample size of 453 exceeded not only this minimum but also the 200+ threshold response size suggested for structural equation modelling **(Sideridis *et al.*, 2014; Wolf *et al.*, 2013)**.

The questionnaire also sought basic demographics of respondents, alongside their behaviour with respect to online banking and AI-based banking services. The study itself assures confidentiality for all participants and respects their consent while collecting data.

3.2 Statistical Techniques

With SmartPLS version 3.3.3, Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied in this study to establish the validity for the conceptual model and assessment of the hypothesized relationships **(Nguyen, Nguyen and Ba Le, 2022)**. This method fits well for non-parametric prediction-oriented analyses, especially in exploratory studies that deal with complex multivariate path mediation models **(Hair *et al.*, 2019; Sarstedt *et al.*, 2019)**. PLS-SEM was especially considered suitable due to the theoretical model's interest in prediction; the involvement of formative and reflective constructs **(Sarstedt and Cheah, 2019)**; mediation analysis and the theory development task in a relatively emerging field of AI trust within Indian banking context.

The examination of first-order and second-order measurement models was mandatory for the assessment of reliability and validity, consuming internal consistency (Cronbach's

Alpha, Composite Reliability), convergent validity (Average Variance Extracted), and discriminant validity (HTMT criterion). Finally, bootstrapping was performed with 10,000 subsamples and Bias-Corrected Percentile Confidence Intervals to test the structural model's significance of path coefficients by a two-tailed test **(Sarstedt, Ringle and Hair, 2021)**. Models were subsequently evaluated by R^2 values, effect size (f^2), predictive relevance (Q^2), and model fit indices, thus determining the robustness of the results.

4. Results and analysis

4.1 Demographic Interpretation

The 453 respondents are primarily young and educated, with 63.6% belonging to Generation Z, that is, 18-24 years old, and 72.8% having undergraduate or postgraduate degrees-an indication towards a digitally aware sample well under consideration for research related to AI adoption. An equitable gender ratio of 53.6% males and 46.4% females, accompanied by over 62% earning under ₹1 lakh from middle-income strata, helps present a class spectrum to gauge inclusive banking perspectives. Most of the respondents were salaried individuals (45.7%) and showed a preference for the public sector bank (53.6%), giving greater credibility to the existence of traditional trust over increasing digital propensity. Digitally, the populace was fairly engaged; 71.3% used online banking "often" or "always" while 75.3% had partial to full knowledge of AI in banking scenario-preparedness evident enough to able them to fairly assess AI-enabled services. With 49.2% coming from urban regions and the remaining split between rural and semi-urban localities, the sample is geographically diversified as well. Filling in demographic pockets only, the respondent profile reflects relevance to the study in customer trust and adoption of AI across different user segments within Indian banking sector. The final findings of the study's descriptive statistics are shown in Table 1.

Table 1: Demographics of Respondents

Frequency Table (N=453)		
		Percent
Educational Qualification	Higher Secondary	27.2
	Post Graduate	40.6
	Under Graduate	32.2
		Percent
Age Group	Generation Alpha (Less than 18)	21.4
	Generation Z (18–24)	63.6
	Millennials / Generation Y (25–34)	12.4
	Millennials / Generation Y – Older (35–44)	2.6
		Percent

Gender	Male	53.6
	Female	46.4
		Percent
Monthly Income	Below 50,000	29.8
	50,000-1 Lac	32.2
	1 Lac to 2.50 Lac	24.5
	2.50 Lac & above	13.5
		Percent
Occupation	Service or salaried	45.7
	Businessman	19.6
	Student	11.5
	House-wife	23.2
		Percent
Type of Bank for primary banking	Public Sector or Govt Bank	53.6
	Private Sector Bank	46.4
		Percent
Frequency of using online banking services	Always	23.4
	Often	47.9
	Sometimes	25.4
	Rarely	3.3
		Percent
Banking service	Bank Account operations (Saving/ Current)	30.2
	Loan Account operation	19.4
	Fixed Deposit account	34.9
	Insurance/ Mutual fund	15.5
		Percent
level of awareness	Completly Not aware	.4
	Moderately aware	1.8
	Neutral	22.5
	aware	50.8
	Completly aware	24.5
		Percent
Type of your bank branch	Rural branch	26.0
	Urban branch	49.2
	Semi-urban branch	24.7
	Total	100.0

4.2 Measurement Model Assessment

4.2.1 Outer Loadings, Confidence Intervals and Collinearity Diagnostics

The outer loading analysis, confidence intervals, and collinearity statistics are consistent with the robustness and validity of the entire measurement model. All outer loadings were observed to be above the standard threshold of 0.70, which confirms indicator reliability **(Hair *et al.*, 2019)**. For instance, items such as PU_1 (0.875), ITUA_3 (0.870), and KAAT_3 (0.891) were demonstrated to be excellently aligned with their respective constructs. Further evidence for the statistical significance of the loadings was obtained, as the 95% confidence intervals for all items were tightly bound aside from zero **(Sarstedt and Cheah, 2019)**. Also, all the VIF values fell between 1.431 and 3.111: well within acceptable ranges, implying there was no multicollinearity concern **(Sarstedt *et al.*, 2019)**. This would mean that each item is able to give its own set of information to its construct. Such results are highly relevant given the Indian banking scenario in which AI adoption is increasing and trust is a major issue. A strong measurement model would, therefore, improve the credibility of results pertaining to customer perceptions, attitudes, and trust in AI-enabled banking services **(Dwivedi *et al.*, 2021; Wang and Siau, 2019)**.

Outer loadings and Collinearity statistics (VIF)

	Beta value	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	CI [2.5%]	CI [97.5%]	VIF
ATA_1 <- ATA	0.736	0.734	0.033	22.087	0.000	0.663	0.793	1.495
ATA_2 <- ATA	0.773	0.772	0.026	29.387	0.000	0.716	0.819	1.492
ATA_3 <- ATA	0.719	0.718	0.034	21.006	0.000	0.644	0.779	1.460
ATA_4 <- ATA	0.808	0.809	0.017	46.314	0.000	0.772	0.841	1.431
CT_1 <- CT	0.792	0.791	0.020	39.275	0.000	0.749	0.828	2.790
CT_2 <- CT	0.789	0.789	0.018	43.809	0.000	0.751	0.822	2.491
CT_3 <- CT	0.827	0.827	0.016	52.308	0.000	0.794	0.856	2.924
CT_4 <- CT	0.758	0.758	0.022	34.212	0.000	0.710	0.798	2.678
CT_5 <- CT	0.790	0.789	0.021	38.388	0.000	0.746	0.827	2.813
CT_6 <- CT	0.756	0.756	0.023	33.020	0.000	0.709	0.800	2.337
CT_7 <- CT	0.776	0.776	0.020	39.229	0.000	0.735	0.813	2.512
CT_8 <- CT	0.708	0.708	0.025	28.812	0.000	0.658	0.754	2.118
CT_9 <- CT	0.757	0.757	0.024	31.776	0.000	0.708	0.801	2.516
ITUA_1 <- ITUA	0.846	0.845	0.017	49.628	0.000	0.810	0.877	2.552
ITUA_2 <- ITUA	0.848	0.847	0.015	56.674	0.000	0.816	0.874	2.343
ITUA_3 <- ITUA	0.870	0.869	0.013	64.840	0.000	0.841	0.893	2.842
ITUA_4 <- ITUA	0.833	0.833	0.016	51.896	0.000	0.799	0.862	2.130
ITUA_5 <- ITUA	0.813	0.813	0.018	44.277	0.000	0.774	0.846	2.011
KAAT_1 <- KAAT	0.884	0.884	0.010	91.329	0.000	0.864	0.901	2.864
KAAT_2 <- KAAT	0.833	0.833	0.015	54.094	0.000	0.801	0.861	2.208

KAAT_3 <- KAAT	0.891	0.891	0.009	98.318	0.000	0.872	0.908	3.111
KAAT_4 <- KAAT	0.834	0.834	0.017	47.879	0.000	0.797	0.865	2.346
KAAT_5 <- KAAT	0.860	0.859	0.015	56.534	0.000	0.826	0.886	2.660
PEOU_1 <- PEOU	0.864	0.864	0.013	67.404	0.000	0.837	0.887	2.311
PEOU_2 <- PEOU	0.863	0.863	0.013	65.559	0.000	0.836	0.887	2.298
PEOU_3 <- PEOU	0.884	0.884	0.012	76.051	0.000	0.859	0.905	2.535
PEOU_4 <- PEOU	0.863	0.863	0.016	54.899	0.000	0.830	0.891	2.431
PS_1 <- PS	0.801	0.800	0.023	35.208	0.000	0.751	0.841	1.969
PS_2 <- PS	0.817	0.816	0.019	44.068	0.000	0.778	0.849	2.055
PS_3 <- PS	0.869	0.869	0.013	64.734	0.000	0.841	0.893	2.503
PS_4 <- PS	0.848	0.848	0.018	47.790	0.000	0.811	0.880	2.348
PS_5 <- PS	0.775	0.774	0.024	32.520	0.000	0.724	0.817	1.864
PU_1 <- PU	0.875	0.875	0.010	83.701	0.000	0.853	0.894	2.693
PU_2 <- PU	0.837	0.836	0.015	57.191	0.000	0.806	0.863	2.283
PU_3 <- PU	0.883	0.883	0.010	84.381	0.000	0.861	0.902	2.867
PU_4 <- PU	0.838	0.837	0.017	49.472	0.000	0.801	0.867	2.415
PU_5 <- PU	0.845	0.844	0.017	49.892	0.000	0.808	0.874	2.334

4.2.1 Reliability and Validity

The reliability and validity of all constructs in study were evaluated through Cronbach's alpha, CR, and AVE.The Cronbach's alpha values were above the recommended level of 0.7; the highest being for the Customer Trust construct (0.916), proving a high degree of internal consistency **(Hair *et al.*, 2019)**. CR values range from 0.845 to 0.935, offered proofs for internal consistency, and all AVE values are more than 0.50 for verifying convergent validity (Fornell & Larcker, 1981). Excellent convergence was shown for PU (0.732) and PEOU (0.755) from the above AVE statistics. These findings establish the robustness of the measurement model, allowing for the reliable interpretation of AI adoption and trust within Indian banking context **(Sarstedt and Cheah, 2019; Henseler, Ringle and Sarstedt, 2015)**.

Construct reliability and validity				
	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
ATA	0.760	0.784	0.845	0.577
CT	0.916	0.916	0.930	0.598
ITUA	0.897	0.898	0.924	0.709
KAAT	0.913	0.918	0.935	0.741

PEOU	0.892	0.894	0.925	0.755
PS	0.880	0.884	0.913	0.677
PU	0.909	0.913	0.932	0.732

4.2.2 Discriminant Validity

Discriminant validity was assessed through the Fornell-Larcker criterion and HTMT ratio. According to Fornell and Larcker (1981), the square root of AVE for every construction was greater than the inter-construct correlations, which confirmed the existence of good discriminant validity in domain of investigation. For illustrative purposes, PU (0.856) and PEOU (0.869) show good discriminatory power from other constructs.

HTMT values were below a conservative threshold of 0.85 (Henseler et al., 2015) except for PU and KAAT (0.977), which suggests conceptual similarity and maybe need further consideration in future. So, in general, constructs are empirically distinguishable, allowing reliable interpretation of structural relationships.

Discriminant validity							
Heterotrait-monotrait ratio (HTMT) - Matrix							
	ATA	CT	ITUA	KAAT	PEOU	PS	PU
ATA							
CT	0.656						
ITUA	0.583	0.654					
KAAT	0.417	0.410	0.398				
PEOU	0.400	0.591	0.470	0.231			
PS	0.550	0.623	0.577	0.315	0.427		
PU	0.450	0.425	0.422	0.977	0.267	0.334	
Fornell-Larcker criterion							
	ATA	CT	ITUA	KAAT	PEOU	PS	PU
ATA	0.760						
CT	0.570	0.773					
ITUA	0.495	0.595	0.842				
KAAT	0.358	0.376	0.362	0.861			
PEOU	0.345	0.534	0.423	0.212	0.869		
PS	0.463	0.561	0.515	0.287	0.380	0.823	
PU	0.381	0.389	0.384	0.589	0.244	0.303	0.856

4.2.3 R-Square and Effect Size

The R-squares for the dependent variables are moderate in predicting behavioural intention: ATA (0.301), ITUA (0.369), and CT (0.454), indicating that these exogenous variables explain a substantial portion of variance in key behavioural outcomes **(Hair *et al.*, 2019)**. Thus, the findings are in agreement with the studies conducted so far in digital banking, where trust and behavioural intention have been shaped by various perceptual factors **(Dwivedi *et al.*, 2021; Wang and Siau, 2019)**.

R-square		
	R-square	R-square adjusted
ATA	0.301	0.295
CT	0.454	0.452
ITUA	0.369	0.363
f-square		
ATA -> CT	0.184	
ITUA -> CT	0.237	
KAAT -> ATA	0.001	
KAAT -> ITUA	0.002	
PEOU -> ATA	0.032	
PEOU -> ITUA	0.072	
PS -> ATA	0.123	
PS -> ITUA	0.165	
PU -> ATA	0.010	
PU -> ITUA	0.008	

Effect sizes (f^2) further emphasize the weight of the individual predictors. Intention to Use AI produced an effect size of 0.237 upon Customer Trust, and Attitude Toward AI produced an effect size of 0.184 upon Customer Trust. Both are between medium and large effect sizes, confirming that customer trust in AI is therefore dependent a lot on both the users' behavioural intentions and their attitude predispositions towards it **(Haydon and Haydon, 2020; Friedrich, 2023)**. PSE had a greater impact on ITUA (0.165), consistent with views suggesting that security is a major concern for AI adoption **(Korada and Somepalli, 2023; Al Badi *et al.*, 2022)**. There are also moderate effects of PEOU on ATA (0.032) and ITUA (0.072), giving evidence to support core TAM relationships in banking in Indian context **(Mokha and Kumar, 2025**; **Marakarkandy, Yajnik and Dasgupta, 2017)**. However, KAAT registered negligible effect sizes ($f^2 < 0.01$), suggesting that awareness itself does not influence any formation of attitude or intention, rather accentuating the effects of functional and security perceptions **(Vafaei-Zadeh *et al.*, 2025)**.

In sum, AI banking trust in India is supported more by perceived security, usefulness, and ease of use rather than by general awareness, thereby prompting banks to prioritize usability, transparency, and data protection in AI.

4.2.4 Model Fit

Model fit was analyzed employing adequacy indices. The SRMR value for the saturated model was 0.054 and for the estimated model, 0.076, both being well below the threshold of 0.08 and indicating good fit **(Sahoo, 2019)**. Acceptable values of NFI were obtained, 0.897 and 0.907, almost reaching the suggested cutoff value of 0.90 **(Ding, Velicer and Harlow, 1995)**. The Chi-square values, though quite large, are common in large samples and therefore should not be used as an indication of poor fit **(Sathyanarayana and Mohanasundaram, 2024)**. The discrepancy values, d_ULS and d_G, were also well within set limits, further indicating the adequacy of the model. The indices altogether confirm that the model is well specified and ready for interpretation.

Model fit Summary		
	Saturated model	Estimated model
SRMR	0.054	0.076
d_ULS	2.075	4.074
d_G	1.974	2.041
Chi-square	4017.494	4102.859
NFI	0.897	0.907

4.2.5 Path Coefficients

From the structural model findings, most of the hypothesized relationships between variables have turned out to be statistically significant. The attitudes toward AI and behavioural intentions to use AI have been found to bear strong effects on customer trust, with attitude toward AI maintaining a standardized coefficient of $\beta = 0.365$ ($p = 0.000$) and intention to use AI maintaining a standardized coefficient of $\beta = 0.414$ ($p = 0.000$), inferring that attitudinal and behavioural aspects each uphold substantial weights in centring customer trust, as per the arguments of **Muthuswamy and Dilip (2024)**.

Path coefficients					
	Beta value	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
ATA -> CT	0.365	0.367	0.045	8.139	0.000
ITUA -> CT	0.414	0.415	0.046	8.917	0.000
KAAT -> ATA	0.066	0.066	0.058	1.141	0.254
KAAT -> ITUA	0.070	0.070	0.059	1.186	0.236
PEOU -> ATA	0.163	0.163	0.044	3.707	0.000
PEOU -> ITUA	0.233	0.233	0.044	5.256	0.000
PS -> ATA	0.326	0.329	0.044	7.404	0.000
PS -> ITUA	0.359	0.362	0.049	7.375	0.000
PU -> ATA	0.184	0.184	0.062	2.957	0.003
PU -> ITUA	0.156	0.155	0.062	2.528	0.012
Total indirect effects					
	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
KAAT -> CT	0.053	0.054	0.039	1.361	0.173
PEOU -> CT	0.156	0.157	0.030	5.237	0.000
PS -> CT	0.268	0.271	0.032	8.307	0.000
PU -> CT	0.132	0.132	0.041	3.245	0.001
Specific indirect effects					
	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
KAAT -> ITUA -> CT	0.029	0.029	0.025	1.175	0.240
PEOU -> ITUA -> CT	0.097	0.097	0.023	4.122	0.000
KAAT -> ATA -> CT	0.024	0.025	0.022	1.111	0.267
PS -> ITUA -> CT	0.149	0.150	0.028	5.390	0.000
PEOU -> ATA -> CT	0.059	0.060	0.019	3.051	0.002
PU -> ITUA -> CT	0.065	0.065	0.028	2.339	0.019
PS -> ATA -> CT	0.119	0.121	0.023	5.228	0.000
PU -> ATA -> CT	0.067	0.067	0.023	2.875	0.004
Total effects					
	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
ATA -> CT	0.365	0.367	0.045	8.139	0.000
ITUA -> CT	0.414	0.415	0.046	8.917	0.000
KAAT -> ATA	0.066	0.066	0.058	1.141	0.254

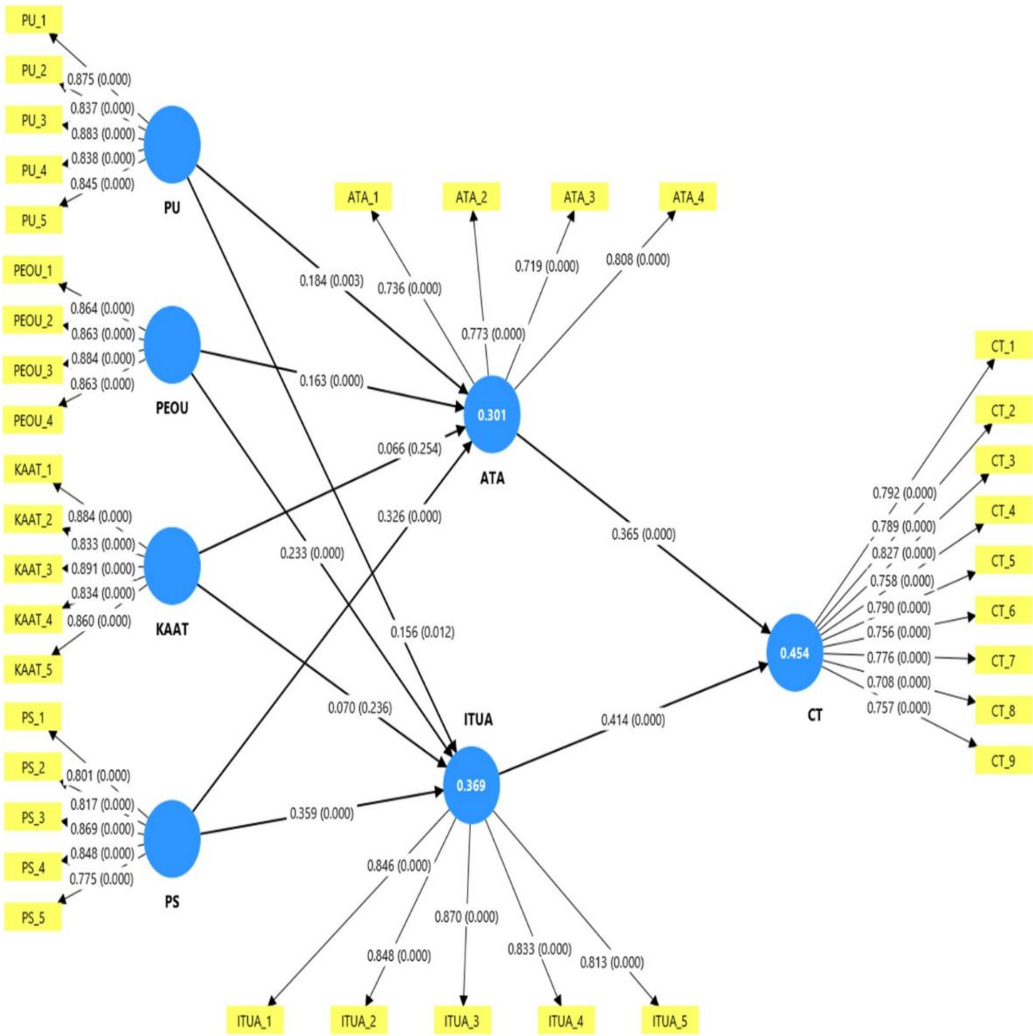
KAAT -> CT	0.053	0.054	0.039	1.361	0.173
KAAT -> ITUA	0.070	0.070	0.059	1.186	0.236
PEOU -> ATA	0.163	0.163	0.044	3.707	0.000
PEOU -> CT	0.156	0.157	0.030	5.237	0.000
PEOU -> ITUA	0.233	0.233	0.044	5.256	0.000
PS -> ATA	0.326	0.329	0.044	7.404	0.000
PS -> CT	0.268	0.271	0.032	8.307	0.000
PS -> ITUA	0.359	0.362	0.049	7.375	0.000
PU -> ATA	0.184	0.184	0.062	2.957	0.003
PU -> CT	0.132	0.132	0.041	3.245	0.001
PU -> ITUA	0.156	0.155	0.062	2.528	0.012

The path analysis confirms the positive effects of Perceived Usefulness and Perceived Ease of Use on Attitude Toward AI ($\beta = 0.184$ and $\beta = 0.163$, respectively) and Intention to Use AI ($\beta = 0.156$ and $\beta = 0.233$, respectively). In essence, these results follow the core principles of the Technology Acceptance Model (TAM), i.e., on the perceived usefulness and ease of use affecting customers' attitudes as well as behavioural intentions concerning AI adoption **(Na *et al.*, 2022; Liu *et al.*, 2024)**.

PS, on the contrary, emerged as the strongest predictor across the paths Positioning significant effects on both ATA ($\beta = 0.326$, $p = 0.000$) as well as ITUA ($\beta = 0.359$, $p = 0.000$). This finding supports several previous research studies which emphasize that trust in AI depends on the perception of the user about safety and security of data **(Pieters, 2011; Omrani *et al.*, 2022)**.

KAAT, contrary to the previous variable, found no significant effect on ATA or ITUA ($p > 0.05$), implying that awareness alone does not impact either attitude or intent meaningfully-an observation consistent with **(Alqaysi, Zahari and Khudari, 2024)** statement of the limited value of cognitive familiarity in trust-building without experiential reinforcement.

In brief, trust in AI-based digital banking is more affected by emotional and performance-based perceptions such as ease of use, usefulness, and security rather than technical knowledge.



4.2.6 Hypothesis Testing and Mediation Analysis

The outcome of the structural model offers strong support for most of the proposed hypotheses. Hypothesis 1 and 2 thus stand confirmed because both Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) positively influence Attitude Toward AI (ATA) from a sign perspective, with beta values of 0.184 ($p = 0.003$) and 0.163 ($p = 0.000$). This confirms the basic premise of the Technology Acceptance Model (TAM), in that when users perceive the system to be both useful and easy to use, they will have a more favourable attitude toward adopting that system **(Davis, 1987)**.

On the other hand, Hypothesis 3, which posited a positive effect of Knowledge About AI Technology (KAAT) on ATA, is not supported. The relationship was positive but statistically insignificant ($\beta = 0.066$, $p = 0.254$), suggesting that general awareness about AI does not meaningfully influence customer attitudes. This finding is congruent with that of **(Horst, Kuttschreuter and Gutteling, 2007)**, who contend that trust and adoption behaviours are shaped more by perceived benefit and experience rather than mere technical familiarity.

Hypothesis 4 is supported since there was a significant effect of ATA on Intention to Use AI (ITUA) ($\beta = 0.365$, $p = 0.000$), which emphasizes the importance of attitudinal disposition toward behavioural intent **(Faruqe, 2023)**. Conversely, Hypothesis 5 is not supported, where KAAT, once again, has no significant effect on ITUA ($\beta = 0.070$, $p = 0.236$), adding more credit to the predictive value of knowledge alone being limited.

Hypothesis 6 is strongly validated, with PS having the highest positive effect on ITUA ($\beta = 0.359$, $p = 0.000$). It therefore underlines that security perceptions are the foundation on which perception and intention are built in AI-enabled financial services, which echoes the works of **(Tulcanaza-Prieto, Cortez-Ordoñez and Lee, 2023)** and **(Roh, Park and Xiao, 2023)**.

Hypotheses 7 and 8 are both supported. The results indicate that ATA and ITUA have a significant influence on CT, with beta values of 0.365 ($p = 0.000$) and 0.414 ($p = 0.000$), respectively. This confirms that attitudinal alignment and behavioural readiness are crucial contributors to trust, thus, aligned with the findings that **(Faruqe, 2023)** and **(Dwivedi *et al.*, 2021)** have arrived with inir study.

Turning to mediation, this result clarifies the role of ATA and ITUA in mediating technological perceptions to trust. Hypothesis 9 is partially supported. ATA mediates the relationship between PU and CT ($\beta = 0.067$, $p = 0.004$), PU and PEOU and CT ($\beta = 0.059$, $p = 0.002$), but it does not mediate significantly between KAAT and CT ($\beta = 0.024$, $p = 0.267$). It shows that attitude is an effective mediator for usability and performance-related constructs, but not for general awareness **(Rodriguez, 2023)**.

Hypothesis 10 receives full support; ITUA significantly mediates the relationship between PU, PEOU, PS, and CT, with strong mediation observed for PS through ITUA to CT ($\beta = 0.149$, $p = 0.000$) and for PEOU through ITUA to CT ($\beta = 0.097$, $p = 0.000$). However, KAAT through ITUA to CT remains non-significant ($\beta = 0.029$, $p = 0.240$), thus further underlining its limited role.

Therefore, findings reveal that trust in AI-driven banking services in India is significantly influenced by perceptions of usefulness, ease of use, and security, with mediation via attitude and behavioural intention. Contrarily, technical awareness without corresponding perception of value does not significantly influence trust, suggesting that banks should, instead of focusing on just awareness creation, channel their efforts to the creation of secure, user-friendly, and outcome-driven AI experiences.

4.3 Multi-Group Analysis (Public vs Private Sector Banks)

The Multi-Group Analysis (or MGA), were conducted to examine if there are any significant differences of perceptions of customers toward AI in banking by users of public sector and private sector banks. The results indicate variations by sector on the impact of main predictors on trust formation and behavioural outcomes.

Public sector bank users were found to have a significantly stronger effect of Perceived Security on Attitude Toward AI (p = 0.031). This could mean that public bank customers care more about security in forming their attitudes toward AI-based banking. Again, the effect of Perceived Security on Customer Trust was significantly different across groups (p = 0.015), underscoring the idea that public bank customers are more concerned about safety and institutional reliability than do their private sector counterparts.

In contrast, Perceived Usefulness tends to have a stronger influence on both Attitude Toward AI and Customer Trust for private bank users, with the difference being only marginally significant (p = 0.109 and p = 0.089, respectively). This would suggest that private sector customers are more performance-oriented, may be due to their being well-versed in digital innovation and so expecting technology to help their everyday life.

Path coefficients			
	Difference (Public Sector - Private Sector)	1-tailed (Public Sector vs Private Sector) p value	2-tailed (Public Sector vs Private Sector) p value
ATA -> CT	-0.142	0.941	0.117
ITUA -> CT	0.042	0.330	0.659
KAAT -> ATA	0.002	0.493	0.986
KAAT -> ITUA	-0.122	0.844	0.312
PEOU -> ATA	-0.058	0.744	0.513
PEOU -> ITUA	-0.068	0.778	0.444
PS -> ATA	-0.193	0.985	0.031
PS -> ITUA	-0.133	0.918	0.163
PU -> ATA	0.200	0.055	0.109
PU -> ITUA	0.205	0.054	0.108
Total indirect effects			
	Difference (Public Sector - Private Sector)	1-tailed (Public Sector vs Private	2-tailed (Public Sector vs Private

		Sector) p value	Sector) p value
KAAT -> CT	-0.056	0.768	0.464
PEOU -> CT	-0.064	0.854	0.293
PS -> CT	-0.158	0.992	0.015
PU -> CT	0.141	0.044	0.089
Specific indirect effects			
	Difference (Public Sector - Private Sector)	1-tailed (Public Sector vs Private Sector) p value	2-tailed (Public Sector vs Private Sector) p value
KAAT -> ITUA -> CT	-0.047	0.835	0.330
PEOU -> ITUA -> CT	-0.018	0.644	0.711
KAAT -> ATA -> CT	-0.009	0.585	0.830
PS -> ITUA -> CT	-0.039	0.755	0.490
PEOU -> ATA -> CT	-0.046	0.867	0.266
PU -> ITUA -> CT	0.090	0.053	0.106
PS -> ATA -> CT	-0.119	0.995	0.010
PU -> ATA -> CT	0.051	0.136	0.273
Total effects			
	Difference (Public Sector - Private Sector)	1-tailed (Public Sector vs Private Sector) p value	2-tailed (Public Sector vs Private Sector) p value
ATA -> CT	-0.142	0.941	0.117
ITUA -> CT	0.042	0.330	0.659
KAAT -> ATA	0.002	0.493	0.986
KAAT -> CT	-0.056	0.768	0.464
KAAT -> ITUA	-0.122	0.844	0.312
PEOU -> ATA	-0.058	0.744	0.513
PEOU -> CT	-0.064	0.854	0.293
PEOU -> ITUA	-0.068	0.778	0.444

PS -> ATA	-0.193	0.985	0.031
PS -> CT	-0.158	0.992	0.015
PS -> ITUA	-0.133	0.918	0.163
PU -> ATA	0.200	0.055	0.109
PU -> CT	0.141	0.044	0.089
PU -> ITUA	0.205	0.054	0.108

No differences, however, were found with regard to the relation of Intention to Use AI and Customer Trust, as well as of Knowledge About AI Technology on Attitude or Intention, thus confirming previous observations that knowledge alone is not significant for trust in either segment.

Given these results, custom strategies may work best. Public sector banks should focus on building trust through transparency, secure system architecture, and clear communication about data protection. Private sector banks could benefit in building customer trust and engagement by marketing the efficiency, convenience, and personalization of AI-units.

5. Discussion and Implications

Trust in Artificial Intelligence (AI) remains a strongest driver for AI adoption in banking systems, especially in digitally emergent countries like India. Empirically, this study has shown that trust in AI-driven banking is not because of customer awareness or any exposure to technology, but more so because of perceived ease of use, usefulness, and especially, perceived security. These results are in accordance with past studies that highlight the role of system usability and risk mitigation in fostering consumer trust in intelligent technologies **(DMello, 2024)**.

The results affirm that attitude toward AI and intention to use AI are the most critical psychological drivers of trust in AI application **(Choung, David and Ross, 2023)**. These variables not only acted as the direct antecedents of trust but also acted as efficient mediators between technological perceptions (like PU, PEOU, and PS) and trust. Following the work of **(Park *et al.*, 2022)**, the mediating roles of attitude and intention emphasize the need for customers' emotional and behavioural reactions to be synergistically linked with their cognitive evaluations concerning technology. For example, AI awareness (KAAT) turned out to be statistically insignificant, which shows that merely informing customers is not sufficient; banks must also develop meaningful, secure, user-centric experiences that influence attitudes and intentions positively **(Karunarathna, 2024)**.

The Multi-Group Analysis exhibited significant differences in Indian context where public and private sector banks work with different service cultures. Trust formation was indeed influenced by perceived security, to which public sector bank customers were more sensitive. This reflects an old consumer perception of public sector banks as reliable and government-backed **(Prasad, 2021)**. Inversely, private sector clients put greater weight on perceived usefulness, signalling that this chunk of customers values performance and convenience granted by AI-based services exactly as **(Ostrom, Fotheringham and Bitner, 2019)** observe in technology-driven retail banking.

Strategically, therefore, differentiated managerial implications arise from the above results. Public sector banks must concentrate on data privacy, algorithmic transparency, and communications that engender trust given the risk-averse nature of some customer groups. Private sector banks can build trust by demonstrating AI tools' capabilities in efficiency, innovation, and personalization **(Lui and Lamb, 2018)**. Across both sectors, however, the topmost priority must be to design intuitive, accessible AI user interfaces that align with user expectations **(Sindiramutty *et al.*, 2025)**.

Demographically, this study shows that most users are young, educated, and digitally literate, especially those from Generation Z. This group shows great attitudes toward AI, but their trust relies on service experience rather than knowledge. This supports the argument by **(Dewalska-Opitek *et al.*, 2024)** that they require emotionally resonant, seamless experiences for long-term loyalty. For financial institutions, this translates into a mental challenge of not only deploying state-of-the-art AI but also investing in training, onboarding support, and trust-oriented UX design to address the shifting needs of customers.

Lastly, the study provides a theoretical contribution by extending the TAM framework by including Perceived Security and Knowledge About AI, the former being a major concern in developing countries still undergoing the evolution of regulatory awareness and data privacy **(Rana *et al.*, 2024; Sharma, 2023).** While Knowledge About AI did not emerge as a significant driver, its explicit examination now encourages future research to unpack how digital literacy, misinformation, or cognitive bias may mediate or moderate trust outcomes across socio-economic segments.

In evidence, this study denotes that trust in AI banking arises not only from what users know but from what they experience. Banking institutions in India must adopt customer-centric AI so as to strike the right balance between security assurance and performance excellence to foster trust and sustainable digital engagement.

5.1 Managerial Implications

The study's findings hold significant implications for banking practitioners, digital transformation leaders, and public policy-makers who want to drive the scale of adoption of AI-enabled services within Indian banking sector. Since Trust emerged as the principal outcome variable, this study puts forth that the construction of customer trust toward AI is not solely due to technological innovation but rather due to how customers perceive and identify with that technology on an emotional level. Particularly, Perceived Security was regarded as the greatest predictor of both Attitude Toward AI and Intention to Use AI, with corroborating studies that have stressed the minimum requirement of data privacy, algorithmic transparency, and safety for digital trust to take hold **(Gerlich, 2023; Leschanowsky *et al.*, 2024; Borra, 2024)**.

Knowledge About AI Technology (KAAT) was found to have no significant impact-on-trust-based either directly or indirectly-throughout the entire research. This necessarily suggests that awareness or familiarity with AI does not imply granting acceptance or confidence upon it. This further agrees with **(Kafali *et al.*, 2024)** who stressed that trusting an entity of AI occurs with repeat interactions that are user-centric versus cognizance of it. Thus, banks need to channelize their efforts towards building trustworthy AI applications that are secure, user-friendly, and performance-based rather than generic awareness campaigns.

Since Attitude Toward AI and Intention to Use AI strongly mediate relationships in this study, there remains no question that trust cannot form alone but rather is shaped on how customers feel about AI and their willingness to associate with it **(Cheng *et al.*, 2022)**. Work of **(Shin, 2019)** supports this contention, where both emotional and behavioural preparedness become significant in trust development for emerging technologies. Bank managers, therefore, should put their investment into UXD that encourages usability paired with emotional comfort through feedback, transparent decisions, and visually communicative consent **(Abbas *et al.*, 2024)**.

From a sectoral perspective, differences experienced from Multi-Group Analysis allow more concrete strategic guidance to be rendered. Those customers who utilized public banking services tended to respond more significantly to Perceived Security, whereas private bank customers responded more towards Perceived Usefulness, implying different psychological determinants working within each separate customer segment. Hence, public banks must promote institutional trust, data security mechanisms, and regulatory backing; private banks, on the other hand, need to cultivate loyalty by underscoring AI in relation to usefulness, speed, and personalization **(Nasution, 2023; Sheth *et al.*, 2022)**.

Moreover, such a demographic profile hence mostly includes young, educated, and digitally aware users, indicating a growing segment that is open but wary toward AI. This supports the assertions of **(Dingli and Seychell, 2015)** that digital-native customers expect emotionally charged service experiences alongside functional tools. Managers must counter with differentiated onboarding processes, multi-language interfaces, and AI-powered personalization aimed at this group while also securing inclusivity for older and less tech-savvy users **(Kapoor and Mehta, 2022; Yu, 2024)**.

From the point of view of strategic planning, banking institutions literally should prioritize constructs according to their total effects and predictive relevance in establishing customer trust. This research indicates the factors of Perceived Security, Perceived Usefulness, and Perceived Ease of Use as having the greatest effect in opening up Paradigm spaces both for attitude and intention to use AI in bank-related earnings **(Thapa, 2025)**. Therefore, managers must devote resources into improving these areas for example, enhancing security perceptions or transparency, simplifying user interfaces, and demonstrating enormous value via AI functions **(Habbal, Ali and Abuzaraida, 2024)**. While Importance–Performance Map Analysis (IPMA) was not carried out in this study, there is sufficient justification using path coefficients, total effects, and mediation analysis for evidence-based prioritization as advocated in strategic decision-making frameworks.

Hence, trusting AI in Indian banking goes beyond introducing some tech. It calls for the mindset of an inclusive international conglomerate that is empathetic, secure, and utilitarian **(Amarnath and Thimothy, 2024)**. Managers need to bring about segmented communications, prepare for user interface design in attitude formation just as much as behavioural intention, and create AI-based services that purely focus on technicality but in all respects be emotionally intelligent and ethically transparent. This will help banks build better engagement and long-term loyalty among the grassroots in transitioning economy.

5.2 Theoretical Implications

The present study has bears significance on how technology adoption and trust-building take place in AI-enabled banking services-the medley of these forming a kind of Technology Acceptance Model (TAM). By incorporating dimensions such as Perceived Security and

Knowledge About AI Technology into the conventional TAM, the study extends the model in such a manner that stands testimony for the trust-based actuation of contemporary digital banking consumers. Attitude Towards AI and Intention to Use AI, having a stringent mediating influence, support the behavioural intention and experiential cognition theories, which emphasize psychological and behavioural routes in building trust through technological means **(Shi, Gong and Gursoy, 2021)**. Moreover, the non-significant role of artificial intelligence knowledge somehow challenges the assertion that adoption is driven by awareness and hence affirms the greater role of emotional assurance and functional reliability, furthering the discourse among scholars over human-AI interaction and trust theory in emerging markets like India **(Khan, Mehmood and Soomro, 2024)**. Hence, this research provides an extended theoretical perspective on understanding AI trust dynamics in service industries.

5.3 Limitations and Future Scope

The present study was carefully designed to assess how perceptions related to AI, such as usefulness, ease of use, security, and awareness, shape customer trust in banking, with attitude and intention being the key mediators. However, like any empirical investigation, it has certain limitations that may become pathways for future research. Firstly, the study was geographically confined to India, with a younger batch dominated mostly by people from urban and semi-urban settings, and thus cannot be said to represent perceptions of elder or rural customers. Future investigations could delve into demographic and regional diversities to establish whether these differences stemming from generations, cultures, or infrastructures may influence AI trust and its adoption. Besides, deeper investigations into organizational factors related to digital maturity or design of digital services themselves could provide more clarity on sector-based trust differences.

Secondly, the cross-sectional nature only grasps perceptions holding at a single moment in time. As trust in technology is known to change upon repeated use and exposure, longitudinal investigation would shed light on how trust evolves or dissolves over time. Moreover, behavioural intention inhabited in this study has rarely been an accurate predictor of the actual use of technology. Usage records or clickstream behaviour could be incorporated to improve the ecological validity of the study and add more details concerning secrets of customer behaviour.

The current study depended entirely on quantitative methods, limiting its healing ability to reach out to her nuanced feelings or contextual constraints. Hence, future study may involve more qualitative elements, such as interviews and thematic content analyses, to better capture emotional issues and mental hurdles blocking adoption of AI technology. In addition, emerging constructs such as algorithmic fairness, ethical concern, or perceived transparency will provide an all-encompassing explication of AI trust.

Finally, incorporating institutional trust, technological self-efficacy, and regulatory awareness into the model might hold some remedies for the still-unexplored interplay between macro-level factors and individual attitude in driving technology acceptance in a fast-digitizing economy such as India.

5.4 Conclusion

The study significantly extends the investigation into the factors that can influence customer trust in AI-enabled banking services in Indian setup. Focusing on the constructs of the Technology Acceptance Model and extending it to encompass perceived security and knowledge of AI, the study contends that trust is less about awareness and more about experiential attributes such as usefulness, ease of use, and security. Attitude toward AI and intention to use AI further provide the pathways of trust formation from the psychological and behavioural lens. With respect to the sector-specific perspective, there is evidence in favour of distinct trust dynamics between public and private bank customers, which calls for customized AI strategies. Hence, the findings provide a useful framework for banks toward building trust for sustainable AI adoption in fast-evolving digital financial ecosystem of India.

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