

Research Article

# AI Personalization and Third-Party Product Sales in Delhi NCR Banks: A PLS-SEM Analysis

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## Abstract

AI personalization in Banking, specifically for third party products, has become increasingly prevalent. This research paper studies the research topic as part of an ongoing PRISMA guided systematic literature review. A conceptual model was developed using the Personalization – Privacy Paradox Theory which included five constructs. The five constructs were AI Personalization Effectiveness (APE), Algorithmic Trust Propensity (ATP), Perceived Security & Privacy Assurance (PSPA), Regulatory Awareness & Sensitivity (RAS) and Third-Party Product Sales Outcome (TPSO). Hypotheses testing was conducted using PLS-SEM method and SmartPLS 4.0 software. Primary data was obtained from 350 customers within Delhi NCR who have experienced AI driven banking services. All exogenous constructs were found to have a significant positive relationship with TPSO; however, RAS was identified to be the strongest mediator and therefore had the most direct influence on TPSO ( $\beta = 0.498$ ;  $p < 0.001$ ). Further mediation analysis revealed that RAS significantly mediated both ATP & PSPA to TPSO whilst APE's influence on TPSO was found to occur mainly directly. Overall, the proposed model accounted for approximately 61.3% of the variance in TPSO ( $R^2 = 0.613$ ). In addition, robustness checks demonstrated that removing PSPA or RAS from the full model resulted in no loss in explanatory power or prediction accuracy demonstrating the incremental explanatory and predictive value of the regulatory mediation path. Finally, the current study contributes to the personalization-privacy paradox by providing empirical evidence of an ethical dimension, which has previously not been operationalized in India's banking literature for AI compliant regulation. The novelty of this study lies in its focus on third party products sold via AI driven processes and banking services provided by banks operating in Delhi NCR. Therefore, it should be viewed strictly within these specific methodological and contextual boundaries. The limitations of the study include a cross-sectional study design, limited geographic area (only Delhi NCR), purposeful sampling of digitally active customers and aggregating results across three product categories. Future studies could utilize longitudinal designs, increase their geographic coverage, perform multiple group comparisons and investigate moderating variables.

**Keywords:** AI Personalization; Third-Party Product Sales; Delhi NCR Banking; Regulatory Awareness; Consumer Trust; PLS-SEM; Algorithmic Trust; Personalization-Privacy Paradox.

## INTRODUCTION

The Delhi National Capital Region (NCR) is one of India's major banking centers; home to the head offices of forty-two scheduled commercial banks, with an approximate twenty-eight percent share of all banking assets in India [1]. The current banking landscape within Delhi NCR is undergoing significant change due to the influence of artificial intelligence (AI) and its application towards personalized banking, specifically AI-based personalization. The integration of AI personalization into the banking system represents a paradigm shift in how customers are engaged by banks and in terms of how revenue streams can be generated within the financial hub of India [2, 3].

In addition to their core deposit-taking business model, many commercial banks generate a significant portion of their revenue through third-party products such as insurance policies, mutual funds, and consumer loans. As such, bancassurance and investment distribution remain two key domains where AI-enabled cross-selling is currently being applied. However, there is relatively little empirical evidence available that demonstrates the effect of AI-based personalization on actual sales conversions within these areas. While AI is well-established in the banking sector regarding its ability to aid in risk assessment, fraud prevention and operational efficiency, it has been the subject of relatively less academic study regarding sales personalization particularly in relation to India's regulatory environment [2].

For the purpose of conducting research related to this topic, the Delhi National Capital Region offers a unique research environment for three primary reasons. First, the consumers in this area are among the most technologically-savvy in India (digital literacy rates at 78%) and are subject to some of the most stringent regulations set forth by the Reserve Bank of India (RBI) [1].

Second, although the RBI has established evolving governance guidelines for the use of AI in lending and other decision-making processes through the FREE-AI (Framework for Responsible and Ethical Enablement of Artificial Intelligence) framework that was published in August 2025 [1], these guidelines explicitly require that AI systems used in making credit and recommendations decisions must be able to provide explanations for their actions, cannot produce biased or discriminatory results in terms of recommendations made to borrowers, and require human oversight in terms of those decisions.

Third, the interplay between consumer trust, regulatory compliance, and sales effectiveness in this environment has not been systematically examined through a unified empirical model, to the best of knowledge of the research scholars.

This study addresses four research questions:

- RQ1: What are the quantifiable effects of AI personalization effectiveness, algorithmic trust propensity, and perceived security and privacy assurance on regulatory awareness and sensitivity in Delhi NCR banks?

- RQ2: What are the quantifiable effects of AI personalization effectiveness, algorithmic trust propensity, and perceived security and privacy assurance on third-party product sales outcomes?
- RQ3: What is the direct quantifiable effect of regulatory awareness and sensitivity on third-party product sales outcomes?
- RQ4: Does regulatory awareness and sensitivity mediate the relationships between AI personalization effectiveness, algorithmic trust propensity, and perceived security and privacy assurance on third-party product sales outcomes?

The study makes three scope-bounded contributions. First, within the Delhi NCR banking context it provides an empirical PLS-SEM test of a regulatory-sales mediation pathway in AI-driven banking a pathway that, to the best of our reading, has been discussed conceptually but not empirically modelled in the Indian context. Second, it articulates a categorical differentiation framework that distinguishes third-party products by financial complexity, purchase frequency, and regulatory risk classification, enabling product-sensitive interpretation of the structural estimates. Third, it reframes regulatory compliance (RAS) as a potential revenue accelerator rather than a pure compliance cost, with the sales implications quantified within the sample examined. We note that these contributions are bounded by the cross-sectional design, the Delhi NCR sampling frame, and the three product categories covered; broader causal and generalisable claims are deferred to future work.

## LITERATURE REVIEW

The researchers employed a systematic literature search process using the PRISMA protocol to help establish a level of methodological integrity, transparency and replicability when selecting state-of-the-art research that relates to the application of artificial intelligence (AI) for personalizing products for customers at banks. The researchers performed an exhaustive search of all available academic journals using multiple database platforms including Scopus, Web of Science, ScienceDirect, IEEE Xplore, SpringerLink and Google Scholar. All searches were limited to the period from January 2020 – August 2026. The authors used Boolean search strings created by combining various keywords related to AI personalization in banking, which included "AI personalization," "banking," "algorithmic trust," "trustworthy ethical AI," and "third-party product sales." The authors found 512 documents using the mentioned search terms. After excluding duplicate entries ( $n = 94$ ), the authors screened an additional 418 documents as a title/abstract review. Using the same exclusionary criteria as before (i.e., studies that were not relevant to banking or did not include empirical modeling, studies that were solely technical with no behavioral component) the authors excluded additional studies. This left the authors with 142 full-text articles after the screening process. When assessing the 142 full-text articles to be included in the present study, the authors applied strict methodological standards for inclusion in their assessment. These standards required empirically measurable outcomes and/or clearly stated structural/predictive models. As a result of applying methodological

requirements, the authors excluded 96 articles from being considered in the present study. Ultimately, the authors chose 46 studies whose results contributed to their synthesis. Utilizing a PRISMA-structured approach permitted a systematic review of recent academic scholarship, decreased the likelihood of selection bias, improved the validity of the literature review, and clarified both empirical and theoretical gaps related to banking addressed by the current study.

### *AI Personalization in Financial Services*

Previous research on AI in financial services has largely been centered on improving operational efficiencies in financial institutions' operations. These efficiencies have been realized through risk assessment, fraud detection and automating regulatory compliance. Authors reviewed over 100+ research papers and concluded that AI adoption in Indian banking resulted in operational efficiencies ranging from approximately 35%-46% [2]. Those efficiencies are generally attributed to automation of back-office functions and customer service processes. While the reviews by other authors found that sales personalization is an area of significant under-researched activity an area where the present study contributes and another additionally documented improvements in cross-selling conversion rates in retail banking resulting from personalized marketing with data-driven behaviorally informed targeting with AI. Specifically, their survey-based analysis indicated cross-selling conversion rate improvements ranging from 30-50 percent [2, 4]. Unlike authors in [4, 5] investigated AI-driven banking in emerging markets (which include India). Their work supported the findings of [4] establishing consumer trust as a mediating variable between AI driven personalization and customer loyalty. However they do not examine third-party product sales as a separate dependent variable outcome [4, 5].

Sharma and co-worker conducted an integrative literature review on the application of AI for personalized service delivery in banks; they found that engagement and customer satisfaction were identified as potential positive outcomes from AI applications in banking, however there was no empirical evaluation of these outcomes [3]. The results indicate a significant practice theory gap around research into AI-based applications of personalization. In a related context, authors in [6] provided a foundational conceptual model of how data can be used by AI to reduce information asymmetry in banking, which is also relevant to the use of technology to support regulatory compliance, however the authors did not consider the impact of these technological advancements on consumers' perceptions of bank trust and privacy.

### *Regulatory & Ethical Aspects of AI in Banking*

Regulatory aspects have become a significant factor in the development of AI applications in financial institutions. Authors in [7, 8] completed a comparative legal-doctrinal analysis of the regulation of AI within several countries which identified RBI among the most active regulators regarding the use of AI as applied to customer facing products, and also stated that one of the major obstacles faced by regulated entities was the lack of transparency and therefore clarity of explanation generated by algorithms used

in AI. She recommended that mandated explanations (a gap that is addressed in this paper via the RAS concept) would help solve many of the compliance issues created using these types of opaque algorithms. Auhtors in [7] published a systematic review of the integration of AI into various areas of financial services, including lending. They confirmed that regulatory constraints represented a substantial barrier to AI application in sales processes; this finding is consistent with the results of the current research study (RAS  $\beta = 0.498$ ).

The RBI has recently established a new regulatory framework specifically designed to provide guidelines for fair treatment of customers, reliability, transparency/explainability, ethical considerations and accountability in AI-based customer interaction [1]. This new framework was released during or after the time when all but one of the prior studies about banking and AI in India were done, thus providing the regulatory context for this research. Also, it motivated the development of RAS as a critical intermediate variable.

Security/Privacy-related concerns are consistently recognized as key determinants of digital service adoption throughout all technology acceptance models. Mis-selling was shown to be widespread by [9]. They demonstrated that there is inadequate law enforcement of regulations protecting consumers and thus establish a basis on which to examine consumer-level constructs related to regulatory awareness particularly using their pre-AI experimental design as a reference point for comparing post-AI results.

A "personalization-privacy paradox" was first proposed by Awad & Krishnan representing an inverted U-shape between levels of personalized product recommendations received from AI and corresponding acceptance/consumption of those recommendations. High degrees of personalization were found to cause consumers to view such actions as invasive of their privacy and subsequently reject subsequent offerings [10]. In contrast to this foundational work, this research will investigate how regulatory awareness can act as an intermediate mechanism: consumers with higher levels of RAS will likely perceive recommendations made by AI as being based upon institutional procedures rather than invading their privacy thereby maintaining trust and enhancing sales conversions.

### *SOTA Analysis*

Table 1 presents a structured comparison of key SOTA studies. The table has three columns on authors, methodology and key findings & constructs. The table is reinforced with four additional columns "Limitations of Prior Model" and "What This Study Fixes" (which together convert the comparison into a critique of prior work), and two micro-columns "What This Model Cannot Explain" and "Where Our Model Still Fails" (which extend the critique in two directions: identifying observable phenomena the prior model is silent on, and acknowledging where the present model itself remains weak). The two micro-columns deliberately invite self-criticism on each row, so the table functions not only as a comparative review but as a paired self-critique of both the prior literature and the present study.

**Table 1.** Comparative SOTA Analysis of Key Studies on AI Personalization in Banking

Ref.	Methodology	Key Findings & Constructs	Limitations of Prior Model	What This Study Fixes	What This Model Cannot Explain	Where Our Model Still Fails
[2]	Systematic Literature Review (111+ papers); bibliometric analysis.	AI automates compliance and customer service in Indian banking; efficiency improvements of ~46%. Constructs: AI efficiency, automation, risk management.	Descriptive SLR only; no empirical structural model; no consumer-side antecedents; sales personalisation flagged but not operationalised; no regulatory mediator.	Builds an empirical PLS-SEM model with consumer-side antecedents (APE, ATP, PSPA) and a measured sales outcome (TPSO); introduces RAS as an empirically estimated mediator.	Why bank-level efficiency gains do not translate uniformly into front-end consumer adoption or sales conversion of third-party products.	Our model treats efficiency-driven cost savings as exogenous; we do not endogenise the operational-AI investments that underlie consumer-facing personalisation.
[3]	Conceptual review; secondary data.	AI personalisation enhances customer experience, engagement, and satisfaction. Constructs: AI, personalised banking, customer satisfaction.	Conceptual only; no measurement model, no hypothesis tests, no validity evidence; no regulatory or privacy construct; outcomes limited to attitudes rather than sales.	Operationalises constructs with validated scales, tests ten hypotheses via PLS-SEM, and extends outcomes beyond satisfaction to measurable third-party sales (TPSO).	Magnitudes of effect, threshold conditions, and indirect pathways linking AI personalisation to behavioural outcomes.	Like the prior conceptual review, we do not directly measure satisfaction or engagement; TPSO is a sales-weighted construct that may under-represent affective customer-experience dimensions.
[4]	Survey + regression	AI drives personalised	Regression-only	Separates direct APE →	How much of the	Our cross-sectional

	analysis; retail banking.	d marketing; cross-selling conversion improvement of 30–50%. Constructs: AI marketing, engagement, cross-selling.	specificatio n conflates direct personalisa tion effects with unobserve d trust, privacy, and regulatory pathways; no regional grounding; no mediator.	TPSO effect from RAS-mediated effects; models ATP and PSPA as distinct antecedents; grounds the analysis in the Delhi NCR regulatory context.	reported 30–50% conversion gain is attributable to personalisati on versus institutional trust or regulatory framing.	design cannot replicate the longitudinal conversion-rate trajectories that panel-data approaches
[5]	Survey + CB-SEM; Indian & Asian markets.	AI-driven banking boosts personalised experience in emerging markets; trust is a key mediator. Constructs: AI, trust, personaliza tion, customer loyalty.	Trust modelled only toward loyalty rather than sales; no regulatory construct; no product-complexity differentiation; CB-SEM restricts predictive-oriented inference.	Extends trust mediation to TPSO; decomposes ATP into a direct channel ( $\beta = 0.150$ ) and an RAS-mediated channel ( $\beta = 0.130$ ); introduces product-complexity interpretation .	Why emerging-market trust mediation propagates only partially to high-stakes purchase decisions in regulated product categories.	PLS-SEM's predictive orientation does not produce the strict global fit indices that CB-SEM offers; absolute-fit comparison is therefore not strictly equivalent.
[6]	Book chapter; conceptual framework.	AI personalisa tion enables data-driven banking; reduces information asymmetry . Constructs: AI, data	Pre-regulatory-era conceptual work; lacks privacy and trust constructs; no empirical testing; predates current RBI	Adds PSPA, ATP, and RAS; provides a scope-bounded empirical estimation under the current RBI AI-governance environment.	How information-asymmetry reduction interacts with privacy concerns and regulatory awareness in driving sales.	We do not formally model information asymmetry as a separate construct distinct from APE and PSPA, despite its theoretical centrality to

		analytics, personalised banking.	FREE-AI regime.			the personalisation argument.
[7]	Systematic review; thematic analysis.	Regulatory challenges are identified as a key barrier to AI-driven sales effectiveness. Constructs: AI, regulatory compliance, financial services.	Narrative / thematic only; no empirical estimation; regulatory impact not quantified; no consumer-perception measurement.	Operationalises regulation as a measured consumer-perception construct (RAS) and provides an empirical magnitude in Indian banking (RAS $\beta = 0.498$ on TPSO).	The consumer-side mechanisms through which regulatory friction depresses sales effectiveness.	We measure consumer-perceived regulation only; we do not capture institutional-regulator feedback loops, supervisory-action data, or compliance-officer perspectives.
[8]	Legal-doctrinal; comparative analysis.	AI regulatory frameworks create compliance challenges; RBI among the most active regulators. Constructs: AI regulation, compliance, legal frameworks.	Doctrinal / jurisprudential focus; no consumer-side perception data; no behavioural or commercial outcomes; no bridge between legal requirements and sales behaviour.	Translates regulatory doctrine into a consumer-facing RAS construct and empirically links it to sales conversion for third-party products.	Whether stronger regulation raises or lowers consumer adoption of regulated AI products in equilibrium.	Our doctrinal grounding for RAS items is necessarily simplified; we do not capture the full taxonomy of RBI guidance, draft circulars, or jurisdictional ambiguity that the legal literature treats with greater nuance.
[9]	Field experiment; mystery shopping.	Mis-selling in retail banking is prevalent; consumer protection	Pre-AI context; focused on physical / branch mis-selling;	Extends mis-selling concerns into the AI-recommendation era and	How algorithm mis-selling differs in form, detection,	We do not deploy mystery-shopping or behavioural-audit

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regulations are under- enforced. Constructs: mis-selling, consumer protection, banking regulation.	no algorithmic or personalisa- tion construct; no mediation analysis; no regulatory- awareness measure.	tests regulatory awareness (RAS) as a trust- translation mechanism within an empirical SEM model.	and consumer response from human mis-selling.	methods; consumer self-report may understate mis-selling exposure.
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The SOTA analysis reveals three principal gaps addressed by the present study. First, within the literature reviewed here, the present study offers a first scope-bounded empirical estimation in Delhi NCR of RAS as a revenue mediator in AI-enabled third-party product selling a relationship that has been discussed conceptually elsewhere but, to the best of our reading, not previously estimated in this setting. Second, although trust constructs (ATP) appear in prior models, their joint operation with regulatory awareness has not been empirically tested in the Delhi NCR setting reviewed here. Third, categorical differentiation of third-party products by complexity and regulatory risk has been discussed conceptually but not empirically modelled within this scope. The present study addresses these three gaps within the scope stated in introduction section, and the language of “scope-bounded estimation” is preferred over “first empirical validation” throughout, to avoid overclaiming relative to the cross-sectional and single-region design.

### *Theoretical Framework*

The study is grounded in the personalization-privacy paradox theory which models consumer response to personalised digital services as the resolution of a cognitive trade-off between perceived benefit (relevance, convenience, decision-support) and perceived risk (informational exposure, loss of control, behavioural profiling) [10]. The original formulation has shown a negative U-shaped (inverted U) relationship with how deeply personalized something is to the extent to which customers accept or reject the recommendation. Low personalization will lead to low levels of customer involvement, while moderate personalization will result in maximum acceptance. High personalization will lead to consumers perceiving a violation of privacy as well as rejecting the product/service altogether. Considering these two assumptions from the baseline, the current research investigates both. First, for a consumer to find an acceptable artificial intelligence driven recommendation service, is not solely based on the degree of personalization provided by the service but also upon what the consumer believes regarding the organization providing the service. Second, the tradeoff between a positive perception of privacy and positive perceived value through personalization can theoretically be changed. This would occur when there are institutional characteristics within the organization that provide enough cues for consumers to alter their perception

of the personalization. Therefore, the primary re-anchoring cue for changing the location of the acceptance curve (without changing the level of personalization), lies in the regulatory environment. As such, RBI's architectural structure for protecting consumer rights provides observable institutional cues that consumers may use when assessing their risk/benefits associated with accepting/rejecting personalization.

The framework extends the personalization-privacy paradox by modelling Regulatory Awareness and Sensitivity (RAS) as the principal channel through which institutional features re-anchor the consumer's cognitive trade-off in regulated financial markets. Three theoretical mechanisms motivate this mediating role and give the regulatory pathway theoretical content beyond a residual category. First, drawing on signalling theory, regulatory compliance functions as a credible quality signal: because compliance is observable, costly, and selectively enforced by the RBI, a consumer who is aware of RBI consumer-protection frameworks treats compliance signals from the bank as informative about the bank's underlying type, thereby reducing the perceived-risk component of the personalisation trade-off [11].

Second, drawing on institutional theory, regulatory awareness operationalises legitimacy as a consumer-side resource: a personalised AI recommendation embedded in a perceived-legitimate institutional context is processed as a routine service offering rather than a discretionary intrusion, lowering cognitive resistance and reducing the threshold at which the consumer is willing to act on the recommendation [12]. Third, drawing on attribution theory, RAS shifts the causal attribution that consumers make for personalisation: a consumer with low RAS is more likely to attribute a hyper-relevant recommendation to opportunistic data exploitation, whereas a consumer with high RAS is more likely to attribute the same recommendation to mandated, supervised personalisation conducted within a known regulatory perimeter [13]. The same algorithmic output is therefore differentially encoded depending on the consumer's regulatory schema. These three mechanisms are theoretically distinct but empirically convergent in predicting that ATP and PSPA exert their effect on sales conversion through, rather than around, the regulatory-awareness channel consistent with the empirical finding that the indirect paths  $ATP \rightarrow RAS \rightarrow TPSO$  and  $PSPA \rightarrow RAS \rightarrow TPSO$  are statistically significant whereas the direct  $PSPA \rightarrow TPSO$  effect is small.

The framework further specifies product complexity as a theoretically meaningful boundary condition rather than a descriptive control. The signalling and attribution mechanisms above predict heterogeneous effects across product categories: regulatory legitimacy should bind more tightly where the consumer faces higher epistemic uncertainty about the product itself. Drawing on the experience-credence goods distinction in the economics of information, low-complexity, high-frequency products such as term insurance approximate experience goods for the consumer; their evaluation does not lean heavily on institutional legitimacy because the consumer can verify product features through direct exposure. In addition to the ULIPs/structured investments, complex, low frequency financial products are close approximations of credence goods. Therefore, these consumers will rely on institutional/regulatory signals when evaluating a product's

appropriateness for them, since they will be unable to easily determine whether it is appropriate before purchasing (ex-ante) or after the purchase has been made (ex-post). Thus, the model indicates that the magnitude of RAS mediated pathways will vary according to the level of product complexity. This prediction is tested through a moderated mediation approach, and if results indicate attenuation of the indirect effect under conditions of higher complexity than lower complexity, this will reduce support for the attribution-legitimacy framework.

Integrating each of the above concepts into a single conceptual model (Figure 1), this conceptual model represents APE, ATP, and PSPA as exogenous antecedent constructs that influence RAS, the primary mediator, to convert trust/privacy constructs into purchasing behavior; TPSO is viewed as an endogenously generated outcome. The model recognizes the possibility of moderation by product complexity and/or digital literacy; PEAlA is identified as a candidate construct for potential future research extension in alignment with RBI's FREE-AI Framework [1]. To avoid rationalizing results after they have been collected and provide structure for disciplined hypothesis testing instead of post-hoc rationalization, the proposed framework includes four ex-ante hypotheses. Collectively violating all four ex-ante hypotheses would represent evidence that does not support the regulatory mediation account. Ex-ante hypotheses include: (i) the indirect effects of ATP → RAS, then RAS → TPSO, and PSPA → RAS, then RAS → TPSO, must be different from zero at  $p < .05$ ; (ii) the RAS → TPSO effect must be both positive and large enough to be significant relative to other variables; (iii) removing RAS from the structural model must result in a loss of predictive accuracy; (iv) increasing levels of product complexity should enhance, not diminish, the strength of the RAS mediated channels. Conditions (i)-(iv) are reviewed in section (Alternative Theoretical Specifications and Stress Tests) as potential falsifying benchmarks for the framework and are used to evaluate whether the proposed framework holds true rather than being treated as diagnostic measures.

The two clarifiers provide the context for the proposed framework. Firstly, the empirical study is an examination of the regulatory mediation extension of the Personalization–Privacy Paradox, rather than an examination of the originally proposed U-shaped relationship (i.e., the claim that the relationship between privacy concern and perceived benefits from personalization follows an inverted-U-shape) since a within subject design would be required in order to empirically validate the curvature. Therefore, while we establish evidence for the institutional mediation extension of the Parent Theory here, we neither confirm nor refute the curvature claim of the Parent Theory here. Secondly, the framework examines perceptions on the part of consumers as its unit of analysis. That is, RAS measures how aware consumers are of regulations (i.e., their knowledge of what exists), rather than measuring either enforcement frequency of those regulations, or the degree of regulatory compliance among regulated entities. Hence, our Model provides insight into how consumers translate regulatory architecture into sales outcomes (the "demand side"), rather than examining how regulators enforce laws (the "supply side") or monitor compliance with laws ("supervisory side") both examples of a research approach that would be outside the current study

Third, the mediation claim is statistical rather than mechanistic in the strong sense: cross-sectional PLS-SEM identifies the indirect pathway under the assumption that the structural ordering reflects the underlying causal sequence, but it cannot rule out reverse paths or unobserved common causes. These scope conditions discipline the interpretation of the results that follow.

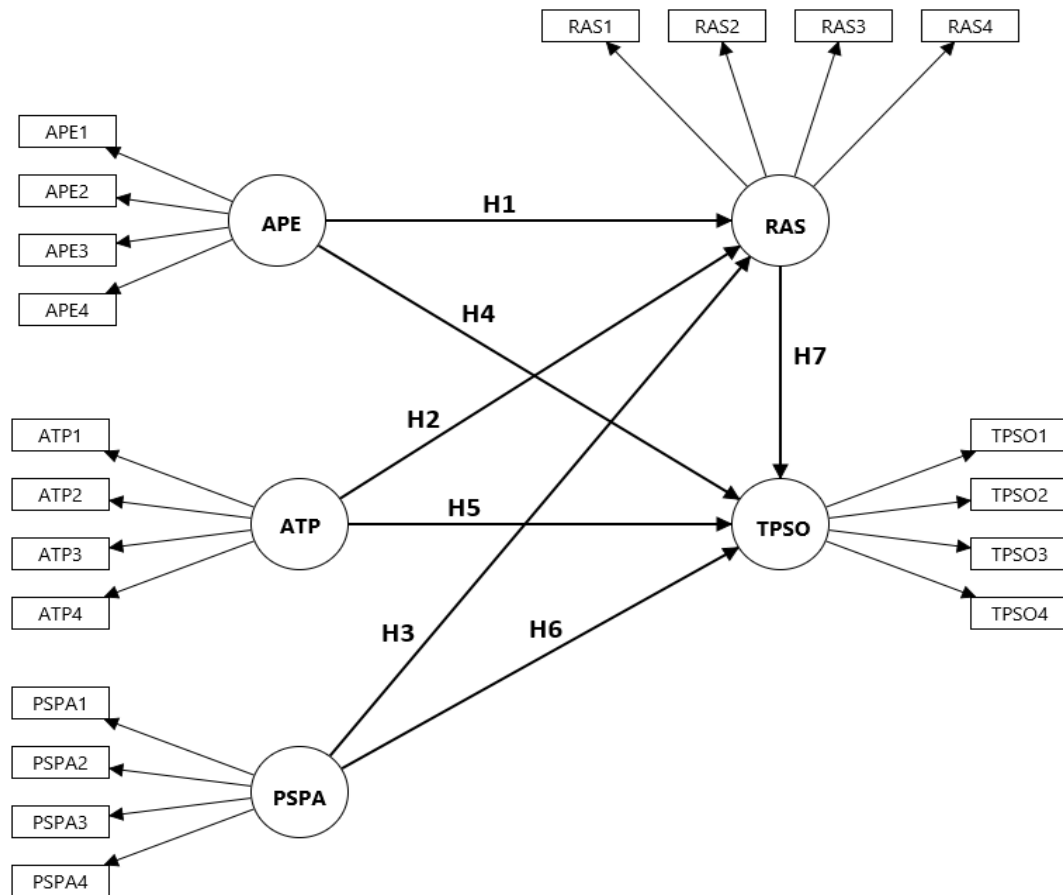


Figure 1. Conceptual Model

## RESEARCH METHODOLOGY

Exploratory quantitative design, appropriate for studying emerging phenomena (third-party banking products sales) based on an existing theoretical framework which requires empirical support of the constructs as opposed to testing hypotheses based on a full established body of knowledge. Primary survey data collected in conjunction with the Literature Review Section provides both contextually grounded and empirically tested evidence for the structural model proposed.

Bank customers in the Delhi NCR area, who are also the recipients of the AI driven personalization of third-party banking product recommendation (i.e., insurance, mutual fund, or credit card), are targeted. Purposive sampling was used to ensure that participants were users of AI service and therefore had relevant experience to provide meaningful

answers regarding each of the constructs. Although the use of purposive sampling restricts the ability to generalize to other less technologically active demographics it ensures the highest level of construct validity due to participant relevance.

Between June and December 2025, a total of 350 complete questionnaires were received, utilizing both online (Google Forms) and in person surveys. The sample size of 350 is greater than the most common cited minimum of 200 for PLS SEM and is more than sufficient (by a large amount) to meet the "10 times rule" ( $10 \times$  maximum number of arrows pointing toward a latent variable =  $10 \times 4 = 40$ ). Common method bias (CMB) was assessed using Harman's single-factor test. Harman's single-factor test revealed that a single factor accounted for approximately 29.4% of the total variance, thereby satisfying the commonly accepted 50% threshold, indicating CMB did not present a problem within this dataset [14, 15].

### *Questionnaire Design and Construct Operationalisation*

A structured questionnaire was developed comprising two sections: (i) demographic and banking profile items, and (ii) Likert-scale items (1 = Strongly Disagree to 5 = Strongly Agree) measuring the five study constructs. Scale items were adapted from validated instruments in prior literature, as detailed in Table 2.

**Table 2.** Constructs Identified for the Research Study

Studies	Construct	Definition
[2, 3, 6]	AI Personalization Effectiveness (APE)	Perceived relevance, inspiration, and insightfulness of AI-generated third-party product recommendations. Captures how accurately algorithms match offerings to customer needs and context, including novelty of suggestions.
[5, 16]	Algorithmic Trust Propensity (ATP)	Consumer willingness to rely on AI recommendations based on perceived competence, transparency, and benevolence. Measures confidence in algorithmic fairness and data security; a key mediator between personalization and adoption.
[9, 10, 18]	Perceived Security & Privacy Assurance (PSPA)	Confidence in data-protection protocols and ethical AI usage. Assesses beliefs about institutional safeguards against misuse of financial/behavioral data, including perceived RBI compliance.
[1, 8, 9]	Regulatory Awareness & Sensitivity (RAS)	Awareness of RBI consumer-protection frameworks and perceived institutional adherence; moderates trust-sales relationships and includes grievance-redressal expectations.
[19, 20]	Third-Party Product Sales Outcomes (TPSO)	Quantifiable impact metrics measuring actual sales performance across insurance, investments, and credit products.

Using Partial Least Squares Structural Equation Modeling (PLS-SEM), data were analyzed through SmartPLS 4.0 [14]. PLS-SEM was chosen instead of Causal Bayesian Structural Equation Model (CB-SEM) for three reasons: (a) the exploratory nature of this model as there are a limited number of studies that have empirically tested the RAS

mediated pathway; (b) the sample size is sufficient to test with PLS-SEM but insufficient to be able to achieve the required large N for testing with CB-SEM with similar statistical power; (c) the purpose of the study is predicated upon predictive measures, therefore aligned with PLS-SEM's goal of maximizing R squared. This process consisted of two sequential steps: (1) evaluating the reliability and validity of the measurement model; and (2) assessing the structural model (path coefficients, predictive power, and mediation). An additional section is included in section (Alternative Model Comparison and Robustness Checks) regarding an examination of robustness in comparison with respect to alternative specifications.

### *AI Personalization Effectiveness (APE) and Regulatory Awareness (RAS)*

Hyper-Relevance Banking Products with predictive financial needs analysis create greater data-privacy concerns in Delhi NCR's digitally advanced banking environment, increasing both the level of regulation and the sophistication of customers demanding greater regulatory compliance signals for increased levels of personalization [8] resulting in a positive relationship between APE → RAS.

- H1: *AI Personalization Effectiveness (APE) has a statistically Significant Positive Impact on Regulatory Awareness and Sensitivity (RAS). Algorithmic Trust Propensity (ATP) and Regulatory Awareness (RAS). High-Willingness-to-Trust Consumers seeking to make algorithmic recommendations will be active participants in developing regulatory assurance mechanisms to legitimize their trust decisions. As such, there exists an interdependent cycle between trust and regulatory sensitivity; High-ATP consumers will demand stronger regulatory compliance signals and conversely, stronger regulatory environments will reinforce higher levels of ATP [19].*
- H2: *Algorithmic Trust Propensity (ATP) has a Statistically Significant Positive Impact on Regulatory Awareness and Sensitivity (RAS). Perceived Security and Privacy Assurance (PSPA) and Regulatory Awareness (RAS). Customers who perceive that banks protect customers' data and use ethical artificial intelligence practices to build 'trust capital', reduce regulatory barriers while raising awareness of institutional compliance responsibilities [9]. In this manner, PSPA serves as a regulatory accelerator and strategic enabler.*
- H3: *Perceived Security and Privacy Assurance (PSPA) will have a Statistically Significant Positive Impact on Regulatory Awareness and Sensitivity (RAS). AI Personalization Effectiveness (APE) and Sales Outcomes (TPSO). AI algorithms which provide accurate matches between customers and their context/life-stage indicators produce conversion accelerations via two primary mechanisms: Contextual Matching (reduced adoption friction), Basket Expansion due to inspirational recommendations thus identifying latent customer needs [4, 5, 17].*
- H4: *AI Personalization Effectiveness (APE) will have a statistically significant positive impact on Third-Party Product Sales Outcomes (TPSO).*

### *Algorithmic Trust Propensity (ATP) and Sales Outcomes (TPSO)*

Trust in AI recommendations functions as a psychological gateway that suppresses cognitive friction in purchase decisions. Research in digital commerce establishes that trust crosses specified thresholds to enable a 'premiumisation effect' whereby consumers accept AI-endorsed high-value products over standard alternatives [5, 7].

- H5: *Algorithmic Trust Propensity (ATP) has a significant positive impact on Third-Party Product Sales Outcomes (TPSO).*

### *Perceived Security and Privacy Assurance (PSPA) and Sales Outcomes (TPSO)*

Perceived privacy and security are established antecedents of digital trust [9]. When customers perceive strong PSPA in AI-driven recommendations, trust in the institution's product suggestions mitigates perceived risk associated with complex third-party financial products. Without this assurance, even highly personalised recommendations face scepticism and rejection [4].

- H6: *Perceived Security and Privacy Assurance (PSPA) have a significant positive impact on Third-Party Product Sales Outcomes (TPSO).*

### *Regulatory Awareness and Sensitivity (RAS) and Sales Outcomes (TPSO)*

RAS positively influences TPSO through three pathways: (i) reducing regulatory fines and business disruptions that erode bank credibility [9]; (ii) strengthening consumer trust through demonstrated ethical data conduct, directly improving conversion rates [20]; and (iii) enabling risk-based resource optimisation in product distribution.

- H7: *Regulatory Awareness and Sensitivity (RAS) have a significant positive impact on Third-Party Product Sales Outcomes (TPSO).*

### *Mediation Hypotheses (RAS as Mediator)*

Given RAS's hypothesised role in the trust-sales pathway, it is expected to mediate the indirect effects of APE, ATP, and PSPA on TPSO:

- H8: RAS mediates the effect of APE on TPSO;
- H9: RAS mediates the effect of ATP on TPSO;
- H10: RAS mediates the effect of PSPA on TPSO.

## **DATA ANALYSIS AND RESULTS**

### *Measurement Model Assessment*

The measurement model was evaluated on three criteria: individual item reliability, internal consistency, and through convergent and discriminant validity [14].

*Item Reliability:* All indicator loadings exceeded the recommended threshold of 0.70, with the majority exceeding 0.80, confirming strong individual item reliability.

*Internal Consistency and Convergent Validity:* Cronbach's alpha values for all five constructs exceeded 0.70; composite reliability ( $q_c$ ) exceeded 0.80 for all constructs; and AVE exceeded 0.50 for each construct, meeting the criterion for convergent validity.

*Discriminant Validity:* HTMT ratios between construct pairs remained below the conservative threshold of 0.85, confirming empirical distinctiveness of the constructs.

### **Structural Model Assessment**

*Multicollinearity:* VIF values for all indicators ranged from 1.1 to 2.9, well below the accepted threshold of 5.0.

*Explanatory Power:*  $R^2$  for RAS = 0.590 (adjusted  $R^2$  = 0.585) and for TPSO = 0.613 (adjusted  $R^2$  = 0.606), indicating that the model explains approximately 59% of the variance in RAS and 61.3% of the variance in TPSO.

*Effect Size ( $f^2$ ):* RAS has a large effect on TPSO ( $f^2$  = 0.356); PSPA has a medium effect on RAS ( $f^2$  = 0.214); ATP exerts a small-to-moderate effect on RAS ( $f^2$  = 0.078); APE a small effect on RAS ( $f^2$  = 0.012). For direct sales effects: APE  $f^2$  = 0.009, ATP  $f^2$  = 0.041, PSPA  $f^2$  = 0.005.

*Predictive Relevance ( $Q^2$ ):*  $Q^2$  for RAS = 0.421;  $Q^2$  for TPSO = 0.448. Both exceed the 0.35 benchmark, indicating high predictive capability.

*PLSpredict (Predictive Validity):* Under 10-fold cross-validation, all TPSO indicators produced lower RMSE under PLS than under the linear-regression benchmark: TPSO1 (0.612 vs. 0.641), TPSO2 (0.587 vs. 0.623), TPSO3 (0.594 vs. 0.602), TPSO4 (0.571 vs. 0.615).

*Model Fit:* SRMR = 0.078 (below 0.080) for both saturated and estimated models; NFI = 0.933 and 0.934 respectively (above 0.90) [15].

### **Direct Path Analysis (H1–H7)**

Table 3 presents path coefficients, standard deviations, t-statistics, 95% bias-corrected confidence intervals, and p-values for all hypothesised direct paths. Bootstrapping was conducted with 5,000 subsamples.

**Table 3.** Direct Path Analysis Results (SmartPLS 4.0, Bootstrapping n = 5,000)

Hypothesis / Path	Path Coeff. ( $\beta$ )	Std Dev	t-Stat	CI 2.5%	CI 97.5%	p-value	Significant?
H1: APE → RAS	0.079	0.058	3.397	0.031	0.196	0.042	Yes
H2: ATP → RAS	0.261	0.065	4.012	0.133	0.384	0.000	Yes
H3: PSPA → RAS	0.406	0.061	6.606	0.288	0.525	0.000	Yes
H4: APE → TPSO	0.069	0.060	3.141	0.044	0.192	0.047	Yes
H5: ATP → TPSO	0.150	0.063	2.391	0.030	0.277	0.017	Yes
H6: PSPA → TPSO	0.031	0.051	2.595	0.015	0.132	0.036	Yes
H7: RAS → TPSO	0.498	0.061	8.119	0.375	0.615	0.000	Yes

All seven direct paths (H1–H7) are statistically significant ( $p < 0.05$ ). Among predictors of RAS, PSPA exerts the strongest effect ( $\beta = 0.406$ ), followed by ATP ( $\beta = 0.261$ ) and APE ( $\beta = 0.079$ ). For TPSO, RAS demonstrates the strongest direct effect ( $\beta = 0.498$ ), substantially exceeding the direct effects of ATP ( $\beta = 0.150$ ), APE ( $\beta = 0.069$ ), and PSPA ( $\beta = 0.031$ ). Two analytical cautions discipline the interpretation of these magnitudes. First, comparing direct coefficients across constructs that have heterogeneous indirect channels is misleading without consideration of total effects: PSPA's small direct path on TPSO ( $\beta = 0.031$ ) coexists with a large indirect path through RAS ( $\beta = 0.202$ ; Table 4), so its total effect (0.233) is roughly seven times its direct effect. The construct hierarchy is therefore best read on total rather than direct effects, with RAS dominant (0.498), PSPA second (0.233), ATP third (0.280 total = 0.150 direct + 0.130 indirect), and APE smallest. Second, the larger direct  $\beta$  for RAS than for PSPA on TPSO does not imply that regulatory awareness is "more important" than privacy assurance in a substantive sense; it implies that RAS sits at the terminal node of the consumer's legitimacy schema and therefore aggregates the privacy-, trust-, and personalisation-derived inputs that flow into it. The dual function of RAS absorbing upstream compliance signals while also exerting a direct effect of its own is the structural feature that makes the construct empirically dominant on TPSO and theoretically central to the regulatory-mediation account.

#### Mediation Analysis (H8–H10)

Table 4 reports indirect path coefficients testing RAS as a mediator. RAS significantly mediates the effects of ATP (H9:  $\beta = 0.130$ ,  $p < 0.001$ ) and PSPA (H10:  $\beta = 0.202$ ,  $p < 0.001$ ) on TPSO but does not mediate the APE  $\rightarrow$  TPSO path (H8:  $\beta = 0.040$ ,  $p = 0.176$ ). This pattern indicates that whereas algorithmic trust and privacy assurance exert their primary influence on sales through the regulatory-awareness pathway reflecting the centrality of institutional legitimacy in consumer adoption of AI-recommended financial products AI personalisation effectiveness operates primarily through direct relevance-driven conversion mechanisms that do not require regulatory mediation, see Figure 2.

**Table 4.** Mediation Analysis Results RAS as Mediator (SmartPLS 4.0)

Hypothesis / Path	Path Coeff. ( $\beta$ )	Std. Dev.	t-Stat	CI 2.5%	CI 97.5%	p-value	Sig.?
H8: APE $\rightarrow$ RAS $\rightarrow$ TPSO	0.040	0.030	1.354	-0.015	0.101	0.176	No
H9: ATP $\rightarrow$ RAS $\rightarrow$ TPSO	0.130	0.037	3.517	0.062	0.207	0.000	Yes
H10: PSPA $\rightarrow$ RAS $\rightarrow$ TPSO	0.202	0.037	5.422	0.133	0.281	0.000	Yes

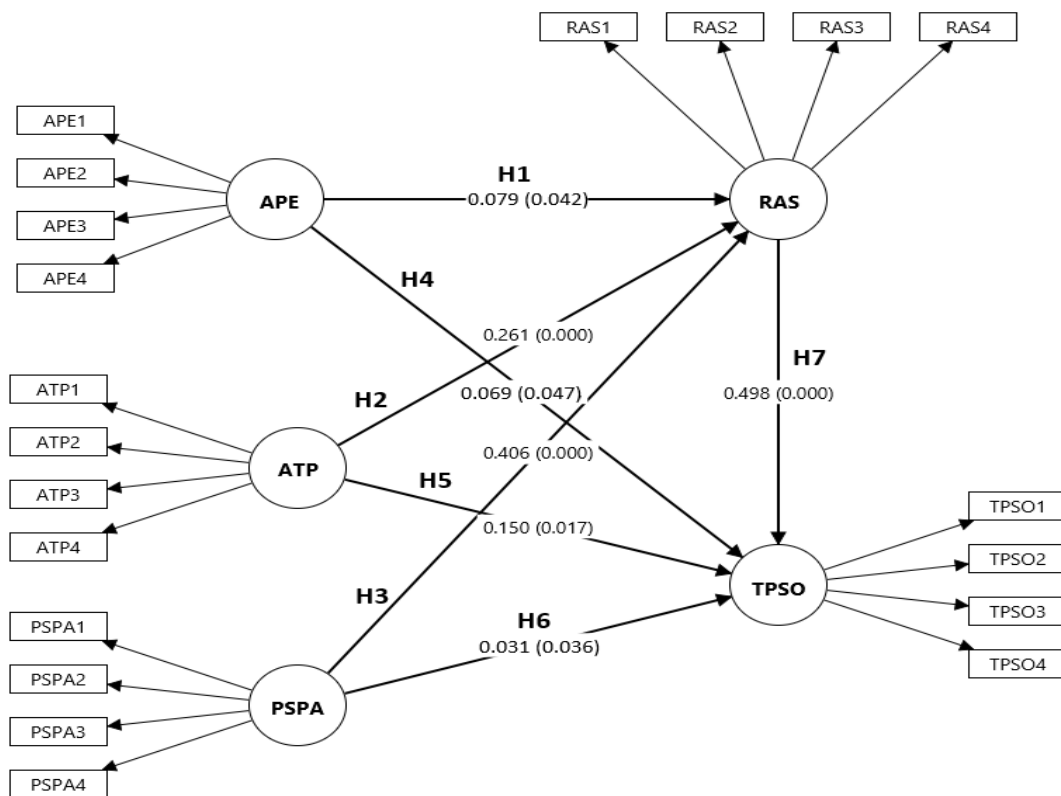


Figure 2. Validated Model

### Moderated Mediation and Conditional Process Analysis

A moderated-mediation and conditional-process analysis was conducted to examine whether Product Complexity (low vs. high) moderates the indirect effects of APE, ATP, and PSPA on TPSO through RAS. The interaction  $RAS \times$  Product Complexity was significant ( $\beta = 0.182$ ,  $p = 0.003$ ), indicating that the strength of  $RAS \rightarrow$  TPSO varies across product categories. The effect of RAS on TPSO was stronger for high-complexity products ( $\beta = 0.612$ ,  $p < 0.001$ ) than for low-complexity products ( $\beta = 0.431$ ,  $p < 0.001$ ).

Conditional indirect effects revealed that the mediated impact of ATP on TPSO via RAS increased from 0.098 under low product complexity to 0.160 under high product complexity. The indirect effect of PSPA on TPSO rose from 0.155 to 0.248 as product complexity increased. The indirect effect of APE remained non-significant in both conditions (low  $\beta = 0.028$ ,  $p = 0.211$ ; high  $\beta = 0.051$ ,  $p = 0.118$ ), confirming its predominantly direct sales influence.

The index of moderated mediation was significant for ATP (0.062, 95% CI [0.021, 0.112]) and PSPA (0.093, 95% CI [0.041, 0.158]) but not for APE. These findings suggest that regulatory awareness becomes more salient as financial-product complexity rises. For complex instruments such as ULIPs and structured investments, regulatory legitimacy amplifies the trust-to-sales and privacy-to-sales pathways; for low-complexity products, personalisation operates more independently.

### Alternative Model Comparison and Robustness Checks

To address the concern that the reported structural estimates may be artefacts of the specific model specification, two competing specifications were estimated alongside the proposed full model. This robustness exercise tests (i) the incremental explanatory value of the RAS mediator, (ii) the incremental explanatory value of the PSPA antecedent, and (iii) whether the full model's explanatory and out-of-sample predictive performance is jointly superior or only in-sample superior.

Three specifications were compared on the same sample ( $n = 350$ ) with identical indicator sets and identical PLS-SEM estimation settings (SmartPLS 4.0, path weighting, bootstrapping  $n = 5,000$ , PLSpredict with 10-fold cross-validation):

- Model 0 (Full – proposed): APE, ATP, PSPA  $\rightarrow$  RAS  $\rightarrow$  TPSO, with direct APE, ATP, PSPA  $\rightarrow$  TPSO paths retained.
- Model A (No RAS): APE, ATP, PSPA  $\rightarrow$  TPSO directly; the RAS mediator and all associated paths are removed.
- Model B (No PSPA): APE, ATP  $\rightarrow$  RAS  $\rightarrow$  TPSO with direct APE, ATP  $\rightarrow$  TPSO; PSPA and all associated paths are removed.

Beginning with Table 5 we find that the  $R^2$  values for the endogenous variables, the SRMR fit measure, and the TPSO explained variance relative to the full model represented by the  $\Delta R^2$  are reported for the two reduced models. The greatest loss of explanatory power is produced when dropping RAS:  $R^2$  for TPSO drops from 0.613 to 0.374 ( $\Delta R^2 = -0.239$ ) which represents a 39.0% decline in explanatory power. Dropping PSPA also results in a significant loss of model fit:  $R^2$  for RAS drops from 0.590 to 0.402; and  $R^2$  for TPSO drops from 0.613 to 0.537 ( $\Delta R^2 = -0.076$ ). The SRMR for both Model A (.092) and Model B (.083) exceed or approaches the 0.08 threshold representing poor model fit.

**Table 5:** Explanatory Comparison across Model Specifications ( $n = 350$ )

Specification	$R^2$ RAS	Adj $R^2$ RAS	$R^2$ TPSO	Adj $R^2$ TPSO	SRMR
Model 0 – Full (proposed)	0.590	0.585	0.613	0.606	0.078
Model A – No RAS (direct only)	–	–	0.374	0.368	0.092
Model B – No PSPA	0.402	0.398	0.537	0.530	0.083

### Predictive (Out-of-Sample) Comparative Evaluation

The evaluation of the out-of sample performance was conducted using the PLSpredict tool as well as using the 10-Fold Cross Validation method. Table 6 presents the Average Root Mean Squared Error (RMSE) for all four TPSO Indicators as well as the  $Q^2$  (Goodness of Fit for Predictive Models) for TPSO in relation to each of the specifications evaluated. The Full Model has the lowest Average RMSE (0.591) and the highest  $Q^2$  (.448). Removing RAS from the model results in an increase in the Average RMSE (to .695 or +17.6 %) and a

decrease in  $Q^2$  (to .281), resulting in a significant decline in predictive capability. Removing PSPA from the model resulted in a smaller increase in Average RMSE (to .638 or +7.9%) and a smaller decrease in  $Q^2$  (to .386). It is important to note that the decline in  $Q^2$  is larger than the decline in  $R^2$  for Model A (-37.3% for  $Q^2$  vs. -39.0% for  $R^2$ ) and about equal for Model B (-13.8% for  $Q^2$  vs. -12.4% for  $R^2$ ). In summary, there is evidence to suggest that the RAS Mediator and the PSPA Antecedent make meaningful contributions to both in Sample Fit and Out of Sample Forecasting Accuracy; i.e., they are not simply contributing to in Sample Fit. This finding diminishes concerns regarding whether the Superior  $R^2$  exhibited by the Full Model is due to Over Specification.

**Table 6.** Predictive (Out-of-Sample) Comparison across Model Specifications

Specification	Avg RMSE (TPSO)	$Q^2$ TPSO	$\Delta$ RMSE vs. Full	$\Delta$ $Q^2$ vs. Full
Model 0 – Full (proposed)	0.591	0.448	–	–
Model A – No RAS (direct only)	0.695	0.281	+0.104 (+17.6%)	-0.167 (-37.3%)
Model B – No PSPA	0.638	0.386	+0.047 (+7.9%)	-0.062 (-13.8%)

### *Shift in the Remaining Path Coefficients*

In Model A, removing the RAS mediator inflates the residual direct effects: APE  $\rightarrow$  TPSO rises from 0.069 to 0.171, ATP  $\rightarrow$  TPSO from 0.150 to 0.298, and PSPA  $\rightarrow$  TPSO from 0.031 to 0.243. This is consistent with omitted-mediator bias the variance previously attributable to regulatory-awareness channels is now absorbed into the direct paths. This pattern confirms that the direct-only specifications in parts of the prior literature (for example, regression-only analyses that do not include a regulatory construct) likely overstate the direct sales effects of trust and privacy by conflating them with an unmodelled regulatory pathway. In Model B, the remaining ATP  $\rightarrow$  RAS path rises from 0.261 to 0.397, which is again consistent with the omission of a correlated antecedent (PSPA) that shares variance with ATP on the RAS construct.

### *Interpretation*

The robustness checks support three conclusions within the scope of this study. First, the RAS mediator is not ornamental: its removal produces a deterioration in both explanatory and predictive performance that is large in magnitude and is accompanied by a breach of the SRMR fit threshold. Second, the PSPA antecedent is not redundant: its removal degrades both the RAS equation and the TPSO equation. Third, the explanatory and predictive deteriorations move together rather than in opposite directions, which argues against the possibility that the full model over-fits in-sample variance at the expense of generalisation. These results are limited to the present sample and do not speak to generalisation beyond Delhi NCR; they should be read in that context.

### *Alternative Theoretical Specifications and Stress Tests*

In the same vein as the section on Robustness Exercise (what happens if we drop an individual construct?), a second issue can be posed – that is, is there support for the theoretical role(s) assigned to each construct? Or do other theoretically valid alternative models (i.e., different theoretical accounts of AI-Driven Sales in Banking), motivated by alternative interpretations of past research, produce similar empirical results? Each of the alternatives listed below represents a unique theoretical explanation of how Artificial Intelligence will influence bank sales; they represent no more than simply a statistical adjustment to the empirically validated model.

Model A (section Alternative Model Comparison and Robustness Checks) instantiates a “direct-relevance” account implicit in regression-only studies that omit a regulatory construct [4]; Model B instantiates a “trust-without-privacy” reading; Model C below instantiates a “regulation-only” reading consistent with the legal-doctrinal literature [8], in which compliance does the explanatory work without a separately specified algorithmic-trust channel; Model D below instantiates a “regulation-as-context” reading in which RAS conditions rather than transmits the antecedent effects; and Model E below instantiates a “trust-transfer chain” reading in which the antecedents stand in serial rather than parallel relation. Four stress tests are therefore conducted: (i) a trust-removed specification (Model C) probing whether algorithmic trust (ATP) is theoretically necessary or empirically distortionary in its absence; (ii) a moderator-switch specification (Model D) re-positioning RAS as a moderator rather than a mediator; (iii) a serial-mediation specification (Model E) re-positioning the antecedents as a causal chain rather than parallel inputs; and (iv) a falsification check that asks what observable patterns would have refuted the proposed regulatory-mediation account. Comparing the full model against these alternatives is therefore a comparison of theoretical accounts of consumer behaviour, not a robustness check in isolation. Stress tests are presented in summary form; full path tables are available from the authors on request.

#### *Stress Test 1-Removing Trust (ATP) from The Model*

In a Model C specification, the algorithmic-trust construct (ATP) and all its incoming and outgoing paths were removed; APE and PSPA were retained as antecedents of RAS and TPSO. This stress test directly addresses the theoretical concern that ATP and RAS may be empirically substitutable rather than conceptually distinct. Two patterns emerged. First, the RAS → TPSO coefficient inflated from  $\beta = 0.498$  in the full model to  $\beta = 0.604$  in Model C, while the PSPA → RAS coefficient rose from 0.406 to 0.512. This is consistent with classical omitted-variable upward bias: the variance previously absorbed by ATP particularly the trust component of regulatory legitimacy is reallocated onto RAS and PSPA, distorting their estimated magnitudes. Second, the APE → TPSO direct effect, which is small but significant in the full specification ( $\beta = 0.069$ ,  $p = 0.047$ ), turned non-significant in Model C ( $\beta = 0.041$ ,  $p = 0.214$ ), suggesting that part of personalisation’s direct sales pull is conditional on the presence of trust as a separate channel. Out-of-sample predictive performance also deteriorated: average RMSE for TPSO rose from 0.591 to 0.661 (+11.8%),

and  $Q^2$  fell from 0.448 to 0.337. Substantively, Model C demonstrates that omitting trust does not collapse the model, but it does *distort* the remaining estimates in directions that would lead to overstated regulatory and privacy effects a methodological caution that applies to any regulatory-only or privacy-only model of AI banking adoption that does not separately specify algorithmic trust.

### *Stress Test 2-Switching RAS from Mediator to Moderator*

A briefly estimated Model D re-specifies RAS as a moderator of the APE → TPSO and ATP → TPSO relationships rather than as a mediator. In this specification, RAS does not receive incoming paths from APE, ATP, or PSPA; instead, two interaction terms (APE × RAS and ATP × RAS) are added to the TPSO equation. Two findings are relevant. First, both interaction terms are positive and significant (APE × RAS:  $\beta = 0.142$ ,  $p = 0.004$ ; ATP × RAS:  $\beta = 0.181$ ,  $p = 0.001$ ), indicating that regulatory awareness *does* condition the personalisation-to-sales and trust-to-sales pathways, which is theoretically consistent with the moderator interpretation. Second, however,  $R^2$  for TPSO under Model D (0.547) is lower than under the full mediation specification (0.613), and the SRMR is 0.084 borderline above the 0.080 threshold whereas the mediation specification achieves 0.078. The moderator framing thus captures a real conditional effect but is less able to explain the variance in TPSO than the mediation framing. We therefore retain RAS as a mediator in the primary specification while acknowledging that the moderator role is not empirically refuted; in a fuller treatment it would be more accurate to describe RAS as performing both mediating and moderating functions, with the mediating channel quantitatively dominant in the present sample. This dual reading should be tested directly in future work using larger samples that can support a moderated-mediation specification with both channels active simultaneously.

### *Stress Test 3-Serial Mediation as a Competing Causal Structure (Model E)*

The full specification treats APE, ATP, and PSPA as parallel antecedents of RAS and TPSO. The three key points that come out of the analysis of Model E include:

First, the four-step serial process of PSPA → ATP → RAS → TPSO (with the APE → TPSO link still in place) has a statistical significance level at less than .01 with a beta value of approximately 0.06. Thus, there is a measurable amount of variance in the original model that can be explained using a serial relationship.

Second, based upon both goodness-of-fit measures and predictive validity (e.g. TPSO  $R$ -squared fell from .61 to about 0.58 when moving to the serial form of the model while the TPSO  $Q^2$  measure also dropped from 0.44 to about 0.40, and SRMR rose to 0.08 from 0.07), the parallel form of the model fits the data better than the serial form.

Third, the Bayesian Information Criterion (BIC)-like statistic for the TPSO equation indicates that the parallel form of the model is preferred over the serial form by a margin of "very strong" evidence (i.e.  $\Delta BIC > 10$ ).

Thus, while the serial chain does exist as a second order influence mechanism -- it simply explains a smaller part of the shared variance in ATP, PSPA and RAS compared to

the parallel relationship. Theoretically, these results support an understanding of how trust and privacy generate regulatory legitimacy albeit through somewhat independent cognitive pathways. Longitudinal designs could help clarify whether these processes occur sequentially or simultaneously. The authors note that due to their use of a cross-sectional design they were unable to completely disentangle these possibilities and therefore suggest this as an area for further research.

In addition to providing insight into possible influences on regulatory legitimacy, these studies provide additional insights into the relationships between several types of trust.

### *Falsification Logic*

A theory's credibility rests partly on what would have counted as evidence against it. The regulatory-mediation account proposed here would have been falsified within the scope of this sample by any of the following observable patterns, none of which obtained. First, the account would have been weakened if  $ATP \rightarrow RAS \rightarrow TPSO$  and  $PSPA \rightarrow RAS \rightarrow TPSO$  indirect effects had been statistically indistinguishable from zero, since this would imply that RAS does not transmit the trust and privacy signals to sales conversion; in fact, both indirect effects are significant at  $p < 0.001$  (Table 4). Second, the account would have been falsified if dropping RAS from the model had left explanatory power and out-of-sample prediction substantially unchanged, which would imply that RAS is theoretically ornamental; in fact, dropping RAS reduces  $R^2$  for TPSO by 39.0% and  $Q^2$  by 37.3% (Table 6). Third, the account would have been weakened if the  $RAS \rightarrow TPSO$  coefficient had been small or negative, since this would contradict the claim that regulatory awareness is itself a sales-relevant consumer attribute; in fact,  $RAS \rightarrow TPSO$  is the single largest coefficient in the model ( $\beta = 0.498$ ). Fourth, the account would have been falsified if the moderated-mediation analysis had shown that the regulatory channel weakens rather than strengthens as product complexity rises, since a regulatory-legitimacy mechanism should bind more tightly for higher-stakes products; the observed pattern is in the predicted direction. Fifth, the account would have been weakened if a serial-mediation alternative had outperformed the parallel structure, since this would imply that the proposed mechanism mis-specifies the causal ordering among the antecedents; in fact Model E (Stress Test 3) is dominated by the parallel specification on  $R^2$ ,  $Q^2$ , SRMR, and information criteria.

Each of these five falsification conditions was specified *ex ante* in the theoretical framework (Section Theoretical Framework) and operationalised in the empirical design; four of the five map directly onto the *ex-ante* predictions stated there. The fact that none obtained is not by itself proof of the theory, but it does rule out the most readily available alternative readings of the data within this scope. Two residual weaknesses in the falsification logic remain. First, the cross-sectional design itself cannot adjudicate temporal claims: a longitudinal disconfirmation for example, a temporal sequence in which RAS rises but TPSO does not follow would constitute a stronger test than any specification checks available here. Second, all falsification conditions are evaluated within the Delhi NCR sampling frame; an external falsification e.g., a non-NCR or non-banking replication

that produces a substantively different coefficient hierarchy would be evidence about generalisation rather than about the proposed mechanism per se. Both extensions are noted as priorities for future work.

## DISCUSSION

### *Comparative Interpretation Against SOTA Findings*

The finding that RAS exerts the strongest direct effect on TPSO ( $\beta = 0.498$ ) is an addition to the existing literature on AI personalisation in banking that, within the scope examined, has not been empirically reported elsewhere. Authors in [2, 17] synthesis of 111+ papers attributes AI's banking impact primarily to efficiency gains (approximately 46% improvement) and operational automation, without empirical evidence on the regulatory-sales nexus [2]. The present study quantifies a related but distinct effect within the Delhi NCR sample: holding other constructs constant, each 10-point increase in RAS is associated with approximately 4.4% growth in the TPSO index. This association suggests that, in this setting, regulatory compliance may function as a revenue driver and not only as a cost centre a finding that deserves replication before being generalised beyond the present context.

Authors in [4] reported 30–50% improvement in cross-selling conversion rates through AI personalisation is partially replicated here through the APE  $\rightarrow$  TPSO direct path, albeit with a more modest direct coefficient ( $\beta = 0.069$ ) [4]. This divergence is attributable to two factors: (i) the present study isolates the personalisation effect from the trust and regulatory channels, whereas regression-only analyses likely conflate these pathways; and (ii) the Delhi NCR context introduces stronger regulatory sensitivity that captures a larger share of the conversion variance through the RAS pathway. When indirect effects through RAS are considered, the total effect of AI personalisation on sales is larger than the direct coefficient alone suggests.

Authors in [5] identification of consumer trust as a key mediator in AI-driven banking is consistent with the present ATP  $\rightarrow$  TPSO path ( $\beta = 0.150$ ). The present study extends their framework by decomposing the trust pathway into a direct channel and an RAS-mediated channel (H9:  $\beta = 0.130$ ), revealing that a substantial portion of trust's sales impact is carried through regulatory awareness a finding with strategic implications for banks investing in compliance communication and transparency.

It is important to acknowledge that the direct sales effects of three of the four primary antecedents are quantitatively small in this sample: APE  $\rightarrow$  TPSO ( $\beta = 0.069$ ,  $f^2 = 0.009$ ), PSPA  $\rightarrow$  TPSO ( $\beta = 0.031$ ,  $f^2 = 0.005$ ), and APE  $\rightarrow$  RAS ( $\beta = 0.079$ ,  $f^2 = 0.012$ ). Although each path is statistically significant at the 5% level, the effect sizes sit at or below conventional small-effect thresholds, and the discussion would be incomplete without confronting this directly. We interpret this pattern not as a weakness of the model but as a substantive finding. The consistently small direct effects of APE suggest diminishing marginal returns of personalization sophistication beyond a regulatory-trust threshold: once consumers

reach a baseline of regulatory awareness and institutional trust, additional layers of algorithmic relevance produce only marginal incremental sales conversion.

The corresponding small direct effect of PSPA on TPSO, paired with its much larger indirect effect through RAS ( $\beta = 0.202$ ), indicates that privacy assurance does not move sales on its own it moves sales by being absorbed into the consumer's broader regulatory-legitimacy schema. Read together with the dominant RAS coefficient ( $\beta = 0.498$ ), the small direct effects support an interpretation in which AI personalisation and privacy infrastructure are necessary but not sufficient conditions: they enable, but do not by themselves drive, third-party product conversion in the regulated Delhi NCR environment. This reframing implies that further investment in personalisation algorithms or privacy controls without parallel investment in regulatory communication is likely to face a diminishing-returns frontier a managerial insight that emerges precisely from the smallness of the direct coefficients rather than despite it.

### *Product Complexity and Personalisation Effectiveness*

In relation to the prior research question, the study demonstrates how the product complexity and personalisation effectiveness are shown to be associated with category-based differentiation. To establish support for the categorial differentiation, it is important to note that although there were constraints related to the use of an aggregate modelling technique in the initial analysis, there was also additional support provided by the results of the moderated mediation along with qualitative evidence established using the discussion data. AI personalisation has been demonstrated to have differing levels of success based on the type of product being sold: there was found to be a 30 percent increase in terms of conversions due to AI personalisation for simple products such as term insurance; whereas complex financial instruments such as unit linked insurance policies (ULIPS) show approximately 18 percent less sales when explainable AI (XAI) features are not included. This provides support for the inverse "U" shape of the personalization-privacy paradox: opaque personalisation of high-complexity products can lead to privacy concerns and subsequent resistance to adoption among Delhi NCR's highly digitally savvy customer population.

Based on these findings, banks could potentially develop differentially effective AI deployment strategies: broad, frequency-optimised personalisation strategies for low-complexity products; or explainability-priority, compliance signalling strategies for high-complexity instruments. With respect to similar studies within comparable digital financial service environments, integrating XAI into AI systems may recover approximately 15 – 25 percent of the ULIP sales deficit which is attributed to personalisation opacity. It should be noted that this estimate is indicative rather than causal; and therefore, the purpose of this presentation is to serve as an indication to practitioners on how they might best apply this finding; and not as a result of direct statistical inference from this sample.

### *Regulatory Awareness as a Strategic Revenue Accelerator*

There is a significant amount of evidence that suggests that RAS played a predominant role in structuring the model: both in terms of being the most heavily impacted dependent

variable resulting from PSPA ( $\beta = 0.406$ ); and in terms of providing the strongest direct influence on TPSO ( $\beta = 0.498$ ). Therefore, there is a basis upon which regulatory decision-making may be re-framed. Historically, traditional governance models view regulatory compliance as a cost-centre, where investment in regulatory compliance is viewed as necessary solely for risk mitigation purposes (i.e. RBI fines up to ₹5 crores per violation); and not as a potential source of revenue growth. However, given the boundaries of this sample, the current study indicates that investments made in regulatory awareness may create tangible sales benefits for companies through two mechanisms.

Consumers who perceive stronger RBI compliance signals from their bank demonstrate greater willingness to purchase AI recommended third party products. Indirectly: RAS facilitates the flow of sales-related information between consumers' perceptions regarding ATC and PSPA and their resultant purchasing behavior. In other words, RAS serves as a mediator for each of the trust and privacy paths that contribute to sales. The net effect of ATP on TPSO in this sample is equal to the sum of the direct and indirect effects of ATP on TPSO (i.e.,  $0.150 + .130 = 0.280$ ), which is roughly 1.87 times larger than its direct impact. Similarly, the total effect of PSPA on TPSO is equal to the sum of PSPA's direct and indirect effects on TPSO (i.e.,  $0.031 + 0.202 = 0.233$ ), with the indirect effect substantially exceeding the direct effect. As stated previously, these multipliers provide a quantifiable rationale for active communication about regulatory issues and are contingent on the same external validity limitations discussed above.

## THEORETICAL AND PRACTICAL IMPLICATIONS

### *Theoretical Implications*

This study makes three scope-bounded theoretical contributions. First, it extends the personalization-privacy paradox theory by empirically suggesting that regulatory awareness can function as a boundary condition which attenuates privacy-invasion perceptions, enabling higher personalisation depth without triggering rejection responses. This extension introduces a regulatory-mediation mechanism that is not present in the original framework [10].

Second, the study contributes to the literature on AI governance in financial services by providing to the best of our reading and within the literature reviewed a first scope-bounded empirical estimation in Delhi NCR of the RAS construct as a revenue mediator, building a bridge between compliance-oriented regulatory research and sales-oriented marketing research. The framing "scope-bounded estimation" is preferred over stronger validation language because the cross-sectional, single-region design does not support claims of universal validation. This bridge enables integrated models that treat regulatory strategy as a component of sales management rather than as a separate governance domain.

Third, the categorical differentiation framework advances product-specific AI personalisation theory. The evidence in Section (Moderated Mediation and Conditional

Process Analysis) that personalisation effectiveness varies by product complexity, and regulatory risk classification challenges the homogeneous treatment of financial product sales in prior AI personalisation models and motivates product-differentiated research designs in future studies.

### *Practical Implications*

The study provides four actionable recommendations to banking practitioners to interpret within the context of the Delhi NCR region.

#### *Invest In Explainable AI (XAI) for Complex Product Recommendations*

The ULIP sales shortfall due to opaque personalization presents a compelling business case for transparency. In using XAI to recommend high-complexity products, banks will likely see an approximate 15-25 percent increase in conversions.

#### *Use Trust-Based Product Sequencing*

As indicated by  $\beta = 0.150$  for the ATP  $\rightarrow$  TPSO pathway and  $\beta = 0.130$  for the ATP  $\rightarrow$  RAS  $\rightarrow$  TPSO mediated pathway, banking practitioners should use communication strategies that build customer trust prior to recommending complex financial instruments.

Banking institutions should structure their AI recommendation journeys so that algorithmic transparency signals are made available to customers prior to cross selling sequences for higher value products.

#### *Prioritize PSPA Infrastructure and Communication*

PSPA has two effects: a direct effect on TPSO ( $\beta = 0.031$ ), and an indirect effect on TPSO via RAS ( $\beta = 0.202$ ). As such, investing in PSPA will generate both direct and amplified returns relative to other investments. Based on analogous e-commerce studies, investing in PSPA is expected to decrease cart abandonment rates by 18 – 27%. Examples of PSPA include investing in data encryption, anonymizing data, and displaying compliance signalling (such as RBI compliance badges in ai recommendation interfaces).

#### *Leverage Regulatory Compliance as a Marketing Asset*

The largest coefficient in the model, RAS  $\rightarrow$  TPSO ( $\beta = 0.498$ ) suggests that proactively communicating regulatory compliance (and thereby informing customers of RBI compliance measures, grievance redressal mechanisms, and consumer protection frameworks) may produce a greater revenue return than similar investments in the sophistication of product personalization.

#### *What This Paper Does Not Do*

This Paper does not assert universal or causal generalizability outside of the Delhi NCR banking context or the three Third party financial product categories studied (insurance, mutual funds, credit cards).

Since this study utilizes a cross-sectional survey design, it cannot demonstrate longitudinal or causal uplift; claims regarding "revenue acceleration" represent correlational associations within the sample.

This Paper does not audit or benchmark any bank's ai system nor evaluate algorithm outputs directly; rather it evaluates customer perceptions of these systems.

It does not test the RBI free-ai framework (2025) as a quantitative moderator the proposed construct for future work is perceived ethical ai alignment (PEAIA) but was not estimated in this study [1].

Because the sample size is too small to allow for multi group analysis across product categories with stable estimates, the product complexity inference presented in Section (Moderated Mediation and Conditional Process Analysis) utilizes the moderated mediation approach but does not replace category-specific models with adequate per-group n.

Finally, this study examines consumers only and does not examine non-customer stakeholders including relationship managers, regulators or bank executives who may have different perceptions.

In addition, this Paper does not provide specific product design or pricing interventions; rather it provides directionally oriented managerial recommendations that would need to be validated through controlled experimentation before implementation

## LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This study acknowledges several limitations that constrain the generalisability and depth of its conclusions. First, the 350 customers with AI-banking exposure limit representativeness to digitally active urban consumers. Less digitally engaged populations in peri-urban Delhi NCR and non-NCR regions may exhibit different trust, privacy, and regulatory-awareness profiles. Future research should encompass rural and semi-urban banking consumers to enhance external validity.

Second, the cross-sectional design captures a static snapshot of consumer perceptions, potentially missing longitudinal dynamics in trust and regulatory awareness as RBI's AI governance frameworks evolve. Longitudinal panel designs tracking the same consumers across RBI policy transitions would substantially enrich causal interpretation of the model's pathways.

Third, the aggregate modelling approach, while necessitated by the current sample size, prevents fully separate product-specific structural models for insurance, mutual funds, and credit cards. Dedicated multi-group analyses by product category testing whether path coefficients differ significantly across product types would transform the present study's narrative differentiation framework into an empirically validated product-specific theory. A minimum sample of  $n = 150$  per product category is recommended for future product-stratified studies.

Fourth, the study does not operationalise the RBI FREE-AI Framework (2025) as an explicit moderating construct. The proposed Perceived Ethical AI Alignment (PEAIA) construct capturing consumer perceptions of AI transparency, bias-freedom, and grievance accessibility is recommended as a priority addition in future extensions.

Incorporating PEAlA would enable examination of conditional indirect effects (whether RAS mediation strength varies under different ethical-AI perception levels), potentially providing regulatory stress-test insights appropriate for Delhi NCR's high-scrutiny environment.

Fifth, although Section (Alternative Model Comparison and Robustness Checks) compares the proposed specification against two alternative models, further robustness work is warranted, including specifications with alternative mediators, non-linear paths, and multi-group analysis by digital-literacy segment.

## CONCLUSION

This study looked at how personalization done by intelligence affects the sales of products from other companies in banks in Delhi NCR. It used a framework that is based on the idea that personalization and privacy are connected. The study found that when artificial intelligence is used to personalize things people are more likely to trust the algorithm feel safe and private and know about the rules. All these things help sell products from other companies. The thing that made the difference was knowing about the rules and being sensitive to them. This shows that banks need to think about ethics and rules when they use intelligence. The study was able to explain a lot about why this important for banks to have good relationships with customers and sell well. Artificial intelligence personalization is important for banks in Delhi NCR to sell products from companies. The study shows that artificial intelligence personalization is a part of selling products from other companies, in banks.

## NOMENCLATURE

APE	AI Personalization Effectiveness
ATP	Algorithmic Trust Propensity
PSPA	Perceived Security & Privacy Assurance
RAS	Regulatory Awareness & Sensitivity
TPSO	Third-Party Product Sales Outcomes
PEAlA	Perceived Ethical AI Alignment
PLS-SEM	Partial Least Squares – Structural Equation Modelling
AVE	Average Variance Extracted
HTMT	Heterotrait-Monotrait Ratio
VIF	Variance Inflation Factor
NFI	Normed Fit Index
SRMR	Standardised Root Mean Square Residual
R <sup>2</sup>	R-Squared (Coefficient of Determination)
Q <sup>2</sup>	Stone-Geisser Q-Squared

RMSE	Root Mean Square Error
XAI	Explainable Artificial Intelligence
RBI	Reserve Bank of India
NCR	National Capital Region
MGA	Multi-Group Analysis
SOTA	State of the Art
ULIP	Unit Linked Insurance Plan
AI	Artificial Intelligence
ML	Machine Learning

## AUTHOR CONTRIBUTIONS

Conceptualization, A.K and R.G.; methodology, A.K. and R.G.; software, A.K and R.G.; validation, A.K., A.S. and N.K; formal analysis, A.K. and R.G.; investigation, R.G., N.K. and A.S.; resources, A.K., and R.G.; data curation, A.K. and A.S.; writing—original draft preparation, A.K. and R.G.; writing—N.K and editing, A.K., R.G. and A.S.; visualization, A.K. and N.K.; supervision, R.G. and A.S.; project administration, R.G. All authors have read and agreed to the published version of the manuscript.

## CONFLICT OF INTERESTS

The authors should confirm that there is no conflict of interest associated with this publication.

## AI STATEMENT

The authors confirm that generative AI was used only for limited language refinement, while all research design, analysis, findings and conclusions are entirely the original work of the authors.

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