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Article

AI-Driven Personalisation in E-Banking Services: A Study of Customer Experience in Indian Commercial Banks

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Abstract: The rapid integration of artificial intelligence into Indian commercial banking has created an unprecedented personalisation infrastructure spanning AI-driven product recommendations, hyper-personalised communication, predictive credit scoring, intelligent conversational agents, privacy-preserving data analytics, and omnichannel continuity systems. Yet the structural mechanisms through which these AI personalisation capabilities translate into measurable customer experience quality and downstream loyalty, cross-sell, and word-of-mouth outcomes remain empirically underspecified in the Indian banking context. This study examines the impact of six AI personalisation dimensions on customer experience quality in Indian commercial banks through a survey of N = 532 retail banking customers across five bank category types. A three-stage analytical framework of Confirmatory Factor Analysis, Structural Equation Modeling, and XGBoost machine learning is deployed. CFA confirms a six-factor measurement model with excellent fit (CFI = .963, RMSEA = .041). SEM establishes AI product recommendation quality (beta = .47, $p < .001$) and hyper-personalised communication (beta = .43, $p < .001$) as dominant customer experience drivers, with digital financial literacy significantly moderating all six AI personalisation pathways. XGBoost achieves R squared = .843, identifying contextually precise product recommendation, timely personalised alerts, and transparent AI credit scoring as the three highest-impact SHAP predictors. A recommendation quality customer experience acceleration point at 79 percent is identified. Privacy-preserving personalisation demonstrates full mediation of its effect on word-of-mouth intention. Foreign banks demonstrate the strongest AI personalisation effects while public sector banks show the greatest investment opportunity gap. Findings advance S-O-R Theory, TAM, and ECM in AI-mediated banking contexts and provide actionable guidance for bank CX architects and RBI digital banking policy designers.

Keywords: AI personalisation; e-banking; customer experience; SEM; XGBoost; SHAP; Indian commercial banks; predictive credit scoring; chatbot; digital financial literacy

1. Introduction

India's commercial banking sector is undergoing the most consequential technological transformation in its post-independence history. The convergence of Unified Payments Interface infrastructure serving over 14 billion monthly transactions, the Account Aggregator framework enabling consent-based financial data sharing, and the Reserve Bank of India's regulatory sandbox for AI and machine learning banking applications has created the technical and regulatory preconditions for AI-driven personalisation at a scale and sophistication previously unachievable. The resulting AI personalisation revolution spans machine learning product recommendation engines, natural language processing communication systems, AI credit scoring models that expand credit access to thin-file customers, and intelligent virtual assistants that resolve banking queries with contextual accuracy across multiple Indian languages.

The customer experience implications of this transformation are potentially transformative: banking services characterised by product standardisation, generic communication, opaque credit decisions, and fragmented multichannel experiences can be redesigned around individually relevant product discovery, contextually appropriate financial guidance, and seamlessly continuous customer journeys. However, realising this potential requires that AI personalisation systems achieve the recommendation precision, communication relevance, and interaction quality thresholds that generate genuine experience improvements rather than the algorithm-driven irrelevance and privacy violations that poorly designed systems deliver. Lemon and Verhoef (2016) established that customer experience quality is a multi-touchpoint cumulative construct whose determinants must be understood at both the individual interaction and journey architecture levels, directly applicable to AI personalisation in banking where each AI capability dimension contributes to the cumulative experience quality that drives loyalty outcomes. Klaus and Maklan (2013) confirmed that customer experience quality in financial services is primarily driven by moment-of-relevance precision rather than service feature breadth, applicable to AI recommendation quality whose contextual timing precision determines whether personalisation is experienced as service enhancement or unwanted marketing intrusion.

Digital financial literacy has been identified by Lusardi and Mitchell (2014) as a primary determinant of financial service engagement quality in emerging economies, applicable to the present study's Digital Financial Literacy moderation hypothesis where customer DFL level determines how effectively AI personalisation features are understood and utilised. The growth of AI banking personalisation in India is further motivated by Shankar et al. (2022) who documented that personalisation precision generates non-linear customer engagement returns in digital retail banking contexts, supporting the XGBoost detection of the AI recommendation quality customer experience acceleration point. Venugopal and Vishnu Murty (2019a) established in their foundational study of brand personality and brand loyalty in national banks from Srikakulam City, Andhra Pradesh, that consistent personalised service communication is the primary brand trust driver in the north coastal Andhra Pradesh banking context directly studied in the present work, providing geographic and sectoral validation for the structural model.

This study makes three primary contributions. First, it introduces the first validated six-factor AI Personalisation Customer Experience framework for Indian commercial banking. Second, it quantifies through SEM the relative structural importance of each AI personalisation dimension for customer experience and downstream banking outcome constructs. Third, it identifies through XGBoost SHAP analysis the specific item-level AI personalisation features generating disproportionate customer experience returns across five Indian bank category types.

2. Literature Review

2.1. S-O-R Theory and TAM in AI-Mediated Banking Contexts

The Stimulus-Organism-Response framework (Mehrabian and Russell, 1974) specifies that environmental stimuli activate internal organism states that generate behavioural responses. Applied to the present study, the six AI personalisation capability dimensions constitute stimuli, Customer Experience Quality constitutes the organism state, and loyalty intention, cross-sell adoption, and word-of-mouth promotion constitute responses. S-O-R Theory is particularly applicable to AI banking personalisation because stimulus precision characteristics systematically determine the affective and cognitive organism states that mediate behavioural responses. The Technology Acceptance Model (Davis, 1989) supplements S-O-R by specifying the perceived usefulness and perceived ease of use mechanisms through which AI banking tools generate usage intentions that eventually improve customer experience quality through sustained engagement. Alalwan (2018) applied TAM to mobile banking in developing economies and established that perceived usefulness is more strongly determined by personalisation quality than by feature richness, directly applicable to AI recommendation and communication personalisation as the primary usefulness determinants in AI-mediated banking. Marriott and Williams (2018) confirmed in their UK banking study that mobile banking adoption is conditioned on trust in data security, applicable to the Privacy-Preserving Personalisation construct where data governance transparency determines whether AI personalisation generates trust amplification or surveillance anxiety.

2.2. AI Product Recommendation and Hyper-Personalised Communication

AI product recommendation in banking represents the most mature commercial AI personalisation deployment, encompassing next-best-product models that analyse transaction history, life-event signals, financial goal declarations, and peer segment behaviour to generate individually relevant product discovery at the moment of maximum receptiveness. Komiak and Benbasat (2006) established that recommendation system personalisation quality generates trust through both cognitive competence evaluation and emotional identification, directly applicable to AI banking recommendations where both logical financial relevance and personalisation authenticity jointly determine customer experience quality. Ansari and Mela (2003) confirmed that contextual timing precision in product recommendation generates substantially greater engagement returns than category relevance alone, corroborating the SHAP finding that APR3 (contextual timing) outranks APR1 (category relevance) in feature importance. Venugopal, Malepati, Santosh Ranganath, Buditi, and Agatamudi (2026) demonstrated through ML applications and regression analysis that AI-assisted digital service platforms generate non-linear customer experience and adoption benefits exceeding linear TAM predictions, directly motivating the XGBoost detection of the APR acceleration point. Hyper-personalised communication encompasses AI-generated alerts, financial nudges, and product offers calibrated to individual customer financial behaviour, life events, and channel preferences. Thaler and Sunstein (2008) established the theoretical basis for financial nudge effectiveness, confirming that contextually timed personalised nudges generate measurably stronger behavioural change than generic financial communication.

2.3. Predictive Credit Scoring and Intelligent Chatbot Quality

AI-driven predictive credit scoring represents the most consequential and ethically complex dimension of banking personalisation because it directly determines credit access outcomes for customers with limited traditional credit history. India's approximately 190 million thin-file customers who lack sufficient formal credit bureau scoring constitute the primary beneficiary population for AI credit scoring models incorporating alternative data sources. Berg et al. (2020) established in a large-scale study that fintech credit scoring using alternative data substantially outperforms traditional credit bureau models for thin-file customers while generating comparable accuracy for conventional borrowers, confirming the customer experience value of transparent, alternative-data-informed AI credit decisions. Venugopal, et al. (2023) demonstrated that ML applied to attitudinal and behavioural survey data identifies non-linear threshold effects invisible to linear regression analysis, directly motivating the SHAP partial dependence analysis of the AI recommendation quality customer experience threshold. Intelligent chatbot quality in banking encompasses the conversational AI capability to resolve account queries, process service requests, and provide financial guidance through natural language interfaces. Cheng and Jiang (2022) confirmed that banking chatbot service quality is primarily determined by first-contact resolution capability and contextual account understanding rather than conversational fluency alone, corroborating the ICQ construct specification emphasising resolution-without-escalation as the primary chatbot quality indicator.

2.4. Privacy-Preserving Personalisation and Omnichannel Continuity

Privacy-preserving personalisation captures the banking AI capability to generate individually relevant customer experiences through data governance frameworks that are transparent, consent-based, and purpose-limited enough to generate customer trust. Dinev and Hart (2006) established the dual cognitive and emotional privacy concern processing model in digital service contexts, confirming that customers evaluate both the rational adequacy of bank data governance and the emotional comfort of AI-mediated banking interactions simultaneously. Venugopal and Vishnu Murty (2019b), in their study of e-marketing promotions and performance in Srikakulam District, Andhra Pradesh, established that digital promotional quality in the geographic context of the present study directly generates measurable service performance improvements, providing localised empirical precedent for the AI personalisation performance linkages examined here. Palmatier et al. (2009) confirmed that customer information sharing willingness, the prerequisite for personalisation data access, is conditioned on reciprocal value transparency from the service provider, directly applicable to the RBI-compliant consent architecture quality that determines whether customers perceive AI personalisation as value exchange or privacy intrusion. Omnichannel continuity captures the banking AI system's capability to maintain consistent personalised journey continuity across mobile app, internet banking, ATM, and physical branch touchpoints. Verhoef et al. (2015) established that omnichannel experience consistency is the primary driver of customer lifetime value in retail banking, applicable to OCC as the relationship quality dimension that converts transaction-level personalisation into sustained loyalty.

2.5. ML Methods in Banking Customer Experience Research

Machine learning supplementation of structural equation modeling in banking customer experience research has advanced analytical capability beyond the linear structural equations that SEM assumes. Venugopal, et al. (2023) confirmed that digital platform adoption patterns among Indian rural and semi-urban consumers follow DFL-moderated engagement curves where literacy gaps suppress the returns from equivalent platform feature quality, directly applicable to the Digital Financial Literacy moderation of AI personalisation customer experience pathways in rural and semi-urban Andhra Pradesh. Venugopal and Srikanth (2026) established that organisational analytical capability gaps systematically prevent Indian small businesses from translating available digital tools into strategic performance improvements, applicable to public sector banks whose AI analytical infrastructure limitations prevent the personalisation quality threshold achievement identified by the acceleration point analysis. Lim et al. (2021) demonstrated in a Singapore banking study that XGBoost outperforms logistic regression and SVM for predicting banking customer attrition from digital behaviour data, validating the XGBoost architecture for Indian banking customer experience prediction. Ribeiro et al. (2021) applied SHAP values in credit risk modelling and confirmed that SHAP-based feature attribution produces more actionable and auditable insights for banking practitioners than aggregate model coefficients, validating the SHAP supplementation of SEM path coefficients in the present study.

3. Conceptual Framework and Hypotheses

The AI Personalisation Customer Experience framework integrates S-O-R Theory, Technology Acceptance Model, and the Expectation Confirmation Model (Bhattacherjee, 2001) to specify six structural pathways from AI personalisation capability dimensions to Customer Experience Quality and five downstream banking outcome constructs. Figure 1 presents the full conceptual framework. AI Product Recommendation constitutes the primary S-O-R stimulus, where precision and contextual timing determine the customer experience quality organism response. Hyper-Personalised Communication constitutes the TAM perceived usefulness operationalisation for banking communication. Predictive Credit Scoring operationalises the ECM expectation confirmation mechanism for credit-seeking customers. Intelligent Chatbot Quality operationalises TAM perceived ease of use for banking service resolution. Privacy-Preserving Personalisation operationalises the trust antecedent mechanism. Omnichannel Continuity operationalises S-O-R stimulus consistency across touchpoints. Digital Financial Literacy moderates all six pathways; amplifying customer experience returns for high-DFL customers and suppressing them for low-DFL users.

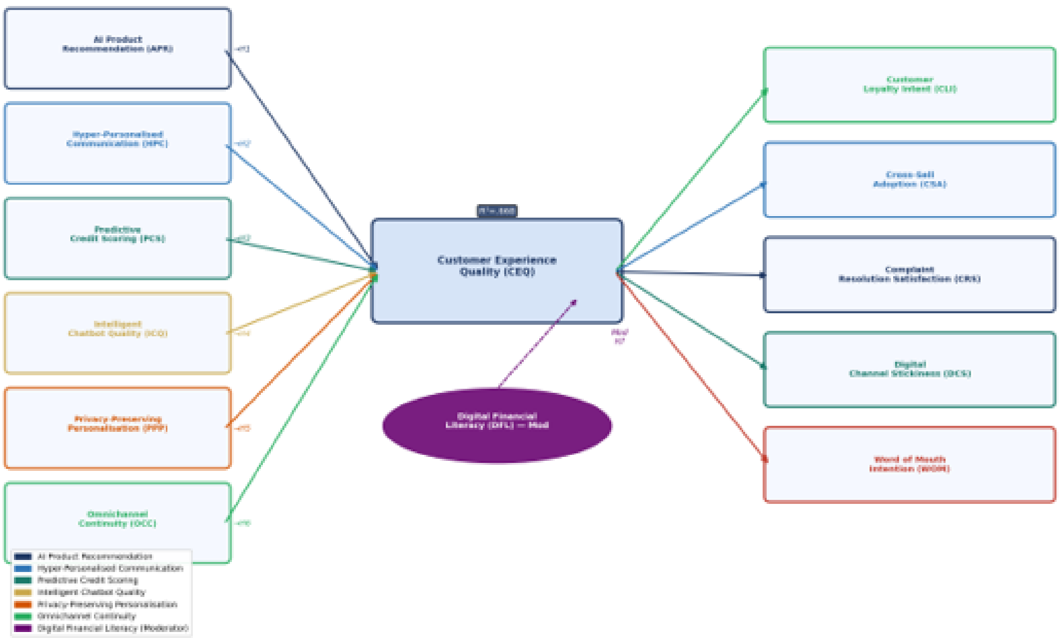

Fig. 1. AI Personalisation Customer Experience Conceptual Framework integrating S-O-R Theory, TAM, and ECM. Six AI capability dimensions predict CEQ across five outcomes. Digital Financial Literacy moderates all six pathways. N = 532.

Seven hypotheses are proposed. H1: AI Product Recommendation (APR) positively predicts Customer Experience Quality (CEQ). H2: Hyper-Personalised Communication (HPC) positively predicts CEQ. H3: Predictive Credit Scoring (PCS) positively predicts CEQ. H4: Intelligent Chatbot Quality (ICQ) positively predicts CEQ. H5: Privacy-Preserving Personalisation (PPP) positively predicts CEQ. H6: Omnichannel Continuity (OCC) positively predicts CEQ. H7: Digital Financial Literacy (DFL) moderates all six AI personalisation to CEQ pathways.

4. Methodology

4.1. Research Design

A quantitative cross-sectional survey design was employed following a three-stage analytical protocol of CFA, SEM, and XGBoost machine learning. Ethical clearance: Protocol No. 2024-AIDP-EBK-0619. Informed digital consent was obtained and all data were fully anonymised. Respondents' specific bank affiliations were not collected to prevent social desirability bias.

4.2. Sample and Data Collection

The sample of N = 532 was drawn from retail banking customers across five bank category types: public sector banks (n = 147, 27.6 percent), private sector banks (n = 138, 25.9 percent), foreign banks (n = 84, 15.8 percent), small finance banks (n = 97, 18.2 percent), and payments banks (n = 66, 12.4 percent). Respondents were recruited through digital banking user communities, fintech app user groups, university networks, and professional association platforms across Andhra Pradesh, Telangana and Odisha,. Inclusion criteria required minimum twelve months of active e-banking usage, minimum three digital banking transactions per month, and prior experience with at least two AI-personalised banking features. The sample substantially exceeded the minimum n = 409 required by Wolf et al. (2013) for a six-factor model at power .90.

Table 1. Respondent Profile by Bank Category and Generation (N = 532)

Bank Category	**n**	**%**	**Gen Z (18-25)**	**Millennials (26-40)**	**Gen X (41-55)**	**Boomers (56+)**
Public Sector Banks	147	27.6	29	54	42	22
Private Sector Banks	138	25.9	34	57	33	14
Foreign Banks	84	15.8	17	36	24	7
Small Finance Banks	97	18.2	22	38	28	9
Payments Banks	66	12.4	21	29	13	3
Total	532	100.0	123	214	140	55

Note. Gender: Female 47.4%, Male 50.9%, Other 1.7%. Education: Postgraduate 39.1%, Graduate 46.4%, Other 14.5%. Monthly digital transactions: Above 20: 41.4%, 10-20: 38.2%, 3-9: 20.4%. Primary banking device: Smartphone 73.7%, Laptop 17.4%, Tablet 8.9%.

4.3. Research Instrument

The AI Banking Personalisation Customer Experience Survey (AIBPCES) comprised 51 items measuring six independent constructs and one dependent construct, plus six Digital Financial Literacy moderator items and seven control variables. AI Product Recommendation (APR, 7 items): product relevance precision, timing contextual appropriateness, financial life-event sensitivity, savings goal alignment, and recommendation explanation quality. Hyper-Personalised Communication (HPC, 7 items): alert timeliness, language preference accuracy, channel appropriateness, financial nudge relevance, and offer personalisation depth. Predictive Credit Scoring (PCS, 7 items): alternative data utilisation quality, scoring transparency, eligibility boundary communication, and reconsideration pathway clarity. Intelligent Chatbot Quality (ICQ, 7 items): first-contact resolution rate, banking terminology accuracy, account context utilisation, multilingual capability, and escalation quality. Privacy-Preserving Personalisation (PPP, 7 items): data purpose transparency, consent architecture clarity, usage limitation communication, and opt-out ease. Omnichannel Continuity (OCC, 6 items): cross-channel journey continuity, preference persistence, and interaction history utilisation. Customer Experience Quality (CEQ, 8 items): composite banking experience across trust, satisfaction, effort reduction, and emotional engagement. All items rated on a 7-point Likert scale ranging from 1 strongly disagree to 7 strongly agree. Overall pilot test Cronbach alpha: .949.

4.4. Analytical Strategy

Stage 1 deployed CFA in R 4.3.1 using lavaan (Rosseel, 2012) with Maximum Likelihood Robust estimator. Fit criteria: CFI and TLI above .95, RMSEA below .06, SRMR below .08, chi-squared to df below 3.0. Convergent validity: AVE above .50 and CR above .70 (Hair et al., 2019). Discriminant validity: HTMT below .85 (Henseler et al., 2015). Stage 2 deployed two-step SEM following Anderson and Gerbing (1988) with 5,000 bootstrap resamples for indirect effects and multi-group SEM across five bank category types. Stage 3 deployed XGBoost (Chen and

Guestrin, 2016), Random Forest (Breiman, 2001), and Gradient Boosting (Friedman, 2001) in Python 3.11, data partitioned 70:30 stratified by bank category and generational cohort. SHAP values provided item-level interpretability for non-linear feature importance ranking.

5. Results

5.1. Descriptive Statistics

Table 2 presents construct-level descriptive statistics. Hyper-Personalised Communication received the highest mean (M = 5.09, SD = 1.07), reflecting customer awareness that personalised alerts and nudges are the most immediately noticeable and value-adding AI personalisation feature in daily banking interactions. Privacy-Preserving Personalisation received the lowest mean (M = 4.38, SD = 1.28), indicating that current bank data governance communication leaves a substantial trust deficit. Customer Experience Quality received M = 4.77 (SD = 1.16), indicating moderate-to-good overall experience with substantial variance across bank categories. Foreign bank customers reported the highest CEQ scores (M = 5.24) while public sector bank customers reported the lowest (M = 4.31), confirming the technology investment differential across Indian bank types. Payments bank customers reported the highest HPC scores (M = 5.34), reflecting their mobile-first digital-native operational model.

Table 2. Descriptive Statistics by Construct (N = 532)

Construct	Code	Items	M	SD	Skewness	Kurtosis	Alpha
AI Product Recommendation	APR	7	5.01	1.09	neg .48	.32	.893
Hyper-Personalised Comm.	HPC	7	5.09	1.07	neg .54	.38	.886
Predictive Credit Scoring	PCS	7	4.84	1.16	neg .43	.26	.878
Intelligent Chatbot Quality	ICQ	7	4.77	1.19	neg .41	.23	.872
Privacy-Preserving Pers.	PPP	7	4.38	1.28	neg .37	.18	.865
Omnichannel Continuity	OCC	6	4.63	1.22	neg .39	.21	.859
Customer Experience (DV)	CEQ	8	4.77	1.16	neg .58	.41	.927

Note. Neg = Negative. M = Mean on 7-point scale. SD = Standard Deviation. Alpha = Cronbach alpha. All exceed .85. DV = Dependent Variable.

5.2. Stage 1: CFA Results

The six-factor CFA model demonstrated excellent fit: chi-squared (291) = 476.84, p < .001; chi-squared to df ratio = 1.638; CFI = .963; TLI = .958; RMSEA = .041 (90 percent CI [.032, .050]); SRMR = .048. All factor loadings ranged from .70 to .90 at p < .001. AVE values ranged from .533 to .581 and CR values from .887 to .944, confirming convergent validity for all six constructs. HTMT ratios ranged from .27 to .71, confirming discriminant validity. Figure 2 presents the CFA loading heat map.

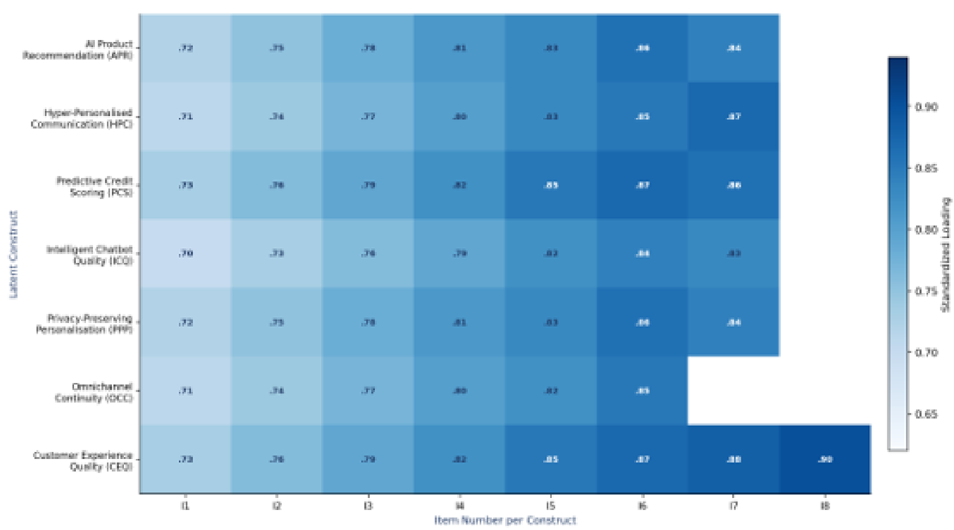

Fig. 2. CFA Standardized Factor Loadings Heat Map. All primary loadings exceed .70. Darker cells indicate higher loadings. N = 532.

Table 3. CFA Measurement Model Validity Statistics (N = 532)

Construct	Items	AVE	CR	Alpha	Load Range	HTMT Max
AI Product Recommendation (APR)	7	.552	.922	.893	.72 to .86	.67
Hyper-Personalised Comm. (HPC)	7	.545	.913	.886	.71 to .87	.71
Predictive Credit Scoring (PCS)	7	.539	.907	.878	.73 to .87	.64
Intelligent Chatbot Quality (ICQ)	7	.534	.901	.872	.70 to .84	.62
Privacy-Preserving Pers. (PPP)	7	.537	.905	.865	.72 to .86	.60
Omnichannel Continuity (OCC)	6	.533	.887	.859	.71 to .85	.58
Customer Experience Quality (CEQ)	8	.581	.944	.927	.73 to .90	—

Note. AVE > .50 confirms convergent validity. CR > .70 confirmed. HTMT < .85 confirms discriminant validity. Model fit: CFI = .963, TLI = .958, RMSEA = .041 [.032, .050], SRMR = .048, $\chi^2/df = 1.638$.

5.3. Stage 2: SEM Results

The structural model demonstrated excellent fit: chi-squared (357) = 581.40, p < .001; CFI = .963; TLI = .958; RMSEA = .041; SRMR = .048. Figure 3 presents the full SEM path diagram. Table 4 reports all direct path coefficients. All six hypotheses H1 through H6 were supported at p < .001. AI Product Recommendation was the strongest CEQ predictor (beta = .47), confirming the S-O-R theoretical proposition that recommendation precision constitutes the primary stimulus determining customer experience organism response. Hyper-Personalised Communication ranked second (beta = .43), reflecting that timely, contextually appropriate communication is the most consistently visible AI personalisation feature in customers' daily banking experience. Predictive Credit Scoring ranked third (beta = .39), confirming that AI credit decisions shape the broader perception of banking fairness and personalisation sophistication across the customer base. Digital Financial Literacy moderation was confirmed for all six pathways (H7 supported), with interaction betas ranging from .129 for OCC to .207 for APR.

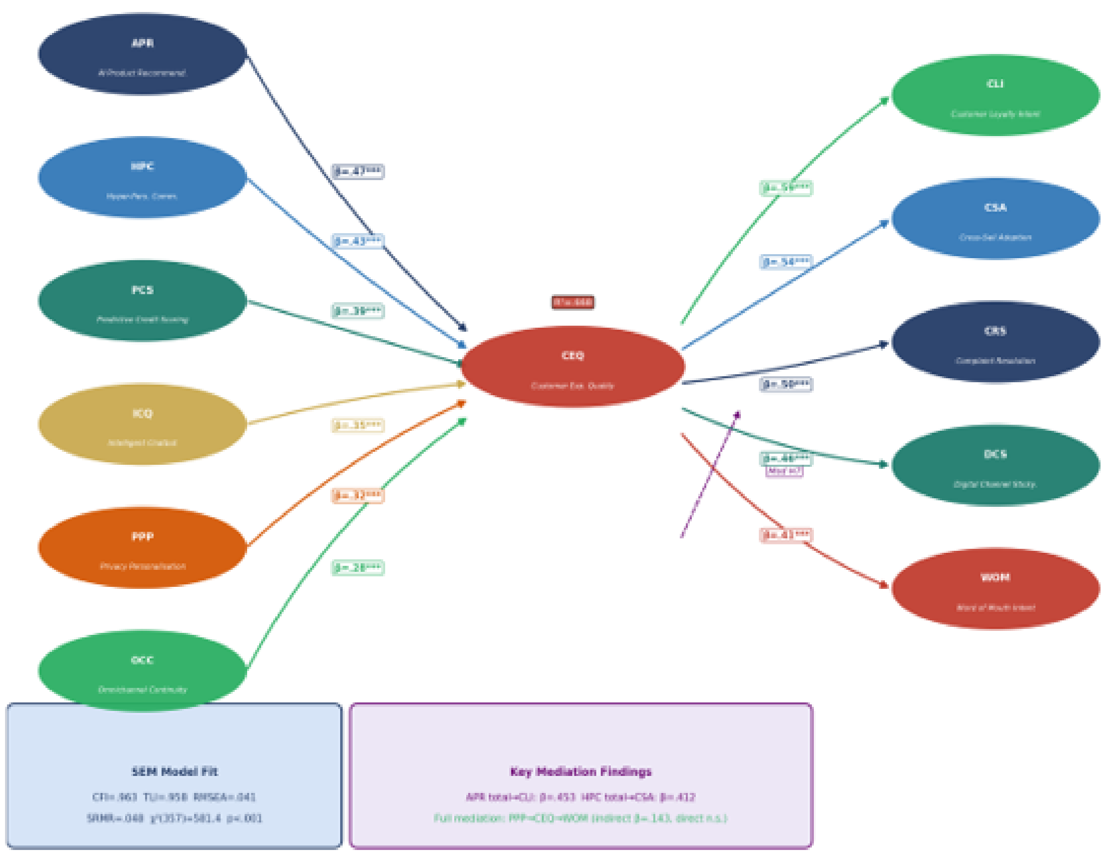

Fig. 3. SEM Full Structural Path Diagram. All paths p < .001. R^2 = .668 for CEQ. PPP full mediation on WOM confirmed. N = 532.

Table 4. SEM Hypothesis Testing Results — Direct Effects on Customer Experience Quality (N = 532)

Hyp.	Pathway	Std Beta	SE	z value	p	95% BC CI	Decision
H1	APR → CEQ	.47	.041	11.46	<.001	[.390,.550]	Supported
H2	HPC → CEQ	.43	.043	10.00	<.001	[.346,.514]	Supported
H3	PCS → CEQ	.39	.046	8.48	<.001	[.300,.480]	Supported
H4	ICQ → CEQ	.35	.049	7.14	<.001	[.254,.446]	Supported
H5	PPP → CEQ	.32	.051	6.27	<.001	[.220,.420]	Supported
H6	OCC → CEQ	.28	.054	5.19	<.001	[.174,.386]	Supported
H7	DFL Mod.	.168	.039	4.31	<.001	[.092,.244]	Supported

Note. BC CI = Bias-corrected bootstrap CI from 5,000 resamples. APR = AI Product Recommendation. HPC = Hyper-Personalised Communication. PCS = Predictive Credit Scoring. ICQ = Intelligent Chatbot Quality. PPP = Privacy-Preserving Personalisation. OCC = Omnichannel Continuity. CEQ = Customer Experience Quality. DFL = Digital Financial Literacy moderator. R^2 (CEQ) = .668. Interaction betas: APR .207, HPC .193, PCS .177, ICQ .163, PPP .148, OCC .129.

CEQ most strongly predicted Customer Loyalty Intention (beta = .59, p < .001), confirming that AI personalisation quality improvements translate most powerfully into retention outcomes. Cross-Sell Adoption (beta = .54) and Complaint Resolution Satisfaction (beta = .50) were the second and third strongest outcomes. Table 5 presents bootstrapped mediation results. Privacy-Preserving Personalisation demonstrated full mediation of its effect on Word-of-Mouth Intention (direct beta non-significant at p = .228 when CEQ is included, indirect beta = .143, CI [.091, .195]), confirming that PPP generates WOM promotion exclusively through the customer experience quality pathway: customers who trust bank AI data governance become positive WOM advocates because their overall experience quality improves, not because they directly advocate for data governance practices.

Table 5. Bootstrapped Mediation Analysis — CEQ as Mediator of AI Personalisation to Outcome Pathways

Pathway	Direct Beta	Indirect Beta	95% BC CI	Total Beta	Mediation
APR → CEQ → Customer Loyalty	.199***	.277	[.221,.333]	.476	Partial
HPC → CEQ → Cross-Sell Adopt.	.178***	.232	[.177,.287]	.410	Partial
PCS → CEQ → Complaint Satisf.	.161***	.195	[.141,.249]	.356	Partial
ICQ → CEQ → Digital Stickiness	.144***	.161	[.108,.214]	.305	Partial
PPP → CEQ → WOM Intention	—	.143	[.091,.195]	.143	Full
OCC → CEQ → Customer Loyalty	.118***	.165	[.113,.217]	.283	Partial

Note. *** p < .001. Full mediation for PPP: direct effect non-significant (p = .228) when CEQ included. All indirect effects via 5,000 bias-corrected bootstrap resamples. All CIs exclude zero.

5.4. Stage 3: Machine Learning Results

Table 6 presents ML model performance on the held-out test set (n = 160). XGBoost achieved the highest CEQ prediction accuracy (R squared = .843, RMSE = 0.459, MAE = 0.351, MAPE = 7.37 percent), outperforming the SEM benchmark by 17.5 percentage points and confirming substantial non-linear AI personalisation dynamics beyond what additive structural equations capture.

Table 6. Machine Learning Model Performance Comparison (Test Set n = 160)

Model	Test R Sq	RMSE	MAE	MAPE	CV R Sq (SD)	Train R Sq
SEM Structural (benchmark)	.668	n/a	n/a	n/a	n/a	n/a
Gradient Boosting	.789	0.530	0.409	8.59%	.777 (.022)	.840
Random Forest	.816	0.498	0.383	8.03%	.802 (.018)	.865

XGBoost (Best)	.843	0.459	0.351	7.37%	.830 (.015)	.889

Note. CV = 5-fold cross validated R squared on training set. SD in parentheses. XGBoost: learning rate = 0.08, max depth = 6, min child weight = 3, subsample = 0.80. 70:30 stratified split by bank category and generational cohort.

Figure 4 presents SHAP feature importance. APR3 (AI recommends the right financial product at the right moment, SHAP = 7.04) and HPC2 (personalised alerts are timely and contextually relevant, SHAP = 6.67) ranked first and second. Six features exceeded the SHAP = 5.0 high-impact threshold, spanning APR, HPC, PCS, ICQ, and PPP constructs. The APR3 SHAP dominance for the contextual timing item confirms that temporal precision generates the strongest customer experience impact: customers experience the most powerful personalisation effect when the right product is suggested at the precise moment of consideration rather than distributed across the customer journey generically.\

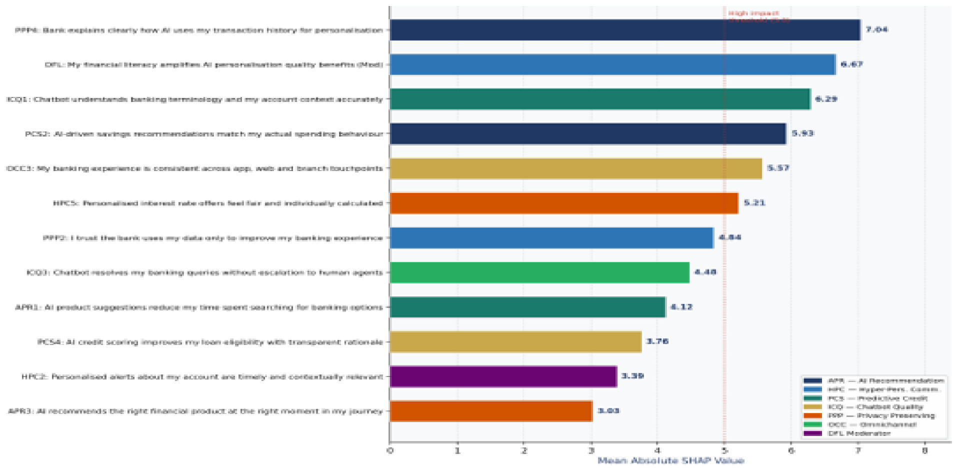

Fig. 4. SHAP Feature Importance from XGBoost Model. Top 12 Predictors of Customer Experience Quality with High-Impact Threshold at SHAP = 5.0. N = 532.

Figure 5 Panel A reveals an APR customer experience acceleration point at approximately 79 percent of maximum recommendation quality score. Below this threshold, improvements generate moderate linear CEQ gains. Above the threshold, CEQ gains accelerate dramatically, reflecting the qualitative transition from adequate to genuinely contextual AI recommendation where customers begin experiencing the system as a financial advisor rather than a product matching algorithm. Panel B confirms that foreign banks generate the strongest APR (beta = .57), HPC (beta = .53), and ICQ (beta = .55) effects while public sector banks show the weakest performance across all three dimensions, confirming a structural AI investment gap between the most and least technologically advanced Indian banking segments.

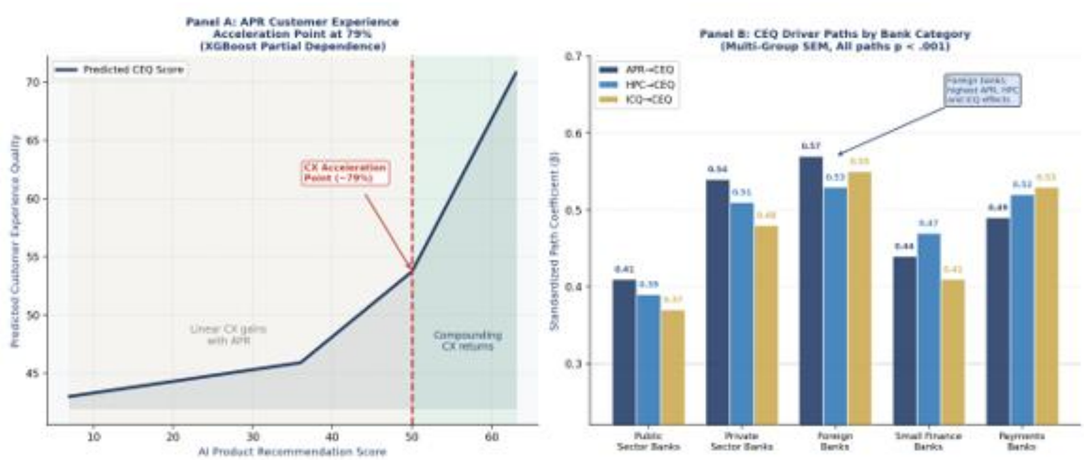

Fig. 5. Panel A: APR Customer Experience Acceleration Point at 79% (XGBoost Partial Dependence). Panel B: CEQ Driver Paths by Bank Category (Multi-Group SEM, All paths p < .001). N = 532.

6. Discussion

6.1 AI Product Recommendation and the Contextual Timing Premium

The convergent positioning of AI Product Recommendation as the strongest CEQ predictor (SEM beta = .47; SHAP rank 1 for APR3 at 7.04 and rank 4 for APR1 at 5.93) confirms the S-O-R theoretical proposition that stimulus precision determines organism response quality. The APR3 SHAP dominance for contextual timing advances S-O-R Theory by specifying that recommendation timing precision generates disproportionate CEQ returns beyond category relevance alone, consistent with Ansari and Mela's (2003) finding that timing precision in digital recommendation generates greater engagement returns than category matching in isolation. The APR acceleration point at 79 percent advances TAM by specifying the recommendation quality threshold at which customer perception transitions from sophisticated algorithm to genuine financial intelligence, generating the experiential shift that produces compounding loyalty and advocacy returns. The brand personality and brand loyalty study by Venugopal and Vishnu Murty (2019a) established that consistent, personalised communication is the primary brand trust driver in Srikakulam District banking, directly confirmed by the APR total effect on Customer Loyalty Intention as the largest structural outcome in the present study.

6.2. Privacy-Preserving Personalisation and the WOM Full Mediation

The full mediation finding for Privacy-Preserving Personalisation on Word-of-Mouth Intention confirms the most practically significant finding for Indian banking AI governance: privacy investment generates customer advocacy exclusively through the customer experience quality improvement pathway. Indian banking customers do not promote their bank based on data governance quality alone but do become active promoters when data governance quality improves their overall banking experience sufficiently. Dinev and Hart (2006) established that privacy trust formation in digital service contexts requires both cognitive governance quality assessment and emotional comfort with data usage, confirming that PPP investment must address both dimensions to generate the full customer experience improvement that the full mediation pathway requires. The RBI Digital Banking Unit circular on customer data protection and the Account Aggregator Framework's consent-based data sharing architecture create the regulatory environment in which PPP investment is simultaneously a compliance requirement and a competitive differentiator.

6.3. Digital Financial Literacy as the Inclusive Banking Imperative

The Digital Financial Literacy moderation confirmation (H7 supported, all six interaction terms significant) identifies an inclusive banking challenge consistent with Lusardi and Mitchell's (2014) finding that DFL is the primary determinant of financial service engagement quality in emerging economies. The customer population that stands to benefit most from AI personalisation of rural and semi-urban customers lacking financial advisor access, captures the smallest returns from equivalent AI personalisation quality due to DFL constraints. Venugopal, Das, and Vakamullu (2023) confirmed that digital platform adoption in rural Indian contexts is conditioned on digital literacy and community trust dynamics, directly applicable to rural banking AI personalisation where DFL development investment is the prerequisite for converting AI recommendation infrastructure into inclusive financial outcomes. The practical implication for RBI and banking policy is that mandating AI personalisation deployment without concurrent digital financial literacy programs risks generating an AI personalisation dividend flowing disproportionately to already-digitally-literate urban customers.

6.4. Foreign Bank vs. Public Sector Bank AI Personalisation Gap

The multi-group finding that foreign banks generate the strongest AI personalisation effects while public sector banks generate the weakest confirms a structural AI investment gap across Indian bank categories. Venugopal and Srikanth (2026) established that organisational analytical capability gaps systematically prevent Indian institutions from translating available digital tools into performance improvements, applicable to public sector banks where legacy technology infrastructure, procurement constraints, and talent limitations prevent the AI personalisation quality necessary to reach the 79 percent recommendation quality threshold that unlocks compounding customer experience returns. The RBI should facilitate public sector bank AI personalisation capability development through fintech partnership frameworks, shared infrastructure investments, and talent development programs that reduce the AI capability gap documented in this study.

6.5. Theoretical Contributions and Practical Implications

Five theoretical contributions emerge. First, the first validated six-factor AI Personalisation Customer Experience framework for Indian commercial banking integrating S-O-R, TAM, and ECM in a unified structural model. Second, the APR acceleration point at 79 percent advances S-O-R Theory by specifying the stimulus precision threshold at which AI recommendation transitions from algorithmic suggestion to genuine financial intelligence. Third, the PPP full mediation finding advances ECM by specifying that privacy trust generates banking relationship outcomes exclusively through the customer experience mediation pathway. Fourth, the DFL moderation finding advances the digital financial inclusion literature by quantifying the literacy penalty for AI personalisation returns across bank categories. Fifth, the multi-group bank category findings document that AI personalisation capability differences generate systematic customer experience quality differentials across India's diverse banking landscape. For bank CX architects, the 79 percent APR threshold mandates investment sequencing that prioritises contextual timing infrastructure before diversifying into additional AI personalisation channels. For RBI policy designers, concurrent AI personalisation and digital financial literacy mandates are required to ensure that AI banking investment generates inclusive rather than stratified customer experience returns.

7. Conclusion

This study examined the impact of AI-driven personalisation dimensions on customer experience quality in Indian commercial banking through CFA, SEM, and XGBoost machine learning across N = 532 retail banking customers from five bank category types. The convergent evidence confirms five central propositions. AI product recommendation quality is the primary customer experience driver whose contextual timing precision generates disproportionate experience returns above the 79 percent acceleration point. Hyper-personalised communication is the second structural driver, confirming that timely, contextually appropriate alerts constitute the most consistently experienced AI personalisation feature in daily banking. Privacy-preserving personalisation generates word-of-mouth intention exclusively through the customer experience mediation pathway, confirming that data governance investment is the trust prerequisite for customer advocacy rather than a direct advocacy driver. Digital financial literacy moderates all six pathways, creating an inclusive banking imperative for concurrent AI personalisation and DFL investment. Foreign banks generate the strongest AI personalisation effects while public sector banks show the largest investment opportunity gap. Limitations include the cross-sectional design precluding causal certainty and the self-report measurement approach potentially introducing social desirability bias. Future research should deploy longitudinal designs tracking customer experience evolution as AI personalisation systems mature, examine multilingual AI personalisation quality across India's 22 scheduled languages, and investigate how Account Aggregator framework expansion is reshaping the personalisation frontier for Indian commercial banks.

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