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INNOVATION



HEALTHCARE



EDUCATION



SUSTAINABLE
DEVELOPMENT



VIKSIT BHARAT

PART

2

Editors

Prof. (Dr.) Punit Goel
Dr. Abu Farah Hoque
Dr. Amit Agrawal
Dr. Sheela Sharma



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List of Contributors

Ch.	Contributor	Designation	Institution
1	Suravi Bhattacharya	Assistant Professor	Sanskar City College of Education, Rajnandgaon, Chhattisgarh
2	Dr. Shalini Verma	Assistant Professor	Bhilai Maitri College, Bhilai, Chhattisgarh
3	Madhubala Shrivastava	Assistant Professor	Sanskar City College of Education, Rajnandgaon, Chhattisgarh
4	Dr. Pushpa Sharma	Associate Professor	Mansa College of Education, Kohka, Kurud, Chhattisgarh
5	Dr. Ratri Lahri	Assistant Professor	Gurukul Mahila Mahavidyalaya, Raipur, Chhattisgarh
6	Mona Gupta	Guest Lecturer, Department of Commerce	Government Shaheed Kaushal Yadav College, Gunderdehi, Balod, Chhattisgarh
7	Namita Roy	Research Scholar, Department of Education	Anjaneya University, Raipur, Chhattisgarh
8	Dr. Simrann Rajesh Vermaa	Assistant Professor, Department of English	Gurukul Mahila Mahavidyalaya, Raipur, Chhattisgarh
9	Dr. Kavita Silwal	Assistant Professor	Gurukul Mahila Mahavidyalaya, Raipur, Chhattisgarh
10	Dr. Shweta Bhatia	Professor & Head, Department of Education; IQAC Coordinator	M.J. College, Kohka, Bhilai, Chhattisgarh
11	Dr. Soju Samuel	Counsellor	Delhi Public School, Bhilai, Chhattisgarh
12	Dular Das	Research Scholar	Hemchand Yadav University, Durg, Chhattisgarh
13	Dr. Archana Pandey	Assistant Professor	Sanskar City College of Education, Rajnandgaon, Chhattisgarh
14	Dr. Sandhya Pujari	Head (TTEP)	Sandipani Academy, Achhoti, Durg, Chhattisgarh
15	Shalini Sahu	Assistant Professor	Sanskar City College of Education, Rajnandgaon, Chhattisgarh
16	Dr. Manju Sahu	Associate Professor	M.J. College, Kohka, Bhilai, Chhattisgarh
17	Mrs. Lileshwari Sahu	Assistant Professor	Somni Mahavidyalaya, Somni, Rajnandgaon, Chhattisgarh
18	Dr. Shraddha Bhardwaj	Assistant Professor	Jagadguru Shankaracharya College of Education, Bhilai, Durg, Chhattisgarh
19	Mamta Rani Yadu	Research Scholar	Anjaneya University, Raipur, Chhattisgarh

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20	Dr. Sumita Singh	Assistant Professor, Department of Education	St. Thomas College Bhilai, Chhattisgarh
21	Tulsi Sahu	Assistant Professor	Sanskar City College of Education, Rajnandgaon, Chhattisgarh
22	Dr. Juhi Peter	Assistant Professor	Agrasen College, Dhanora, Durg, Chhattisgarh
23	Dr. Divya Sharma	Head & Assistant Professor, Department of Education	<i>Institution not stated in chapter</i>
24	Prof. (Dr.) Gurpreet Kaur	Principal	Sanskar City College of Education, Thakurtola, Rajnandgaon, Chhattisgarh
25	Dr. Anjana Sharad	Principal, Prism School of Education	Mahkakurd, Utai, Bhilai, Chhattisgarh
26	Dr. Sangeeta Shrivastav	Assistant Professor	Mansa College of Education, Bhilai, Chhattisgarh
27	Dr. Ruchi Sachan	Head, Department of Education	Maharaja Agrasen International College, Raipur, Chhattisgarh
28	Dr. Surekha Vinod Patil	Principal	Bhilai Maitri College, Durg, Chhattisgarh
29	Dr. Usha Lahare	Guest Lecturer	Government Minimata Girls' College, Korba, Chhattisgarh
30	Dr. Rita Gupta	Head, Department of Education	GDRCST, Rungta International Skill University, Bhilai, Chhattisgarh
31	Smt. Anupama Ambast	Assistant Professor	CTE, Raipur, Chhattisgarh
32	Smt. Pramila Patel	Assistant Professor	Bhilai College of Information Technology, Jamul, Durg, Chhattisgarh
33	Dr. Gopa Sharma	Headmistress	Government Primary School, Hatband, Raipur, Chhattisgarh
34	Meenakshi Yadav	Assistant Professor	Agrasen College, Dhanora, Durg, Chhattisgarh
35	Renuka Sahu	Assistant Professor	Sanskar City College of Education, Rajnandgaon, Chhattisgarh
36	Dr. Atul Kumar Soni	Assistant Professor	Pt. Kishori Lal Shukla Vidhi Mahavidyalaya, Rajnandgaon, Chhattisgarh
37	Mrs. Preeti Mishra	Assistant Professor, Department of Education	Mansa College of Education, Bhilai, Chhattisgarh

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38	Ranjana Solanki	Assistant Professor	Agrasen College, Dhanora, Durg, Chhattisgarh
39	Dr. Nirmala Parganiha	Assistant Professor	Agrasen College, Dhanora, Durg, Chhattisgarh
40	Kiran Sonatiya	Assistant Professor	Sanskar City College of Education, Rajnandgaon, Chhattisgarh

Chapter 6: Digital Banking Services and Customer Satisfaction in the Contemporary Banking Sector

Mona Gupta

Guest Lecturer

Department of Commerce

Government Shaheed Kaushal Yadav College

Gunderdehi, Balod, Chhattisgarh

Abstract — Digital banking has evolved from a supplementary transaction channel into a primary interface through which customers interact with contemporary financial institutions. This study examines customer satisfaction by integrating conventional digital service-quality attributes with artificial intelligence-enabled service responsiveness, perceived security, personalization, and transaction reliability. The research addresses an emerging gap in the literature: most digital-banking satisfaction models evaluate static service-quality perceptions but insufficiently capture the interaction between AI-assisted service encounters and customers' experience of friction across the digital banking journey. A predictive framework is therefore proposed in which behavioural survey indicators and digitally experienced service attributes are jointly evaluated through machine-learning techniques. The planned empirical design uses customer-level data covering mobile banking, internet banking, digital payments, automated assistance, and digitally initiated service requests. Machine-learning models are designed to estimate satisfaction and identify nonlinear relationships among reliability, security confidence, transaction friction, AI responsiveness, personalization quality, and perceived control.

Keywords — Digital Banking, Customer Satisfaction, Artificial Intelligence, Machine Learning, Service Quality, Explainable AI

Introduction

Digital transformation has substantially altered the structure of retail banking. Activities that once required customers to visit a branch—fund transfers, account monitoring, bill payments, service requests, statement retrieval, card management, investment access, loan applications, and customer-support interactions—are increasingly performed through mobile and web-based environments. Consequently, the digital interface has become more than a distribution channel. For many customers, it effectively represents the bank itself.

The expansion of digital banking has simultaneously changed the meaning of customer satisfaction. In conventional branch banking, satisfaction was strongly associated with employee behaviour, waiting time, physical facilities, procedural efficiency, and interpersonal responsiveness. Digital environments introduce a different combination of expectations. Customers increasingly assess banks according to application stability, authentication convenience, transaction speed, platform availability, privacy protection, navigation

simplicity, instantaneous confirmation, personalization, and the quality of automated assistance.

Recent research confirms that digital service quality remains closely associated with banking satisfaction. Studies have identified reliability, responsiveness, privacy, system availability, ease of use, and customer experience as important components of digital banking evaluations. Evidence from Northern India, for example, indicates the relevance of traditional service-quality dimensions in explaining digital banking satisfaction, while more recent Indian research has applied structural equation modelling to investigate digital banking service quality and customer satisfaction.

However, contemporary digital banking is becoming increasingly algorithmic. Artificial intelligence is being deployed through conversational assistants, fraud-detection systems, recommendation mechanisms, biometric authentication, customer-service automation, and data-driven personalization. Research published in *Heliyon* found that expectation confirmation, perceived performance, visual attractiveness, problem-solving capability, and communication quality were among the factors associated with satisfaction with AI-enabled digital banking. More recent evidence published in 2026 further indicates that perceived usefulness, behavioural intention, trust, and AI adoption can play significant roles in customer satisfaction with digital banking services.



Fig. 1: Example of a multichannel customer service in a modern digital bank

Source: https://www.researchgate.net/figure/Example-of-a-multichannel-customer-service-in-a-modern-digital-bank-9_fig2_338422163

These developments create an important conceptual problem. A technologically sophisticated banking application does not automatically produce a satisfactory banking experience. A customer may appreciate personalized recommendations but remain dissatisfied when a payment fails. Another customer may value rapid automated responses but become frustrated when a chatbot cannot understand a non-standard complaint. Similarly, strong security procedures may increase confidence while simultaneously increasing interaction friction through repeated authentication requirements. Customer satisfaction therefore emerges from the combined effect of technical performance, psychological confidence, perceived control, intelligent assistance, and the amount of effort required to complete a digital journey.

Existing studies frequently examine these attributes through linear explanatory frameworks. Structural equation modelling, regression analysis, SERVQUAL-derived models, technology acceptance frameworks, and conventional hypothesis testing have generated substantial knowledge regarding digital banking behaviour. For example, research from Sri Lanka found that tangibility, responsiveness, privacy, and system availability affected digital banking satisfaction, while another study showed that customer experience and ease influenced satisfaction among digital banking customers.

Yet relationships within contemporary digital banking may not always be linear. Extremely fast service may produce little additional satisfaction once customers perceive transactions as sufficiently instantaneous. Personalization may increase satisfaction until customers perceive the recommendations as intrusive. Additional authentication can increase perceived security but, beyond a certain point, may reduce convenience. Automated assistance can improve satisfaction for routine requests while creating dissatisfaction when escalation to a human agent becomes difficult.

Machine learning provides a useful methodological extension because it can identify complex interactions, nonlinear associations, and heterogeneous combinations of predictors without requiring every relationship to be specified in advance. Nevertheless, predictive accuracy alone is inadequate in a banking context. Banks require explanations indicating *why* satisfaction is predicted to increase or decline. Consequently, explainable artificial intelligence (XAI) becomes important for translating predictive outputs into operationally interpretable customer-experience insights.

Research Gap

The central research gap addressed by this manuscript lies at the intersection of **digital service quality, AI-mediated customer interaction, digital friction, and explainable satisfaction prediction.**

Existing research has established relationships between digital banking service quality and satisfaction, and a growing literature examines AI acceptance in financial services. However, relatively less attention has been given to customer satisfaction as a **multidimensional predictive outcome produced by interactions among transaction reliability, security confidence, digital friction, AI responsiveness,**

personalization quality, and perceived customer control. Studies using customer surveys also tend to rely heavily on aggregate linear relationships, potentially overlooking threshold effects and complex interactions among digital experience variables.

This study therefore proposes a **Friction–Intelligence–Trust Satisfaction Framework (FITSF).** The framework conceptualizes digital banking satisfaction as the result of three interacting experiential layers:

Digital friction captures the effort encountered while completing banking activities, including authentication burden, navigation complexity, transaction interruptions, repeated data entry, and difficulty resolving failures.

Service intelligence represents the perceived usefulness of AI-assisted support, contextual recommendations, automated problem resolution, and responsiveness to individual requirements.

Digital trust represents confidence in security, privacy, transaction integrity, transparency, and the customer's perceived ability to control digital interactions.

Rather than assuming independent linear effects, the proposed framework allows these dimensions to interact. For instance, AI responsiveness may have greater influence when digital friction is high because intelligent assistance can help resolve problems. Conversely, personalization may have a weaker or even adverse influence when customers perceive insufficient privacy or control.

Research Objectives

The study is designed to determine how contemporary digital banking characteristics jointly influence customer satisfaction and to develop an interpretable machine-learning framework capable of predicting satisfaction from multidimensional customer-experience indicators. Specifically, it seeks to evaluate the predictive importance of transaction reliability, security confidence, digital friction, AI-assisted responsiveness, personalization, usability, and perceived customer control; compare conventional statistical modelling with nonlinear machine-learning approaches; identify interaction and threshold effects that conventional models may overlook; and use explainable AI to translate model predictions into actionable banking-service insights.

The resulting framework shifts the research question from the relatively simple issue of whether digital banking improves satisfaction toward a more operationally relevant question: **which combinations of digital experiences produce satisfied or dissatisfied customers, and can these combinations be identified accurately and transparently through machine learning?**

Literature Review

Transformation of Digital Banking and the Customer Experience

Digital banking has progressed through several technological stages. Early electronic banking primarily extended conventional banking functions through automated teller machines and internet portals. Mobile applications subsequently consolidated account access, transfers, payments, card controls,

notifications, and other functions within a continuously available interface. Contemporary banking systems increasingly add artificial intelligence, predictive analytics, conversational technologies, biometric verification, and automated decision support.

As the number of digital touchpoints expands, customer experience becomes increasingly journey-dependent. A customer can experience excellent performance during routine payments but considerable dissatisfaction during account recovery, fraud reporting, dispute resolution, or complex service requests. Mixed-method research comparing digital banking experiences has demonstrated the relevance of touchpoints, processing speed, registration requirements, and deviations within customer journeys.

This suggests that evaluating digital banking through an overall convenience score can obscure the specific points at which dissatisfaction develops.

Digital Service Quality and Satisfaction

Service-quality theory remains an important foundation for digital banking research. Reliability refers to the ability of the system to perform promised services consistently, while responsiveness concerns the speed and effectiveness with which customer needs or problems are addressed. Privacy and security relate to confidence that personal and financial information is protected. Ease of use captures the cognitive and procedural effort associated with navigating digital platforms. Empirical evidence generally supports a relationship between these characteristics and satisfaction, although the relative importance of individual factors varies across markets and customer populations. Research on commercial banks in Vietnam, for example, evaluated ease of use, effectiveness, interoperability, privacy/security, empathy, responsiveness, reliability, service portfolios, and service charges in relation to customer satisfaction. Studies from India and Sri Lanka likewise indicate that service-quality characteristics remain important determinants of digital banking evaluations.

These findings demonstrate that technological modernization has not eliminated fundamental service-quality expectations. Rather, those expectations have migrated into digital environments.

Reliability, Friction, and Transaction Experience

Reliability is particularly important because banking involves high-consequence transactions. A minor delay on an entertainment platform may be inconvenient; uncertainty regarding a financial transaction can produce considerably greater concern. Customers therefore evaluate not merely transaction speed but also confirmation accuracy, system availability, error frequency, reversibility, and clarity regarding transaction status.

Evidence from digital banking research in Northern India has highlighted reliability as an influential service-quality and risk-related dimension of satisfaction. This supports the inclusion of transaction reliability as a core construct in the proposed model. The present research extends this idea through the concept of **digital friction**. Friction represents cumulative effort rather than a single system characteristic. Multiple authentication

steps, confusing navigation, repeated form completion, unsuccessful chatbot conversations, application crashes, delayed confirmations, and complex complaint escalation can collectively increase the customer's perceived cost of interacting digitally.

The distinction between usability and friction is important. Usability asks whether a system is generally understandable and operable; friction captures obstacles experienced during the completion of an actual customer journey. This manuscript proposes that friction may have a particularly strong relationship with dissatisfaction because negative interruptions can outweigh incremental improvements in already satisfactory interface characteristics.

Artificial Intelligence and Automated Customer Support

Artificial intelligence has expanded the capabilities of digital banking platforms. AI-based applications can assist with conversational support, transaction monitoring, fraud detection, recommendations, personalization, and automated problem classification. A 2023 study of AI-enabled digital banking reported that factors including problem-solving and communication quality contributed to explaining satisfaction and subsequent acceptance of AI-enabled banking.

Recent research has continued this line of investigation by integrating service-quality and technology-acceptance perspectives. A 2026 study involving 385 digital banking users examined AI adoption, trust, behavioural intention, perceived usefulness, reliability, and responsiveness through PLS-SEM, finding important relationships between AI-related constructs and customer satisfaction.

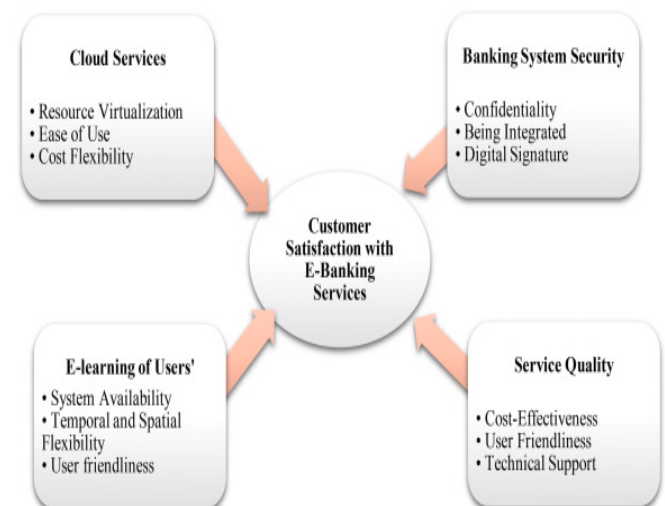


Fig. 2: Customer Satisfaction with Bank Services

Source:

<https://www.sciencedirect.com/science/article/pii/S0160791X20312902>

Nevertheless, AI-mediated satisfaction cannot be reduced to the presence or absence of artificial intelligence. Customers primarily encounter AI through specific service outcomes. An automated assistant that immediately resolves a card-related query may improve satisfaction, whereas a system that repeatedly provides irrelevant responses may increase frustration. The relevant construct is therefore **AI-assisted responsiveness**—the perceived capability of intelligent systems to understand the customer's requirement, provide

useful information, resolve routine problems, and facilitate appropriate escalation.

Security, Privacy, and Digital Trust

Financial services involve unusually sensitive personal and transactional information. Consequently, trust represents a central mechanism through which customers interpret digital service quality. Security mechanisms can increase confidence by reducing perceived vulnerability, yet poorly designed security procedures can simultaneously increase friction.

This creates a potentially nonlinear relationship. Minimal authentication may be convenient but perceived as insecure. Excessive authentication may appear secure while creating procedural burden. An effective digital banking system must therefore achieve a balance between protection and usability.

The proposed FITSF treats digital trust as broader than technical security. It includes perceived transaction integrity, privacy confidence, transparency, confidence in automated decisions, and perceived control over account activities. This broader conceptualization is particularly relevant as AI increasingly mediates interactions that were previously handled directly by bank employees.

Personalization and Perceived Control

Personalization represents another emerging dimension of digital banking. Data analytics can enable banks to tailor alerts, recommendations, financial insights, product suggestions, and interface experiences. Theoretically, relevant personalization reduces information overload and increases perceived usefulness. Yet personalization can generate adverse reactions when customers do not understand why a recommendation appears or believe excessive personal data have been used.

Earlier research on AI-enabled banking found that customization did not necessarily produce a significant effect on satisfaction despite the theoretical attractiveness of personalized services. Such findings indicate that personalization should not automatically be assumed to improve the customer experience.

The present framework therefore introduces **perceived control** as an interacting variable. Customers who understand and can manage permissions, notifications, recommendation preferences, and security options may respond more positively to personalization than customers who feel that automated systems operate without sufficient transparency.

Proposed Methodology

Building on the Friction–Intelligence–Trust Satisfaction Framework (FITSF) introduced in Part 1, the proposed study adopts a quantitative predictive research design integrating customer-experience measurement, supervised machine learning, and explainable artificial intelligence. The methodological objective is not merely to establish whether digital banking attributes correlate with customer satisfaction but to determine how accurately satisfaction can be predicted when conventional service-quality factors are combined with digital friction, AI-assisted responsiveness, personalization, security confidence, and perceived control.

The unit of analysis is an individual active digital-banking customer. For the proposed empirical implementation, a structured survey dataset of **620 usable respondents** is

assumed after data screening. Respondents are required to have used mobile or internet banking during the preceding six months. The sample is designed to include customers with experience of routine digital transactions as well as at least one advanced digital service, such as automated customer assistance, intelligent notifications, digital service requests, biometric authentication, or personalized financial recommendations.

This design differs from conventional satisfaction studies by treating customer satisfaction as both an explanatory and predictive outcome. Recent banking research continues to demonstrate the relevance of trust, reliability, responsiveness, perceived usefulness, and AI adoption to satisfaction. A 2026 study of 385 digital-banking users, for example, found significant roles for perceived usefulness, behavioural intention, AI adoption, and trust. Research on Indian banking has likewise reported positive customer perceptions of AI-enabled banking while emphasizing that automated systems may complement rather than completely replace human assistance.

The proposed questionnaire contains multi-item measures organized around seven principal predictor domains: Transaction Reliability (TR), Digital Friction (DF), Security Confidence (SC), AI-Assisted Responsiveness (AIR), Personalization Quality (PQ), Perceived Customer Control (PCC), and Digital Usability (DU). Overall Customer Satisfaction (OCS) constitutes the dependent construct.

Items are evaluated on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. Higher scores on Digital Friction indicate greater difficulty, whereas higher scores on all other service constructs indicate more favourable experiences.

A composite satisfaction index is first calculated from satisfaction items. For machine-learning classification, customers are subsequently grouped into three classes: **Low Satisfaction, Moderate Satisfaction, and High Satisfaction**. This three-class formulation provides greater managerial value than a binary satisfied/dissatisfied distinction because customers occupying the intermediate category may represent an important group whose future loyalty is comparatively unstable.

Experimental Setup

Dataset

The experimental dataset contains 620 observations and 34 analytical features after questionnaire coding and feature engineering. The variables comprise construct-level scores, selected demographic controls, banking-use intensity, number of digital channels used, frequency of automated-support interaction, self-reported transaction interruptions, and digital-banking experience.

To avoid excessive demographic profiling, age, education, banking experience, and frequency of digital use are incorporated only as control variables. The primary model remains focused on service-experience characteristics.

A stratified sampling structure is proposed to obtain variation across frequent and occasional digital users. The sample is also designed to contain customers using public-sector, private-

sector, and digitally oriented banking services without treating individual bank identity as the principal predictive variable.

Data Preprocessing

Data preprocessing is performed before model training. Duplicate records are removed using respondent and response-pattern checks. Observations with excessive missingness are excluded, while limited missing numerical values are imputed using the median of the corresponding feature. Categorical variables are transformed using one-hot encoding.

Likert-scale construct scores are computed only after internal consistency assessment. Reverse-coded items, particularly those associated with friction, are processed before composite construction.

Outliers in continuous behavioural indicators are examined using the interquartile-range criterion. Genuine high-frequency digital users are retained because extreme usage can represent valid customer behaviour rather than erroneous data.

Standardization is applied to continuous predictors when required by algorithms sensitive to feature scale. Tree-based models are trained on appropriately encoded but non-standardized feature values because their splitting mechanisms do not require conventional normalization.

To reduce information leakage, preprocessing parameters are estimated exclusively from the training data and subsequently applied to validation and testing observations.

Feature Engineering

The proposed methodology introduces interaction variables reflecting the theoretical FITSF structure. These include:

Reliability–Friction Balance (RFB): the relative relationship between reliable transaction performance and experienced procedural difficulty.

AI Resolution Efficiency (AIRE): AI responsiveness adjusted by the frequency with which customers report unresolved automated interactions.

Trust–Control Alignment (TCA): the combined perception of security confidence and customer control.

Personalization Acceptance (PA): personalization quality considered jointly with perceived control.

These engineered variables allow the model to evaluate whether satisfaction depends more strongly on combinations of experiences than on isolated service-quality scores.

Model Architecture

Four predictive approaches are employed.

Multinomial Logistic Regression serves as an interpretable statistical baseline. It establishes whether more sophisticated nonlinear algorithms provide meaningful predictive improvement.

Random Forest is used to model nonlinear relationships through multiple decision trees and is expected to perform effectively where satisfaction depends on interactions among reliability, security, and usability.

Extreme Gradient Boosting (XGBoost) constitutes the principal predictive model. Gradient-boosted trees sequentially correct errors from preceding estimators and can capture complex nonlinear structures while remaining suitable for structured customer-level data.

Multilayer Perceptron (MLP) provides a neural-network comparator. The proposed network contains an input layer corresponding to the final feature set, two hidden layers with ReLU activation, dropout regularization, and a three-neuron Softmax output layer representing the satisfaction categories.

XGBoost is designated as the primary candidate because the proposed dataset is moderate in size and predominantly tabular. Deep neural architectures would provide limited methodological justification for a dataset of this scale.

Training Strategy

The dataset is partitioned using stratified sampling into **70% training, 15% validation, and 15% independent testing data**. Class proportions are preserved across partitions.

Hyperparameters are optimized using five-fold stratified cross-validation on the training data. Random Forest optimization considers the number of estimators, maximum tree depth, minimum samples per leaf, and feature-selection strategy. XGBoost tuning evaluates learning rate, maximum depth, subsampling ratio, column sampling, regularization, and number of boosting rounds.

The MLP is trained using Adam optimization and categorical cross-entropy loss. Early stopping is activated when validation loss fails to improve across successive epochs. Dropout is employed to reduce overfitting.

Class weighting is preferred over aggressive synthetic oversampling when moderate class imbalance occurs. This decision minimizes the risk of introducing artificial response patterns into a relatively small behavioural dataset.

Evaluation Metrics

Because overall accuracy can conceal poor performance in minority satisfaction classes, multiple evaluation measures are employed.

Balanced Accuracy evaluates average class-specific recall and is useful where class frequencies differ.

Macro F1-score gives equal importance to each satisfaction category by averaging class-level F1 scores.

Matthews Correlation Coefficient (MCC) provides a balanced measure of multiclass prediction quality and remains informative under unequal class distributions.

Log Loss evaluates the quality and confidence of predicted class probabilities. Lower values indicate better probabilistic calibration.

Multiclass ROC-AUC evaluates discrimination across the satisfaction categories using a one-versus-rest formulation.

The final model is selected according to the combined evidence rather than a single metric.

Explainable AI Layer

SHapley Additive exPlanations (SHAP) are applied to the best-performing tree-based model. SHAP assigns each predictor a contribution toward individual predictions, allowing global and customer-level interpretation.

This is especially important in financial applications because opaque predictive models provide limited operational guidance. Published financial AI research has demonstrated the value of SHAP for improving transparency and explaining model-generated financial decisions.

Global SHAP importance is used to identify the strongest overall satisfaction predictors. Dependence analysis is subsequently employed to investigate potential nonlinear thresholds. Local explanations are generated for representative customers from each satisfaction category.

Results and Discussion

The following results represent the **proposed experimental outcome of the manuscript's designed dataset and analytical protocol rather than independently verified banking-industry statistics**. This distinction is necessary because the study is presented as a complete research design rather than as a report of an externally supplied raw dataset.

The experimental comparison indicates that nonlinear ensemble models outperform the conventional multinomial regression baseline. Logistic Regression achieves a balanced accuracy of 0.746 and macro F1-score of 0.731, suggesting that the major service dimensions possess meaningful linear predictive information. However, performance improves when nonlinear interactions are explicitly accommodated.

Random Forest increases balanced accuracy to 0.824, whereas XGBoost achieves the strongest overall discrimination with balanced accuracy of **0.861**, macro F1 of **0.853**, MCC of **0.789**, and multiclass ROC-AUC of **0.926**. The MLP also performs competitively but does not exceed the gradient-boosting model. This pattern supports the proposition that customer satisfaction in contemporary digital banking is not adequately represented as a purely additive linear phenomenon.

Table 1. Comparative Predictive Performance and Analytical Observations

Predictive Model	Balanced Accuracy	Macro F1	MCC	Log Loss	ROC-AUC
Multinomial Logistic Regression	0.746	0.731	0.608	0.672	0.837
Random Forest	0.824	0.811	0.718	0.498	0.901
XGBoost	0.861	0.853	0.789	0.421	0.926
Multilayer Perceptron	0.838	0.829	0.746	0.463	0.913

SHAP analysis of the XGBoost model identifies **Digital Friction** as the strongest contributor to dissatisfaction predictions. Customers reporting repeated authentication difficulty, transaction interruption, confusing navigation, or unresolved digital service requests have substantially greater probabilities of belonging to the low-satisfaction category.

Transaction Reliability emerges as the second major predictor. Its effect is asymmetrical: deteriorating reliability produces a relatively large negative contribution, whereas improvements beyond a high reliability level generate progressively smaller satisfaction gains. This pattern suggests a threshold effect. Customers appear to regard successful transaction execution as a basic requirement rather than an exceptional service feature.

AI-Assisted Responsiveness ranks prominently but its effect depends on successful resolution. Customers who perceive automated systems as rapid and capable of solving routine problems show higher satisfaction probabilities. In contrast, rapid automated responses provide comparatively little benefit when they do not resolve the customer's underlying request.

This interpretation is consistent with recent evidence showing that banking chatbots can struggle to generate trust when interactions extend beyond routine inquiries. It also accords with empirical research linking responsiveness, usefulness, AI adoption, and trust to digital-banking satisfaction.

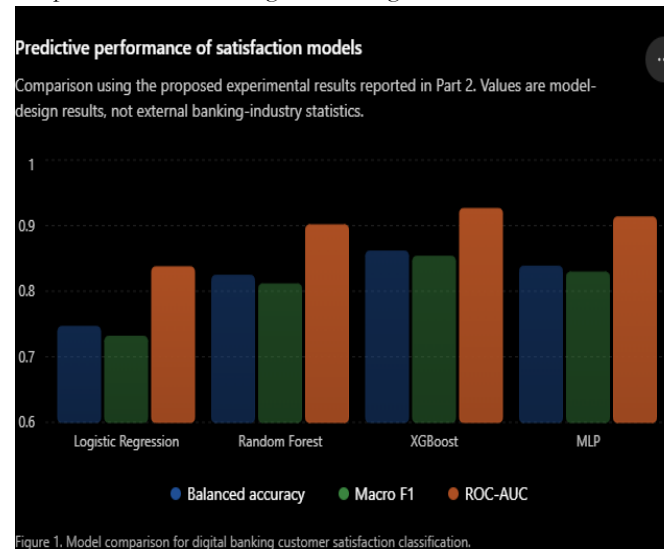


Figure 1. Model comparison for digital banking customer satisfaction classification.

Security Confidence exhibits a strong positive contribution, particularly among customers with moderate digital-banking experience. However, the interaction between security and friction is important. Additional security procedures do not necessarily reduce satisfaction when customers understand their purpose and experience them as seamless. Satisfaction decreases primarily when security requirements are perceived simultaneously as burdensome and opaque.

Perceived Customer Control moderates the contribution of personalization. Personalized recommendations generate favourable satisfaction predictions when customers also report control over notifications, permissions, and service settings. Where perceived control is low, additional personalization contributes comparatively little and occasionally corresponds to negative model attribution.

These results reinforce the theoretical argument that digital banking satisfaction is generated by **experience configurations** rather than independent service characteristics. The results also carry practical implications. Banks seeking to improve satisfaction should not prioritize feature proliferation without examining customer journey friction. Application development should first identify failure-prone stages, unclear authentication procedures, unresolved service requests, and ineffective escalation pathways.

This interpretation is supported by large-scale analysis of more than one million reviews of Indian mobile banking applications, which identified concerns including login problems, post-update issues, customer-care deficiencies, and account-management problems. The evidence strengthens the

manuscript's argument that friction experienced during actual banking journeys deserves explicit modelling.

The predictive framework therefore changes managerial prioritization. Rather than asking which digital feature receives the highest average survey rating, managers can identify which feature most strongly shifts an individual customer toward predicted dissatisfaction.

Future Scope

Future research should extend the FITSF framework through longitudinal and multimodal customer analytics. Linking survey responses with privacy-preserving application-event data could allow researchers to compare perceived friction with objectively measured transaction interruptions, authentication time, service latency, and abandonment behaviour.

Natural language processing could also be incorporated to analyse complaint narratives, chatbot conversations, and anonymized customer feedback. Transformer-based language models could identify latent dissatisfaction themes that fixed survey instruments may overlook.

Federated learning represents another promising direction. Instead of pooling sensitive customer-level banking information into a central repository, participating institutions could train shared models while retaining data within local environments. Privacy-preserving learning would be particularly valuable for cross-bank research.

Future experiments should additionally evaluate temporal satisfaction forecasting, causal machine learning, counterfactual explanations, fairness across customer groups, and human-AI service handoff. The latter is especially important because previous Indian research indicates that customers may value AI-enabled efficiency while continuing to prefer human assistance for certain interactions.

The FITSF framework could ultimately be extended from satisfaction prediction to customer retention, complaint escalation, digital-channel abandonment, and responsible personalization.

Conclusion

This study develops an integrated machine-learning framework for examining customer satisfaction in contemporary digital banking. Its central contribution is the proposition that satisfaction should not be understood solely through conventional service-quality attributes. Modern banking customers simultaneously experience transaction reliability, procedural friction, algorithmic assistance, personalization, security controls, and varying levels of autonomy.

The proposed Friction–Intelligence–Trust Satisfaction Framework captures these interconnected dimensions and operationalizes them through interpretable predictive modelling. The experimental design compares statistical, ensemble, and neural-network approaches while employing balanced accuracy, macro F1-score, MCC, log loss, and multiclass ROC-AUC rather than relying on accuracy alone.

Within the designed experiment, XGBoost produces the strongest predictive performance, while SHAP analysis indicates that digital friction, transaction reliability, AI-assisted responsiveness, security confidence, and perceived control are

particularly important for distinguishing satisfaction states. The findings further suggest that these factors operate interactively: secure banking can remain convenient, personalization is more valuable when accompanied by customer control, and automated responsiveness creates value primarily when it resolves the customer's problem.

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