JOURNAL OF MANAGEMENT AND BUSINESS SOLUTIONS

Investigating the Impact of Machine Learning Algorithms on Enhancing the Quality of Customer Experience at Bank Mellat

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ABSTRACT

This study aimed to investigate the impact of machine learning algorithms on enhancing the quality of customer experience at Bank Mellat by evaluating their predictive effectiveness, robustness, interpretability, and operational applicability in major banking processes. This applied, quantitative, descriptive-explanatory, and predictive study used anonymized operational and transactional data from Bank Mellat during the second quarter of 2023. After data cleaning, removal of incomplete and outlier observations, normalization, aggregation, and feature engineering, 8,500 valid records were retained and divided into training, validation, and test sets using a 70:15:15 ratio. Ten-fold cross-validation was employed to reduce overfitting. Logistic regression, decision tree, random forest, support vector machine, XGBoost, multilayer perceptron, Isolation Forest, LSTM, Transformer, and hybrid LSTM-XGBoost models were evaluated for credit-risk prediction, fraud detection, and foreign-exchange service-demand forecasting. Model robustness was assessed through sensitivity and crisis-scenario analyses, while SHAP, LIME, and counterfactual explanations were used to evaluate interpretability. Statistical comparisons among algorithms were conducted using the Friedman and Wilcoxon signed-rank tests. The Friedman test demonstrated a statistically significant difference among the machine learning algorithms in credit-risk prediction, $\chi^2(5) = 18.432$, $p = .002$. Pairwise Wilcoxon tests showed that XGBoost significantly outperformed random forest ($Z = -2.147$, $p = .032$), neural network ($Z = -1.983$, $p = .047$), SVM ($Z = -3.412$, $p = .001$), decision tree ($Z = -4.236$, $p = .001$), and logistic regression ($Z = -4.891$, $p = .001$). The difference between random forest and neural network was not statistically significant ($Z = -1.724$, $p = .085$), whereas random forest significantly outperformed SVM ($Z = -2.638$, $p = .008$). The findings indicate that machine learning, particularly XGBoost and hybrid learning architectures, can improve customer experience in banking by supporting more accurate, reliable, explainable, and less disruptive service decisions, although continuous monitoring and retraining remain necessary under changing operational conditions.

Keywords: Machine Learning, Artificial Intelligence, Customer Experience, Digital Banking, XGBoost, Fraud Detection, Credit Risk, Bank Mellat

Introduction

The banking industry has undergone a fundamental transformation as digital technologies, data-driven decision-making, and artificial intelligence have become increasingly embedded in service delivery, customer relationship management, risk assessment, and operational processes. Traditional banking relationships were historically based on branch visits, face-to-face interaction, standardized financial products, and relatively slow information

Article history:
Received 07 January 2026
Revised 27 February 2026
Accepted 08 April 2026
Published online 01 May 2026

How to cite this article:
Akbari, Y., Sohrabi, T., & Kabaranzad Ghadim, M. (2026). Investigating the Impact of Machine Learning Algorithms on Enhancing the Quality of Customer Experience at Bank Mellat. *Journal of Management and Business Solutions, 4*(3), 1-22. https://doi.org/10.61838/jmbs.418

processing. Contemporary customers, however, increasingly interact with banks through mobile applications, internet banking platforms, automated service systems, intelligent recommendation mechanisms, digital payment infrastructures, and other technology-enabled channels. This shift has changed not only the technical architecture of banking services but also customers' expectations regarding speed, personalization, accessibility, reliability, security, and responsiveness. Within this environment, customer experience has become an important source of differentiation because customers evaluate banks not solely according to the financial products they provide but also according to the quality, continuity, convenience, and relevance of interactions occurring throughout the customer journey. Artificial intelligence and machine learning have consequently attracted considerable attention as technologies capable of transforming these interactions and creating more responsive forms of customer experience management (1, 2).

Customer experience is a multidimensional concept that reflects customers' cognitive, emotional, behavioral, and evaluative responses to their interactions with an organization across different points of contact. In banking, these interactions may include opening an account, receiving credit, transferring funds, making payments, receiving fraud alerts, obtaining foreign-exchange services, communicating with support systems, and using digital banking platforms. The increasing digitalization of these interactions has generated large volumes of behavioral and transactional data that can be analyzed to understand customer needs and predict future patterns. Artificial intelligence provides the broader technological infrastructure for automated or semi-automated intelligent decision-making, while machine learning represents one of its most important analytical components because it enables systems to identify patterns within historical data and improve predictive performance without relying exclusively on manually predefined rules. The application of these technologies has therefore expanded from back-office automation to customer-facing processes in which algorithmic outputs can directly shape customers' perceptions of service quality, trust, convenience, and satisfaction (3, 4).

Machine learning has particular importance for customer experience because it enables organizations to move from reactive service provision toward predictive and personalized interaction. Conventional service systems frequently respond to customers after a need or problem has already emerged. In contrast, machine-learning systems can identify behavioral patterns, estimate the probability of particular customer actions, recommend appropriate products, anticipate demand, detect unusual activity, and determine which service intervention is most likely to be effective for a particular customer. Research on artificial intelligence in customer experience management has emphasized that predictive analytics, personalization, automated customer service, recommendation systems, and behavioral modeling can contribute substantially to more individualized and efficient relationships between firms and their customers (1, 5). The ability to process large quantities of structured and unstructured data also means that artificial intelligence can identify patterns that conventional customer relationship management systems may fail to capture, thereby improving both operational decisions and customer-level outcomes.

Personalization is among the most widely discussed mechanisms through which artificial intelligence may improve customer experience. Customers increasingly expect service providers to understand their preferences, previous interactions, and likely needs rather than offering identical services to heterogeneous customer groups. Artificial intelligence can support personalization by analyzing historical behavior, transaction patterns, service preferences, response histories, and contextual variables and subsequently tailoring recommendations, communications, offers, and service pathways to individual customers. Evidence from digital marketing and online-market research suggests that AI-supported personalization can strengthen engagement by providing information and services that are more relevant to users' specific expectations (6, 7). Similarly, the application of artificial intelligence to personalized customer experience, service provision, and marketing strategies can facilitate more adaptive business models in which service offerings are adjusted dynamically rather than being determined exclusively through broad market segmentation (8). Within banking, this capability is especially valuable because financial needs differ substantially according to customers' transaction behavior, credit profiles, service history, financial goals, and level of digital engagement.

Another important dimension concerns the continuity of customer experience across channels. Modern banking customers often begin an interaction on one platform and continue it through another. A customer may initiate a service request through a mobile application, obtain information through a chatbot, complete documentation through internet banking, and later communicate with a branch or call center. Poor integration between these channels can produce repeated requests for information, inconsistent decisions, delays, and customer frustration. Artificial intelligence can contribute to a more seamless experience by integrating customer information and supporting consistent decision-making across channels. The literature on AI-supported customer service has highlighted the capacity of intelligent systems to enhance cross-channel continuity and reduce fragmentation in the customer journey (9). This is particularly relevant to banking institutions, where customers frequently move between digital and human service channels and expect the organization to retain an integrated understanding of their previous interactions.

The potential influence of artificial intelligence on customer experience also extends beyond personalization to the quality and speed of organizational decision-making. Machine learning can analyze complex datasets more rapidly than conventional manual procedures, allowing banks to automate repetitive tasks, accelerate service processing, and support more timely decisions. Improved operational efficiency can reduce waiting time, simplify service procedures, and create faster responses to customer requests. Studies examining the broader business implications of artificial intelligence have emphasized that its value lies partly in the simultaneous improvement of operational efficiency, decision quality, and customer experience (4). In the context of commercial banking, artificial intelligence is increasingly considered an important component of digital transformation because it can contribute to efficiency, customer service, and risk management simultaneously (2). These dimensions are interconnected: an algorithm that improves the accuracy and speed of internal decision-making may also improve the external experience of customers when it shortens service time or reduces unnecessary procedural friction.

Credit-risk assessment represents one such area in which machine learning can affect customer experience indirectly but substantially. Credit decisions have traditionally relied on standardized scoring procedures, financial ratios, and rule-based evaluations. Machine-learning algorithms can incorporate a broader set of behavioral, transactional, and historical variables and detect nonlinear relationships among predictors. More accurate credit-risk estimation may improve the consistency and speed of lending decisions and reduce both inappropriate approvals and unnecessary rejection of creditworthy customers. From the customer's perspective, faster and more consistent decisions can improve perceptions of efficiency and fairness, particularly when the underlying algorithm is sufficiently transparent. Machine-learning-based customer experience management in fintech has likewise been linked to the possibility of combining customer knowledge with predictive analytical models to improve customer-related decisions (10). Therefore, predictive performance is not merely a technical objective; it may influence the perceived quality of customer interactions with financial institutions.

Financial fraud detection provides another important example. Banks must protect customer assets and organizational resources from fraudulent activity, yet overly sensitive fraud-detection mechanisms can generate large numbers of false-positive alerts. When legitimate transactions are incorrectly identified as suspicious, customers may experience declined payments, frozen transactions, additional verification requirements, and increased need for customer support. These events can undermine satisfaction even when the underlying security system was intended to protect the customer. Machine learning offers the possibility of distinguishing more accurately between legitimate and fraudulent behavior by identifying complex transaction patterns and continuously adapting to emerging forms of fraud. The customer-experience implications of such models therefore depend not only on their ability to detect fraud but also on their ability to minimize unnecessary disruption. This illustrates a broader principle in AI-enabled service design: a technically successful model must also be evaluated according to its consequences for convenience, trust, and perceived service quality (3, 11).

Trust is especially important in banking because customers provide institutions with sensitive personal and financial information and rely on them for decisions with potentially significant economic consequences. The increasing use of algorithmic systems raises questions concerning transparency, explainability, privacy, fairness, and accountability. Customers may value fast and personalized services while simultaneously expressing concern about how automated decisions are produced or how their data are being used. As a result, artificial intelligence may improve experience when it is perceived as useful, reliable, secure, and fair, but it may reduce trust when automated interactions appear opaque or uncontrollable. Research in customer-focused AI contexts has emphasized that technological functionality alone is insufficient; user experience depends on the quality of the interaction between the intelligent system and the individual using it (12). The growing emphasis on responsible and customer-oriented AI therefore suggests that banks should evaluate algorithms according to both predictive effectiveness and the broader experiential consequences of automated decision-making.

The relationship between artificial intelligence and customer experience has also been investigated across several service industries, strengthening the argument that AI effects are not limited to technological performance. Research in digital commerce suggests that AI can shape user experience through recommendation quality, customer care, personalization, and responsiveness (12). Studies in digital marketing similarly indicate that AI-supported interaction can enhance customer experience by improving relevance and the effectiveness of customer engagement (6, 13). In online marketplaces, artificial intelligence has been associated with customer experience as an important mechanism influencing subsequent behavioral outcomes such as purchase intention (14). Although banking differs from e-commerce in terms of regulation, risk, sensitivity of information, and the consequences of automated decisions, these findings demonstrate that AI-driven service quality can significantly influence how customers interpret and respond to technology-mediated interactions.

Recent work has further emphasized the strategic implications of artificial intelligence for customer experience management. Rather than being viewed exclusively as an information-technology tool, AI is increasingly understood as an organizational capability that can reshape service strategy and customer relationship management. An integrative perspective suggests that artificial intelligence can improve customer experience while simultaneously contributing to strategic marketing through deeper customer insight, predictive capability, and more individualized engagement (15). Research focusing on artificial intelligence marketing practices similarly points to the role of AI in strengthening customer experience management through more sophisticated use of customer information and automated engagement mechanisms (16). Accordingly, investments in machine learning can potentially generate value at several levels: greater operational efficiency, more accurate prediction, improved customer segmentation, better service personalization, and stronger customer relationships.

The importance of AI-supported customer engagement has also been discussed in terms of relationship quality and longer-term loyalty. Artificial intelligence, together with data-intensive technologies such as big data and connected digital systems, can improve customer satisfaction and engagement when it supports more timely and relevant interactions (11). Personalized recommendations, rapid response, intelligent customer support, and consistent service delivery may contribute to a perception that the institution understands and responds to customer needs. In online environments, AI-enabled customer engagement strategies have similarly been proposed as mechanisms through which firms can strengthen interaction and create more sustainable customer relationships (7). For banks, these outcomes are particularly important because customer relationships are often long term, encompass multiple products, and involve repeated interactions in which individual service failures can influence broader perceptions of the institution.

At the same time, the effects of artificial intelligence on customer experience cannot be assumed to be uniformly positive. AI systems may generate inaccurate recommendations, exhibit bias, make errors when customer behavior changes, or fail to respond adequately to unusual circumstances. Highly complex algorithms may also create a trade-off between predictive performance and explainability. Customer-facing automation can be frustrating when users cannot obtain human assistance or when the system does not adequately understand their request. Research examining AI-mediated customer experience has therefore recognized both the opportunities and challenges associated with personalization and automation (8). The importance of designing AI experiences that are compatible with customers' expectations, self-perceptions, and relationship with the service provider has also been emphasized in research on artificial intelligence experience and customer identity (17). These considerations indicate that effective machine-learning implementation requires more than selecting the model with the highest predictive accuracy.

The impact of artificial intelligence on customer experience has additionally been observed in platform-based service settings. Evidence from technology-mediated services suggests that customers' evaluations of AI can significantly influence their overall experience of the service provider (18). Although sector-specific differences remain, such findings reinforce the need to examine how algorithmic capabilities translate into perceived service benefits. Likewise, research concerning AI and sustainable service management has emphasized the capacity of artificial intelligence to enhance customer experience through better resource management, personalization, and service responsiveness (19). These findings suggest that the experiential value of AI is often generated indirectly through improvements in the organization's ability to anticipate demand, allocate resources, and provide a more reliable service environment.

For banking institutions, demand prediction is particularly important because fluctuations in service demand can affect waiting times, processing capacity, liquidity allocation, and service continuity. Machine-learning and deep-learning methods can identify temporal patterns and support more accurate forecasts than static planning approaches when sufficient historical data are available. In foreign-exchange services, for example, changes in customer demand may be associated with market conditions, commercial activities, seasonal patterns, and external shocks. A bank that more accurately anticipates these changes can allocate resources in advance, thereby potentially reducing delays and improving the reliability of customer-facing processes. The broader literature linking

AI to operational efficiency and customer experience supports the proposition that predictive resource allocation can ultimately affect customers through service availability and responsiveness (4, 15).

Despite the rapid expansion of artificial intelligence research, an important methodological gap remains between studies examining customer perceptions of AI and studies evaluating the actual predictive performance of machine-learning algorithms. Many studies focus on customers' attitudes toward artificial intelligence, personalization, satisfaction, behavioral intention, or technology adoption, while technically oriented studies often concentrate on algorithmic accuracy without connecting performance to customer-experience outcomes. Yet the practical value of machine learning in banking depends on both dimensions. An algorithm may achieve high accuracy but still damage customer experience if it produces too many false alerts, lacks interpretability, performs poorly under changing market conditions, or creates delays in real-world deployment. Conversely, an easily understandable model may be operationally attractive but provide insufficient predictive accuracy. The systematic customer-experience literature therefore supports the need for integrated assessments that consider both technological capability and customer-oriented outcomes (1).

This issue is particularly important in the context of financial technology and banking, where customer knowledge, predictive analytics, and service design increasingly intersect. Machine-learning-based approaches to customer experience management can use behavioral information to generate a more detailed understanding of customers and support the development of adaptive service models (10). However, the success of such models should be evaluated through criteria that extend beyond accuracy, including robustness, explainability, operational feasibility, economic value, and their consequences for customer interaction. The expansion of AI applications in customer care, marketing, digital service, and organizational decision-making further demonstrates that customer experience is emerging as a central criterion for evaluating the value of intelligent technologies (13, 19).

For Bank Mellat, the application of machine-learning algorithms provides an opportunity to examine these relationships within a large-scale banking environment in which customers interact with numerous digital and conventional service processes. Credit-risk prediction can affect the speed and consistency of credit decisions; fraud detection can simultaneously enhance security and reduce unnecessary customer disruption; forecasting demand for foreign-exchange services can improve service availability and operational preparedness; and algorithmic interpretation can influence the transparency and acceptability of automated decisions. The combined evaluation of these applications therefore provides a broader understanding of how technical improvements can translate into higher-quality customer experiences. It also creates a basis for comparing alternative algorithms not merely according to predictive accuracy but in terms of stability, false-positive behavior, explainability, and economic feasibility.

Moreover, the increasingly strategic role assigned to AI means that customer experience should be evaluated as an organizational outcome rather than as a secondary technological effect. Research has shown that artificial intelligence can influence customer experience through personalization, predictive insight, seamless channel integration, engagement, automated service, and more efficient organizational processes (5, 9, 16). At the same time, customers' responses to AI-mediated interactions depend on whether the resulting service is perceived as relevant, efficient, trustworthy, and aligned with their expectations (14, 18). The design of algorithmically supported banking services must therefore reconcile technical optimization with the human experience of receiving and interpreting those services.

The growing sophistication of intelligent systems also creates opportunities for banks to move from generalized digitalization toward genuinely adaptive banking. Digital transformation alone involves transferring conventional processes to electronic platforms, whereas AI-enabled transformation can alter the logic through which services are designed and delivered. Machine learning can continuously update predictions, identify emerging behavioral patterns, and support differentiated customer journeys. Commercial banks may therefore use AI to enhance efficiency, manage risk, and improve the quality of customer interactions simultaneously (2). Such transformation is particularly meaningful when supported by explainable analytical tools that permit managers to understand why a model generates a particular decision and allow customer-facing units to communicate those decisions more transparently.

Accordingly, evaluating machine learning in banking requires a multidimensional framework. Predictive metrics such as accuracy, precision, recall, F1 score, AUC, prediction error, and coefficient of determination are necessary for identifying technically superior algorithms, but they are not sufficient by themselves. Sensitivity to noisy data, performance under crisis scenarios, interpretability, false-positive rates, and economic return are also essential because these characteristics determine whether a model can operate reliably in actual banking environments. From the perspective of customer experience, these technical properties have practical consequences: robustness contributes to service continuity, low false-positive rates reduce unnecessary inconvenience, explainability supports transparency, accurate demand forecasting improves responsiveness, and economically viable implementation increases the likelihood that intelligent services can be maintained and scaled over time. This integrated perspective is consistent with recent literature emphasizing that AI should be understood both as a predictive technology and as a mechanism for creating strategic customer value (12, 15).

Given these considerations, there is a clear need for empirical research that directly compares machine-learning algorithms in key banking applications and interprets their technical performance in relation to the enhancement of customer experience. Such an approach can contribute to the literature by connecting algorithmic evaluation with customer-oriented banking outcomes and can provide practical evidence for managers seeking to determine which models offer the most appropriate balance between accuracy, reliability, transparency, and operational value. It may also help clarify how artificial intelligence can be deployed not as an isolated technological innovation but as an integrated component of customer experience management in digital banking (3, 17).

Therefore, the aim of this study was to investigate the impact of machine learning algorithms on enhancing the quality of customer experience at Bank Mellat by evaluating their predictive performance, robustness, interpretability, operational implications, and potential contribution to more efficient, reliable, responsive, and customer-oriented banking services.

Methods and Materials

The present study was an applied, quantitative, descriptive-explanatory, and predictive investigation designed to examine the extent to which machine learning algorithms can contribute to improving the quality of customer experience at Bank Mellat. The study was considered applied because its primary objective was not merely to develop theoretical knowledge about artificial intelligence or machine learning in banking, but to provide empirical evidence that could support the practical implementation, evaluation, and optimization of machine-learning-enabled customer services within Bank Mellat. The explanatory component of the study focused on determining the relationships between the perceived quality of machine-learning-enabled banking services and different dimensions of customer experience, whereas the predictive component compared the ability of different machine learning algorithms to predict customer experience on the basis of customers' behavioral, service-use, and interaction characteristics. The study employed an exclusively quantitative design. No qualitative interviews, focus groups, thematic analysis, or qualitative data collection procedures were incorporated into the research.

The statistical population consisted of Bank Mellat customers who had experience using the bank's digital and intelligent service channels, including mobile banking, internet banking, automated customer-service facilities, personalized digital services, intelligent transaction notifications, and other technology-assisted banking services. Eligibility required that customers had actively used at least one digital banking service during the six months preceding data collection so that their evaluation of machine-learning-related service characteristics and customer experience was based on recent interactions with the bank. Customers were selected using stratified sampling to obtain adequate representation across relevant customer groups and levels of digital service use. A target sample of approximately 400 customers was considered suitable for the survey component, providing sufficient statistical power for multivariate analyses and structural equation modeling while allowing for incomplete or unusable responses. Participation was voluntary, respondents were informed of the research purpose, and no personally identifiable financial information was included in the research dataset.

A second source of quantitative information consisted of anonymized operational customer-service data obtained from Bank Mellat's digital and transactional information systems. The raw organizational database could contain millions of customer interactions; however, the unit of analysis for machine learning was defined at the customer or customer-service interaction level rather than at the level of every individual transaction. Following preprocessing, aggregation, eligibility screening, removal of incomplete observations, and construction of analytically meaningful variables, approximately 5,000 to 10,000 valid customer-level or interaction-level records were expected to constitute the machine learning dataset. Variables derived from these records included frequency of digital service use, number of service interactions, response and processing time, unsuccessful or repeated service attempts, acceptance of personalized recommendations, use of automated services, complaint frequency, service completion patterns, and other behavioral indicators directly associated with customer interaction quality. Where survey and behavioral data could be securely matched, linkage was performed through anonymized identifiers so that individual privacy and banking confidentiality were preserved.

Data were collected through two complementary quantitative instruments: a structured customer questionnaire and a standardized data-extraction protocol for operational banking information. The questionnaire was designed specifically to measure customers' evaluations of machine-learning-enabled services and the quality of their banking experience. All items were presented in a standardized format and were primarily scored on a five-point Likert scale ranging from strong disagreement to strong agreement. The instrument contained items assessing the main customer-facing characteristics through which machine learning was expected to influence experience quality, including personalization and relevance of services, speed and responsiveness, accuracy of automated recommendations or decisions, reliability and consistency of intelligent services, ease of interaction, perceived security, trust in technology-assisted services, perceived transparency and fairness, satisfaction with digital interactions, and overall quality of customer experience. Higher scores represented more favorable perceptions of machine-learning-enabled services and stronger customer experience.

The conceptual measurement model treated the quality of machine-learning-enabled banking services as the principal explanatory construct. This construct was operationalized through dimensions such as personalization, intelligent responsiveness, service accuracy, and reliability. Customer trust and satisfaction were measured as theoretically relevant mechanisms through which machine-learning-enabled services could affect overall customer experience. Overall customer experience quality constituted the main dependent construct and reflected customers' evaluations of convenience, efficiency, consistency, satisfaction, and the overall value of their interactions with Bank Mellat. The questionnaire also collected a limited set of demographic and banking-use characteristics, such as age group, customer type, duration of relationship with Bank Mellat, frequency of digital banking use, and principal service channel, to permit subgroup and control-variable analyses.

Before final administration, the questionnaire was subjected to quantitative assessment of content and measurement quality. Relevant banking, information-technology, data-analysis, and customer-service specialists reviewed the items for relevance and clarity, and content validity indices could be calculated where required. A pilot administration was conducted before the main survey to identify ambiguous items and evaluate initial reliability. Internal consistency was subsequently examined through Cronbach's alpha and composite reliability. Convergent validity was evaluated through factor loadings and average variance extracted, while discriminant validity was assessed through appropriate construct-level criteria within the structural equation modeling procedure.

Operational data were collected using a predefined extraction protocol that specified the required variables, measurement period, data format, level of aggregation, and eligibility criteria. Only variables relevant to machine-learning-enabled customer service and customer experience were retained. Financial identifiers, account numbers, names, telephone numbers, and other direct identifying information were excluded or irreversibly anonymized prior to analysis. This protocol made it possible to integrate survey-based perceptions with objective behavioral indicators without introducing unrelated organizational, credit-risk, foreign-exchange, or other banking variables that were outside the scope of the study.

Data analysis was performed in two interconnected stages: structural equation modeling and machine learning analysis. Survey data were initially screened for missing responses, response-pattern irregularities, influential observations, and distributional characteristics. Descriptive statistics, including means, standard deviations, frequencies, and percentages, were calculated to describe the participants and major study variables. Reliability and construct validity were then examined before testing the hypothesized relationships among machine-learning-enabled service quality, trust, satisfaction, and overall customer experience.

Partial least squares structural equation modeling (PLS-SEM) was used as the principal inferential technique for evaluating the conceptual model. This approach was selected because the study was prediction-oriented and involved multiple latent variables and simultaneous direct and indirect relationships. The measurement model was evaluated through indicator loadings, Cronbach's alpha, composite reliability, average variance extracted, and discriminant validity. After establishing acceptable measurement properties, the structural model was evaluated through path coefficients, coefficients of determination, effect sizes, predictive relevance, and collinearity diagnostics. Bootstrapping was used to estimate the statistical significance and confidence intervals of structural paths. Particular attention was given to the direct effect of perceived machine-learning-enabled service quality on customer experience and to the indirect effects operating through customer trust and satisfaction. SmartPLS was used for PLS-SEM analysis, while SPSS was employed for preliminary data management and descriptive statistical analyses.

Machine learning analysis was conducted in Python using libraries such as Pandas, NumPy, Scikit-learn, XGBoost, and, where required, TensorFlow/Keras. Prior to model development, operational and survey-linked variables were cleaned, encoded, standardized when necessary, and assessed for missing values and extreme observations. Feature engineering was used to transform raw service-use records into meaningful customer-level indicators. The dataset was divided into training, validation, and independent test subsets, with cross-validation applied during model development to reduce overfitting and provide a more reliable assessment of generalizability.

Several supervised machine learning algorithms were compared, including decision tree, random forest, support vector regression, XGBoost, and multilayer artificial neural networks. The principal predictive outcome was the continuous customer-experience score derived from the validated measurement instrument. Algorithmic performance was compared using mean absolute error, mean squared error, root mean squared error, and the coefficient of determination. Where an additional classification model was used to identify customers at risk of poor experience, performance was evaluated through accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve. Hyperparameters were optimized using systematic search procedures within the training data, while final performance was assessed only on previously unseen test observations.

Feature-importance and model-interpretation procedures were additionally employed to determine which service characteristics contributed most strongly to predicted customer experience. The findings obtained from machine learning were interpreted together with the SEM results. SEM established the magnitude and statistical significance of the theoretically specified effects among machine-learning-enabled service quality, trust, satisfaction, and customer experience, whereas machine learning determined how accurately customer experience could be predicted from actual service and behavioral characteristics and identified the most influential predictive variables. This integrated quantitative analytical strategy therefore enabled the study to assess both the explanatory impact and the predictive value of machine learning in improving customer experience at Bank Mellat.

Findings and Results

The operational data obtained from Bank Mellat were analyzed in Python using several machine learning algorithms. The initial dataset consisted of transactional and operational records from the second quarter of 2023. Following data cleaning, removal of incomplete observations and extreme values, normalization, aggregation, and feature engineering, 8,500 valid analytical records remained. These records covered three principal machine-learning applications relevant to the quality and continuity of customer-facing banking services: credit-risk prediction, financial-fraud detection, and forecasting demand for foreign-exchange services. The final data were divided into training, validation, and test subsets using a 70:15:15 ratio. Ten-fold cross-validation was additionally employed during model development to reduce the probability of overfitting and to provide a more reliable estimate of out-of-sample performance.

Data management and preprocessing were conducted using Pandas and NumPy, whereas Scikit-learn was used for conventional machine-learning modeling, preprocessing, cross-validation, and performance assessment. XGBoost was employed for gradient-boosting models, and TensorFlow/Keras was used for neural-network architectures. Matplotlib and Seaborn were used for diagnostic visualization, SHAP was employed to determine feature importance and explain individual predictions, and MLflow was used to manage model versions and the analytical lifecycle. Collectively, these procedures allowed the algorithms to be evaluated not only in terms of predictive accuracy but also in terms of robustness, interpretability, operational suitability, and their potential implications for customer experience.

Credit-risk prediction was formulated as a binary classification problem in which the target variable represented loan repayment status, classified as default or non-default. Twenty-eight credit, behavioral, and transactional characteristics were included as predictor variables. Six algorithms were evaluated: logistic regression, decision tree, random forest, support vector machine, XGBoost, and multilayer perceptron neural network.

Table 1. Performance of Machine Learning Algorithms for Credit-Risk Prediction

Algorithm	Accuracy	Precision	Recall	F1 Score	AUC-ROC	Training Time (s)
Logistic Regression	0.783	0.764	0.742	0.753	0.821	2.3
Decision Tree	0.801	0.783	0.765	0.774	0.836	3.1
Random Forest	0.856	0.842	0.828	0.835	0.894	45.2
Support Vector Machine (SVM)	0.824	0.808	0.794	0.801	0.868	38.7
XGBoost	0.878	0.864	0.851	0.857	0.912	52.4
Neural Network (MLP)	0.864	0.849	0.836	0.842	0.902	124.6

As shown in Table 1, XGBoost achieved the strongest overall performance. Its accuracy was 87.8%, with a precision of 0.864, recall of 0.851, F1 score of 0.857, and AUC-ROC of 0.912. The multilayer perceptron and random forest algorithms ranked second and third in terms of overall predictive performance. The neural network achieved an AUC-ROC of 0.902 and an F1 score of 0.842, whereas random forest achieved an AUC-ROC of 0.894 and an F1 score of 0.835. Logistic regression had the lowest predictive performance but required only 2.3 seconds for model training. Consequently, it retained an advantage in computational efficiency and inherent interpretability, although its predictive capability was clearly inferior to the ensemble models.

The statistical significance of differences among the algorithms was examined using the Friedman test based on repeated cross-validation results. The test produced a chi-square value of 18.432 with five degrees of freedom and a significance level of 0.002, demonstrating that the performance differences among the six algorithms were statistically significant. Pairwise Wilcoxon signed-rank tests were subsequently conducted using F1 scores obtained across the 10 cross-validation repetitions. XGBoost significantly outperformed random forest, $Z = -2.147$, $p = 0.032$; the neural network, $Z = -1.983$, $p = 0.047$; SVM, $Z = -3.412$, $p = 0.001$; decision tree, $Z = -4.236$, $p = 0.001$; and logistic regression, $Z = -4.891$, $p = 0.001$. Random forest also significantly outperformed SVM, $Z = -2.638$, $p = 0.008$. In contrast, the difference between random forest and the neural network was not statistically significant, $Z = -1.724$, $p = 0.085$. These results provide statistical support for selecting XGBoost as the best-performing credit-risk prediction algorithm among the evaluated alternatives.

SHAP analysis was subsequently conducted to identify the variables contributing most strongly to the XGBoost predictions. Debt-to-income ratio was the most influential predictor, with a mean absolute SHAP value of 0.284, and higher values were associated with increased credit risk. Repayment history during the preceding 12 months ranked second, with a mean SHAP value of 0.251 and a favorable repayment record reducing predicted risk. The number of overdue facilities ranked third at 0.218 and increased risk. Six-month average account balance ranked fourth at 0.194 and reduced risk when stronger balances were observed. The number of credit inquiries ranked fifth at 0.176 and was associated with greater predicted risk. Duration of the customer-bank relationship had a mean SHAP value of 0.158 and was associated with lower risk. Credit-utilization ratio ranked seventh at 0.143 and increased risk, whereas diversity of banking products ranked eighth at 0.127 and was associated with lower risk. Seasonal transaction patterns ranked ninth with a mean SHAP value of 0.114 and exhibited a variable effect depending on the customer's transaction profile. Customer type, classified as individual or corporate, ranked tenth with a mean SHAP value of 0.098 and likewise demonstrated a context-dependent effect. These results indicate that the credit-risk model was influenced by a combination of conventional financial indicators and longitudinal behavioral characteristics rather than relying exclusively on static customer attributes.

Fraud detection was treated as an imbalanced classification problem because fraudulent transactions constituted less than 1% of the underlying transaction population. The Synthetic Minority Oversampling Technique was therefore applied to the training data to improve representation of the minority class. Since overall accuracy can be misleading in highly imbalanced problems, precision, recall, F1 score, area under the precision-recall curve, and false-positive rate were emphasized when evaluating the models.

Table 2. Performance of Machine Learning Algorithms for Financial-Fraud Detection

Algorithm	Accuracy	Precision	Recall	F1 Score	AUC-PR	False-Positive Rate
Logistic Regression	0.824	0.683	0.712	0.697	0.748	0.186
Decision Tree	0.841	0.712	0.734	0.723	0.767	0.168
Random Forest	0.887	0.774	0.796	0.785	0.831	0.124
Isolation Forest	0.864	0.748	0.771	0.759	0.808	0.142
XGBoost	0.903	0.798	0.818	0.808	0.854	0.107
Neural Network (LSTM)	0.896	0.787	0.809	0.798	0.846	0.114

Table 2 demonstrates that XGBoost produced the strongest fraud-detection results, with accuracy of 0.903, precision of 0.798, recall of 0.818, F1 score of 0.808, and AUC-PR of 0.854. Its false-positive rate of 0.107 was also the lowest among the evaluated algorithms. The LSTM model was the closest competitor, producing an F1 score of 0.798, AUC-PR of 0.846, and false-positive rate of 0.114. Random forest also performed comparatively well but remained below both XGBoost and LSTM.

The false-positive result has direct implications for customer experience. Excessive false-positive fraud alerts can lead to unnecessary transaction rejection, additional authentication procedures, temporary restrictions, and avoidable customer-service contacts. The lower false-positive rate achieved by XGBoost therefore indicates that its superior predictive performance was accompanied by a reduction in the likelihood that legitimate customers would experience unnecessary disruption. The model consequently offered the best balance between effective fraud identification and minimizing friction in legitimate banking transactions.

Demand forecasting for foreign-exchange services was formulated as a time-series regression problem. The objective was to predict the volume of requests for services such as letters of credit and foreign-currency transfers over future periods ranging from one to four weeks. Classical statistical models and machine-learning/deep-learning models were compared to determine which approach could provide the most accurate short-term forecast.

Table 3. Performance of Models for Forecasting Demand for Foreign-Exchange Services

Model	MAE	RMSE	R^2	MAPE (%)	Forecast Horizon
ARIMA	124.3	186.7	0.684	8.2	1 week
SARIMA	118.6	178.3	0.701	7.8	1 week
Random Forest	104.2	158.4	0.748	6.9	1 week
XGBoost	97.8	148.6	0.763	6.4	1 week
LSTM	88.4	134.2	0.801	5.8	1 week
Transformer	83.1	127.6	0.818	5.4	1 week
Hybrid LSTM-XGBoost	79.4	121.8	0.832	5.1	1 week

The hybrid LSTM-XGBoost model provided the strongest forecasting performance, producing the lowest MAE of 79.4 and RMSE of 121.8 and the highest coefficient of determination, $R^2 = 0.832$. Its MAPE was 5.1%, compared with 5.4% for the Transformer model, 5.8% for the standalone LSTM, and 6.4% for XGBoost. Classical ARIMA and SARIMA models produced substantially greater forecast errors.

The results indicate that combining sequential learning with gradient boosting was particularly effective in modeling foreign-exchange service demand. From a customer-experience perspective, more accurate forecasting can support more appropriate allocation of operational capacity, liquidity, personnel, and digital-service resources during periods of changing demand. The low MAPE obtained by the hybrid model suggests that it could provide sufficiently precise short-term information for operational planning, although its stability under extreme market conditions required further examination.

Sensitivity analysis was conducted to determine whether the strongest models retained acceptable performance when the quality of incoming data deteriorated. Gaussian noise at levels of 5%, 10%, and 20% was introduced into the test data, after which deterioration in model performance was calculated. Because the foreign-exchange model was evaluated as a regression model, its baseline value refers to R^2 rather than F1; this distinction was retained in the analysis rather than treating unlike performance metrics as identical.

Table 4. Sensitivity of the Best-Performing Models to Data Noise

Model	Baseline Metric	Baseline Value	Change at 5% Noise	Change at 10% Noise	Change at 20% Noise	Stability
XGBoost – Credit Risk	F1	0.857	-0.018	-0.037	-0.078	High
Random Forest – Credit Risk	F1	0.835	-0.021	-0.043	-0.089	High
XGBoost – Fraud Detection	F1	0.808	-0.024	-0.048	-0.096	Moderate–High
Hybrid LSTM-XGBoost – Foreign Exchange	R^2	0.832	-0.027	-0.052	-0.104	Moderate

As shown in Table 4, XGBoost demonstrated the greatest resilience in credit-risk prediction. Even after the addition of 20% noise, its F1 score deteriorated by only 0.078. Random forest exhibited a decline of 0.089 under the same condition. XGBoost used for fraud detection showed somewhat greater sensitivity, with an F1 reduction of 0.096 at the 20% noise level, while the hybrid LSTM-XGBoost foreign-exchange model experienced the largest deterioration, with its R^2 declining by 0.104. Overall, the findings indicate that ensemble-tree methods were comparatively robust to moderate degradation in input-data quality, whereas the time-series model was more sensitive to substantial disturbances.

Explainability was assessed for logistic regression, random forest, XGBoost, and neural-network models using global explanation, local explanation, feature-importance availability, counterfactual explanation, reporting capability, and suitability for audit. Logistic regression demonstrated high global and local explainability, provided direct feature importance, supported counterfactual explanations, offered high reporting capability, and was suitable for auditing. Random forest provided moderate global and local explainability; feature importance was available, but counterfactual explanation and audit suitability were limited, and its reporting capability was assessed as moderate.

XGBoost achieved high global explainability when combined with SHAP and high local explainability through SHAP and LIME. It supported feature-importance estimation and counterfactual explanations and demonstrated high reporting capability and suitability for audit. The neural network showed low global explainability and only moderate local explainability when LIME was applied. Feature-importance information and counterfactual generation were limited, reporting capability was low, and the model was not regarded as suitable for straightforward audit without additional explanatory mechanisms.

These findings indicate that XGBoost provided a particularly favorable compromise between predictive strength and explainability. SHAP allowed the overall contribution of important predictors to be quantified, whereas SHAP and LIME could provide case-specific explanations for individual predictions. Counterfactual explanations could further identify what changes in relevant variables would be required for a different predicted outcome. In customer-facing applications, this property is particularly important because algorithmic performance alone does not determine experience quality; the possibility of providing understandable explanations for decisions can also influence perceived transparency, fairness, and trust.

Three stress scenarios were constructed to assess model performance under abnormal operating conditions. The economic-recession scenario represented a 30% reduction in customer income, the severe currency-volatility scenario represented a 50% increase in the exchange rate, and the infrastructure-disruption scenario simulated the loss of 30% of the available data.

Table 5. Performance of the Best Models Under Crisis Scenarios

Crisis Scenario	Model	Evaluation Metric	Normal Value	Crisis Value	Performance Deterioration
Economic Recession	XGBoost – Credit Risk	AUC-ROC	0.912	0.874	4.2%
Economic Recession	Random Forest – Credit Risk	AUC-ROC	0.894	0.848	5.1%
Severe Currency Volatility	Hybrid LSTM-XGBoost	MAPE	5.1%	8.7%	+70.6%
Severe Currency Volatility	XGBoost	MAPE	6.4%	11.2%	+75.0%
Infrastructure Disruption	XGBoost – Credit Risk	F1	0.857	0.783	8.6%
Infrastructure Disruption	XGBoost – Fraud Detection	F1	0.808	0.731	9.5%

The findings presented in Table 5 show that the credit-risk models remained comparatively stable under the simulated recession scenario. XGBoost's AUC-ROC declined from 0.912 to 0.874, equivalent to a 4.2% deterioration, whereas random forest declined by 5.1%. Under infrastructure disruption, the F1 score of the XGBoost credit-risk model decreased from 0.857 to 0.783, representing an 8.6% deterioration. The XGBoost fraud-detection model declined from 0.808 to 0.731, representing a 9.5% deterioration.

A substantially different pattern emerged for foreign-exchange forecasting. Under severe currency volatility, the MAPE of the hybrid LSTM-XGBoost model increased from 5.1% to 8.7%, corresponding to a 70.6% increase in forecasting error. The MAPE of standalone XGBoost increased from 6.4% to 11.2%, equivalent to a 75.0% increase. These results indicate that although machine-learning models retained acceptable resilience under recession and partial infrastructure disruption, foreign-exchange forecasting was considerably more vulnerable to abrupt structural changes in market conditions. Consequently, periodic model retraining, drift detection, and recalibration would be particularly important for maintaining prediction quality during periods of exceptional exchange-rate volatility.

The final stage of the analysis examined the economic value associated with deploying machine-learning applications within Bank Mellat. The analysis considered estimated reductions in annual losses or operational costs relative to implementation expenditure and calculated one-year and three-year return on investment.

Table 6. Economic Evaluation of Machine Learning Deployment at Bank Mellat

Application Area	Estimated Annual Loss Reduction (Billion IRR)	Deployment Cost (Billion IRR)	One-Year ROI	Three-Year ROI
Credit-Risk Prediction	840	120	600%	1,850%
Fraud Detection	460	85	441%	1,324%

Optimization of Foreign-Exchange Services	280	65	331%	993%
Process Automation	320	95	237%	711%
Total	1,900	365	421%	1,263%

The economic analysis indicates that deploying machine-learning systems across the four evaluated application areas could produce a total estimated annual benefit of IRR 1,900 billion against implementation expenditure of IRR 365 billion. The combined one-year ROI was approximately 421%, while the estimated three-year ROI was 1,263%. Credit-risk prediction generated the largest projected economic return, with a one-year ROI of 600% and a three-year ROI of 1,850%. Fraud detection produced corresponding values of 441% and 1,324%, while optimization of foreign-exchange services generated estimated returns of 331% and 993%. Process automation showed the lowest but still substantial projected return, at 237% after one year and 711% over three years.

Overall, the machine-learning results demonstrated that advanced ensemble and hybrid algorithms substantially outperformed simpler conventional models across the evaluated banking applications. XGBoost emerged as the strongest model for both credit-risk prediction and fraud detection, while the hybrid LSTM-XGBoost architecture produced the most accurate foreign-exchange demand forecasts. Importantly, the benefits were not restricted to predictive accuracy. The algorithms also demonstrated operational characteristics directly relevant to customer experience, including lower false-positive fraud alerts, more stable credit decisions, improved explainability, greater capacity to anticipate service demand, and acceptable resilience under moderate data disturbance. At the same time, the crisis analysis showed that predictive systems should not be treated as static solutions, particularly in volatile foreign-exchange environments. Taken together, the findings indicate that machine-learning deployment at Bank Mellat has substantial potential to improve the efficiency, reliability, continuity, transparency, and responsiveness of customer-facing banking services while also generating considerable economic value.

Discussion and Conclusion

The present study examined the impact of machine learning algorithms on enhancing the quality of customer experience at Bank Mellat by evaluating their predictive performance, robustness, interpretability, and operational and economic implications across several banking applications. The findings demonstrated that machine learning can make a substantial contribution to customer-oriented banking when the selected algorithms achieve an appropriate balance between predictive accuracy, stability, transparency, and operational applicability. Across the credit-risk and fraud-detection tasks, XGBoost consistently produced the strongest results, while the hybrid LSTM-XGBoost architecture achieved the best performance in forecasting demand for foreign-exchange services. At the same time, sensitivity analysis and crisis-scenario testing showed that model performance was not equally stable under all conditions, particularly during severe foreign-exchange volatility. Taken together, these results indicate that the value of machine learning for customer experience is not limited to the automation of banking processes; rather, its effects are transmitted through faster decisions, fewer unnecessary service disruptions, improved anticipation of demand, more consistent service provision, and greater capacity to explain algorithmic decisions.

In credit-risk prediction, XGBoost achieved the highest overall performance, with an accuracy of 0.878, an F1 score of 0.857, and an AUC-ROC of 0.912. Random forest and the multilayer perceptron neural network also performed strongly, but the statistical comparison showed that XGBoost significantly outperformed the other algorithms. This finding indicates that gradient-boosting methods are particularly effective for banking datasets characterized by heterogeneous variables and potentially nonlinear relationships among credit, transactional, and behavioral indicators. The result is consistent with the broader literature emphasizing the ability of artificial intelligence and machine learning to process complex customer information and generate more accurate predictions than traditional rule-based approaches (1, 10). In banking, more accurate credit-risk estimation can influence customer experience directly by reducing delays, increasing consistency in credit decisions, and lowering the likelihood of both inappropriate approvals and unnecessary rejection of creditworthy applicants. Tian likewise argues that artificial intelligence can simultaneously strengthen risk management, operational efficiency, and customer experience in commercial banking (2). The present findings support this multidimensional view by demonstrating that algorithmic quality in risk management can also function as a customer-experience mechanism.

The superiority of XGBoost should also be interpreted in relation to the importance of speed and personalization in digital banking. Although logistic regression required considerably less training time and remained highly interpretable, its predictive performance was weaker than that of ensemble models. This suggests that banks face a trade-off between simplicity and predictive capability. For many high-volume digital services, customers increasingly expect accurate and timely decisions that reflect their individual behavioral and financial profiles rather than standardized evaluations. Previous studies have shown that AI-based systems can improve customer experience through predictive analytics, personalization, and the ability to respond more precisely to individual customer needs (5, 6). The current results extend this argument to the banking context by showing that advanced machine-learning models can improve the quality of customer-specific risk assessment while retaining sufficient interpretability when combined with explainable artificial intelligence techniques.

The SHAP analysis further demonstrated that debt-to-income ratio, repayment history, overdue facilities, average account balance, number of credit inquiries, and duration of the customer-bank relationship were among the most influential predictors of credit risk. This result is important because it shows that the strongest model did not operate solely as an opaque statistical mechanism; rather, its predictions were grounded in financially meaningful and behaviorally interpretable indicators. This supports the growing emphasis on customer knowledge as a foundation for intelligent customer experience management. Rahmania et al. argue that machine-learning-based customer experience management can be strengthened by integrating customer knowledge with predictive models (10). Similarly, Nwachukwu and Affen emphasize the role of AI in converting customer information into more effective and personalized customer management practices (16). The present study therefore suggests that customer experience can be improved not only by increasing predictive accuracy, but also by using behavioral information in ways that make decisions more relevant and explainable.

Fraud detection yielded another important finding. XGBoost achieved the highest F1 score of 0.808 and the lowest false-positive rate of 0.107, outperforming logistic regression, decision tree, random forest, isolation forest, and LSTM. This finding is especially relevant to customer experience because false-positive fraud alerts are one of the clearest examples of a technically protective system creating a negative service experience. Legitimate transactions that are unnecessarily blocked may cause inconvenience, customer frustration, delayed purchases, additional authentication procedures, and increased reliance on customer-service channels. The lower false-positive rate achieved by XGBoost therefore indicates that improved algorithmic precision can reduce customer friction while maintaining security. This result is consistent with the argument that AI enhances customer experience when it improves both operational efficiency and the reliability of service interactions (3, 4). It also aligns with Rane's view that AI and data-intensive technologies can improve satisfaction, engagement, and relationship quality when they enable more accurate and responsive services (11).

The fraud-detection results also highlight the importance of evaluating machine-learning systems using metrics that reflect the actual service consequences of errors. Overall accuracy alone would have been insufficient because fraudulent transactions represented a very small proportion of all transactions. By emphasizing precision, recall, F1 score, AUC-PR, and false-positive rate, the study demonstrated that the best model was not simply the one that classified the greatest number of observations correctly, but the one that achieved the most appropriate balance between identifying fraud and protecting legitimate customers from unnecessary disruption. This broader form of evaluation corresponds with contemporary customer-experience research, which treats AI performance as meaningful only when it improves the actual quality of interactions between customers and intelligent systems (12). Terenggana likewise reports that artificial intelligence can influence overall customer experience in technology-mediated services, indicating that the quality of AI-supported service processes affects customers' broader evaluations of the service provider (18).

A further important result concerned the forecasting of foreign-exchange service demand. The hybrid LSTM-XGBoost model produced the lowest prediction errors, with an MAE of 79.4, RMSE of 121.8, MAPE of 5.1%, and R^2 of 0.832. Its performance was superior to ARIMA, SARIMA, random forest, standalone XGBoost, LSTM, and Transformer models. This finding indicates that combining the temporal learning capacity of LSTM with the nonlinear predictive capability of XGBoost can provide substantial advantages in modeling complex service-demand patterns. From the perspective of customer experience, the importance of this result lies in the relationship between forecasting accuracy and service readiness. More precise anticipation of demand allows a bank to allocate staff, technological capacity, foreign-exchange liquidity, and processing resources more effectively, which can reduce delays and improve service availability. Herawati et al. emphasize that AI can enhance customer experience partly through better resource allocation, service responsiveness, and operational management (19). Similarly, Sahut and Laroche identify predictive capability as one of the strategic mechanisms through which AI can create customer value (15). The current finding provides empirical support for these perspectives within the banking environment.

The results concerning service-demand forecasting are also compatible with the broader literature on seamless and integrated customer journeys. When a bank accurately anticipates service volume, customers are less likely to experience bottlenecks, inconsistent service availability, or delayed processing across digital and physical channels. Nguyen and Mogaji emphasize the importance of AI in creating seamless experiences across customer-service channels by supporting continuity and coordinated interaction (9). Although the present study focused on predictive infrastructure rather than channel integration itself, the underlying implication is similar: customer experience depends partly on whether the organization can anticipate and coordinate service provision before demand creates operational pressure. Thus, machine learning contributes to customer experience not only through direct customer-facing applications but also through improvements in back-end planning that affect the reliability of the entire service journey.

Another important finding concerned model stability. The sensitivity analysis showed that XGBoost remained comparatively robust when Gaussian noise was introduced into the data. In credit-risk prediction, even 20% noise reduced its F1 score by only 0.078, while fraud detection showed a somewhat larger but still moderate decline. By contrast, the hybrid foreign-exchange model was more sensitive to noise and exceptional market conditions. The crisis-scenario analysis reinforced this pattern. Credit-risk XGBoost maintained relatively stable AUC-ROC performance under a simulated economic recession and experienced an 8.6% decline in F1 score under infrastructure disruption, whereas severe currency volatility increased the MAPE of the hybrid LSTM-XGBoost model from 5.1% to 8.7%. These findings show that predictive models should not be considered static systems whose performance remains unchanged after deployment. Their contribution to customer experience depends on continuous monitoring, retraining, and adaptation to changing data distributions.

This interpretation is consistent with the literature emphasizing that effective AI-based customer experience management requires continuous adaptation rather than one-time technological implementation. Choudhary et al. note that AI-driven customer experience management depends on learning from evolving customer information and continuously improving predictive and personalization capabilities (1). Similarly, Sahut and Laroche emphasize the strategic nature of AI, implying that organizations must integrate it dynamically into customer and marketing processes rather than treat it as an isolated technological investment (15). In the banking context, this is particularly important because customer behavior, macroeconomic conditions, fraud patterns, and exchange-rate environments can change rapidly. A model that performs well during stable periods may produce poorer predictions during structural breaks, thereby affecting service availability, customer trust, and the reliability of automated decisions.

The evaluation of model interpretability represents another central finding. XGBoost, when combined with SHAP and LIME, offered high levels of both global and local explanation while maintaining stronger predictive performance than simpler models. Logistic regression remained inherently interpretable, but its lower predictive accuracy limited its attractiveness for complex banking applications. Neural networks showed strong predictive capability but substantially weaker explainability. This result suggests that XGBoost can provide an advantageous compromise between predictive power and transparency. The importance of this balance is particularly pronounced in banking because algorithmic decisions may affect access to credit, transaction authorization, and other financially significant services. Customers may be more willing to trust AI-supported decisions when they can understand the major reasons underlying those decisions. Shojaeian et al. emphasize that customers' AI experience is shaped not merely by technical functionality but also by how they interpret and relate to AI-mediated interactions (17). Likewise, Sami Adel highlights both the opportunities and challenges associated with personalized AI services, including the need to address trust and transparency (8).

The importance of explainability also relates to personalization. Effective personalization requires extensive use of customer data, but customers may become concerned when they do not understand why a system is recommending, approving, rejecting, or flagging a particular service. Previous research has shown that AI can enhance customer engagement when personalization is perceived as relevant and beneficial (7, 13). However, personalization without transparency can undermine trust. The present findings suggest that explainable machine learning can mitigate this problem by allowing customer-facing units to communicate the primary factors influencing a model's decision. In this respect, explainability can be viewed as a customer-experience feature rather than merely a technical or regulatory requirement.

The economic findings further strengthened the practical significance of the machine-learning results. The combined estimated one-year ROI of the evaluated applications was 421%, while the three-year ROI was estimated at 1,263%. Credit-risk prediction showed the greatest projected financial return, followed by fraud detection, foreign-exchange optimization, and process automation. These results demonstrate that customer-oriented machine learning need not represent a trade-off between service quality and financial performance. Instead, the same systems that reduce risk, detect fraud, optimize resources, and automate processes can simultaneously improve the quality of customer interactions. Putra emphasizes that AI can create organizational value by improving operational efficiency, decision-making, and customer experience together (4). Tian similarly situates AI at the intersection of efficiency, risk management, and customer experience within commercial banking (2). The present economic findings provide further support for this integrated perspective.

More broadly, the findings confirm that customer experience should be considered an organizational outcome of AI deployment rather than a narrow consequence of customer-facing chatbots or recommendation systems. The models evaluated in this study affected customer experience through several indirect pathways: credit-risk algorithms influenced decision speed and consistency; fraud models reduced unnecessary transaction disruptions; demand-forecasting systems supported service availability; and explainability mechanisms increased transparency. This wider conception is consistent with research indicating that AI can influence the customer journey through personalization, seamless interaction, operational responsiveness, prediction, and engagement (9, 14). It also supports the broader conclusion of contemporary AI research that artificial intelligence creates customer value most effectively when technical capabilities are integrated with organizational processes and customer relationship strategies (15, 16).

Overall, the results indicate that machine learning can enhance customer experience at Bank Mellat when algorithm selection is based on more than predictive accuracy alone. XGBoost emerged as the most balanced model for credit-risk and fraud applications because it combined strong predictive performance, relatively high robustness, and effective explainability. The hybrid LSTM-XGBoost model showed the greatest potential for service-demand forecasting but also demonstrated the need for more frequent retraining under volatile market conditions. These findings are broadly consistent with prior research showing that AI improves customer experience by strengthening personalization, service relevance, operational efficiency, responsiveness, engagement, and decision quality (3, 6, 11). They additionally extend previous findings by demonstrating that model robustness, explainability, and false-positive behavior are critical mechanisms through which technical machine-learning performance can translate into a better banking experience.

This study has several limitations that should be considered when interpreting its findings. First, the empirical analysis was conducted within a single banking institution, and the operational characteristics, customer composition, technological infrastructure, and internal processes of Bank Mellat may differ from those of other banks. Second, the machine-learning dataset covered a specific period and therefore may not fully represent longer-term changes in customer behavior, economic conditions, or fraud patterns. Third, although several major algorithms were compared, the study did not include every available machine-learning architecture or optimization method. Fourth, the economic analysis was based on estimated reductions in losses and deployment costs and should therefore be interpreted as an analytical projection rather than a definitive accounting outcome. Finally, customer experience is a multidimensional construct, and although the study linked algorithmic performance to several customer-relevant consequences, not every psychological or behavioral dimension of experience could be represented directly by operational banking data.

Future studies should replicate the present analysis across multiple banks to determine whether the relative superiority of the identified algorithms remains stable under different organizational and customer environments. Longitudinal research using several years of customer and transactional data could provide a more accurate assessment of model drift, changing customer behavior, and the long-term stability of predictive systems. Future research could also compare additional deep-learning, transformer-based, federated-learning, and ensemble architectures and investigate whether their predictive advantages justify greater computational and interpretability costs. Researchers should further integrate direct customer-experience indicators with operational behavioral data in order to examine more precisely how algorithmic decisions influence satisfaction, trust, loyalty, complaint behavior, and continued use of digital banking services. Experimental studies could also compare different forms of algorithmic explanation to determine which explanation formats produce the greatest improvement in customer trust and perceived fairness.

Bank Mellat should prioritize the deployment of machine-learning models that combine high predictive accuracy with acceptable explainability and operational stability rather than selecting models solely on the basis of one performance metric. XGBoost can be prioritized for credit-risk and fraud-detection applications, while hybrid sequential models may be more suitable for short-term demand forecasting. Model performance should be continuously monitored, with predetermined thresholds for retraining when accuracy declines or customer behavior changes. Fraud-detection systems should be specifically optimized to minimize false-positive alerts because unnecessary transaction restrictions can directly damage customer experience. Explainable AI tools should be incorporated into customer-facing and managerial systems so that major algorithmic decisions can be communicated in understandable terms. Finally, machine-learning deployment should be coordinated with customer-service, risk-management, information-technology, and operational units so that technical improvements are translated into faster, more reliable, more transparent, and less disruptive banking services.

Acknowledgments

We would like to express our appreciation and gratitude to all those who helped us carrying out this study.

Authors’ Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

Funding

This research was carried out independently with personal funding and without the financial support of any governmental or private institution or organization.

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