



ARTIFICIAL INTELLIGENCE IN DIGITAL BANKING: TRANSFORMING CUSTOMER EXPERIENCE, RISK MANAGEMENT, AND FINANCIAL DECISION-MAKING

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Abstract

Artificial intelligence (AI) is now transforming digital banking in ways that enhance customer engagement and operational efficiency, guide risk-based decision making, and drive predictive financial analytics. But there is not much empirical evidence comparing machine learning models to predict customer subscription. This study examined the role of artificial intelligence in digital banking by evaluating how machine learning models predict customer subscription behavior and support customer-focused financial decision-making. A quantitative secondary-data approach was applied using 45,211 customer observations and 17 variables. The dataset was preprocessed through data quality checks, categorical encoding, and stratified train-test splitting. Three supervised machine learning models—Logistic Regression, Decision Tree, and Random Forest—were evaluated using accuracy, precision, recall, F1 score, confusion matrices, ROC-AUC, and feature importance analysis. The results showed that Random Forest achieved the strongest overall performance, with 90.51% accuracy, 69.01% precision, and an AUC of 0.921. Decision Tree achieved the highest recall at 39.60%, indicating better identification of actual subscribers. Feature importance analysis revealed that duration, previous campaign outcome, month, age, and previous contact timing were the most influential predictors of subscription behavior. The findings indicate that AI-driven predictive analytics can strengthen digital banking by improving customer targeting, supporting personalized engagement, and enhancing data-based financial decision-making. Customer interaction variables were more influential than basic liability indicators, highlighting the importance of behavioral data in intelligent banking systems.

Keywords: Artificial Intelligence, Digital Banking, Machine Learning, Customer Experience, Predictive Analytics

1. Introduction

Digital banking has redefined the banking business by moving it away from a branch-based banking system to a technology-driven, customer-centric banking system. Digital financial services have had a profound impact on the nature of financial institutions' interactions, activities and processes for delivering services to their clients. Digital technologies have increased the level of accessibility, efficiency of transactions and responsiveness of services in banking settings (De Venn, 2023). AI has emerged as one of the most game-changing technologies in the banking sector. AI has become a vital part of the financial landscape, helping financial institutions streamline operations, enhance customer experience, bolster financial analysis, and facilitate the implementation of intelligent decision-making processes. The use of artificial intelligence has helped to speed up the evolution of intelligent banking ecosystems that can process a vast amount of customer and financial data in real time (Broby, 2021).

Predictive and personalized banking services have gone hand-in-hand with the use of artificial intelligence in financial institutions. With machine learning systems, financial institutions can distinguish which are the money habits, examine monetary preferences and enhance strategic banking choices. These have improved the targeting of customers, automated service delivery and operational efficiency in digital banking contexts (Ashta & Herrmann, 2021). In addition, customer experience is now a major focus for financial institutions in today's very competitive digital environment. Today's banking consumers are looking for customised financial solutions, efficient communication channels and digital interactions that are seamless across banking channels. Therefore, the focus on providing a service to the customer has become more and more important, which has brought intelligent analytical systems to the forefront that can support engagement and service optimization strategies (Chauhan et al., 2022).

The potential of AI in the financial sector has been increasingly recognized, particularly in the context of financial systems that are becoming "intelligent" and in banking applications that are increasingly taking place automatically. AI technologies, such as machine learning and deep learning, have played a role in the advancement of predictive analytical systems, which have enhanced customer analytics, financial forecasting, and banking automation processes (Paramesha et al., 2024). Artificial intelligence is also known to play a significant role in enhancing customer engagement and personalization in the banking industry. Financial institutions can enhance the quality of customer communications and reinforce customer retention initiatives through intelligent recommendation systems, predictive customer analytics, and automation. These abilities have enabled AI to become a crucial force in the ongoing transformation of banking toward customers (Bhattacharya & Sinha, 2022). Likewise, past research has focused on the use of AI for enhancing personalized banking services and systems with customer communication. Predictive analytical tools are helpful for financial institutions to analyze customer interaction history and offer personalised financial advice, which boosts customer fulfilment and the effectiveness of their financial services in digital banking settings (Sheth et al., 2022). In the financial sector, artificial intelligence has also emerged as a key component in decision-making processes. For banking institutions, predictive machine learning models offer assistance in assessing customer behavior, forecasting consumer subscription predictions, and enhancing information-driven monetary choice-making processes. In addition to operational automation, artificial intelligence has also contributed to its analytical capabilities and transformed into a strategic financial intelligence tool (Huang & You, 2023). In recent years, there's been significant focus on the operational efficiency and risk management aspects of artificial intelligence. Through the use of intelligent analytical systems, banks can minimize uncertainty in their operations, make more informed strategic decisions, and allocate resources efficiently. AI-driven predictive financial models aid in improving risk management within banking sectors and decision-making processes in banks (Reddy & Muthyala, 2023). Prior studies also identify the benefits and drawbacks of implementing AI in financial institutions. Although AI offers bankers enhanced efficiency and predictive powers, there are also important considerations regarding model reliability, model complexity, and implementation issues in banking systems (Ghandour, 2021). AI's contribution to strengthening operational performance and decision support systems within an enterprise has also been discussed recently, as part of discussions on enterprise risk management. Within digital financial ecosystems, intelligent predictive systems play a growing role in optimizing operations and strategic management of banks (Comite et al., 2025). In more general instances of business and finance, the transformative power of AI in customer engagement, automation, and managerial decision-making has also been highlighted. In today's digital world, AI-powered systems are helping companies to enhance their analytical agility and boost their data-driven operations (Nalini, 2024).

While the significance of artificial intelligence in banking and financial services has been extensively discussed in the past, most of the previous literature has been conceptual and theoretical. Previous studies have mostly centered around customer service automation, digital banking transformation, and other general topics related to the applications of AI in bank settings, but lacked empirical evidence for predictive customer analytics specifically in banking settings. Moreover, there are limited comparative studies that show the performance of various machine learning models predicting customer subscription behavior using large-scale banking data. The comparative effectiveness of the traditional statistical models and ensemble learning models in the customer targeting and financial decision-making process in digital banking systems has received limited empirical interest in the existing literature. The goal of the current research is to investigate how AI can reshape customer interactions, streamline operations, and boost financial forecasting in digital banking settings. The study aims to compare specifically the predictive ability of Logistic Regression, Decision Tree and Random Forest models to predict customer subscription behavior. Besides, the paper examines the impact of demographic, financial and customer engagement factors on predictive outcomes to offer empirical perspectives into the contribution of artificial intelligence to intelligent banking analytics and customer-oriented financial decision systems.

2. Methodology

2.1 Research Design

The quantitative research approach was used to investigate the use of AI in digital banking with predictive analytics methods. A secondary data approach was used to analyze the behavior of customers in terms of subscription using machine learning models. Quantitative design was deemed suitable for the study since it was meant to reveal patterns, relationships and predictive performance in a large banking database. Supervised machine learning models, such as Logistic Regression, Decision Tree and Random Forest models, were used to perform the analysis. The models chosen were because they are commonly used in financial analytics and customer behavior prediction research. The research design facilitated the comparison of the traditional statistical approaches and the new approaches based on artificial intelligence in digital banking.

2.2 Data Source

The data of this study were taken from Syamsuddin et al. (2025). The data is related to customers for banking predictive financial analysis and customer classification applications. Contains demographic, financial and customer interaction variables appropriate for assessing machine learning accuracy in a banking decision-making context. The data included 45,211 observations of customers and 17 variables that included customer demographics, interactions with the bank, loan status, bank account balance, campaign history, and customer subscription results. The target variable was related to customer subscriptions, allowing supervised machine learning classification models to be implemented.

2.3 Data Preparation and Preprocessing

Data preprocessing was performed to ensure uniformity and the suitability of the data for machine learning analysis. Data was initially reviewed for missing, duplicated and inconsistently structured data. The analysis did not show any missing values or any duplication of observations, suggesting that the data were complete and could be used for predictive modelling. Label encoding methods were used to convert categorical variables into numerical values for processing by the machine learning algorithms. The target variable was also transformed into a binary class: subscriber vs. non-subscriber, outcome. The data was then split into predictor variables and the target variable after undergoing preprocessing. The dataset was divided into 80% training and 20% testing to perform the evaluation of the predictive performance objectively. Splitting was done using stratified sampling so as to maintain the class distribution present in the original sample in both daughter samples.

2.4 Machine Learning Models

Three machine learning supervised models were used in the study, namely Logistic Regression, Decision Tree and Random Forest. A logistic regression statistical classification model was used as a baseline model to explore the linear relationships between predictor variables and the outcome of subscription. A Decision Tree model was used to capture the nonlinear decision structures and the customer behavioural patterns. This model was informative of the classification rules and allowed for the identification of influential customer

properties. Random Forest, an ensemble learning method, was employed by creating a combination of multiple decision trees to enhance the stability of prediction and accuracy of classification. The model was chosen because of its ability to handle the vast amount of data found in a bank, to avoid over-fitting and to produce better predictive results.

2.5 Model Evaluation

The accuracy, precision, recall, and F1-score were used to assess the performance of the machine learning models. The proportion of correctly classified observations was used to measure the accuracy, while the proportion of correctly predicted positive cases was used to measure precision. The precision and the recall were evaluated using recall, and the model that had a balanced evaluation of precision and recall was calculated as the F1-score. In addition, confusion matrices were generated to analyse the classification results and the prediction mistakes for both subscriber and non-subscriber groups. The discriminative ability of the models was also evaluated by the Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) values.

2.6 Feature Importance Analysis

The Random Forest model was used to perform feature importance analysis and determine which variables are the most significant in the prediction of customer subscription. The analysis allowed assessing the role of customer engagement, socio-demographic and financial variables in predicting the outcomes within the digital banking context. A random forest model was used to generate importance scores for each predictor variable, which were used to interpret the relative contribution of each predictor variable to the classification process. This analysis was useful in gaining more insights into how artificial intelligence can be used for customer targeting and financial decision-making.

3. Results

3.1 Dataset Characteristics and Class Distribution

The data set consisted of 45,211 customer observations and 17 variables from a banking marketing data set. These data were utilized to assess the performance of AI/machine learning models in predicting customer subscription behavior in the context of a digital banking environment. The distribution of the target variable was highly imbalanced, with non-subscribers substantially outnumbering subscribers. In particular, a high number of customers did not subscribe to the banking product, and a smaller number went through the process of subscribing to the product. This imbalance is the result of “realistic banking conditions” where the conversion rate for successful customers is typically low. The overall data quality and class distribution are shown in Table 1.

Table 1. Dataset Summary and Class Distribution

Characteristic	Value
Total observations	45,211
Total variables	17
Non subscribers	39,922
Subscribers	5,289
Non-subscriber percentage	88.3%
Subscribers percentage	11.7%

Notice here the difference in the number of the two customer classes, showing that there is a need to use other performance evaluation metrics than the overall accuracy. For instance, the skill of correctly recognizing real customers, precision, recall, and F1-score are required to evaluate how well machine learning models work. The distribution of customers' subscriptions is shown in Figure 1.

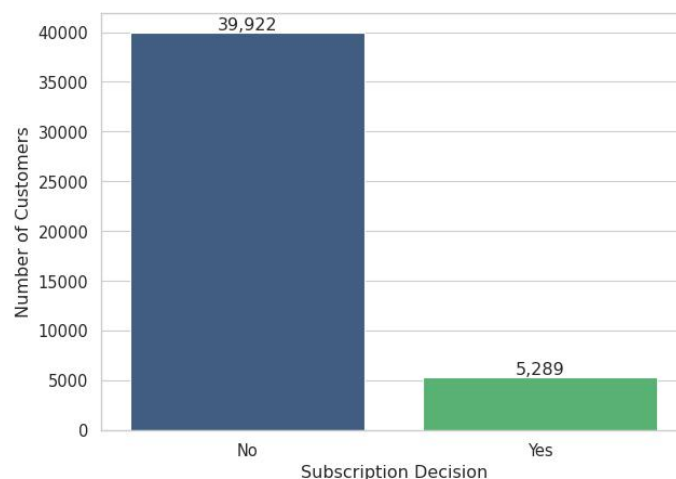


Figure 1. Customer Subscription Distribution

3.2 Descriptive Statistics and Correlation Analysis

The descriptive analysis showed that there was a lot of variation in the variables of customers' demographics and banking engagement. The average age of the customers was about 41 years, suggesting that the bulk of the customers were in their middle age. Likewise, the account balance variable had a high standard deviation, indicating significant differences in the financial status of customers. The descriptive statistics of the numerical variables used in the analysis are summarized in Table 2.

Table 2. Descriptive Statistics of Numerical Variables

Variable	Count	Mean	Standard Deviation	Minimum	First Quartile	Median	Third Quartile	Maximum
Age	45,211	40.94	10.62	18.0	33.0	39.0	48.0	95.0
Balance	45,211	1362.27	3044.77	-8019.0	72.0	448.0	1428.0	102127.0
Day	45,211	15.81	8.32	1.0	8.0	16.0	21.0	31.0
Duration	45,211	258.16	257.53	0.0	103.0	180.0	319.0	4918.0
Campaign	45,211	2.76	3.10	1.0	1.0	2.0	3.0	63.0
Pdays	45,211	40.20	100.13	-1.0	-1.0	-1.0	-1.0	871.0
Previous	45,211	0.58	2.30	0.0	0.0	0.0	0.0	275.0

The duration variable showed a high dispersion; thus, the intensity of the customers' interactions ranged widely across banking campaigns. Likewise, the campaign variable, as well as the previous contact variables, showed high positive skewness and extreme values, which indicated that the previous contact histories of the customers were not evenly distributed. The numerical variables in this study are included in a correlation matrix as shown in Figure 2.



Figure 2. Correlation Matrix of Numerical Variables

The correlation analysis showed mostly low correlations between the numerical variables, which indicated the lack of strong multicollinearity in the data. Previous ($r = 0.45$) had the strongest positive association with Pdays, suggesting that previous customer interaction had a positive effect on the timing of the following interactions. There is no significant correlation between most of the predictors, which is a good indicator of the feasibility of the data for machine learning modeling.

3.3 Comparative Performance of Machine Learning Models

To see which of the three machine learning models could be effective in predicting the subscription behavior of customers, Logistic Regression, Decision Tree, and Random Forest models were evaluated. The comparison showed that the models differed with regard to their predictive accuracy. The performance evaluation results of machine learning models are shown in Table 3.

Table 3. Machine Learning Model Performance

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.8916	0.5956	0.2297	0.3315
Decision Tree	0.8970	0.5893	0.3960	0.4737
Random Forest	0.9051	0.6901	0.3431	0.4583

The model with the highest overall accuracy was the Random Forest model, which recorded an overall accuracy of 90.51% and an overall precision of 69.01%. The model with the best recall value was the Decision Tree (39.60%), which means that it has a better ability to detect true subscribers. Logistic Regression yielded relatively low values on all the evaluation metrics. The performance of the three machine learning models is compared with each other visually on the selected evaluation metrics in Figure 3.

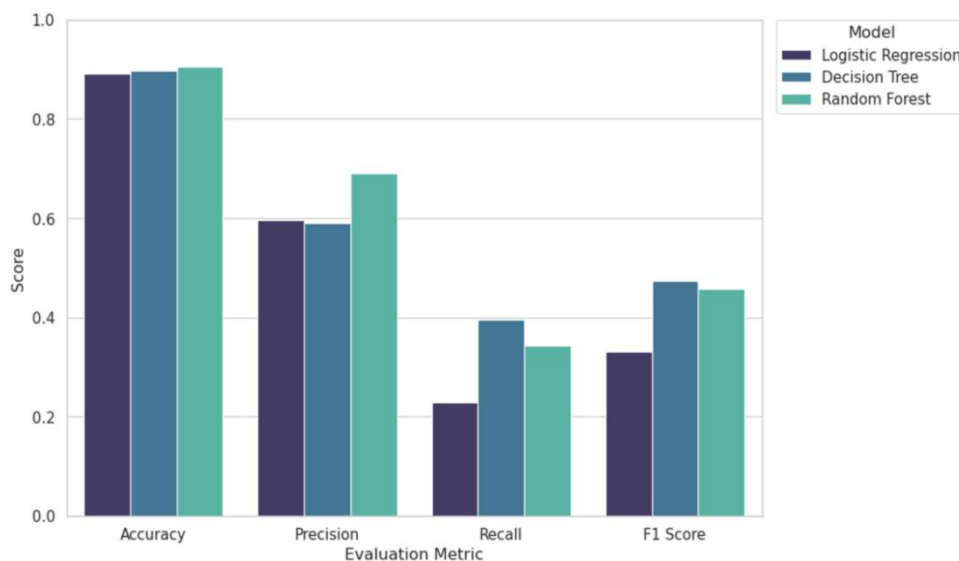


Figure 3. Model Performance Comparison

The results show that the advanced AI methods surpass the traditional statistical methods in digital banking prediction tasks. Ensemble learning methods seem to work better for capturing the patterns of customer nonlinear behavior in banking data sets, as evident from the superior performance of Random Forest.

3.4 Classification Performance and Predictive Accuracy

The machine learning models were further assessed using confusion matrices that were analysed for the distribution of correct and incorrect classifications. The analysis showed significant differences in the accuracy of the models regarding the identification of subscribing customers. The confusion matrix for the Logistic Regression model is shown in Figure 4A, for the Decision Tree model in Figure 4B and for the Random Forest model in Figure 4C.

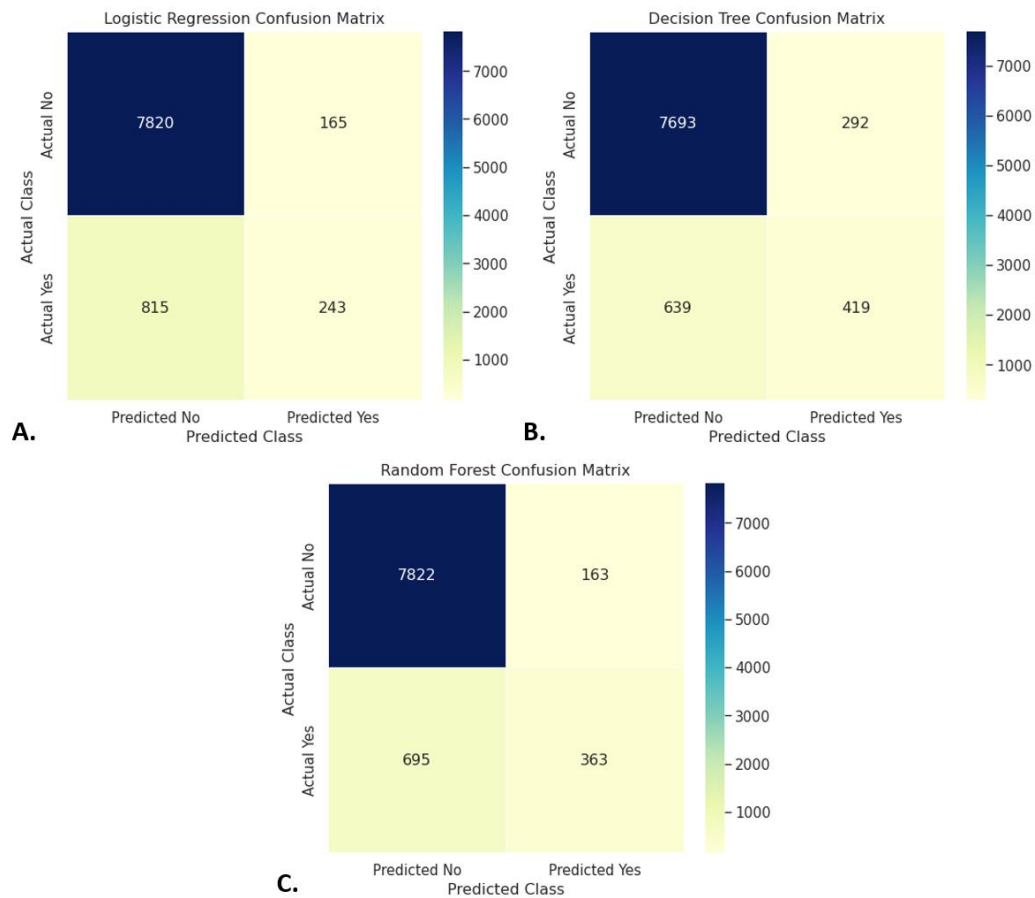


Figure 4. Confusion Matrices of Machine Learning Models

The Logistic Regression was accurate at predicting the non-subscribers, but it didn't capture a significant number of the subscribers. The Decision Tree model was superior in the detection of the subscribers with greater accuracy, as it made a better number of correct positive call classifications. In the meantime, the Random Forest model had the best balance of false positives and false negatives, which meant that it was more stable when it came to classification and provided greater consistency for prediction. The Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) values for the models evaluated are shown in Figure 5.

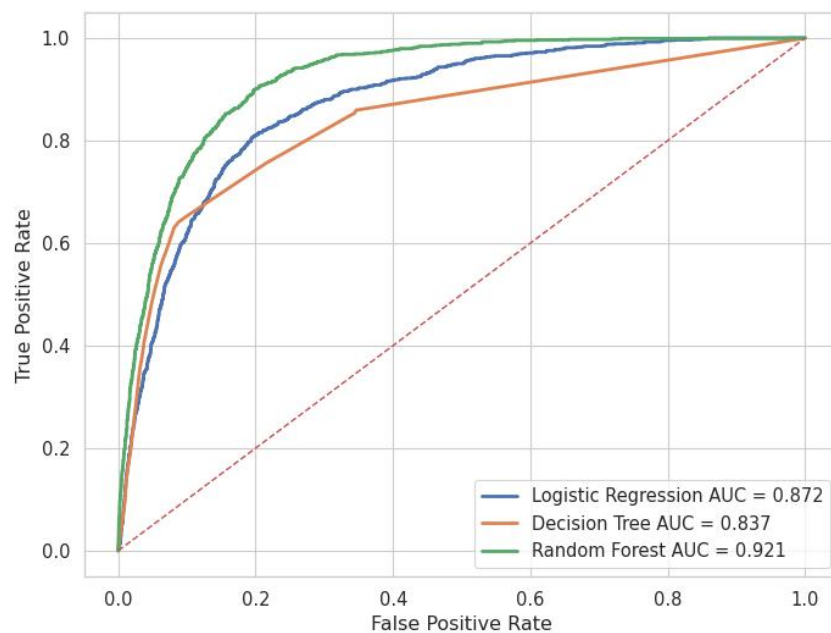


Figure 5. Receiver Operating Characteristic Curves

The Random Forest model had the greatest AUC value of 0.921, which signifies that the model had the best discriminative power between the two classes (subscribers vs. non-subscribers). Logistic Regression gave an AUC value of 0.872, and the Decision Tree model gave the lowest AUC value of 0.837. The results are further evidence of the greater predictive power of ensemble-based artificial intelligence models in digital banking analytics.

3.5 Feature Importance Analysis

A Random Forest model was used to perform feature importance analysis to determine which variables are most important in determining customer decisions to subscribe or not. The importance of the predictor variables is shown in Figure 6.

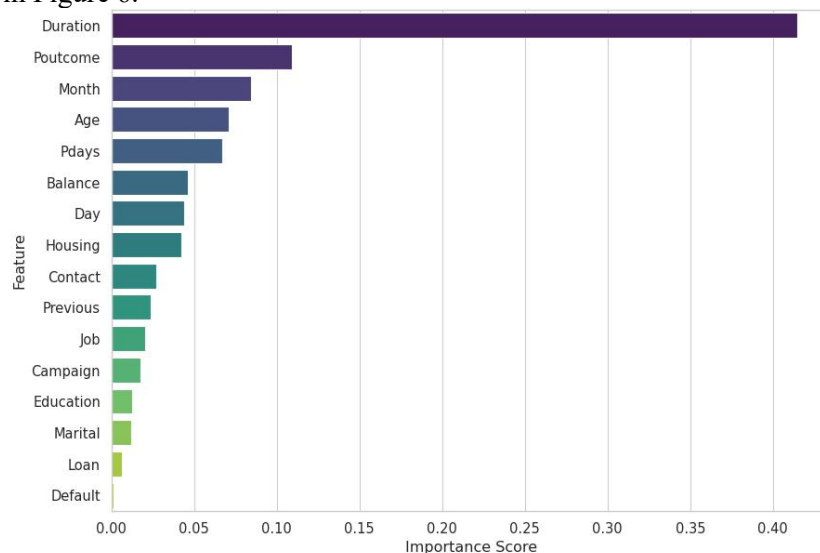


Figure 6. Random Forest Feature Importance

The variable that most strongly predicted was the duration, with a significant contribution from all other variables. This discovery suggests that both the quality and quantity of the interaction with the customer are important factors in their decision to subscribe to a banking product. The previous campaign outcome (Poutcome) and contact timing variables (Month and Pdays) also had significant predictive power. Conversely, other variables that had been part of a person's past financial obligations had relatively low

importance scores, including loan status and default history. The results indicate that customer interactions and communication patterns have a greater influence on subscription decisions than traditional financial risk factors. The feature importance analysis demonstrates the ability of the AI systems to reveal intricate patterns in customer behaviour and provide data-driven insights for informed decision-making in digital banking contexts.

4. Discussion

The results show that machine learning can give valuable predictive assistance in the decision-making process when it comes to digital banking, especially when predicting customer subscription behavior. The class distribution resulted in a very skewed outcome pattern in which the majority of observations were of non-subscribers. This imbalance is significant as it represents a typical situation in banking campaigns, where only a fraction of customers is willing to accept financial product offers. Therefore, accuracy is not the only measure to interpret the performance of the model; precision, recall, F1 score, confusion matrices, and ROC performance are more balanced measures of the model's predictive effectiveness. Random Forest was the highest in the accuracy and precision among the evaluated models, which made it the most robust model for the overall classification and for minimizing the number of false positive predictions. Such a finding indicates that ensemble-based artificial intelligence techniques outperform linear classification techniques in learning complex customer behavior patterns. Logistic Regression was not very successful as a baseline model and had the lowest recall and F1 score, bad at identifying the real subscribers. The Decision Tree model had the best recall, meaning that it was better at finding customers who actually subscribed, but had less precision than the Random Forest model.

The ROC results also support the conclusion that the best predictive performance was obtained using the Random Forest. It shows that it has better discriminatory performance between subscribers and non-subscribers with its higher AUC value. From a practical point of view, this translates into Random Forest being able to help in customer targeting decisions by prioritizing the ranking of potential customers based on their probability of signing up. This forecasting is beneficial for digital banking as it helps financial institutions allocate their marketing efforts more effectively and enhance customer engagement strategies. The feature importance results offer more information about the behavior of the prediction. The duration appeared to be the most significant, indicating that the quality and length of the customer interactions played a significant role in the likelihood of conversion to a subscription. The previous campaign outcome, month, age and previous contact timing were also significant, suggesting that prior engagement results and timing have an impact on customer financial decisions. Interestingly, the loan and default variables were the least significant predictors in this data set, suggesting that more salient factors of customer interactions were likely to be more significant than more basic liability indicators.

The findings of the present study are in line with the latest research, which has shown that explainable and ensemble ML systems can boost financial classification processes and enhance banking decision support systems (Chang et al., 2025). In the context of loan approval prediction, ensemble models have been demonstrated to enhance the reliability of predictions and the practical application of banking decisions (Uddin et al., 2023). The findings also align with the larger body of evidence demonstrating how cutting-edge machine learning techniques enhance financial forecasting and predictive analytics, as they are able to detect intricate patterns that traditional machine learning techniques might not be able to see (Thakkar et al., 2024). Furthermore, the application of classification models in banking prediction aligns with previous studies indicating that machine learning approaches can aid the institutional risk assessment and early warning system in financial settings (Petropoulos et al., 2020). The role of customer interaction variables is aligned with a study that found that personalized experiences are at the top of the list of things that can make a digital banking experience better (Kodali, 2022). The results of this study also align with earlier postulations on the importance of personalized financial products and decision-making systems in digital banking environments to improve customer experience (Sondinti & Reddy, 2022).

The focus of this study on the use of predictive analytics in decision making is also aligned with the literature, which emphasizes the importance of the integration of business intelligence and predictive analytics in banking decision optimization (Adeniran et al., 2024). In financial management studies, the benefits of predictive analytics in decision-making and risk management have also been highlighted (Aro, 2024). The results are also backed by research on AI tools for customer engagement, with evidence indicating how AI can enhance customer interaction and service responsiveness in the financial industry (Egbuhuzor et al.,

2021). The results also corroborate the general digital transformation literature, reinforcing the use of artificial intelligence in increasing the efficiency of banks, improving customer experience, and risk management (Tian, 2024).

Overall, the results hold significant implications for digital banking practice. Machine learning models can enhance customer targeting, product recommendations, and minimize wasted campaign efforts in banks. Random Forest can prove useful when the goal is to maximize the overall predictive accuracy and precision, while a Decision Tree can be beneficial when it is desired to capture a higher percentage of prospective subscribers. Based on the feature importance, banks should be more mindful of the quality of engagement with the customer, campaign results that have been achieved so far and the timing of the communication. A digital banking system should not simply use demographic or financial liability indicators, but should also incorporate behavioral interaction data in decision-making processes. This aligns with a more customer-focused perspective on the implementation of AI, where predictive systems are not just about efficiency but about ensuring that communication with customers is relevant and timely. On the managerial side, the outcomes reveal that AI can aid in optimizing operational processes and contribute to the efficient distribution of marketing and service investments among financial institutions. Predictive models can help banks determine who is more likely to take a subscription, limit their outreach, and be more productive.

Some caveats must be noted. The study was conducted with a pre-existing secondary data set, thus with less control over the selection of variables and the design of the data collection. Customer satisfaction, variables related to interactions with the chatbot and real-time digital banking behavior were not included as direct measures in the dataset. Additionally, the analysis was limited to three supervised learning models and excluded state-of-the-art optimization and deep learning techniques.

The analysis could be expanded to include real-time digital banking data, customer experience metrics, and other AI models in the future. Explainable AI methods could also be explored further to enhance the transparency of the banking prediction systems, thereby boosting confidence in automated financial decision-making.

5. Conclusion

AI provides significant benefits for digital banking, such as enhanced customer targeting, predictive decision-making, and operational efficiency. The empirical findings indicated that machine learning models have the potential to accurately predict the customer subscription behavior, with the Random Forest model achieving the best overall performance both in terms of accuracy and precision and AUC. Decision Tree was more successful in determining what the actual subscribers were, suggesting that the choice of model should be based on whether it is the goal of the bank to maximize precision or generalize customers. The most significant variables were related to customer interactions, such as length of interaction, previous campaign response, timing of contact, and prior interaction. This means that the customer experience and communication quality play a key role in AI banking decision-making. The results indicate that financial decision-making could be better with the inclusion of behavioral data in the banks' predictive systems, and not only the demographic or financial data. The findings show that AI-powered predictive analytics can play a role in more personalized customer interactions, cut down on unnecessary outreach, and improve data-driven decision-making in digital banking. The study could be expanded with the inclusion of authentic real-time digital banking data and transparent AI techniques to enhance transparency and feasibility in the future, as this will assist in delivering deeper insights and practical applications.

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