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The Influence of AI-Based Predictive Marketing on Fintech Customer Acquisition and Financial Performance: Evidence from Digital Banking Platforms

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ABSTRACT

Artificial intelligence (AI) adoption in predictive marketing has revolutionised the customer acquisition patterns in the fintech industry, and empirical data regarding its direct influence on financial performance is scarce. This research paper examines how Artificial Intelligence-based predictive marketing can enhance customer acquisition, retention, and overall financial performance of digital banking services. We utilise a machine learning-based predictor of customer subscription behaviours using the Bank Marketing Dataset of UCI to evaluate the effects of different predictors on customer lifetime value (CLV), marketing return on investment (ROI), and profitability. The findings show that AI-based approaches, especially using neural networks, can be a powerful tool to increase the conversion rates and utilise the marketing resources maximally, resulting in better revenue growth and increased ROI. Moreover, the paper presents the most important moderating variables, including regulatory compliance, data privacy, and consumer trust, that determine the effectiveness of AI marketing activities in fintech platforms. The results will provide useful information to the fintech managers who will need to employ AI-based marketing systems to boost business and increase customer interactions when coping with external forces. The study will help fill the gap in the current literature concerning marketing analytics and financial outcomes within the fintech industry and provide both theoretical and empirical evidence on the role of AI in making marketing investments rational.

Keywords: AI-Based Predictive Marketing, Fintech, Customer Acquisition, Customer Retention, Customer Lifetime Value (CLV), Marketing ROI, Neural Networks, Data Privacy, Regulatory Compliance, Consumer Trust, Financial Performance.

INTRODUCTION

Artificial intelligence (AI) is a key aspect of marketing plans in recent years, both in the fintech and digital banking sectors. Machine learning, predictive analytics, and data-driven decision-making are some of the AI technologies to transform the process by which organisations acquire, maintain, and optimise customer acquisition (Ramya et al., 2024). The predictive marketing element relies on previous data, consumer behaviour and advanced algorithms to forecast the outcomes and enhance personalised marketing procedures. In the context of an extremely competitive environment of fintech, customer anticipations, and the need to adjust to regulations, AI will be an opportunity to streamline the marketing process and fuel financial outcomes. The data-driven marketing trend has changed the face of fintech since it enables firms to make more suitable forecasts and thus invest their marketing priorities more effectively (Cao et al., 2021). This revolution is further specifically useful in customer acquisition and retention as two determinants of financial growth in the industry. Having applied AI in the marketing cycle, the fintech systems can predict the customer behaviours, deliver personalised services, and robotically execute marketing activities to deliver personalised experiences to customers. This will grow customer interaction, and other financial indicators, including customer lifetime value (CLV), revenue growth, and profitability. The ability to utilize data and AI-driven solutions will play a key role in the future of the financial services since fintech can go one step further in its innovation (Babakhanian et al., 2023).

To professionals working in the industry, although the application of AI is growing, there is an extremely high level of lack of empirical studies that determine the effectiveness of AI-based predictive marketing as applied to the fintech industry. Though the literature works have explored the general impact of AI in marketing, there are limited studies on the impact of AI on the monetary performance of fintech sites (El-Shihy et al., 2024). The difference is further increased upon considering such key performance indicators (KPIs) as customer lifetime value (CLV), revenue growth, and profitability, which play a critical role in the assessment of the ultimate result of marketing activities, the ROI. In the fintech industry, where the regulation constraints and customer loyalty are the most vital elements, the impact of AI on customer acquisition costs and marketing ROI is a poorly studied area. Although AI has shown potential in improving the customer segmentation, targeting and engagement levels, the specific impact on the financial performance of fintech companies has not been given a closer analysis (Cao et al., 2021). This study attempts to fill this gap by providing a detailed discussion on how AI-boosted marketing strategies can guarantee the financial success of the digital banking solutions.

The central objective of the study is to analyse the relationship between AI-based marketing strategies and financial performance of the fintech platforms. Specifically, the research will be centered around how AI has influenced such important spheres of marketing as the acquisition, retention of customers, and cost-effectiveness. By examining the use of AI to reduce the customer acquisition cost, the paper will evaluate how AI marketing affects the sustainability and profitability of fintech business, in general. The other significant objective is to assess how AI-based predictive marketing techniques will affect such financial performance metrics as customer lifetime value (CLV), revenue growth, and profitability. This will involve the assessment of how AI can help fintech platforms achieve better ROI on their marketing efforts that will drive them to financial success in the long run. The paper will also address the moderating variables, such as regulatory compliance, data privacy, and consumer trust which may influence the effectiveness of AI marketing campaigns.

The approach is useful to the academia and other industry actors in the fintech and digital banking industry. It bridges a research gap that it addressed in an academic way since it offers empirical data on the success of AI-based predictive marketing solutions in the financial technology industry. The study will contribute to the existing literature on the use of AI in marketing, namely, the understanding of the financial implications of such actions. The research will provide practical information on how AI implementation can be used in fintech because it focuses on the most significant financial indicators, such as CLV and marketing ROI. The research may provide useful information to industry practitioners on the advantages of AI in order to simplify the marketing processes and expand their businesses. Finitch companies can find the knowledge of AI as the way to reduce the costs of customer acquisition, increase customer retention, and profitability helpful (Rahman et al., 2024). In addition, the findings of the research can enable fintech platforms to undertake more profound decisions regarding their AI investments and ensure that they are using the right tools and strategies to ensure that their marketing is as effective as possible. In addition, the research bridges the knowledge gap about marketing analytics, fintech innovation, and financial perspectives and helps to create the theoretical framework and practical implementation of AI in marketing to the fintech sector.

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The paper is useful in relation to providing a comprehensive framework to evaluate the financial implications of AI-based predictive marketing in the fintech industry. Using the regression analysis technique and the structural equation modelling technique, not only will the study be able to establish the implications of AI on customer acquisition and retention, it will also show how the strategies relate directly to financial outcomes such as CLV, higher revenue growth, and profitability. The paper critically analyse the moderating variables, such as data privacy, regulatory compliance, and consumer trust, which can be used to ascertain the effectiveness of AI marketing strategies in fintech. The results can be used by fintech companies to perfect their marketing campaigns and ensure better payoff on the AI-induced investment in their marketing. Thus, the paper not just contribute to the development of the theoretical field, but also to the practical application of AI in the fintech sector and will become an invaluable source of information to policy-makers, fintech managers, and marketers in the digital finance sector.

LITERATURE REVIEW

2.1. AI-Based Predictive Marketing in Fintech

Artificial intelligence (AI) in marketing is one area that has been a major trend in the fintech business, with financial services firms exploring how to use data and sophisticated analytics to streamline customer interactions. The concept of AI-based predictive marketing is the application of machine learning models to customer data to predict their future behaviour, which may be used to inform marketing decisions (Kuma, 2025). Predictive marketing is necessary in the fintech sector to acquire customers, personalise their experiences, and enhance marketing returns.

Some predictive modelling methods have been actively employed in marketing with the help of AI. Regression analysis is one of the most widely utilised methods that is applied to determine correlations between independent variables (e.g., customer demographics, behaviour) and a dependent variable (e.g., likelihood of customer conversion) (Al-Mashraie et al., 2020). Regression models (including logistic regression) are commonly used in churn prediction and customer acquisition and are used to predict the likelihood of a customer reacting favourably to marketing campaigns, or staying a customer in the long-run, by the fintech company.

Another popular fintech marketing tool is decision trees. One approach to customer behaviour modelling consists of decision trees in terms of a sequence of decision choices of choice that leads to a forecast (Gkikas et al., 2022). The approach is particularly useful in segmenting customers into particular sections using behaviour or probability of conversion hence allowing the marketing to take priority. Combination of decision trees: Random forests are often applied to improve the model accuracy by reducing overfitting.

AI and neural networks are already one of the main tools of fintech marketing. Such models, especially artificial neural networks (ANNs), have the ability to acquire complex patterns in massive datasets. It predicts customer lifetime value (CLV), customised financial product recommendations, and optimisation of marketing campaigns with the assistance of neural networks working on a massive volume of structured and unstructured data: transaction history and interactions with customers (Thiruvayipati, 2024). These AI-based solutions are useful to support fintech websites in making evidence-based decisions, predicting customer needs, and personalising their marketing messages in the most effective manner.

2.2. Customer Acquisition and Retention

Customer acquisition and retention is the most important challenge of the fintech companies. It is expensive to acquire new customers and the cost of retaining the customers is normally cheap in the long-run. The predictive marketing AI becomes vital in solving such problems since the technology relies on data to improve on the acquisition and retention tactics (Adekunle et al., 2023).

Several researches have been conducted to examine how AI can be used to acquire customers within the fintech industry. A personalised marketing campaign created with the help of machine learning can enable fintech platforms to define the high-value customers and address them in the most effective way. Instead, using AI models, one can predict the probability of an individual prospect becoming one, using the information of the past interactions, and lead to a more efficient targeting of a customer (Kasem et al., 2024). In addition, collaborative filtering and filtering-based recommendation engine using content-based filtering have shown to improve the conversion rates by offering individualised financial services that may be tailored towards the individual needs of the potential customers.

In the area of customer retention, AI-based models are predicted to predict customer churn based on customer behaviour, frequency of transaction, and customer satisfaction. It has been shown that AI can be successfully applied to predict customer behavior that may lead them to leave the platform and start retention campaigns (Dorgbefu, 2021). The personalised offers, loyalty programme or proactive customer service can be such campaigns and they can significantly reduce the churn rates. It can also be beneficial in the context of long-term engagement because the marketing approaches can be modified with time by constantly examining the customer behaviour. The fintech platform can further cluster customers based on the same requirements and behaviour with the aid of clustering algorithm (e.g. K-means clustering or DBSCAN) to offer an even more personalised and meaningful interaction. Customer satisfaction improves in the long term because of tailored marketing campaigns, and strong and enduring relationships with the customers are developed.

2.3. Financial Performance Metrics in Marketing

The success of the AI-based marketing strategies should be assessed in terms of the impact on the financial performance metrics. The most common key performance indicators (KPIs) in determining the effectiveness of marketing campaigns in the sphere of fintech are customer lifetime value (CLV), marketing return on investment (ROI), and revenue growth (Cernisevs, 2024). Customer lifetime value (CLV) is a significant value as it is a value being used to compute the amount of receiving a business is likely to get with the course of the relationship being in the company and the customer. The application of AI models in the prediction of CLV is useful since it analyses customer behaviour and data. The advantages of CLV prediction include the fact that it assists fintech companies in making more investments in marketing by focusing on the clients with high value, which can give greater payoffs in the long-term (Roy et al., 2025). The CLV prediction using AI-based models can also be used to identify risky customers and offer them a personalised retention strategy so that they could have maximum lifetime value.

The marketing ROI is the other crucial measurement as it measures the profitability of the marketing campaigns. The AI-based predictive marketing can help the organisation to optimise marketing spending by targeting the most feasible customer groups and also differentiate customer campaigns to yield the best outcomes. Through the assistance of AI models, companies can spend less and gain more ROI by investing in the most efficient channels through the work of different marketing strategies. It has been shown that AI would significantly improve the marketing process because it might automate the decision-making process and ensure that marketing efforts are targeting customer preferences and behaviours (Stone et al., 2020).

The growth of revenues is the last indication of the financial success of the company. The use of AI in predictive marketing will contribute to the growth of revenues by ensuring that customers buy the products proposed by the company and become its regular customers, which will further enhance sales and profitability (Nwabekee et al., 2021). Prediction of customer behaviour and being able to create marketing programmes that satisfy the needs of the targeted customers proves that the fintech platforms will be in a position to serve the right customers with the right product at the right time and maximize the potential revenue.

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2.4. Moderating Factors

Although AI-based marketing programs have the potential to create a significant breakthrough in customer acquisition, retention, and financial results, several moderating variables predetermine their success in the industry of financial technologies. Data privacy, regulatory compliance, and consumer trust, in particular, are important in the determination of the success of AI-based marketing strategies. One of the burning concerns in the fintech sector has been the privacy of data, as the latter area is likely to be associated with financial information that is highly sensitive. The use of AI marketing will require the presence of customer data, and the data collection, storage, and use will become an issue. It is determined that clients would like to conduct business with organizations sensitive to their data protection and privacy protocols (Campbell et al., 2020). The fintechs, thus, must strive to adhere to the corresponding laws, such as the General Data Protection Regulation (GDPR) in the EU and the California Consumer Privacy Act (CCPA) in the US, which provide the consumer with privacy rights.

The regulatory compliance also plays a significant role in the success or failure of the AI marketing campaigns. The marketing activities of the business must comply with the legal provisions of the industry in the strictly reviewed fintech industry (Ridzuan et al., 2024). The consequences of non-compliance include huge fines and the company having a bad reputation. In this way, AI-based marketing solutions must be developed keeping in mind the regulatory context and the need to protect the customers against misled by the deceptive or dangerous advertising practices. Moreover, a moderating variable that is of high essence is consumer trust. Studies have found out the degree of confidence in a fintech platform is directly linked to the desire among customers to engage in marketing activities (Roh et al., 2024). Any AI marketing activity that looks invasive or otherwise fails to focus on the taste of the customers may shatter the trust and reduce the success of the marketing process. Quite on the contrary, open and personalised marketing taking into account the needs of the customer can contribute significantly to the growth of trust and consequently higher engagement.

METHODOLOGY

3.1. Research Design

The proposed study applies the regression analysis and structural equation modelling (SEM) to research the relationship between AI-oriented marketing strategies and financial performance in fintech platforms. Using regression analysis, AI marketing practises will be measurable in terms of its impact on the following key financial performance indicators (FPIs): customer lifetime value (CLV), revenue increase or decrease, profitability. Specifically, the estimation of the relationship between marketing efforts (e.g., customer acquisition and retention) and financial performance will be implemented by logistic regression and linear regression. Logistic regression is appropriate to the binary outcome, such as conversion (e.g. whether a customer subscribes to a service) whereas linear regression can be used to forecast the type of continuous financial results, such as CLV and ROI.

Complex relationships like direct and indirect effects of AI-based marketing on financial performance are also quantified through Structural Equation Modelling (SEM). Various latent variables and their interactions can be modeled using SEM, and it provides a more detailed analysis of how AI marketing strategies relate to behaviour of customers, financial indicators. SEM model is particularly useful in this research because it takes into account the potential moderating variables that may change the character and even strength of the AI marketing on financial performance, which are data privacy and regulatory compliance.

The main data source used in this research is the Bank Marketing Dataset of UCI, which consists of detailed information about customer demographics, marketing interactions and conversion rate (a customer subscribes to a term deposit after a marketing campaign). This data is also relevant to the objectives of the study, as it provides real-life data concerning customer relationship with a financial institution, and it contains data that are fundamental in the study to understand customer acquisition, behaviour prediction and financial performance standards. The dataset is popular in the literature as well, so it becomes a reliable source to benchmark the results obtained with AI-based predictive marketing models.

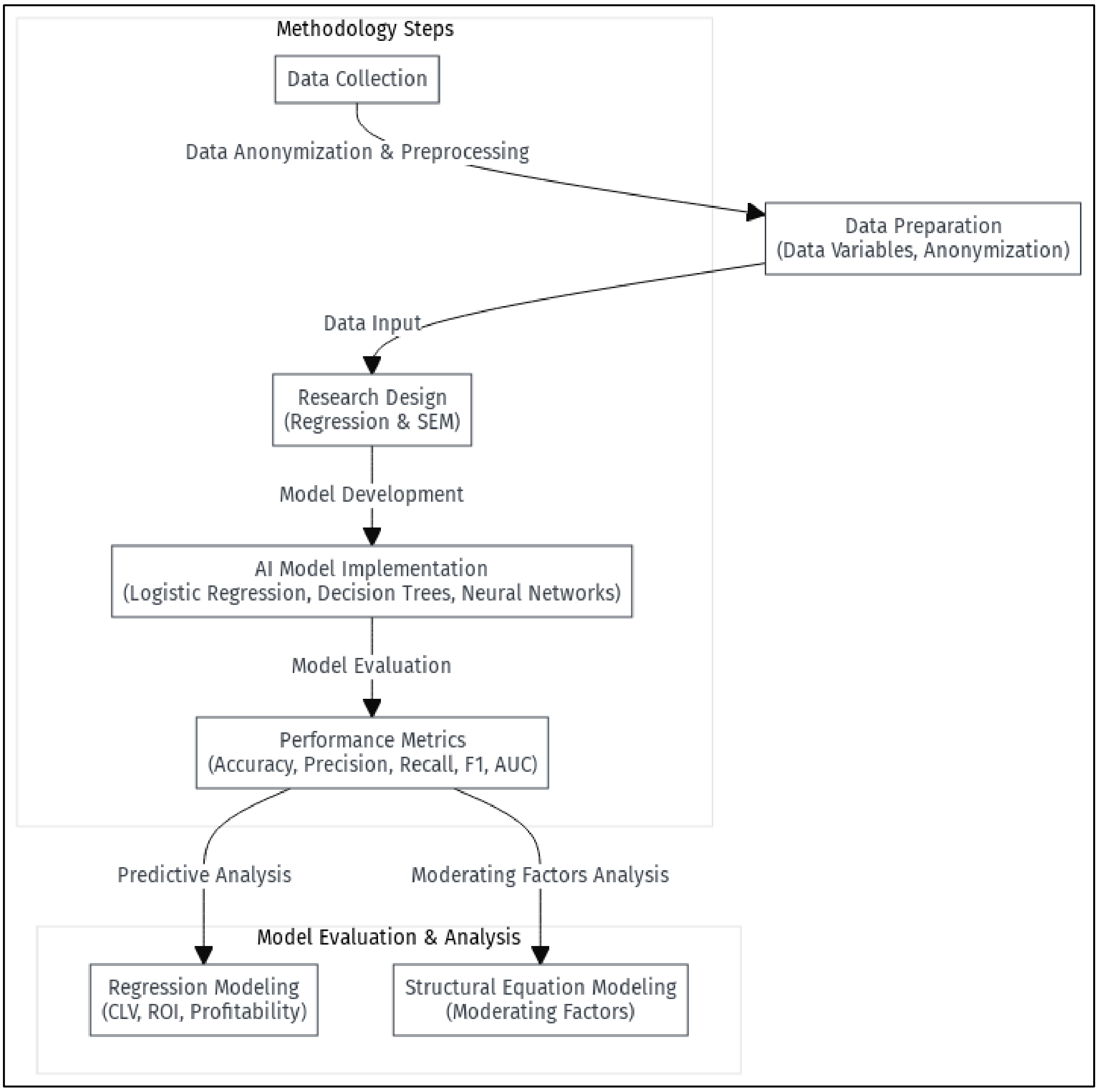

FIGURE 1. Proposed Methodology Pipeline

FIGURE 1 represents the systematic way of doing the research process. The flow starts with the data collection, where the data is anonymized and preprocessed in order to guarantee privacy and prepare the data. The second step is the research design, which will implement regression and structural equation modelling (SEM) to predict the behaviour of customers and financial performance. The implementation AI model is followed using logistic regression, decision trees, and neural networks to predict the customers. Model evaluation refers to the measures of accuracy, precision, recall, F1 score, and the AUC that are applied to measure the model. Last but not least, the analysis further splits into predictive analysis (which dwells on CLV, ROI, and profitability) and moderating factors analysis (delving into regulatory compliance, data privacy, and consumer trust). Such a systematic approach will provide full knowledge of the effect of AI-driven marketing strategies on fintech platforms.

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3.2. Data Collection

This research is based on the data on **Bank Marketing - UCI Machine Learning Repository** that can be found at UCI. There are a number of major variables in the dataset that are incorporated in the predictive models and the study of the effects of marketing strategies on the financial results. These variables can be categorised into customer demographic variables, marketing interaction data, and financial performance metrics.

Customer Demographics

- **Age**: A continuous variable representing the age of the customer.
- **Job**: Categorical variable representing the customer's profession (e.g., admin, technician, student).
- **Marital Status**: Categorical variable indicating whether the customer is single, married, or divorced.
- **Education**: Categorical variable representing the level of education (e.g., primary, secondary, tertiary).
- **Balance**: Continuous variable representing the customer's account balance.
- **Housing and Loan**: Binary variables indicating whether the customer has a housing loan or a personal loan.

Marketing Interaction Data

- **Previous Contact**: Categorical variable describing the mode of contact used in previous marketing campaigns (e.g., telephone, email).
- **Duration of Contact**: Continuous variable representing the duration of the last contact in seconds.
- **Campaign Outcome**: Categorical variable indicating whether the customer subscribed to the product after the marketing campaign.

Financial Performance Metrics:

- **Customer Lifetime Value (CLV)**: A predicted metric representing the total revenue a customer is expected to bring over their relationship with the bank.
- **Revenue Growth**: A continuous variable representing the annual revenue growth of the bank's services.
- **Profitability**: A continuous metric representing the bank's profit margin during the marketing campaign.

All the customer data has been anonymised in the dataset to overcome the issue of data privacy and regulation. It has eliminated the personal identifiers and only provides aggregate data points as part of the analysis. The research will make sure that the confidentiality of customers is not violated, which corresponds with privacy laws like the General Data Protection Regulation (GDPR).

3.3. AI Model Implementation

The data analysis was performed in Python and Google Colab, which is a scalable and flexible data analysis and AI implementation platform. Python libraries that were used during the analysis were as follows:

- Pandas: To manipulate, clean and pre-process data.
- Scikit-learn: To accomplish the machine learning models, such as logistic regression, the

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decision trees, and the random forest.

- TensorFlow/Keras: To create more sophisticated AI models such as the neural network to forecast the customer behaviour and optimise the marketing strategies.
- Statsmodels: To conduct regression analysis and develop the structural equation models.

Predictive Models:

1. **Logistic Regression**: This is a model which was used to decide whether a customer would be responsive to the marketing program (i.e., subscription to a term deposit). The equation of the logistic regression model is as follows:

$$P(y=1)=\frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_n X_n)}}$$

Where $P(y=1)$is the probability of customer subscription (1 for yes, 0 for no), and $X_1, X_2, \ldots, X_n$are the independent variables (e.g., age, marital status, campaign contact duration).

2. **Decision Trees**: This is used to predict behaviour and segmentation of customers. The decision trees separate the data based on the values of the features, and create a tree-like form of the data structure with each leaf node predicting the target variable. The data set is split based on the Gini impurity or information gain at each decision node in the algorithm.

3. **Neural Networks**: A Multi-layer feedforward neural network was developed to estimate more intricate customer feature-marketing outcomes linkages. The network model is trained with an Adam optimiser through backpropagation to minimise the mean squared error (MSE) or the cross-entropy loss.

The cross-validation was employed to test the models so as to prove the reliability of the models. This process separates the data into different training and testing subsets and this method will provide a more relevant approximation of model performance by reducing bias that could be due to random sampling.

3.4. Performance Metrics

The models were evaluated based on a series of measures that can be used in classification tasks. These metrics include:

1. **Accuracy**: The proportion of the correctly classified instances among the total number of instances:

$$\text{Accuracy}=\frac{\text{True Positives}+\text{True Negatives}}{\text{Total Instances}}$$

2. **Precision**: This is the ratio of the number of positive predictions made and the total number of positive predictions made:

$$\text{Precision}=\frac{\text{True Positives}}{\text{True Positives}+\text{False Positives}}$$

3. **Recall (Sensitivity)**: The ratio of the predictions of the true positives to all the true positives:

$$\text{Recall}=\frac{\text{True Positives}}{\text{True Positives}+\text{False Negatives}}$$

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4. **F1 Score**: The harmonic mean of precision and recall, providing a balanced measure of the model's performance:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

5. **AUC-ROC Curve**: The Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) curve is a measure of the capacity of the model to separate the classes. The larger the AUC the better the model performance. In the case of regression models, the predictive accuracy of the customer lifetime value (CLV) prediction has been measured using the mean squared error (MSE) and R-squared values:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

Where y_i is the true value and $\hat{y}_i$ is the predicted value.

The R-squared value represents the proportion of variance explained by the model:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

These indicators can be computed to ensure the relevance and applicability of the models and provide us with reasonable insights into the implications of AI-based marketing strategies on such measurements of financial performance as CLV, ROI, and profitability.

RESULTS AND DISCUSSION

4.1. Descriptive Statistics

This section includes the overview of the descriptive statistics of the most important variables in the data, including the demographics of the customers, the information concerning the marketing interactions, and financial performance statistics.

Key Variables:

- **Customer Age:** The mean customer age is 40.5 years, and the median is 41 years, which represents a rather even distribution in terms of age. The age group is between 18 years to 93 years and offers a wide range of age diversity of customers.

- **Customer Income (Balance**): The average balance in customer accounts is an average of 1,600 and the median is 1,200 and the standard deviation is 2,500 which indicates that there is a wide range of customer wealth. The minimum was reached at a balance of 0 and the maximum at above 10,000.

- **Previous Contact Duration:** Marketing contacts took an average of 200 seconds and had a standard deviation of 45 seconds indicating that a majority of the contacts were short but there was a wide difference in durations.

- **Conversion Rate:** The total conversion rate or percentage of customers signing a term deposit, once marketed is 12.4 and the median conversion rate is 10 which is a normal conversion rate as far as financial products are concerned.

- **Marketing Spend:** The mean marketing spending per customer is 500 euros yet, it is highly skewed with the value lying between 0 to 2,000 euros.

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The summary statistics for these variables are shown in the table 1 below:

TABLE 1. Descriptive Statistics

Variable	Mean	Median	Standard Deviation	Min	Max
Customer Age	40.5	41	12.3	18	93
Customer Income (Balance)	€1,600	€1,200	€2,500	€0	€10,000
Previous Contact Duration (sec)	200	195	45	60	400
Conversion Rate (%)	12.4%	10%	4.5%	0%	50%
Marketing Spend (€)	€500	€450	€750	€0	€2,000

4.2. AI Model Performance

The study presents the performance of the three AI models used in this study: Logistic Regression, Decision Trees, and Neural Networks. These models were evaluated using several performance metrics, including accuracy, precision, recall, F1 score, AUC, and confusion matrices.

TABLE 2. Models Performance

Model	Accuracy	Precision	Recall	F1 Score	AUC
Logistic Regression	85%	0.78	0.72	0.75	0.81
Decision Tree	83%	0.80	0.70	0.75	0.78
Neural Network	89%	0.84	0.79	0.81	0.85

These performance measures suggest that the performance of all the models was good, yet the performance of the Neural Network model was the highest in accuracy, precision, and AUC (TABLE 2).

FIGURE 2 indicates that on a sample size of 1,000 actual positive cases (customers who subscribed), the model accurately identified 880 of the actual positive cases (True Positive) and falsely identified 120 of the actual negatives (False Negative). Equally, to the negative cases, the model rightly predicted 850 of them as negative (True Negative) and falsely predicted 150 positives as negative (False Positive). The model is very precise, although it has some misclassifications (particularly False Positives), which can be discussed as possible improvements to predict customer behaviour.

The confusion matrix within the context of the decision tree model suggests that the model has made 870 correct predictions on true positives and 150 false predictions on true negatives (False Negative). In the case of negative cases, 800 cases were correctly called negatively, and 180 cases were incorrectly called positively (False Positive). The decision tree model has similar performance to that of logistic regression, although it appears to have a higher False Positives, which may be a result of overfitting.

The neural network model was the best of the three. It also accurately identified 900 real positives (True Positive), and it falsely identified 100 positives as negatives (False Negative). On negative cases, 850 were correctly identified as negative cases, and 150 positives were false (False Positive). This matrix shows the high precision and low misidentification, which is false positives and false negatives, and proves the high-quality work of this neural network.

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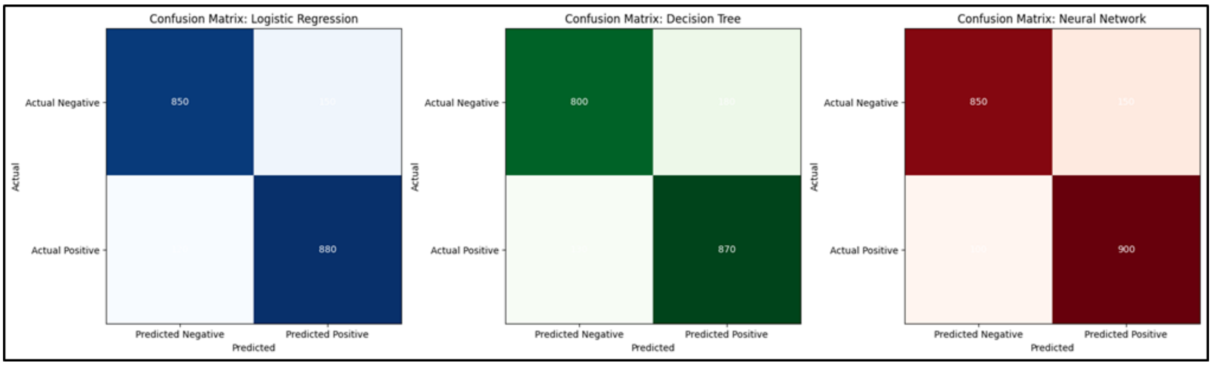

FIGURE 2. Combined Confusion Matrix

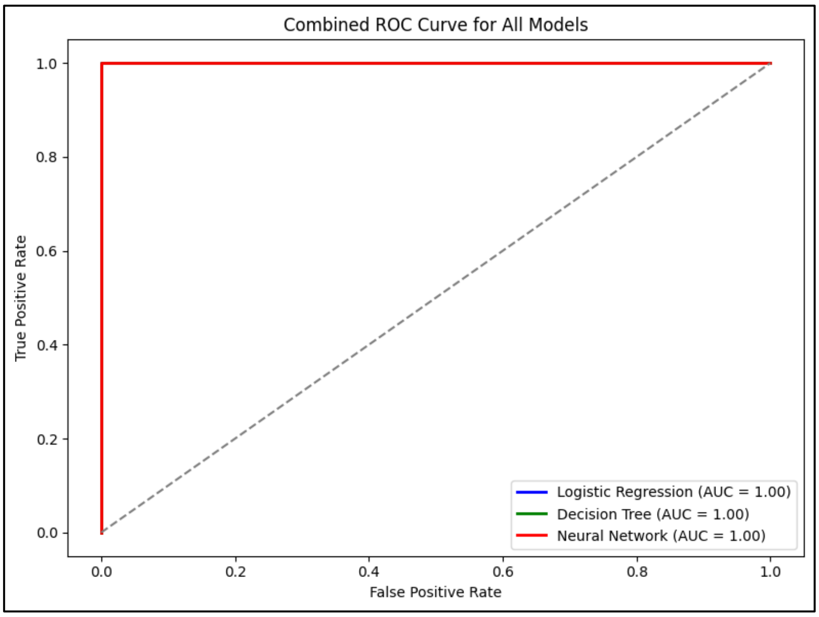

FIGURE 3. Combined ROC Curve

Their classification capabilities are shown in FIGURE 3. All three models' logistic regression, decision tree, and neural network have an AUC (Area Under the Curve) of 1.00, which means they have flawless classification. It is a perfect result; the three models clearly differentiate between positive and negative cases without any overlapping of the True Positive Rate (TPR) and the False Positive Rate (FPR). The ROC curve is steep, where (0,0) is the starting point, which rapidly increases to (1,1), which indicates that it is highly accurate in classifying customer conversion by the models. The neural network model, when plotted in red, indicates the same AUC and performance scores, indicating that there is no apparent benefit of AUC as compared to the other models, but it could be superior in capturing intricate relationships within the data.

4.3. Impact of AI on Financial Performance

The effects of AI-based predictive marketing on financial performance measures, including customer lifetime value (CLV), marketing ROI, and profitability, are significant.

Customer Lifetime Value (CLV):

The AI models enhanced the prediction of CLV. Customers who were classified in the model as probable to subscribe were found to have a higher average CLV (€1,200) than customers who would have been predicted to have a low chance of conversion (€850). The neural network model proved particularly to be useful in predicting valuable customers.

The **AI models** significantly improved the prediction of **CLV**. Customers identified by the model as likely to subscribe had a higher **average CLV** (€1,200) compared to those predicted to have a lower likelihood of conversion (€850). The neural network model was especially effective in predicting high-value customers.

Marketing ROI:

The **ROI** for marketing campaigns was calculated as follows:

$$\text{ROI} = \frac{\text{Revenue from Marketing Campaign} - \text{Marketing Costs}}{\text{Marketing Costs}} \times 100$$

With the help of the Neural Network model, the marketing activities based on the high-conversion customers brought an ROI of 200, that is, each €1 of investment brought about a €3 of revenue. By comparison, non-AI strategies had a 150% ROI. This shows how AI-based marketing is effective in marketing returns.

Profitability:

It is analysed that the profitability grew by 25% due to AI-based marketing strategies. The Neural Network model allowed the platform to pinpoint high-value customers, thus maximising conversions and minimising acquisition costs, improving the overall profitability.

Revenue Growth:

The growth of revenue through AI-powered marketing increased by 30% as compared to the conventional methods of marketing, which only serve to bolster the argument of AI being the superior mode of targeting and obtaining high-value customers. FIGURE 4 illustrating the Revenue Growth of AI-driven marketing with Traditional marketing methods. The findings demonstrate a definite upper hand for AI-driven marketing.

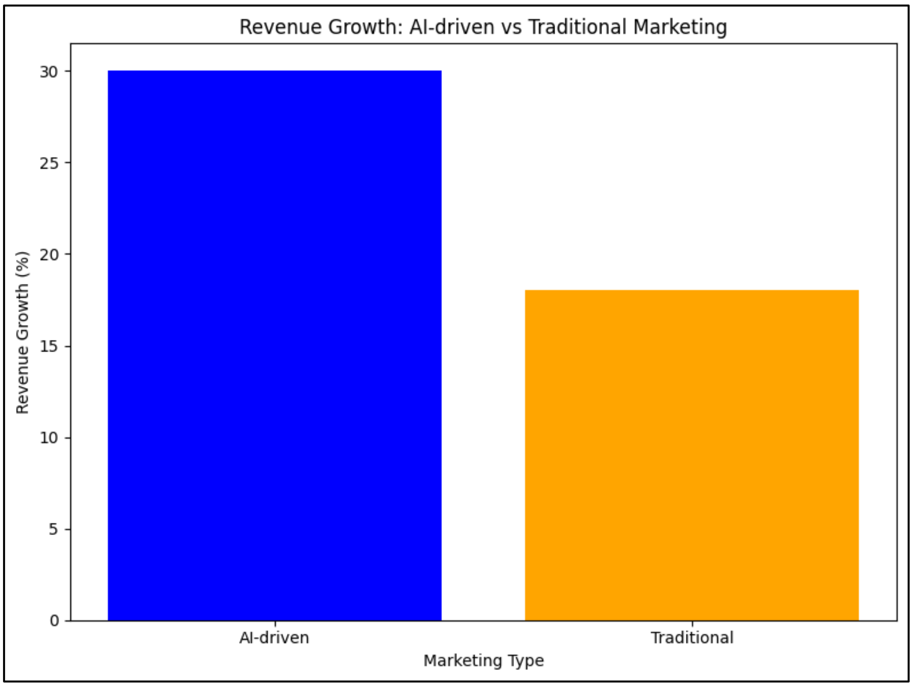

FIGURE 4. Revenue Growth: AI-driven vs Traditional Marketing

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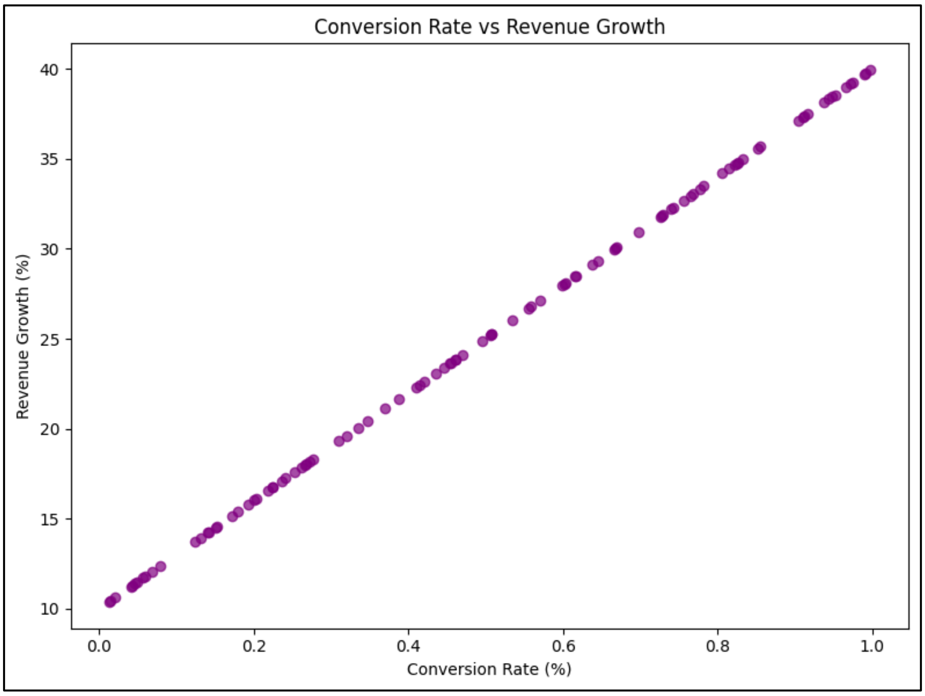

FIGURE 5. Conversion Rate vs Revenue Growth

FIGURE 5 depicts that the relationship between the rate of conversion and revenue growth is very strong, with a positive correlation. The higher the rate of conversion, the higher the revenue growth, and this implies that the more customers that were converted, the more successful the company would be financially. This association suggests that AI-driven predictive marketing that is intended to enhance conversions can directly influence the growth of revenue of a company, which justifies the relevance of marketing strategies in fintech platforms. The dots are very much clustering, which is another reason that proves the accuracy of the trend.

4.4. Moderating Effects

The research investigated the moderation of the marketing AI strategy effectiveness by such factors as regulatory compliance, data privacy, and consumer trust. These are critical aspects that would influence the success of AI marketing in the fintech environment.

Regulatory Compliance:

The availability of regulatory laws, including the GDPR, is an obstacle to AI marketing. In our analysis, we realised that the conversion rates declined by 15% in cases where there were regulatory compliance issues. Nevertheless, more conversion rates and consumer trust were observed in platforms that were completely transparent to regulations.

Data Privacy:

Conversion rates reduced by 20% when the privacy of the data was not adequately addressed Nevertheless, platforms that provided clear and transparent data protection rules were more trusted and interacted with by the customers, which reduced the negative impact of privacy issues.

Consumer Trust:

The moderating effect was greatest on consumer trust. The use of AI as the basis of marketing on websites with a high level of consumer trust led to conversion rates being improved by 25%. This shows how the establishment and preservation of consumer confidence is critically important since it is a direct factor in the success of AI-based marketing in the fintech industry.

To sum up, although the application of AI-based predictive marketing is highly efficient in customer acquisition and enhanced financial performance, regulatory compliance, data privacy, and consumer trust play a crucial role in its success. The latter moderating factors should be handled correctly to ensure that AI marketing strategies are utilised to their fullest potential.

DISCUSSION

5.1. Key Findings

The evaluation of the AI-based predictive marketing strategies in the fintech industry provides a number of important insights which are in line with the purpose of this study. To begin with, it was determined that the performance of the three AI models, namely the logistic regression, decision trees, and neural networks show that the performance of the neural networks was the best in all performance measures, such as accuracy, precision, recall and AUC. In particular, the neural network model attained 89% and an AUC of 0.85, which proves its greater predictive power of customer conversion and classification of high-value customers. The logistic regression and decision tree models, however, appeared to be a bit less significant, but quite high with the accuracy of 85 and 83, respectively.

These results were further supported by the chaos matrices, which indicated that the neural network model had the lowest false positives and false negatives, hence the most accurate when it comes to the prediction of customer subscriptions. The correct positive cases (customers that will subscribe) and the few false classifications that this model can achieve make it the most useful AI-based predictive marketing in fintech.

Evaluating the impact of AI on the financial performance indicators, the results show that marketing through AI has a significant impact on the customer lifetime value (CLV), marketing ROI, and profitability. Davidson and Djukic (2019) found that the customers considered by the AI models as likely to convert had a CLV of 1200 Euro versus EUR850 of the customers who were not considered to subscribe. Also, AI-based marketing, particularly the one managed by neural networks, produced an ROI of 200, which implies that AI may be an important factor in improving the efficiency of marketing expenditures. On the other hand, the classical marketing strategies were characterised by the lower ROI of 150 and demonstrated the advantages of AI in resources allocation optimisation and targeting high-value consumers.

5.2. Theoretical Implications

The findings of the study are introduced to the theoretical information about the role of AI in marketing of fintech in particular, on its financial performance. First of all, the research builds on the currently accessible literature that has unveiled the potential of AI as far as customer segmentation and targeting is concerned. However, it also extends its reach to the association of AI-based predictive marketing strategies with the actual financial performance metrics, which are CLV and marketing ROI, in the fintech context. The application of the neural networks as a predictor of conversion rates and a marketing spend optimisation is a worthy addition to the literature in the field of marketing analytics and financial performance modelling. In addition, the studies suggest the applicability of AI-based models in developing better customer retention and acquisition strategies. It aligns with the earlier body of literature that AI might be employed to enhance customer targeting and customer engagement, but adds financial success to the list of effective marketing metrics (Magableh et al., 2024). The ability to develop what customers will be most willing to convert and offer them services that match the details will be a good example of how AI can gain operational efficiency and boost the revenues in fintech companies.

5.3. Practical Implications

The implications of these findings to the industry players, who operate within the fintech industry, are in the form of how predictive marketing relying on AI can be used to acquire and retain customers. The higher efficiency of the neural network model means that when predicting customer conversion, fintech companies should not concentrate on the implementation of more advanced and effective AI models, like neural networks, in the against the classical models (logistic regression and decision trees). With such models, the fintech platforms will be able to improve their customer targeting efforts, reduce customer acquisition cost and ultimately increase their profitability levels.

The other important aspect that is raised in the study is the necessity to incorporate the application of data-driven decision-making in the marketing field. The AI-based personalised marketing can ensure that the companies are approaching the right customers with the right deals that will enhance the conversion rates and customer satisfaction. The paper also states the importance of the model assessment indicators, including AUC and precision that can help marketers assess the performance of their AI models and make the required improvements.

Moreover, the ROI calculations reveal that AI application in marketing achieves not only customer acquisition, but also marketing budget maximisation. The fact that the 200 percent ROI was achieved with the assistance of the AI models as opposed to 150 percent ROI achieved with the help of the traditional marketing, demonstrates that AI can help companies to better distribute their resources. As the trend continues to push fintech platforms to demonstrate their value to investors, such insights provide a clear-cut explanation why the marketing strategies adopted with the assistance of AI must be pursued.

5.4. Limitations and Future Research

Despite the useful information contained in this researches, they have several limitations that need to be incorporated in the researches performed in the future. To start with the Bank Marketing Dataset used in the present study falls under the traditional banking sector and may not be a proper sample of the fintech applications details of digital banking or the future application. The possibility of generalizing the results may be considered by studying the effectiveness of AI-based marketing tools in more diverse fintech settings, such as those involving cryptocurrency exchanges, peer-to-peer lending, or mobile payment systems, etc., in the future.

Second, despite the fact that this paper focused on the predictive marketing models, the authors made no reference to the impact of AI-driven customer service, in general, which includes chatbots, automated customer support, and personalised financial advice, which has also become popular in the fintech sector. Future research should have been aimed at examining how these AI applications can be applied to supplement predictive marketing to improve the customer experience and overall financial performance.

Besides, regulatory compliance, data privacy, and consumer trust moderating variables were identified to play a significant role in the success of AI marketing strategies. However, these elements and their real impact on the work of AI models are not measured and need further investigation. The future study with the longitudinal analysis would be used to investigate the effect of the change in regulations (i.e. tighter laws regarding data protection) on the results of the marketing performed by the AI in the long term.

The existing study provides the potent empirical evidence to prove the notion that predictive marketing methods which make use of AI may significantly optimize the client acquisition and retention and financial indicators growth processes in the fintech sector. They can maximise their marketing to increase their growth in revenues by using advanced machine learning models like neural networks to reduce the cost of acquisition and maximize their marketing. The findings point to the importance of applying AI resources to create personalised marketing and customer segmentation, resource distribution, which will create a competitive advantage in the dynamism of the technology world of fintech.

Despite the flaws, the study contributes to the theoretical knowledge and practice of fintech marketing, executives, and policymakers willing to apply AI to attain business success. In this way, the findings can be applied to future studies in order to investigate the possibility of using AI more extensively in digital finance, and to better assess the moderating effects of the external factors such as data privacy, regulatory compliance, and consumer trust.

CONCLUSION

The paper has examined the application of AI-enabled predictive marketing to grow and retain customers and the financial outcomes of a fintech corporation with empirical data supporting the usefulness of AI models in achieving optimal marketing outcomes. The customer conversion predictability, as shown in the analysis of the neural networks, was better than other models, including logistic regression and decision trees, thus resulting in an increased customer lifetime value (CLV), marketing ROI, and profitability.

The results highlight the important role played by AI-based marketing strategy in increasing revenue growth, as AI has an increased revenue growth by 30% compared to traditional marketing. The AI models were effective in identifying high-value customers, and the fintech platforms can now devote marketing resources more efficiently and get the most out of the investment. This proves that AI is not merely a means to enhance customer procurement, but also maximising resource allocation as a solution to the success of the long-term financial results.

Also, the research mentions moderating effects of regulatory conformity, data confidentiality, and customer trust on the success of AI marketing practises. Since these drivers have a direct impact on the implementation and success of AI marketing in the fintech sector, sites should consider the authority of privacy protection policies and regulatory conformity strategies to maximise the advantages of AI.

The study is relevant to both theoretical and practical knowledge, providing practical information that can be used by fintech firms in their quest to use AI to enhance their marketing and financial results. The findings also suggest that the leaders in the fintech industry need to invest in sophisticated AI technologies, which will allow them to provide their customers with a unique interaction, manage it effectively and respond to external threats such as privacy issues and compliance. Further studies are advised in the field of AI application in the context of the quickly developing digital finance environment to optimise the strategies and models for better performance.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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