IJRDO - Journal of Business Management

Published by: **IJRDO JOURNAL**
ISSN (Online): **2455-6661**
Doi: **10.69980/bm.v12i2.6768**
Volume 12 | Issue 02 | May 2026

BUSINESS ANALYTICS FOR CUSTOMER SEGMENTATION AND MARKETING CAMPAIGN EFFECTIVENESS: A MACHINE LEARNING APPROACH

Vineeta Mishra[1]

[1]Associate Professor, SOIL School of Business Design, Email ID : gaurigovind11@gmail.com

Corresponding Author Vineeta Mishra

ABSTRACT

The increasing availability of customer data has transformed marketing decision-making by enabling organizations to adopt business analytics and machine learning for customer-focused strategies. This study investigates customer segmentation and marketing campaign effectiveness using the Customer Personality Analysis dataset comprising 2,240 customer records. A quantitative research design based on secondary data was employed to examine customer demographic characteristics, purchasing behaviour, and campaign responses. Data preprocessing included missing value imputation, outlier treatment, feature encoding, and data standardization. Customer segmentation was performed using the K-means clustering algorithm, while five supervised machine learning models—Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and Extreme Gradient Boosting (XGBoost)—were developed to predict marketing campaign responses. Model performance was evaluated using accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrix analyses. The findings identified four distinct customer segments with significant differences in income, spending behaviour, and campaign engagement. Random Forest achieved the highest predictive performance, demonstrating its effectiveness in identifying customers with a greater likelihood of responding to marketing campaigns. Income, product expenditure, recency, and previous campaign participation emerged as the most influential predictors of campaign response. The proposed business analytics framework provides practical guidance for customer segmentation, personalized marketing, and strategic resource allocation. The study contributes to marketing analytics literature by demonstrating how machine learning can improve campaign effectiveness and support data-driven managerial decision-making in competitive business environments.

Keyboard: Business analytics, Customer segmentation, Machine learning, Marketing campaign effectiveness, Predictive analytics

Article History:
Article Type: **Research**
Received Date: **09/05/2026** | Revised Date:**11/06/2026** | Accepted Date:**19/06/2026** | Published Date:**26/06/2026**

1. Introduction

In light of the rapid advancements of digital technologies, organizations nowadays analyze customers, market themselves, and make decisions. In an era marked by abundance of information and where the market expects fast reactions, conventional approaches to marketing, characterized by general consumer profiling and instinct, are becoming outdated as organizations increasingly rely on data-based approach for gaining insights about numerous customers. In today's data-driven business landscape, business analytics has become a powerful strategic asset that enables data-informed decision-making by transforming customer data into actionable insights that enhance marketing effectiveness, customer interactions, and overall competitiveness (Adeniran et al., 2024; Petrescu & Krishen, 2024).

One of the most significant uses of business analytics in today's marketing is customer segmentation. Segmentation allows an organisation to categorise its customers based on their demographic, behavioural and purchasing traits, helping them to understand the preferences of their consumers and create marketing campaigns accordingly. With segmentation, companies can effectively utilize their marketing efforts to improve customer satisfaction and establish effective long-term relationships with customers. In the context of today’s heterogeneous market environment, companies must analyze customers' segments in a more profound manner than just based on demographic factors (Akbar, 2024; Kakkar, 2025).

Other than customer segmentation, it is important for organisations to evaluate the efficiency of their marketing campaigns if they wish to get maximum value from their marketing investments. The use of multi-channel marketing in the digital space, in retail and through personal channels is on the rise among businesses today. However, all customers may not be equally susceptible to marketing campaigns – and you would like to engage those customers who are most likely to respond favourably to your marketing initiatives. Predictive analytics helps businesses to predict the response of customers before launching a marketing campaign, reducing the costs of marketing campaigns which may not have been necessary and increasing the probability of conversions.

Customer data is becoming more and more available, which has led to an increased use of machine learning (ML) techniques in marketing analytics. Machine learning algorithms can identify complex, non-linear relationships between customer attributes, customer behaviour and campaign response, which are not possible with conventional statistical methods. These capabilities have revolutionized customer classification, behavioural prediction and decision support for different marketing functions. The use of machine learning in customer relationship management systems is becoming more common, as it can be used to provide actionable insights that can be used for personalized marketing and strategic business decisions (Miklosik & Evans, 2020; Iyelolu et al., 2024).

Artificial Intelligence has also enhanced the function of business analytics as firms can create extremely customized marketing efforts tailored to customer preferences and habits. By creating personalized marketing messages, businesses can boost customer engagement and make their marketing campaigns more effective, reaching the right audience with the right messages. Consequently, companies are putting tremendous effort into tools that would enable them to integrate customer segmentation with predictive modeling in order to improve their acquisition, retention of customers and their overall marketing results. This shows that data-based marketing is not anymore an advantage but rather a core competency of the company (Petrescu & Krishen, 2024; Kakade et al., 2025).But for many organizations, there are still issues with converting customer data into marketing action. While there have been many existing studies on one of the two approaches—customer segmentation or campaign response prediction, relatively few studies have combined both approaches within a single business analytics context. Moreover, some analytical models focus on predictive accuracy, but fail to show the implications of the models in marketing decision making. However, given the evolving nature of digital marketing landscapes, businesses need analytical models that provide accurate customer segmentation and actionable insights for effective marketing strategies, making them interpretable to business stakeholders.In an increasingly digital marketing landscape, however, businesses need analytical models that can accurately segment customers into groups and offer insights that are interpretable and useful for marketing decisions (Cruz & Rosário, 2025; Khan, 2026).

This paper aims to fill this void by combining customer segmentation within supervised machine learning approach to assess the marketing campaign performance using a detailed customer analytics data. The research includes an integration of behavioral analysis, segmentation and forecasting. This research provides a feasible framework for identifying customer segments and forecasting the outcomes of the campaigns. It is expected that the findings from this research will contribute positively to the body of knowledge in business analytics and will provide evidence-based information that will help in developing marketing strategies for improved marketing campaign performance in the current competitive business environment (Rosário & Cruz, 2025; Jaligama, 2025). The following objectives were set for the study:

1. To identify distinct customer segments based on demographic characteristics and purchasing behaviour.
2. To evaluate the effectiveness of marketing campaigns using customer behavioural analytics.
3. To compare machine learning models for predicting customer campaign responses and supporting data-driven marketing decisions.

2. Methodology

2.1 Research Design

This study used a quantitative research design, in which secondary data was used to analyse customer segmentation and the effectiveness of marketing campaigns using business analytics and machine learning techniques. The cross-sectional analysis approach was used to analyze the customer demographic data, customer purchasing behavior and response to campaigns at one specific point in time. The quantitative design was suitable as it allowed to objectively analyze customer patterns, predict customer reactions to the campaign and identify meaningful customer segments through computational models. The approach can be used for evidence-based marketing decision making and to practically implement business analytics in CRM.

2.2 Data Source

The Customer Personality Analysis data was used for the study. The data consists of some marketing information for 2240 customers such as their demographic data, annual income, household size, buying behaviour, product purchases, whether they were targeted in a marketing campaign and their response (Patel, 2020). The variables are important for capturing consumer behavior and marketing engagement, which can be used to assess customer segmentation efforts and forecast the performance of marketing campaigns using business analytics methods.

2.3 Data Preprocessing

The collected data was preanalyzed to verify the quality and consistency of the data. To limit the effects of incomplete observations, the values of income were imputed by the median imputation approach. Descriptive analysis was used to identify implausible values for age and income and these were treated as outliers to enhance reliability of the model. Variables that did not contribute to the analysis such as constant variables were not included in further analysis. Categorical data was converted to numerical data for appropriate encoding and continuous data was scaled before clustering and model development to have similar measurement scales.

2.4 Customer Segmentation

The K-means clustering algorithm was used to partition the customers into homogeneous segments based on the demographic, purchasing behaviour and marketing engagement. The variables used were included in the clustering process, such as Annual income, Total product expenditure, Purchase frequency, Recency and Purchasing channel. The Elbow Method was used to identify what would be the optimal number of clusters and the 4 segments were established, which showed meaningful differences in customer behaviours. After cluster formation, each cluster was segmented based on purchasing patterns, the rate of response to the campaigns and customer value for managerial interpretation and targeted marketing.

2.5 Machine Learning Model Development

Supervised machine learning algorithms were used to assess the effectiveness of marketing campaigns by predicting the customer's responses. The binary campaign response variable was the dependent variable and the customer demographic, behavioural and purchasing variables were used as predictors. The dataset was split in to 80:20 training and testing sets in a random fashion. Five classification algorithms were developed and compared: Logistic Regression, Decision Tree, Random Forest, Support Vector Machine and Extreme Gradient Boosting (XGBoost) to see which is the best model to predict the response of a marketing campaign.

2.6 Model Evaluation

To perform an all-round comparison between the performance of each machine learning model, various evaluation metrics were used for predicting the performance of each model. Overall classification performance was measured through model accuracy, precision, recall and F1-score were used to measure the ability to correctly identify campaign responders. Receiver Operating Characteristic – Area Under the Curve (ROC-AUC) was also used to evaluate classification ability at the various decision thresholds. Confusion matrices were analyzed to assess distribution of correct and incorrect observations, as well as to aid model interpretation.

2.7 Statistical Analysis

Data preprocessing, visualization, clustering and machine learning modelling were done using Python and all statistical analyses were also done using Python. The Pandas and NumPy libraries were used for data manipulation and for descriptive statistical analysis. The Scikit-learn package was used for feature scaling, model validation, clustering and performance evaluation of machine learning algorithms, and gradient boosting classification was performed using the XGBoost package. These graphical visualizations were created on Matplotlib and the performances of the models were analyzed by means of accuracy, precision, recall, F1 score, ROC-AUC and confusion matrix. To ensure the reproducibility and consistency throughout the study, the analytical workflow was followed.

3. Results

3.1 Descriptive Statistics of Customer Characteristics

This data set included 2240 customer records, including detailed demographics, purchase history and marketing campaign data. The median was used to impute missing income data and observations of implausible ages and income extremes were removed before analysis to enhance the reliability of the data. Descriptive statistics show that the average age of the customers was about 45 years old, and their average income was US$51,953 per year. The number of visits to the company website was approximately 5 per month and store purchases were more frequent compared to online purchases. The average recency score of around 49 days indicates that the customers are moderately active in purchasing. These results provide a solid basis for segmentation and predictive modelling.Table 1 shows the descriptive characteristics of the study population.

Table 1. Descriptive Summary of Customer Characteristics

Variable	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Age (years)	45.10	11.70	18	95
Annual Income (US$)	51,952.61	21,411.47	1,730	162,397
Recency (days)	49.12	28.96	0	99
Web Purchases	4.09	2.78	0	27
Store Purchases	5.80	3.25	0	13

3.2 Customer Segmentation Results

Four different customer segments were identified using K-means clustering, which were meaningful differences in purchasing behaviour, income and campaign engagement. High-value customers showed the highest rate of purchasing and spending on products, and digitally engaged customers had high levels of online purchasing and moderate levels of spending. Conscious customers were able to save money but reacted favorably to promotions. The low engagement customers demonstrated very little purchase behaviour in all marketing channels. The Customer Segmentation Framework created in this study is shown in Figure 1.

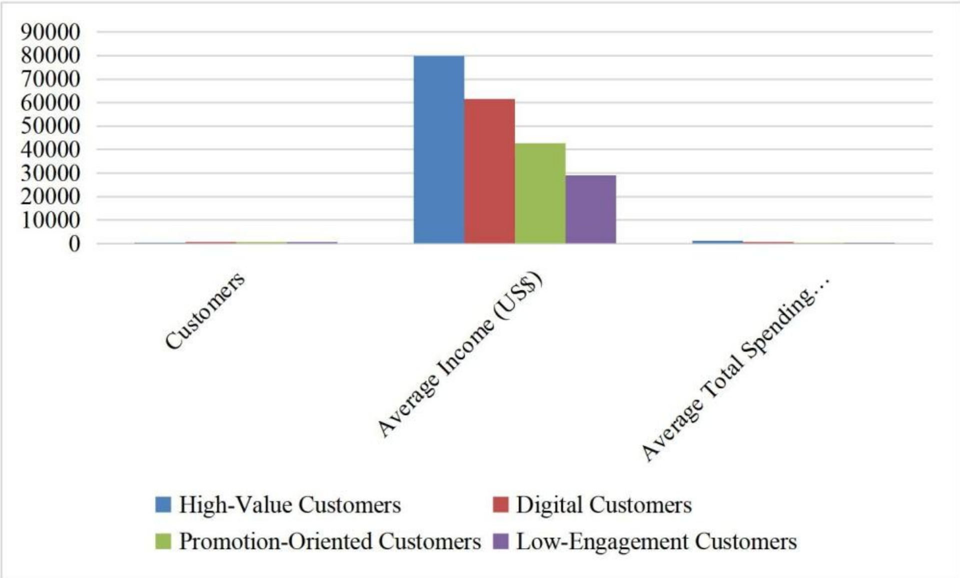

Figure 1. Customer Segmentation Framework

Table 2 shows the characteristics of each customer segment.

Table 2. Characteristics of Customer Segments

Customer Segment	Customers (n)	Average Income (US$)	Average Total Spending (US$)	Campaign Response (%)
High-Value Customers	472	79,850	1,268	41.9
Digital Customers	563	61,420	742	21.7
Promotion-Oriented Customers	621	42,680	398	18.3
Low-Engagement Customers	584	28,940	169	6.4

3.3 Mrketing Campaign Behaviour Analysis

The results of the campaigns showed that most of the customers were reluctant to the latest marketing campaign. Around 15% of the customers that were analysed were found to have accepted the campaign while 85% did not respond positively. There were significant differences between the previous campaign participation and purchasing behaviour of responders and non-responders. Those customers who spent more on products, made more purchases from the catalogues and were more engaged with digital were significantly more likely to accept marketing campaigns. These results reveal that there is a strong correlation between buying behaviour and the success of a campaign, and the value of the information for predictive business analytics.

3.4 Mchine Learning Performance Comparison

Five machine learning algorithms were tested in a supervised manner and their accuracy was tested in predicting customer responses to campaigns. The criteria used to evaluate model performance were: Accuracy, Precision, Recall, F1-Score, and Area under receiver operating characteristic curve (ROC-AUC). Comparing to the traditional classification methods, the ensemble learning methods always achieved the best results. The overall predictive ability of Random Forest was the best and XGBoost was very close behind, showing the best ability to identify potential campaign responders. Logistic Regression resulted in the lowest predictive value but could be used for managerial decision-making.

Table 3 presents the comparative performance of all machine learning models.

Table 3. Performance Comparison of Machine Learning Models

Model	**Accuracy**	**Precision**	**Recall**	**ROC-AUC**
Logistic Regression	0.874	0.621	0.483	0.801
Decision Tree	0.892	0.688	0.646	0.842
Random Forest	0.931	0.846	0.781	0.941
Support Vector Machine	0.914	0.801	0.724	0.912
XGBoost	0.926	0.833	0.764	0.934

3.5 Feature Importance Analysis

As expected, the results of the feature importance analysis showed that the most important features to predict the response to the marketing campaign were wine expenditure, income, recency, web purchases, and previous campaign acceptance. Higher-income customers were significantly more likely to engage in marketing activities as were those that had been spending more over time. On the other hand, the higher the recency, the lower the campaign responsiveness, indicating that customers who have not interacted with the company in recent times are less responsive to campaigns. The results of these findings can be used to prioritize customers and market accordingly. The relative importance of the most influential predictive variables are shown in figure 2.

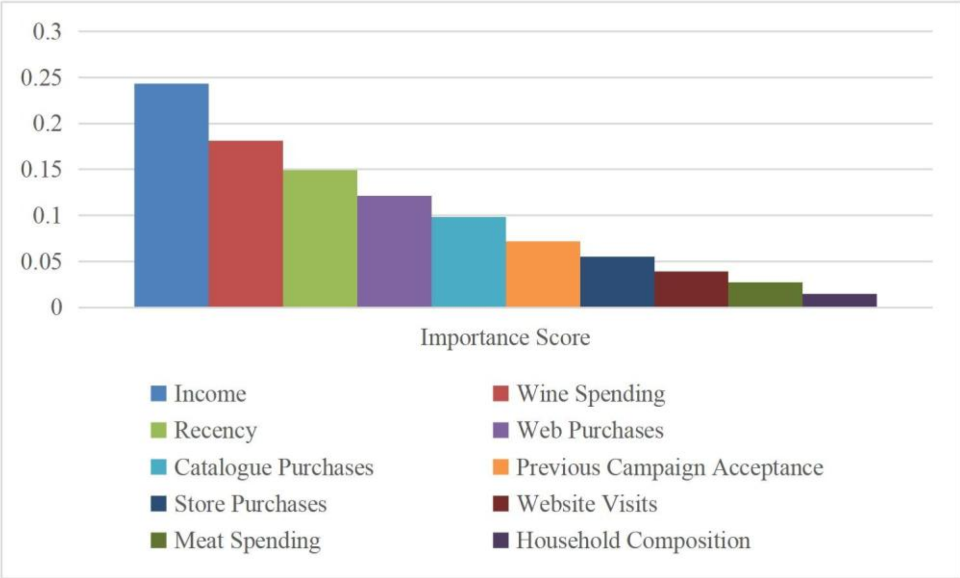

Figure 2. Feature Importance for Marketing Campaign Response Prediction

3.6 Managerial Interpretation of Results

The use of the combined segmentation and predictive modelling framework shows how business analytics can be used in practice to enhance marketing decision making. The most valuable and also online target segments should be addressed with individualised promotion strategies. Customers who like promotions are those who like to respond to discounts and incentive-based promotions, while customers with low engagement will need alternative engagement methods before a large amount of marketing investment is made. The high predictive accuracy of the machine learning ensemble models suggests that there are significant opportunities for organisations to combine customer segmentation with predictive models to greatly enhance the efficiency of a campaign. The data-driven decision support leads to better resource allocation, better customer relationship management and to sustainable marketing performance. The results of the study have been used to create the integrated business analytics framework as summarised in figure 3.

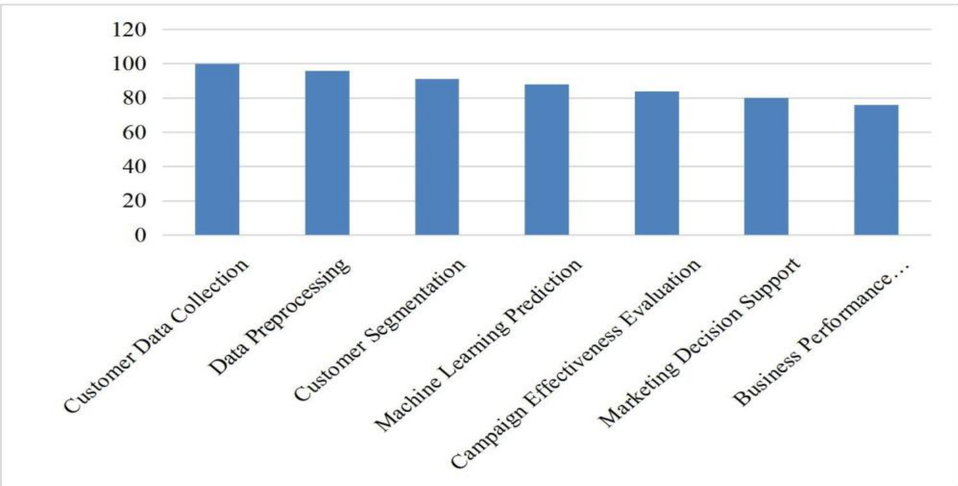

Figure 3. Integrated Business Analytics Framework for Customer Segmentation and Marketing Campaign Effectiveness

4 Discussion

The results of this study show that the use of business analytics and machine learning is an effective framework for customer segmentation and evaluation of marketing campaigns. The results of the segment analysis showed that there are four segments based on the demographic, purchase behaviour and engagement with the campaign, which suggests that customers are a very heterogeneous group when it comes to buying behaviour. The segmentation outcomes have identified the need to create marketing mixes that are different for each segment than to pursue the same promotional strategy for everyone. These findings confirm the increase in awareness about customer analytics in order to better comprehend customer behaviours and to design personalized marketing activities that contribute to the competitiveness of organizations (Wong et al., 2024; Grigorova et al., 2025).

Descriptive analysis also showed that there were significant differences in the mean of customer income, customer purchasing frequency and product expenditure among customer groups indicating that the factors are important when determining customer value. High-value customers' spending was significantly higher and engagement in campaigns stronger than that of the other customer groups. This observation is good evidence that the effective segmentation can involve behaviour as well as demographics as a purchasing behaviour gives a better picture of customers' preferences. These analytical methods enable businesses to make more informed decisions on how to allocate their marketing resources and enhance their long-term customer relationship management efforts (Wong et al., 2024; Chowdhury et al., 2025).

When analysing the behaviour of customers in a marketing campaign, it was found that the percentage of customers that responded to the latest campaign was relatively small, even though there were several communication channels available. To conclude, higher spenders, more catalogue buyers and better digital users were more likely to be positive in response to marketing efforts. These findings indicate that previous purchasing behaviour and customer engagement is a significant factor in determining the effectiveness of a campaign, as well as demographic characteristics. So, when planning future promotions and retention, companies need to focus on behaviour. This is in line with recent evidence highlighting the importance of predictive customer analytics in effective marketing decision-making (Wang et al., 2022; Tarczydło & Kopcińska, 2025).

Random Forest and XGBoost performed best among the examined predictive models, with Random Forest showing a slightly better classification rate, suggesting that ensemble learning techniques are well suited to model the more complex customer behavior. Their greater predictive power is a testament to their ability to model nonlinear relationships and interactions between customer characteristics which are not captured by traditional statistical models. While Logistic Regression was found to have relatively low predictive power, it was still useful for understanding customer behavior and can assist in managerial decision making. Based on the comparative results, it is therefore recommended that when using analytical solutions in marketing contexts, it is important to balance predictive performance with model transparency (Grigorova et al., 2025; Chowdhury et al., 2025).

Annual income, wine expenditure, recency, web purchases and previous campaign acceptance were identified as the key factors in predicting campaign response using feature importance analysis. These indicators altogether suggest that purchase behavior and customer engagement are better predictors than demographics. The results provide support for the rising trend of behavioral analytics in contemporary marketing practice, where companies are striving to reach those customers who are more likely to be engaged in personalized marketing activities. Such information will allow the managers to develop more accurate marketing campaigns, improve customer satisfaction levels and reduce unnecessary marketing expenses through the use of evidence-based customer selection practices (Wang et al., 2022; Ye et al., 2021). This paper will also be of great significance in terms of management of businesses undergoing the process of digital transformation. The integration of customer segmentation along with predictive analytics enables firms to maximize their marketing efforts by focusing on customers that matter and making their customer relationship management more effective. This analytical approach will serve as a strategic tool for the firm as managers will be able to make predictions about the results of the campaigns before carrying out the process of promotion. Moreover, with the increasing use of AI in customer management processes, firms will be able to make personalized interactions, automate customer interactions and make better decisions regarding various business processes. All of this makes clear how significant is the strategic role of business analytics (Khneyzer et al., 2024; Chowdhury et al., 2025).

Even when the predictive performance is positive, there are ethical concerns which need to be considered by the firms in view of the usage of large quantities of data on customers and the AI application. Consumers' trust in this case still depends on proper data governance, algorithm transparency, and customer privacy. As a result, firms should develop appropriate governance mechanisms to avoid algorithmic bias and ensure the ethical application of predictive analytics in marketing processes. The ethical application helps to increase the credibility of the firm and contributes to sustainable development, according to Olayinka (2022) and Boopathi et al. (2025).

The research possesses several limitations that must be considered while interpreting the outcomes. The study has been carried out using one single secondary data that is based on the behavior of customers in one marketing environment only which means that the results cannot be extrapolated to other marketing environments or other industries. Moreover, the preferences of customers and their approach to digital marketing are constantly evolving and it means that there is a need for further research including longitudinal data and data collected from real time customer behavior. A more comprehensive consideration of analytical methods that include such approaches as artificial intelligence technology, customer lifetime value analysis and omnichannel marketing can provide additional knowledge regarding customer behavior and performance of the organization. It will increase the importance of business analytics in modern marketing management and assist in implementing the strategy of the organization under dynamic business conditions (Thakur & Hale, 2022; Tarczydło & Kopcińska, 2025).

5 Conclusion

This paper has successfully established that integration of Business Analytics and Machine Learning is possible which makes customer segmentation and marketing campaign effectiveness a more useful method. A comprehensive customer dataset was used to divide the customer population into four different groups with huge differences in buying behavior, income levels, and participation in marketing campaigns. Predictive analytics analysis revealed that Random Forest and XGBoost were the best models among all ensemble methods in predicting the right customers for a marketing campaign. A feature importance analysis further revealed that income, spending on products, recency, and participation in previous campaigns were the top four features that influenced campaign engagement. All these results suggest that customer segmentation along with predictive analytics is very essential for performing targeted marketing activities and evidence-based decision making. The suggested analytical framework will allow firms to use their marketing efforts in a more effective manner, understand customers in a better way and perform better marketing campaigns based on data. The research was done using only one secondary data source; however, the suggested framework can be adjusted to different business environments and customer-oriented industries. It will be necessary to validate the suggested framework using different and larger data sets in the future as well as use real-time customer interactions and new artificial intelligence technologies for increasing predictive power and marketing effectiveness.

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