Improving Customer Experience Using a Hybrid Decision Tree and Support Vector Machine Approach

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Abstract. In the competitive telecommunications sector, enhancing customer experience (CE) is crucial for business success. The Net Promoter Score (NPS) is a key indicator of customer loyalty and satisfaction. To boost CE, operators monitor Quality of Experience (QoE) metrics, such as call drop rates, successful installation rates, and data transmission speeds, to identify and address service shortcomings. However, analyzing the primary drivers of NPS remains challenging. This study introduces a hybrid approach combining decision trees (DT) and support vector machines (SVM) to advance CE in telecommunications. This method utilizes SVM for predictive modeling of CE and DT to determine the significant factors affecting it. Customer satisfaction data from a telecommunications provider validates the proposed hybrid model's effectiveness. Results demonstrate the model's ability to accurately predict CE and identify essential influencing factors, offering practical implications for companies aiming to enhance customer satisfaction and overall CE.

Keywords: Telecommunication · customer experience (CE) · Net Promoter Score (NPS) · Quality of Experience (QoE) · decision tree (DT) · support vector machine (SVM)

1 Introduction

In the current market, businesses strive relentlessly to cultivate enduring relationships with customers, with superior customer service at the heart of sustaining loyalty programs. Yet, mere service excellence is insufficient to differentiate market players and

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sustain competitiveness [1]. The telecommunications sector is especially fierce and dynamic. To thrive, Jordanian telecom firms face the challenge of achieving operational excellence through pivotal platforms like the customer relationship management system (CRMS), which enables engagement and fosters customer satisfaction [2]. The essence of any profit-seeking, growth-oriented company is its capacity to deliver superior service quality. Loyal customers, willing to invest more with the company, lead to increased profitability and market share while reducing handling costs. This is contingent upon their satisfaction with the service level provided [3].

As demand for telecom networks grows, operators vie for customers by delivering top-notch services, a crucial determinant of success in the sector. Beyond superior network infrastructure, effective customer experience management (CEM) is key, yielding positive customer-business interactions and reinforcing loyalty to the company's offerings. NPS serves as a prevalent metric for gauging satisfaction and correlating it with revenue growth [4]. A myriad of factors, including brand, pricing, service quality, customer support, and culture, influence customer experience, which in turn dictates loyalty to a telecom provider [5]. This paper proposes a novel ADT-SVM approach that synergizes decision trees with support vector machines to enhance CE. This dual-method employs SVM for constructing a predictive CE model, and DT to discern the pivotal factors influencing it.

Emerging frameworks like the Integrated Predictive Experience Management Framework (IPEMF) center the customer within business processes to enhance CE [6]. Research in different sectors, from travel agency interactions [7] to digital transformation success [8], underscores the broad relevance of CE. Innovations such as the AeCX system track emotional responses on social media post-crisis to evaluate CE [9], while others probe AI systems' trust factors to improve CE [10]. In banking, E-CRM dynamics are scrutinized for impacts on customer satisfaction and loyalty [11]. New AI technologies redefine customer interactions across all transaction phases, offering a fresh lens to assess shopping journeys [12]. Studies also examine the digital banking's influences on CE and financial performance [13], the benefits of IoT internal supply chains in retail [14], capability-based frameworks for digital transformation with a CE focus [15], and conceptualize smart customer experiences in new retail contexts [16]. In aligning with these developments, the ADT-SVM approach stands to not only predict CE outcomes but also illuminate the drivers behind customer satisfaction, tailoring strategic improvements in the telecom sector.

2 Study of NPS Promoter Score

The Net Promoter Score (NPS) is a widely recognized tool for evaluating customer experience (CX) across various industries. It relies on regular customer feedback, often referred to as "Voice of the Customer," which primarily hinges on a single survey question:

NPS question: "On a scale from 0 (not at all likely) to 10 (extremely likely), how likely are you to recommend [company x] to friends or colleagues?".

The resulting scores reflect customer satisfaction for numerous CX elements, including product experience, touchpoint interactions, and significant milestones in the customer journey. Occasionally, brand attributes such as trust and innovation are incorporated into the evaluations.

Not all respondents will answer every question, as some may lack relevant experience (e.g., non-users of roaming services in telecom). This leads to partially completed NPS surveys. Based on the distribution of Net Promoter Scores, respondents are segmented into three categories (see Table 1). Evidence suggests that Promoters are more loyal and likely to purchase than Detractors.

The company's NPS KPI is calculated as follows:

$$NPS(D) = \frac{N_{prom}(D) - N_{detr}(D)}{N(D)} \times 100 \tag{1}$$

Here, $N_{prom}(D)$, $N_{detr}(D)$, and $N(D)$ represent the number of Promoters, Detractors, and total survey respondents, respectively. As previously defined, a company's NPS can range from $+100$ (every respondent is a Promoter) to -100 (every respondent is a Detractor).

Table 1. NPS categorization of customer.

Label of NPS	Value of response
Detractor	0–6
Promoter	9–10
Passive	7–8

2.1 Analysis of NPS

The basic NPS analysis compares the NPS trends and the competitiveness of the satisfaction score efficiencies.

Figure 1(a) display preliminary findings from a collection of genuine NPS analyses of data processing from the Greek telecommunications industry. The illustration of Fig. 1(a), it seems that Organisation 1 is the market leader, Organisation 4 pursues a CX enhancement plan, and Organisations 2 and 3 most likely concentrate on preserving their NPS ratings. It is clear from Fig. 1(b) that Organization 1 outperforms Organisation 2 in the efficiency of critical features like Network Data and Network Coverage, although Company 2 excels in some areas, such as call centers and traveling. This type of study makes it possible to track pertinent trends and have a comprehensive knowledge of a company's competitive position in the CX space. Statistical regression models are often used to analyze the NPS main drivers using the pertinent customer survey data. Customers' satisfaction ratings on the CX qualities are treated as independent variables in these frameworks, whereas NPS is treated as the dependent variable.

2.2 Classification of NPS Bias

Consideration of respondent subgroups with similar score patterns is a typical strategy to specify the problem of low NPS drivers' statistical fit, according to the related research. In

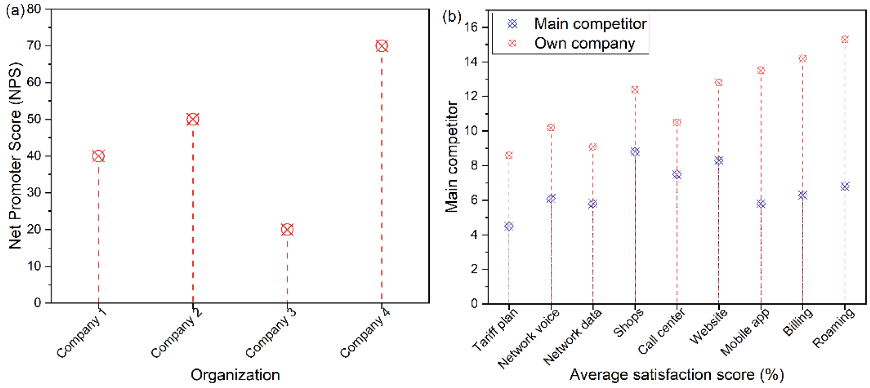

Fig. 1. (a) NPS trends over time for the industry participants (b) Experience of Customer characteristics: contentment with the business and the primary rival.

the current study, this idea of customer segmentation into subgroups is explored through the formulation of a novel metric termed "NPS bias," which is described for every NPS analysis of respondents as follows:

$$NPS - BIAS(l) = NPS(l) - E[CS_A(l)] \tag{2}$$

Here, $NPS(l)$, l = 1,2,3…N, N is the NPS of responder k, $E[CS_A(l)]$ the average respondent satisfaction score across all CX metrics. It should be noted that the aforementioned criteria also apply to responses that are only partially completed; in such cases, classifications can be done without first using procedures for imputed missing data. Customers are categorized in Table 2 with the aforementioned description.

Table 2. NPS bias consumer categorization.

Category of Bias	NPS Bias
Negatively Biased	NPS_BIAS less than 0
Positively Biased	NPS_BIAS greater than 0

Labels can be used to categorize NPS bias, such as 1 for 2 for positively biased customers and negatively biased consumers. The goal of the investigation is to enhance the accuracy of the model of regression by taking into account this label as an extra independent variable in the NPS categorization issue. The classification focuses mostly on enhancing descriptive NPS analytics because the concept of NPS bias necessitates understanding NPS for each respondent. This category of challenges includes NPS key driver analysis, where the goal is to identify the NPS drivers given information on NPS and CX qualities.

2.3 Dataset

An assortment of information from NPS analysis conducted in the Greek mobile telecommunications sector is used to examine the NPS Bias categorization. Nine CX elements were covered in the surveys, which were directed at a post pay market portion: network data, network voice, tariff plan, website, shops, call center, roaming, billing, and mobile application. The datasets that are readily accessible cover 24 successive monthly analyses with 450 samples. Since the aim of the study is on the efficiency of algorithms rather than specific market efficiency, analysis was completely blindfolded in terms of the attribute's names, and operators that the findings were used for reasons of confidentiality. It must be mentioned that the pertinent data were gathered and processed completely anonymously, by the applicable legal approach for the prevention of secure information, and the guiding process of data processing ethics [17].

3 Proposed Methodology

The volume and temporal changes of the variables used in the NPS score procedure are just two of the major issues facing the NPS analysis. It should be emphasized that the importance and effectiveness of the majority of CX factors can change over time, influencing how they affect NPS. The use of DT and SVM techniques appears to be a viable answer to these problems. Provided the training phase of the approach needs a dataset of great size, the sparse amount of data that is now accessible could prove to be a significant barrier. NPS surveys are typically conducted monthly, as opposed to the six- or 12-month intervals used by many businesses. The main statistical variables of the original collection, including mean value, standard deviation, and correlation matrices, are used to generate a realistic NPS survey dataset to address the data availability issues.

Decision trees can significantly enhance the consumer experience. They are a kind of algorithm that assists companies in making decisions dependent on a set of guidelines or standards. The following are some examples of how decision trees can improve the customer experience:

- Personalization: By providing tailored suggestions dependent on the customer's previous behavior, interests, and requirements, decision trees can be utilized to personalize the consumer experience. An e-commerce site, for instance, could employ a decision tree to suggest things to customers depending on what they've previously bought.
- Customer service: Decision trees can be utilized to develop interactive customer service experiences which lead clients through a series of questions to assist them in locating the data they require. By using a sequence of questions to get more specific answers from customers, a decision tree might be utilized, for instance, to solve a technical problem.
- Marketing: By using decision trees, it is possible to design focused marketing campaigns that are based on the preferences and interests of the target audience. For instance, a decision tree may be utilized to divide up the consumer base into groups according to their region, gender, or age and then provide those tailored promotions or deals.

- Sales: Sales teams may find new clients and lead them through the sales procedure with the use of decision trees. For instance, a decision tree can be employed to qualify leads by posing a series of inquiries to them to ascertain whether they are a good fit for the good or service being provided.

Table 3 contains a list of the decision tree parameters we used in this investigation.

Table 3. Decision-tree classifier variables.

Values	Parameters
3	The depth of the tree is higher
1	Weights associated with classes
entropy	Function determining the quality of a split

Support Vector Machine (SVM) is a well-known machine learning technique. Additionally, there are numerous methods to employ SVMs to enhance the client experience. SVMs may be utilized to analyze consumer data and generate tailored product and service suggestions. Giving clients pertinent and practical data can enhance customer experiences. SVMs may be utilized for sentiment analysis of consumer feedback and sentiment data, including social media postings, product evaluations, and customer care interactions. This can assist businesses in recognizing consumer issues as soon as possible and promptly resolving them. SVMs can be used for customer segmentation, which divides customers into groups according to their behavior, preferences, and demographics. By doing this, businesses may better target certain client segments with their products and services, enhancing the customer experience. SVMs may be employed in predictive analytics to forecast consumer behavior, such as the possibility that a customer will make a purchase or leave the company. By anticipating and proactively addressing consumer demands, businesses can enhance the customer experience. In general, SVMs may be a useful tool for businesses aiming to enhance customer experience. Utilizing consumer data and predictive analytics, businesses may gain a deeper understanding of their clients and deliver individualized, personalized experiences that fit their demands. SVM are learning techniques and supervised learning models. To put it another way, SVM needs a training set. Following the creation of a structure, the SVM training procedure assigns each new sample to one of two categories creating a non-probabilistic binary linear classifier. Next, each input is designated to fall into one of two categories, with each marked to belong to one or the other. Table 4 denotes the classifier variables for SVM.

4 Result and Discussion

To connect to auxiliary devices used in consumer consumption, telecommunications businesses require efficient, secure, on-premise solutions. To increase the company's performance, these solutions will assist companies in gathering information and insights on

Table 4. Classifier variables for SVM.

Values	Parameters
3	The proportion of the polynomial kernel function
1	Weights corresponding to classes
linear	Kernel types

their network or apps are being used by customers. The development of strong commercial connections is facilitated by quick and effective customer service. Positive telecom customer service is crucial to generating revenue in the sector. So, here we analyzed our suggested technique with other traditional methods like artificial neural network (ANN [18]), Artificial intelligence (AI [9]), and deep learning (DL [19]) and our suggested technique is Decision tree-support vector machine (DT-SVM).

The degree to which a measured value is accurate with a reference or known value. In the context of enhancing the customer experience in telecommunications, accuracy relates to the capacity of telecommunication providers to offer clients exact and error-free services. This covers proper billing, the efficiency of networks, and communications with customers. Customers must only be billed correctly and consistently for the services they utilize. Having reliable and constant access to telecommunication services, such as phone calls, text messages, and internet data, is essential for accurate network performance. Dropped calls, sluggish data speeds, and other problems that might have a negative effect on the experience of customers can result from network performance errors. The accuracy of efficiency is defined by Eq. (3):

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{3}$$

Here, TP determines the true positive, TN determines the true negative, FP determines the false positive, and FN determines the false negative.

Figure 2(a) denotes the result of accuracy with other traditional techniques. For the customer experience to be improved, accurate information and solutions must be given to customers throughout customer service encounters. When customers contact customer service professionals, they anticipate receiving accurate and quick answers to their questions and problems. Our suggested method DT-SVM provides a high level of accuracy, which is greater than other traditional methods.

The amount of information that a number can convey through its digits is called precision, and it shows how closely two or more measurements are separated from one another. It is independent of correctness. The precision can be determined by following Eq. (4):

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{4}$$

Figure 2(b) denotes the comparison of precision with other traditional methods. Our suggested method DT-SVM provides a high level of precision, which is more efficient than other traditional methods.

The percentage of data samples from a class of "positive class" interest that a machine learning model accurately determines as being a part of the class is known as the true positive rate (TPR), also known as recall. The recall can be calculated by Eq. (5):

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

Figure 2(c) denotes the comparison of recall with other traditional methods. Our suggested method DT-SVM provides a high level of recall, which is more efficient than other traditional methods.

The F1 score is an ML assessment metric that rates a model's accuracy. It combines a model's accuracy and recalls ratings. The metric accuracy measures how often a model correctly predicts the complete dataset. The f1 score can be measured by the following Eq. (6):

$$\text{F1score} = \frac{(\text{precision}) \times (\text{recall}) \times 2}{\text{precision} + \text{recall}} \tag{6}$$

Figure 2(d) denotes the comparison of the f1score with other traditional methods. Our suggested method DT-SVM provides a high level of f1score, which is more efficient than other traditional methods.

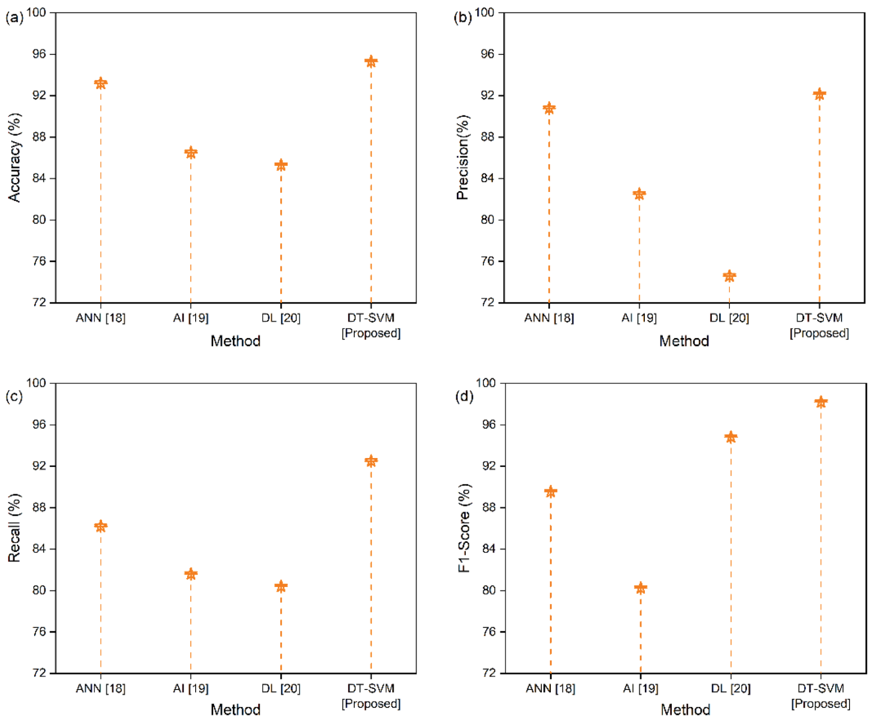

Fig. 2. Comparison of (a) Accuracy (b) Precision (c) Recall and (d) F-score with other traditional methods.

5 Conclusion

The customer experience can be improved in the telecommunications industry through a variety of tactics, including delivering personalized services, prompt and effective customer support, streamlining the billing process, and guaranteeing network uptime. In summary, telecommunications firms that put the customer experience first can boost brand loyalty, boost customer happiness, and eventually expand their business. Telecommunications firms can differentiate themselves from their rivals by offering a smooth client experience by paying attention to consumer input, constantly enhancing their services, and utilizing new technology. In the communications industry, poor customer service can significantly hinder the client experience. Customers could become irritated and disappointed as a result of lengthy wait times, ineffective staff, and challenges with problem resolution. To overcome this issue, we proposed DT-SVM method provides 95% of accuracy, 98.2% of f1score, 92.5% of recall, and 97.85% of precision, which is more efficient than other traditional methods. In a future study, we can explore methods to apply data analytics to enhance the customer experience, such as through personalization, segmentation, and predictive analytics. Data analytics can offer insightful information into the behavior and preferences of customers.

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