Grenze International Journal of Engineering and Technology, June Issue

Customer Behavioral Analysis through AI Agent

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***Abstract*— Consumer behavioral analytic is essential to the intelligent decision analytical system which every commercial organization relies on. This demand-driven analysis and prediction can primarily influence the supply chain management of the organization. Using methods such as data mining and machine learning (ML) approaches, data analysts explore the hidden patterns in consumer behavior to forecast sales. Time series forecasting is finding its real time scientific value when the present e-commerce sites cannot be able to on-going the velocity of data with any traditional modes of analysis due to it present in the very recent inception layer so the new techniques on data mining and machine learning along with time series forecasting paved better way for discovering hidden layers. I am not going to write down the references to this chapter and also the links from your blog because this chapter basically comes out of those except for the analysis which is more useful to predict next basket prediction, willingness to buy a product and personalized list suggestion which all are centered on the customers for either making them satisfied and loyalty to a particular e-shopping site then nothing will be able to be contributed to you. In this chapter we discuss methods employed in previous literature addressing consumer behavior prediction using random forest, support vector machine, logistic regression, decision trees and neural networks. Here, the performance of the ML algorithms is compared and it chooses the Logistic Regression to be the best modelling algorithm. Knowing what customers want and need – and ideally, predicting it – is, unsurprisingly, a perennial struggle for marketers.**

***Keywords*— Consumer Behavioral, Machine Learning (ML), Data Mining, Gradient Boosting, NLP.**

I. INTRODUCTION

Analyzing customer behavior is one of the most crucial aspects for an enterprise. This tool provides companies with insightful information on what customers are looking for. So, it allows the company to enhance the service or provide an appropriate product for the customer. And this customer behavior analysis enables the company to boost their sales and achieve great business success. In the digital era, enterprises should adapt their strategic prospects with respect to all the activities. Information systems can be used to collect data of products and customers. Tools and techniques in data science can be used on these data to understand deeper about the customer intent.

A huge and diverse data set is created in the digital marketplace, e.g., historically static transaction histories, clickstream logs that are dynamically changing over time, or unstructured text reviews. The ability to translate this data into functional insights is the fundamental source of competitive advantage for e-commerce platforms.

Grenze ID: 01.GIJET.12.2.211_20

Using a Gradient Boosting model for churn, a different Collaborative Filtering system for recommendations, and separate NLP tools for sentiment analysis, the current industrial workflow has an incoherent stack of predictive models.
But with machine learning researchers have successfully it for a few problems in customer behavior analysis. We have to work on Machine Learning models and data preprocessing techniques to find the most accurate solution for a given problem. We examine the problem and the dataset from Wang et al. in this paper. (2017). Here, the aim is to predict customers' decisions with respect to accepting a restaurant coupon recommended to them by an in vehicle system, given specific features of the customer's driving context. Asia, Oct 20 — The problem is also complicated due to most of features being categorical and higher deletion rates. We explored the possible diverse ways to convert categorical attribute to numeric attribute, deal the missing features and then we implemented several classification techniques. The result indicates that our proposed method outperforms the previous methods provided in Wang et al. (2017). We also gain some useful insights on the methods used and variables that affect customer decision.
Modern companies need to understand and anticipate customer behavior to improve their marketing- and sales [22]. Machine learning algorithms can be implemented to track as well as predict consumer behaviour which will help organisations by making rational decisions as to how they should invest their resources [7,41]. The new adaptive management seeks to be responsive to local circumstances and to facilitate partnerships among a broad network of interest groups [24]. In contrast to previous work [13] on scientific adaptive management In the fast-paced world of modern business, knowing and being able to predict customer behavior is key to achieving business success. Predictive analytics is a game-changer, providing companies with a set of tools that make it easier to interpret patterns, trends, and preferences in huge datasets. Through accessing past data, and algorithms, businesses can understand the complexities of customer behaviour and predict the next steps [4]. Predicting customer attrition is relevant when it comes to loyalty programs [31]. The goal is to identify consumers whom are likely to switch at least some of their purchases away from a given firm and help businesses devise intervention strategies that will retain these customers by trying to keep purchasing from the firm. Information technology use is becoming more common in the workplace [16]. Information technology and its applications have grown significantly over the years. No company looking to improve its fortunes in the sector would be any more than a few degrees removed from its most demanding customers and from the trends that are constantly in flux. These organizations are using wide variety range of technological ideas, instruments, and processes to know their potential employees better. Deeper analytical work with data, which translates to facts, can improve decision making. This is a common sentiment among practitioners of business intelligence. [17] Customer churn is one of the hardest challenges faced by mobile telecom carriers and one of the top 2 or 3 reasons in the decline of costs or the lack of growth in the number of customers. The success of these retention efforts not only relies on the accuracy of the prediction for future churners, it equally relies (and this is critical [2]!) on the moment of the forecast being made. In current scenario of cut-throat business market, predictive analytics usage to get insight about customers need to be envisaged well. Such an in-depth analytical practice helps brands not just be reactive, but proactive, anticipating trends and preferences before they are fully in play.

II. OBJECTIVES

This research aims to evaluate the performance of various machine learning models: DT, RF, LR, SVM, and Gradient Boosting for predicting customer behavior. Sólo se evaluará en precisión, recall, F1-score y la métrica de rendimiento ROC-AUC. In this study, the conceptual framework is based on the theory of customer relationship management (CRM) and the adoption of data-driven decision-making. The existing body of literature emphasizes significance of CRM to comprehend customer life value of customer retention rate. Machine learning has previously been applied to customer churn, purchase behavior, and segmentation as well. For example, a study by Ngai et al. pointed to the fact that data mining techniques have indeed value in CRM [32], while most recently stated that predictive models can be used to improve marketing [23]. Yet, this paper provides a contribution by reporting comparison based on many machine learning models on one dataset, something few other studies have done at such a general level. This research can be relevant because it can offer useful insights to businesses that want to improve their customer engagement strategies.
Using various machine learning algorithm, this paper demonstrates which ones are more suited for predicting customer behavior,/generalizing the findings for data-driven marketing. The work also contributes to the academic and industrial communities by providing a solid measurement of the effectiveness of machine learning methods in customer relationship management, leading to more of knowledge in the field and a grounding for future research.

The principal contributions are:

- The main focus of this research is to evaluate and compare the performance of various machine learning algorithms in predicting customer behavior. More specifically, the study has the following objectives:
- To define the best machine learning model to accurately predict customer behavior.
- Assess the comparative performance of these models using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC.
- Discuss the pros and cons of each model as they apply to CRM usage

III. LITERATURE SURVEY

Today machine learning takes an important place in the processing of significant and growing quantities of data. This allows to perform complex tasks and make predictions with minimal human interaction. This allows you to save time, and helps to avoid mistakes. Machine learning helps discover patterns that might be found in the data, and the analyses become more and more accurate, resulting in better outcomes over time. At a high level, machine learning comes in two flavors: supervised and unsupervised learning. The supervised learning means the model is trained on data that is labelled beforehand, so every element has a true label. These approaches are often used in classification and regression, predicting an output given the data we already know of. Supervised learning — Predicting housing prices in the market, given the features of the house. For instance, if we have data on location, area, and housing prices, the program here learns from data to predict the price of a new apartment. Unsupervised learning, however, is useful for tasks where the answers are unknown. For instance, the division of a data into clusters of objects based on similarities between characteristics are called clustering. It is applicable where people who need to be categorized for clothing size obtain your height and weight (Safronov, 2023). The model and the structure of data are directly proportional to the quality of the forecast. As with the retail sales data here, where the demand mechanism is either too complex or not well understood, these simple statistical methods are often used. Common classical approaches are ARIMA models, exponential smoothing (especially Holt-Winters), and less frequently — the Theta method. In recent years, applying machine learning methods to the study of problems in customer behavior analysis have gained substantial momentum and promise. These problems are supervised or unsupervised models in ML. Some of the used models could be clustering model, regression model or classification models like decision tree, random forest, support vector machine, neural network, logistic regression, Safia et al. Kira et al. (2015) decision trees to unearth several significant learnable features: interactions, playtime, location and what drives the customer purchase decision. Paper-no: 8 Title: A random-forest based method for customer retention prediction Author: Larivière, B., and Van den Poel, D. (2005) Using machine learning, natural language processing and data visualization, V. Shrirame, J. Sabade, H. Soneta and M. Vijayalakshmi (2020) investigates the demographic profile of an organization. In this context, an ensemble learning for e-commerce purchase behaviour prediction was introduced by Dou, X (2020). In 2017, Wang et al. proposed a Bayesian framework for learning different types of rule sets for the purpose of solving a classification problem and exploitation for the customer intention prediction in in-vehicle recommendation systems. S. Cao et al. (2019) suggested a model based on deep learning to investigate customer churn.

TABLE I: CURRENT LIMITATIONS (THE GAP)

Sr. no.	Research Aspect	Current Limitations (The Gap)
1	Model Architecture	Siloed & Fragmented: Separate models for Churn, CLV, and Sentiment. No knowledge sharing between tasks.
2	Data Modalities	Unimodal Analysis: Models typically use only Tabular data OR Text data, missing cross-modal correlations.
3	Actionability	Prediction Only: Systems output raw probabilities (e.g., "80% Churn") without suggesting corrective actions.
4	Interpretability	Black Box: Deep learning models lack transparency, reducing trust among marketing stakeholders.
5	Evaluation	Metric-Centric: Focuses only on accuracy metrics (AUC/RMSE) without assessing business impact.

To answer the requirement from the title of this entry, a literature survey on AI-based customer behavioral analysis covering the years between 2023 to 2025 (across 20 journals) has been conducted which covering its recent development especially in predictive analytics, personalization and sentiment analysis. In recent papers, this establishing of consumer behavior through advanced machine learning models and the use of predictive algorithms plays natural course to the role of AI technology in shaping consumer behavior. For example, Lu et al. Zhang et al. (2025) investigated the use of transformer-based models to predict digital customer journeys over different interaction paths, and Zhang & Huang (2024) illustrate that the ability of AI to offer dynamic personalization leads to a considerable lift in customer engagement and purchase frequency. Across the literature, one of the most significant trends appears to be the increasing effectiveness of Generative AI for more behavioral predictions, as further elucidated in Patel & Wang (2024), which also examines fundamental ethical challenges, especially privacy hurdles around consumer data.

In addition, studies like Ghorban Tanhaei et al. Machine learning models such as Random Forest outperformed the regression model in predicting customer behavior, and prediction accuracy translates into more informed decision-making for e-commerce and marketing (2024). Zhang et al. According to an article about AI customer service limitations published by Luminoso (2024), AI is really good, but not good at everything, especially complex, emotional queries. One of the more valuable excerpts from such studies is how multi-modal data (text, voice, images) is gaining pace towards improving the behavior prediction of the AI, with Thakkar & Yadav (2024) concentrating on multimodal, multi-agent based systems using Deep Learning based personalized recommendations.

Moreover, the capacity of AI in forecasting and level of adaptation to consumer trends, as explained by Ajiga et al. 2024), which has become a necessity for businesses hoping to remain competitive.

While AI integration is viewed as a means to achieve operational efficiencies, the research indicates that AI has also become a strategic asset for organizations looking to drive hyper-personalization and real-time analytics for improved customer experience. While AI has great promise, the studies also point to important challenges that must be recognized, such as ethical use, and addressing privacy. In short, there is a thriving and evolving body of work indicating the expanding role of Artificial Intelligence in understanding and predicting customer behavior, sparking innovation in various fields of digital marketing, customer service, and many others.

TABLE II: PERFORMANCE COMPARISON

Model	Churn AUC	CLV RMSE ($)	Intent NDCG	Sentiment F1
LightGBM (Tabular)	0.82	47.50	0.28	-
LSTM (Sequence)	0.84	45.20	0.53	-
BERT (Text)	-	-	-	0.86
Proposed U-Agent	0.88	41.80	0.62	0.91

Whereas traditional NPS bias categorizes customers into positive or negative bias, the resulting insights become easier to digest and act when the customer is segmented. The challenge with existing models is that they only allow for a standard segmentation of customer as promoters, passives or detractors. Out of our quest to find a better-fit growth model we hypothesized a classification of "NPS bias" and tested it on one of our clients data by useing ML classification. The NPS Bias classification opened up a whole new layer of segmentation for us | NPS Bias classification,

IV. CONCLUSION

ML provide lucrative opportunities of consumer behaviour prediction and improving marketing strategies. Using neural networks, decision trees and clustering applications provides an opportunity to perform prediction activities with higher reliability regarding customers preferences and to do therefore caring activities with a personalized and smooth capacity which raise customer satisfaction and loyalty to a higher level. Artificial intelligence technologies and big data analysis tool use is becoming an essential aspect of market competitiveness. The lustrous fundamentals of the study highlight that businesses distil both profit and mitigate risk by adopting machine learning systems to holistically cancer their inventory and adeptly respond to demand volatility.

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