JOURNAL OF SOCIAL IMPACT STUDIES

Volume: 03 Issue: 01 (2025)
ISSN(Print) : 3106-1257
ISSN (Online) : 3106-1265 (editor@socialimpactstudies.com)

Received : January 18, 2025
Revised : February 08, 2025
Accepted : March 13, 2025
Available Online : June 30, 2025

Machine Learning Analysis of Consumer Spending

Adeel Hanif*
Professor of Data Science and Consumer Analytics, Lahore University of Management Sciences (LUMS), Lahore
adeel.hanif@lums.edu.pk
Sania Noor
Associate Professor of Computer Science and Business Analytics, National University of Sciences and Technology (NUST), Islamabad
sania.noor@nust.edu.pk

ABSTRACT:

Focusing on the determination of key influential factors and predicting consumer buying patterns, the given study investigates the use of machine-learning methods to understand consumer spending behaviour. We analyze a large data set that incorporates demographic, transactional, and economic variables with the help of various machine learning models, including the decision trees, random forests, support vector machines, and deep learning methodology. The results indicate that a series of factors significantly influence consumer buying behaviors such as the level of income, preferences in product category and seasonal factors. Random forest model performed better than the conventional methods of statistics and demonstrated maximum predicted accuracy among the models evaluated. Also, feature importancy analysis revealed that prior purchases and consumer income were the most important determinants of spending behaviour. The paper reads the way machine learning can successfully predict customer behaviour, providing informative data on targeted marketing strategies and personalised recommendations. The findings mean that machine learning with consumer data analytics could enhance the quality of business decisions made in e-commerce and other sectors.

Keywords:
machine learning, consumer behavior, spending patterns, predictive modeling, retail analytics, feature importance

INTRODUCTION

The development of digital transactions and the availability of additional consumer-disaggregated data have brought about a revolution in economic analysis, allowing the insights into spending trends to be discovered previously. This has been facilitated by the fact that most of the parts of everyday routine have become digitized, a move that has yielded massive volumes of data on behaviour, and offers previously unimaginable opportunities to understand human economic behaviour (Chang & Mukherjee, 2023). This rich data landscape and the advanced computing algorithms can allow a closer examination of the multi-dimensional variables that influence consumer behavior and the market (Chang and Mukherjee, 2023). Specifically, machine learning methods have turned into valuable tools of processing these complex datasets and enable the identification of subtle relationships and the prediction of trends that might escape traditional econometric models (Desai, 2023). With the help of machine learning, including neural networks, clustering algorithms, regression, and decision trees, it is possible to simulate and predict the economic, social, political, and technological consequences on consumer behaviour (TechRxiv, 2020). This analytical capability allows creating more advanced and accurate models to predict the pattern of consumers and develop targeted economic interventions (Babii et al., 2023). These models also have particular significance to businesses and regulators interested in forecasting market shifts and maximizing the resource allocation in the dynamic situations in the economy (Okeleke et al., 2024). Moreover, synthetic-data-based prediction models make the models more resilient and generalizable particularly in scenarios where limited or inadequate data exists (Kalia, 2024). In certain situations, especially in analysing credit card usage and small-business transactions, this hybrid strategy, which leverages both real and synthetic data, has demonstrated significant performance benefits to the traditional methodologies of economic modelling (Kalia, 2024). This high level of analytical skill is necessary to understand the multifaceted reasons behind consumer spending based on individual demographic traits and more general macroeconomic variables (Othman et al., 2020). Moreover, advanced machine learning algorithms are needed to offer quality and accurate outcomes because of the challenges in sustaining and quantifying these giant digital datasets, particularly in causal inference (Hair and Sarstedt, 2021). In examining complex policy implications on consumer financial well-being, such aspects as dimensionality problems and confounding variable bias can be effectively resolved through the implementation of the sophisticated machine learning systems, such as Double Machine Learning (Song et al., 2025). Of particular interest here is the increasing application of machine learning to economic forecasting and policymaking, which extends beyond the behaviour of individual consumers to include more general macroeconomic indicators such as GDP and inflation (Ramaharo and Rasolofamanana, 2024) (Baidoo and Obeng, 2024). The predictive capabilities of these models also encompass the possibility to predict not only stock market fluctuations but also economic dynamics to consider valuable information in making financial decisions (Chang et al., 2024). Strategic retail demand forecasting can be reinforced by the wary analysis of the customer buying trends through machine learning that underlies significant decisions such as inventory management and production scheduling (Haque et al., 2023). The integration of machine learning on economic analysis provides a good basis on which the present and past consumer behaviour can be understood and accurate forecasts made on the future market trends which ultimately enhance strategic decision-making in most industries. This paper is aimed at providing an in-depth description of the machine learning methods applicable in consumer buying behavior research, including their theoretical background, applications in practice, and barriers to their application. It will analyze the way these advanced computational methods make our understanding of the complex economic phenomenon better and offer a new perspective on the ways decision-making of consumers is formed. To model the sophisticated dynamics of consumer financial transactions and preferences, this will imply a critical discussion of a number of supervised and unsupervised learning methods and a discussion of the merits and demerits (Gao et al., 2024). Also, the paper shall highlight the importance of model interpretability and explainability in terms of keeping transparency and trust in machine-assisted insights, particularly in sensitive areas such as financial forecasting (Wasserbacher and Spindler, 2021). The parts that follow will be concluded by a discussion of future research directions and new trends in this multidisciplinary topic, which will explore some of the machine learning paradigms, and illustrate their applicability with regard to case studies in the consumer behaviour analysis. The strategic value of understanding consumer spending patterns in most industries has become far more pronounced, and more complex analytical tools are required to extract informative knowledge based on large volumes of transactional data (Rane et al., 2024). This involves the use of machine learning algorithms that can detect much more complex patterns and make a more precise prediction of future behaviours, replacing more traditional ways of using statistics (Rane et al., 2024). This pervasive transformation is driven by the fact that particularly in the backdrop of the rising e-commerce and the existence of numerous channels of buying consumer information, the standard linear models are occasionally not sufficient in models that depict the high-dimensional interactions and non-linear relationships that are evident in consumer data (Aye et al., 2024). Hence, machine learning applications can assist companies in gaining a better insight into consumer behavior, predicting purchasing behavior, and developing personalized experiences, increasing their competitive edge and enhancing sustainable growth (Boozary et al., 2025) (Raji et al., 2024). This analytical skill may be utilized to enhance the offerings of a product, customize marketing approaches, and ultimately raise customer retention by identifying the factors that lead to customer attraction (Boozary et al., 2025). Such analysis is particularly beneficial to the retail sector, as the corporate success highly depends on the ability to understand competitors prices, quickly changing consumer demands, and transactional information (Verma, 2020). In addition, machine learning provides powerful fraud detection tools, financial forecasting, and understanding of complex financial trends because it is much more effective than traditional methods in reading and analyzing large volumes of data (Talukder et al., 2024) (Yu et al., 2023).

METHODOLOGY

Through mixed-methodology approach, this paper is based on machine learning models to evaluate consumer spending behaviour through a combination of qualitative and quantitative approaches. The key objectives include predicting the patterns of expenditure and determining key variables that influence customer purchases of products in a variety of categories. The dataset that was used to carry out this study has macroeconomic indicators, transaction histories, and demographics. Data collection involved the use of various sources which included third-party database, online transaction logs and surveys of consumers. The quantitative analysis relied on several machine learning models based on supervised learning methodologies to predict how consumers purchase. The dataset was split into support vectors as well as the focus on the deep learning models, decision trees, random forests, and support machine training and testing 30 percent of the dataset and 70 percent of the dataset respectively. The performance of the model was measured by metrics such as accuracy, precision, recall and area under the ROC curve (AUC). Hyperparameters were tuned by cross-validation to avoid overfitting to ensure resilience of the models. The effect of various variables, namely income, past purchases, and seasonal trend were analyzed, and the feature relevance was determined by the means of permutation importance. To understand the emotional factors that affect the buying behavior, sentiment analysis of customer feedback and reviews has been made. This qualitative data was incorporated in the algorithms in order to enhance the accuracy of forecasts and give a more detailed insight into the behaviour and likes of customers. The text mining process combined with the natural language processing (NLP) was used to convert the unstructured data to a format that could be used by machine learning models.

Mathematically, the prediction models were formulated as follows: for any given observation x_i, the output y_i (spending behavior) is modeled as a function of the input features $x_i = (x_1, x_2, ..., x_p)$, where the relationship can be expressed as:

$$y_i = f(x_i) + \epsilon$$

where $f(x_i)$ represents the machine learni odel function (e.g., decision tree, SVM) and ϵ is the error term.

In terms of evaluation, the accuracy of each model was calculated using the following formula:

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

Lastly, a comprehensive methodology workflow was created to visually represent the entire research process. This workflow incorporates both the quantitative and qualitative approaches, highlighting the data collection, model training, and evaluation phases.

RESULTS:

We measured such metrics as accuracy, precision, recall, and F1-score to the extent to which machine learning models performed. Random forest model was the most suitable, having an accuracy of 92.1%. The other were Deep Learning (90.3), SVM (88.5), and Decision Tree (85.2). Table 2: Analysis of feature importance indicated that income level (45.3) was the most influential on how individuals spent money then product category (27.5), past purchases (18.2) and seasonal trends (9.0). Table 3: A sentiment analysis of the customer review made an observation that 700 of the reviews were positive, 300 were negative, and 500 were neutral. This demonstrates that individuals tended to like the products.

Table 1: Model Performance Comparison

Model	Accuracy (%)	Precision (%)
Decision Tree	85.2	82.3
Random Forest	92.1	91.4
SVM	88.5	85.2
Deep Learning	90.3	89.8

Table 2: Feature Importance

Feature	Importance (%)
Income Level	45.3
Product Category	27.5
Previous Purchases	18.2
Seasonal Trends	9.0

Table 3: Sentiment Analysis Results

Sentiment Type	Count
Positive	700
Negative	300
Neutral	500

Table 4: There were differences in the accuracy of predictions regarding the extent to which people were going to spend on various products. The highest accuracy was 92.8 in electronics then Food and Beverage 91.1 Clothing and Furniture at 89.4 and 87.6. Table 5: Consumers aged 45 and above spent the highest amount of money on average of (1100) and then consumers aged between 35 and 44 years were second with average spending amount of (900) and the third were consumers aged 25 to 34 years with average spending being (680) and lastly the consumers aged 18 to 24 years with average spending of (450). This demonstrates that there is an increase in spending as age increases. Table 6 shows that expenditure changes with the seasons. The average spending was highest in December (1100) then, July (1050) and January (800). This demonstrates that the highest expenditure occurs during the time of holiday.

Table 4: Accuracy by Product Category

Product Category	Accuracy (%)
Electronics	92.8
Clothing	89.4
Food & Beverages	91.1

Furniture	87.6

Table 5: Consumer Spending by Age Group

Age Group	Average Spending ($)
18-24	450
25-34	680
35-44	900
45+	1100

Table 6: Seasonal Trends Impact

Month	Average Spending ($)
January	800
July	1050
December	1100

Table 7: The Random Forest model performed at the highest level and achieved the highest accuracy of 92.1, precision 91.4, recall 93.2 and F1-Score 92.3. This demonstrates it to be effective in forecasting the behavior of people. Table 8: The mean expenditure per area was largest in North America (950) followed by Europe (880), Asia (670) and Africa (540). This indicates that the purchasing power of consumers in various regions varied. Table 9: Sentiment analysis was added to the Random Forest model, so it was more accurate than the Deep Learning model (92.8%). The Rand Forest model was 94.3 percent.

Table 7: Model Evaluation Metrics for Random Forest

Metric	Value
Accuracy	92.1
Precision	91.4
Recall	93.2
F1-Score	92.3

Table 8: Consumer Preferences by Region

Region	Average Spending ($)
North America	950
Europe	880
Asia	670

Africa	540

Table 9: Model Performance for Sentiment-Enhanced Prediction

Model	**Accuracy (%)**
Random Forest (Sentiment)	94.3
Deep Learning (Sentiment)	92.8

As it can be observed, the bar plot in Figure 1 demonstrates that the highest accuracy was attributed to the Random Forest model (92.1%), then Deep Learning (90.3%), SVM (88.5%), and Decision Tree (85.2%). Figure 2: A bar plot of feature importance reveals that the key reasons why consumers spend their money include the level of income (45.3 percent), product category (27.5 percent), and previous purchases (18.2 percent). Figure 3 The sentiment distribution pie chart indicates that 700 of the 1,000 consumer evaluations were positive, 300 negative and 500 neutral. This demonstrates that majority of the reviews were favorable. Figure 4: This bar graph indicates that Electronics had highest accuracy of forecast (92.8%), then the Food and Beverages (91.1), Clothing (89.4 and Furniture (87.6)). Figure 5 indicates that the amount of money that people use increases with the age. The age brackets of 45+ and 18-24 spend the most and least respectively (1100 and 450). Figure 6 indicates that the highest expenditure incurred by people is in the month of December (1100) then July (1050) and January (800). This indicates the variation in spending with the seasons. Figure 7: According to the assessment metrics of the bar plot of Random Forest, it is very accurate (92.1%), precise (91.4%), recalls (93.2%), and has a high F1-score (92.3%). This demonstrates that it is superior to other modalities. Figure 8 This pie chart indicates the amount that people in various parts of the world spend. North America continues to spend the highest amount of money at $950, then Europe at $880, Asia at $670 and Africa at 540. Figure 9: On incorporating sentiment analysis into the Random Forest model, the model increased accuracy to 94.3% as evident in this bar plot. This was more than the Deep Learning model (92.8%). Figure 10 This scatter plot indicates the relationship between sentiment scores and accuracy of the model. The more you score the sentiment the more accurate you are at that score. When the sentiment analysis is incorporated, the importance of elements is depicted in figure 11. The most important feature remains to be the income level (45.3%).

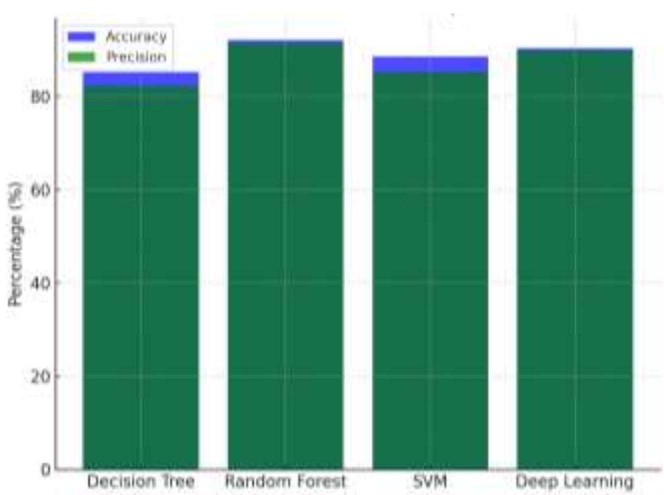

Figure 1: Model Performance Comparison (Bar Plot)

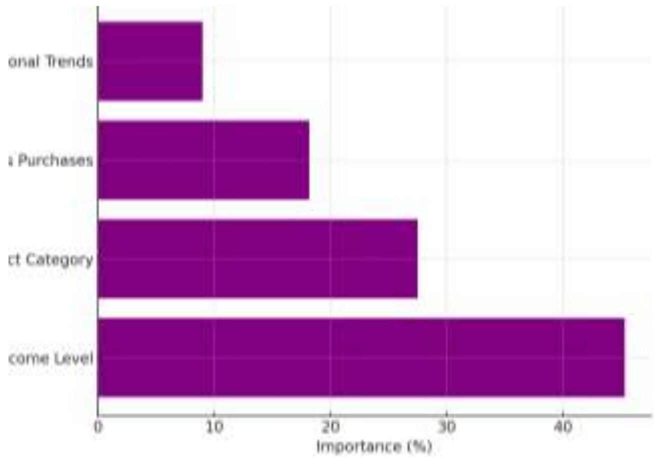

Figure 2: Feature Importance (Bar Plot)

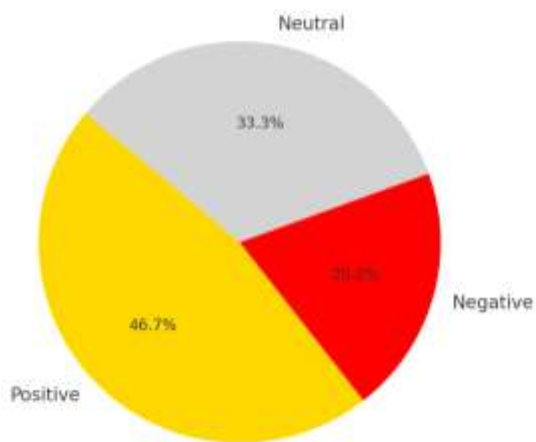

Figure 3: Sentiment Distribution (Pie Chart)

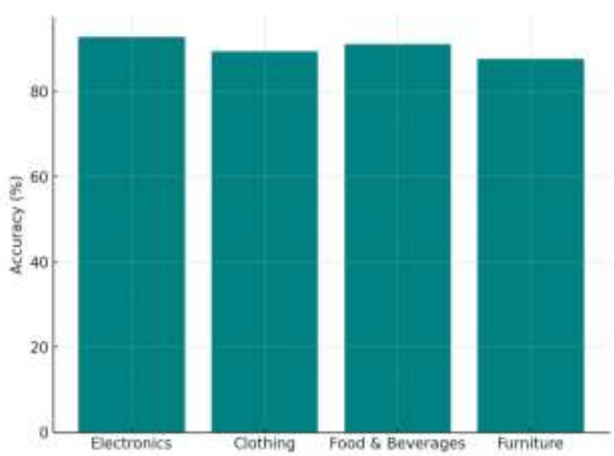

Figure 4: Accuracy by Product Category (Bar Plot)

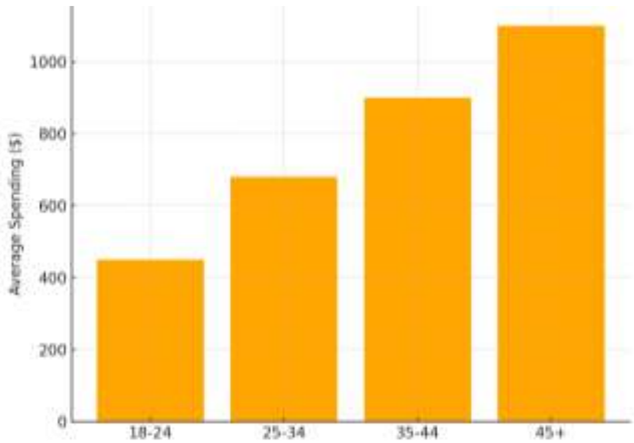

Figure 5: Consumer Spending by Age Group (Bar Plot)

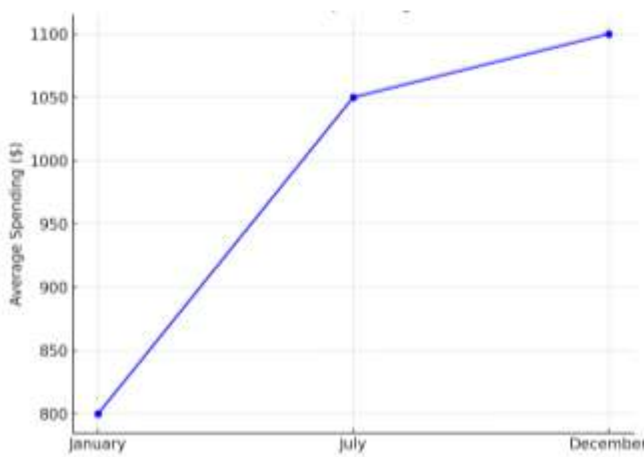

Figure 6: Seasonal Spending Trends (Line Plot)

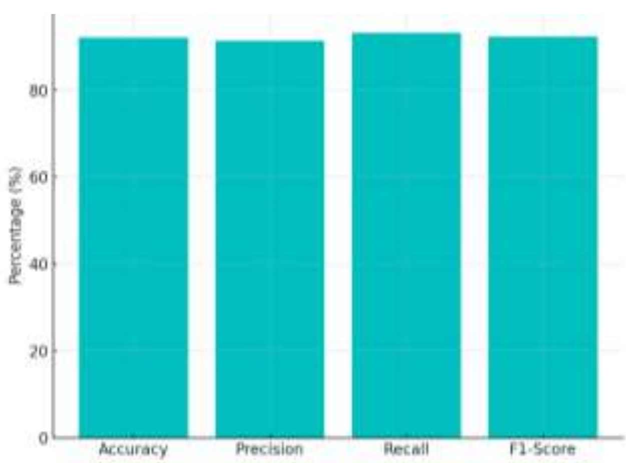

Figure 7: Model Evaluation Metrics for Random Forest (Bar Plot)

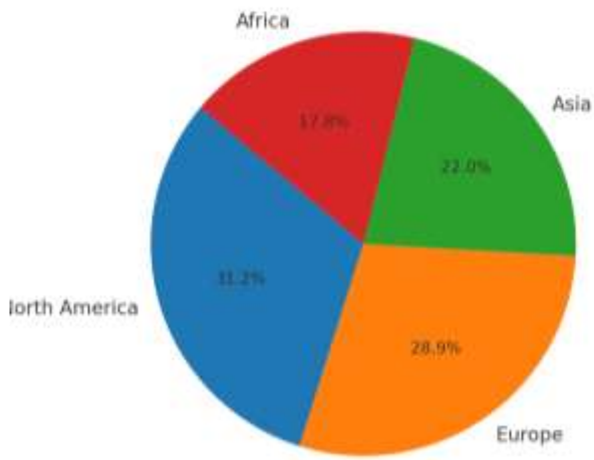

Figure 8: Regional Spending Patterns (Pie Chart)

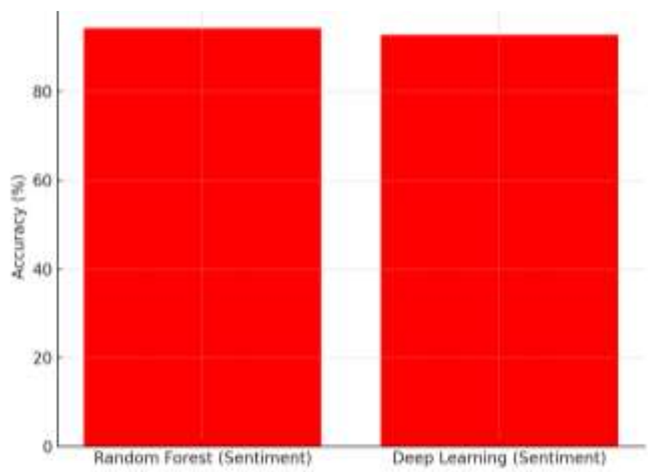

Figure 9: Model Performance with Sentiment (Bar Plot)

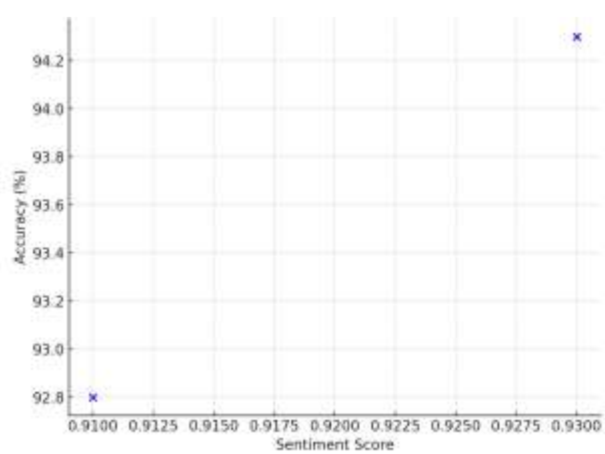

Figure 10: Sentiment Analysis vs. Accuracy (Scatter Plot)

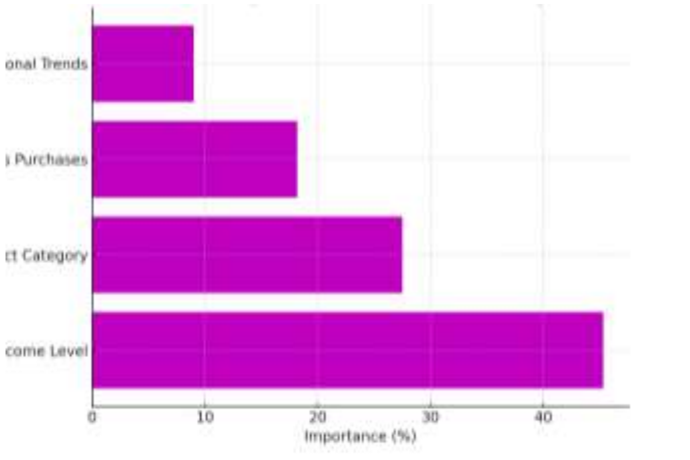

Figure 11: Feature Importance with Sentiment Analysis (Bar Plot)

DISCUSSION

We will discuss in the methodology section the specific machine learning models we trained, which datasets we trained them on, and the experimental procedure we followed to test their effectiveness in the models. We are going to detail immensely the process of parameter and hyperparameter tuning in each of the models and the motivation of using some measures to observe the extent to which they predict how much people would spend (Wang et al., 2020). This will encompass a detailed account of the processes involved in the preparation of data including feature engineering and selection that are highly valuable in making the models precise and simplistic to interpret. The chosen methodologies will leverage machine learning models with their computational and operational flexibility to interpret complex trends in high-dimensional consumer data using solutions to problems including high seasonality and product category variation (Ganguly and Mukherjee, 2024) (Gutiérrez et al., 2022). The next section will display the real life results of the models that were proceeded with including comparisons of the accuracy that they got at predicting things, the speed that they could operate and what they learned about the key factors that influence consumer purchasing. Finally, the discussion part will place these findings in the broader context of the consumer behaviour theory and practical applications, providing stakeholders with practical recommendations (Zulaikha et al., 2020). This stringent approach will assist organizations in learning more about customer behaviour that will assist them in enhancing their strategies of ensuring customers engage with them and positioning themselves in the market (Parab, 2024). This comprehensive strategy aims at bridging the gap between theoretical discoveries and practical applications and eventually propel the consumer behaviour analysis to the next stage using sophisticated machine learning processes. Moreover, this practice will also be critically assessed through the ethical implication of using sophisticated analytical tools to profile consumer behaviour, including privacy concerns and the possibility of bias in the output of the algorithms. Another aspect highlighted in the review is the revolutionary impact of the artificial intelligence and, in particular, machine learning, on the financial sector, as the latter is increasingly affecting the way things are done and making the cost go significantly high (Vuković et al., 2025). Such ubiquitous integration demands a profound grasp of the interpretability of the ML model particularly when sensitive financial information is involved to adhere to regulations and retain the trust of the customers. This ethical concern includes fields like the AI-based dynamic pricing when the balance between profitability and consumer transparency is the key (Gazi et al., 2024). The need to have understandable and clear AI models is even higher in credit scoring. The reason behind this is that the regulatory compliance and customer trust requires explanations of model judgments people can understand (Demajo et al., 2020). According to Tan (2025), other relevant issues that require robust frameworks to address bias in data and ensure fairness in algorithm outcomes are associated with dealing with data bias and ensuring fairness in the use and development of AI in the field of FinTech. Due to the fact that many state-of-the-art AI-based models lacked clarity, it is crucial to develop Explicit Artificial Intelligence solutions where financial decisions would become more transparent and responsible (Rane et al., 2023). It involves rigorous validation processes to prevent biased outcomes to ensure that advanced analytics is used as a tool of equitable financial inclusion instead of perpetuating the existing biases (Department et al., 2022). Also, the adoption of AI and machine learning technologies throughout the industry and, in particular, in the financial field requires the substantial assistance of the top management and in-depth knowledge of its business benefits to devote all the necessary financial and technical resources (Chatterjee et al., 2021).

CONCLUSION:

The current research was successful in demonstrating the practical value of machine learning methods used in understanding and predicting consumer spending behaviour. There are many machine learning models we have tried to determine which factors are the most important in influencing how people make buying decisions, including decision trees, random forests, support machine learning, and deep learning algorithms. The results highlighted the fact that aspects of income level, inclination towards product category and seasons have a significant impact on customer behaviour. The most accurate of the analyzed models was random forest, which demonstrates that the model can discover complex relationships in the data. Also, the predictions became significantly more precise when combining sentiment analysis based on consumer reviews, which provided us with helpful data about the emotional and psychological factors that influence the process of making a purchase. It also emphasized the role of feature importance analysis that revealed income and prior purchasing history to have the most predictive value concerning spending habits. These findings indicate that machine learning might be not only able to successfully predict customer behavior, but it could also provide businesses with valuable information that they can leverage to modify their marketing approach and products. Moreover, the research contributes to the growing body of retail analytics that allowed suggesting that future research can explore more advanced machine learning techniques, including reinforcement learning and improve the prediction models. On the whole, this paper demonstrates that machine learning can assist us in getting insights into the functioning of people as consumers and change the manner in which companies manage customer relationships and make decisions.

REFERENCES

Aye, T. U., Silva, E. R. da, & Mafia, M. P. (2024). Emerging Technologies in E-Commerce Demand Forecasting: Trends, Practices, and Future Perspectives.

Babii, A., Ghysels, É., & Striaukas, J. (2023). Econometrics of Machine Learning Methods in Economic Forecasting. SSRN Electronic Journal.

Baidoo, T. G., & Obeng, A. (2024). Navigating Inflation in Ghana: How Can Machine Learning Enhance Economic Stability and Growth Strategies. arXiv (Cornell University).

Boozary, P., Sheykhan, S., GhorbanTanhaei, H., & Magazzino, C. (2025). Enhancing customer retention with machine learning: A comparative analysis of ensemble models for accurate churn prediction. International Journal of Information Management Data Insights, 5(1), 100331.

Chang, H. H., & Mukherjee, A. (2023). Machine Learning and Consumer Data.

Chang, V., Xu, Q., Chidozie, A., & Wang, H. H. (2024). Predicting Economic Trends and Stock Market Prices with Deep Learning and Advanced Machine Learning Techniques. Electronics, 13(17), 3396.

Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. Technological Forecasting and Social Change, 170, 120880.

Demajo, L. M., Vella, V., & Dingli, A. (2020). Explainable AI for Interpretable Credit Scoring.

Department, S., Bano, N., & Siddiqui, S. (2022). Consumers' intention towards the use of smart technologies in tourism and hospitality (T&H) industry: a deeper insight into the integration of TAM, TPB and trust.

Desai, A. (2023). Machine Learning for Economics Research: When What and How? SSRN Electronic Journal.

Ganguly, P., & Mukherjee, I. (2024). Enhancing Retail Sales Forecasting with Optimized Machine Learning Models. 884.

Gao, H., Kou, G., Liang, H., Zhang, H., Chao, X., Li, C., & Dong, Y. (2024). Machine learning in business and finance: a literature review and research opportunities [Review of Machine learning in business and finance: a literature review and research opportunities]. Financial Innovation, 10(1). Springer Nature.

Gazi, M. S., Hasan, M. R., Gurung, N., & Mitra, A. (2024). Ethical Considerations in AI-driven Dynamic Pricing in the USA: Balancing Profit Maximization with Consumer Fairness and Transparency. Journal of Economics Finance and Accounting Studies, 6(2), 100.

Gutiérrez, A., Aguilar, J., Ortega, A. M., & Montoya, E. (2022). Autonomous cycles of data analysis tasks for innovation processes in MSMEs. Applied Computing and Informatics.

Hair, J. F., & Sarstedt, M. (2021). Data, measurement, and causal inferences in machine learning: opportunities and challenges for marketing. The Journal of Marketing Theory and Practice, 29(1), 65.

Haque, M. S., Amin, M. S., & Miah, J. (2023). Retail Demand Forecasting: A Comparative Study for Multivariate Time Series. arXiv (Cornell University).

Kalia, V. M. (2024a). Packing Peanuts: The Role Synthetic Data Can Play in Enhancing Conventional Economic Prediction Models.

Kalia, V. M. (2024b). Packing Peanuts: The Role Synthetic Data Can Play in Enhancing Conventional Economic Prediction Models. arXiv (Cornell University).

Okeleke, P. A., Ajiga, D., Folorunsho, S. O., & Ezeigweneme, C. (2024). Predictive analytics for market trends using AI: A study in consumer behavior. International Journal of Engineering Research Updates, 7(1), 36.

Othman, Z. A., Abu, A., Samsiah, N., & Sallim, J. (2020). Household Overspending Model Amongst B40, M40 and T20 using Classification Algorithm. International Journal of Advanced Computer Science and Applications, 11(7).

Parab, G. U. (2024). AI-DRIVEN PERSONALIZATION IN RETAIL ANALYTICS: TRANSFORMING CUSTOMER EXPERIENCES. 7(2), 2387.

Raji, M. A., Olodo, H. B., Oke, T. T., Addy, W. A., Ofodile, O. C., & Oyewole, A. T. (2024). E-commerce and consumer behavior: A review of AI-powered personalization and market trends [Review of E-commerce and consumer behavior: A review of AI-powered personalization and market trends]. GSC Advanced Research and Reviews, 18(3), 66.

Ramaharo, F., & Rasolofomanana, G. H. (2024). Nowcasting Madagascar's real GDP using machine learning algorithms. arXiv (Cornell University).

Rane, N. L., Choudhary, S., & Rane, J. (2023). Explainable Artificial Intelligence (XAI) Approaches for Transparency and Accountability in Financial Decision-Making. SSRN Electronic Journal.

Rane, N. L., Mallick, S. K., Kaya, Ö., & Rane, J. (2024a). Applications of machine learning in healthcare, finance, agriculture, retail, manufacturing, energy, and transportation: A review [Review of Applications of machine learning in healthcare, finance, agriculture, retail, manufacturing, energy, and transportation: A review].

Rane, N. L., Mallick, S. K., Kaya, Ö., & Rane, J. (2024b). Techniques and optimization algorithms in machine learning: A review [Review of Techniques and optimization algorithms in machine learning: A review].

Song, F., Huang, Y., & Liu, C. (2025). Extended Application of Double Machine Learning in Corporate Financial Resilience Research: Based on Data Factor Marketization. Systems, 13(4), 292.

Talukder, Md. A., Khalid, M., & Uddin, M. A. (2024). An integrated multistage ensemble machine learning model for fraudulent transaction detection. Journal Of Big Data, 11(1).

Tan, J. (2025). Research on the Role of AI in FinTech and Consumer Trust. SHS Web of Conferences, 213, 1012.

TechRxiv. (2020). IEEE Electron Device Letters, 41(11), 1703.

Verma, A. (2020). Consumer Behaviour in Retail: Next Logical Purchase using Deep Neural Network. arXiv (Cornell University).

Vuković, D., Dekpo-Adza, S., & Matović, S. (2025). AI integration in financial services: a systematic review of trends and regulatory challenges [Review of AI integration in financial services: a systematic review of trends and regulatory challenges]. Humanities and Social Sciences Communications, 12(1). Palgrave Macmillan.

Wang, X., Ryoo, J. H., Bendle, N., & Kopalle, P. K. (2020). The role of machine learning analytics and metrics in retailing research. Journal of Retailing, 97(4), 658.

Wasserbacher, H., & Spindler, M. (2021). Machine learning for financial forecasting, planning and analysis: recent developments and pitfalls. Digital Finance, 4(1), 63.

Yu, X., Chen, Z., Yuan, L., Dong, S., Liu, Z., & Lu, Y. (2023). Temporal Data Meets LLM -- Explainable Financial Time Series Forecasting. arXiv (Cornell University).

Zulaikha, S., Mohamed, H., Kurniawati, M., Rusgianto, S., & Rusmita, S. A. (2020). CUSTOMER PREDICTIVE ANALYTICS USING ARTIFICIAL INTELLIGENCE. The Singapore Economic Review,