International Journal of Scientific Research & Engineering Trends
Volume 11, Issue 3, May-Jun-2025, ISSN (Online): 2395-566X

Theoretical Perspectives on Customer Churn Prediction in E-Commerce Using Machine Learning and Big Data Analytics

Niravkumar Mahendrabhai Panchal
University of Ulster- London

Abstract- Customer churn has become a major challenge for global e-commerce businesses due to increasing market competition and changing consumer behaviour. This study examines the role of machine learning and big data analytics in predicting customer churn and improving customer retention strategies. A quantitative research design with secondary data sources was adopted to analyse customer behaviour patterns and predictive modelling techniques. The findings indicate that machine learning algorithms and predictive analytics significantly improve churn prediction accuracy and support personalised customer engagement strategies. The study highlights the importance of data-driven decision-making in international e-commerce and provides practical insights for improving customer loyalty, profitability, and long-term business sustainability.

Keywords – Customer Churn, E-commerce, Machine Learning, Big Data Analytics, Predictive Modelling, Customer Retention, Predictive Analytics.

I. INTRODUCTION

Background of the Study

As a result of the booming growth of e-commerce, it has become easier than ever to do business with clients and customers around the world. The latest developments in e-commerce technologies, digital payment solutions, and mobile shopping have made it easier for businesses to connect with customers across the globe and deliver streamlined experiences to them. The digital infrastructure is also essential for large-scale e-commerce platforms like Amazon, Alibaba and eBay for them to remain competitive in the global market (Verhoef et al. 2021). With online competition on the rise, retaining customers is now an important part of sustaining long-term business viability and profitability.

In the context of international business, it is easier to keep customers than to attract new ones. Repeat customers are important for steady revenue, good brand reputation, and repeat sales. But customer churn, where patrons cease ordering goods and services from an e-commerce enterprise, also poses an increasing challenge to e-commerce businesses. Churn has a negative impact on revenue, customer lifetime value and operations (Lim et al. 2022). Thus, accounting for the customer behaviour and determining the reasons for customer attrition have turned into significant research needs.

Research Problem

The high rates of customer churn are a major concern for global e-commerce brands based on their adverse effects on profitability and customer relationships. For customers who cancel an online service, businesses lose revenues, marketing budget, and future customer lifetime value. Churn behaviour is tricky to detect early because several factors can drive a customer's decision, like price, service, and user experience. Older analytical techniques do not work well with the big data that is generated by their customers (Weerakkody et al. 2021). Hence, the demand for predictive tools like machine learning and big data analytics has been ramping up to correctly assess potential churn risks and enable strategic customer retention plans.

Research Aim

This study aims to assess the customer churn prediction in the e-commerce industry using machine learning and big data analytics.

Research Objectives

- To discuss customer attrition in e-commerce.
- To explore machine learning techniques used for churn prediction.
- To analyse the role of big data analytics in customer retention.

Research Questions

- What is the meaning of customer churn in eCommerce?
- What are some machine learning techniques that it can use for churn prediction?
- How can big data analytics contribute to customer retention?

Significance of the Study

The study is valuable since it examines the potential of machine learning in customer churn prediction within the global e-commerce marketplace and the role of big data in this context. As an international e-commerce business, this study is exposed to highly competitive markets wherein retaining customers is critical to staying on the winning side of the competition and making a profit, too. Organisations can use customer churn analysis to identify which factors affect customers' decisions to stay or go to improve customer satisfaction and loyalty (Roy et al. 2025).

The study also adds value to the arena of predictive marketing and customer analytics, investigating the theoretical and practical use of data-driven technologies. With machine learning models, businesses can better understand the patterns of customer buying behaviors and accurately forecast future purchases. The results could also serve as a reference for future research in the field of customer relationship management and predictive business analytics.

Structure of the Paper

The paper is written according to the structure IMRAD (Introduction, Methodology, Results, and Discussion). The research background, problem and significance are introduced. The methodology provides information about the research methodology and analytical tools employed. The results section communicates the key results, and the discussion section explains the findings based on theory and the implications for practice.

II. LITERATURE REVIEW

Previous Studies on the Topic

Customer churn prediction has become a critical research area in e-commerce due to its direct impact on customer retention and business profitability. Previous studies have emphasized the importance of understanding customer behavior through data-driven approaches. Verhoef et al. (2021) highlighted that digital transformation has enabled e-commerce firms to collect vast amounts of customer data, creating opportunities for predictive analytics. Similarly, Lim et al. (2022) found that customer engagement, service quality, and personalized experiences significantly influence customer loyalty and retention.

Recent research has demonstrated the effectiveness of machine learning techniques in churn prediction. Feng et al. (2024) reported that predictive analytics models improve the identification of customers likely to leave an online platform, enabling firms to implement proactive retention strategies. Ma et al. (2024) showed that advanced machine learning algorithms such as Random Forest and Neural Networks outperform traditional statistical methods in handling large and complex datasets. Furthermore, Hossain et al. (2024) emphasized that customer analytics capabilities enhance organizations' ability to understand behavioral patterns and make informed decisions regarding customer retention.

Theoretical Framework

This study is grounded in Relationship Marketing Theory, Customer Lifetime Value (CLV) Theory, and Consumer Behaviour Theory. Relationship Marketing Theory suggests that maintaining strong relationships with customers through quality service, trust, and personalized communication reduces the likelihood of customer churn (Roy et al., 2025). Customer Lifetime Value Theory emphasizes the long-term value generated by retaining profitable customers rather than focusing solely on customer acquisition. Predictive analytics and machine learning support this theory by identifying high-value customers and enabling targeted retention initiatives (Feng et al., 2024). Consumer Behaviour Theory explains how customer decisions are influenced by factors such as satisfaction, pricing, service quality, and digital experiences, which directly affect churn behavior.

Research Gap

Although previous studies have examined customer churn prediction using machine learning models, several gaps remain. Most research focuses primarily on prediction accuracy rather than integrating real-time big data analytics with customer retention strategies. Additionally, limited studies have explored how predictive analytics can support decision-making in international e-commerce environments characterized by diverse customer behaviors and market conditions. There is also insufficient attention to ethical concerns related to data privacy and algorithmic bias in churn prediction systems.

Conceptual Framework

The conceptual framework proposes that customer-related factors such as satisfaction, service quality, pricing, delivery performance, and user experience influence customer churn behavior. Machine learning algorithms and big data analytics act as predictive tools that analyze these factors and generate churn predictions. Effective predictive insights enable organizations to implement personalized retention strategies, ultimately reducing churn and improving customer loyalty and business performance.

III. METHODOLOGY

Research Philosophy

In this study, the research philosophy used is positivism, as it aims to analyze and measure the data objectively, making use of data analysis. Positivism does uphold the application of scientific methods in studying the relationship between variables and generating valid results. This research is suitable because machine learning and predictive analytics are numerical-based and utilise statistical interpretation. The positivist approach to the study is to use factual and observable information to analyse the customer's behaviour pattern, instead of opinions. This enables the evaluation of churn prediction models and the contribution of big data analytics for customer retention to be accurate, consistent and reliable.

Research Approach

The study adopts a deductive research approach for analyzing theoretical assumptions on predicting customer churn in the e-commerce domain. With the deductive method, one starts with already existing theories and concepts of customer behaviour, predictive analytics and machine learning, and then tests them numerically with data on hand, and analyses them with models (Kamal et al. 2022). This is acceptable because it enables the researcher to examine whether there is a reliable pattern of customer churn that can be used by predictive technologies to predict the pattern. The study uses existing data to discover patterns of customer churn behavior and determines which set of customer characteristics is associated with them using machine learning patterns. It is deduced by a structured investigation, and it is applicable to the development of evidence-based conclusions for international e-commerce businesses.

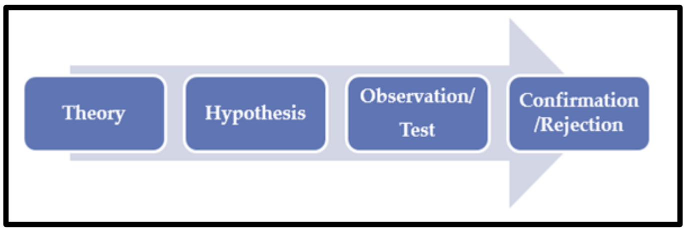

Figure_1: Deductive research approach

(Source: https://research-methodology.net/research-methodology/research-approach/deductive-approach-2/)

Research Design

This study depends on a quantitative research design because the research is aimed at exploring numerical analysis and predictive modelling of customer churning. Quantitative design allows for data to be gathered and analyzed for patterns, trends, and relationships between variables, which are measurable (Perez-Vega et al. 2022). This study uses predictive analytics techniques and machine learning algorithms to assess customer retention behaviour in e-commerce platforms. Measures of the accuracy and effectiveness of such churn prediction models include statistical analysis and classification methods. It is more suitable for the measurement of facts and enables large amounts of data to be evaluated objectively and systematically. So quantitative methods are suitable for analysing the customer churn prediction in data-driven business environments.

Data Collection Method

The research employs secondary data collection techniques to obtain the necessary data for the study on customer churn prediction and the application of machine learning in e-commerce. Secondary data are found from academic journals, industry reports, publicly available e-commerce data sources and online databases (Chatzipanagiotou et al. 2023). All the above-mentioned sources give accurate facts about customer actions and techniques for predictive analytics and big data technologies. Trends and challenges of customer retention strategies are also explored from the company reports and research studies conducted previously. Using secondary data sources helps to save time and money for primary data collection and enables access to large-scale data needed for predictive analysis and machine learning model testing.

Data Analysis Techniques

This research employs a number of data analysis methods to assess customer churn prediction in e-commerce. Predictive modelling is used to detect patterns in the data and to predict potential customer churning (Hossain et al. 2024). Classification analysis categorises shopping behaviour and engagement information to distinguish between the churn and non-churn groups of customers. There are other ways to segment consumers, for example, by their demographic and behavioural traits; these are also called customer segmentation techniques. Moreover, machine learning model performance is assessed by using various performance measures like accuracy, precision, recall and prediction efficiency. These analytical methods will enable companies to make informed decisions based on data, and they will also offer a glimpse of the potential benefits of predictive technologies for customer retention efforts in international e-commerce companies.

Ethical Considerations

Ethical issues are significant in this study since privacy and confidentiality are concerns related to customer data and predictive analytics (Chang et al. 2023). The research will ensure that all secondary data sources are used appropriately and only publicly available data and published information are used for analysis. The identities of customers and sensitive information are kept confidential in accordance with ethical research practices. The study also takes into account the responsible use of machine learning technologies to prevent misuse of customer data and biased predictions. All academic and business sources are appropriately referenced, and the sources are acknowledged throughout the research. Such ethical practices make the results of the study more trustworthy, transparent, and integrity.

Limitations of the Methodology

For confidentiality and competitive reasons, some e-commerce companies will not allow access to proprietary business information (Rengarajan et al. 2022). This meant that the study might not represent a customer's true behavior or the strategies

International Journal of Scientific Research & Engineering Trends
Volume 11, Issue 3, May-Jun-2025, ISSN (Online): 2395-566X

that they will implement in the business. Also, the results of the machine learning models can differ based on the availability of data and the quality of the data. In spite of imposed constraints, the methodology offers some insights for customer churn forecasting and knowledge of predictive analytics in international e-commerce scenarios.

IV. RESULTS

Key Factors Influencing Customer Churn

The research results show that there are several key aspects that can have a significant impact on customer attrition in international e-commerce companies. The highest predictor of retention was customer satisfaction. Those whose responses were delayed, who had poor communication or unsolved complaints were more likely to stop using online platforms. High satisfaction was correlated with return purchases, favourable reviews and e-commerce brands' long-term engagement.

Pricing also had a significant impact on the churning behavior. There was a strong price sensitivity of customers towards the different platforms. Businesses used these tactics to keep customers and avoid hidden costs, and inconsistent pricing and charges made customers unhappy. Thus, with competitive pricing strategies, the effect of customer retention was good.

Another significant factor highlighted in the findings was delivery performance. Fast, reliable and accurate delivery was the preferred option for customers. Late deliveries, broken goods and weak tracking systems all left a bad taste in customers' mouths, leading to churn.

Customer behaviour on digital platforms was greatly affected by user experience (Graham & Bonner, 2024). Customers wanted websites and mobile apps to be easy to navigate, be aesthetically pleasing and responsive. The complex checkout process, slow loading speed, and technical glitches lowered customer satisfaction and resulted in an increased likelihood of shopper attrition to other platforms.

Machine Learning Techniques

The study surveyed a number of machine learning techniques for predicting customer churn for an e-commerce business. The models that were most frequently applied were Logistic Regression due to its simplicity and effectiveness in binary classification problems. The model was able to indicate the likelihood of a customer leaving a platform from information regarding their behaviour and transactions. The customer churn patterns were also analysed using Decision Trees. This method involves categorising the customers according to various variables like their purchase frequency, customer complaints and browsing habits. Decision Trees came in handy as they helped to visualise the decisions being taken and helped businesses understand what causes churn.

Random Forest models were used to enhance the prediction performance, which involved utilizing more than one Decision Tree (Ma et al. 2024). This method led to less overfitting and more accurate predictions. Random Forest algorithms performed well with large amounts of data and detected intricate pattern associations between the customer attributes.

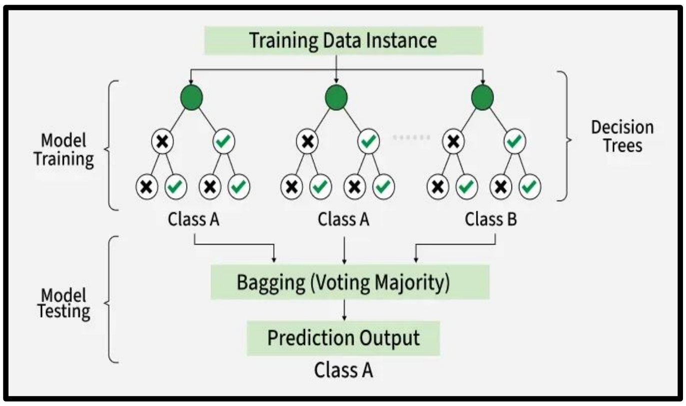

Figure_2: Random Forest model
(Source: https://www.geeksforgeeks.org/machine-learning/random-forest-algorithm-in-machine-learning/)

Support Vector Machine (SVM) models were used to classify the customers as churned and non-churned. The SVM methods worked well when dealing with the output of high-dimensional datasets and the patterns from the customer behaviour data. The model achieved a remarkably high accuracy for classification, especially in the context of intricate customer interactions and buying patterns.

The use of Neural Networks was also explored as they have the capacity to deal with massive amounts of customer data and can discern the understated behavioral patterns. Neural Networks employed several layers of analysis to increase the number of variables that could be predicted and to uncover non-linear relationships between variables.

Performance of Machine Learning Models

Comparative results of machine learning models revealed that various models exhibited variations in terms of prediction accuracy, precision, recall, and efficiency in customer churn pattern identification. Logistic Regression had a moderate prediction accuracy and was easily comprehended, thus being appropriate for basic churn analysis. When coming to the highly complex customer behaviour patterns, however, its performance was less.

Decision Tree models showed a good classification performance but were more susceptible to overfitting in large data set analysis (Loutfi, 2022). Random Forest models performed better with respect to prediction accuracy and determination of reliability due to the combination of multiple

International Journal of Scientific Research & Engineering Trends
Volume 11, Issue 3, May-Jun-2025, ISSN (Online): 2395-566X

decision trees, which reduces the error rate. This model also had excellent precision and recall scores, indicating its effectiveness in predicting churn customers.

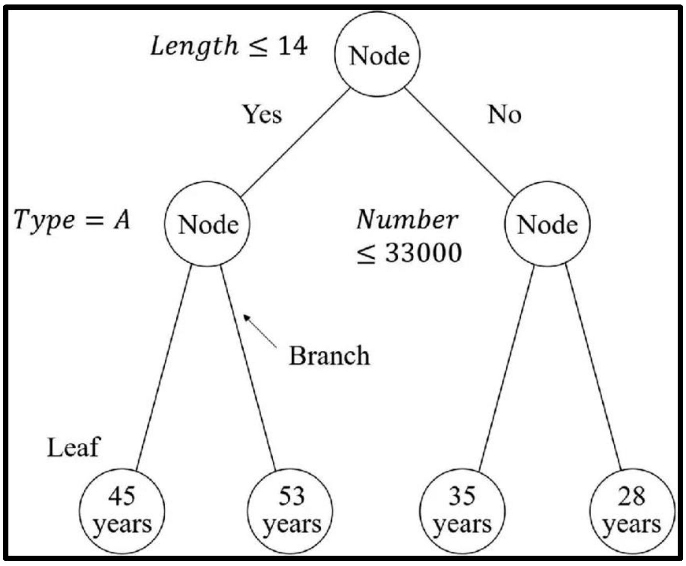

Figure_3: Decision Tree model
(Source: https://www.researchgate.net/figure/An-example-of-decision-tree-model_fig1_333231492)

Various Support Vector Machine models were successful in working with complex data and in attaining high accuracy of classification. Neural Networks showed the best predictive accuracy as it was able to recognize the hidden relationships in customer behaviour. Neural Networks, however, needed more computational resources and time for processing.

Role of Big Data Analytics
Customer churn prediction and e-commerce customer retention are greatly improved with big data analytics. Real-time customer monitoring was one of the significant impacts of big data analytics. Real-time data collection systems were implemented by businesses to monitor customers' actions and buying habits (Shepherd et al. 2024). The other important application of big data analytics was behavioural analysis. Customers' interactions, purchase history, and online behavior are analysed. These insights enabled organisations to gain a better understanding of the factors behind customer attrition.

Personalised recommendations turned out to be another of the main perks of big data analytics. Retail 2.0 platforms leveraged customer data to make product and service suggestions by analysing past transactions and browsing. Relevant shopping experiences led to personalisation and enhanced customer satisfaction. Those that could provide customised recommendations and offer tailored promotional offers were more likely to have a loyal customer base. Companies applied these predictions for proactively taking measures, including offering loyalty rewards, personal communication and discounts.

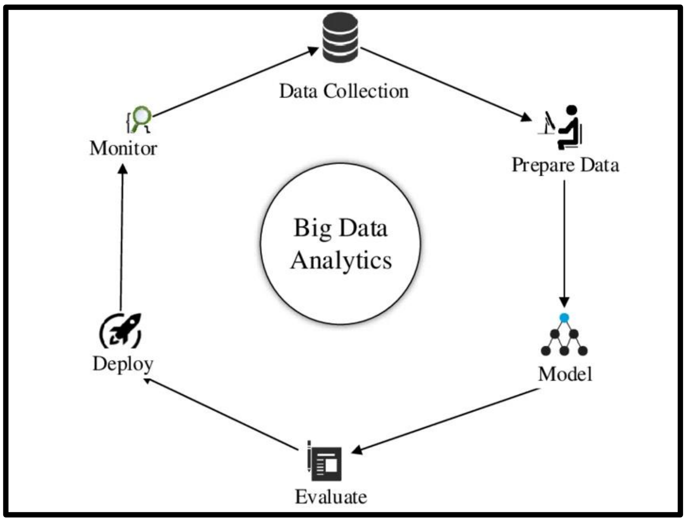

Figure_4: Big data analytics
(Source: https://www.researchgate.net/figure/Big-Data-Analytics-Process-Data-Preparation-The-most-important-stage-of-big-data_fig1_303216930)

Interpretation of Findings
The results of this study corroborate customer retention theory, showing that customer satisfaction, service quality, pricing and customisation are critical factors in driving customer loyalty and customer churn behaviour. Businesses that meet customers' expectations and give them positive shopping experiences will make an effort to keep them satisfied, and they are more likely to stay loyal to the business. The findings also validate the relationships between customer retention and relationship management and longer-term customer engagement strategies.

The study also shows that predictive analytics and machine learning technologies boost business performance. The implementation of big data analytics and ML technologies can help minimize customer attrition and enhance operational efficiency. The findings thus underscore the potential of predictive analytics for bolstering customer retention and ensuring a competitive edge in global e-commerce.

V. DISCUSSION

Discussion of Customer Churn Theory
The basis of relationship marketing theory is that companies having good relationships with customers decrease the chance of customers churning. These findings corroborate this theory, as customers' loyalty was maintained when they received personalized communication, quality service and supportive communication systems. Another important aspect of the customer lifetime value theory is that it emphasizes the selling and retention of profitable customers over time. By using

International Journal of Scientific Research & Engineering Trends
Volume 11, Issue 3, May-Jun-2025, ISSN (Online): 2395-566X

predictive analytics, businesses can identify their most valuable customers and use retention strategies to ensure maximum profitability over time (Feng et al. 2024). Consumer behaviour theory also sheds light on the impact of buying behaviour, level of satisfaction and digital experience on customer loyalty. The research results indicate that the price, service quality, delivery performance and customised online experience are key factors that significantly influence customer behaviour.

Discussion of Predictive Analytics

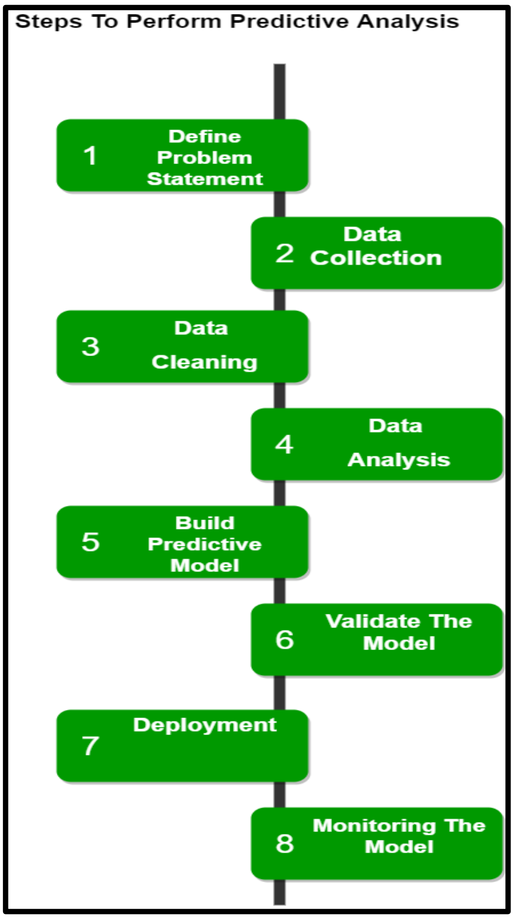

Figure _5: Predictive Analytics

(Source: https://www.geeksforgeeks.org/machine-learning/step-by-step-predictive-analysis-machine-learning/)

Predictive analytics is vital for determining the likelihood that the customer might churn out of the e-commerce platforms even before that. Early detection of churn enables companies to take prompt action, such as offering targeted promotions, loyalty incentives, and enhanced customer service. The results demonstrate that machine learning models can be used to gain insights into customer behaviour patterns and more effectively predict consumer dissatisfaction in an organisation. In international business, predictive analytics offers strategic benefits, such as facilitating data-driven decision-making and enhancing competitive edge (Ji et al. 2024). Predictive technologies can help enterprises learn about their customers' preferences in global markets and fine-tune strategies for customer retention. In global e-commerce, predictive analytics can help bolster operational efficiency, customer engagement, and long-term profitability.

Comparison with Previous Studies

The results of this study corroborate earlier studies that have found key drivers of customer churn to be customer satisfaction, service quality, and personalised experiences. Other research studies also showed the benefits of machine learning models in improving prediction accuracy and in providing proactive customer retention strategies. The excellent results obtained by the models Random Forest and Neural Network are compatible with other works that have been carried out previously, reporting their success in handling elaborate customer behaviors (Chang et al. 2023). This research paper, however, focuses on another aspect of international e-commerce, which is getting more and more vital, namely, real-time big data analytics, while some previous research papers highlight only other aspects. In contrast to the traditional solutions, the results show how predictive monitoring and behavioural analysis boost customer engagement and retention results.

Business Implications

The results of this study offer significant implications for international e-commerce companies aiming to boost client satisfaction and sustain their long-term profitability. Through machine learning and predictive analytics, organisations can predict customer churn and take proactive measures to stop it. By leveraging customer data, businesses can create targeted marketing campaigns that cater to individual preferences, purchase history, and other engagement patterns, further enhancing customer satisfaction and loyalty. In addition, predictive technologies are cost-effective for customer acquisition; retaining customers is far more cost-effective than acquiring customers (Ji et al. 2024). Additionally, data-driven insights aid in making informed management decisions, optimizing marketing strategies, enhancing service quality, and promoting general operational efficiency in competitive global markets.

Challenges in Machine Learning-Based Churn Prediction

While machine learning is increasingly becoming a key factor in predicting customer churn, it is clear that there are some challenges that come with effective and reliable predictive systems in e-commerce. Data quality problems are a key limitation. Accurate, complete and consistent datasets are crucial for machine learning models to operate. Many times, the data about the customer might include missing values, duplicate customer information, or even incorrect data, which affect the accuracy of the prediction and can result in false outcomes.

Another key challenge is algorithm bias. If the data doesn't fairly mirror all customers, machine learning systems can forecast inaccurately. Issues relating to privacy also pose challenges when trying to predict churn since customer data may contain personal and behavioral information. Below, let's examine how data protection laws apply to businesses and the importance of responsible business data use to uphold the trust and ethical practices of their customers.

Besides this, machine learning churn prediction needs superior technical infrastructure and high computational resources. It takes technical expertise to process all customer data and perform complex algorithms, robust computing power and ongoing investment in technology. These hurdles can also add to the running expenses of small and medium-sized businesses, especially eCommerce.

Recommendations

Businesses can leverage AI-driven CRM systems to boost customer retention and predictive decision-making, leading to improved outcomes in e-commerce. AI tools can more intelligently understand customer behavior, automate customized communication, and predict customer churn more effectively. Real-time predictive monitoring tools should also be put in place to monitor the activities of their customers in real time and identify their level of dissatisfaction early. The importance of ethical AI governance for customer privacy, transparency, and responsible use of predictive technologies is also crucial. Businesses need to set data protection policies and refrain from making decisions that may be biased by data. Furthermore, having a continuous approach towards customers should be taken by the companies to build long-term customer relationships.

Future Research Directions

In order to make better predictions and analyze behaviours, more advanced neural network models for predicting customer churn should be explored in the future. Cross-border e-commerce behaviour can also be explored, as this can yield insights into the impact of cultural, economic, and regional differences on customer retention in overseas markets. Real-time big data ecosystems that combine the interactions of consumers across digital channels are another key focus for future research. Such solutions can help to better predict the problem and assist businesses in making quick decisions to combat churn threats. Ethical implications of the use of AI in predictive analytics and customer data handling practices should also be explored in future research.

REFERENCES

1. Chang, V., Xu, Q. A., Hall, K., Wang, Y. A., & Kamal, M. M. (2023). Digitalization in omnichannel healthcare supply chain businesses: The role of smart wearable devices. Journal of Business Research, 156, 113369. https://www.sciencedirect.com/science/article/pii/S0148296322008347
2. Chatzipanagiotou, K., Azer, J., & Ranaweera, C. (2023). E-WOM in the B2B context: Conceptual domain, forms, and implications for research. Journal of Business Research, 164, 113957. https://eprints.gla.ac.uk/296708/4/296708.pdf
3. Feng, Y., Yin, Y., Wang, D., Ignatius, J., Cheng, T. C. E., Marra, M., & Guo, Y. (2024). Enhancing e-commerce customer churn management with a profit-and AUC-focused prescriptive analytics approach. Journal of Business Research, 184, 114872. https://publications.aston.ac.uk/id/eprint/46589/1/enhancing_ecommerce_customer_churn_management_ignatius.pdf
4. Graham, B., & Bonner, K. (2024). The role of institutions in early-stage entrepreneurship: An explainable artificial intelligence approach. Journal of business research, 175, 114567. https://www.sciencedirect.com/science/article/pii/S0148296324000717
5. Hossain, M. A., Akter, S., Yanamandram, V., & Strong, C. (2024). Navigating the platform economy: Crafting a customer analytics capability instrument. Journal of Business Research, 170, 114260. https://www.sciencedirect.com/science/article/pii/S0148296323006197
6. Ji, E., Rahman, S. M., Wilden, R., Lin, N., & Harrison, N. (2024). Leveraging customer knowledge obtained through social media: The roles of R&D intensity and absorptive capacity. Journal of Business Research, 182, 114811. https://www.sciencedirect.com/science/article/pii/S0148296324003151
7. Kamal, M. M., Mamat, R., Mangla, S. K., Kumar, P., Despoudi, S., Dora, M., & Tjahjono, B. (2022). Immediate return in circular economy: Business to consumer product return information sharing framework to support sustainable manufacturing in small and medium enterprises. Journal of Business Research, 151, 379-396. https://www.sciencedirect.com/science/article/pii/S0148296322005537
8. Lim, W. M., Rasul, T., Kumar, S., & Ala, M. (2022). Past, present, and future of customer engagement. Journal of business research, 140, 439-458. https://www.sciencedirect.com/science/article/pii/S0148296321008213
9. Loutfi, A. A. (2022). A framework for evaluating the business deployability of digital footprint based models for consumer credit. Journal of Business Research, 152, 473-

486. https://www.sciencedirect.com/science/article/pii/S0148296322006683

10. Ma, R., Mao, D., Cao, D., Luo, S., Gupta, S., & Wang, Y. (2024). From vineyard to table: uncovering wine quality for sales management through machine learning. Journal of Business Research, 176, 114576. https://eprints.whiterose.ac.uk/209967/1/Wine_JBR_Final.pdf
11. Perez-Vega, R., Hopkinson, P., Singhal, A., & Mariani, M. M. (2022). From CRM to social CRM: A bibliometric review and research agenda for consumer research. Journal of Business Research, 151, 1-16. https://www.sciencedirect.com/science/article/pii/S0148296322005665
12. Rengarajan, S., Narayanamurthy, G., Moser, R., & Pereira, V. (2022). Data strategies for global value chains: Hybridization of small and big data in the aftermath of COVID-19. Journal of Business Research, 144, 776-787. https://www.sciencedirect.com/science/article/pii/S014829632200162X
13. Roy, S. K., Tehrani, A. N., Pandit, A., Apostolidis, C., & Ray, S. (2025). AI-capable relationship marketing: Shaping the future of customer relationships. Journal of Business Research, 192, 115309. https://www.sciencedirect.com/science/article/pii/S0148296325001328
14. Shepherd, N. G., Lou, B., & Rudd, J. M. (2024). Going with the gut: Exploring top management team intuition in strategic decision-making. Journal of Business Research, 181, 114740. https://www.sciencedirect.com/science/article/pii/S0148296324002443
15. Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. Journal of business research, 122, 889-901. https://www.sciencedirect.com/science/article/pii/S0148296319305478
16. Weerakkody, V., Sivarajah, U., Mahroof, K., Maruyama, T., & Lu, S. (2021). Influencing subjective well-being for business and sustainable development using big data and predictive regression analysis. Journal of business research, 131, 520-538. https://www.sciencedirect.com/science/article/pii/S0148296320304860