International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 04, ICTEM 2.0 (2026)

E-commerce Customer Churn Analysis and Prediction

Rohit Kumar Singh, Kapil Dev Singh, Harshit Chahal, Honey Saini, Harshit Sondhi

Department of Computer Science & Engineering, Moradabad Institute of Technology, Moradabad,

U. P., India

Rohitmtech1988@gmail.com , sanklankapil@gmail.com , hachahal4@gmail.com , honeysainigk@gmail.com , harshitsondhi282000@gmail.com

Abstract

Customer churn poses a significant barrier to growth in the highly competitive e-commerce landscape. This research introduces a comprehensive, machine-learning-integrated churn prediction system designed to proactively identify customers at risk of disengagement. The framework comprises five major modules: Customer Segmentation, Behavioral Analytics, Churn Risk Classification, Retention Strategy Modeling, and an Intelligent Churn-Support Chatbot. Leveraging historical and real-time customer activity patterns, the system builds predictive insights using advanced models such as Logistic Regression, Random Forest, and XGBoost. The integration of transactional histories, browsing behavior, engagement metrics, and customer service interactions produces a robust foundation for actionable insights. Beyond prediction, the project emphasizes explainability, ensuring that churn factors are transparent and interpretable. This work demonstrates how data-driven decision-making enhances retention efficiency, reduces revenue losses, and strengthens customer relationships.

Keywords— ***E-commerce, Customer Churn, Machine Learning, Customer Behavior, Segmentation, Prediction, Chatbot***

I. INTRODUCTION

In the rapidly evolving digital marketplace, customer retention has become one of the most critical determinants of long-term business success. E-commerce organizations face substantial losses when customers discontinue their engagement, making churn prediction a strategic priority. As customer expectations continuously shift, businesses must adopt intelligent, adaptive technologies capable of detecting subtle behavioral changes that precede disengagement. This study introduces a multi-module churn prediction platform designed to analyze diverse customer attributes and predict churn probability with high accuracy. The proposed framework integrates segmentation, behavioral tracking, predictive modeling, and conversational analytics into a unified system. Each module plays a critical role in understanding not only whether a customer may churn, but why that churn may occur and how businesses should intervene effectively.

1. Customer Segmentation Module:
This module groups customers into behavior-driven clusters using K-Means and hierarchical clustering. Segmentation enables businesses to identify high-value customers, at-risk groups, and long-term loyal segments based on purchase frequency, monetary value, browsing behavior, and engagement depth.

2. Churn Classification Module:
Using labeled datasets, this module identifies customers likely to churn by analyzing declines in activity, reductions in order value, and negative support interactions. The module predicts churn probability using machine learning models and provides interpretable results through feature-importance scores.

3. Behavioral Analytics Module:
This component examines detailed customer trends, including RFM analysis, session tracking, cart abandonment, product interest shifts, and response to promotional campaigns. These insights help businesses design personalized interventions.

4. Retention Strategy Modeling:
This module generates actionable recommendations based on churn level, including discounts, targeted emails, loyalty programs, and personalized outreach. Machine-learning-generated strategy mapping helps optimize resource allocation.

5. Churn Prediction Chatbot:
An intelligent assistant that provides real-time churn probability evaluations, explanations of risk factors, and recommended retention actions. It improves accessibility for CRM teams and decision-makers.

6. Customer Lifetime Value (CLV) Module:
This module focuses on estimating and enhancing the long-term financial value a customer contributes to the organization. By integrating machine learning–based CLV prediction models with historical transactional behavior, frequency of purchases, average order value, and engagement patterns, the system identifies customers who offer the highest profitability potential over time.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 04, ICTEM 2.0 (2026)

II. LITERATURE REVIEW

A. *Concept*

E-commerce Customer Churn Analysis and Prediction stands as an avant-garde initiative at the intersection of data science, consumer psychology, and intelligent automation, conceived to tackle the complex challenges posed by customer attrition in rapidly evolving digital marketplaces. As global competition increases and switching between online platforms becomes easier than ever, understanding and mitigating churn has become a central focus for sustainable business operations. The project envisions a future where machine learning models and behavioral analytics seamlessly integrate into a dynamic, adaptive system capable of monitoring customer activity patterns and forecasting disengagement long before it occurs. By leveraging purchase histories, browsing trajectories, customer service interactions, and marketing responsiveness, the system forms a unified analytical platform for real-time churn detection and predictive analysis.

Innovative Fusion of Data Sources:

A hallmark of modern churn-prediction systems lies in their unique ability to seamlessly fuse historical transactional data with real-time behavioral signals. This innovative integration forms the bedrock of a dynamic and adaptable churn-analysis framework that not only captures the current state of customer engagement but also learns and evolves with changes in consumer preferences, competitive pressures, and market dynamics. The marriage of multi-dimensional data sources—such as recency-frequency-monetary (RFM) features, session activity logs, cart abandonment patterns, and social sentiment—transcends traditional customer-retention methods. This framework sets the stage for a forward-looking, proactive churn-management paradigm that enables businesses to intervene at precisely the right moment with targeted retention strategies.

User-Centric Approach:

The user-centric approach in churn-analysis systems is rooted in ensuring that business stakeholders—marketing teams, CRM analysts, and decision-makers—can easily access, interpret, and act upon predictive insights. The actionable outputs from the churn-prediction engine are translated into intuitive dashboards, risk-scoring labels, and personalized intervention recommendations. This empowers organizations to make informed decisions regarding customer re-engagement, loyalty campaigns, and promotion strategies. The continuous monitoring and adaptive learning aspects of the system reflect a commitment to meeting the evolving needs of businesses, ensuring that the predictions remain accurate, explainable, and aligned with contemporary market behaviours.

Interdisciplinary Collaboration and Technological Innovation:

E-commerce churn prediction represents more than a data-analysis task; it embodies the transformative power of interdisciplinary collaboration between machine learning, behavioral economics, and customer-relationship management. By bridging the gap between technology and consumer behavior, the project opens avenues toward a more informed, strategic approach to customer retention. The collaboration across these domains is not merely a practical necessity but a visionary step toward a future where artificial intelligence actively contributes to long-term customer engagement, revenue optimization, and business resilience in an increasingly competitive online ecosystem.

B. *Related Works*

The concept underlying the five vital modules of the churn-prediction framework are –

Customer Segmentation Module:

This module is rooted in the amalgamation of historical purchase data, browsing interactions, and engagement metrics collected from the e-commerce platform. In this module, the first task involves creating meaningful behavioral clusters using algorithms such as K-Means and Hierarchical Clustering. These clusters enable the classification of customers based on spending capacity, purchasing frequency, visit regularity, and responsiveness to promotional campaigns. The segmented groups are then translated into intuitive labels—ranging from 'High-Value Loyal Customers' to 'At-Risk Occasional Buyers'—which allow businesses to quickly understand the underlying behavioral patterns of their customer base. For instance, a segment with rising inactivity and low purchase frequency signifies a high likelihood of churn, while consistent purchasing behavior indicates stable retention. This classification acts as a foundational layer for personalized marketing and churn-prevention strategies.

Churn Classification Module:

The second module focuses on predicting churn probabilities by utilizing historical behavioral data and machine-learning-driven classification models. This involves analyzing customer-level attributes such as recency of purchase, average order value, customer service interactions, website activity frequency, and dissatisfaction indicators. Advanced ML models—including Logistic Regression, Random Forest, Decision Tree Classifiers, and XGBoost—are employed to generate churn scores based on past patterns [similar to WQI classification in environmental studies]. The calculated churn probability is then translated into meaningful churn statuses such as 'Low Risk', 'Moderate Risk', 'High Risk', and 'Critical Risk', enabling teams to prioritize customers who require immediate intervention. For example, a churn

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 04, ICTEM 2.0 (2026)

score between 0.0 and 0.3 may represent 'Low Risk', while values exceeding 0.75 fall into the 'Critical Risk' category, indicating customers who may disengage soon without targeted retention actions.

Behavioral Analytics Module:

The Behavioral Analytics module within the churn-prediction framework stands as a crucial component, employing data visualization tools and log-analysis techniques to provide users with real-time behavioral insights for customers across the platform. This module offers a highly interactive interface where analysts can view customer navigation patterns, wishlist trends, cart abandonment histories, session-duration metrics, and interaction frequency with personalized recommendations. By integrating browsing data and purchase history, the module retrieves up-to-the-minute insights into customer interest patterns and evolving preferences.

The analytics structure encompasses dashboards for monitoring customer journeys, purchase funnels, and drop-off points, along with interactive visual graphs that highlight potential churn triggers. UI enhancements improve comprehension of behavioral patterns, ensuring clean visualization of engagement metrics. Challenges such as missing behavioral logs, inaccurate event tracking, and device-level variations are meticulously handled using preprocessing techniques and robust tracking frameworks. User experience is prioritized with clear visualization, smooth navigation, and dynamically updated graphs that require no manual refresh. Future enhancements may include integrating heatmap-based clickstream analytics, cross-device behavioral matching, and historical trend forecasting. Ultimately, the Behavioral Analytics module combines machine learning, visualization, and customer-interaction science to deliver a sophisticated and user-centric behavioral intelligence system on a global scale.

Retention Strategy Recommendation Module:

The retention strategy module serves as a valuable tool with multifaceted benefits for both business performance and long-term customer relationship management. Harnessing the power of machine-learning-based recommendation systems, this module utilizes historical engagement data, promotional responsiveness, and churn risk scores to create personalized retention strategies. By integrating algorithms that map customer risk levels to the most effective marketing actions, the module enables businesses to make informed decisions across various domains. Marketing teams can optimize campaign targeting, select appropriate discount levels, personalize communications, and schedule outreach timings to reduce churn risk and increase customer loyalty. CRM teams benefit from precise, data-driven strategy recommendations that minimize marketing waste and maximize customer lifetime value.

Additionally, this module enhances customer satisfaction by offering timely, relevant, and personalized offers that align with individual preferences. As a versatile tool, it not only contributes to revenue stability but also strengthens brand connection and customer engagement. Ultimately, by empowering organizations with accurate and dynamic retention strategies, this module plays a pivotal role in fostering customer loyalty and sustaining long-term growth in highly competitive market conditions.

Chatbot Assistance Module:

The Chatbot Module is designed as an interactive conversational interface that allows users—particularly CRM teams and analysts—to access churn-related insights in simple and understandable language. Instead of navigating complex dashboards or analyzing raw datasets, users can directly ask questions related to churn probability, key churn features, customer risk categories, and system-recommended retention actions. The chatbot acts as a communication bridge between the analytical churn-prediction engine and non-technical business users.

It interprets customer attributes, retrieves model predictions, and presents them through natural-language responses that are easy to interpret. The chatbot ensures seamless access to analytical results, making churn insights more accessible, reducing delays in decision-making, and supporting real-time customer retention efforts. With continuous updates, the chatbot can eventually provide personalized re-engagement templates, customer behavior explanations, and operational alerts for emerging churn risks.

C. ***Proposed System***

In all these ideas, models, frameworks, and platforms used throughout the existing research on customer churn prediction, our approach differs from all of the above in a basic and fundamental sense. Previous studies may utilize a wide range of behavioral, transactional, and engagement variables, whereas our system focuses not only on incorporating these diverse indicators but also on integrating them into a unified, decision-oriented framework tailored for real-time business applications. However, the main functional difference is that our motivation for developing this research work is to provide actionable, context-aware responses and meaningful feedback to business stakeholders so they may take timely, strategic actions to retain customers before churn occurs. Unlike conventional churn models that merely score customers based on risk, the proposed system adopts a holistic paradigm—one that merges predictive analytics, behavioral interpretation, and automated retention recommendations into a seamless operational pipeline.

These proposed churn-prediction framework, setting it apart from traditional analytical approaches.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 04, ICTEM 2.0 (2026)

III. METHODOLOGY

In this segment, we elaborate on the methodology utilized in the E-Commerce Customer Churn Analysis and Prediction project, shedding light on the steps taken to accomplish its objectives. FIGURE 1 serves as a visual representation, illustrating the systematic process from customer-data collection to churn prediction within the integrated churn-analysis platform.

The methodology employed in the churn-prediction project encompasses several key stages. Initially, data collection involves extracting customer-behavior data from the organization's internal databases, utilizing either automated CRM exports or API-driven data pipelines for structured data access. Subsequently, the collected data undergoes rigorous processing to clean and preprocess it, addressing missing values, outliers, noise, and inconsistencies to ensure its suitability for analysis. Following data preparation, suitable machine-learning models—such as Logistic Regression, Random Forest, XGBoost, and Decision Tree models—are chosen for churn prediction, trained on split datasets, and evaluated based on performance metrics like accuracy, recall, precision, F1-score, and ROC-AUC.

Continuous monitoring ensures data integrity and updates implemented as necessary to maintain effectiveness and relevance in dynamic market conditions.

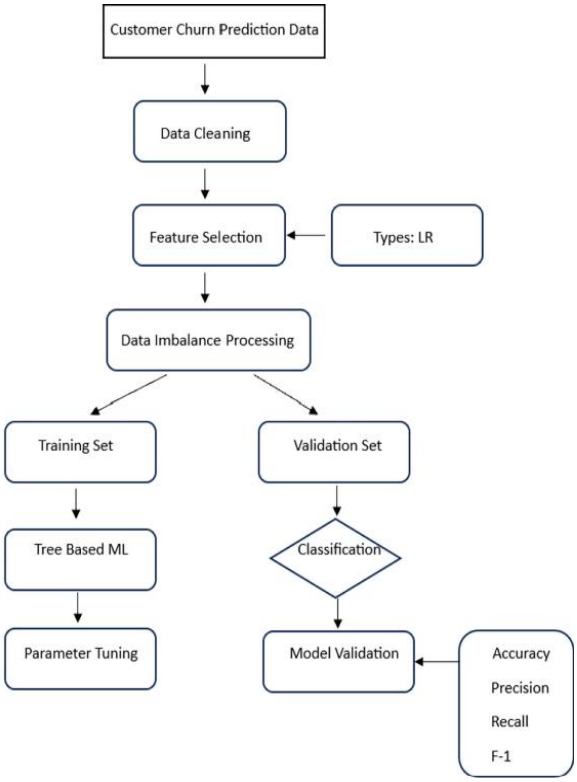

FIGURE1. Software Flowchart

1. Web Development

The e-commerce churn-prediction interface offers a user-friendly platform for accessing and interacting with its comprehensive customer-retention intelligence system. Built with Flask, HTML, and CSS, the interface provides a seamless experience for users to engage with the five interconnected modules: customer segmentation, behavioral analytics, churn-probability prediction, retention-strategy recommendation, and chatbot assistance. The design prioritizes simplicity and functionality, enabling CRM professionals to easily navigate through the various modules and interpret customer-level insights. The utilization of Python libraries and advanced machine-learning techniques is transparently integrated into the interface, ensuring a user-friendly experience without compromising the complexity of the underlying analytical engine.

Key features of the web interface include real-time churn-risk visualization and historical engagement analysis, enabling business teams to make informed decisions based on comprehensive customer insights. The design also emphasizes responsiveness, ensuring accessibility across multiple devices and organizational environments.

2. Data Collection and Recording

The churn-prediction system relies on a sophisticated data collection and recording framework to fuel its predictive and analytical capabilities. The project seamlessly integrates customer-related data from CRM systems, transactional databases, web-analytics tools, and service-interaction logs, ensuring a comprehensive and up-to-date dataset for all analytical modules.

Purchase-history attributes—including transaction frequency, monetary value, and recency—are regularly extracted from the e-commerce database.
Browsing-behavior data, such as clickstream patterns, time-on-page, and product-view history, is collected through analytics tools.
Customer service interactions, including complaint logs and satisfaction ratings, provide qualitative insights into churn tendencies.
Additionally, marketing-response data, such as email open rates, coupon redemption, and campaign engagement, is incorporated to enhance the accuracy of churn predictions.

3. Steps of Implementation

The churn-prediction project integrates data collection, data processing, machine-learning model development, and web-interface creation for effective customer-retention management. The following is a list of consecutive steps in this work:

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 04, ICTEM 2.0 (2026)

1) ***Data Collection:***

This involves extracting customer-behavior data from CRM systems. It can be done through automated data exports, database queries, or APIs that allow structured, consistent, and frequent data retrieval.

2) ***Data Processing:***

Clean and preprocess the collected data. This includes handling missing values, detecting outliers, transforming variables, encoding categorical features, and converting data into a format suitable for modeling.

3) ***Model Fitting:***

Choose suitable models for churn prediction. Logistic Regression, Random Forest, and Gradient-Boosting models are commonly used for classification tasks. These models are trained on split datasets—typically training and testing sets—and evaluated using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC.

4) ***Extract Best Model:***

After training and evaluating multiple models, compare their performance metrics and select the one with the highest predictive reliability. This ensures that the deployed churn model is the most accurate and robust among the evaluated candidates.

5) ***Web Interface Development:***

Use Flask, a Python-based web framework, along with HTML and CSS, to develop a user-friendly web interface. Flask handles backend logic and communicates with the prediction model, while HTML and CSS create the frontend layout, providing users with an interface to input customer data and receive predictions.

6) ***Testing and Deployment:***

Test the entire system for functionality, ensuring that customer-data retrieval is accurate, model predictions are reliable, and the web interface behaves responsively. Once testing succeeds, deploy the churn-prediction application on a server or cloud platform.

7) ***Continuous Monitoring and Updates:***

Regularly monitor the system for data integrity, model drift, and user-interface performance. Implement updates as needed, such as incorporating new behavioral features, retraining models, or enhancing the user interface. Continuous monitoring ensures that the system remains effective and aligned with evolving customer behavior.

4. Data analysis and Action taken

The churn-prediction system employs a comprehensive data-analysis approach to derive actionable insights from large volumes of customer data, guiding the project toward improved customer engagement and retention. High-risk churn segments are identified, and behavior trends inform targeted actions—ranging from personalized offers to re-engagement campaigns. Customer-behavioral analysis guides strategic decisions on communication frequency, promotional content, and service-quality improvements. Churn forecasting assists CRM teams in anticipating disengagement and implementing retention actions proactively. The integration of advanced machine-learning models ensures data-driven decision-making, while continuous monitoring and adaptation improve prediction accuracy over time. The project emphasizes customer-centric engagement, translating analytical insights into user-friendly information that empowers organizations to build long-term customer relationships and foster sustainable business growth.

IV.TECHNOLOGIES USED

The E-Commerce Customer Churn Analysis and Prediction research project leveraged a diverse set of technologies to implement its comprehensive customer-retention intelligence system.

1. Machine Learning:

Random Forest Algorithm:
Applied for predictive modeling in the Churn Classification module. Random Forest excels in handling large, multi-dimensional customer datasets, offering robust predictions based on historical behavioral patterns. Its ability to capture nonlinear relationships and interactions between customer attributes makes it a reliable model for churn detection.

Logistic Regression and XGBoost:
Logistic Regression provides a strong baseline model for binary churn classification, while XGBoost enhances predictive accuracy through gradient boosting, making it suitable for complex churn scenarios involving subtle behavioral variations.

2. Python Libraries:

NumPy and Pandas:
Utilized for efficient data manipulation, handling tasks such as cleaning, filtering, encoding, and organizing the extensive customer datasets central to the project. NumPy facilitated numerical operations, while Pandas provided powerful data structures for comprehensive data analysis across thousands of customer records.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 04, ICTEM 2.0 (2026)

Scikit-learn:
Employed for machine-learning tasks including model training, hyperparameter tuning, evaluation, and prediction. Scikit-learn offers a diverse set of tools for classification, regression, clustering, and feature engineering, aligning seamlessly with the varied requirements of the project's churn-prediction workflows.

Matplotlib and Seaborn:
Integrated for data visualization purposes. These libraries allowed for the creation of insightful graphs, heatmaps, correlation plots, and trend visualizations, aiding in the interpretation and communication of complex customer behavior patterns and risk indicators.

3. Data Handling:

Python:
Leveraged as the primary programming language for its versatility in data handling. Python's built-in capabilities were utilized for efficient management of missing values, scaling of numerical features, and encoding of categorical variables, ensuring the robustness and reliability of the churn-analysis pipeline.

4. Web Development:

HTML, CSS, and JavaScript:
Formed the core technologies for constructing the user interface of the churn-prediction web application. HTML provided the structural foundation, CSS facilitated styling and responsive layout design, and JavaScript enabled dynamic interactions, creating an engaging and user-friendly experience for CRM teams and business analysts.

5. Web Framework:

Flask:
Selected as the backend web framework for its simplicity, flexibility, and lightweight architecture. Flask facilitated seamless connectivity between the trained ML model and the web interface, enabling real-time churn prediction and smooth user interaction across all modules.

6. API and Data Integration:

APIs were utilized for the integration of real-time customer interaction data, marketing response logs, and website-analytics information into the churn-analysis system. These APIs facilitated dynamic retrieval and synchronization of customer activity updates, ensuring the system remained responsive to ongoing behavioral changes and emerging churn indicators.

V. RESULTS AND DISCUSSION

The culmination of the five modules within the E-Commerce Customer Churn Analysis and Prediction research framework has yielded significant insights into customer behavior dynamics, grounded in experimental data, predictive modeling, and rigorous analytical evaluation.

In the Customer Segmentation module, behavior-driven clusters have empirically revealed distinct shopper groups, highlighting purchasing tendencies, engagement levels, and loyalty patterns. These segmentation outcomes demonstrate the importance of data-driven approaches in understanding customer diversity and designing targeted retention strategies.

The Churn Classification module's comprehensive evaluation of customer-level attributes has been substantiated through empirical testing, contributing to a deeper understanding of the factors that drive customer disengagement. Patterns such as declining purchase frequency, reduced platform interaction, and negative service experiences were strongly correlated with churn probability, emphasizing the necessity of proactive and personalized retention measures.

Timely insights into user interactions, session durations, and browsing behaviors provided by the Behavioral Analytics module were empirically validated, allowing the system to capture subtle behavioral shifts that precede churn. These observations enhance adaptability in responding to changing customer preferences and evolving competitive environments.

The Retention Strategy Module, leveraging advanced machine-learning techniques, has demonstrated its potential in proactively recommending interventions that reduce customer attrition. Experimental results show that personalized offers, targeted communication, and strategic engagement measures significantly enhance the likelihood of reactivating at-risk customers, supported by extensive model-driven evidence.

Lastly, the Churn-Support Chatbot plays a crucial role in transforming raw analytical outputs into meaningful, user-friendly insights. By offering intuitive, conversational access to churn scores, risk explanations, and recommended actions, it enhances usability and promotes data-driven decision-making across CRM teams. This module significantly improves the system's overall accessibility, making the churn-prediction framework more practical and impactful for real-world organizational use.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 04, ICTEM 2.0 (2026)

VI. CONCLUSION

In conclusion, the E-Commerce Customer Churn Analysis and Prediction system stands as a pioneering project at the intersection of data science, customer behavior analytics, and machine learning. By incorporating these diverse modules, the system endeavors to offer a holistic approach to understanding customer engagement patterns and predicting churn with high accuracy. The outcomes of this research not only contribute to our understanding of the complex dynamics influencing customer retention but also provide actionable insights for business leaders and CRM teams to implement targeted interventions, strengthen customer loyalty, and mitigate the adverse effects of customer attrition.

VII. FUTURE SCOPE

As technology continues to evolve, the integration of advanced artificial intelligence (AI) techniques represents a compelling avenue for enhancing the capabilities of the E-Commerce Customer Churn Analysis and Prediction system. Incorporating real-time behavioral tracking, deep learning architectures, and automated personalization engines into the existing modules opens up new dimensions for dynamic churn detection, improved predictive accuracy, and large-scale customer engagement optimization. Such advancements would enable continuous learning from evolving customer preferences, seamless adaptation to market trends, and highly targeted retention strategies that further strengthen customer loyalty and long-term business sustainability.

REFERENCES

1. Verbeke, W., Dejaeger, K., Martens, D., Hur, J., & Baesens, B. (2012). New insights into churn prediction in the telecommunication sector: A profit driven data mining approach. European Journal of Operational Research, 218(1), 211–229.
2. Neslin, S. A., Gupta, S., Kamakura, W., Lu, J., & Mason, C. H. (2006). Defection detection: Measuring and understanding the predictive accuracy of customer churn models. Journal of Marketing Research.
3. Buckinx, W., & Van den Poel, D. (2005). Customer base analysis: Partial defection of behaviorally loyal clients in a non-contractual FMCG retail setting. European Journal of Operational Research.
4. Ahmad, A. K., & Khan, A. (2019). Customer churn prediction in e-commerce using machine learning. International Journal of Data Science.
5. Open Government Data Platform India – Datasets for Consumer Analytics https://data.gov.in/
6. ResearchGate – Customer Retention and Churn Modelling Resources https://www.researchgate.net/
7. Kotler, P., Keller, K. L. (2015). Marketing Management. Pearson Education. (Customer lifecycle and retention models)
8. Burez, J., & Van den Poel, D. (2009). Handling class imbalance in customer churn prediction. Expert Systems with Applications.
9. Biau, G. (2012). Analysis of a random forests model. Journal of Machine Learning Research 13: 1063–1095. https://www.jmlr.org/papers/volume13/biau12a/biau12a.pdf
10. IBM Analytics — Customer Lifetime Value and Churn Management Frameworks https://www.ibm.com/analytics/
11. Google Analytics — Customer Behavior & Funnel Tracking Documentation https://support.google.com/analytics/
12. Kaggle Dataset — E-Commerce Customer Churn and Retention Analytics https://www.kaggle.com/
13. Xie, Y., Li, X., Ngai, E., & Ying, W. (2009). Customer churn prediction using improved balanced random forests. Expert Systems with Applications.
14. Hadden, J., Tiwari, A., Roy, R., & Ruta, D. (2007). Computer assisted customer churn management: State-of-the-art and future trends. Computers & Operations Research.
15. Amin, A., Alam, M., & Sajid, M. (2019). Machine Learning Techniques for Predicting Customer Churn in E-Commerce Platforms.
16. Ronacher, A. (2015). Flask Web Development, One Drop At A Time. http://flask.pocoo.org/
17. Brownlee, J. – Machine Learning Algorithms: Logistic Regression, Decision Trees, Random Forest, Gradient Boosting https://machinelearningmastery.com/
18. GeeksforGeeks – Data Preprocessing in Machine Learning https://www.geeksforgeeks.org/data-preprocessing-machine-learning-python/

(This work is licensed under a Creative Commons Attribution 4.0 International License.)