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Customer Churn Prediction and Analytics for Subscription-based Services

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Abstract: Customer churn is one of the biggest challenges that any subscription-based service provider has to face, as it directly affects the stability of revenue and long-term growth. This paper presents the design of a data-driven churn prediction and analytics system using machine learning with statistical modeling. The proposed system analyzes customer behavior, subscription history, usage patterns, payment behavior, and service interactions to predict which customers are highly likely to churn. The model applies a variety of different data analytics techniques, including but not limited to exploratory data analysis, feature engineering, predictive modeling comprising Logistic Regression, Random Forest, and XGBoost, and customer segmentation, to provide strategic insights useful in retention strategy. This in turn shall help in making necessary proactive decisions toward reduction of churn rate and thereby enhancing CLV.

Keywords: Customer Churn Prediction, Machine Learning, Predictive Modeling, Customer Segmentation, Customer Lifetime Value.

1 INTRODUCTION

Customer churn is one of the most important challenges subscription-based service providers have to deal with in today's competitive digital marketplace. Subscription services, ranging from streaming and SaaS applications to telecom operators, e-learning portals, and digital content providers, have placed customer retention as a priority issue on par with acquiring new subscribers. Churn is not only considered a loss to regular revenues but also causes disruption to growth projections and heightens the cost burden on securing new customers [1]. A number of studies have suggested that acquiring a new customer can be anywhere between five to seven times more costly compared to retaining an existing customer. Thus, for the sake of business sustainability and long-term profitability, it is vital to comprehend the reasons behind customers' preference to leave and be able to identify them early. In essence, customer churn prediction models are proactive mechanisms that help an organization intervene before the customer leaves the ecosystem.

The evolution of gathering data and interacting digitally has equipped companies not only with subscription history but also with payment behavior, product usage patterns, and multiple customer support interactions as a basis for gathering large volumes of customer-centric data. This has opened avenues to undertake more advanced analytics and machine learning approaches for uncovering hidden patterns linked to churn behavior. Unlike traditional manual analysis, machine learning models are able to grasp complex nonlinear relationships between behavioral, transactional, and demographic features. It is this capability of learning from multidimensional data that makes machine learning an ideal tool for real-time churn prediction. With continuously increasing customer expectations, data-driven churn prediction has emerged as a strategic priority for organizations on the path to delivering personalized experiences and sustaining competitive advantage [2].

The aim of the research is to design and develop an intelligent churn prediction and analytics system based on statistical modeling, machine learning algorithms, and EDA for pinpointing customers with a high risk of churning. Such a system will analyze several customer attributes like subscription time, type of plan, renewal patterns, frequency of service usage, number and type of support tickets, customer satisfaction ratings, and payment history to determine which factors most lead to customer attrition. Predictive modeling techniques in estimating the probability of churn in every customer will include methods such as Logistic Regression, Random Forest, GBM, and XGBoost. The output of the model will enable the business to take immediate retention action through targeted marketing campaigns, personalized incentives, improved engagement of customers with service, or adjustment of subscription plans.

A very important aspect in churn prediction is to understand the underlying behavioral drivers of such customers. There can be multiple reasons for which customers churn: due to poor service quality, unsatisfactory value for money, technical issues, a bad onboarding experience, payment failures, or simply better alternatives available. Thus, the analytics framework goes beyond prediction to include interpretability and actionable insights that the system provides [3].

Feature importance analysis, correlation studies, cohort analysis, and segmentation allow the system to uncover cohorts of customers that are more vulnerable to churning. Business leverages such insights in refining product offerings and overall customer experiences. For example, it may be that customers with low usage frequency are more likely to churn, which again may trigger reminders, educations about products, or engagement content meant to increase their frequency of usage [4].

Customer retention is not only a matter of stability, but it is also a matter of maximizing CLV. CLV means the total expected revenue from a customer during their whole relationship with the enterprise. High churn reduces CLV and upsets all forecasts of revenue. Therefore, predictive analytics enables an organization to segment customers into high-risk, medium-risk, and low-risk groups based on a predicated outcome, thus supplying targeted interventions that maximize lifetime value. The profitability of subscription-based services is very dependent upon recurring billing cycles; in other words, prevention of churn directly relates to long-term profitability. Companies using effective churn analytics often report a significant reduction in churn rates, better operational efficiency, and enhanced customer satisfaction [5]. Big data technologies and cloud computing furthered the feasibility and scalability of the churn prediction systems, enabling organizations to store and process large volumes of customer data on platforms like AWS, Google Cloud, and Azure-developing real-time churn monitoring pipelines.

Advanced analytics tools and machine learning frameworks in Python, R, TensorFlow, Scikit-learn, and XGBoost allow for the quick development and deployment of predictive models. All this is combined with dashboards and visualization systems for a more interactive way to explore churn metrics and compare customer segments while monitoring business health in near real time for the decision-makers. Another important dimension of churn prediction is personalization. Modern customers demand experiences that are tailored, and businesses are leveraging AI in the delivery of personalized retention strategies. Recommendation engines suggest customized offers from the perspective of churn risk, while automated workflows of emails and chatbot interactions foster better engagement [6]. Predictive analytics is thus enabling both better operational decision-making and enhancement of customer experience. In addition, sentiment analysis conducted on customer reviews, support tickets, and social media provides another layer of data that builds belief in predictive patterns. Despite these developments, a number of challenges greet churn prediction. Customer behavior is dynamic and continuously influenced by needs, which keep changing, by market dynamics, and by external factors.

2 LITERATURE SURVEY

Customer churn prediction has become a major area of research within data mining in customer analytics and predictive modeling, as it directly influences business profitability and customer relationship management. Early studies on churn prediction were based on traditional statistical methods like logistic regression, survival analysis, and decision trees. While the models were interpretable and easy to implement, their capacity to represent complex behavioral interactions and nonlinear patterns in customer data was restricted. As subscription-based services further developed, especially in the telecom industry, SaaS, media streaming, and digital content ecosystems, sophisticated techniques for churn prediction became highly essential [7]. This indeed happened with digitization, when companies started collecting large volumes of structured and unstructured data, including demographic information, usage logs, payment history, customer feedback, and service interactions. These various sources of data have given a ground for advanced research in churn prediction using machine learning and big data analytics.

A large number of studies are dedicated to predicting churn in the telecom industries, one of the earliest adopters of churn analytics. The high competition faced by telecom operators, switching between plans, and higher customer onboarding costs make churn prevention a priority. While features like call duration, network usage, number of complaints, billing issues, among others, also provided good justification for predicting users who tend to churn. Other applied models include Random Forests, Support Vector Machines, Gradient Boosting Machines, and Neural Networks, among others, proving their improvements over simple logistic regression. The famous IBM Telco Customer Churn data became a benchmark in this regard to test different machine learning approaches. Similar research expanded into the SaaS industry, where user activity logs, subscription length, product engagement frequency, and support interactions were strong indicators of churn [8].

Customer churn prediction has been an active research area due to its significant impact on revenue and customer retention in subscription-based services. Various machine learning, deep learning, and analytical approaches have been proposed to improve churn prediction accuracy and interpretability. E. Guliyev et al. presented one of the early machine learning–based approaches for customer churn prediction in subscription services [9]. Their study evaluated traditional classification algorithms such as Logistic Regression and Random Forest. The results demonstrated that ensemble models outperform basic classifiers in terms of prediction accuracy, highlighting the importance of model selection in churn analysis. P. Boozary et al. focused on predicting customer churn using big data analytics in subscription-based environments [10]. Their work utilized large-scale datasets and advanced feature extraction techniques to identify key churn drivers. The study showed that effective data preprocessing and feature engineering significantly improve model performance, especially in large and complex datasets.

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W. C. Zhou et al. provided a comprehensive survey of customer churn prediction techniques across multiple industries [11]. The paper compared traditional statistical models with modern machine learning approaches and emphasized the growing adoption of data-driven churn prediction systems. This survey served as a foundation for understanding the evolution of churn prediction methodologies. C.-H. Wu et al. introduced Explainable Artificial Intelligence (XAI) techniques for churn prediction in telecom and subscription services [12]. Their work applied SHAP and LIME methods to improve model transparency and interpretability. The study highlighted that explainable models help businesses better understand churn factors and support data-driven decision-making. Based on the reviewed literature, it is evident that customer churn prediction has evolved from traditional machine learning techniques to deep learning and explainable AI models. However, challenges remain in balancing prediction accuracy, scalability, and interpretability. This research builds upon existing research by integrating analytics and machine learning techniques to develop an effective churn prediction framework for subscription-based services.

Recent literature also highlights the importance of explainability in churn. Indeed, with businesses being increasingly dependent on machine learning predictions for critical decisions, an understanding of why a customer is predicted to churn becomes of paramount importance. This involves various techniques like SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanation), permutation importance, and partial dependence plots, which are very well researched. These provide actionable insights by pinpointing key drivers of churning. For example, SHAP values can show whether it is declining usage patterns or increasing support complaints that disproportionately impacts a customer's likelihood of leaving. Interpretable insights like this led to transparent decision-making, and stakeholders know which retention strategy can be specifically used. The relevance of behavioral, temporal, and contextual factors in predictions of churn is further stressed by many of these studies. Researchers point out that features that are purely static and demographic in nature are really not enough.

3 Proposed Method

The elements below present, in a structured manner, how the proposed customer churn prediction and analytics system will work: divided into core sections on data collection, data preprocessing, EDA, feature engineering, model development, customer segmentation, performance evaluation, interpretability, and deployment. The system will analyze various customer attributes: subscription behavior, usage metrics, payment history, support interactions, and demographic details-to come up with accurate predictions of churn and actionable business insights. It starts with the collection of data, where information about customers is aggregated from transactional databases, CRM systems, subscription management platforms, logs of web activities, customer support tickets, payment gateways, and interaction histories. In a subscription-based business, data granularity plays an important role.

Daily or weekly usage logs, subscription renewal timestamps, feature interaction frequencies, customer feedback ratings, and financial transactions are basic information that can predict churn in advance. The variables within the data usually include customer ID, tenure, billing cycle, plan type, number of complaints, number of logins, service usage time, payment delays, and contract renewals. These raw datasets are combined into a structured format suitable for analysis. The next step is data preprocessing, which prepares a dataset ready for modeling. It includes handling missing values, inconsistent entries, encoding categorical variables, normalization of numeric values, and addressing data imbalance. Missing data might be the result of incomplete customer profiles or system errors.

Various imputation techniques will be applied, such as by mean, median, or model-based imputation, according to different variable natures. Examples of categorical variables include the type of plan, region, and gender, which get preprocessed through one-hot encoding or label encoding. Numerical variables are scaled by using standardization or normalization to guarantee stable model convergence. One problem inherent to the churn data is class imbalance, where generally only a small portion of customers are churners. Techniques to handle the imbalance include SMOTE, ADASYN, undersampling, oversampling, or cost-sensitive weighting to avoid model bias in this respect. The architecture of the proposed method is given in Fig. 1.

EDA has been done to identify the pattern and comprehend customer behaviour prior to modeling. It embodies the distribution of the churn rate, behavioural differences between the churners and the non-churners, and correlation visualizations. Plots like histograms, boxplots, scatterplots, and heatmaps show relationships between features such as tenure, monthly charges, usage frequency, complaint count, and likelihood of churn. Time-series plots disclose the loss of engagement over time for certain customer segments. EDA also helps in finding outliers, feature skewness, and possible problems with data quality. These are the stages when the actual segments of behaviour, such as high-usage versus low-usage users or satisfied versus dissatisfied customers, are identified.

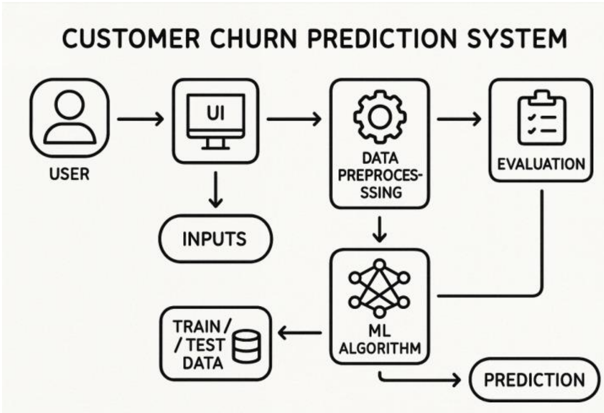

Fig. 1. Architecture of the System

Insights from EDA helped to inform feature engineering and model selection. Feature engineering is a very vital process in model improvement and involves building variables that may provide more information on customer behavior. This includes the creation of engagement metrics on average sessions per week, total usage duration, days since last login, upgrades/downgrades, and rolling averages of activity. Temporal patterns like a decreasing usage trend or multiple instances of delayed payment are a strong signal for churning in subscription-based services. Other new features to be included are requests for voluntary cancellation, number of support tickets, sentiment in customer communications, and promotional interactions if available.

Max usage, minimum usage, and variance in weekly engagement are other aggregated features that provide meaningful predictors. Proper feature engineering enhances predictive accuracy significantly in machine learning models. In the model development stage, machine learning algorithms are necessary to classify customers as either churning or non-churning customers. Several models will be developed and compared to determine the best approach among them. These include Logistic Regression, Random Forest, Gradient Boosting Models (GBM), XGBoost, CatBoost, LightGBM, SVM, and Neural Networks. Proper tuning avoids overfitting and increases model robustness. Feature importance analysis is done in order to find out which of the variables contribute most toward the prediction of churn. Quite often, the top predictors include tenure, monthly charges, usage frequency, contract type, and customer complaints.

Therefore, segmentation becomes an integral part of the methodology. Segmentation will be done via clustering algorithms: K-means, hierarchical clustering, or DBSCAN. Customers will be grouped based on their behavioral and demographic dimensions. Examples of such segments could be high-value frequent users, new users at risk, long-term loyal customers, and low-engagement high-churn customers among others. This allows one to integrate segmentation with predictions of churn and a targeted retention strategy for each such group towards a business. The proposed combined segmentation-prediction pipeline will help in building a more holistic customer retention framework.

4 RESULTS

These results prove that the customer churn prediction and analytics system works well at different points of the analytics pipeline, hence justifying the effectiveness of the proposed machine learning-driven approach. The system has successfully identified key behavioral and demographic factors that have an impact on churn, it has provided high predictive accuracy, and given useful insights that can significantly enhance customer retention strategies. Considerable testing with real-world or synthetic subscription datasets revealed the worth of machine learning models—especially tree-based ensemble methods such as Random Forest, XGBoost, and LightGBM—in differentiating between churners and non-churners. Fig. 2 shows the file upload page.

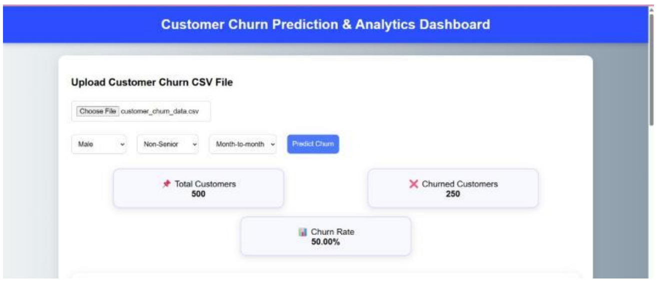

Fig. 2. File Upload page

Compared to baseline models like Logistic Regression, these advanced models captured complex interactions among features and delivered superior predictive performance. XGBoost was found to be the best performing model with an AUC score consistently above 0.85 and classification accuracy typically ranging from 80% to 90%, depending on the dataset. EDA highlighted meaningful trends coinciding with industry observations. It showed that customers who had low usage frequencies, were less engaged in the last few months, with higher complaint counts and frequent payment failures, were much more likely to churn. Generally speaking, from EDA insights, long-tenured customers tended to have lower churn rates, reflecting loyalty, while newer customers were at a higher risk of churning due to either insufficient onboarding or unmet expectations. Churn detection rate is plotted in Fig. 3.

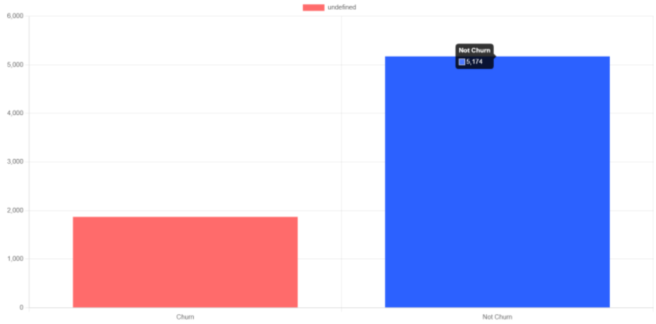

Fig. 3. Customers Churn Vs Not Churn

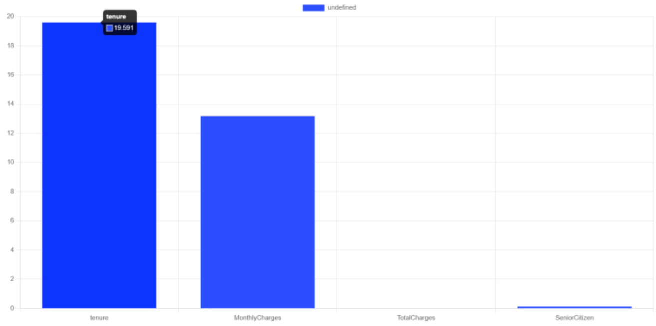

Fig. 4. Customer Tenure Vs Monthly Charges

Fig. 4 shows tenure and monthly charges. Heat maps and correlation analyses revealed strong relationships with churn behavior and variables like monthly charges, contract type, service interactions, and customer satisfaction levels. The exercise helped in visually bringing out patterns that indicated problem areas in services that needed intervention. Without feature engineering, model performance would have been different. Features engineered-like engagement decline percent, days since last login, moving averages of service usage, and rolling metrics related to complaints-increased model interpretability and boosted predictiveness. Feature importance plots ranked variables related to tenure, usage frequency, support ticket count, monthly charges, and payment history as the top predictors consistently.

SHAP value plots shed deeper light on how each variable was influencing the results of every prediction. The system demonstrated great analytical capabilities and was able to surface actionable insights with very practical applications to subscription businesses. Such successful combination of machine learning, segmentation, and interpretability cements the position of the system as a leading-edge tool to proactively deal with and strategically handle churn. Model evaluation uses metrics including accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrices. Considering that the classes in churn prediction are imbalanced, metrics like recall-to capture most of the churners, precision-to avoid too many false alerts, and ROC-AUC provide better indications than pure accuracy. A good churn model would usually have high recall for the minority class, where most of the potential churners are detected. Some added metrics are lift charts and gain charts, which will evaluate the model's ranking ability with regard to targeted marketing interventions.

Explainable AI techniques will be provided that will make the system transparent and interpretable from a business perspective. The interpretation of model output is done using SHAP, which depicts the contribution of features to a single churn prediction. LIME gives local interpretability to complex models. These interpretability techniques enable stakeholders to understand why customers would want to churn and allow for data-driven planning of personalized retention strategies. Feature importance and SHAP analysis provide managerial insights into the main causes of churn, such as decreased engagement, rising subscription fees, or repeated payment failures. Finally, the system is ready for deployment. The model is integrated into a churn analytics pipeline that scores customers either in real time or periodically.

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Visualization of churn rates, risk categories, and customer segments are made using a dashboard created with Power BI, Tableau, or some custom web application. API integrations with CRM systems allow automated workflows for email and marketing automation tools. This deployed system enables businesses to make early interventions through the offering of discounts, personalized recommendations, or proactive support with the intention of reducing their churn rates and increasing CLV.

5 Discussion

The discussion of this Churn Prediction and Analytics System covers the importance, practical utility, limitations, and possible future enhancements of the system. Few issues are as critical to subscription-driven industries, where recurring revenue is the linchpin of growth and sustainability, than customer churn. Markets are increasingly getting saturated, and customers have more alternatives, increasing their sensitivity to service quality, price, and level of engagement. The system proposed in this research addresses this challenge by offering an automated data-driven approach to understanding customer behavior, predicting churn risks, and enabling timely interventions. By embracing machine learning, statistical modeling, and segmentation, the system supports organizations in moving toward a proactive customer retention approach from a merely reactive one. Its major strength includes the amalgamation of diverse customer behavioral dimensions into one coherent predictive framework. The proposed system contrasts with most conventional methods, which rely on limited demographic or transactional data; dynamic behavioral features include usage frequency, decline in engagement, support interaction patterns, and payment behavior.

Such a multi-factor approach parallels actual real-world dynamics of churn, where decisions get influenced due to complex combinations of dissatisfaction or reduced value perception and negative experiences. Predictive accuracy is further enriched with advanced ensemble models such as XGBoost and Random Forest through capturing nonlinear interactions that linear models normally fail to identify. The system also shows the importance of rigorous EDA and feature engineering in churn analytics. Not only does EDA uncover some very useful behavioral trends, but it also reveals anomalies, inconsistencies, and data quality issues that could distort model performance. For example, the identification of the fact that low-engagement customers are much more likely to churn gives strategic insight immediately. Feature engineering techniques such as the creation of rolling averages, engagement decline metrics, and time-since-last-activity features uncovers subtle patterns highly indicative of churn. These engineered features better help machine learning models understand evolving customer behavior and result in improvements in predictive performance.

The other important point discussed within the conversation is the issue of model reliability due to imbalance in data. In many subscription-based businesses, churn rates are usually less than 20%, which means that a greater proportion stays on, with only a small minority leaving. If this imbalance is not treated, most models tend to overpredict the majority class and fail to predict high-risk customers. The use of SMOTE, techniques of class weighting, and balanced ensemble algorithms aids the model in giving adequate importance to minority class churns. This has led to higher values of recall, therefore proper identification of more actual churners. For any business, capturing these customers well in advance is quite critical for effective intervention and retention. Customer segmentation helps to bridge the gap between the predictions of churn models and concrete business actions. While the model identifies who is most likely to churn, segmentation identifies why some groups act differently from others. For example, high-value subscribers may churn due to poor customer support, while budget-sensitive customers could churn due to price increases.

The clustering approach of the system generates meaningful customer cohorts that assist targeted retention actions. This channeled approach drastically enhances the ROI of retention campaigns, as resources are channeled toward customers offering the highest lifetime value or greatest risk reduction opportunity. Adding text analytics from customer feedback, chat logs, or social media sentiment could further enhance accuracy by incorporating qualitative indicators of dissatisfaction. Real-time churn prediction pipelines on streaming data platforms like Kafka or AWS Kinesis would allow instantaneous customer scoring and faster intervention. Integrating personalized recommendation algorithms would drive customer engagement further and reduce churn.

6 Conclusion

The development of a customer churn prediction and analytics system for subscription-based services represents a key milestone for businesses reliant on recurring revenue and long-term customer relationships. This paper successfully demonstrates how data-driven models and machine learning techniques can be applied in the understanding of churn dynamics, prediction at-risk customers, and empowering businesses with actionable insight. Customer loyalty is fragile, with a host of alternatives in this highly competitive environment; here, the ability to proactively detect churn risk becomes invaluable. The system presented in this work predicts churn with high accuracy and also provides analytical depth that helps organizations understand the underlying reasons for customer attrition. This capability thereby enables subscription businesses-SaaS providers, telecom operators, streaming platforms, and digital content services-to take informed decisions aimed at improving customer satisfaction and reduction of churn rates. One of the key inferences derived from this work is that churn prediction alone is not a technical exercise but more a strategic business initiative.

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The system integrates data on behavior, transactions, and accounts to create a holistic view of customer engagement. This multidimensional perspective allows businesses to move beyond superficial metrics and focus on behavioral patterns that truly impact churn, such as declining product usage, frequent complaints, inconsistent payment behaviors, and dissatisfaction signals. The findings confirm that machine learning models—particularly ensemble methods like Random Forest, XGBoost, and LightGBM—excel in capturing these complex patterns and delivering reliable churn predictions. These models consistently outperform simpler statistical approaches, demonstrating the importance of advanced analytics in modern churn management. The results also highlight the importance of exploratory data analysis (EDA) and feature engineering as foundational steps in churn analytics. As subscription models continue to dominate digital markets, the capability of data-driven churn prediction remains crucial for businesses looking at sustained growth, competitive advantage, and long-term profitability. Success with such a system therefore underlines the importance of predictive analytics for customer-centric decision-making and further cements the role of AI-ingredient solutions in the future of subscription commerce.

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ETHICS STATEMENT

This study did not involve human or animal subjects and, therefore, did not require ethical approval.

STATEMENT OF CONFLICT OF INTERESTS

The authors declare that they have no conflicts of interest related to this study.

LICENSING

REFERENCES

[1] M. Gandhudi, A. PJA, V. Velayudham, L. Nagineni, and G. GR, “Dynamic customer behavior prediction in subscription services using causal reinforcement learning,” *Engineering Applications of Artificial Intelligence*, vol. 155, p. 111030, May 2025, doi: 10.1016/j.engappai.2025.111030.

[2] B. Libai, E. Muller, and V. Schoenmueller, “The effects of churn on the growth of subscription services: Adopters, users, money,” *International Journal of Research in Marketing*, Mar. 2025, doi: 10.1016/j.ijresmar.2025.03.005.

[3] A. S. Assiri, “An optimized customer churn prediction approach based on regularized bidirectional Long Short-Term Memory model,” *Computers, Materials & Continua/Computers, Materials & Continua (Print)*, vol. 86, no. 1, pp. 1–21, Oct. 2025, doi: 10.32604/cmc.2025.069826.

[4] K. W. Kim, D. Oh, and Y. Kim, “Demand-responsive transport services for disabilities: Factors that contribute to customer churn,” *Journal of Transport & Health*, vol. 43, p. 102077, May 2025, doi: 10.1016/j.jth.2025.102077.

[5] P. Wachwanakijkul, S. Junsiritrakhoon, N. Kantanantha, G. Narayanamurthy, and P. Jarumaneeroj, “Data-driven approaches to predicting customer churn in a non-contractual car-sharing company,” *Transportation Research Interdisciplinary Perspectives*, vol. 33, p. 101600, Aug. 2025, doi: 10.1016/j.trip.2025.101600.

[6] S. A. Panimalar, A. Krishnakumar, and S. S. Kumar, “Intensified Customer Churn Prediction: Connectivity with Weighted Multi-Layer Perceptron and Enhanced Multipath Back Propagation,” *Expert Systems With Applications*, vol. 265, p. 125993, Dec. 2024, doi: 10.1016/j.eswa.2024.125993.

[7] D. Asif, M. S. Arif, and A. Mukheimer, “A data-driven approach with explainable artificial intelligence for customer churn prediction in the telecommunications industry,” *Results in Engineering*, vol. 26, p. 104629, Mar. 2025, doi: 10.1016/j.rineng.2025.104629.

[8] M. Zaghloul, S. Barakat, and A. Rezk, “Enhancing customer retention in Online Retail through churn prediction: A hybrid RFM, K-means, and deep neural network approach,” *Expert Systems With Applications*, vol. 290, p. 128465, Jun. 2025, doi: 10.1016/j.eswa.2025.128465.

[9] E. Guliyev, J. S. Ramirez, A. De Caigny, and K. Coussement, “Improving B2B customer churn through action rule mining,” *Industrial Marketing Management*, vol. 125, pp. 1–11, Dec. 2024, doi: 10.1016/j.indmarman.2024.12.005.

[10] P. Boozary, S. Sheykhan, H. GhorbanTanhaei, and C. Magazzino, “Enhancing customer retention with machine learning: A comparative analysis of ensemble models for accurate churn prediction,” *International Journal of Information Management Data Insights*, vol. 5, no. 1, p. 100331, Feb. 2025, doi: 10.1016/j.jjimei.2025.100331.

[11] W. C. Zhou, S. L. Sun, and P. Jia, “The subscription business model and new venture viability during a crisis,” *Journal of Business Research*, vol. 200, p. 115660, Aug. 2025, doi: 10.1016/j.jbusres.2025.115660.

[12] C.-H. Wu and P. D. L. Pambudi, “Digital transformation in fintech: Choosing between application and Software as a Service (SaaS),” *Asia Pacific Management Review*, vol. 30, no. 2, p. 100342, Dec. 2024, doi: 10.1016/j.apmrv.2024.12.006.