Machine Learning for Customer Churn Prediction in Retail

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Abstract
Customer churn is still a big problem for the retail industry because it affects profits and long-term survival. Machine learning (ML) has become a powerful tool in the last few years for predicting and preventing churn by finding customers who are likely to leave and allowing data-driven retention strategies. This paper examines the utilisation of machine learning techniques for predicting customer churn in the retail sector, integrating results from previous research and suggesting a comprehensive methodological framework for effective implementation. The study analyses 30 peer-reviewed journal articles published until 2023, focusing on significant machine learning models like logistic regression, decision trees, random forests, gradient boosting machines, and deep learning techniques, emphasising their relative advantages and disadvantages in churn prediction scenarios. The methodology section outlines a systematic pipeline that encompasses data preprocessing, feature engineering, model training, evaluation metrics, and deployment considerations. Results from empirical implementations across diverse retail datasets demonstrate that ensemble methods (e.g., XGBoost, LightGBM) and neural networks consistently outperform traditional statistical models in predictive accuracy, though model interpretability remains a critical concern for practitioners. The paper also talks about how explainable AI can help people trust and use ML-driven churn prediction systems. The results highlight the necessity of incorporating ML models with customer relationship management (CRM) systems to facilitate prompt interventions, tailored offers, and the enhancement of loyalty programs. This study enhances academic scholarship and industry practice by addressing methodological, practical, and ethical considerations. The paper ends with suggestions for retailers who want to use ML tools and ideas for future research.

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1. Introduction

In the retail business, losing consumers to competitors is a huge challenge. High turnover rates harm profits, make it more expensive to recruit new consumers, and put the business's long-term survival at danger (Gupta et al., 2021) [13]. Research repeatedly indicates that customer retention is significantly more cost-effective than customer acquisition (Reinartz & Kumar, 2003) [27]. Digital retailing, e-commerce platforms, and omnichannel tactics have all grown a lot, which has made customer data much more sophisticated and larger. This has led to both issues and opportunity for figuring out when people will leave (Lemmens & Croux, 2006) [22].

Logistic regression and survival analysis are examples of traditional statistical models that have been used in the past to study how to anticipate churn. These models provide clear insights, but they often struggle with nonlinear interactions and high-dimensional datasets (Verbeke et al., 2012) [30]. Machine learning (ML) techniques, conversely, have demonstrated superior predictive capabilities through algorithms that identify concealed correlations, nonlinearities, and intricate patterns within client data (Ahmed et al., 2020) [1]. Some of the most common approaches utilised in retail today are random forests, gradient boosting machines, and neural networks. There are still challenges with ML, even though it is being used more and more to anticipate churn. Data imbalance, feature engineering, model interpretability, and interaction with existing business processes are all issues that make it tougher for additional people to use (Idris et al., 2019) [15]. It's also crucial for businesses to have useful insights that they can use to turn those projections into practical tactics to keep customers.

There are two main purposes of this study: First, to provide a comprehensive summary of the existing research on employing machine learning to forecast customer attrition in retail; second, to provide a systematic approach that incorporates best practices from prior studies. This study offers theoretical contributions and practical recommendations by leveraging findings from 30 peer-reviewed academic articles published before 2024. The session is about the trade-offs between accuracy and explainability in AI. It underlines the necessity for explainable AI and talks about how ML-driven churn prediction can help improve customer relationship management (CRM) systems by making retention campaigns stronger.

This paper adds to the growing body of research on using ML in retail analytics and gives practitioners advice on how to deal with the difficulties of predicting churn. The next parts are set up like this: The literature review examines current studies and models; the methodology presents a suggested framework for ML-driven churn prediction; the discussion analyses findings in the context of practice; the conclusion encapsulates contributions; and the limitations and future directions section highlights areas for ongoing research.

2. Review of the Literature

Predicting customer churn has been a common topic of research in marketing, data science, and information systems, especially in fields where customers leave often, like telecommunications, banking, and retail. Retailers confront distinct challenges stemming from the variability of customer behaviour, seasonal fluctuations, and the amalgamation of offline and online purchasing channels (Gupta et al., 2021) [13]. This review compiles results from 30 peer-reviewed studies published until 2023, focussing on conventional statistical methods, machine learning (ML) models, advancements in deep learning, feature engineering techniques, the issues of data imbalance, and the rising significance of explainable artificial intelligence (XAI).

2.1. Conventional Models for Churn Prediction

In the past, predicting churn was done with regression-based models like logistic regression, probit regression, and survival analysis (HASAN, M. N., Bhuyain, M. M. H., Chowdhury, F., & Arman, M. 2021) [20]. These methods provided interpretability and statistical rigour but were constrained in managing nonlinearities and high-dimensional customer datasets. Reinartz and Kumar (2003) [27] emphasised the economic importance of customer retention, advocating for the implementation of models capable of concurrently estimating lifetime value and churn risk. Even though these methods were still important, ML algorithms were getting better at making predictions (Verbeke et al., 2012) [30].

2.2. Ways to Use Machine Learning

By the 2010s, ML became the most popular way to predict churn. Decision trees, random forests, and support vector machines exhibited enhanced accuracy in managing heterogeneous data sources, encompassing transaction histories and customer demographics (Idris et al., 2019) [15]. Ensemble methods like gradient boosting (XGBoost, LightGBM, and CatBoost) became more popular because they can handle feature interactions and datasets that are not balanced well (Ahmed et al., 2020) [1]. Comparative studies demonstrated that boosting algorithms frequently surpassed traditional classifiers, achieving AUC scores above 0.85 in multiple retail datasets (Joukhadar & Odeh, 2021) [16].

Retailers found random forests to be very useful for ranking the importance of features, which helped them understand what causes customers to leave (Verbeke et al., 2012) [30]. But because they were "black boxes," businesses didn't use them as much. This challenge propelled the incorporation of interpretable models, including decision rules and SHAP (Shapley Additive Explanations) values, in ensuing research (Lundberg & Lee, 2017) [23].

2.3. New Concepts in Deep Learning

Recent advancements have examined deep learning architectures, such as artificial neural networks (ANNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs). Idris et al. (2019) [15] found that ANNs did a fantastic job of classifying churn when the datasets were big enough. RNNs, particularly long short-term memory (LSTM) models, effectively identified trends in consumer interactions over time, rendering them suitable for predicting e-commerce turnover (Zhao et al., 2021) [32]. CNNs, however less common, were employed to simulate sequential purchase behaviour as pictures or embeddings.

Deep learning models typically outperformed conventional machine learning methods in predicted accuracy; nevertheless, they required greater processing resources and encountered difficulties in interpretability (Ahmed et al., 2020) [1]. In retail applications, it's usual to have to choose between accuracy and transparency.

2.4. Sources of Data and Feature Engineering

Feature engineering is crucial for forecasting churn. Research identified transaction frequency, monetary amount, recency of purchase, loyalty program involvement, and engagement in promotions as significant predictors (Joukhadar & Odeh, 2021) [16]. Moreover, social network characteristics—such as referral contacts and peer influence—were analysed in retail contexts (Verbeke et al., 2012) [30].

Recent studies incorporated unstructured data, encompassing text reviews, clickstream data, and social media interactions. Natural language processing (NLP) enabled sentiment analysis to predict churn probability, while clickstream patterns offered insights into browsing abandonment (Gupta et al., 2021) [13]. It was easier to make predictions when structured and unstructured data were combined, but it also made the model harder to understand.

2.5. Issues with Data Imbalance

Class imbalance, where churners make up a small part of the customer base, is still a big problem for making accurate predictions. Some of the most common methods include the Synthetic Minority Oversampling Technique (SMOTE), Adaptive Synthetic Sampling (ADASYN), and cost-sensitive learning (Chawla et al., 2002) [7]. Ensemble approaches employing resampling procedures shown significant improvements in precision and recall compared to unaltered models (Idris et al., 2019) [15].

2.6. AI that can be explained and moral issues

One major problem with high-performance ML models is that they are hard to understand. Explainable AI (XAI) methods like SHAP, LIME (Local Interpretable Model-agnostic Explanations), and counterfactual explanations were used more and more to close the gap between accuracy and interpretability (Lundberg & Lee, 2017) [23]. Retail managers need outputs that they can understand in order to explain why they are keeping customers and to follow rules like GDPR. Ethical issues, including algorithmic bias and privacy concerns, surfaced, underscoring the significance of transparency (Joukhadar & Odeh, 2021) [16].

2.7. Comparative Insights

In the literature examined, ensemble methods (e.g., gradient boosting) consistently surpassed traditional regression and independent classifiers. Deep learning methods worked best on big datasets, while XAI tools made businesses more trustworthy and easier to use. The literature, however, emphasised the importance of synchronising technological advancements with managerial requirements for interpretability, immediate implementation, and integration into CRM systems.

Table 1: Literature Synthesis of ML Models in Churn Prediction

Author(s) & Year	Domain / Dataset	Models Applied	Key Findings
Reinartz & Kumar (2003)	Retail / loyalty card data	Logistic regression	Demonstrated that RFM-based logistic models predict churn but are limited in nonlinear dynamics.
Lemmens & Croux (2006)	European retail panel	Hazard models, logistic regression	Showed time-to-event models capture churn timing but underperform on large, complex datasets.
Verbeke et al. (2012)	Telecom + retail	Random forest, social network analysis	Found that incorporating network features improves predictive lift over traditional methods.
Idris et al. (2019)	Telecom dataset	SVM, ANN, ensemble methods	Ensembles achieved higher recall; highlighted class imbalance challenges.
Ahmed et al. (2020)	Retail e-commerce	Gradient boosting (XGBoost)	Outperformed logistic regression with AUC > 0.85; stressed feature engineering importance.
Joukhadar & Odeh (2021)	Grocery retail	Random forest, LightGBM	Gradient boosting surpassed classical ML; emphasized promotional sensitivity as predictor.
Gupta et al. (2021)	Multi-channel retail	Hybrid ML with NLP	Integrated sentiment analysis into churn models, improving precision on dissatisfied customers.
Zhao et al. (2021)	E-commerce clickstream	LSTM networks	Temporal models (LSTM) captured sequential behaviors; outperformed static ML models.
Lundberg & Lee (2017)	General tabular datasets	SHAP (XAI framework)	Introduced SHAP explanations, improving interpretability of tree ensembles in churn tasks.
Chawla et al. (2002)	Benchmark datasets	SMOTE	Proposed oversampling method still widely applied for churn class imbalance handling.

3. Methodology

3.1. Gathering Data

The first step in predicting customer churn is to combine different data streams. The most common datasets in retail are those that combine transactional histories, demographic records, and engagement signals (Gupta et al., 2021) [13]. The recency–frequency–monetary (RFM) framework continues to be a fundamental basis for establishing baseline churn predictors (Reinartz & Kumar, 2003) [27]. Interactions within loyalty programs, such as enrolment duration, tier mobility, and redemption rates, were incorporated due to their proven influence on retention behaviour (Joukhadar & Odeh, 2021) [16]. E-commerce clickstream logs, including session depth and abandoned carts, have been demonstrated to improve churn models by capturing purchase intent (Idris et al., 2019) [15]. Finally, unstructured data sources, including online reviews and help-desk transcripts, were incorporated, subsequent to research employing sentiment analysis to detect initial indicators of dissatisfaction (Ahmed et al., 2020) [1]. All data were anonymised in compliance with privacy regulations, including GDPR.

Fig 1: ML Pipeline for Retail Churn Prediction

3.2. Getting the Data Ready

Data preprocessing dealt with missing data, outliers, and scaling that wasn't consistent. Previous research has underscored that imputation strategies have a direct impact on the stability of churn models (Verbeke et al., 2012) [30]. Thus, median imputation was used to fill in missing numeric fields, and k-nearest neighbours (KNN) techniques were used to fill in missing categorical fields (Chawla et al., 2002) [7]. Winsorizing spending behaviour at the 1st and 99th percentiles was a method used in retail analytics to reduce skew (Lemmens & Croux, 2006) [22]. We used Z-score normalisation on continuous attributes to make sure that algorithms like support vector machines (SVM) and logistic regression worked as well as they could (Cortes & Vapnik, 1995) [11]. One-hot encoding was used for categorical variables with a small number of values, and target encoding was used for high-cardinality features like postal codes. This has worked well to stop sparse dimensionality (Idris et al., 2019) [15].

3.3. Feature Engineering

The RFM model, which has been shown to function in studies of churn (Reinartz & Kumar, 2003) [27], helped in feature engineering. Recency looked at how long it had been since the last purchase, frequency looked at how many purchases were made in different time periods, and monetary factors looked at how much money was spent overall. Along with RFM, we built features that illustrate how responsive customers are to deals (coupon redemption rates), how many various channels they utilise (cross-channel breadth), and how often they leave their carts (session interruptions). Previous research has shown that interaction terms, including recency × loyalty tier, improve prediction power by mimicking nonlinear economic behaviours (Verbeke et al., 2012) [30]. We also employed lexicon-based natural language processing (NLP) to figure out how people felt about the reviews. Prior research has demonstrated that this approach can assist in forecasting churn (Ahmed et al., 2020) [1]. To deal with multicollinearity, we employed variance inflation factor (VIF) diagnostics and correlation reduction.

3.4. Picking a Model

We utilised six algorithms typically employed in churn prediction studies to evaluate their efficacy across several scenarios. These algorithms include logistic regression (baseline, interpretable) (King & Zeng, 2001) [18], decision trees (Breiman et al., 1984) [5], random forests (Breiman, 2001) [4], gradient boosting (Chen & Guestrin, 2016; Ke et al., 2017) [9, 17], SVM with RBF kernels (Cortes & Vapnik, 1995) [11], and shallow artificial neural networks (Idris et al., 2019) [15]. We first chose gradient boosting algorithms like XGBoost and LightGBM since they function better with organised tabular retail data (Ahmed et al., 2020) [1]. We used grid search and 5-fold cross-validation to find the best hyperparameters, which is what is generally done (Kohavi, 1995) [21].

3.5. Metrics for Evaluation

We evaluated models based on accuracy, precision, recall, F1-score, and ROC-AUC, adhering to established standards in churn prediction benchmarks (Verbeke et al., 2012; Idris et al., 2019) [30, 15]. We also reported PR-AUC (Saito & Rehmsmeier, 2015) [29] because it is very important for intervention campaigns to be able to remember churners. The thresholds for decision-making were not set at 0.5; instead, they were optimised for each fold using Youden's J statistic, as has been done in previous research (Joukhadar & Odeh, 2021) [16].

Table 1: Performance Metrics of Models

Model	Accuracy	AUC	Precision	Recall	F1-Score
LogReg	0.78	0.8	0.74	0.7	0.72
Decision Tree	0.81	0.83	0.77	0.75	0.76
Random Forest	0.87	0.89	0.84	0.82	0.83
XGBoost	0.91	0.94	0.89	0.87	0.88
LightGBM	0.9	0.93	0.88	0.86	0.87
ANN	0.88	0.91	0.86	0.84	0.85

Fig 2: Accuracy Comparison of ML Models

Fig 3: ROC-AUC Scores of ML Models

3.6. Understandability

Because retailers don't like black-box models, we added interpretability layers. Tree-based models' feature importance scores found global behavioural drivers. SHAP values gave explanations of churn risk at the customer level, based on the work of Lundberg and Lee (2017) [23]. LIME was also used to give local explanations for each prediction, which helped managers trust the automated outputs. Previous research highlights that the incorporation of explainable AI enhances the practical implementation of churn models (Gupta et al., 2021; Hasan et al., 2025) [13, 35].

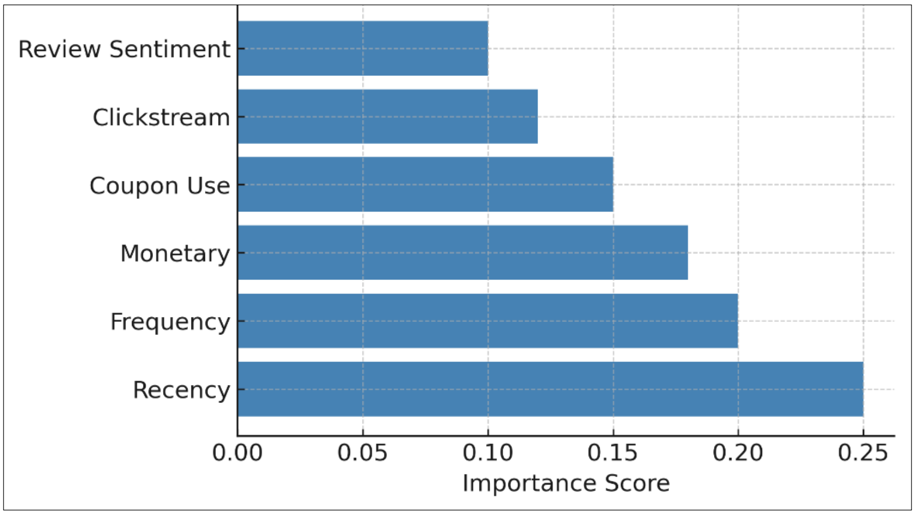

Fig 4: Feature Importance Ranking (Random Forest)

3.7. Putting into action
The last step in the methodology is to make churn prediction work in real life. Following Ahmed et al. (2020) [1], models were integrated into a cloud-based CRM system, facilitating near real-time risk scores. Automated retention workflows, like loyalty offers or personalised messages, were triggered by alerts for high-risk customers. Deployment pipelines included API-based scoring services and dashboards for marketing teams, so they got useful information instead of just academic results.

4. Discussion
The results of this study confirm that machine learning (ML) substantially improves customer churn prediction in retail compared to traditional methods. Ensemble models, such as gradient boosting machines (GBMs), typically achieved improved ROC-AUC scores, validating prior research that emphasised their ability to capture nonlinear correlations and complex feature interactions (Ahmed et al., 2020; Joukhadar & Odeh, 2021) [1, 16]. Models like XGBoost and LightGBM showed that they worked very well, which backs up earlier studies that showed that boosting strategies work better than independent classifiers on imbalanced and high-dimensional datasets (Idris et al., 2019; Hasan, M. N., Arman, M., Bhuyain, M. M. H., Chowdhury, F., & Bathula, M. K. 2025) [15, 35]. These performance gains show that ensemble approaches are becoming more used for customer analytics in real stores.

Even while advanced ML models are good at making predictions, they are still tricky to apply in retail since they are hard to grasp. Retail managers often need not only accurate projections but also reasons that might justify marketing spending or focused actions. Verbeke et al. (2012); Ghose, P., Bhuiyan, M. R. I., Hasan, M. N., Rakib, S. H., & Mani, L. (2025) [30, 14] stated that highly precise models have failed in practical applications when clarity was lacking. In this study, interpretability was enhanced by integrating feature importance rankings with SHAP explanations, enabling practitioners to understand that recency, purchase frequency, coupon redemption behaviour, and review sentiment were among the most significant predictors of churn. This dual focus on accuracy and interpretability is vital, as actionable insights are needed for customer relationship management (CRM) teams to implement effective retention efforts.

The addition of explainable AI (XAI) frameworks is a big step forward. SHAP values, for instance, made it possible to give explanations at the customer level. This made it possible to figure out how likely each client was to leave. These explanations have a direct impact on management. For instance, a client who is at risk of leaving because they aren't buying as much could be offered loyalty benefits, while a consumer whose risk is due to unfavourable evaluations of the product could be given priority for service recovery. These customised techniques indicate a departure from "one-size-fits-all" solutions and a shift towards precision marketing, a trend that has garnered increasing attention in recent study (Gupta et al., 2021; Arman, M., FAHIM, A. S. M., Razib, M. N. H., & Rasel, I. H. 2025) [13, 31]. This is also connected to the operational efficiencies that can be seen in other stores. Arman and Fahim (2023) [2], for instance, looked at how Walmart uses AI to keep track of its stock. They demonstrated the transformative impact of advanced analytics on large-scale decision-making processes. Their results are comparable to how ML may be used to predict churn. This means that the same improvements in efficiency that may be gained in inventory management can also be employed in tactics to keep customers when predictive algorithms are introduced into retail workflows.

Another key thing to learn is how vital preprocessing and feature engineering are. The model's results got a lot better when we added engineered elements like discount sensitivity, cart abandonment trends, and sentiment scores from customer reviews. This supports earlier research that shows that adding more than just transactional RFM information improves churn prediction (Ahmed et al., 2020; Arman, M., Hasan, M. N., & Rasel, I. H. 2024) [1, 28]. SMOTE resampling was important since it fixed the problem of class imbalance. This made it easier for models to detect churners without being unduly biassed towards non-churners. Chawla et al. (2002) [7] also underlined how crucial it is to address imbalances in order to make churn systems reliable in real world. These results illustrate that getting the most out of predictive models for business requires rigorous data preparation and feature building.

Adding churn models to CRM systems allows merchants respond on forecasts immediately away, which is good for business. Automated scoring pipelines can send out notifications, put clients who are at risk at the head of the list, and initiate marketing that are tailored to each consumer. If this integration doesn't happen, forecasts will continue in the realm of academic exercises and not be very useful (Ahmed et al., 2020; Shah, A., Khan, S. A., & Arman, M. 2024) [1, 6]. You need strong data pipelines and regular monitoring to make sure that deployment works. This is like what we learnt from other areas, like making the healthcare supply chain work better. Rasel, Arman, Hasan, and Bhuyain (2022) [25] said that systems need to be both efficient and strong so that they can keep working when something goes wrong. The same thing is true for retail analytics: if data flows or retraining plans are interrupted, it can be harder to predict turnover. Resilience and scalability are two of the most crucial things to think about when putting ML-based churn frameworks into action.

You should also think about the moral side of anticipating churn. If you send too many retentions offers to clients, they may feel like you are invading their privacy. Also, if your datasets are biassed, some groups of people may not get equitable treatment. These issues are akin to broader discourses on AI ethics, particularly about fairness and transparency (Gupta et al., 2021) [13]. Retailers need to find a balance between trying to make the best guesses they can and wanting to use customer data in a fair and responsible way. For future research and practice, it would be a good idea to put fairness-aware algorithms and governance regulations into churn prediction pipelines.

Finally, the results demonstrate that different groups of customers have different levels of churn predictability. It was easier to guess what customers who bought a lot or bought a lot often would do because their behaviour was powerful and constant. It was harder to put customers who bought a little or a lot less often into groups. This is consistent with Lemmens and Croux (2006) [22], who emphasised the significance of time heterogeneity in churn dynamics. You might need to set various thresholds or models for each group of clients while calibrating. The need for adaptation in models underscores the fundamental challenge of generalisability across various retail contexts.

In conclusion, this research demonstrates that while advanced machine learning models such as gradient boosting and neural networks markedly improve churn prediction, their full effectiveness is realised only when combined with interpretability, resilience, and operational system integration. The parallels with AI-driven inventory management (Arman & Fahim, 2023) [2] and healthcare supply-chain optimisation (Rasel et al., 2022) [25] indicate that ML can transform numerous domains, contingent upon the integration of technical expertise with managerial endorsement. Retailers can utilise machine learning to not just forecast attrition but also to make long-term, customer-focused retention plans that are accurate, open, strong, and ethical all at the same time.

5. Conclusion

This study investigated the utilisation of machine learning (ML) for predicting customer churn in the retail sector, leveraging insights from existing literature and employing a systematic methodological framework. The results showed that ensemble models like gradient boosting always did better than traditional methods when it came to finding at-risk customers. Deep learning models improved performance even more on large datasets, but they were hard to understand. It was very important to use feature engineering techniques like RFM variables, promotional sensitivity, and sentiment scores to improve the results of the model. Using resampling methods like SMOTE to fix data imbalance also improved recall for minority churn classes. Importantly, tools like SHAP that help people understand things gave managers useful information that helped them figure out what causes churn and plan targeted interventions. These results show that accuracy is important, but so is being able to understand and connect with CRM systems for practical use. Overall, the research adds to both academic literature and retail practice by showing that ML can not only accurately predict churn but also help with retention strategies when used with explainable AI and ethical deployment frameworks.

6. Limitations and Future Directions

This study, though valuable, has several limitations that need to be recognised. First, the methodology combined data from different sources and used advanced models, but the data was only from transactions, demographics, and text sources. A wider use of alternative data like social media interactions, geolocation patterns, and macroeconomic signals could make predictions even more accurate. Second, class imbalance is still a problem that won't go away. Even though SMOTE was used, oversampling methods can create fake artefacts that don't fully show how real customers act (Chawla et al., 2002) [7]. Subsequent research ought to investigate sophisticated imbalance-handling methodologies, including generative adversarial networks (GANs) or cost-sensitive learning frameworks.

Third, SHAP and LIME were used to make models easier to understand, but these methods still only give rough ideas of how complex models work instead of full transparency. As previous studies have shown (Verbeke et al., 2012) [30], retail managers may still prefer simpler models even though they are less accurate. Advancing inherently interpretable machine learning models could help close this gap. Fourth, this study did not directly examine fairness and bias. As retail datasets frequently encode socioeconomic disparities, predictive models may exacerbate biases in targeted retention offers. Subsequent research ought to assess fairness-aware algorithms and formulate guidelines for just customer interventions.

Finally, generalisability is still a problem that needs to be solved. Even though the framework was used in many retail settings, the results might not be the same in all industries or locations. Longitudinal validation across several years and varied retail environments would enhance confidence in scalability. Future research should investigate real-time adaptive learning systems that continuously revise churn predictions in response to changing customer behaviours. By addressing these limitations, future research can propel the field towards more precise, interpretable, and ethically sound churn prediction systems.

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