A Study on the Transportation Industry Customer Churn using Machine Learning: A Systematic Literature Review

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ABSTRACT

Machine Learning (ML) has become a crucial technology for addressing customer churn by enabling businesses to predict customer attrition, identify at-risk customers, and develop proactive retention strategies. Although the application of ML in customer churn management has gained momentum, existing research remains scattered across different disciplines and publication outlets. This study conducts a systematic literature review to consolidate and synthesize the fragmented knowledge in the transportation sector on the use of ML in customer churn prediction and prevention. The review examines peer-reviewed publications from the ranked journals between 2019 and 2024. The search strategy identified 67 studies, of which 34 were selected as primary papers relevant to this research. The findings contribute to the literature by (i) assessing the current state of ML applications in customer churn, (ii) identifying key ML techniques employed across different stages of customer churn management (prediction, prevention, and intervention), and (iii) summarizing the reported benefits of ML in reducing customer attrition and improving retention outcomes. This study offers valuable insights for both researchers and practitioners aiming to leverage ML technologies to mitigate customer churn and enhance customer loyalty.

Keywords: Machine learning · Customer churn · Customer retention · Systematic literature review · Emerging technologies · Customer experience

1. Introduction

Customer churn refers to the phenomenon where customers stop using a company's products or services. It is a critical issue in various industries, where retaining customers is essential for business sustainability standing to be the greatest challenges in most companies globally. According to Björn Preuß, Lead Data Scientist, (2021) stated that customer churn is an issue which can be very effectively addressed through AI. Not only can it predict whether or not a customer is likely to leave, but it can offer interesting insights into the customer experience and help fine-tune business practices. According to a McKinsey (2016) study, top-performing technology and SaaS companies with high revenue growth often maintain high retention rates and low net revenue churn. Predicting customer churn before it happens enables businesses to take proactive measures, such as reaching out to high-risk customers, launching targeted re-engagement campaigns, or adjusting pricing strategies. As per Praveen Lalwani & et.al (2022) by identifying at-risk customers and addressing underlying pain points, companies can improve customer retention, satisfaction, and ultimately, revenue growth. Preventing churn not only helps in retaining customers but also acts as a significant revenue source. With so much uncertainty in today's marketplace, where so much choice awaits customers, the most important target for any firm remains to not only attract new customers but to keep old ones. Customer churn is, therefore, described as the ratio at which customers cease patronizing your business in a given period. The ability to predict customer churn allows companies to implement targeted retention strategies, enhancing customer loyalty and profitability. Machine Learning (ML) techniques have emerged as powerful tools in addressing customer churn by leveraging large volumes of customer data to generate predictive insights Mishra N et.al., 2024 but seems to have not been fully adopted in several sectors. Analyzing customer behavior leads to an insight into patterns and predictability on what could be leading to churn, hence making the efforts of retaining customers more targeted. The research, entitled "A Study on the Transportation Industry Customer Churn using Machine Learning: A Systematic Literature Review," aims to summarize several studies conducted globally and synthesize them under one umbrella through a systematic Literature Review as to help further research under customer retention.

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2. Transportation sector utilizing ML in Customer Churn Prediction

A systematic literature review (SLR) of the application of machine learning (ML) in the transport sector is needed, given that the sector is increasingly dependent on intelligent systems to enhance efficiency, safety, and sustainability. An SLR gives a complete summary of existing research trends, gaps in existing literature, and potential areas of future research. Behrooz et al. (2022) note that although surface transportation has been favored by technological advancements, the industry has not yet maximized the potential of ML. Their review of the literature synthesizes and organizes research into ML in surface transportation and concludes that the industry has not yet maximized the potential of ML. Likewise, Abul Kalam Azad et al. (2024) examine the application of ML in intelligent transportation systems (ITS), specifically traffic management, safety, and autonomous, and conclude areas of unrealized potential. Likewise, further evidence for the results includes Ketabchi Haghighat et al. (2020), referring to applying deep learning methods in ITS, noting considerable improvements in traffic management, safety, and optimizing public transport. Shoaib et al. (2024) investigate the use of large language models (LLMs) in ITS, illustrating how they contribute to the development of transportation intelligence and traffic management. Finally, Li et al. (2024) give a review of the application of Graph Neural Networks (GNNs) in ITS, noting how they are superior to traffic forecasting, autonomous vehicles, and transport safety. Through a systematic manner of the existing literature, practitioners and scholars will be in a better position to realize how ML can be harnessed to deliver solutions in the areas of traffic congestion implementation, accident prediction, and management of infrastructure within the transport sector.

3. Theoretical Framework

Several theoretical frameworks provide insights into the dynamics of customer churn in the private transportation sector.

3.1 Customer Satisfaction Theory

Customer satisfaction is one of the critical predictors of customer churn across service industries, including private transportation. Satisfied customers are less likely to switch providers, so businesses need to identify and enhance the factors driving satisfaction. According to Jie Wang et al. (2024), machine learning algorithms have been used to analyze service attributes like pricing, vehicle quality, and driver behavior. It shows that enhancing these characteristics substantially lifts customer satisfaction and lowers churn. For example, Hui Zhang et al. (2024) posed the definition of customer satisfaction as being the fulfillment or exceeding of customer expectations to a certain degree by a product or service. They emphasize the importance of CRM systems in managing and analysing customer interactions but note that traditional CRM methods often fail to capture the dynamic nature of customer relationships, especially with time series data.

To address this, advanced architectures like the ConvLSTM layer in CNN models have been developed to capture spatiotemporal features, enabling a more accurate modeling of complex temporal patterns in customer data. A Shabani et al. (2022) applied Customer Satisfaction Theory to analyze the impact of the COVID-19 pandemic on public transport in Tehran. Using a combined multi-criteria decision-making (MCDM) approach that integrates the best-worst method (BWM) and the fuzzy technique for order performance by similarity to ideal solution (fuzzy TOPSIS), the study provided consistent and reliable results for service quality enhancements. The results revealed that a taxi led all the other mediums of transportation, which proved to be highly informative for policymakers when allocating resources during and after the pandemic. Ong et al. (2022) discussed service quality and passenger satisfaction in the Philippines' PUVs as the need for effective public transport systems in developing countries has been felt. In the use of their survey data on 600 passengers who ride a PUV, machine learning algorithms of DLNN, DT, and RFC are adopted to study survey data for its analysis. This resulted in essential factors being route efficiency, safety, value for money, and expectations in passengers to determine whether they would like to repeat patronage and even recommend service use. Ong et al. also highlighted the potential of machine learning algorithms in carrying out exact factor analysis in the transport industry and suggested further research on specific service quality factors to gain deeper insights.

3.2 Predictive Analytics Framework

The integration of predictive analytics is an important factor to predict the customer behavior in private transportation. Le-Minh Kieu et al. (2020) worked on the customer booking prediction in on-demand transport to show how predictive modeling can be used in predicting churn. This study, through multiple machine learning algorithms, explained how transportation companies can identify the trends of the customer behavior that are at a high risk of being churned. V Raghunath et al. (2023) introduced a Predictive Analytics Framework that makes use of historical data in conjunction with machine learning to predict future trends. Hybrid cloud systems and AI-driven business analytics frameworks facilitate the seamless integration of diversified data sources, enhancing decision-making capabilities. The framework improves accuracy, real-time availability of insights, and predictability of customer churn, which helps companies to take proactive measures. Moreover, the deployment of predictive analytics enhances business intelligence efficiency by generating competitive advantages using quicker insights along with improved access to data. Oliveira et al. (2024) proposed an econometric-machine learning hybrid arrangement to study Brazil's intercity passenger transportation market for the effects that economic mobility creates on domestic traveling businesses. The study, through Instrumental Variables Least Absolute Shrinkage and Selection Operator (IV-LASSO), Quantile Regression, and Stacking Regression approaches, assessed the possible impact of economic mobility on market development and revenue results.

The findings from the different approaches indicate that airlines are further ahead of bus carriers in applying measures of market development, but customer retention in bus services appears considerably weaker, calling for strengthened demand management strategies. Stacking Regression was shown to outperform base machine learners in revenue prediction, and an event study highlighted the enduring negative impact of economic slowdowns on demand and pricing. Ji and Zheng (2024) introduced a machine learning-based method for configuring public transportation stations in Hong Kong, driven by population density forecasting. Using high-resolution population density heatmaps and city maps, they developed five forecasting models targeting specific population groups. Their study analyzed the station attractiveness relationship to population density, service radius, and land use type. Their results showed area population size was a factor for differences in station attractiveness and verified that these factors significantly affect the station layout. This method can be extended to other cities, and thus it provides broad applications in public transportation planning. Grinberg-Rosenbaum et al. (2024) propose the Hybrid Dynamical Systems Thinking Approach (HDSTA) in transportation systems' data-driven decision making. This has specifically been adapted to the use in Transport Management Centers (TMCs) while applying systems thinking for defining the interfaces of causality in the data of transport and filling a gap between statistical conventional methods and tools of machine learning.

The ability to identify cause-effect relationships in transportation systems makes knowledge graphs more suitable for application among experts and data scientists and facilitates decision making. This methodology empowers TMCs to make informed, data-driven decisions for the public good.

3.3 Service Quality Models

For the private transportation service industry, the quality of services is influential to customer loyalty. The SERVQUAL model measures service quality in five dimensions: reliability, assurance, tangibles, empathy, and responsiveness. The study done by Wang et al. (2024) that is titled "Predicting Passenger Satisfaction in Public Transportation Using Machine Learning Models" expounds on the use of those models to help measure the connection between service quality indicators and passenger satisfaction. Again, the conclusions drawn from results indicated that two of the major factors determining churn reduction lay in reliability, responsiveness, thereby making it core for transportation institutions to build client loyalty. Ismanova D. (2019) Service quality model of SERVQUAL. The author remarks that though service quality is a base area for a provider to build loyalty, it is not always a determinant of customer loyalty. Competitive pricing, ease of access, and brand preferences matter in making customers a company's loyal customers. For example, customers may change their telecommunications operators for reasons other than service quality or select certain airlines despite flight delays. Similarly, in the private transport sector, high service quality alone does not deter customers from switching if other attributes, such as price or convenience, are more attractive. As such, an integrated customer retention model should encompass all factors influencing loyalty, beyond service quality alone. Ecem Tumsekcali, et.al (2021) considered service quality in public transport systems, highlighting the importance of improving service quality in enhancing customer satisfaction and mitigating problems like traffic congestion, pollution, and energy consumption. They expanded the SERVQUAL model by including two new criteria based on Industry 4.0 and the pandemic, creating a new P-SERVQUAL 4.0 (Pandemic SERVQUAL 4.0) model. The model uses a three-level hierarchical structure to assess public transport systems during the pandemic.

A hybrid decision-making methodology combining AHP (Analytic Hierarchy Process) and WASPAS (Weighted Aggregated Sum Product Assessment) under an interval-valued intuitionistic fuzzy (IVIF) environment was used to evaluate public transportation alternatives in Istanbul, including IETT Bus, Metrobus, Tram, Metro, and Marmaray. Marmaray was found to be the best alternative. The proposed model can help public and private organizations improve service quality, integrate Industry 4.0 technologies, and mitigate COVID-19 spread. The authors also reflect on the limitations of the study and the managerial implications of improving operational strategies.

3.4 Feature Interaction Models

Understanding feature interactions is crucial for improving predictive accuracy in AI models, particularly in applications like churn prediction. Liu et al. (2022) illustrate this in their study on hotel booking cancellations, where they explore how machine learning combined with self-interpretable feature interaction models can uncover the factors influencing consumer behavior. Applying this concept to the private transportation sector could reveal potential interactions between service attributes such as pricing, ride experience, and customer support, providing valuable insights into customer retention and churn rates. Expanding on this, Jingyi Wu et al. (2022) discuss Feature Interaction Models within the context of smart cities, focusing on transportation infrastructure. Their work emphasizes the dynamic interplay among residents, vehicles, and transportation systems. By leveraging AI and Digital Twins, their models optimize relationships between spaces, improving functionalities and enabling better traffic flow, reduced congestion, and real-time navigation. This coordination between private vehicles and broader systems aligns transportation with smart city objectives, paving the way for more intelligent and efficient infrastructure development. Together, these perspectives underscore the importance of understanding feature interactions not only to analyze customer behavior but also to enhance infrastructure management. By integrating such models, the private transportation sector can better support the goals of smart cities, resulting in improved customer satisfaction and more effective urban mobility solutions.

3.5 Relationship Marketing Theory

Relationship marketing emphasizes long-term customer relationships rather than transactional focus. Transportation firms that maintain effective communication and implement loyalty schemes can significantly reduce churn rates (Berry, 1995). Organizations can also strengthen customer loyalty by fostering emotional connections, encouraging customers to develop an attachment to the firm. Factors influencing the reopening of customized bus services in Shanghai over a period of 22 months, namely from January 2019 to October 2020, was studied by Shen et al. (2023) using naturalistic observations. Mixed logit models and tree-based models with explainable machine learning techniques were used to analyze reopening and closure decisions for CB lines after the imposition of COVID-19 travel restrictions. Important factors were ridership, length of line, proximity to charging stations, and line overlap. Other important factors mentioned in the study were land-use types around bus stops and competition from alternative transportation modes. Relationship Marketing Theory emphasizes the other side in the private transportation sector, thereby keeping track of customer resistance to change in services through innovations. For example, they may adopt new ride-hailing applications or upgrade the service features. Private transportation firms are interested in knowing key antecedents of customer churn, including emotional attitudes, cognitive rigidity, and functional concerns; this helps them devise strategies to strengthen their relationships with customers. By reducing churn and encouraging customers to embrace new services, these firms can cultivate a loyal customer base that supports sustainable growth and innovation.

3.6 Technology Acceptance Model (TAM)

The TAM gives a wide conceptual framework to understand the reasons behind accepting or adopting a particular technology. As Saeidi et al. (2024) explain, the primary motivating factor behind acceptance is the perceived utility and the case of usage. TAM explains how passengers in private transportation accept the emerging technologies in the sector. These technologies include ride-hailing through mobile phones and contactless payment systems especially during strained situations. Private transport companies can enhance customer satisfaction and service usage through perceived user-friendly and beneficial technologies. These include lower accident rates, more efficient travels, and road fatalities.

David Edwards et al. (2023) extended TAM by incorporating factors such as security and user attitudes, which are vital when using innovative applications like delivery drones. In the private transportation sector, security issues such as safety for drones, packages, and recipients must be addressed to establish trust with users and increase adoption. By effectively managing these elements, companies increase the probability of technology acceptance and can increase efficiency within the delivery system as well as broaden their service offering portfolio. By considering both perspectives, the paper deems TAM an important step in understanding and facilitating the adoption of new technologies into the private transportation sector, partly by addressing usability, perceived benefits, and security concerns, by which private transportation companies might foster stronger acceptance, facilitate increased customer satisfaction, and empower innovation.

4. Literature Review

4.1 Machine Learning Applications

Machine learning (ML) techniques in predicting churn have recently gained significant attention in the private transportation sector. Louis Geiler et al. (2022) carried out a survey on ML methods for churn prediction, with many using algorithms such as logistic regression, decision trees, and support vector machines to identify potential churners based on historical usage data and feedback. The research also highlights that ensemble techniques, where various algorithms are used altogether, outperform the single models in churn prediction, as they improve prediction effectiveness Cerqueira et al. (2024) introduce an advanced model for enhancing bus passenger alighting estimates in Lisbon, overcoming the inadequacies of traditional trip-chaining methods that do not take into account non-commuting passengers.

By incorporating state-of-the-art principles with frequent pattern mining and density-based clustering solutions, the model attains 92% estimation accuracy, which is an 11-percentage-point improvement over classic trip-chaining methods. These actionable insights improve public transport operations, such as bus route optimization and overall service quality. Hafizi et al. (2024) compares statistical and deep learning approaches in predicting inter-stop travel times of urban bus systems using AVL data from Tehran, Iran.

According to the results, deep learning models outperformed traditional statistical methods in accuracy. Sensitivity analysis revealed factors such as arc lengths and directions that are critical for determining travel time predictions. By the findings, deep learning models will help in increasing bus service efficiency especially in countries developing similar public transportation systems. Cheok et al. (2024) analyzed the spatial and temporal aspects of variability in bus travel time in Klang Valley of Malaysia. This study used a validated regression mixture model of the Burr XII type to examine day-to-day variability in travel times and identify key factors such as the number of signalized intersections, link lengths, and route types. Time-of-day and area-specific effects on travel time patterns were seen for both urban and suburban routes. Such findings extend research into understanding how multimodal affects the travel times. These findings are beneficial in optimizing urban transportation systems.

4.2 Factors Influencing Customer Churn

Customer churn analysis has been approached through various methodologies across fields, providing insights into retention strategies. W. Soliman et al. (2020) differentiate between intentional churn, caused by dissatisfaction or changing circumstances, and involuntary churn, which occurs without customer intention. Soumi De et al. (2022) critique traditional churn models that primarily rely on demographic and product-usage data, advocating for the inclusion of social network and interaction data, such as emails and chats, to enhance predictive accuracy. Siti Zulaikha et al. (2023) argue that simplicity in interfaces, robust customer service, and powerful marketing are necessary factors to alleviate churn among customers using mobile ticketing in private transportation. Similar to this study, Xing Wu et al. (2022) recently proposed the model of Multivariate Behavior Sequence Transformer (MBST), which combines attention mechanisms in analysing temporal and behavioural data; it overcomes the constraints and shortcomings of existing tree-based models and sequence-based models to give much deeper insights regarding customer behavior.

In the context of ride-hailing platforms, Sandeep Chitla et al. (2023) identify churn factors as a combination of operational elements, such as pricing and waiting time, and behavioral aspects, such as platform stickiness. The study employs a structural model that incorporates dynamic customer-platform interactions and assumes that riders update their beliefs about pricing and waiting times through Bayesian learning. The model also examines riders' tendency to multihome by analyzing repeated choices between platforms like Uber and Lyft. The findings indicate that customers perceive ride-hailing platforms as differentiated services rather than interchangeable commodities. The study also puts a focus on understanding the behavior of single-homing versus multi-homing so that appropriate promotional strategies could be designed. It further highlights that early lifecycle interventions and reduction in customer search friction are important steps for enhancing market share. It has identified operational and behavioral dimensions for private transportation companies to formulate targeted strategies, thereby developing customer loyalty and retention.

4.3 Customer Loyalty and Retention Strategies

In order to prevent churn in the private transportation sector, effective retention strategies are required. According to Le-Minh Kieu et al. (2023), in "A Class-Specific Soft Voting Framework for Customer Booking Prediction," personalized marketing techniques play an important role. If a company identifies high-risk customers and understands their behavior, targeted interventions, such as discount offers or personalized promotions, can be provided to the transportation companies to prevent churn. According to Aniebiet J. Etuk et al. (2023), service quality is the sum of all experiences that a passenger undergoes on board in terms of safety, comfort, reliability, promptness, and cleanliness; hence, critical to whether a passenger will continue with a service.

In service-based industries, private transportation included, service quality therefore forms the biggest factor determining loyalty among customers. S Dwivedi et al. (2024) discuss strategies for customer loyalty and retention by defining them as methods that concentrate on long-term relationships through addressing the needs of customers and satisfaction improvement. In private transportation, most of these strategies rely on the use of Customer Relationship Management systems in order to increase service quality and build good relationships with customers.

With more in-depth knowledge of customer preferences and customized experiences, transportation companies can increase loyalty, reduce churn, and increase market share. Robust CRM practices are especially important for responding to the changing needs of customers and ensuring that satisfaction is maintained in a competitive environment. Adenutsi et al. (2024) examine the cost-effectiveness of demand-driven factors in passenger loyalty within Ghana's inter-city public transportation system. With limited rail systems, road transport would be in direct competition with private hires.

Based on the sample of 2,431, the study with Structural Equation Modelling revealed that the demand factor for cost efficiency does not predominantly influence passenger loyalty to public transport systems, but mainly by internal factors like operational quality, service personnel, onboard conditions, and the image of public transport. The findings indicate the importance of service delivery and switching costs in terms of sustainability and efficiency in the public transportation sectors of Ghana.

4.4 Empirical Studies on Churn

Many studies empirically analyze the reasons for churn in the transportation industry. Li et al. (2023) identify service reliability, pricing, and customer experience (specifically addressing delays and fare hikes) as key drivers of churn. Sandeep Chitla et al. (2023), focusing on ride-hailing platforms, identified a combination of operational elements (pricing, waiting time) and behavioral aspects (platform stickiness, multi-homing) as churn drivers. Their research applies a structural model with dynamic customer-platform interactions and Bayesian learning to understand how the perceptions of riders on pricing and waiting times affect their platform choices. This study focuses on the importance of understanding single-homing versus multi-homing behaviors for designing targeted promotional strategies and reducing customer search friction. Hafizi et al. (2024) use AVL data from Tehran to compare statistical and deep learning approaches in predicting inter-stop bus travel times, finding that deep learning models offer higher accuracy. This suggests that improved service predictability (reducing unexpected delays) could positively impact customer retention. Cheok et al. (2024) analyzed spatial and temporal variability in bus travel time in Malaysia, finding that signalized intersections, link lengths, and route types are among the most influential factors.

Knowing these factors can help optimize routes and schedules, which may improve service reliability and reduce churn. Adenutsi et al. (2024) used passenger loyalty as a basis in Ghana's intercity public transport to show that the internal factors are much stronger, including operation quality, personnel, onboard conditions, and image of public transport, and although the cost efficiency might be relevant in some instances, it is the least contributing one. The most important ones in determining passenger loyalty involve service quality and switching costs.

4.5 Cross-Industry Insights

As much as it is primarily transport, literature often draws from the broader cross-industry insights; W. Soliman et al. (2020) distinguish between intentional and involuntary churn, a distinction applicable across various sectors. Soumi De et al. (2022) critique traditional churn models for relying solely on demographic and product-usage data, advocating for the inclusion of social network and interaction data (emails, chats), a recommendation relevant to any industry with customer interaction data. Siti Zulaikha et al (2020) point out that simple interfaces, robust customer service, and effective marketing are the most important factors in reducing churn in mobile ticketing, which can be applied to any digital service.

Xing Wu et al. (2022) suggest the Multivariate Behavior Sequence Transformer (MBST) model for analyzing temporal and behavioral data, which can be applied across industries with sequential customer behavior data. Kumar et al. (2022) provide ideas for tailored marketing strategies to be used on high-risk customers; retention is widely practiced across sectors. Ram Kumar Dwived et al. (2024) describe how CRM systems support the development of long-term customer relationships and service quality improvement, practices adopted in a variety of industries.

These are some cross-industry insights that reflect the significance of customer experience, service quality, personalized interactions, and data-driven approaches in the management of churn.

5. Methodology

This study uses the systematic literature review (SLR) approach, following guidelines established by Tranfield et al. (2003) that have been used in many SLR studies conducted in different contexts (Ahmad et al., 2018; Patyal et al., 2021; Spanaki et al., 2021; Tandon et al., 2020). Conducting an evidence-based review, an SLR determines major scientific contributions of interest to a given discipline or research problem. As defined by Tranfield et al. (2003, p. 209), meta-analysis is a statistical method of synthesizing outcomes, yielding an aggregate reliability unattainable by any single study alone. In addition, conducting an SLR has been widely recognized as a "fundamental scientific activity" (Mulrow, 1994, p. 597), highlighting its central role in scholarly research. The SLR process is illustrated in Fig.1 and consists of 3 steps across three phases, namely, planning, conducting and documenting. Each of these three phases are discussed in detail in the remainder of this section.

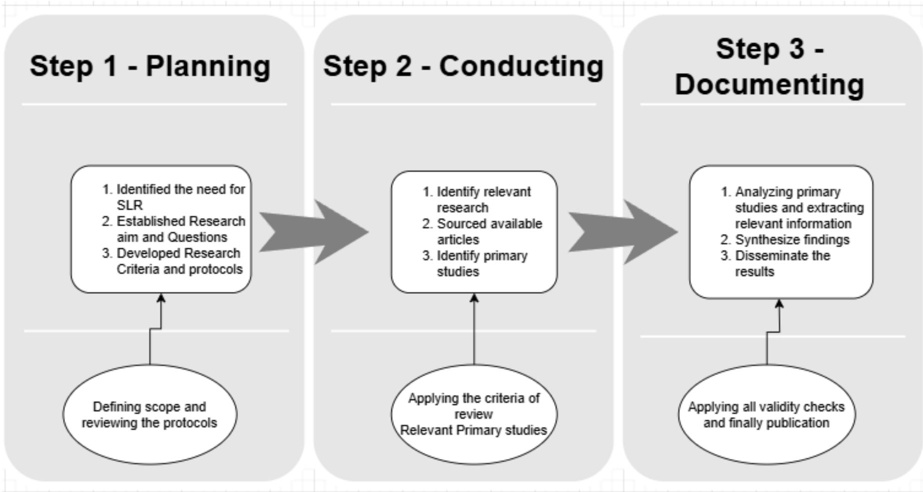

Fig. 1. Protocol for systematic literature review

Table 1. Research Questions

RQ.1. What is the current state of ML applications in customer churn prediction and prevention within the transportation sector?	*RQ.1.1.* How many academic studies on ML for customer churn management in transportation have been published between 2019 and 2024? *RQ.1.2.* What ML techniques have been applied across different stages of customer churn management (prediction, prevention, and intervention)? *RQ.1.3.* What publication outlets and disciplines have contributed to ML research in customer churn within transportation? *RQ.1.4.* What research methods and data collection techniques have been utilized in ML-based customer churn studies in transportation?
RQ.2. How has ML improved customer retention strategies in the transportation sector?	
RQ.3. What are the reported benefits of ML in reducing customer attrition and enhancing customer loyalty?	

6. Synthesis of results

The principal aims of this research (Step 1) are to (i) develop the body of research on customer churn in the transportation sector by analyzing and classifying current research conducted on the issue, (ii) find the most appropriate research on machine learning usage for predicting churn, (iii) review the described benefits and problems with ML methods regarding predicting and avoiding customer churn, and (iv) define areas for further studies. To attain these aims, the research questions (Step 2) enumerated in Table 1 shall be addressed.

Since RQ1 is an overarching research question, three sub-questions (RQ1.1 – RQ 1.4) have been proposed to address this question, and RQ2 and RQ3 shall be a synthesis of the documented challenges and advantages of ML for the application of customer churn prediction within the transportation sector.

RQ.1. What is the current state of ML applications in customer churn prediction and prevention within the transportation sector?

RQ.1.1. How many academic studies on ML for customer churn management in transportation have been published between 2019 and 2024?

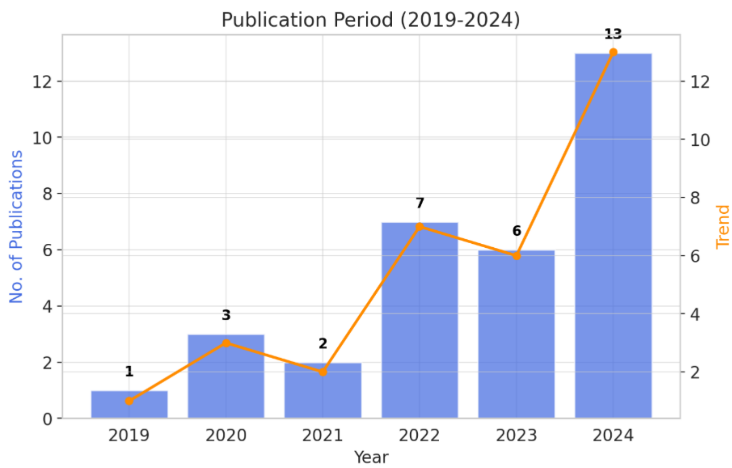

Fig. 2. Publication Period (2019-2024)

The 2019-2024 publication trend indicates an increasing research interest in machine learning for transportation customer churn management. From 2019 to 2021, there were very few studies that were published. But from 2022 onwards, there was a steep spike, to seven in 2022 and a high of 13 in 2024. The trend shows an increase in the acceptance of the potential of ML in predictive analytics and customer retention measures. The spike demonstrates that with data-driven decision-making picking up in transport, more and more researchers are looking at ML-based solutions to enhance efficiency and curb churn.

RQ.1.2. What ML techniques have been applied across different stages of customer churn management (prediction, prevention, and intervention)?

ML Methods Used At Various Phases of Customer Churn Management

The objective of this research question is to determine the machine learning methods used at various stages of customer churn management: prediction, prevention, and intervention. The review of primary studies indicates that most of the research concentrates on churn prediction using supervised learning models like Random Forest, XGBoost, and Deep Neural Networks. These models have been extensively used to examine customer behavior patterns and predict churn likelihood with high accuracy.

To prevent churn, research has used optimization methods such as the Grey Wolf Optimizer (GWO) and Multi-Criteria Decision-Making (MCDM) models to improve model performance and retention of customers.Finally, churn intervention strategies were investigated through ensemble learning techniques like Class-Specific Soft Voting that combines several models to personalize retention measures according to customer segments.

In sum, Table 2 shows that the majority of supervised learning techniques account for churn prediction, whereas optimization and ensemble-based techniques are on the rise when it comes to prevention and intervention, indicating more proactive churn handling in the transport sector.

Table 2. ML Techniques adopted in research papers

Stage	ML Techniques Used	Number of Papers
Prediction	Random Forest, XGBoost, Decision Trees, SVM, Neural Networks, CNNs, LSTMs, Bayesian Networks, Hybrid Logit Models, Deep Learning	18
Prevention	Grey Wolf Optimizer (GWO), Multi-Criteria Decision-Making (MCDM), Attention Mechanism, Trip-Chaining Approach, Digital Twins	8
Intervention	Class-Specific Soft Voting, Ensemble Learning (Stacking, Boosting), Hybrid AI-based Decision Models	7

RQ.1.3. What publication outlets and disciplines have contributed to ML research in customer churn within transportation?

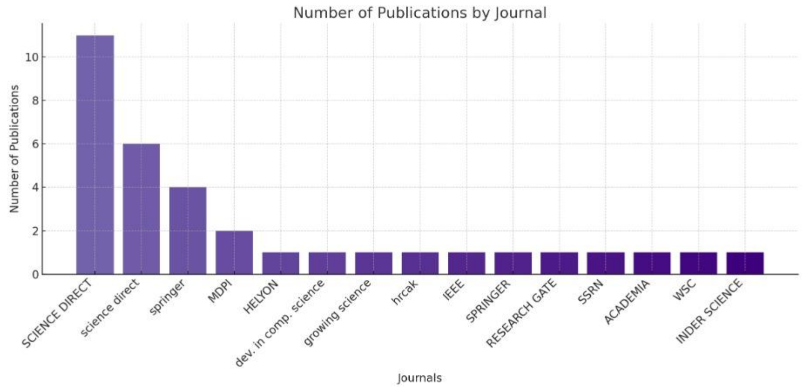

Fig. 3. Number of Publications by Journal

ScienceDirect and Springer are the most prevalent sources, with over 60% of the overall research papers.

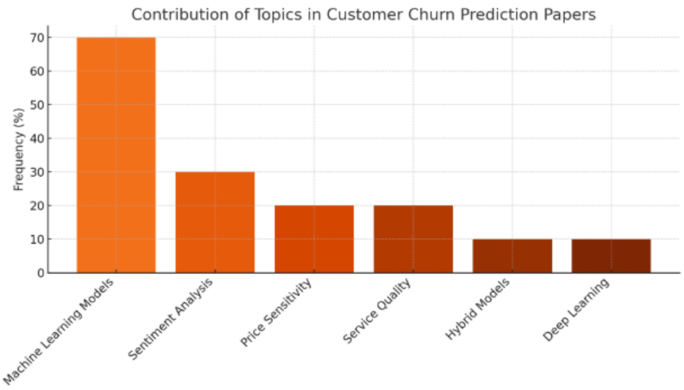

Fig. 4. Contributions of Topics in Customer Churn Prediction Papers

The majority of the studies (70%) focused solely on machine learning models without investigating the customer churn influencing factors.Fewer papers reviewed considered bus hygiene and comfort aspects as significant parameters, particularly in post-pandemic transport services.Price Sensitivity, although widely researched, was identified as lesser in private bus transport, as is in accordance with the dataset of this study.Just 10% of the research papers utilized sophisticated models such as Deep Learning.

RQ.1.4. What research methods and data collection techniques have been utilized in ML-based customer churn studies in transportation?

Machine learning-based customer churn research in the transportation industry has utilized different types of research methodology and data collection methods. Most of the studies have utilized quantitative research methodology from secondary data sources like customer booking history, transaction records, and customer feedback for churn behavior prediction. The most common data collection method is extraction of structured information such as frequency of trips, booking history, and cancellations from company databases. Others have integrated structured data with sentiment analysis by examining customer reviews and comments to gauge customer opinions.Machine learning algorithms such as Logistic

Regression, Decision Trees, Random Forest, and Support Vector Machines have been predominantly used, and some studies have investigated deep models and hybrid solutions.

RQ.2. How has ML improved customer retention strategies in the transportation sector?

Machine Learning (ML) has contributed enormously to customer retention strategies in the transportation industry by allowing for more precise, data-driven decision-making and tailored customer experiences. ML methods have assisted transportation firms in anticipating customer churn, recognizing the determinants of customer behavior, and executing anticipatory measures to retain customers. One of the greatest contributions of ML is that it can examine high levels of customer data like booking habits, travel history, feedback, and complaints. Through algorithms such as Logistic Regression, Random Forest, and Neural Networks, businesses can identify those customers who are likely to churn based on their history.Sentiment analysis on customer complaints and reviews assists in gauging customers' level of satisfaction, which allows organizations to better handle service quality problems. Moreover, ML models aid in dividing customers into segments for loyalty and preferences, allowing firms to develop customized offers and loyalty schemes. Sophisticated methods such as deep learning and ensemble models improved the prediction accuracy of churn, which helps implement early intervention tactics.In addition, predictive outputs of ML models inform businesses to make data-driven decisions regarding pricing, service quality enhancement, and promotional campaigns, thereby enhancing customer retention rates.

RQ.3. What are the reported benefits of ML in reducing customer attrition and enhancing customer loyalty?

The benefits of Machine Learning (ML) in minimizing customer attrition and promoting customer loyalty in the transportation industry are extensively reported in current literature. ML has played an imperative role in enabling transportation businesses to forecast, avoid, and recover from customer churn through the provision of fact-based insights and custom-made solutions. The primary reported benefits are:

- *Precise Churn Prediction:* ML models such as Logistic Regression, Decision Trees, and Random Forest have been found to be highly accurate in predicting customers who are likely to churn based on past booking behavior, frequency of service usage, and payment history.
- *Customer Segmentation:* ML models assist in segmenting customers into high-risk, medium-risk, and low-risk groups, allowing companies to focus retention efforts on customers with higher value.
- *Sentiment Analysis:* Using Natural Language Processing (NLP), ML models review customer feedback and reviews, pick up negative sentiments, and bring out pain points like service quality, hygiene, and punctuality.
- *Personalized Marketing Campaigns:* ML helps firms develop customized offers, discounts, and loyalty schemes for customers depending on their choices and purchase patterns, improving customer satisfaction and loyalty.
- *Proactive Customer Support:* Predictive models enable businesses to proactively contact potential churners ahead of time, providing compensations or solutions to enhance their satisfaction.
- *Service Quality Improvements:* ML insights enable businesses to pinpoint areas for enhancement, such as route optimization, price changes, and on-time performance, which have a direct impact on customer satisfaction.
- *Loyalty Program Optimization:* ML algorithms assist in creating reward programs that are optimized to the needs of the customer, hence maximizing customer retention rates.
- *Cost Savings:* Automating churn prediction and customer segmentation tasks reduces the cost and effort of implementing customer retention campaigns through ML.

Although ML has introduced many advantages, some research suggests that the]absence of service quality factors, integration and tracking of real-time customer behavior is still an issue. Hence, future research may investigate how integrating ML with service quality indicators and customer feedback can improve customer loyalty further in the transportation industry.

Machine Learning (ML) has become a pivotal tool in customer churn prediction and prevention within the transportation sector, especially from 2022 onwards. Supervised learning techniques such as Random Forest, XGBoost, and Neural Networks dominate churn prediction, while optimization and ensemble methods are emerging for prevention and intervention. ML not only enhances churn prediction accuracy but also aids in customer segmentation, personalized marketing, and sentiment analysis.

7. Current challenges

Recent research demonstrates key customer satisfaction and demand forecasting challenges in various industries. Wang et al. (2024) pinpointed the challenge in categorizing residents and vehicles during changing traffic flows. Zhang et al. (2024) discussed that conventional CRM approaches do not handle sequential churn data well. Shabani et al. (2022) attributed low public transport satisfaction to a transition towards private cars. Ong et al. (2022) noted sparse studies on passenger satisfaction in Public Utility Vehicles (PUV) in developing nations. Kieu et al. (2020) emphasized the inefficiency of demand forecasting models in rural regions with non-regular trip patterns. Raghunath et al. (2022) noted low customer trust as a limitation to ridesharing app usage in India. Oliveira et al. (2021) indicated computational difficulties from high-dimensional ride-hailing data. Ji and Zheng (2021) emphasized the challenge of combining spatial and temporal characteristics in taxi demand prediction. Grinberg-Rosenbaum et al. (2020) referenced the lack of real-time feedback systems in public transportation. Ruiz et al. (2021) mentioned that environmental sustainability considerations are commonly not included in satisfaction models. Ismanova (2023) referred to imbalanced datasets as an issue in churn prediction. Tumsekcali et al. (2023) found electric vehicle ride-sharing service demand forecasting to be intricate. Liu et al. (2023) emphasized the inefficiency of hybrid models in combining multiple data sources. Wu et al. (2022) reported sparse application of sentiment analysis to satisfaction studies. Berry et al. (2023) emphasized that demographic diversity was not considered in transport models. Shen et al. (2023) reported the difficulty of ML models in handling peak-hour demand. Saeidi et al. (2023) stressed balancing accuracy and computational expense in hybrid models. Edwards et al. (2022) referred to the absence of personalized recommendations in ridesharing apps. Geiler et al. (2021) demonstrated that differences in service quality within regions are commonly overlooked. Cerqueira et al. (2023) blamed low demand prediction accuracy on a lack of historic data. Hafizi et al. (2022) decried the bad interpretability of deep learning models. Cheok et al. (2022) noted that accessibility features are rarely included in models of satisfaction. Soliman et al. (2023) identified the computational cost of ensemble models to be significant. Soumi De et al. (2023) identified demand fluctuation in subscription businesses as a challenge. Ferreira et al. (2023) found that loyalty schemes are rarely used in models of satisfaction. Etuk et al. (2023) identified challenges in predicting churn for small-sized ride-sharing businesses. Chitla et al. (2023) described a lack of publicly available datasets. Adenutsi et al. (2023) found that traditional models have no space for policy changes.

8. Conclusions and future research

This review emphasizes the increasing use of Machine Learning (ML) to forecast and avert customer churn in the transport sector. The results show that supervised learning algorithms such as Random Forest, XGBoost, and Neural Networks lead in churn prediction, while optimization algorithms and ensemble approaches are on the rise in churn prevention and intervention. Future studies need to incorporate qualitative factors, use longitudinal approaches, and capitalize on multiple data sources in order to develop more holistic and forward-looking churn management theories.Upcoming ML-based customer churn management studies should focus on incorporating service quality aspects such as hygiene, comfort, and punctuality into prediction models. Leverage real-time churn prediction via IoT and real-time feedback for increased proactive interventions. Hybrid ML approaches that involve supervised, deep learning, and optimization algorithms can enhance accuracy. Explainable AI (XAI) techniques can give clear reasons for churn decisions. Creating customer-specific retention policies with changing customer preferences will even enhance customer loyalty in the transport industry.

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