

CHAPTER 2 - LITERATURE REVIEW

2.1 Introduction to Customer Churn

Customer churn, also known as customer turnover, is an important indication in the dynamic and competitive environment of the telecommunications industry, notably among Internet Service Providers (ISPs) in Indonesia. It denotes the rate at which customers abandon their services, which has a direct impact on a company's income and long-term viability. Churn rates have historically been associated with customer satisfaction, service quality, and market rivalry (Edwine et al., 2022; Ribeiro et al., 2023).

Customer turnover has serious financial consequences for telecom firms. The substantial costs of churn highlight the need for precise forecasting and appropriate management measures (Peng et al., 2023). As a result, knowing the elements that contribute to churn is critical for telecom businesses in order to successfully customize their client retention efforts.

The importance of data analytics, including machine learning, in forecasting and assessing churn has grown (Edwine et al., 2022). For prediction accuracy, techniques such as Random Forest, Support Vector Machines, and K-nearest neighbors have been investigated. These developments show the telecom industry's trend toward more sophisticated, data-driven ways to analyze and reducing customer churn (Edwine et al., 2022).

Several factors, including service quality, customer demographics, and pricing structures, have been identified as contributing to churn (Ribeiro et al., 2023). Several research studies (Salma & Aprianingsih Ph.D, 2021b; Triyafebrianda & Windasari, 2022) have been conducted to demonstrate the relationships between the factors that drive customer churn.

Table 2.1 Factors Impacting Customer Churn (Salma & Aprianingsih Ph.D, 2021b;
Triyafebrianda & Windasari, 2022)

Factor	Description	Impact on Churn
Service Quality	Includes network quality, customer support, and reliability.	High quality reduces churn.
Pricing & Price Satisfaction	Perception of price fairness and value.	Fair pricing can lower churn.
Customer Support & Complaint Management	Efficiency in handling complaints and providing support.	Effective management reduces churn.
Switching Costs	Costs associated with changing providers.	High switching costs lower churn.
Customer Satisfaction & Dissatisfaction	Level of fulfilment with the service.	High satisfaction reduces churn, and vice versa.
Customer Loyalty	Commitment and positive attitude towards the ISP.	High loyalty decreases churn.
Multi-Brand Attitude	Behaviour towards multiple brands in a category.	Influences loyalty and churn.

Recent developments in churn prediction models have enhanced model performance by adding data transformation methods and feature selection (Sana et al., 2022). This development reflects an industry trend toward using analytics to predict churn and analyze underlying problems (Sana et al., 2022).

Telecom firms must not only estimate churn but also identify the underlying reasons, allowing them to take proactive efforts to increase customer loyalty and minimize churn rates. ISPs may design more successful customer retention strategies by integrating insights from machine learning forecasts with an awareness of major churn variables like service quality, price, and customer assistance (Edwine et al., 2022).

The combination of machine learning and data analytics with conventional customer churn research provides ISPs with a complete strategy to understand and dealing with customer churn. This story emphasizes the need for a multifaceted approach in telecom industry that combines technology developments with a thorough grasp of consumer wants and market dynamics (Edwine et al., 2022; Ribeiro et al., 2023; Sana et al., 2022).

2.2 Churn Prediction Models

Customer retention techniques' churn prediction algorithms have developed dramatically over time. Traditional statistical approaches such as logistic regression and survival analysis were widely used at first. These approaches, which were founded on classical statistics, offered a strong basis but often struggled with complicated, non-linear data patterns observed in recent datasets (Geiler et al., 2022).

Machine learning methods started to take the front stage with the introduction of powerful computers. Artificial Neural Networks (ANN) have been at the vanguard of this change, including Multi-Layer Perceptron (MLP), Support Vector Machines (SVM), and decision trees. MLPs excel at managing enormous datasets and capturing subtle patterns because of their deep, layered architecture. Several studies have shown that they adapt efficiently to new data, which is critical for accurate churn forecasts (Bogaert & Delaere, 2023; Fareniuk et al., 2022).

A comparison of different approaches shows a definite pattern. While classic statistical approaches are useful for their simplicity and interpretability, machine learning models, particularly those based on sophisticated neural networks such as MLPs, often outperform. Ensemble approaches, which mix many models to improve prediction accuracy and resilience (Bogaert & Delaere, 2023), are a prime example of this.

Furthermore, the use of data transformation techniques and feature selection has been critical in the refinement of these models. Weight-of-Evidence (WOE) techniques have proved useful in enhancing the predictive ability of logistic regression and neural networks, particularly MLPs. This implies that the future of churn prediction rests in the collaboration of old and contemporary methodologies (Sana et al., 2022).

Overall, the topic of churn prediction exemplifies how combining conventional statistical approaches with new machine learning techniques, notably MLPs, may result in more effective and economical predictive models. This domain's ongoing growth reflects the dynamic nature of consumer behaviors and the increasing complexity of datasets in the digital world, a subject highlighted throughout your collection of papers.

Table 2.2 Churn Prediction Model Comparison (Bogaert & Delaere, 2023; Geiler et al., 2022; Sana et al., 2022)

Technique	Characteristics	Typical Applications	Effectiveness for Churn Prediction
Logistic Regression	Probabilistic approach, good for binary classification, outputs have a nice probabilistic interpretation	Binary Classification	High, especially for binary outcome prediction (churn/no churn)
Principal Component Analysis (PCA)	Dimensionality reduction technique, orthogonal transformation to convert correlated features into linearly uncorrelated	Data Preprocessing, Visualization	Moderate, more used as a preprocessing step
MultiLayer Perceptron (MLP)	Type of ANN, consists of multiple layers of nodes in a directed graph, capable of capturing complex patterns	Pattern Recognition, Classification	Very High, excellent for capturing nonlinear relationships

2.3 Machine Learning in Churn Prediction

The use of Machine Learning in churn prediction, particularly Multilayer Perceptron (MLP), has transformed customer retention methods in telecoms. MLP is a feedforward artificial neural network that excels at modeling complicated, non-linear data interactions. This is obvious in telecommunications case studies, such as those performed on SyriaTel's telecom data, where MLP's involvement in successfully processing massive datasets to anticipate customer churn is shown (Ahmad et al., 2019).

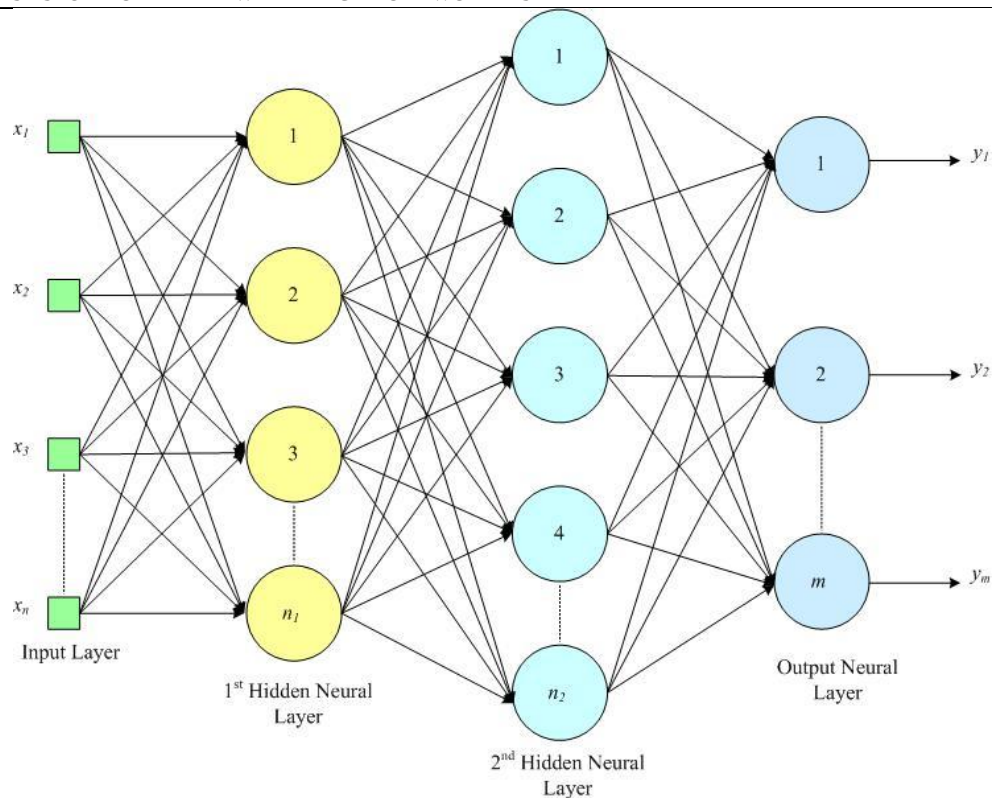


Figure 2.1 Multiple-Layer Perceptron Architectures (da Silva et al., 2017)

By studying customer behavior and use trends, MLP's predictive capabilities allow telecom firms to detect prospective churners. This proactive strategy enables focused actions to promote customer happiness and loyalty, resulting in lower churn rates (Lalwani et al., 2021).

Despite its precision and adaptability to a wide range of data types, MLP requires extensive computer resources and careful calibration to prevent overfitting. Because of these constraints, a trade-off must be struck between model complexity and actual application efficiency (Lalwani et al., 2021).

Despite these obstacles, MLP has a considerable impact on churn prediction. Its implementation in the telecom industry demonstrates ML's transformational potential in improving customer retention methods, which is critical in today's competitive market (Ahmad et al., 2019; Lalwani et al., 2021).

Finally, MLP in churn prediction is an example of the convergence of technology and customer relationship management. It gives telecom firms a valuable tool for

understanding and forecasting consumer behavior, which is critical for staying competitive in the telecoms market (Ahmad et al., 2019).

2.4 Marketing Strategies to Mitigate Churn

Customer churn in the telecoms business needs new retention marketing methods. This issue, which is the topic of this research, presents a substantial danger to telecom businesses' stability and development. A Danish university research offers unique insights into consumer behavior in the Nordic telecom market. This research (Saleh & Saha, 2023) highlights the complexities of churn by emphasizing geographical variances in consumer preferences and behavior patterns.

Relationship marketing's development (Steinhoff et al., 2018) represents a substantial change in consumer interaction techniques. This shift from conventional e-commerce to sophisticated digital interactions emphasizes the significance of adjusting to shifting customer expectations in the digital age. A comparison with the banking industry, especially via the perspective of South African social media sentiment (Lappeman et al., 2022), finds analogous characteristics impacting customer churn. This cross-industry viewpoint adds to the knowledge of turnover dynamics.

Another critical factor is the efficiency of service recovery techniques in reducing churn, especially in developing countries. (Borah et al., 2019) emphasize the need of customizing these techniques to various failure circumstances to improve client retention. Relationship marketing takes on a new dimension in the context of business-to-business transactions.

The research (Palmatier et al., 2007) investigates the influence of relationship orientation on the efficacy of various methods, highlighting the nuanced approach needed in B2B environments. This review also contains a larger analysis, which compares the data from different sectors and geographical locations. This synthesis provides a more comprehensive picture of the measures needed to successfully prevent churn. Finally, this literature analysis stitches together multiple research strands to provide a holistic knowledge of the churn mitigation measures required in the highly

competitive telecom business. This research synthesis provides essential insights on establishing successful client retention tactics.

2.5 Research Comparison

Here are some overviews of the previous research the researcher use as a comparison:

1. Title: Customers Churn Prediction using Artificial Neural Networks.

Author: Khan, Y., Shafiq, S., Naeem, A., Ahmed, S., Safwan, N., & Hussain, S. (2019).

Summary: The research focused on Pakistani telecom companies where the data were taken. The data were taken from October to December 2018 and consist of 20,468 instances and 26 attributes such as demographic data, billing information, and usage patterns. The data was used to predict customer churn in the telecom industry. In this research, the ANN model achieved an accuracy of 79% in predicting churn in Pakistan.

2. Title: Customer Churn Prediction in Telecommunication Industry Using Classification and Regression Trees and Artificial Neural Networks Algorithms.

Author: Abdulsalam, S. O., Arowolo, M. O., Saheed, Y. K., & Afolayan, J. O. (2022).

Summary: The research focused on telecom industry operators, where the data was taken from the BigML website, a company that provides a platform for machine learning and predictive analytics. The dataset consists of 20 attributes and 3333 instances, which include information about telephony account features and whether the customer has churned. In this research, the ANN classifier achieved a high predictive capacity of 93.88%.

3. Title: Predicting Customer Churn Using Artificial Neural Networks.

Author: Kumar, S., & Kumar, M. (2019).

Summary: The research utilizes a dataset obtained from the telecommunications industry, including 21 variables and 7043 observations. The dataset includes service-based information, customer account information, and demographic information variables. In this research, the ANN classifier has a predictive capacity of 75% on validation data.

4. Title: Predicting Customer Churn in Telecom Industry using Multilayer Perceptron Neural Networks: Modelling and Analysis.

Author: Adwan, O., Faris, H., Jaradat, K., & Ghatasheh, N. (2014).

Summary: The research focused on Umniah, a Jordanian mobile cellular company where the data were taken. The dataset contains 11 attributes of randomly selected 5000 customers for a time interval of three months. In their research, the ANN classifier has a predictive capacity of 62%.

5. Title: A Neural Network-Based Approach for Predicting Customer Churn in Cellular Network Services.

Author: Sharma and Kumar Panigrahi (2011).

Summary: The churn dataset from the UCI Repository of Machine Learning Databases at the University of California, Irvine, was utilized in the research. It comprises information on cellular service provider customers and their voice call data. The dataset includes 20 variables, and the results achieve 92% accuracy in predicting customer churn.

The previous research served as a valuable reference for the author's research, improving the theoretical framework used in this research. The primary objective is to understand and analyse the intricate nature of customer churn within the unique setting of an Internet Service Provider (ISP) in Indonesia. Utilizing knowledge gained from previous research, the research explicitly investigates the forecasting skills of artificial neural networks in predicting customer churn.

Table 2.3 Research Comparison

Author	Title	Journal	Method	Result
Khan, Y., Shafiq, S., Naeem, A., Ahmed, S., Safwan, N., & Hussain, S. (2019).	Customers Churn Prediction using Artificial Neural Networks	International Journal of Advanced Computer Science and Applications	ANN, Decision Tree (DT), Logistic Regression (LR), SVM	ANN predict telecom churn with 79% accuracy in Pakistan.
Abdulsalam, S. O., Arowolo, M. O., Saheed, Y. K., & Afolayan, J. O. (2022, June 12)	Customer Churn Prediction in Telecommunication Industry Using Classification and Regression Trees and Artificial Neural Networks Algorithms	Indonesian Journal of Electrical Engineering and Informatics	Artificial Neural Networks (ANN) and Classification and Regression Trees (CART)	ANN classifier has a predictive capacity of 93.88%
Kumar, S., & Kumar, M. (2019)	Predicting Customer Churn Using Artificial Neural Networks	Part of the Communications in Computer and Information Science book series	Artificial Neural Networks (ANN)	ANN classifier has a predictive capacity of 75%
Adwan, O., Faris, H., Jaradat, K., & Ghatasheh, N. (2014, January 29)	Predicting Customer Churn in Telecom Industry using Multilayer Perceptron Neural Networks: Modelling and Analysis	Life Science Journal 2014;11(3)	Artificial Neural Networks (ANN) with Multilayer Perceptron (MLP)	ANN classifier has a predictive capacity of 62%
Sharma and Kumar Panigrahi (2011)	A Neural Network based Approach for Predicting Customer Churn in Cellular Network Services	International Journal of Computer Applications 27, 26–31.	Artificial Neural Networks (ANN)	Has a predictive capacity of 92%