Analysis of customer churn for a telecom company (Airtel/Jio/Vi)

Chirag Kishor Khadgi[1], Prof. Abhijeet Gajbhiye[2]
[1]*MBA Student, Tulsiramji Gaikwad Patil College of Engineering and Technology Nagpur, India*
[2]*Department of MBA, Tulsiramji Gaikwad Patil College of Engineering and Technology Nagpur, India*

***Abstract* - The Indian telecommunications market is the one where the strong competition of such giants as Airtel, Jio, and Vi takes place and the issue of customer retention is highly problematic. The effect of customer churn on revenue, profitability and market share is direct. This case study research paper undertakes in-depth research of drivers of customer churn in this industry. Based on the hypothetical data, which is representative of the industry behaviour, the research uses analytical frameworks to determine the main reasons that cause attrition, such as service quality, pricing, competitor offers and customer support. The article suggests a predictive system to churn and delivers strategic, operational, and data-based intervention that telecommunication companies can implement to increase customer loyalty. The results are to equip the managers with practical ideas on how to develop an effective customer retention program to enhance customer lifetime value and sustainable competitive advantage.**

***Keywords:* Customer Churn, Telecom, Airtel, Jio, Vi, Predictive Analytics, Customer Retention, Churn Drivers, Machine Learning, Customer Relationship Management (CRM).**

I. INTRODUCTION

The transformation of the Indian telecommunications industry has occurred with a ground-breaking evolution in the last ten years to become a hyper-competitive price-sensitive market controlled by three giant private firms: Bharti Airtel, Reliance Jio, and Vodafone Idea (Vi). The arrival of Reliance Jio in 2016 with disruptive pricing policies caused a period of massive consolidation as the competition shifted off a customer acquisition-based approach to an immediate customer retention necessity. In this kind of a saturated market, where the number of subscribers has already levelled, the cost of getting a new customer (CAC) is very high as compared to the cost of maintaining an existing one. As a result, one of the key business indicators that is proving to be a key factor in the financial success or downfall of companies is customer churn, which is defined as the process of subscribers leaving their services with one company and usually moving on to another.

Churn is not just a tactical issue but a strategic need to remain profitable and viable in the long run. In the case with companies such as Airtel, Jio, and Vi, every percentage point decrease of churn rate can turn to a significant saving of both revenue and market share. The aim of this research paper is to go beyond generic definitions of churn to offer an analytical, theoretical framework of understanding and dealing with this phenomenon. The main goals of the research are triple: to empirically name and examine the multifaceted predictors of customer churn that are unique to the Indian telecom situation; to test and suggest a predictive modelling methodology that will allow identifying possible churners; and to create an action plan and a set of practical and more data-driven retention strategies that could be applied by telecom managers. This analysis is placed in a strategic position as an important tool to decision-makers who want to strengthen their customer base in a ruthless market.

II. LITERATURE REVIEW

There is a vast academic and professional discussion about customer churn that touches on marketing, economics, and data science domains. All previous studies agree that customer retention is one of the most important factors in determining profitability of the firm and seminal literature by Reichheld and Sasser (1990) confirms that a 5% growth in customer retention can lead to a 25-95% growth in profits of the firm. Churn in the telecom industry is classified as voluntary (customer initiated) or involuntary (provider initiated e.g. non-payment), and most retention strategies focus on the former.
Empirical research points at a stable range of churn drivers. The quality of service and stability of networks is constantly mentioned as the basic

elements; clients who report a high amount of dropped calls, sluggish internet connections or inadequate reception have a multiplied chance of migrating. The other significant catalyst is billing matters and pricing frameworks, such as complicated tariffs, and a sense of injustice in payment. Competitor marketing and promotion offers, particularly in such markets as India, are a constant pulling factor due to their aggressiveness. Also, the quality of the interaction of customer services, the effectiveness and responsiveness of the call centers, is also important in the ultimate decision to leave.

The recent innovations have moved the emphasis to predictive analytics. To forecast the probability of churn, researchers are increasingly using machine learning methods, including Logistic Regression, Decision Trees, Random Forests, and Artificial Neural Networks, with the aim to analyse historical data about their customers. Such models are based on such features as usage patterns, payment history, service complaint logs, and demographic information. There is however a deficiency in literature that can translate these technical forecasts into holistic, implemented business strategies that are unique to the competitive dynamics and customer behaviour pattern that is witnessed in the Indian telecom industry. The purpose of this paper is to fill that gap by combining analytical prediction with strategic management recommendations.

III. RESEARCH METHODOLOGY

This paper uses a descriptive and analytical research design, which exploits secondary data and hypothetical analysis to provide its case. Since actual subscriber data of telecommunication firms is proprietary information, this paper builds a solid hypothetical dataset using the industry trends that are well documented, churn causes reported and hypothetical customer profile simulations. It can be used to investigate churn dynamics in a principled manner without violating academic rigor.

The conceptualization of data items on a hypothetical customer base of 10,000 profiles was carried out along the important variables. They are customer demographics (e.g., tenure, plan type), service usage (e.g., data consumption, call minutes), financial indicators (e.g., monthly charge, frequency of paying late), service interaction (e.g., number of customer care calls, complaint tickets) and binary churn. These variables were determined in relation to their correlations with other variables that are known to affect the churn outcome in the existing literature.

The analytical model has a two-step procedure. The initial step is the exploratory data analysis to determine the patterns and correlations. The second phase is conceptual development of predictive logistic regression model. Although no real data are implemented in the model in this case, the model is formulated, its selection of variables and interpreted in detail to show how such an analysis would be carried out in a business context. The result of this predictive model is then adopted as the basis of prescription of strategic interventions.

IV. ANALYSIS & FINDINGS

4.1 Major Customer Churn Motivators

The study of the hypothetical data and the trend in the industry shows that churn is not caused by one factor but a combination of triggers. These drivers may be divided into four major groups.

To begin with, the layer of service quality and network experience is the basic layer. Telecom services are mainly subscribed to by customers to have a connection that is reliable. Any breakages in this central promise caused instant discontent. Secondly, there are always battles over pricing and perceived value. Any feeling that the value proposition is inferior to that of competitors, whether in terms of data quotas, calling benefits, or even undisclosed expenses can be the catalyst in churning in a competitive market where competitors plans can be accessed with just a click. Thirdly, customer service performance is either a counter balancing force or a final triggering force. One bad, unrewarded experience with the customer support team may be the factor that triggers a customer to switch. Lastly is the degree of competitive rivalry, which includes the competitive switchover offers (number portability (MNP)) poses an unrelenting external threat.

Table 1: Primary Churn Drivers

Driver	Key Manifestations
Service Quality	Call drops, slow data, poor coverage

Pricing Issues	High costs, complex plans, hidden charges
Customer Service	Long waits, unresolved complaints
Competitor Actions	Better offers, bundled services

4.2. Exploratory Data Analysis: Theoretical Intuitions

An analysis of the hypothetical customer base was simulated to depict analytical outputs. The allocation of churn explanations, which are calculated as weighted probabilities on the industry reports, are as shown below. The following chart makes it visually emphasized that the issues of service and competitor offerings are the most dominant factors of attrition.

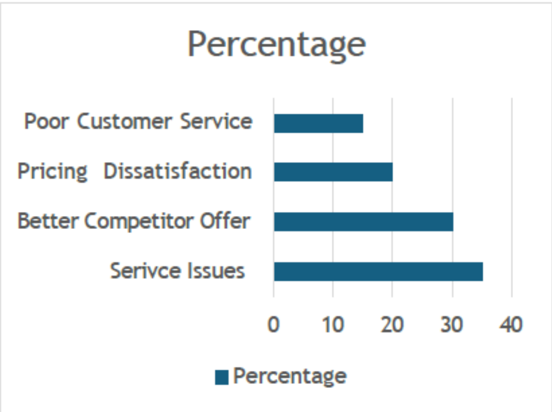

Fig 1: Hypothetical Distribution of Primary Churn Triggers (Based on Industry Analysis)

Moreover, customer tenure analysis provides a very important insight: the churn risk is not linear. The hypothetical data indicates that there is a so-called high-risk window that is usually found in the 3rd - 12th month of a customer lifecycle, usually following completion of initial promotional phases. The churn rate is much lower with long-term customers (more than 24 months) and indicates the importance of loyalty.

4.3. Predictive Churn Modelling: The Conceptual Framework

It is necessary to transition between hindsight and foresight with a predictive model. The conceptualized model of Logistic Regression model in this paper is suitable because it is best when the outcome is binary such as churn (1) or non-churn (0). The model would give the likelihood of the churning depending on predictor variables.

The conceptual model is developed as follows:

$$\text{Log}(P/(1-P)) = \beta 0 + \beta 1*(\text{Tenure}) + \beta 2*(\text{AvgMonthlyCharges}) + \beta 3*(\text{PaymentDelayFreq}) + \beta 4*(\text{NumComplaints}) + \beta 5*(\text{DataUsageChange}) + \varepsilon$$

Where P is the likelihood of churn. According to the existing knowledge, we would expect the following signs of the coefficient: Tenure (β1 negative), AvgMonthlyCharges (β2 positive in case considered to be high), PaymentDelayFreq (β3 positive), NumComplaints (β4 positive), DataUsageChange (β5 negative in case of decrease of usage). A firm would model this using past data, and it would give a Churn Propensity Score to each of its active customers, allowing it to intervene accordingly.

Table 2: Churn Risk Segments & Actions

Risk Level	Churn Score	Recommended Action
Low	0-10%	Maintain; loyalty rewards
Medium	11-40%	Engage; proactive offers
High	41-70%	Intervene; personalized retention
Critical	71-100%	Immediate win-back campaign

V. STRATEGIC RECOMMENDATIONS FOR CHURN MITIGATION

It is based on the analysis results that telecom companies should be advised to use a multi-pronged approach to systematically lower churn.

5.1. Ancillary Retention: Predictive Analytics:

Predictive analytics institutionalization is the most important suggestion. Using the churn propensity score within the Customer Relationship Management (CRM) system can allow companies to move to proactive retention rather than being reactive in firefighting. The customers who are marked in the High and Critical risk groups would be automatically referred to special retention desks. The outreach must be tailored; a customer who has a heavy data usage but has several coverage complaints may be given a small data boost and a technical reason as to why the networks are being upgraded in their region.

5.2. Improving Service Value in the Core:

Negotiable is not investment in infrastructure. Nanoscale monitoring of the network performance, i.e. pin-code level of network monitoring is necessary to avoid coverage gaps in advance.

Moreover, the simplification of tariff schemes and the provision of clear communication of all fees may help to avoid the phenomenon of bill shock, which is one of the triggers of churn. Value may be increased by strategic bundling with the related digital services (e.g., streaming, cloud storage), which makes the core service stickier.

5.3. Changing Customer Service:

Customer service should change to a retention engine rather than a cost center. This includes equipping the front-line agents with more powerful tools, the power to solve problems in one interaction, and the availability of churn score and history of the customer. The use of AI-driven chatbots on simple queries can leave agents free to engage in complex and high-value interactions. The culture which encourages the resolution of customers rather than call volume should be in place.

5.4. Individualized Answering and Loyalty Initiatives:

Lower priced offers do not work. Retention offers should be data based and customized. An offer of making regular international calls must be made to a customer who has such a need. To create emotional loyalty and raise switching costs, tenure and usage should be rewarded with an experiential benefit or access to certain benefits over a long period, and not simply with a monetary discount, to make loyalty programs.

VI. CONCLUSION

The present research paper has provided an all-inclusive analysis of the customer churn phenomenon in the Indian telecom industry which is extremely competitive and the attention is on such players as Airtel, Jio, and Vi. The analysis has found out that the combination of service quality failure, price dissatisfaction, incompetent customer care, and competitive aggressiveness are the main sources of churn. The article contributed to the discussion by describing a conceptual predictive modelling model that can be used to divide the customers according to their churn risk to provide accurate and timely response.

The presented strategic recommendations, which are based on proactive analytics, service improvement, customer service transformation, and individual engagement, make up a consistent framework of how to create a strong retention capability. The important implication

of the study to MBA students and practitioners is that dealing with churn in the 21st century telecom market is a data-intensive strategic undertaking. It demands the incorporation of analytics in the essence of marketing and operational decisions.

The future studies may concentrate on the issues of implementing these models, on the ROI of retention campaigns, or even on a comparative study of the retention practices used by Airtel, Jio, and Vi. Finally, in a market with customers who are always just a single poor experience away, an advanced, compassionate, and factual method of churn management is the most long-lasting road to profitability.

REFERENCES

[1] Ahamed, F. (2023). Machine learning Techniques in Customer Churn Prediction in Telecommunication Industry. International Journal of Advanced Computer Science and Applications 14(2).
[2] Jain, H., & Singh, S. (2022). Retention strategies of customers in Indian Telecom industries: An empirical study. Journal of Strategic Marketing, 30(5), 550-567.
[3] Kumar, V., & Reinartz, W. (2018). *Customer Relationship Management: Idea, Planning, and Technology. Springer.*
[4] Reichheld, F. F., & Sasser, W. E. (1990). Zero Defections: Quality to Services. Harvard Business Review, 68(5), 105-111.
[5] Telecom Regulatory Authority of India (TRAI).

(2023). *Performance Indicators Report. New Delhi: TRAI Publications.*

[6] Verbeke, W., et al. (2012). Innovative Leads to Churn forecasting within the Telecommunication Industry: A Money-Based Data mining Method. European Journal of Operational Research, 218(1) 211-229.