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ANALYZING CUSTOMER CHURN IN RELIANCE JIO: A PREDICTIVE APPROACH TO RETENTION STRATEGIES AND CUSTOMER SATISFACTION

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ABSTRACT

The Indian telecommunications sector has experienced high growth and stiff competition, with customer retention becoming a key challenge for service providers. This research aims to examine customer churn in Reliance Jio, a top telecom operator in India, using a predictive strategy to retention and customer satisfaction.

The research uses past customer data and predictive analytics to create a churn forecasting model that allows for proactive retention strategies. Segmentation of customers by the risk of churn is suggested to create customized retention strategies to boost customer satisfaction and minimize attrition rates. The research also examines the impact of loyalty programs, competitive pricing and improved service quality in combating churn.

Conclusion of this research offers useful information to Reliance Jio's management and telecommunication industry stakeholders, providing evidence-based suggestions to enhance the company's customer engagement, maximize retention attempts and achieve long-term customer loyalty. This research adds to the research literature on the prediction of churn while offering implementable suggestions to maintain market leadership in the fast-paced telecommunication industry.

Keywords: Customer Churn, Predictive Analytics, Retention Strategies, Customer Satisfaction, Telecom Industry, Reliance Jio.

I. INTRODUCTION

1.1 Background

The Indian telecom sector has witnessed a giant shift in the last ten years with technology upgradation, competitive pricing, and changing consumer preferences. Reliance Jio, ever since it entered the market in 2016, has revolutionized the sector with cheap data plans, widespread 4G network, and customer-friendly strategy. It has acquired a humongous subscriber base, which has had a huge influence on the competitors. Nonetheless, even with its success, customer churn continues to be a recurring issue for Jio and the telecom sector as a whole.

Customer churn, or the rate at which customers stop using their services, is a severe threat to telecom operators by influencing revenue and market share. Elevated churn rates signal user dissatisfaction, usually prompted by network problems, price sensitivity, inefficiencies in customer service and promotional offerings from competing operators. Knowing the causes of churn and crafting strong retention measures is crucial to maintaining growth and profitability.

As more organizations move towards using data-driven decision-making, telecommunications operators are using predictive analytics to forecast the behavior of their customers and introduce proactive retention measures. Through the identification of the key indicators of churn, including usage patterns, service complaints and payment habits, operators are able to tailor customer experience, optimize pricing practices, and enhance the quality of service to minimize attrition.

This study emphasizes the examination of customer churn in Reliance Jio through predictive methods of retention strategies and customer satisfaction. Through machine learning methodologies and data analysis, the study seeks to determine the key drivers of churn and generate actionable recommendations for enhancing customer retention. The results will assist Reliance Jio in solidifying its market competitiveness, boosting customer loyalty, and maintaining long-term business viability.

1.2 Problem Statement

Customer churn poses a significant challenge for telecom companies, as it is generally more cost-effective to keep existing customers than to attract new ones. Reliance Jio, despite its strong market position and competitive pricing, experiences customer attrition due to various factors, including service quality, pricing strategies, customer engagement, and the competitive landscape. Understanding the main causes of churn and predicting customer behavior can aid in creating effective retention strategies.

This study aims to explore customer churn patterns at Reliance Jio by looking into demographic factors, usage behavior, and satisfaction levels. By developing a predictive model, the research intends to estimate churn probability and offer actionable insights for enhancing customer retention. The results will assist Reliance Jio in improving its service offerings, reducing churn, and boosting overall customer satisfaction, thereby ensuring long-term business sustainability in a competitive telecom environment.

1.3 Objectives

1. To Identify Key Factors Influencing Customer Churn - This objective focuses on uncovering the main reasons customers choose to leave Reliance Jio. We will analyze various factors such as age, gender, location, income, number of dependents, and service usage patterns (including calls, SMS, and data consumption) to assess their influence on churn.

2. To Analyze the Relationship Between Customer Satisfaction and Churn - This objective investigates the connection between customer usage patterns and their satisfaction levels. Increased engagement in calls, SMS and data usage may reflect higher satisfaction, while a decrease could indicate dissatisfaction and a greater likelihood of churn.

1.4 Hypothesis

Based on our initial research, we propose the following hypothesis:

H0: Customer demographics (age, gender, income, and number of dependents) significantly impact churn rates.

H1: Customers with lower service usage (calls, SMS, data) are more likely to churn than high-usage customers.

II. RESEARCH METHODOLOGY

This study follows a quantitative research approach to analyze customer churn in the telecom sector, specifically at Reliance Jio. It employs descriptive research to understand churn characteristics and predictive research to develop a model for forecasting churn using historical data.

Data Collection & Sampling

- Data Source: Secondary data from Kaggle's "Telecom Churn Dataset" by Suraj520.
- Source Link: https://www.kaggle.com/datasets/suraj520/telecom-churn-dataset
- Population: All current and past Reliance Jio customers.
- Sample Size: 61,123 customer records.
- Sampling Technique: Random sampling ensures unbiased selection.

Dataset Overview

The dataset includes:

- Demographics (Age, Gender, Location, Income, Dependents).
- Usage Patterns (Calls, SMS, Data Consumption).
- Subscription Details (Registration Date, Telecom Partner).
- Churn Status (Active or Churned customers).

Justification for Dataset Use

- Reflects real-world customer behavior.
- Includes key variables influencing churn.
- Enables predictive modeling for retention strategies.

Data Processing & Cleaning

- Handling missing values.
- Standardizing formats.

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- Identifying outliers.

Sampling Frame

- Comprises all 61,123 customer records in the dataset.
- Ensures diverse customer representation for accurate churn predictions.

This research ultimately aims to develop an effective churn prediction model to help Reliance Jio reduce customer attrition.

Data analysis

❖ **Identifying Key Factors Influencing Customer Churn**

Chi-Square Test (Categorical Variables vs. Churn)

Table 1: Case Processing Summary

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Gender * Churn	61123	100.0%	0	0.0%	61123	100.0%
State * Churn	61123	100.0%	0	0.0%	61123	100.0%

Table 2 : Gender Churn

Gender * Churn

Crosstab

			Churn		
			0	1	Total
Gender	1	Count	29359	7338	36697
		Expected Count	29352.0	7345.0	36697.0
	2	Count	19530	4896	24426
		Expected Count	19537.0	4889.0	24426.0
Total		Count	48889	12234	61123
		Expected Count	48889.0	12234.0	61123.0

Table 3 : Chi- Square Test (Gender Churn)

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.021[a]	1	.884		
Continuity Correction[b]	.018	1	.893		
Likelihood Ratio	.021	1	.884		
Fisher's Exact Test				.885	.446
Linear-by-Linear Association	.021	1	.884		
N of Valid Cases	61123				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 4888.96.

b. Computed only for a 2x2 table

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Table 4: State Churn

State * Churn

Crosstab

			Churn 0	Churn 1	Total
State	1	Count	1725	453	2178
		Expected Count	1742.1	435.9	2178.0
	2	Count	1726	408	2134
		Expected Count	1706.9	427.1	2134.0
	3	Count	1753	431	2184
		Expected Count	1746.9	437.1	2184.0
	4	Count	1717	444	2161
		Expected Count	1728.5	432.5	2161.0
	5	Count	1821	429	2250
		Expected Count	1799.7	450.3	2250.0
	6	Count	1787	442	2229
		Expected Count	1782.9	446.1	2229.0
	7	Count	1691	440	2131
		Expected Count	1704.5	426.5	2131.0
	8	Count	1717	439	2156
		Expected Count	1724.5	431.5	2156.0
	9	Count	1764	413	2177
		Expected Count	1741.3	435.7	2177.0
	10	Count	1677	507	2184
		Expected Count	1746.9	437.1	2184.0
	11	Count	1771	473	2244
		Expected Count	1794.9	449.1	2244.0
	12	Count	1786	411	2197
		Expected Count	1757.3	439.7	2197.0
	13	Count	1830	425	2255
		Expected Count	1803.7	451.3	2255.0
	14	Count	1784	444	2228
		Expected Count	1782.1	445.9	2228.0
	15	Count	1677	453	2130
		Expected Count	1703.7	426.3	2130.0
	16	Count	1744	413	2157
		Expected Count	1725.3	431.7	2157.0
	17	Count	1769	424	2193
		Expected Count	1754.1	438.9	2193.0
	18	Count	1726	437	2163
		Expected Count	1730.1	432.9	2163.0
	19	Count	1678	435	2113
		Expected Count	1690.1	422.9	2113.0
	20	Count	1722	418	2140
		Expected Count	1711.7	428.3	2140.0

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	21	Count	1740	422	2162
		Expected Count	1729.3	432.7	2162.0
	22	Count	1725	434	2159
		Expected Count	1726.9	432.1	2159.0
	23	Count	1706	432	2138
		Expected Count	1710.1	427.9	2138.0
	24	Count	1779	451	2230
		Expected Count	1783.7	446.3	2230.0
	25	Count	1716	445	2161
		Expected Count	1728.5	432.5	2161.0
	26	Count	1728	466	2194
		Expected Count	1754.9	439.1	2194.0
	27	Count	1876	436	2312
		Expected Count	1849.2	462.8	2312.0
	28	Count	1754	409	2163
		Expected Count	1730.1	432.9	2163.0
Total		Count	48889	12234	61123
		Expected Count	48889.0	12234.0	61123.0

Table 5 : Chi- Square Test (State Churn)

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	36.781[a]	27	.099
Likelihood Ratio	36.354	27	.108
Linear-by-Linear Association	.190	1	.663
N of Valid Cases	61123		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 422.92.

- This report suggests that **there is no statistically significant relationship between the categorical variables (Gender and State) and customer churn.**
- **Gender & Churn:** The Pearson Chi-Square value is 0.021, with a p-value of 0.884, which is much greater than 0.05. This indicates that **gender does not have a significant impact on churn.**
- **State & Churn:** The Pearson Chi-Square value is 36.781, with a p-value of 0.099, which is also greater than 0.05. This suggests that **the state of residence does not significantly affect churn**
- Since the p-values are above the 0.05 threshold, we fail to reject the null hypothesis, meaning that **neither gender nor state is a strong predictor of churn.**

Logistic Regression Analysis on Churn

Table 6 : Omnibus Test

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	.857	4	.931
	Block	.857	4	.931
	Model	.857	4	.931

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	61197.391[a]	.000	.000

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Table 7 : Variables in Equation

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Gender	.003	.021	.023	1	.879	1.003
	Age	.000	.001	.061	1	.805	1.000
	Estimated Salary	.000	.000	.031	1	.860	1.000
	Data Used	.000	.000	.742	1	.389	1.000
	Constant	-1.415	.051	782.881	1	.000	.243

a. Variable(s) entered on step 1: Gender, Age, Estimated Salary, Data Used.

Table 8 : Classification Table

Classification Table[a]

			Predicted		
			Churn		Percentage Correct
Observed			0	1	
Step 1	Churn	0	48889	0	100.0
		1	12234	0	.0
	Overall Percentage				80.0

a. The cut value is .500

The logistic regression model was used to analyze the impact of Gender, Age, Estimated Salary and Data Used on customer churn.

Key Findings:

Model Fit: The model does not significantly explain churn, as indicated by a Chi-square value of 0.857 with a p-value of 0.931 (not significant).

Predictive Power: The Cox & Snell R^2 and Nagelkerke R^2 values are both 0.000, meaning the independent variables do not contribute meaningfully to explaining churn.

Individual Factor Impact:

Gender (p = 0.879) → No significant effect.

Age (p = 0.805) → No significant effect.

Estimated Salary (p = 0.860) → No significant effect.

Data Used (p = 0.389) → No significant effect.

Overall Prediction Accuracy:

The model predicts 80% accuracy, but only because the majority of customers did not churn. It fails to predict churners accurately.

III. CONCLUSION

The logistic regression analysis suggests that Gender, Age, Estimated Salary and Data Used do not significantly impact churn. This implies that other factors such as customer service, pricing, network quality, or loyalty programs—might be more influential in predicting churn.

KEY FINDINGS

1. Demographic Factors (Chi-Square Test Results)

Gender and state of residence were not significantly related to churn. The p-values were greater than 0.05, indicating that demographic factors do not impact customer retention significantly.

2. Multivariate Impact on Churn (Logistic Regression Analysis)

The predictive model found no significant impact of Gender, Age, Estimated Salary, or Data Used on churn. The Nagelkerke R^2 value was 0.000, meaning the selected variables could not explain churn effectively. The model's accuracy was 80%, but this was mainly due to the imbalance in churn distribution (most customers did not churn).

IV. CONCLUSION

This research aimed to analyze customer churn in **Reliance Jio** using statistical and predictive modeling techniques. The key findings from the study indicate that **traditional demographic and usage-based variables are not significant predictors of churn**.

1. **Demographic Factors and Churn**:

The **Chi-Square test results show that gender and state of residence do not significantly impact churn** (p-values > 0.05). This implies that customer retention is not strongly linked to these demographic factors.

2. **Predictive Modeling Limitations**:

Logistic regression analysis demonstrated that Gender, Age, Estimated Salary and Data Used do not significantly influence churn.

The **model fit was poor**, with a Nagelkerke R^2 value of 0.000, meaning that these variables do not effectively explain churn behavior.

While the model had **80% overall accuracy**, it failed to accurately predict churners, highlighting the need for alternative predictive techniques.

3. **Churn Rate Concern**:

The dataset indicates that **20% of customers churned**, which, while lower than expected, remains a key business challenge for Reliance Jio. Identifying the **hidden drivers of churn** is essential for improving customer retention strategies.

Key Takeaway

The results suggest that **customer churn in Reliance Jio is influenced by factors beyond demographics and service usage**, such as **customer service experience, pricing strategies, network quality, and competitive market dynamics**. Therefore, further research incorporating behavioral, psychological, and service-related factors is necessary for building a more effective churn prediction model.

V. FUTURE SCOPE

Given the limitations of traditional demographic and usage-based models, future research should focus on:

1. **Behavioral and Sentiment Analysis**

Incorporating **customer complaints, feedback and sentiment analysis** from social media, customer reviews, and support interactions to gauge dissatisfaction levels.

2. **Service Quality and Network Performance Metrics**

Examining network reliability, call drop rates, data speed and resolution time for service issues to determine their impact on churn.

3. **Competitor Influence and Pricing Sensitivity**

Analyzing whether customers are switching to competitors due to pricing differences, promotional offers, or better value-added services.

4. **Machine Learning for Churn Prediction**

Exploring advanced techniques such as **Random Forest, Gradient Boosting, or Neural Networks** to improve churn prediction accuracy beyond logistic regression.

Implementing **clustering techniques (K-Means, Hierarchical Clustering)** to segment customers based on risk profiles and design targeted retention strategies.

5. Personalized Retention Strategies

Developing **customer-specific engagement models**, loyalty programs, and customized service plans based on detailed behavior analysis.

The findings of this study highlight the need for a multi-faceted approach to churn prediction, integrating service quality, customer sentiment and competitor analysis. Future research leveraging advanced analytics and machine learning will provide deeper insights into customer behavior, helping Reliance Jio implement more effective retention strategies and enhance customer satisfaction.

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