Customer Churn Pattern in Telecom Sector

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Abstract

Customer churn is a persistent issue that affects businesses across industries worldwide. It is particularly relevant in the telecommunications industry due to its competitive nature and customers' propensity to switch providers. Retaining existing customers is generally more cost-effective than acquiring new ones. Businesses can mitigate churn by monitoring at-risk customers, investing in customer satisfaction, and implementing strategies that prioritize customer retention. By understanding the importance of customer churn and taking proactive measures to address it, companies can safeguard their financial stability and foster long-term growth.

Keywords: Customer Churn, Pattern, Business Intelligence

1. INTRODUCTION

Customer churn can occur due to various reasons, but there are several key drivers that are often identified as major contributors to customer attrition. One significant factor is poor customer service. A negative customer service experience has been found to be the cause of nearly nine out of ten customer defections. In today's customer-centric era, customers have high expectations for exceptional service and personalized experiences. When these expectations are not met, it can lead not only to the departure of the dissatisfied customer but also to the loss of many more customers who witness or hear about the negative experience.

Another factor that contributes to customer churn is a lack of ongoing customer success. If customers do not perceive continuous value or experience positive outcomes from using a product or service, they may choose to discontinue their relationship with the company. This highlights the importance of maintaining engagement with customers, understanding their evolving needs, and proactively addressing any issues or concerns they may have.

Furthermore, natural business events can also trigger customer churn. These events may include mergers or acquisitions, changes in leadership, or shifts in the company's strategic direction. Such transitions can create uncertainty or disruptions in the customer-provider relationship, leading some customers to explore alternative options.

A lack of perceived value is another significant driver of customer churn. If customers feel that the product or service they are receiving does not align with their expectations or does not provide sufficient benefits or advantages, they may seek alternatives. It is crucial for companies to regularly assess and communicate the value proposition of their offerings to ensure that customers understand the benefits they receive and are satisfied with their investment.

Increasing rates or pricing changes can also contribute to customer churn. Customers are sensitive to changes in costs and may reevaluate their loyalty if they perceive a lack of fairness or affordability. Companies should carefully consider the impact of pricing adjustments and proactively communicate the value they provide to help customers understand and appreciate any changes in cost.

The relationship between customer churn and business growth is tightly intertwined. Higher customer churn rates are associated with lower odds of business growth. The financial impact of customer attrition on firms is significant, making it crucial for companies to monitor and manage customer turnover effectively in order to sustain and retain their customer base.

Poor customer service, a lack of ongoing customer success, natural business events, a perceived lack of value, and increasing rates are among the major drivers of customer churn. To mitigate churn and foster business growth, companies must prioritize exceptional customer service, maintain engagement and value delivery, navigate business transitions effectively, communicate the value proposition clearly, and carefully consider pricing strategies. By understanding and managing customer churn, companies can work towards retaining their customers and ensuring long-term business success. It is critical to comprehend why clients have lost interest in the company. To enhance the profitability of the firm, it is necessary to study and develop a proper model in order to correctly solve this problem.

Churn prediction refers to determining which customers are most likely to abandon a service or terminate their subscription. It's a crucial prediction for many firms because getting new customers is sometimes more expensive than keeping old ones. It is necessary to secure long-term profitability and can significantly enhance a company's revenue.

Churn prediction plays a pivotal role in reducing customer attrition for telecom companies. By identifying customers who are at high risk of churn, companies can take proactive measures to retain them, potentially saving significant resources and maximizing long-term profitability. Predictive analytics and machine learning techniques are often employed to develop churn prediction models, leveraging historical customer data and various predictive features.

Factors that contribute to customer churn in the telecom industry can vary, but some common drivers include dissatisfaction with service quality, billing issues, competitive offers from rival companies, changes in customer needs or preferences, and poor customer experiences. Understanding these factors enables companies to implement targeted retention strategies, such as personalized communication, tailored offers, and improved customer service.

Churn prediction models in the telecom industry often incorporate a wide range of variables to achieve accurate predictions. These variables may include call patterns, data usage patterns, billing information, customer demographics, customer complaints, contract details, and service usage data. By analyzing these variables, telecom companies can identify patterns and trends that are indicative of potential churn.

To build effective churn prediction models, various machine learning algorithms are utilized, including random forests, gradient boosting, and AdaBoost, as mentioned in the initial statement. These algorithms leverage the power of ensemble learning to combine multiple decision models or weak learners, enabling accurate predictions based on diverse features and patterns.

The output of churn prediction models is typically a probability score indicating the likelihood of a customer churning. Telecom companies can use these scores to prioritize and target their retention efforts on high-risk customers.

Implementing churn prediction models and retention strategies can have significant benefits for telecom companies. By reducing customer churn, companies can improve customer satisfaction, enhance customer loyalty, and increase customer lifetime value. Moreover, retaining existing customers reduces the need for expensive customer acquisition campaigns, resulting in cost savings for the company.

Churn prediction is a critical aspect of customer retention for telecom companies. By employing predictive analytics and machine learning algorithms, companies can accurately identify customers at risk of churn and take proactive measures to retain them. By reducing customer attrition, telecom companies can improve their profitability, enhance customer satisfaction, and foster long-term success in a highly competitive industry.

1.1 CUSTOMER CHURN

Customer churn, also referred to as customer attrition or customer turnover, is a term that encompasses the phenomenon of customers discontinuing their business relationship with a company. It is a crucial metric for businesses across industries, particularly those that operate on recurring revenue models or rely heavily on customer loyalty and retention.

In industries such as telecommunications, subscription-based services, SaaS, and many others, customer churn can have a substantial impact on a company's financial health and overall success. When customers churn, it means that they have decided to stop using the company's products or services, either by switching to a competitor or by completely terminating their relationship with the company.

There are several reasons why customers may choose to churn. One common factor is dissatisfaction with the product or service. If customers feel that the company's offerings no longer meet their needs, do not deliver the expected value, or fail to meet their expectations, they may decide to seek alternatives (Sarkar et al., 2017).

Competitive offerings also play a significant role in customer churn. If a competitor introduces a superior product or service, offers more attractive pricing, or provides a better overall customer experience, existing customers may be enticed to switch providers.

Price sensitivity is another driver of churn. If customers perceive that the company's pricing is too high or does not align with the value they receive, they may opt to explore more cost-effective options, leading to churn.

Poor customer service experiences can also contribute to customer churn. If customers encounter difficulties in getting support, have unresolved issues, or feel that their concerns are not adequately addressed, they may become frustrated and choose to discontinue their relationship with the company.

Moreover, changes in customer circumstances, such as relocating, financial constraints, or changes in needs or preferences, can also lead to churn. As customers' situations evolve, their requirements may change, and they may no longer find the company's offerings relevant or beneficial.

The impact of customer churn on a business's revenue and profitability cannot be overstated. Acquiring new customers typically involves significant marketing and sales expenses, making it more costly than retaining existing customers. Customer churn, therefore, represents a loss of potential future revenue and can hinder a company's growth and financial stability.

To mitigate customer churn, companies must prioritize customer satisfaction, continuously monitor customer feedback, and proactively address any issues or concerns. Implementing effective customer retention strategies, such as personalized communication, loyalty programs, upselling or cross-selling initiatives, and ongoing customer support, can significantly reduce churn rates and enhance customer loyalty.

1.2 BUSINESS INTELLIGENCE

The telecommunication sector is characterized by intense competition and rapidly evolving technologies, making customer retention a critical factor for the success of telecom companies. Customer churn, the phenomenon of customers discontinuing their services and switching to competing providers, poses significant challenges to the profitability and growth of telecommunication companies. It is essential for telecom companies to identify and understand the patterns and factors that contribute to customer churn in order to develop effective retention strategies.

Business intelligence (BI) refers to the use of data analysis, reporting, and visualization techniques to gain insights and make informed business decisions. In recent years, BI has emerged as a powerful tool in various industries, including the telecommunication sector, to understand customer, optimize operations, and enhance customer satisfaction. By leveraging BI techniques, telecom companies can analyze large volumes of customer data and uncover meaningful patterns that can help in identifying potential churn factors.

The identification and prediction of customer churn patterns in the telecommunication sector using business intelligence offer significant advantages. It enables companies to proactively address customer needs, personalize offerings, and implement targeted retention strategies. By understanding the factors that contribute to customer churn, such as network quality, service issues, pricing, and competition, telecom companies can take timely actions to mitigate churn risks and improve customer retention rates.

Overall, this study on customer churn pattern identification and prediction in the telecommunication sector using business intelligence provides valuable insights for telecom companies to develop data-driven strategies and maintain a competitive edge in the market. By leveraging the power of business intelligence, telecom companies can effectively manage customer churn, improve customer retention rates.

1.3 PATTERN IDENTIFICATION

Pattern identification is a fundamental aspect of analyzing customer churn in the telecommunication sector. Through data exploration and visualization, telecom companies can identify recurring patterns and correlations among various churn events. By understanding patterns, telecom companies can gain a deeper understanding of the underlying causes and triggers of customer churn.

By leveraging the insights from pattern identification and predictive modeling, telecom companies can implement targeted retention strategies to mitigate customer churn.

1.4 Scope

Identifying customer churn in the telecom sector encompasses a comprehensive process that integrates various data sources, analytical techniques, and predictive modeling. Initially, data is collected from diverse channels including customer demographics, usage patterns, billing history, customer service interactions, and network performance. This data is then synthesized from different systems such as CRM platforms, billing systems, call detail records (CDRs), and network monitoring tools. Subsequently, relevant features are engineered from the collected data, spanning usage patterns, billing information, customer demographics, interactions, and network performance metrics. Following feature engineering, data preprocessing steps are undertaken to address missing values, outliers, and inconsistencies, while also encoding categorical variables and normalizing numerical features.

1.5 Importance of the Study

In today's hyper-connected world, the telecommunications sector serves as the backbone of global communication, providing essential services that empower individuals, businesses, and societies. Amidst the dynamic landscape of this industry, one persistent challenge stands out: customer churn. Customer churn, the phenomenon where subscribers terminate their relationship with a telecom provider, poses significant implications for both service providers and consumers alike. The successful adoption and implementation of business intelligence techniques for churn management. This study identifies and predicts customer churn patterns in the telecommunication sector which is extremely important to understand. To solve the problem of customer churn it is mandatory to identify customer churn rate and also to suggest a model to identify the customers at the risk of churn with respect to the telecommunication sector.

In the telecommunication sector, customer churn poses a significant challenge for companies seeking to maintain their market share, profitability, and customer loyalty.

Traditional churn management methods often do not have effective pattern identification and prediction models limits the ability of telecom companies to proactively address churn risks and implement targeted retention strategies.

To address these challenges, this research aims to utilizes business intelligence techniques to identify and predict customer churn patterns in the telecommunication sector.

2. LITERATURE REVIEW

Gupta et al., (2014) conducted a comprehensive review of customer churn in the telecommunications industry, aiming to provide valuable insights for practitioners in this sector. The study delved into the various factors that influence customer churn, shedding light on important considerations for telecom companies. One of the factors explored in the review was call patterns. By analyzing call data, the researchers aimed to understand how customer behavior, such as call frequency, duration, and timing, can impact churn. Identifying patterns within call data can help telecom companies identify at-risk customers and take proactive measures to retain them. Billing issues were also examined as a significant driver of customer churn. The review investigated how billing accuracy, transparency, and timeliness can affect customer satisfaction and loyalty. Telecom companies that prioritize addressing billing concerns and providing clear, accurate invoices are more likely to retain customers and minimize churn.

Another critical factor explored in the study was service quality. By examining the impact of factors such as network reliability, call quality, and customer support, the researchers sought to understand how service-related issues can lead to customer dissatisfaction and ultimately churn. Telecom companies that consistently deliver high-quality services are more likely to retain customers and foster long-term relationships. Customer demographics were also taken into account in the review. By analyzing demographic data, such as age, gender, location, and income level, the study aimed to identify any variations in churn behavior among different customer segments. This information can help telecom companies tailor their retention strategies to better meet the specific needs and preferences of different customer groups. By highlighting the factors that influence churn, such as call patterns, billing issues, service quality, and customer demographics, the study offered telecom companies a deeper understanding of the dynamics involved in customer attrition.

Panda et al., (2016) conducted a research study focusing on customer churn in the telecommunications industry. The study aimed to analyze customer behavior and understand the factors that contribute to churn within the telecom sector. The researchers employed decision trees, k-nearest neighbors, and Naive Bayes in their study. Decision trees were utilized to create a hierarchical structure of rules that can predict customer churn based on the provided variables. This allowed the researchers to identify the most influential factors contributing to churn and create decision rules that could be applied in real-world scenarios. K-nearest neighbors was employed to classify customers based on their similarities in terms of call patterns, service usage, billing information, and demographics. This enabled the researchers to identify clusters of customers who exhibit similar churn behavior. By understanding the characteristics of each cluster, telecom companies can develop targeted strategies to retain customers in each group. Naive Bayes was utilized to calculate the probabilities of customer churn based on the given variables. By analyzing call patterns, service usage, billing information, and customer demographics, the study aimed to uncover patterns and correlations that contribute to customer churn in the telecom sector. Understanding these factors can help telecom companies identify at-risk customers and take proactive measures to retain them.

Sharma et al., (2017), the focus was on customer churn in the telecommunications industry using social network analysis. This research approach considered not only individual customer behavior but also the social connections within a network and their impact on churn. The study analyzed customer interactions, call patterns, and social connections to identify influential customers within the network and understand how their behavior influences churn. By considering the relationships and influence of customers on each other, the research aimed to provide a holistic understanding of churn dynamics within a social context. This study shed light on the importance of social connections and customer interactions in predicting and managing churn. By identifying influential customers and understanding their impact on the network, telecom companies can develop targeted strategies to retain these influential customers and mitigate the risk of churn.

Abualsoud et al. (2011) focuses on customer churn prediction in the telecommunications industry using data mining techniques. It explores the application of various algorithms, including decision trees, neural networks, and logistic regression, for churn prediction. The study utilizes customer data, such as call patterns, service usage, billing information, and customer demographics, to build predictive models. It discusses the importance of feature selection, model training, and evaluation in churn prediction. The findings contribute to understanding the effectiveness of data mining techniques in predicting customer churn and aid in developing targeted retention strategies.

Akter et al. (2018) presents a framework for customer churn prediction in the telecommunication sector. It proposes a systematic approach that combines data preprocessing, feature selection, model training, and evaluation to build churn prediction models. The study utilizes customer data, such as call patterns, service usage, billing information, and customer demographics, to identify relevant features for churn prediction. It employs various machine learning algorithms, including logistic regression, decision trees, and support vector machines, to develop predictive models. The findings contribute to the development of an effective churn prediction framework that can be utilized by telecom companies to reduce customer churn and enhance customer retention.

Balasubramanie et al. (2019) focuses on customer churn prediction in the telecommunications industry using ensemble methods. It explores the application of ensemble learning techniques, such as random forests, gradient boosting, and stacking, for churn prediction. The study utilizes customer data, including call patterns, service usage, billing information, and customer demographics, to build predictive models. It discusses the benefits of ensemble methods in improving churn prediction accuracy by combining the strengths of multiple algorithms. The findings contribute to enhancing the effectiveness of churn prediction models in the telecom industry.

Singh et al. (2019) focuses on customer churn prediction in the telecommunications industry using social network analysis. It explores the use of social network characteristics, such as customer influence, network centrality, and community structure, in predicting customer churn. The study analyzes customer communication patterns and network connections to identify influential customers and their impact on churn. It discusses the integration of social network analysis with traditional churn prediction models to improve churn prediction accuracy. The findings contribute to understanding the influence of social interactions on customer churn and provide insights into leveraging social network information for effective churn management in the telecom industry.

Rajput et al. (2020) focuses on customer churn prediction in the telecommunication industry using machine learning algorithms. It explores the application of various algorithms, such as logistic regression, decision trees, random forests, and gradient boosting, for churn prediction. The study utilizes customer data, including call patterns, service usage, billing information, and customer demographics, to build predictive models. It evaluates the performance of different algorithms based on metrics like accuracy, precision, recall, and F1-score. The findings contribute to understanding the strengths and limitations of different machine learning algorithms for churn prediction and provide insights into selecting appropriate models for customer churn analysis.

Sharma et al. (2020) provides a comprehensive review of customer churn in the telecommunications sector. It examines various factors influencing customer churn, including pricing strategies, service quality, customer satisfaction, and competition. The study explores different theoretical frameworks and models used to understand and predict customer churn. It discusses the role of customer segmentation, customer lifetime value, and customer relationship management in churn management. The findings contribute to a deeper understanding of customer churn dynamics and provide insights into effective strategies for customer retention in the telecom industry.

Kumar et al. (2021) focuses on predicting customer churn in the telecommunications industry using a machine learning approach. It explores the application of various machine learning algorithms, including logistic regression, decision trees, support vector machines, and neural networks, for churn prediction. The study utilizes customer data, such as call patterns, service usage, billing information, and customer demographics, to build predictive models. It evaluates the performance of different algorithms using metrics like accuracy, precision, recall, and F1-score. The findings contribute to understanding the effectiveness of machine learning in predicting customer churn and provide insights into selecting suitable models for churn prediction tasks.

Srivastava et al. (2000) analyzes customer churn from service quality and customer satisfaction perspectives in the telecommunications industry. It examines the relationship between service quality dimensions, customer satisfaction, and churn behavior. The study utilizes survey data to measure customer perceptions of service quality and satisfaction. It discusses the importance of service recovery, customer loyalty, and retention strategies in reducing churn rates. The findings contribute to understanding the role of service quality and customer satisfaction in customer churn dynamics.

Murthy et al., (2002) provides a comprehensive review of customer churn prediction in the telecommunications sector. It uses statistical method. It also highlights the challenges in customer churn. The findings contribute to understanding churn prediction.

3. RESEARCH METHODOLOGY

3.1 Research

Research is a systematic and methodical inquiry conducted to discover new knowledge, validate existing knowledge, or solve specific problems. It involves gathering, analyzing, and interpreting information in a structured manner to answer questions or address issues. Research is conducted across various disciplines and fields, including science, social science, humanities, business, and technology, with the aim of advancing understanding and contributing to the body of knowledge in a particular area.

3.2 Research Process

This research is carried out by making use of the CRISP-DM research method. CRISP-DM is a widely-used methodology for guiding data mining and analytics projects. It provides a structured approach to managing the lifecycle of data mining projects, from understanding business objectives to deploying and maintaining the solutions.

3.3 Research Tools and Techniques:

3.1.1 Random Forest is an ensemble learning method that constructs a multitude of decision trees during training and outputs the mode of the classes (classification) or the average prediction (regression) of the individual trees

3.1.2 Percentage Method:

The formula for calculating a percentage is very simple:

Percentage = (part / whole) x 100

part is the number to express as a percentage of the whole.

whole is the total amount or group that the part represents.

3.4 Variables of the Study

- The columns of the dataset are detailed below:

- Customer Name – Customer Name identifies every customer. (Independent Variable)
- Gender – Defines the Gender of customer.
- Partner – Defines whether the customer has a partner or not. (Independent Variable)
- Dependents – Defines whether the customer has any dependents. (Independent Variable)
- Tenure – Number of months the customer has been a subscriber of the telecom company’s services. (Independent Variable)
- Phone Service –Defines whether the customer has a phone service or not. (Independent Variable)
- Multiple Lines – Defines whether the customer has multiple phone lines or not. (Independent Variable)
- Internet Service – Defines whether and the type of internet service the customer. (Independent Variable)
- Online Security – Defines whether the customer has online internet security or not. (Independent Variable)
- Online Backup –Whether the customer has online backup or not. (Independent Variable)
- Device Protection –Defines whether the customer has device protection or not. (Independent Variable)
- Tech Support – Whether the customer has technical support or not. (Independent Variable)
- Streaming TV – Whether the customer has streaming TV or not. (Independent Variable)

- Streaming Movies –Whether the customer has streaming movies or not. (Independent Variable)
- Contract –Defines the type of contract the customer has with the telecom company. (Independent Variable)
- Paperless Billing – Checks whether the customer has paperless billing or not. (Independent Variable)
- Payment Method –Defines the method of payment by the customer. (Independent Variable)
- Monthly Charges – The monthly charges accrued by the customer. (Independent Variable)
- Total Charges – Total charges accumulated by the customer. (Independent Variable)
- Churn – Defines whether the customer churned or not. (Dependent variable)
- Primary Data: Primary data was collected from Customers of Telecom Sector lives in Delhi. The primary dataset includes total of 510 records using survey method. Standard questionnaire (Johnson et al., 2021) is used in this research study is a part of IBM's sample datasets for analytics. The questionnaire was sent to the customers of the telecom sector for collection of data using Convenience sampling method.
- Secondary Data Collection: Secondary dataset is a part of IBM's sample datasets for analytics. The dataset includes total of 7043 records of various customer related information. The dataset is used for predicting customer churn. It includes Customer ID, Gender, Tenure, Phone Service, Multiple Lines, Internet Service, Online Security, Online Backup, Device Protection, Tech Support, Streaming TV, Streaming Movies, Contract, Partner, Dependents, Paperless Billing, Payment Method, Monthly Charges, Total Charges, Churn.

4. DATA ANALYSIS

4.1 Pattern Analysis of Customers Churn Using Primary Data

In this section I have described the data analysis and interpretation with respect pattern analysis of customer churn. It is very important to understand the pattern of churn in this study.

4.1.1 Pattern Analysis of Gender

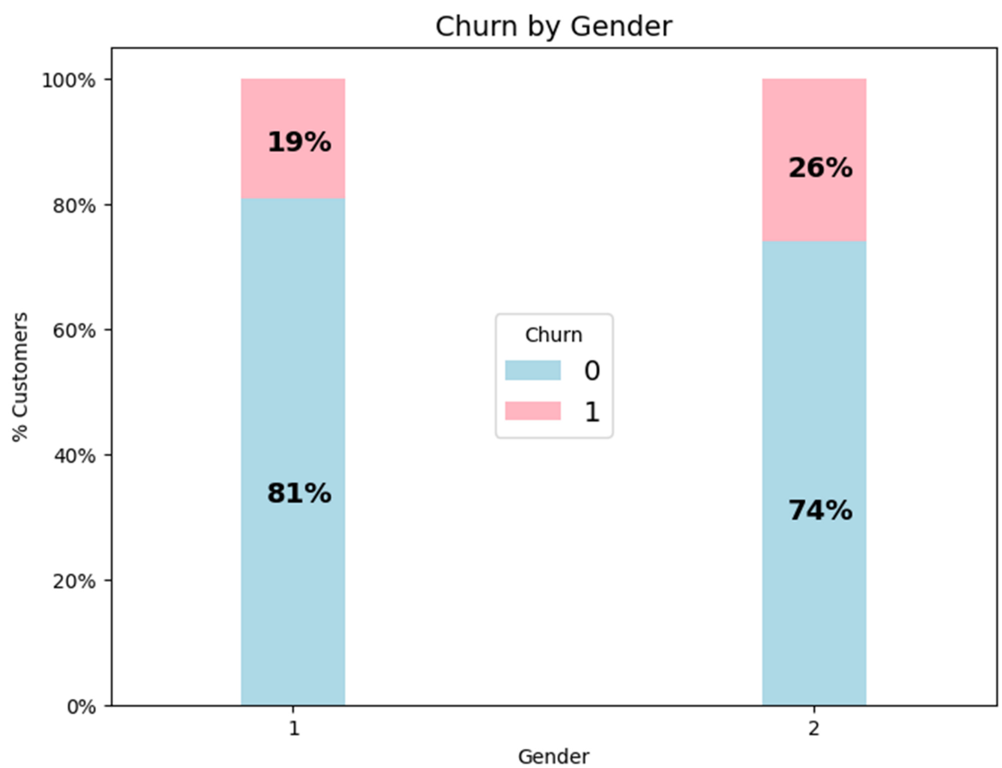

Figure 1: Pattern Analysis of Gender

In the above figure 1, 1 is indicating male, whereas 2 is indicating female. From the above pattern of customer churn on the basis of gender it has been analysed that the customer churn rate is found 19% for Males category and 26% churn is found in Females. It has been analysed that the likelihood of churn of female category is more comparatively than male category.

4.1.2 Pattern Analysis of Partner

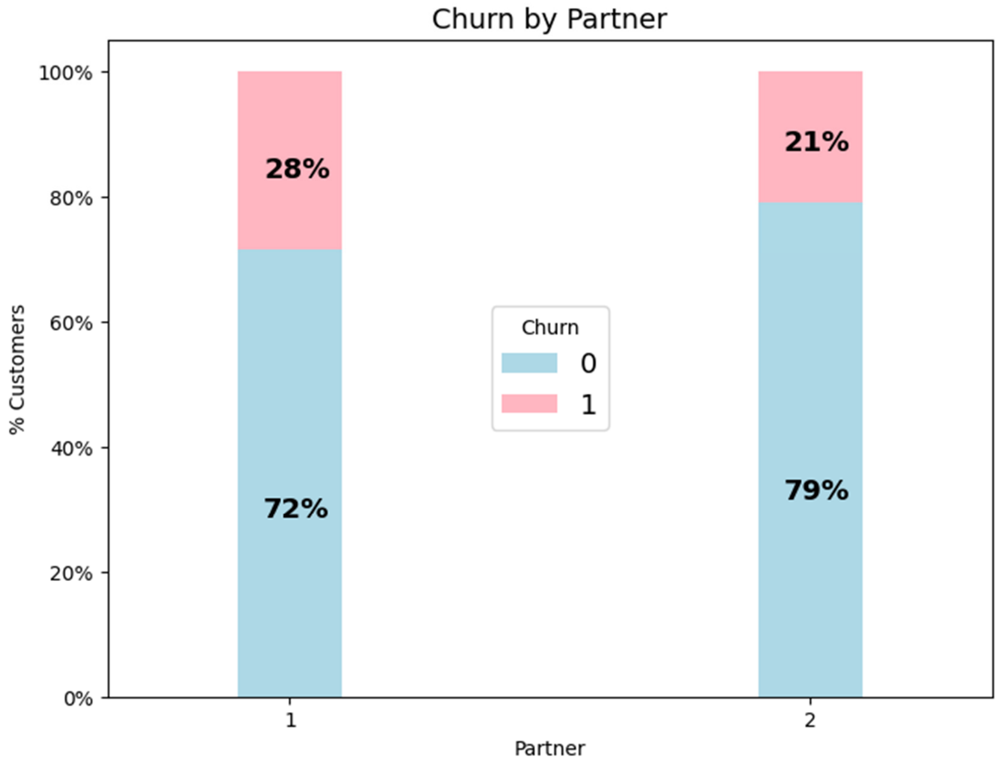

Figure 2: Pattern Analysis of Partner

In the above figure 2, 1 is indicating yes i.e. representing that the customer is having a partner plan, whereas 2 is indicating no means the customer does not have any partner plan. It has been analysed that 28% customers churn is found when customer has partner plan available and 21% customers churn is found when they do not have the partner plan. It has been identified and analysed that the likelihood of churn is more if customer has partner plan.

4.1.3 Pattern Analysis of Dependents

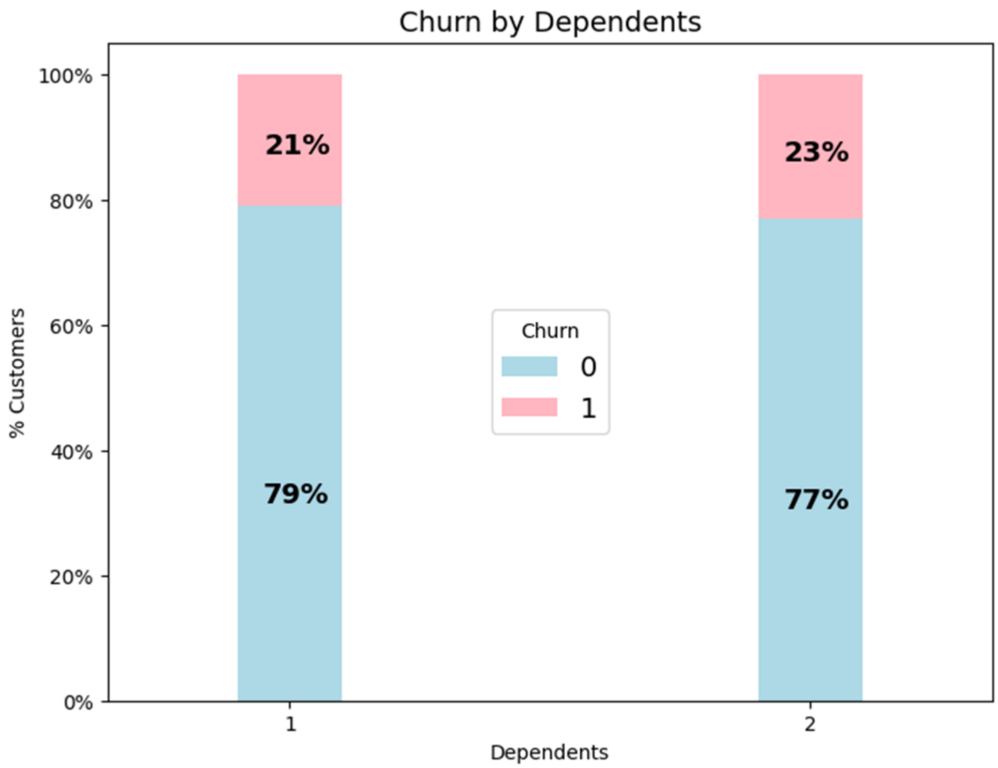

Figure 3: Pattern Analysis of Dependents

In the above figure 3, 1 indicates that customers are having dependents, whereas 2 is indicating that the customer does not have dependents. It has been identified and analysed that 21% customers churn is found when customers have dependents and 23% customers churn is found when they do not have dependents. It has been analysed that the likelihood of churn is more if customers do not have dependents.

4.1.4 Pattern Analysis of Phone Service

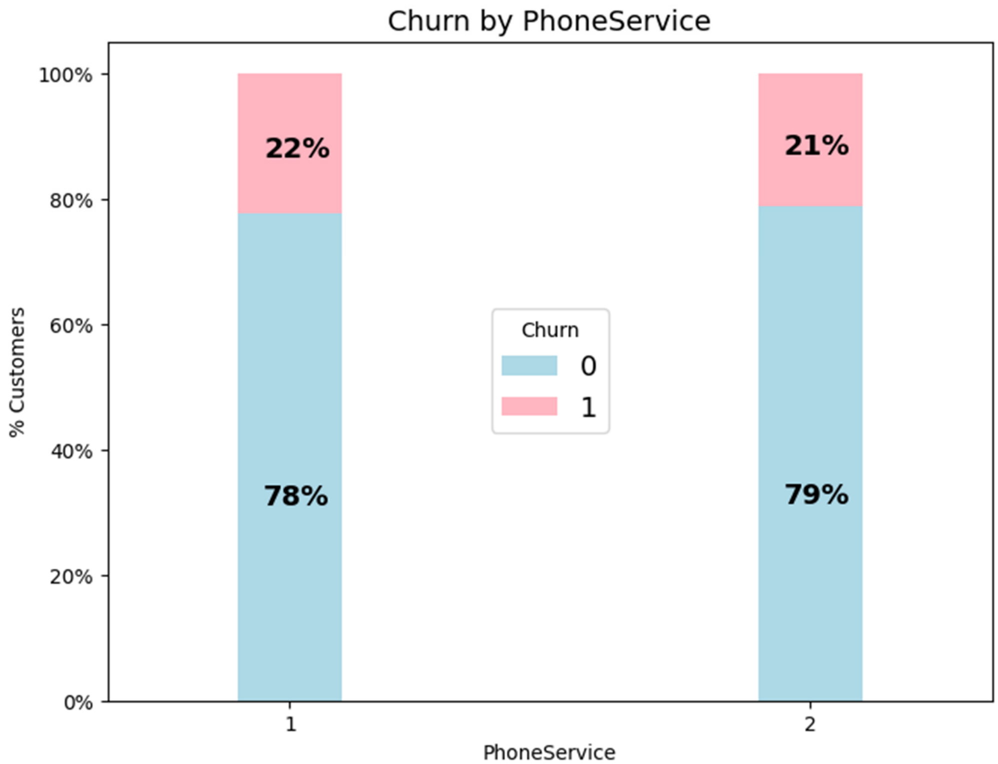

Figure 4: Pattern Analysis of PhoneService

In the above figure 4, 1 represents that the customer is having phone service, whereas 2 is indicating that customer does not have phone service. It has been analysed that 22% customer churn is found when customer has phone service and 21% customers churn is found when they do not have phone service. It has been analysed that the likelihood of churn is more if the customer has phone service.

4.1.5 Pattern Analysis of Multiple Lines

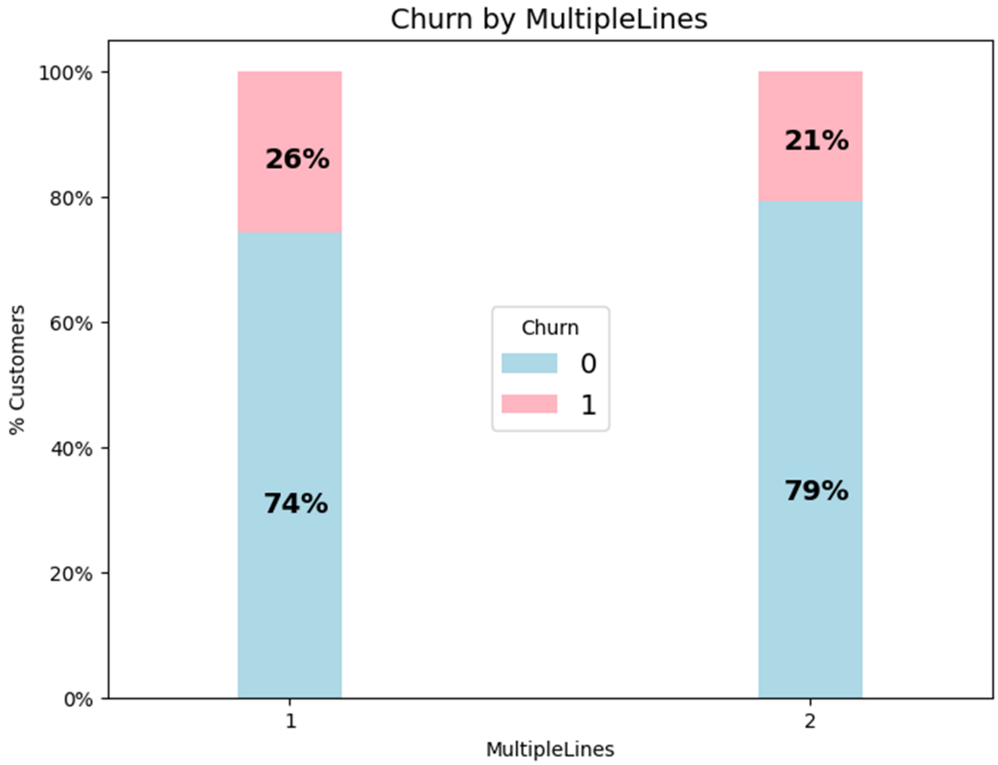

Figure 5: Pattern Analysis of Multiple Lines

In the above figure 5, 1 is indicating that the customer is having multiple lines, whereas 2 is indicating that the customer does not have multiple line service. It has been analysed that 26% customers churn is found when customers have multiple lines and 21% customers churn is found when they do not have multiple lines. It has been analysed that the likelihood of churn is more if customer has multiple lines.

4.1.6 Pattern Analysis of Internet Service

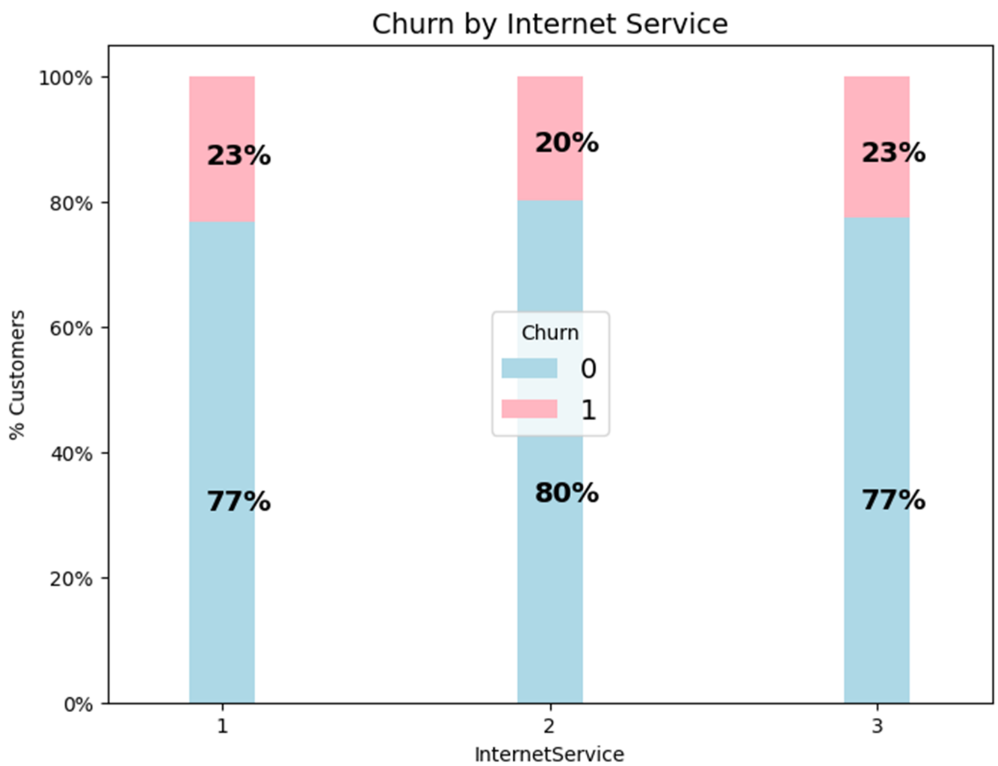

Figure 6: Pattern Analysis of Internet Service

In the above figure 6, 1 is indicating that the customers are having DSL Internet service, whereas 2 is indicating that the customers do not have internet service and 3 is indicating that customers have Fiber optic internet service. It has been analysed that the 23% customers churn is found when the customer has DSL Internet service, 20% customers churn is found when they do not have internet service and 23% churn is found when customer has Fiber optic internet service. It has been analysed that the likelihood of churn is more for DSL & fiber optic internet service.

4.1.7 Pattern Analysis of Online Security

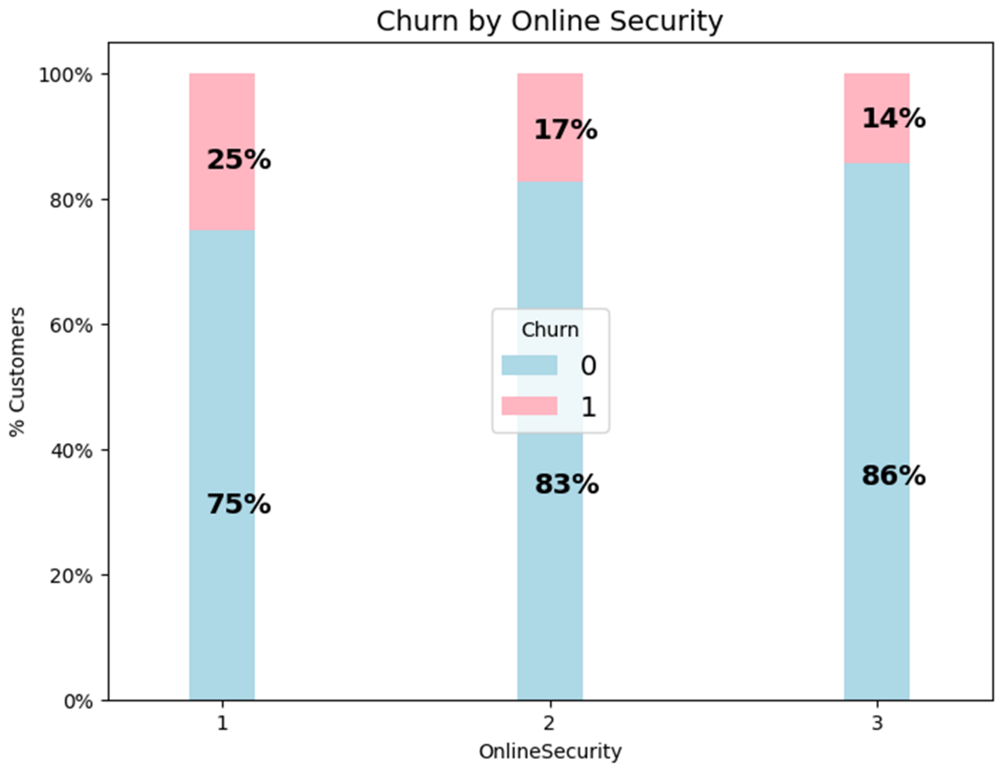

Figure 7: Pattern Analysis of Online Security

In the above figure 7, 1 is indicating that the customer has opted for online security service, whereas 2 is indicating that the customers do not have online security service and 3 is indicating that customers have Fiber optic internet service. It has been analysed that 25% customers churn is found when customer has online security, 17% customers churn is found when they do not have online security and 14% churn is found when customer do not have internet service also. It has been analysed that the likelihood of churn is more if customer has online security.

4.1.8 Pattern Analysis of Online Backup

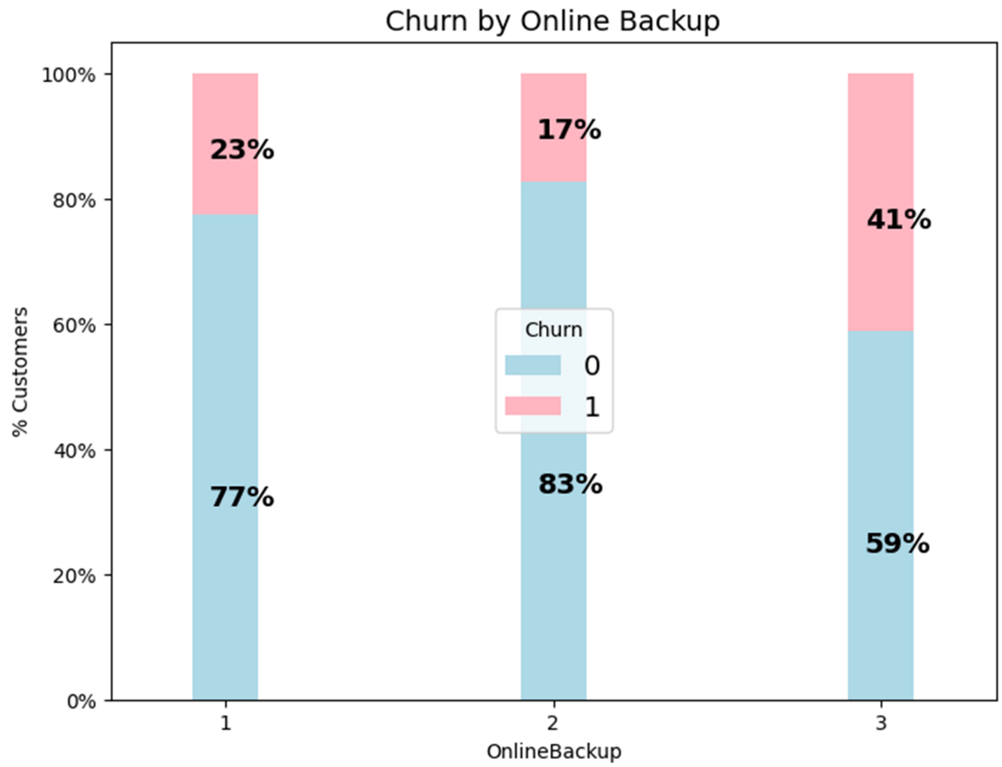

Figure 8: Pattern Analysis of Online Backup

In the above figure 8, 1 is indicating that the customer has online backup service, whereas 2 is indicating that the customers do not have online backup service and 3 is indicating that customers do not have internet service. It has been analysed that 23% customers churn is found when customer has online backup, 17% customers churn is found when they do not have online backup and 41% churn is found when customer do not have internet service. It has been analysed that the likelihood of churn is more if customer do not have the internet service.

4.1.9 Pattern Analysis of Device Protection

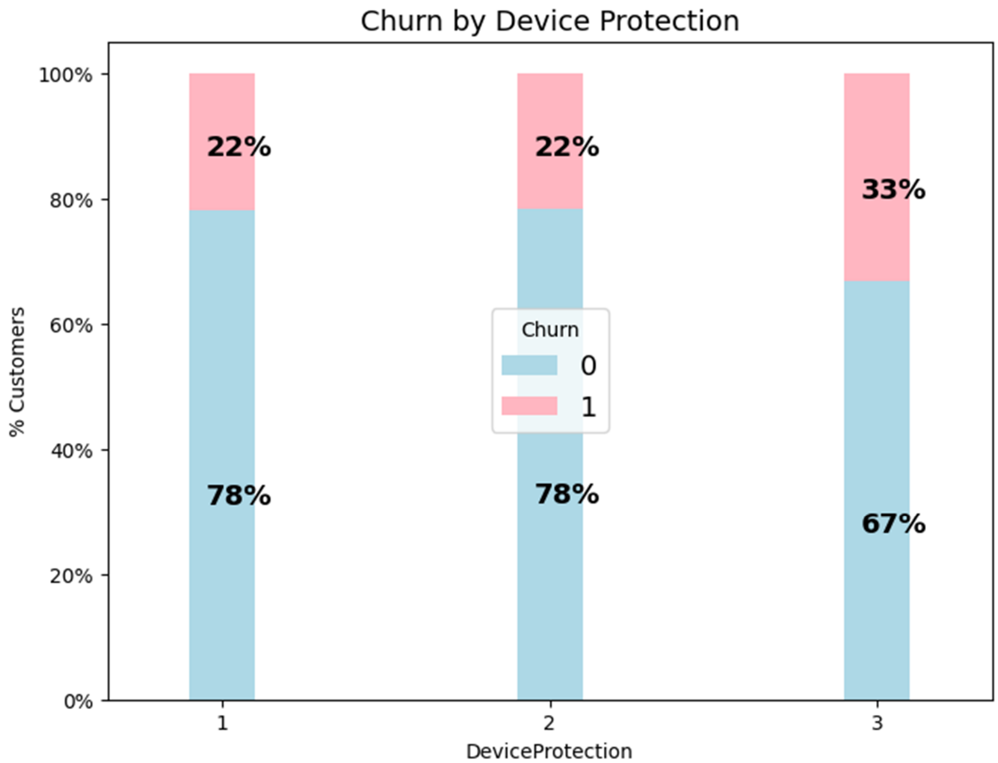

Figure 9: Pattern Analysis of Device Protection

In the above figure 9, 1 is indicating that the customer has device protection, whereas 2 is indicating that the customers do not have device protection and 3 is indicating that customers do not have internet service. It has been analysed that 22% customers churn is found when customer has device protection, 22% customers churn is found when they do not have device protection and 33% churn is found when customer do not have internet service. It has been analysed that the likelihood of churn is more if customer do not have internet service.

4.1.10 Pattern Analysis of Tech Support

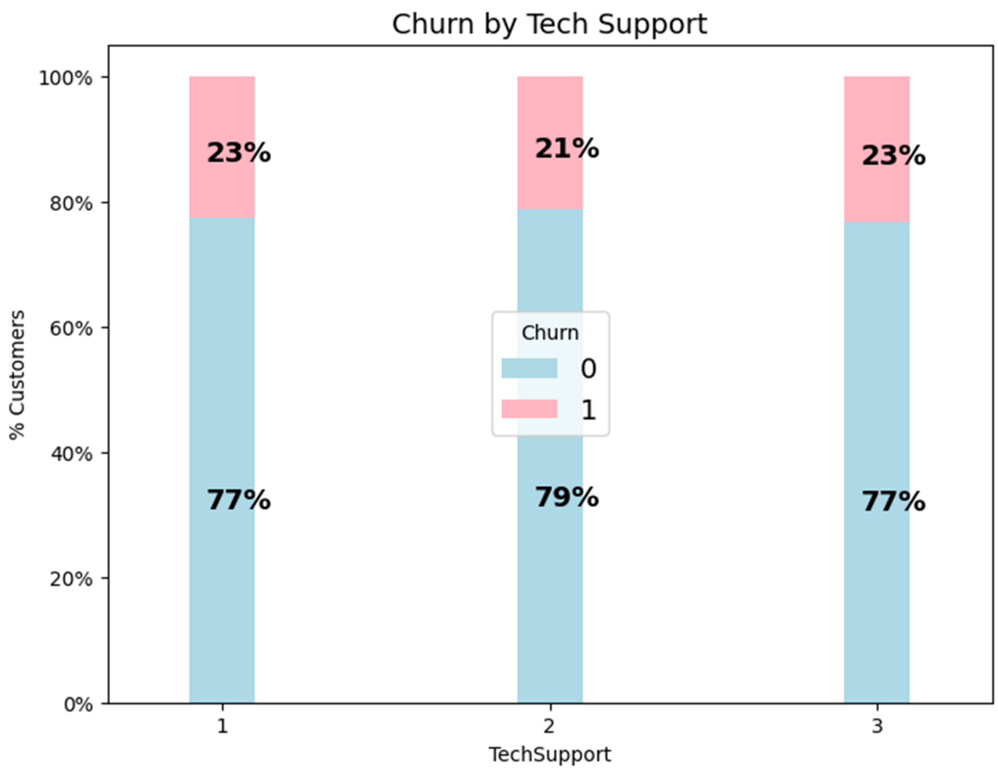

Figure 10: Pattern Analysis of Tech Support

In the above figure 10, 1 is indicating that the customer has tech support, whereas 2 is indicating that the customers do not have tech support and 3 is indicating that customers do not have internet service. It has analysed that 23% customers churn is found when customer has tech support, 21% customers churn is found when they do not have tech support and 23% churn is found when customer do not have internet service. It has been analysed that the likelihood of churn is more if customer do not have the internet service and when customer has tech support.

4.1.11 Pattern Analysis of Streaming TV

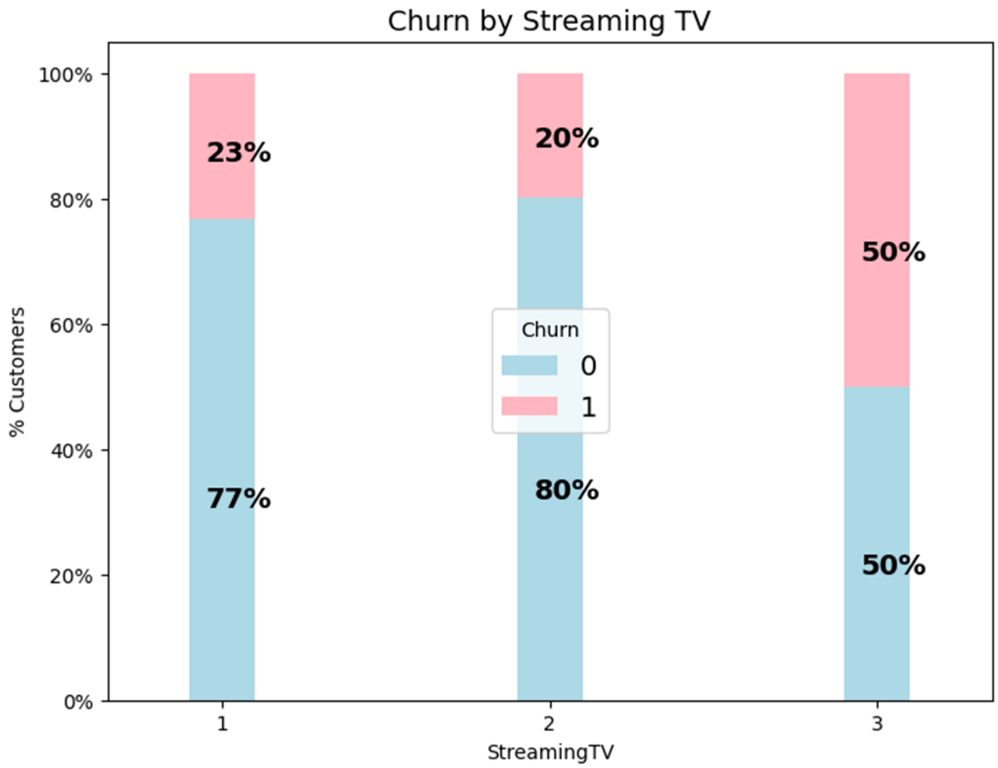

Figure 11: Pattern Analysis of Streaming TV

In the above figure 11, 1 is indicating that the customer has Streaming TV service, whereas 2 is indicating that the customers do not have Streaming TV service and 3 is indicating that customers do not have internet service. It has been analysed that 23% customers churn is found when customers have Streaming TV service, 20% customers churn is found when they do not have Streaming TV service and 50% churn is found when customer do not have internet service. It has been analysed that the likelihood of churn is more if customer do not have the internet service.

4.1.12 Pattern Analysis of Streaming Movies

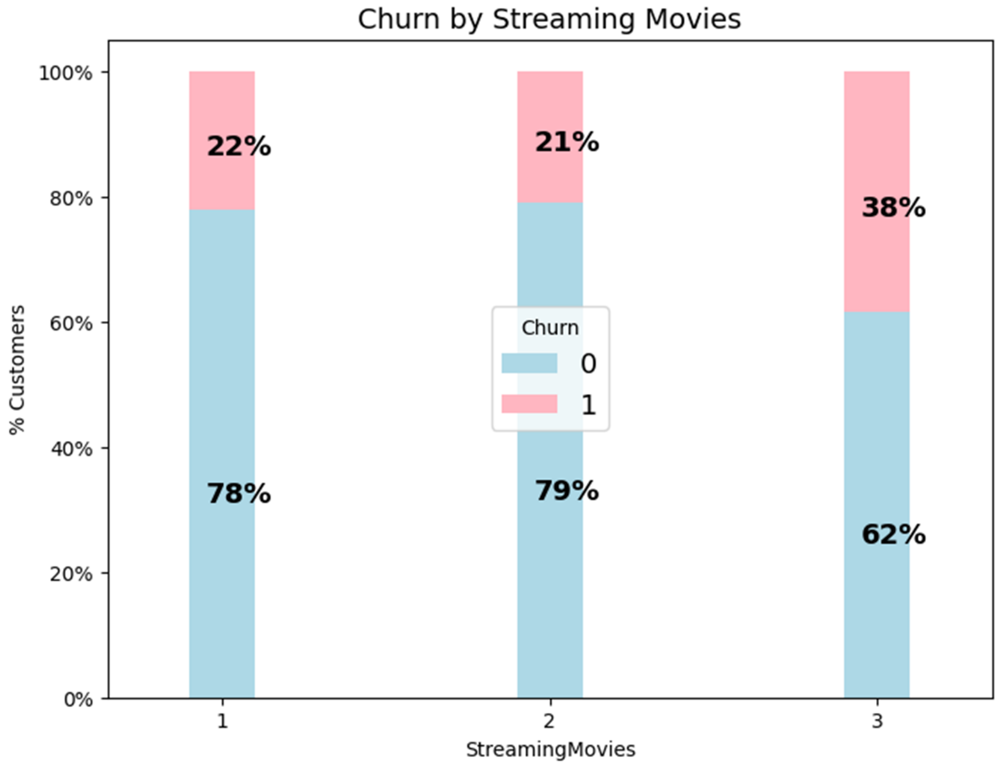

Figure 12: Pattern Analysis of Streaming Movies

In the above figure 12, 1 is indicating that the customer has Streaming Movies service, whereas 2 is indicating that the customers do not have Streaming Movies service and 3 is indicating that customers have Fiber optic internet service. It has been analysed that 22% customer churn is found when customer has Streaming Movies service, 21% customers churn is found when they do not have Streaming Movies service and 38% churn is found when customer do not have internet service. It has been analysed that the likelihood of churn is more if customer do not have the internet service.

4.1.13 Pattern Analysis of Contract

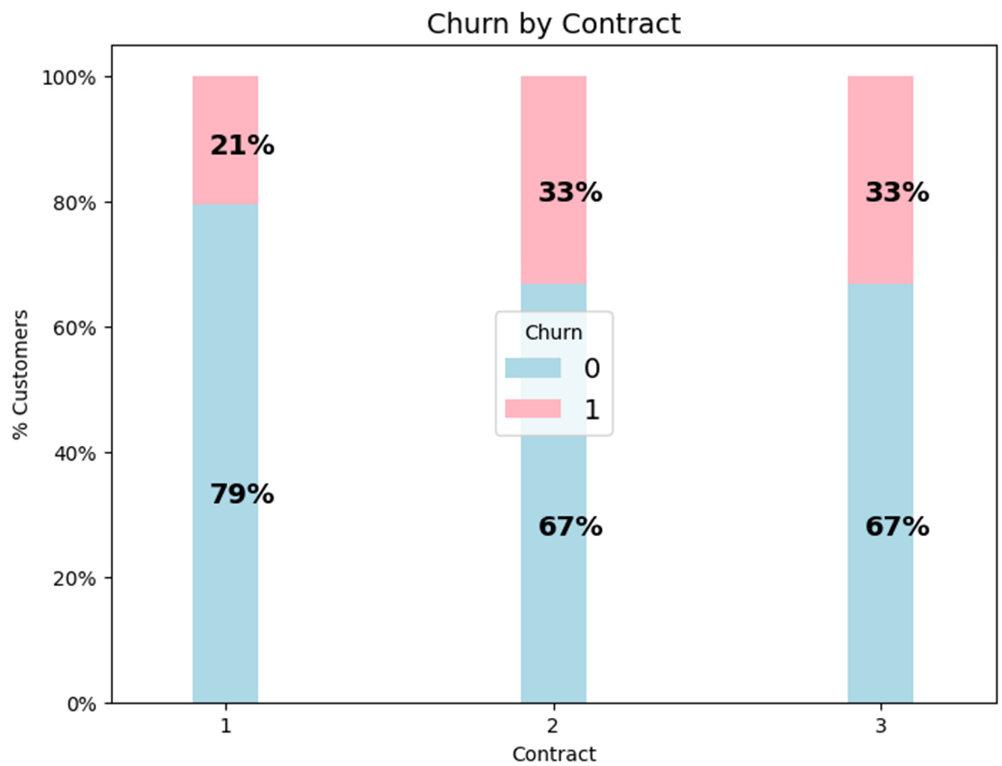

Figure 13: Pattern Analysis of Contract

In the above figure 13, 1 is indicating that the customers have monthly contract, whereas 2 is indicating that the customers have one year contract and 3 is indicating that customers have two year contract. It has been analysed that 21% customers churn is found when customer has monthly contract, 33% customers churn is found when customer has one year contract and 33% churn is found when customer has two years contract. It has been analysed that the likelihood of churn is more if customer has one year and two years contract.

4.1.14 Pattern Analysis of Paperless Billing

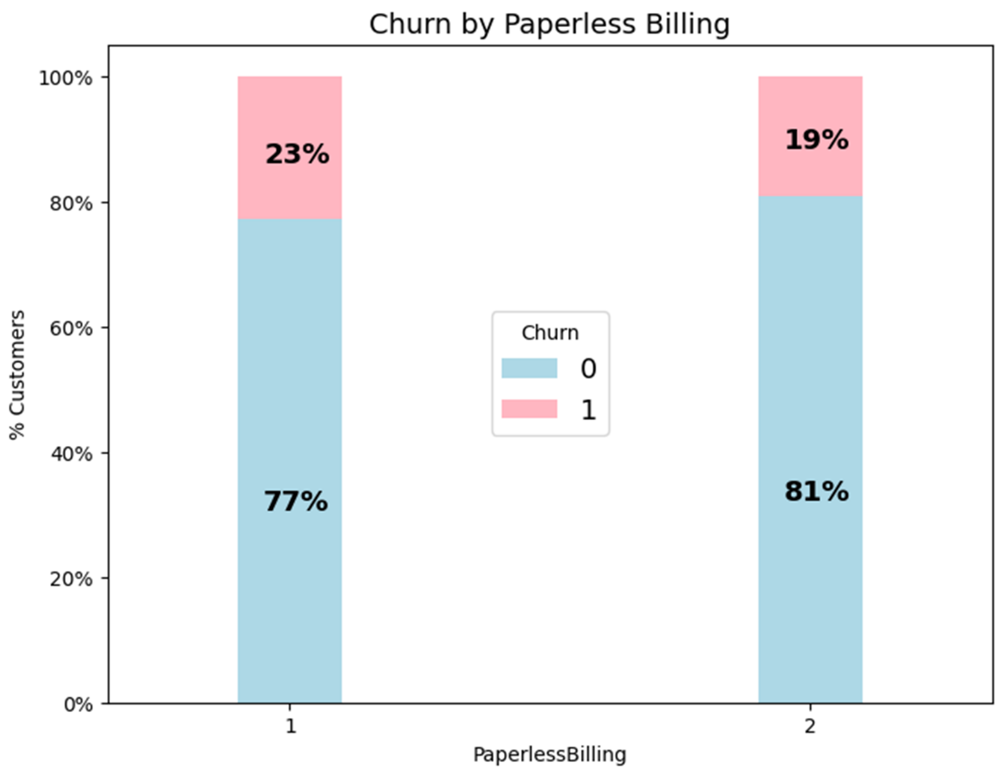

Figure 14: Pattern Analysis of Paperless Billing

In the above figure 14, 1 is indicating that the customer has paperless billing, whereas 2 is indicating that the customers do not have paperless billing. It has been analysed that 23% customers churn is found when customer has paperless billing and 19% customers churn is found when they do not have paperless billing. It has been analysed that the likelihood of churn is more if customer has paperless billing.

4.1.15 Pattern Analysis of Payment Method

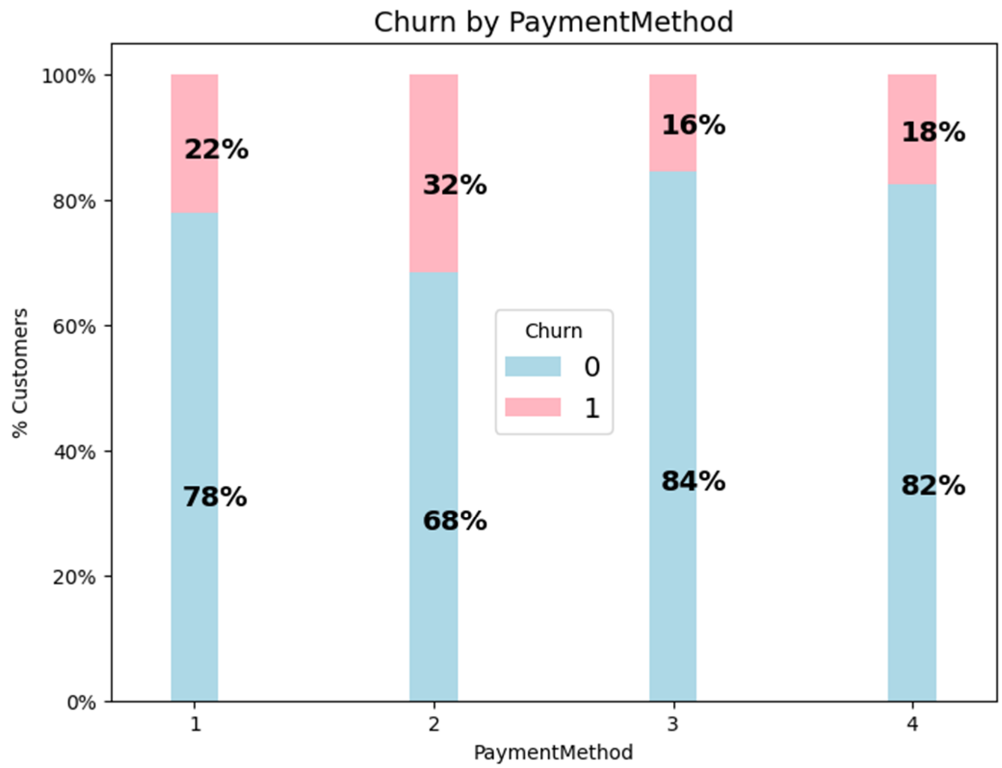

Figure 15: Pattern Analysis of Payment Method

In the above figure 15, 1 is indicating that the customer has bank transfer payment method, whereas 2 is indicating that the customer has credit card payment method, 3 is indicating that customers have electronic check payment method and 4 is indicating that customer has mailed check payment method. It has been analysed that 22% customers churn is found when customer has bank transfer payment method, 32% customers churn is found when customer has credit card payment method, 16% churn is found when customer has electronic check payment method and 18% churn is found if customer has mailed check payment method. It has been analysed that the likelihood of churn is more if the customer has credit card payment method.

4.1.16 Pattern Analysis of Monthly Charge

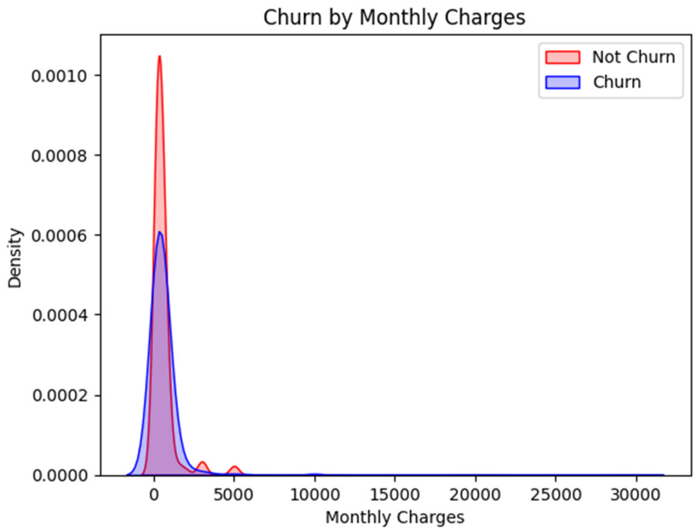

Figure 16: Pattern Analysis of Monthly Charges

It is found that if monthly charges increase then churn is also increases. It has been analysed that the likelihood of churn is more with more monthly charges.

4.1.17 Pattern Analysis of Total Charges

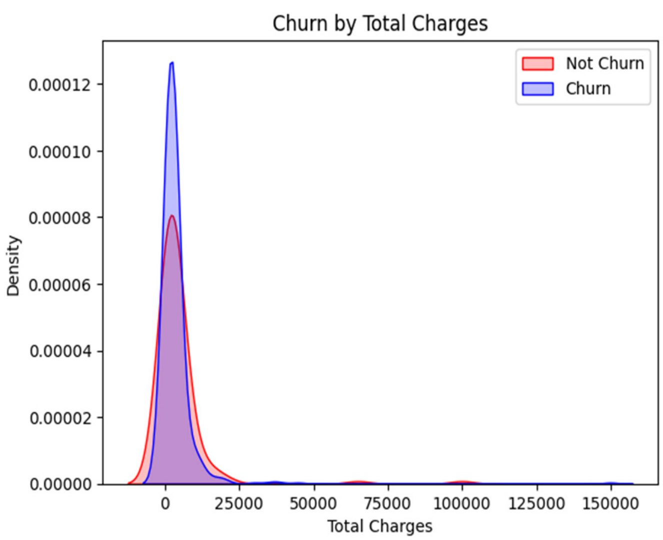

Figure 17: Pattern Analysis of Total Charges

It is found that if Total Charges increases then Churn is also increases. It has been analysed that the likelihood of churn is more with more Total charges.

4.1.18 Pattern Analysis of Tenure

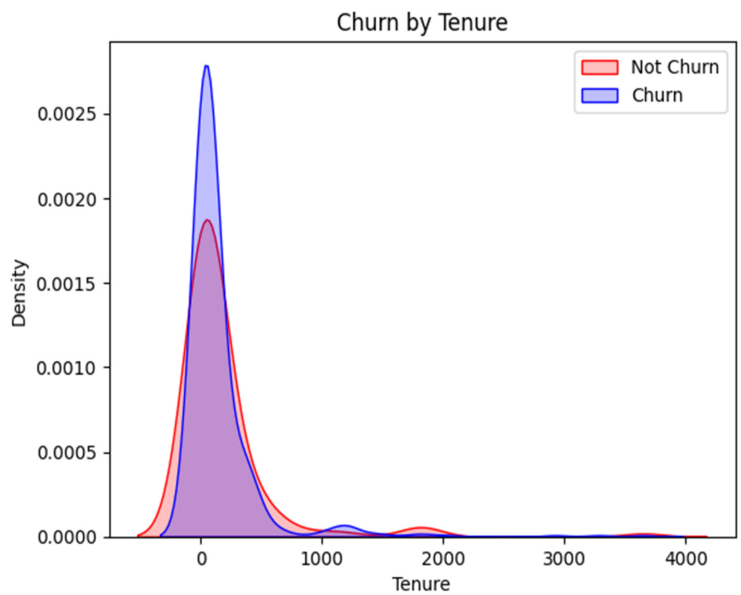

Figure 18: Pattern Analysis of Tenure

It is found that if Tenure increases then Churn is also increases. It has been analysed that the likelihood of churn is more with higher Tenure.

4.2 Pattern Analysis of Customers Churn Using Secondary Data

In this section I have described the data analysis and interpretation with respect pattern analysis of customer churn. It is very important to understand the pattern of churn in this study.

4.2.1 Gender Pattern Analysis

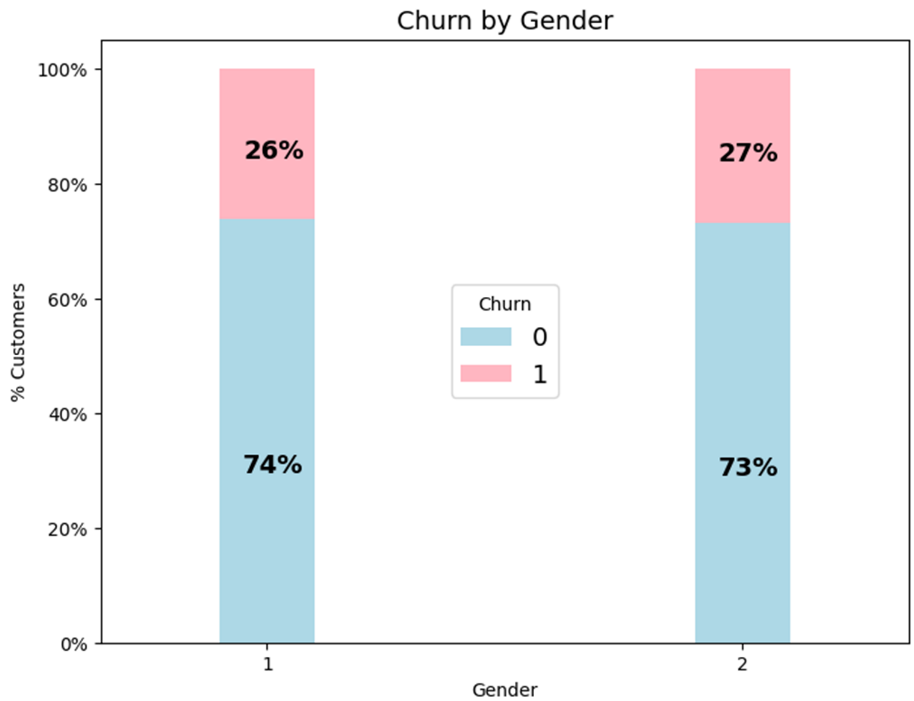

Figure 19: Gender Pattern Analysis

In the above figure 19, 1 is indicating male, whereas 2 is indicating female. It has been analysed that 26% customer churn is found in Males and 27% churn is found in Females. It has been analysed that the likelihood of churn of female category is more comparatively than male category.

4.2.2 Partner Pattern Analysis

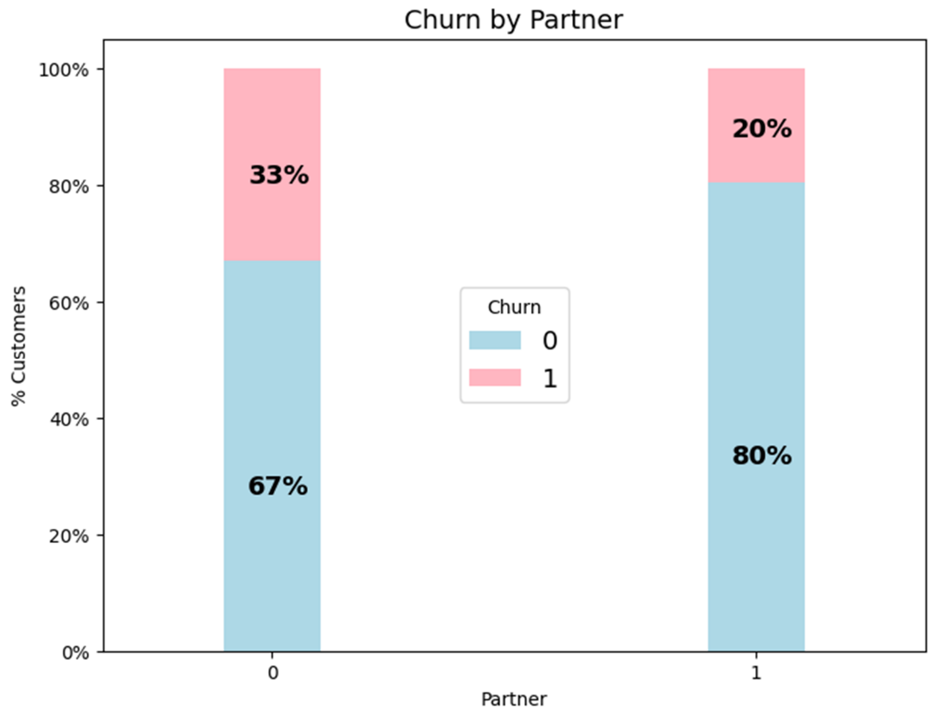

Figure 20: Partner Pattern Analysis

In the above figure 20, 1 is indicating yes i.e. representing that the customer is having a partner plan, whereas 2 is indicating no means the customer does not have any partner plan. It has been analysed that 33% customers churn is found when customer do not have partner plan available and 20% customers churn is found when they have partner plan. It has been analysed that the likelihood of churn is more if customer do not have partner plan.

4.2.3 Dependents Pattern Analysis

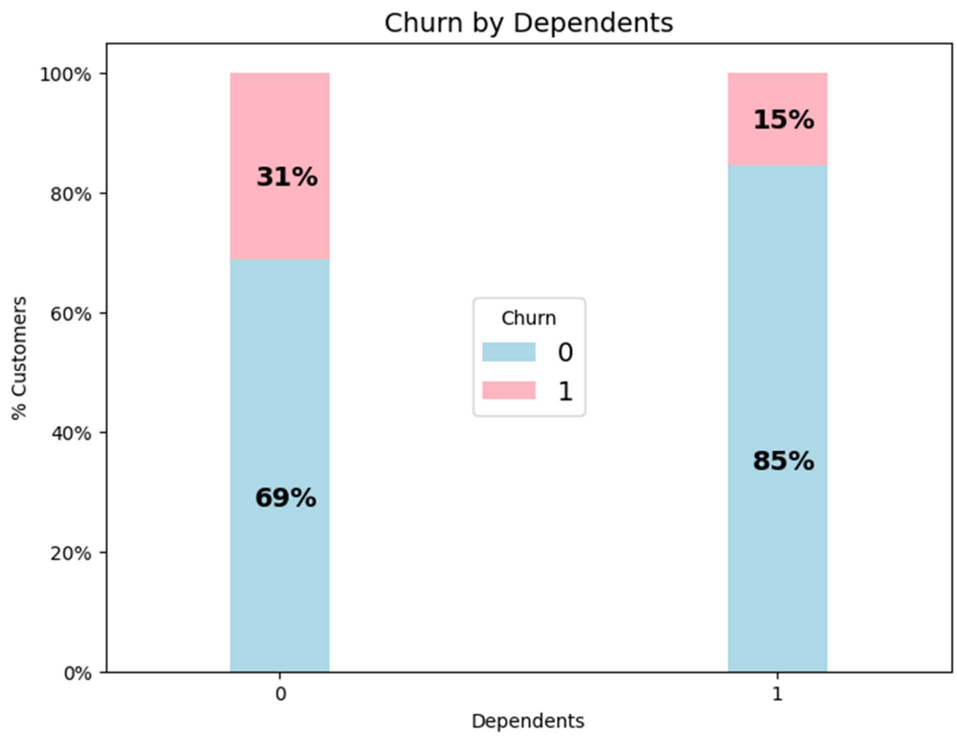

Figure 21: Dependents Pattern Analysis

In the above figure 21, 1 indicates that customers are having dependents, whereas 2 is indicating that the customer does not have dependents. It has been identified and analysed that 31% customers churn is found when customer do not have dependents and 15% customers churn is found when they have dependents. It has been analysed that the likelihood of churn is more if customer do not have dependents.

4.2.4 Phone Service Pattern Analysis

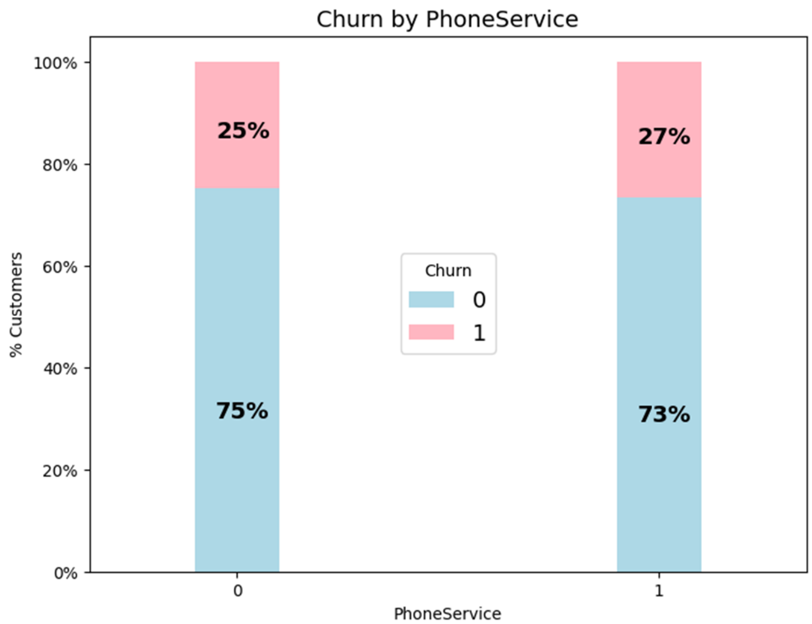

Figure 22: PhoneService Pattern Analysis

In the above figure 22, 1 represents that the customer is having phone service, whereas 2 is indicating that customer does not have phone service. It has been analysed that 25% customers churn is found when customer do not have phone service and 27% customers churn is found when they have phone service. It has been analysed that the likelihood of churn is more if customer has phone service.

4.2.5 Multiple Lines Pattern Analysis

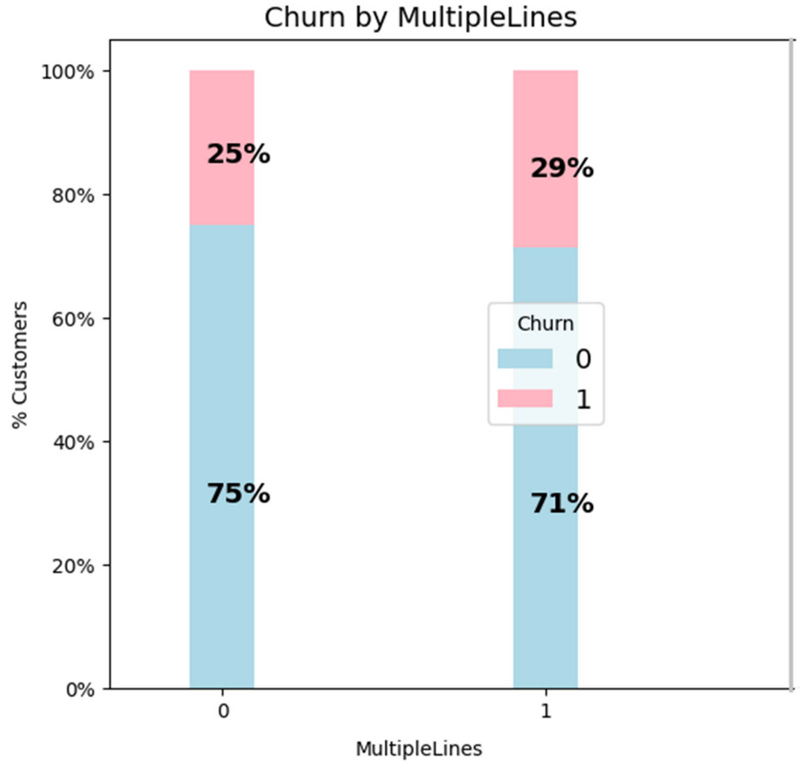

Figure 23: Multiple Lines Pattern Analysis

In the above figure 23, 1 is indicating that the customer is having multiple lines, whereas 2 is indicating that the customer does not have multiple line service. It has been analysed that 25% customers churn is found when customer do not have multiple lines and 29% customers churn is found when they have multiple lines. It has been analysed that the likelihood of churn is more if customer has multiple lines.

4.2.6 Internet Service Pattern Analysis

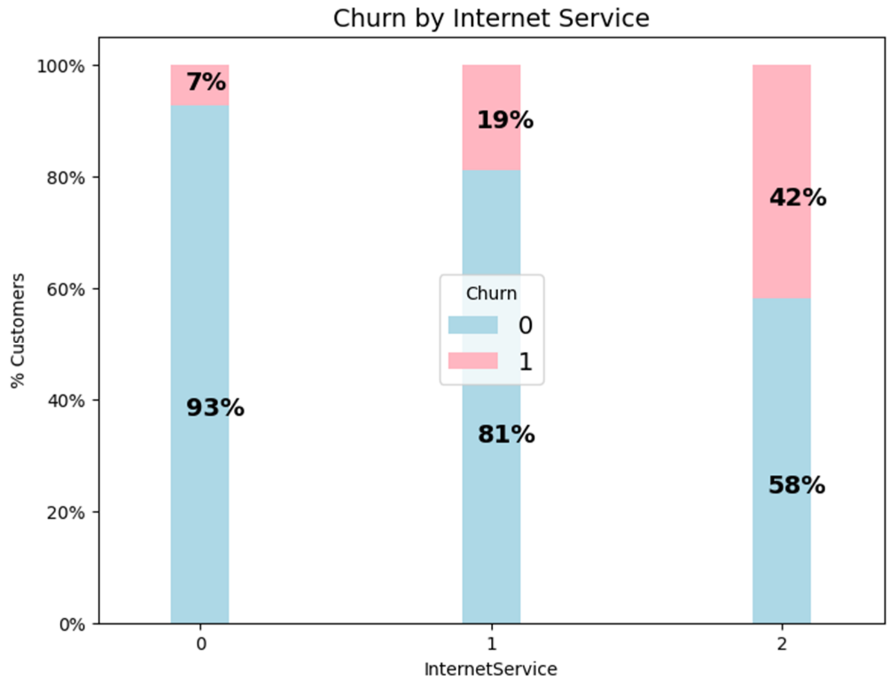

Figure 24: Internet Service Pattern Analysis

In the above figure 24, 1 is indicating that the customers are having DSL Internet service, whereas 2 is indicating that the customers do not have internet service and 3 is indicating that customers have Fiber optic internet service. It has been analysed that 7% customers churn is found when customer has DSL Internet service, 19% customers churn is found when they have fiber oprtic internet service and 42% churn is found when customer do not have internet service. It has been analysed that the likelihood of churn is more if internet service is not there.

4.2.7 Online Security Pattern Analysis

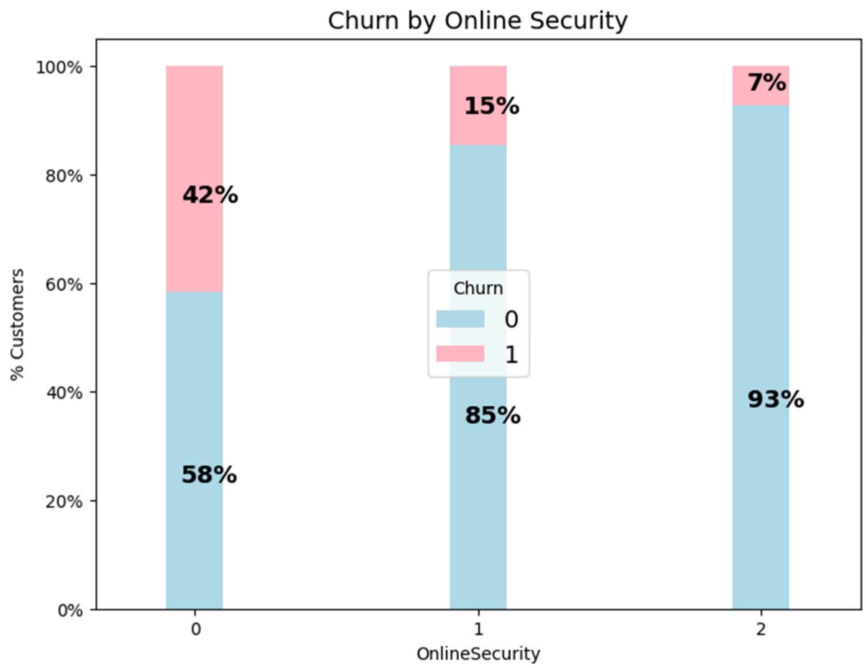

Figure 25: Online Security Pattern Analysis

In the above figure 25, 1 is indicating that the customer has opted for online security service, whereas 2 is indicating that the customers do not have online security service and 3 is indicating that customers have Fiber optic internet service. It has been analysed that 42% customers churn is found when customer do not have online security, 15% customers churn is found when they have online security and 7% churn is found when customer do not have internet service also. It has been analysed that the likelihood of churn is more if customer do not have online security.

4.2.8 Online Backup Pattern Analysis

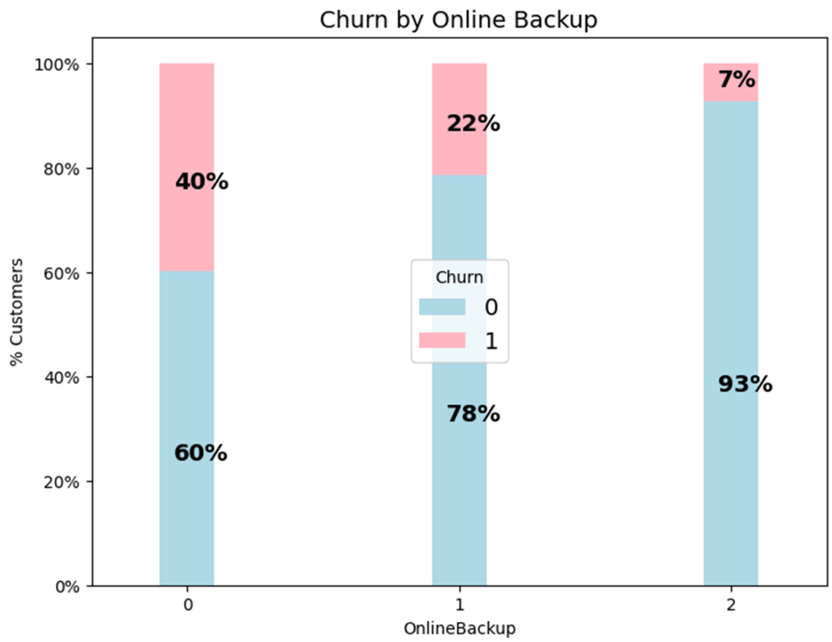

Figure 26: Online Backup Pattern Analysis

In the above figure 26, 1 is indicating that the customer has online backup service, whereas 2 is indicating that the customers do not have online backup service and 3 is indicating that customers do not have internet service. It has been analysed that 40% customers churn is found when customer do not have online backup, 22% customers churn is found when they have online backup and 7% churn is found when customer do not have internet service. It has been analysed that the likelihood of churn is more if customer do not have online backup.

4.2.9 Device Protection Pattern Analysis

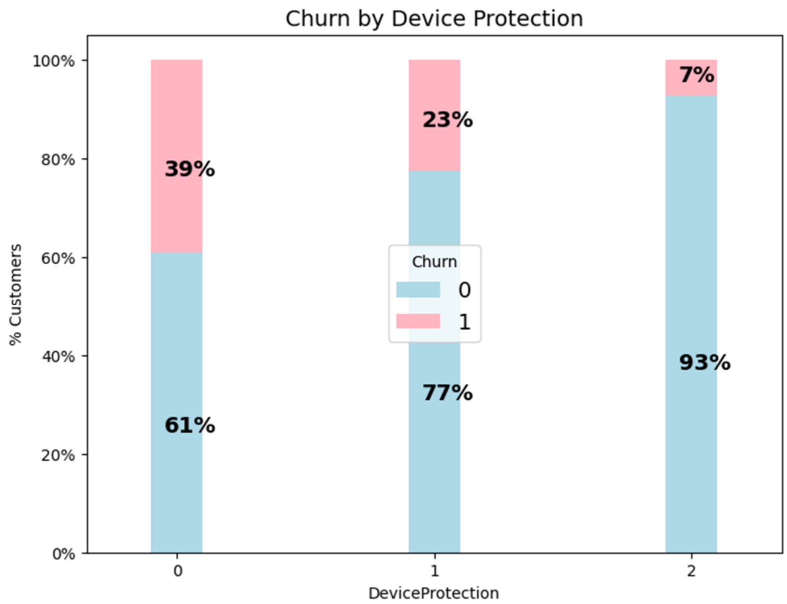

Figure 27: Device Protection Pattern Analysis

In the above figure 27, 1 is indicating that the customer has device protection, whereas 2 is indicating that the customers do not have device protection and 3 is indicating that customers do not have internet service. It has been analysed that 39% customers churn is found when customer do not have device protection, 23% customers churn is found when they have device protection and 7% churn is found when customer do not have internet service. It has been analysed that the likelihood of churn is more if customer do not have device protection.

4.2.10 Tech Support Pattern Analysis

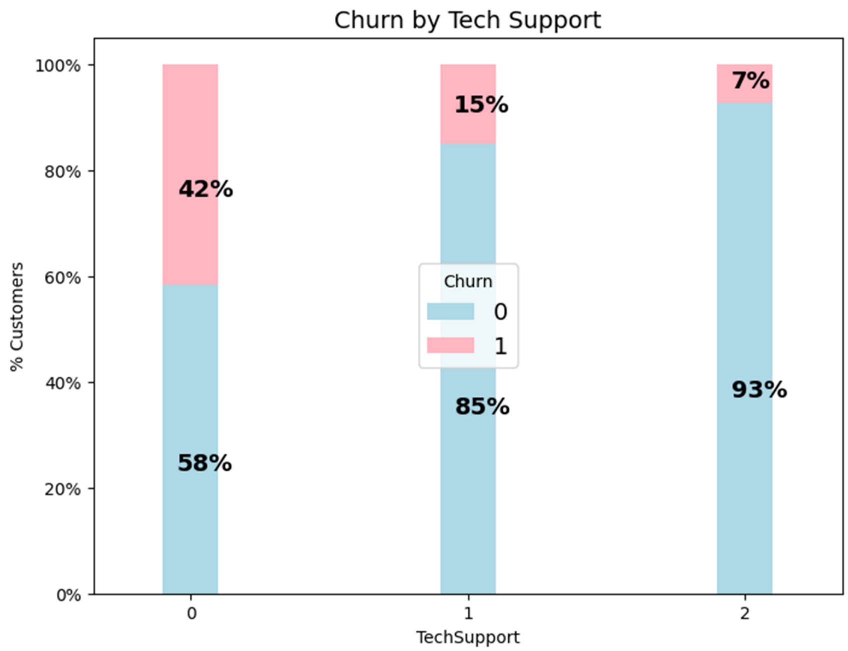

Figure 28: Tech Support Pattern Analysis

In the above figure 28, 1 is indicating that the customer has tech support, whereas 2 is indicating that the customers do not have tech support and 3 is indicating that customers do not have internet service. It has analysed that 42% customers churn is found when customer do not have tech support, 15% customers churn is found when they have tech support and 7% churn is found when customer do not have internet service. It has been analysed that the likelihood of churn is more if customer do not have tech support.

4.2.11 Streaming TV Pattern Analysis

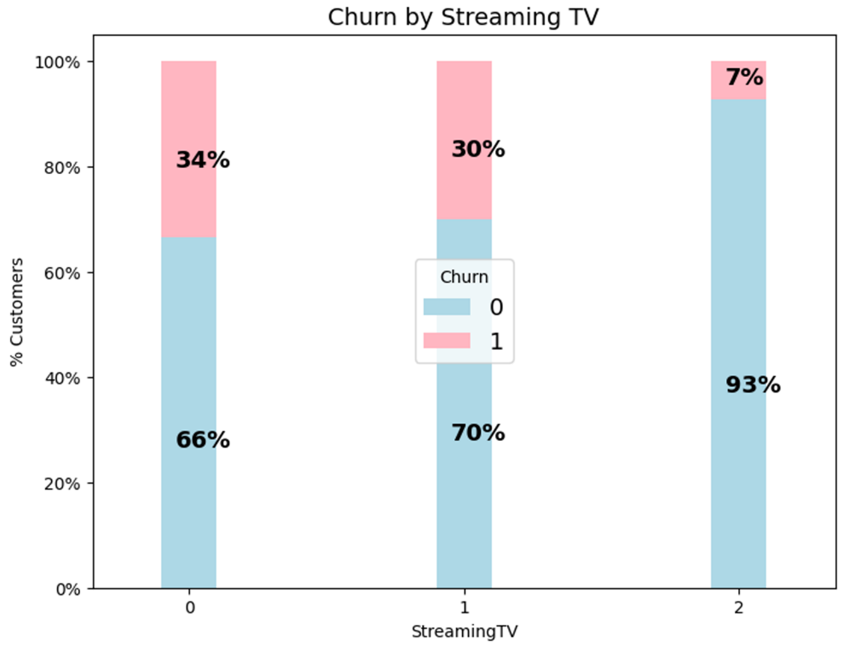

Figure 29: Streaming TV Pattern Analysis

In the above figure 29, 1 is indicating that the customer has Streaming TV service, whereas 2 is indicating that the customers do not have Streaming TV service and 3 is indicating that customers do not have internet service. It has been analysed that 34% customers churn is found when customer do not have Streaming TV service, 30% customers churn is found when they have Streaming TV service and 7% churn is found when customer do not have internet service. It has been analysed that the likelihood of churn is more if customer do not have Streaming TV.

4.2.12 Streaming Movies Pattern Analysis

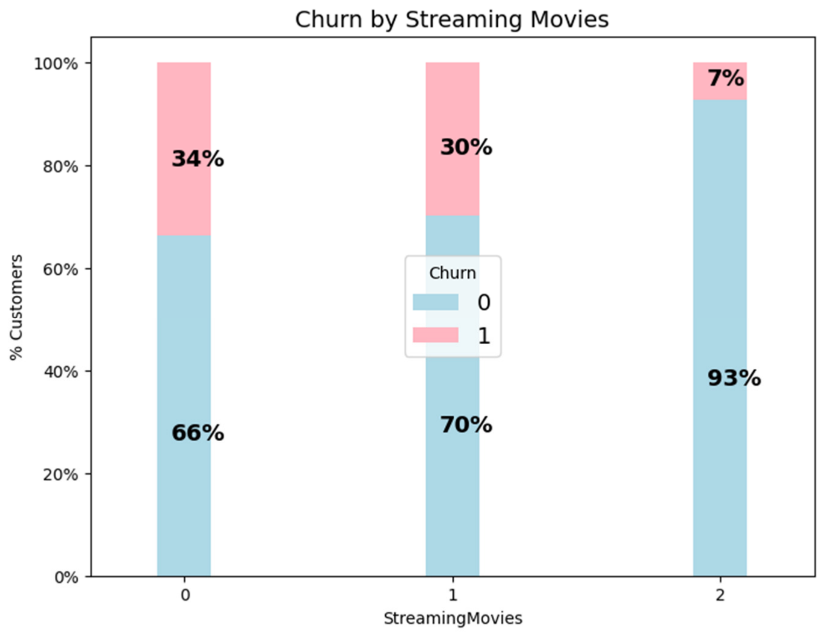

Figure 30: Streaming Movies Pattern Analysis

In the above figure 30, 1 is indicating that the customer has Streaming Movies service, whereas 2 is indicating that the customers do not have Streaming Movies service and 3 is indicating that customers have Fiber optic internet service. It has been analysed that 34% customers churn is found when customer do not have Streaming Movies service, 30% customers churn is found when they have Streaming Movies service and 7% churn is found when customer do not have internet service. It has been analysed that the likelihood of churn is more if customer do not have Streaming Movies service.

4.2.13 Contract Pattern Analysis

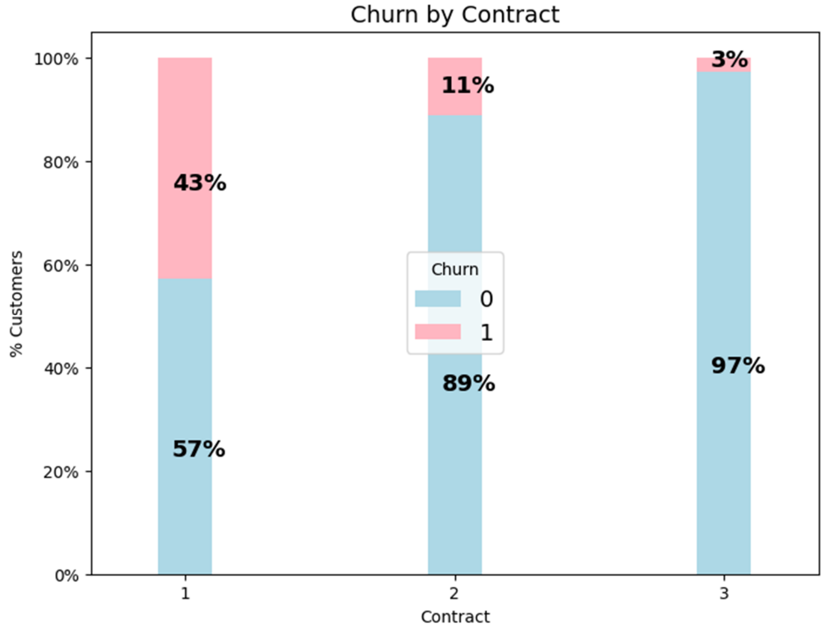

Figure 31: Contract Pattern Analysis

In the above figure 31, 1 is indicating that the customers have monthly contract, whereas 2 is indicating that the customers have one year contract and 3 is indicating that customers have two year contract. It has been analysed that 43% customers churn is found when customer has monthly contract, 11% customers churn is found when customer has one year contract and 3% churn is found when customer has two years contract. It has been analysed that the likelihood of churn is more if customer has monthly contract.

4.2.14 Paperless Billing Pattern Analysis

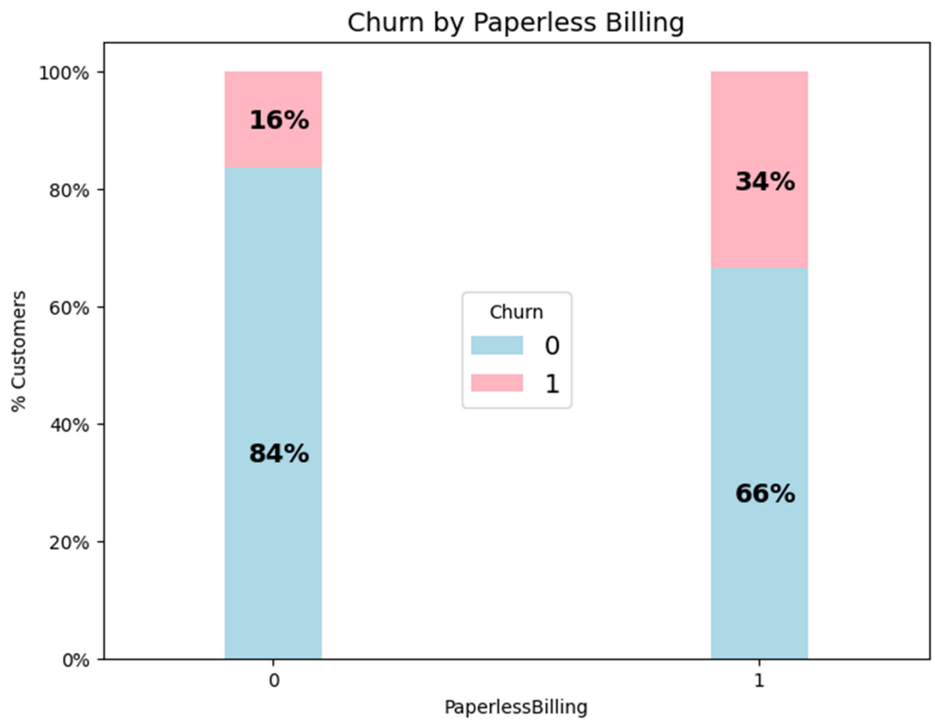

Figure 32: Paperless Billing Pattern Analysis

In the above figure 32, 1 is indicating that the customer has paperless billing, whereas 2 is indicating that the customers do not have paperless billing. It has been analysed that 16% customers churn is found when customer do not have paperless billing and 34% customers churn is found when they have paperless billing. It has been analysed that the likelihood of churn is more if customer has paperless billing.

4.2.15 Payment Method Pattern Analysis

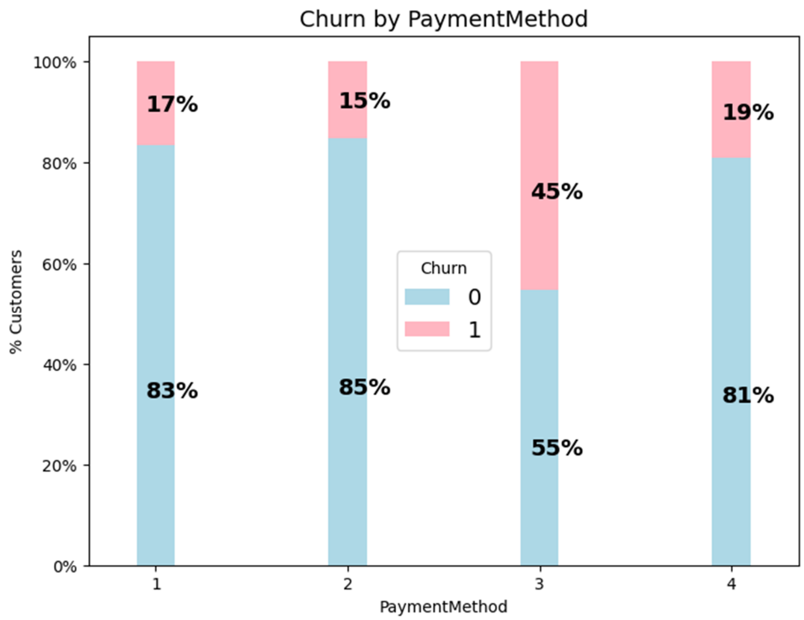

Figure 33: Payment Method Pattern Analysis

In the above figure 33, 1 is indicating that the customer has bank transfer payment method, whereas 2 is indicating that the customer has credit card payment method, 3 is indicating that customers have electronic check payment method and 4 is indicating that customer has mailed check payment method. It has been analysed that 17% customers churn is found when customer has bank transfer payment method, 15% customers churn is found when customer has credit card payment method, 45% churn is found when customer has electronic check payment method and 19% churn is found if customer has mailed check payment method. It has been analysed that the likelihood of churn is more if customer has electronic check payment method.

4.2.16 Monthly Charge Pattern Analysis

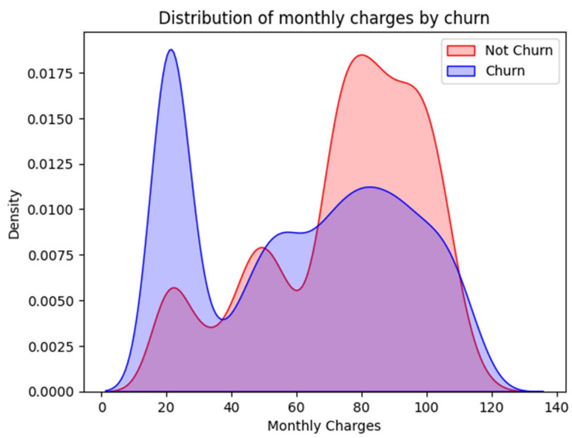

Figure 34: Monthly Charges Pattern Analysis

It is found that if monthly charges increases then churn is also increases. It has been analysed that the likelihood of churn is more with more monthly charges.

4.2.17 Total Charges Pattern Analysis

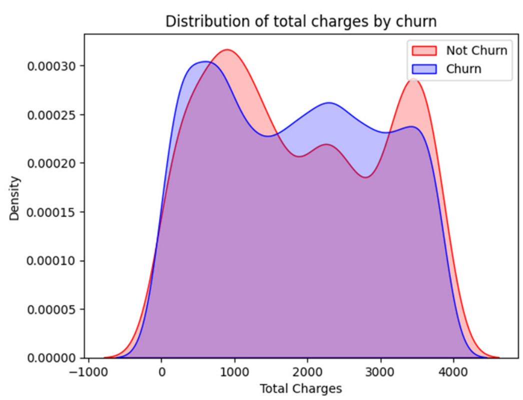

Figure 35: Total Charges Pattern Analysis

It is found that if Total Charges increases then Churn is also increases. It has been analysed that the likelihood of churn is more with more Total charges.

4.2.18 Tenure Pattern Analysis

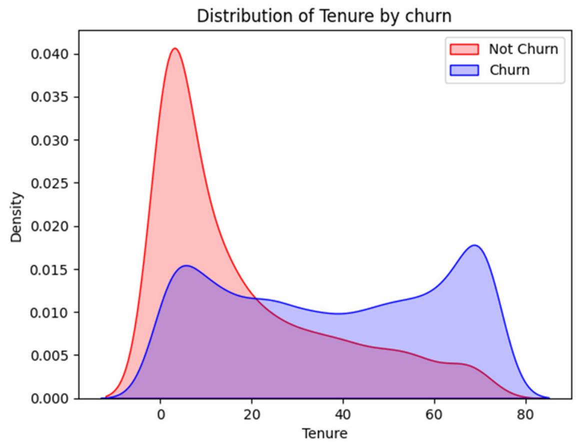

Figure 36: Pattern Analysis of Tenure

It is found that if Tenure increases then Churn is decreases. It has been analysed that the likelihood of churn is less with higher Tenure.

4.3 Data Analysis on Factors of customer churn

Data Analysis and interpretation of factors impacting customer churn has been described in this section.

4.3.1 Factors Impact on Churn using Primary Data

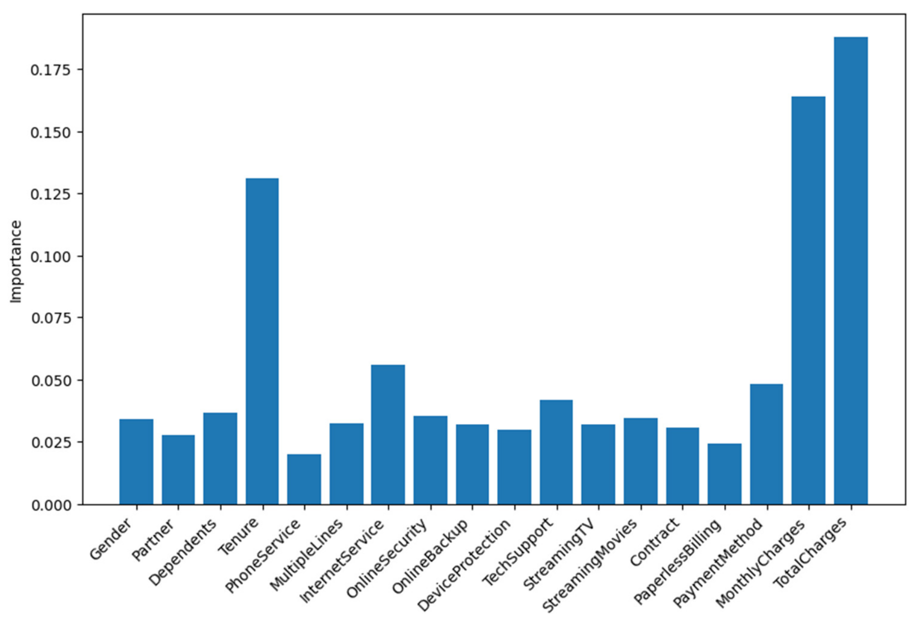

Figure 37: Factors Impact on churn

It is analyzed that Gender of the customer has 3.4% impact on churn whereas selection of partner plan has 2.7% impact on customer churn, further it is found that if customer has dependents then there is 3.6% impact on customer churn, Tenure has 13% impact, Phone service has 2% impact, multiple lines has 3% impact, Internet services has 5.6 impact, Online security has 3.5% impact, online backup has 3.2% impact, Device Protection has 3% impact, Tech Support has 4.1% impact, Streaming Tv has 3.2% impact, Streaming Movies has 3.4% impact, Contract has 3% impact, Paperless billing has 2.4%, Payment method has 4.8%, Monthly charges has 16%.

Total charges has 18.8% impact on identification of customer churn. It is found that Total charges, Monthly charges, Tenure and internet services has major impact in identification of customer churn. High positive loading is found on Online Security as 0.705968.

Online Backup as 0.718834, Device Protection as 0.784651, and Tech Support as 0.453108 included in first factor in this study. High positive loading is found on Streaming TV as 0.714397, Streaming Movies as 0.926995, Multiple Lines as 0.234968 included in Second factor in this study. High positive loading is found on Partner as 0.399118, Dependent as 0.464594 included in the Third factor in this study. High positive loading is found on Monthly Charges as 0.405746, Total Charges as 0.333004, Contract as 0.292176 included in Forth Factor in this study.

4.4.2 Impact on Churn using Secondary data

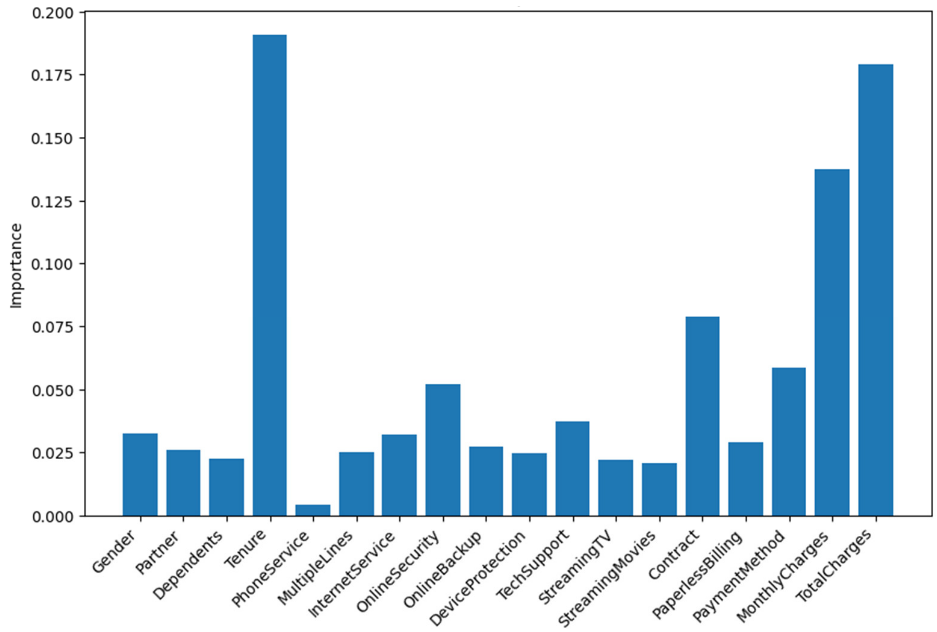

Figure 38: Impact on Churn using Secondary Data

It is analyzed that Gender of the customer has 3.2% impact on churn whereas selection of partner plan has 2.6% impact on customer churn, further it is found that if customer has dependents then there is 2.2% impact on customer churn, Tenure has 19% impact, Phone service has .4% impact, multiple lines has 2.4% impact, Internet services has 3.2% impact, Online security has 5% impact, online backup has 2.7% impact, Device Protection has 2.4% impact, Tech Support has 3.7% impact, Streaming TV has 2.2% impact, Streaming Movies has 2% impact, Contract has 7.9% impact, Paperless billing has 2.9%, Payment method has 5.8%, Monthly charges has 13%, Total charges has 17% impact on identification of customer churn. It is found that Total charges, Monthly charges and Tenure has major impact in identification of customer churn.

4.5 Customer Churn Rate

In this section I have described the data analysis and interpretation with respect to customer churn rate. It is very important to understand the customer churn rate in this study.

4.5.2 Customer Churn Rate using Primary Data

The churn rate is a crucial metric in the telecommunications industry, indicating the percentage of customers who stop using a service over a given period. It's calculated by dividing the number of customers lost during that period by the total number of customers at the beginning of the period. Here's the formula:

Churn Rate = (Number of Customers Lost during Period / Total Number of Customers at Beginning of Period) x 100

Number of Customers Lost during Period: This refers to the total number of customers who terminate their subscription or cease using the service during the specified period. It includes voluntary cancellations, non-renewals, or customers switching to competitors.

Total Number of Customers at Beginning of Period: This represents the total number of customers at the start of the period under consideration. It serves as the denominator for calculating the churn rate. In this study churn Rate using the primary data is found as 22.14%

4.5.3 Customer Churn Rate using Secondary Data

Using the formula: Churn Rate = (Number of Customers Lost during Period / Total Number of Customers at Beginning of Period) multiply by 100. Churn rate using the secondary data is found as 26.53%.

5. CONCLUSION

Customer churn refers to the situation when customers choose to discontinue their business relationship with a specific company or service. It is a crucial metric for any business, as retaining existing customers typically incurs lower costs compared to acquiring new ones. Acquiring new customers typically involves marketing efforts, advertising campaigns, sales activities, and other resources aimed at attracting and onboarding new clients. On the other hand, retaining existing customers involves building strong relationships, delivering quality products or services, and providing excellent customer support. While these efforts require ongoing investments, they are often more cost-effective in the long run. Customer churn is a persistent issue that affects businesses across industries worldwide. It is particularly relevant in the telecommunications industry due to its competitive nature and customers' propensity to switch providers. Retaining existing customers is generally more cost-effective than acquiring new ones. Businesses can mitigate churn by monitoring at-risk customers, investing in customer satisfaction, and implementing strategies that prioritize customer retention. By understanding the importance of customer churn and taking proactive measures to address it, companies can safeguard their financial stability and foster long-term growth. In this study it is concluded that Total charges, Monthly charges, Tenure and internet services has major impact in identification of customer churn. It has been concluded that likelihood of churn of female customers is more comparatively than male customers, also churn is more if customer do not have dependents, If Internet service is not available then churn rate is more. The likelihood of churn is more with more Total charges and with higher Tenure.

6. References

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