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Enhancing Customer Retention From Churn Analysis Using Power BI And Machine Learning Techniques

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Abstract: Market deregulation and globalization have caused competitive situations across a range of industries to constantly change, which has resulted in a rise in customer attrition. In order to maintain business development and keep their client base, organizations must effectively anticipate and mitigation of customer churns. This study explores the use of machine learning techniques in the Power Bi tool to anticipate client turnover. Emphasis is placed on the incorporation of these features, while focusing on well-known industries like telecommunication, employee churn for developing a predictive model, and features capturing customer social interaction and communications graphs and customer feedback are highlighted in the review. The findings encourage the use of profit-based evaluation criteria to increase profitability, improve customer retention, and support decision-making.

Additionally, they draw attention to the dearth of studies on the profitability aspect of churn prediction models. In order to promote further advancements, the research concludes with recommendations that support the usage of ensembles, machine learning techniques, interaction visualization data utilizing Power BI, and explainable methodology. Churn prediction, which identifies customers who are likely to leave for a rival, has become the most important Business Intelligence (BI) application as a result. The purpose of this study is to provide widely used data mining approaches for identifying potential churning customers. These techniques look for patterns in past data that may point to potential churners.

I. INTRODUCTION

1.1 Introduction to Churn Analysis

Businesses frequently implement new strategies and technology to boost income as a result of the difficulty in staying competitive and upholding positive consumer relations. Nevertheless, it is typically more costly to acquire new clients than to keep current ones. As a result of this tactics for predicting and retaining consumers have been developed, with a particular emphasis on keeping clients who provide a better rate of return on investment. spreading good word of mouth about a company, retaining consumers can also lower the cost of marketing for their acquisition.

A major problem for firms is customer churn, which occurs when clients leave or move to another service provider. As a general rule, different sectors use different criteria to categorize churners. For example, if a customer's average annual account balance and annual transactions drop by more than 25%, banking industry professionals classify them as a churner. According to Edwine et al, a customer is considered a churner if they show no activity for ninety days in a row. In the telecom industry, churn can happen for a number of reasons, including discontent with the quality of the services or in reaction to price hikes.

Businesses must anticipate customer attrition by analyzing customer behavior and addressing probable root causes of unhappiness in order to reduce churn rates. According to research, even a little improvement in a company's client retention rate can result in significant increases in its net present value; for example, software and advertising companies have seen gains of up to 35% and 95%, respectively.

Technical problems like subpar performance, out-of-date services, poor customer support, inadequate coverage, or budgetary worries like pricey plans could be the cause of this discontent. Incidental churn, on the other hand, occurs when users discontinue using the service because of changes in their situation, like moving to a different city where the service is unavailable, changing jobs that restrict their use of a particular service provider, or the services becoming too expensive for the user. Since the company is already aware of involuntary clients who violate terms and conditions or neglect to pay bills, the main objective of churn prediction is to foresee intentional churn.

A minor percentage of churn is incidental churn, which is hard to forecast because even consumers may not anticipate changes like a job or place change before a particular shift in actuality. Furthermore, anticipating unintentional churn is useless because it becomes unable to keep those clients for reasons other than the company's goods and services. The necessity of churn prediction in the business setting is covered in detail in the following section.

Businesses' ability to grow economically in a fiercely competitive worldwide market depends on both increasing the average lifespan of current clients and boosting their consumption. Understanding the elements that lead to the establishment of customer loyalty and anticipating customers' intents to leave are essential for creating successful retention strategies. Businesses can create plans to keep current clients and create enduring loyalty relationships with them by understanding this mechanism, which is more efficient and less expensive than bringing in new clients.

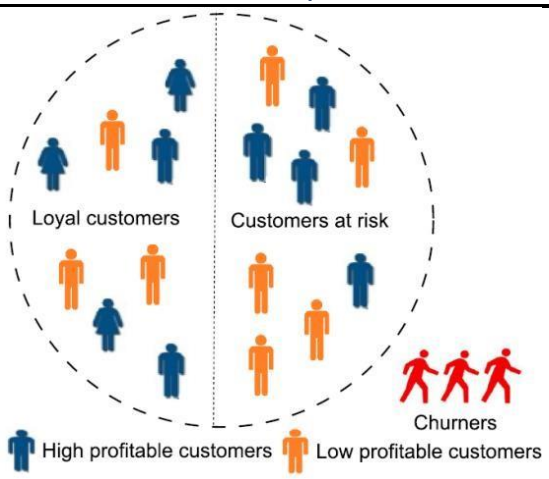

Figure: Representation of Churners

Because it can be costly to lose lucrative clients, the market paradigm has shifted from emphasizing customer acquisition to focusing on customer retention. Furthermore, because of the reciprocal dependence of customers, churn influence spreads throughout the social circle, and when churn occurs, it also raises the probability of churn in the social circle. Customers' exposure to competing advertising offers and market awareness provide hurdles for organizations attempting to cultivate customer loyalty. It is essential to comprehend the process of creating customer loyalty connections in order to guarantee the long-term viability and expansion of the company.

Consumers are any company's most valuable asset, and it is the duty of businesses to develop and execute strategies that increase their lifespan. Since it dictates their future commercial path, business enterprises should prioritize extending the lifespans of their clients. A company's reputation may suffer if it forces customers to upgrade their purchases without meeting their actual demands, as this can result in high customer abandonment and low customer satisfaction.

1.2 Approach

*T*he customer churn dataset, which includes data on a 12-month telecom provider that offers internet and home phone services to 11,260 subscribers, is used in the study to gain insights into customer retention and attrition patterns. This dataset is particularly valuable as it not only captures the churn mark label that indicates whether or not a client discontinued their service in the previous month but also encompasses a variety of other essential features that can influence customer decisions. These features include detailed account information such as billing methods, payment history, and service plans, as well as demographic data like age, gender, and geographical location. Additionally, it outlines subscription services, which provide further context regarding the types of packages customers are utilizing and their respective satisfaction levels.

To analyze the complexities of customer churn, numerous machine learning models, including Naive Bayes, K-Nearest Neighbors (KNN), logistic regression, decision trees, and random forests, were compared in the study to determine which algorithm would yield the most accurate predictions. The research employed advanced ensemble techniques, specifically Bagging, AdaBoosting, and XGBoost, to identify the best-performing machine learning model. These ensemble methods are particularly effective in improving

accuracy by combining the strengths of multiple models, thereby enhancing predictive performance and reliability.

Recognizing the challenge of imbalanced data—where the number of customers who churn is significantly lower than those who remain—a crucial step was taken to prepare the dataset further. This involved identifying pertinent features that might contribute to the churn behavior and applying the Synthetic Minority Oversampling Technique (SMOTE) to mitigate the effects of this imbalance. SMOTE works by generating synthetic samples for the minority class, which in this case refers to the customers who churned, thus ensuring that the models trained on this data are not biased towards the majority class.

To evaluate how these modifications influenced model performance, ensemble approaches such as Bagging, AdaBoosting, and XGBoost were subsequently applied to the SMOTE- processed data in conjunction with the aforementioned machine learning models, including Naive Bayes, KNN, logistic regression, decision trees, and random forests. This comprehensive analysis allowed for a thorough comparison of each model's predictive capability, offering insights into which algorithms are most effective in forecasting customer churn within the telecom sector. The results of this study not only contribute to the academic understanding of customer behavior in service industries but also provide actionable insights for telecom providers aiming to enhance their customer retention strategies and minimize churn rates effectively.

By evaluating these models' performance using metrics like accuracy, precision, recall, and F1-score, train and test them to make sure they predict churn appropriately, ensuring that the algorithms are not only accurate but also reliable in their predictions under various conditions. This rigorous evaluation process involves cross-validation techniques and tuning hyperparameters to optimize model performance, enabling me to select the most effective models. After the data is ready, work on creating the churn data connector for Power BI, a critical step that involves integrating with data sources, ensuring data cleanliness of data.

Once the connector is established, I delve into the intricacies of Power BI to visualize the outcomes, building interactive dashboards that provide important metrics, forecasts, and useful information that stakeholders can easily interpret. These dashboards feature not only the overall churn rate but also granular breakdowns by customer segments, product lines, and geographical areas, allowing decision-makers to identify trends and patterns at a glance. By identifying at-risk customers, classifying them according to churn risk, and putting targeted retention tactics into place, this method helps firms lower churn rates and enhance overall business performance.

Moreover, through continuous monitoring and iterative improvements based on feedback and changing market conditions, I ensure that the churn prediction models remain relevant and effective over time. By employing predictive analytics and machine learning techniques, I empower organizations to proactively engage with their customers, fostering loyalty and ultimately driving growth.

1.3 Proposed System

This approach provides a robust churn analysis solution by utilizing Python's potent data analytic capabilities within the dynamic and user-friendly Power BI environment. By harnessing the seamless integration of these two powerful tools, businesses can analyze vast datasets with remarkable efficiency and precision. The combination allows for the application of advanced machine learning techniques, enabling organizations to uncover hidden patterns and trends within customer behavior that may signal potential churn risks. Furthermore, the interactive visualization options offered by Power BI empower users to explore this data in an engaging manner, facilitating deeper insights and promoting collaborative discussions among team members.

With the ability to create comprehensive dashboards and visual reports, stakeholders can easily grasp complex data narratives and identify key performance indicators related to customer retention. This comprehensive visibility enables businesses to craft targeted strategies tailored to specific segments of their customer base, ensuring that interventions are not only timely but also relevant. For instance, by identifying high-risk customers through predictive modeling, companies can implement personalized outreach initiatives, such as special offers, loyalty programs, or improved customer service interactions, designed to enhance the overall customer experience.

Moreover, this analytical approach fosters a culture of data-driven decision-making within organizations. By continuously monitoring churn metrics and adjusting strategies based on real-time feedback, businesses can remain agile and responsive to changing market conditions and customer expectations. This iterative process not only helps in mitigating churn but also in building stronger relationships with customers, ultimately enhancing brand loyalty.

As a result, this approach does not merely serve as a reactive measure to combat churn; it evolves into a proactive strategy that contributes significantly to long-term success and profitability. In an increasingly competitive landscape, where customer preferences are continually shifting, being equipped with the right tools and methodologies to understand and anticipate customer needs is paramount. Companies that successfully implement such robust churn analysis solutions will not only retain their existing customers but also position themselves as industry leaders, capable of attracting new clientele through a reputation for exceptional customer care and engagement.

II. DESIGN OF CHURN ANALYSIS

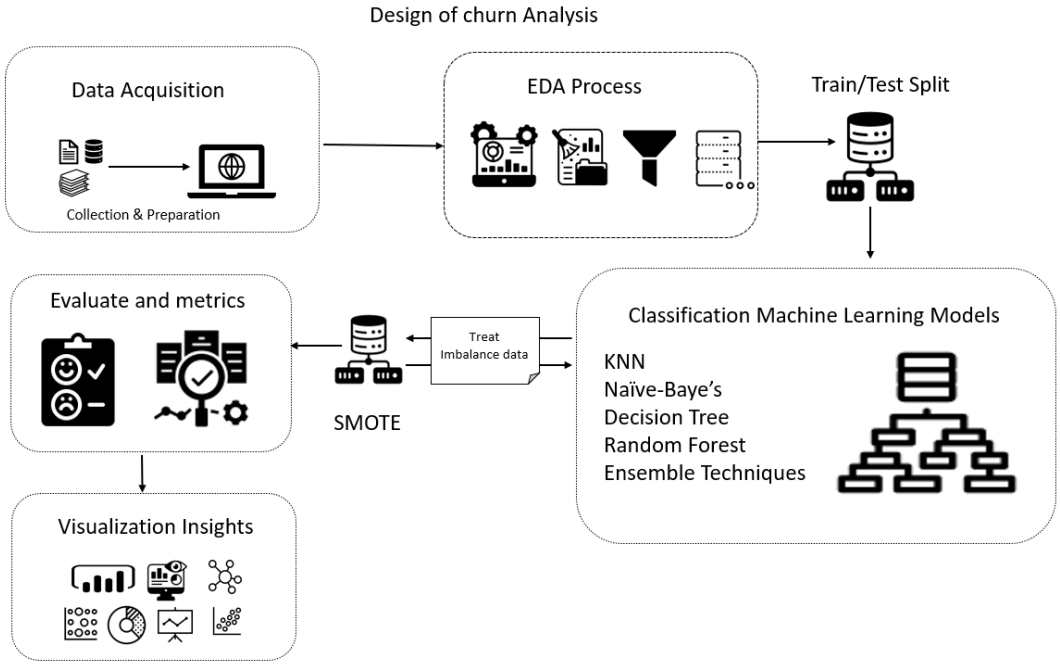

Figure: Design of Churn Analysis

2.1 Churn Analysis

There are numerous crucial elements involved in creating a churn analysis with machine learning models that use ensemble and SMOTE approaches. First, gathering and preprocessing your data is crucial. This entails compiling past information on consumer demographics, transactions, and behavior, which provides a comprehensive view of customer interactions with your business. After obtaining your data, you will need to clean it up by normalizing numerical features and dealing with missing values and outliers. This phase, where you develop new features that could aid in forecasting customer attrition, is also critical for feature engineering.

Feature engineering involves creating additional relevant variables that can enhance the model's predictive capabilities. For instance, you might consider deriving metrics such as customer tenure, average purchase value, or the frequency of transactions over time. These variables can provide deeper insights into customer behavior and help create a more robust model.

Any data imbalance issues must then be addressed. Churn datasets frequently contain a higher proportion of non-churned customers than churned ones, which can lead to biased predictions that favor the majority class. This can be addressed by creating synthetic samples of the minority class (churned customers) using the Synthetic Minority Over-sampling Technique (SMOTE), which balances your dataset by generating new, synthetic instances based on the existing minority class samples. This process not only helps to mitigate the risk of overfitting but also enhances the model's ability to learn from the minority class effectively, which is essential for accurately predicting customer churn.

Once you have a balanced dataset, you can proceed to model selection and training. Select a number of machine learning models, including K-Nearest Neighbors (KNN), Random Forest, XGBoost, and Logistic Regression, among others, for ensemble learning. Each of these models has unique strengths and weaknesses,

and training each one on the balanced dataset allows you to evaluate their performance individually before combining them.

The next stage is ensemble learning, in which you use strategies like stacking, boosting, and bagging to integrate the predictions from several models. Stacking involves training a new model to combine the predictions of base learners, while boosting focuses on sequentially training models that emphasize the mistakes made by previous ones; bagging, on the other hand, reduces variance by averaging predictions from multiple models trained on different subsets of the data. This approach enhances your prediction system's overall performance, often resulting in significantly improved accuracy and reliability.

Assess your ensemble model's performance using metrics such as ROC-AUC, F1-score, recall, accuracy, and precision. Each of these metrics provides insight into different aspects of model performance, allowing you to understand not just how often your model is correct but also how well it identifies churned customers among the entire customer base. Model tuning and validation are necessary after you have a functional model. Utilize techniques like Grid Search or Random Search to optimize the hyperparameters of your models, then implement cross- validation strategies to confirm the model's generalizability across different subsets of your data.

Once your data is in place, choose the Python visual icon from the Visualizations pane to build a Python Script Visual. Power BI will generate a placeholder visual and launch a Python script editor at the bottom when you drag the pertinent fields into the Values area of the Python visual. In this editor, you can write your churn analysis Python code, integrating libraries such as scikit-learn for model training, pandas for data manipulation, and unbalanced-learn to handle imbalanced data using SMOTE.

To run your script and render the output in the visual, click the Run button in the Python script editor. This action triggers Power BI to execute your Python code and display the results, enabling you to visualize the churn analysis effectively. By utilizing Power BI's interactive features to examine and analyze the churn data, you may further personalize your research by including increasingly intricate scripts or visualizations. This flexibility allows you to explore various angles of the data, uncovering insights that may not be immediately apparent.

III. MODEL BUILDING

3.1 Build various models

Prepared the following model procedures to analyze and review the dataset and get the performance available on the dataset which can gathers more information about the dataset. We are looking to predict the customer churn based on different parameters that are provided. This model will classify each account into 0 & 1.0 means they do not churn and 1 means they will churn.

We have tried different classification model and following is the list of model building procedure used in this project:

(1) Decision Tree
(2) Random Forest
(3) K Nearest Neighbors
(4) Naive Bayes
(5) Bagging
(6) Ada Boosting
(7) Gradient Boosting

3.2 Data Split

Dataset is spitted into train and test with 70:30 ratio.

3.3Model validation

Test your predictive model against the test set using various appropriate performance metrics For every model building, we have gone through the following steps get outputs generated by the algorithms:

(a) Model Performance
(b) ROC-AUC Graph

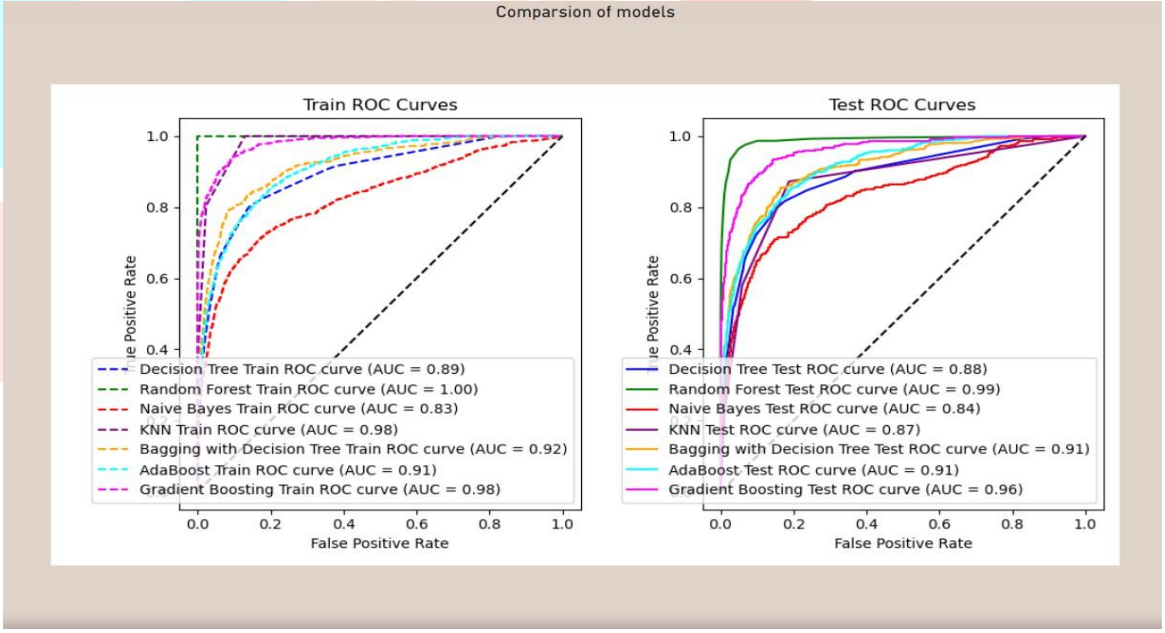

Figure: Comparison of models

3.4 Comparison of Models with SMOTE

After applying smote to imbalanced count { 0 : 6556 , 1 : 6556}

- Found duplicated data of 306 records but as when compared to over all data count duplicate count very less which insignificant.
- Given Dimension of rows and columns are 11260 and 19 Features after removing Account id.
- Column dataset is remained with 18 features i..e(11260,18)

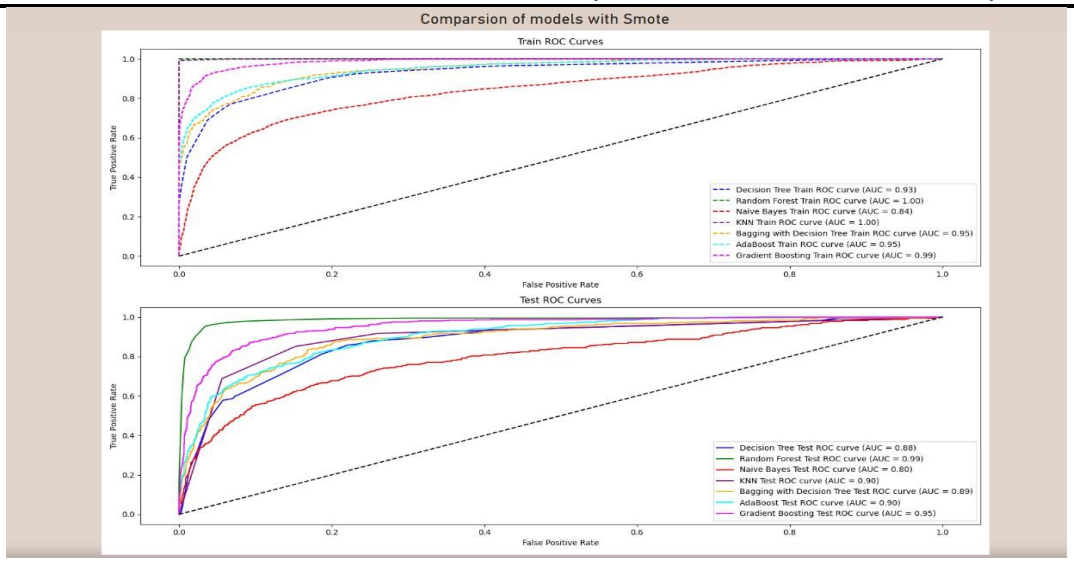

Figure: Comparison of models with SMOTE

3.4.1 INSIGHTS

- By above model comparison of train and test best optimum model is gradient boosting with Smote.
- By comparing all accuracy, Recall, precision and F1 **gradient boosting with Smote model performed well.**
- By comparing cross validation of model with negative mean squared error show Gradient Boosting smote is best optimum model because of low mean squared error.

IV. POWER BI RESULTS

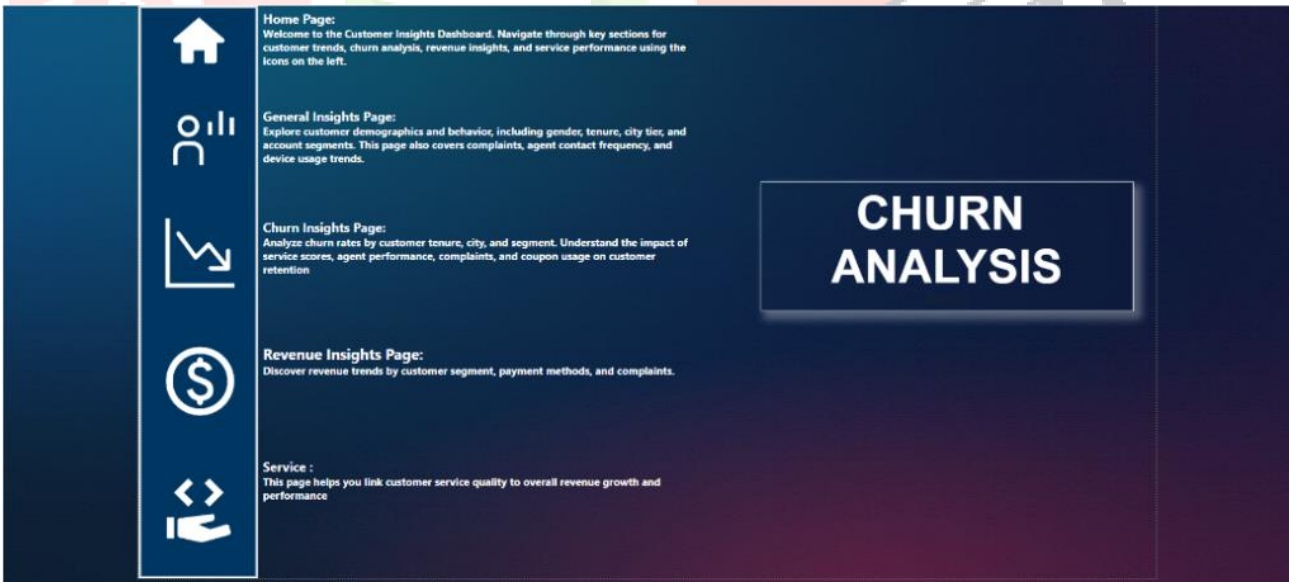

Figure: Home Page

Figure: General Insights

Figure: Revenue Insights

Figure: Service

4.1 Insights

- Navigate through the General, Churn, Revenue and Service insights
- Login details of customer from two different kinds computer and mobile
- Gender based customers male 6.81k and female 4.45k
- Account segment : Regular plus, super, HNI, Super plus and Regular
- Payment methods: Debit card, Credit card, E wallet, Cash on Delivery and UPI
- Created measure for churn rate calculation and assessed churn by account segment, city tier
- Revenue based on Account segment month wise and Year wise details capture according churn status

V. CONCLUSION

Compared to other payment methods, a large percentage of people utilize debit cards, primarily due to their convenience and the sense of financial control they provide. The churn rate for e-wallet and cash on delivery users is significant, indicating that while these methods may attract users initially, they struggle to retain them over time. This trend highlights the importance of understanding consumer preferences and behaviors in the evolving landscape of payment solutions.

Similarly, when we look at the digital realm, the disparity in user retention becomes apparent: compared to users of other login devices, mobile users have a higher rate of user attrition, often driven by issues such as app performance, user experience, and the availability of features that cater to their needs.

Moreover, the churn rate for Regular Plus and Super Plus users stands in stark contrast to that of High Net Worth Individuals (HNI), with the former groups exhibiting a significant turnover. This suggests that the value proposition offered to these tiers may not meet their expectations or that they are seeking alternatives that better align with their lifestyles and preferences.

In addition, the churn rate for customers who have not utilized coupons for payment is notably high, paralleling the growing trend of coupon users benefiting from discounts that enhance their shopping experience. This dual observation points to the necessity for businesses to incentivize coupon usage while also addressing the needs of those who prefer traditional payment methods.

When a customer's service score falls below 3, it indicates that they are dissatisfied, a clear warning sign for businesses to take corrective action. A customer's contact service score of less than three indicates poor customer service, which can dramatically impact their likelihood to remain loyal to a brand.

Interestingly, consumers who have not contacted customer service at the last level tend to report higher satisfaction levels and are less likely to leave, suggesting that proactive customer service may sometimes backfire if not executed effectively.

The most crucial aspect in this equation is tenure; research consistently shows that there is a lower likelihood of client attrition the longer a customer stays with us. This correlation underscores the importance of nurturing long-term relationships with customers through consistent engagement and value delivery.

Additionally, when comparing different tiers of customers, it becomes clear that Tier 3 consumers are churning more frequently than other tier customers, indicating a potential gap in satisfaction or benefits that could be addressed to enhance retention strategies.

Finally, another crucial component for keeping customers engaged and satisfied is cash back; the more cash back received, the lower the likelihood of turnover, as consumers are often drawn to the tangible rewards that enhance their overall purchasing experience. By strategically implementing cash back offers and ensuring a seamless experience across various payment methods, businesses can foster loyalty and reduce churn rates effectively.

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