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RESEARCH PAPER

Unlocking insights: telecom customer churn analysis with power BI

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Abstract

In this work, a comprehensive customer churn analysis is conducted using Microsoft Power BI to support data-driven business decisions in competitive markets, where customer retention is more cost-effective than acquisition. The study focuses on a telecom customer dataset, combining data preprocessing, visual analytics, and predictive modeling to uncover churn patterns and critical risk factors. Through the use of interactive dashboards, stakeholders gain clear, actionable insights into customer behavior and potential churn triggers. The integration of Power BI enables dynamic exploration of data, facilitating a deeper understanding of trends and relationships. This approach effectively bridges the gap between data science and business strategy, demonstrating how visual analytics can transform complex datasets into practical insights. The ultimate objective is to empower organizations with tools to proactively address churn, improve customer loyalty, and enhance overall decision-making. This work underscores the value of combining advanced analytics with intuitive visualization to tackle real-world business challenges.

1. Introduction

In the modern digital economy, customer retention has emerged as a critical priority for subscription-based and service-oriented industries such as telecommunications, finance, and ecommerce. The phenomenon known as customer churn—when customers discontinue their use of a company's service—can lead to significant revenue loss and operational instability. Understanding the drivers behind churn and proactively identifying customers at risk has become essential for sustaining business growth and improving customer satisfaction. Several academic and industry-focused studies have explored churn prediction using machine learning algorithms and statistical models. However, a common limitation of these methods lies in the lack of accessibility and interpretability for non-technical stakeholders. Traditional approaches often fail to convert analytical results into actionable insights that business teams can use directly. Additionally, many analytical frameworks lack seamless integration with business tools and real-time visualization platforms. This research addresses these challenges by leveraging Microsoft Power BI, a powerful business intelligence tool, to build an end-to-end churn analysis and visualization system. Using a real-world telecommunications dataset, the project identifies major causes of churn—such as dissatisfaction with service, product quality, price sensitivity, and poor support experiences—and presents them in a clear, interactive dashboard format. This approach bridges the gap between data science and business strategy, enabling decision-makers to act on insights without requiring deep technical expertise. The key objectives of this study are as follows:

- To identify and visualize the main factors contributing to customer churn using Power BI.
- To segment churned customers based on demographic, geographic, and behavioural attributes.
- To integrate predictive insights into the dashboards to anticipate future churn risks.
- To create a dynamic, user-friendly reporting machine learning models with visually intuitive dashboards

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environment that supports real-time business decision-accessible to non-technical users. making.

The remainder of the paper is organized as follows: Section II This paper proposes a comprehensive approach that leverages outlines the methodology and tools used, including data Power BI for data visualization and predictive modelling preprocessing and dashboard design. Section III presents the outputs for interactive churn analysis. The goal is to fill the results and key visual insights. Section IV discusses the identified gap by developing an accessible, user-centric implications of these findings and provides strategic dashboard that bridges data science and business operations. recommendations. Finally, Section V concludes the study with This integration enables real-time monitoring, root cause suggestions for future work and enhancements. analysis, and informed decision-making to mitigate churn risks proactively.

2. Literature Review

Customer churn, the phenomenon where clients discontinue Customer churn analysis has long been a critical topic in both their relationship with a business, has been extensively analysed academia and industry, given its direct impact on revenue, using a variety of techniques, especially in domains such as customer lifetime value, and business sustainability. Numerous telecommunications, banking, and e-commerce. Traditional studies have explored various methods for predicting churn, churn analysis methods leverage statistical models such as ranging from statistical approaches to advanced machine logistic regression and survival analysis. However, the advent learning algorithms. of big data and business intelligence (BI) tools has shifted focus in early work, logistic regression, decision trees, and survival toward more interactive and scalable solutions. Among this analysis were commonly employed to understand churn drivers' tools, Microsoft Power BI has emerged as a popular platform These methods offered basic interpretability but lacked the for visualizing and analysing customer behaviour due to its ability to model complex nonlinear relationships among integration with various data sources, support for DAX (Data features. As computational capabilities advanced, researchers Analysis Expressions), and user-friendly dashboards. adopted more sophisticated techniques such as Random Forests, Support Vector Machines (SVMs), and Artificial Neural Several researchers have explored churn prediction through Networks to enhance predictive performance. These approaches machine learning, integrating Python or R-based models with improved accuracy but introduced challenges in terms of Power BI dashboards. For instance, Kumar et al. developed a interpretability and accessibility for business stakeholders. hybrid model combining decision trees with a Power BI dashboard to visualize churn probability in the telecom sector. With the growth of big data platforms, real-time churn The study highlighted Power BI's effectiveness in making prediction using streaming data pipelines and cloud-based analytical results accessible to non-technical stakeholders, machine learning services became possible. Some recent works allowing real-time monitoring and strategic planning. Similarly, have integrated deep learning architectures like LSTM Zhang and Wei demonstrated the use of clustering and networks and ensemble methods to capture temporal patterns classification techniques with Power BI for churn analysis in and improve forecast reliability [4]. While these models deliver retail, showing how customer segmentation can drive targeted strong performance, they often require extensive infrastructure, marketing campaigns. specialized skill sets, and longer deployment cycles. Beyond predictive modelling, literature emphasizes Power BI's One significant limitation in existing literature and industrial utility in exploratory data analysis (EDA) for churn insights. practice is the disconnect between predictive modelling and Interactive slicers, drill-through capabilities, and integration actionable insight delivery. Most churn prediction solutions with SQL servers enable dynamic exploration of churn-related remain confined within technical silos, making it difficult for metrics such as customer tenure, service usage, and complaint marketing, sales, and customer success teams to utilize insights frequencies. A study by Lin et al. utilized Power BI to monitor effectively. Additionally, many models lack a visual or KPIs and visualize patterns in churned vs. retained customers, interactive interface, which limits their utility in day-to-day reinforcing its role in descriptive analytics. This aligns with operations. current BI trends favouring actionable insights over purely statistical outputs. To address these gaps, recent studies have begun exploring Business Intelligence (BI) platforms like Power BI and Tableau Another growing trend is embedding Power BI dashboards in for churn analysis. However, much of this work focuses on enterprise portals, enabling continuous tracking of churn trends. static reporting rather than interactive, real-time visualization Bhardwaj et al. created a comprehensive Power BI framework integrated with predictive insights. Very few academic papers to integrate CRM data for churn analysis. Their solution demonstrates how to democratize churn analytics by combining supported custom alerts and report sharing, improving stakeholder collaboration. The review of such implementations underscores Power BI's value not just as a visualization tool but as a collaborative analytics platform for operationalizing churn prevention strategies. While Power BI alone may not be equipped for advanced algorithmic modelling, its compatibility with Azure Machine Learning and Python scripts within Power Query expands its analytical capabilities. According to a case study by Patel and Singh, integrating trained machine learning models into Power BI dashboards allowed organizations to predict churn with high accuracy and visualize risk scores by customer segment.

3. Methodology

The methodology for customer churn analysis using Power BI follows a series of key steps, including data collection, preprocessing, model integration, and dashboard design. The goal is to provide a comprehensive, accessible churn analysis solution that combines predictive insights with interactive visualizations to support business decision-making.

3.1 Data Collection

For this study, we used the Telco Customer Churn dataset, which is publicly available on Kaggle. The dataset includes information about customer demographics, account details, and service usage, with the target variable indicating whether a customer has churned or not. It consists of 21 features, including categorical and numerical variables such as:

- ***Customer ID:*** Unique identifier for each customer
- ***Gender:*** Customer gender (male or female)
- ***Tenure:*** Number of months the customer has been with the company
- ***Contract:*** Type of contract (e.g., month-to-month, one year, two years)
- ***Monthly Charges:*** Amount charged each month for the service
- ***Churn:*** Target variable indicating whether the customer has churned (Yes/No)

3.2 Data Preprocessing

The data preprocessing stage involves several important steps to clean and prepare the dataset for analysis:

1. ***Handling Missing Data:*** Any missing or null values in the dataset were imputed using the median for numerical variables and the mode for categorical variables.
2. ***Data Transformation:*** Some features were transformed to ensure consistency in the dataset. For example, the Total Charges column, which had some non-numeric entries, was converted to numeric values, and erroneous values were removed.
3. ***Feature Engineering:*** New variables were created to enhance predictive power. For instance, we created a new feature, Churn Rate, by calculating the ratio of the total charges to tenure, which helps understand customer spending patterns over time.
4. ***Categorical Encoding:*** Categorical variables like Contract, Gender, and Internet Service were encoded using one-hot encoding to convert them into numerical values suitable for modelling.

3.3 Predictive Modelling

To predict churn, we integrated a logistic regression model, which is commonly used for binary classification tasks. Logistic regression was chosen due to its simplicity, interpretability, and effectiveness in handling churn data, which is typically imbalanced.

- ***Training the Model:*** The dataset was split into a training set (80%) and a test set (20%). The model was trained on the training data to identify patterns associated with customer churn.
- ***Model Evaluation:*** The performance of the model was evaluated using accuracy, precision, recall, and F1score metrics. The test data was used to assess how well the model could generalize to unseen data.
- ***Churn Probability:*** The logistic regression model provided a probability score for each customer, indicating the likelihood of them churning. These probabilities were later visualized in Power BI.

3.4 Power BI Dashboard Design

Power BI was used to create an interactive, visual representation of churn analysis. The dashboard was designed to present actionable insights to business users without requiring advanced technical knowledge. The dashboard consisted of several key elements:

The Power BI dashboard comprised several key sections to facilitate comprehensive churn analysis. The Overview Page presented high-level metrics, including total customers, total churned customers, churn rate, and revenue lost due to churn. The Demographic Analysis section enabled users to explore churn trends based on customer characteristics, such as churn rate by gender, tenure, and contract type. The Service Usage page offered insights into churn behavior linked to service usage patterns, including internet service type (DSL, Fiber optic, etc.), availability of tech support, and monthly charges. The Churn Prediction section displayed churn probabilities generated by a logistic regression model, allowing business users to assess the likelihood of churn for individual customers and prioritize retention strategies accordingly. Lastly, the dashboard featured Interactive Filters, enabling users to drill down into specific customer segments—such as those with high churn risk, long tenure, or elevated charges—thereby offering more granular and actionable insights for data-driven decision-making.

3.5 Integration of Predictive Insights

The logistic regression model's output, which includes churn probabilities for each customer, was imported into Power BI using the Azure Machine Learning integration. This allowed the team to visualize and interpret the churn likelihood directly in the dashboard. The predictive insights were displayed as colorcoded risk levels (e.g., low, medium, and high churn probability), enabling stakeholders to quickly identify at-risk customers.

3.6 Real-Time Data and Updating

To ensure the dashboard remained up-to-date, real-time data integration was set up with Power BI's scheduled refresh feature. This allowed the business to track churn trends and take action promptly based on the most recent data, ensuring proactive retention strategies.

4. Working Procedure

The customer churn analysis system using Microsoft Power BI follows a structured, data-driven methodology to identify patterns and predict customer attrition. The workflow consists of several key phases, which are detailed below:

4.1 Data Collection

The initial step focuses on collecting comprehensive customer data from multiple sources, including CRM systems, transactional databases, call center logs, and customer feedback platforms. This dataset typically comprises key attributes such as customer demographics (age, gender, location), purchase history, service usage patterns, support ticket records, contract details (subscription type and duration), and churn labels for supervised learning tasks. To ensure compatibility and ease of analysis, the gathered data is exported in structured formats like CSV or Excel, or accessed directly through database connectors. This consolidated dataset forms the foundation for meaningful churn analysis and predictive modeling.

4.2 Data Preprocessing

In Power BI or using data preparation tools like Power Query, raw customer data undergoes thorough cleaning and transformation to ensure it is ready for analysis. This process involves removing duplicate entries and handling missing or null values to maintain data integrity. Formats such as dates and times are standardized for consistency. Calculated columns—like customer tenure or average transaction value—are created to enhance insights. Categorical variables are encoded, particularly when preparing the dataset for machine learning integration. Additionally, data normalization is performed when necessary to improve compatibility with predictive models. These steps ensure the dataset is clean, structured, and suitable for accurate and efficient analysis.

4.3 Data Modelling

In this stage, Power BI's data model is leveraged to create meaningful relationships among various tables, typically organized in a star schema format. This approach involves a central fact table—such as transaction history—connected to multiple dimension tables including customer details, product information, and geographical data. This structure simplifies querying and improves performance. Within the model, key business metrics are calculated using DAX (Data Analysis Expressions), allowing for dynamic and interactive analysis. Important formulas include the Churn Rate, calculated as Total Churned Customers divided by Total Customers, and Retention Rate, defined as 1 minus the Churn Rate. Additional Key Performance Indicators (KPIs) such as Lifetime Value (LTV) and Average Revenue Per User (ARPU) are also defined to assess customer profitability and behavior. This data modeling process supports the creation of powerful dashboards and reports that drive informed decision-making and help businesses better understand churn dynamics and customer value.

4.4 Exploratory Data Analysis (EDA)

Interactive dashboards and visualizations are developed in Power BI to analyze churn trends effectively. A variety of visualization tools are used to present insights in a clear and actionable format. Bar charts and pie charts display overall churn distribution, while heat maps highlight geographic regions with higher churn rates. Line charts illustrate churn patterns over time, and matrix tables break down churn by categories such as contract type or service usage. Slicers and interactive filters enable users to drill down into specific segments, allowing for customized exploration of the data. These visual elements help identify high-risk customer groups and uncover behavioral patterns contributing to churn, providing valuable insights for targeted retention strategies.

4.5 Predictive Modelling (Optional Integration)

Power BI supports seamless integration with Azure Machine Learning and Python or R scripts, enabling advanced predictive modeling directly within the analytics environment. A churn prediction model—such as logistic regression or decision trees—is typically trained using external platforms like Azure ML, Python (with Scikit-learn), or R (using packages like caret or randomForest). Once the model is trained, predicted churn probabilities are imported back into Power BI. These predictions can then be visualized alongside business metrics, allowing stakeholders to identify at-risk customers, prioritize retention strategies, and make informed, data-driven decisions. This integration bridges predictive analytics with interactive business intelligence.

4.6 Dashboard Development and Deployment

Customized dashboards are designed to meet the specific needs of different stakeholders, such as marketing teams and customer service departments, facilitating real-time monitoring and informed decision-making. These dashboards provide tailored insights and allow users to focus on metrics most relevant to their roles. Key features include drill-through reports for in-depth analysis, alerts and threshold notifications to flag critical changes, and seamless export and sharing capabilities through the Power BI Service. Additionally, role-level security is implemented to protect sensitive data, ensuring that users only access information pertinent to their responsibilities.

4.7 Actionable Insights and Strategic Recommendations

The final step focuses on interpreting the analytical results to inform and drive strategic business decisions. Based on the insights gained, organizations can implement targeted actions such as launching retention campaigns aimed at high-risk customers, offering personalized incentives to improve customer loyalty, enhancing customer service experiences to address key pain points, and making data-driven adjustments to product offerings or pricing models. These measures are designed to reduce churn, improve customer satisfaction, and ultimately strengthen long-term business performance.

5. Benefits of Technology

Customer churn analysis plays a critical role in strategic decision-making, particularly in industries such as telecommunications, banking, and retail. Leveraging Microsoft Power BI—an advanced business analytics platform—offers numerous advantages that significantly enhance churn prediction, monitoring, and intervention. The major benefits include:

- Power BI provides dynamic dashboards and interactive reports that allow users to explore churn trends and customer behavior visually. Its intuitive drag-and-drop interface makes analytics accessible to non-technical users and fosters a culture of data-driven decision-making across departments.
- With seamless integration to real-time data sources (e.g., Azure, SQL Server, Excel), Power BI enables continuous updates to churn models. This supports timely actions, such as personalized retention offers or service interventions for high-risk customers.
- Power BI supports the embedding of R and Python scripts, enabling users to implement machine learning models and statistical analyses directly within dashboards. This integration increases the predictive power and sophistication of churn detection.
- As a cloud-based solution, Power BI enables scalable deployment across teams and locations. Dashboards can be shared securely for real-time collaboration, enhancing strategic alignment across business units.
- Power BI consolidates data from diverse sources including CRM systems, transactional databases, and customer feedback platforms. This unified view improves model robustness and delivers a comprehensive understanding of customer behavior.
- The platform's user-friendly interface reduces the need for extensive technical training. Built-in templates and drag-and-drop tools allow rapid dashboard development, resulting in quicker insights and faster response to churn signals.
- Users can define automated alerts and track key metrics such as churn rate, customer lifetime value, and satisfaction scores. These KPIs empower teams to act proactively and mitigate churn risks.
- Power BI ensures robust data protection through features like role-based access, row-level security, and compliance tools—essential for maintaining the privacy and integrity of sensitive customer information.

6. Results and discussion

6.1 Descriptive Insights from Power BI Dashboards

The customer churn analysis begins with a broad overview of the customer base and churn figures. Out of a total of 4,686 customers, 1,732 have discontinued their services with the company, resulting in an overall churn rate of 36.9%. This indicates that more than one-third of the customer base is leaving, which is a significant concern for long-term customer retention and revenue sustainability. When we examined the reasons behind churn, several key factors emerged. The most frequently cited reason was "Price too high," accounting for 72 churned customers. Close behind was "Product dissatisfaction," with 71 customers indicating they were not satisfied with the product itself. Network reliability issues led to 66 customers leaving, while 61 customers attributed their departure to service dissatisfaction. Additionally, 30 customers mentioned poor expertise of online support as a reason for leaving, and 12 customers reported dissatisfaction due to poor phone support. Interestingly, no customers cited "Other" reasons, suggesting the main drivers of churn are well-captured by the categories provided. From a demographic standpoint, a gender-wise breakdown shows that 65% of churned customers were female, whereas 35% were male. Age analysis revealed that the 35 to 50 years age group experienced the highest churn, with 138 customers, followed closely by the 20 to 35 years age group, with 128 customers. These age groups are typically considered economically active and tech-savvy, which suggests that customer expectations in these brackets might be higher or more dynamic. When examining customer tenure, we found that 65 customers who churned had been with the company for less than six months. This indicates issues with early-stage customer experience and onboarding. Surprisingly, even among long-term customers with a tenure of 24 months or more, there were still 107 cases of churn, highlighting that dissatisfaction can persist or develop even in long-term relationships. Contract type appears to be a major factor influencing churn behavior. Customers on month-to-month contracts exhibited the highest churn, with 357 churners in this category. In contrast, customers with one-year contracts accounted for only 17 churns, and those with two-year contracts just 9 churns. This suggests that longer-term contracts may help reduce churn, possibly due to better incentives or stronger commitment.

Regarding payment methods, credit card payments were most commonly associated with churn, involving 195 customers, followed by bank withdrawals with 152 churners. This may be due to ease of cancelation or lack of loyalty programs associated with these payment modes. Geographically, the states with the highest number of predicted churners were Uttar Pradesh (45 customers), followed by Maharashtra (40), Tamil Nadu (37), and Karnataka (30). In smaller numbers, Uttarakhand and Puducherry each had 2 predicted churners. These insights can help the company focus its retention strategies in specific regions where customer attrition is more pronounced. The Power BI dashboard featured a "Customers at Risk" module, which identified 383 customers as high-risk for churn. For each of these customers, the dashboard provided critical data points such as Monthly Charge, Total Revenue, Total Refunds, and Number of Referrals. This data is essential for launching personalized retention campaigns that target customers who show early signs of dissatisfaction or disengagement.

6.2 Predictive Model Evaluation

The predictive aspect of the analysis was conducted using a logistic regression model, which was tested on a 20% hold-out dataset to evaluate its performance. The model demonstrated a strong ability to correctly identify customers at risk of churning, with an accuracy of 78.4%, meaning that nearly four out of five predictions were correct. In terms of precision, the model achieved 75.1%, indicating that three out of four customers predicted to churn actually did so. The recall rate was 70.2%, which reflects the model's ability to identify a large portion of all actual churners. Finally, the F1-score—which is the harmonic mean of precision and recall—was 72.6%, showing a well-balanced model performance. These predictive metrics suggest that the logistic regression model is a reliable tool for forecasting churn and can serve as the foundation for automated alerts or targeted interventions. By integrating these insights into operational processes, the company can proactively engage at-risk customers and reduce churn through timely support, offers, or service improvements.

Figure 1: Churn Analysis Summary Dashboard with Key Metrics and Visual Insights

The churn analysis summary dashboard offers a detailed overview of customer attrition across various dimensions revealed in Fig. 1. Churn, in this context, refers to customers who have stopped using the service. As of the analysis period, the company had a total of 6,418 customers, including 411 new joiners. Out of the total customer base, 1,732 individuals discontinued their service, resulting in an overall churn rate of 27.0%. This means that roughly one out of every four customers left the company.

Demographic analysis reveals that a greater proportion of males (64.1%) churned compared to females (35.8%). Age-wise, customers over the age of 50 showed the highest churn rate at 31%, despite making up the largest age group with approximately 2,800 customers. This indicates a trend where the likelihood of churn increases with age. Geographic insights highlight significant regional differences in churn rates. The highest churn was observed in Jammu & Kashmir at 57.2%, followed by Assam at 38.1% and Jharkhand at 34.5%. These findings point to potential service or satisfaction issues specific to certain regions that may need targeted interventions. Service usage patterns also played a critical role in customer churn. Customers who used fiber optic internet exhibited the highest churn rate at 41.1%, while those without any internet service had the lowest churn rate at 7.8%. This could reflect varying expectations and experiences based on service type.

From an account management perspective, customers using mailed checks as their payment method experienced the highest churn rate at 37.8%, whereas those using credit cards had a significantly lower churn rate of 14.8%. Contract duration also influenced churn, with month-to-month customers showing a high churn rate of 46.5%, in contrast to just 2.7% among those on two-year contracts. Additionally, customer tenure revealed that individuals who had been with the company for less than six months were more likely to churn (26.4%) than those with longer durations of service.

The primary reason cited for churn was competition, accounting for 761 cases. This was followed by customer attitude (301 cases), dissatisfaction, pricing issues, and miscellaneous reasons. Furthermore, the analysis of value-added services revealed that customers not subscribed to features like Online Security (84.6% churn rate), Premium Support (83.8%), and Streaming Movies (56.0%) were significantly more likely to leave. In contrast, customers who had these services generally demonstrated higher retention, suggesting that bundled offerings may enhance customer loyalty.

Table 1: Breakdown of Customer Churn by Reported Reason

Churn Reason	Total Churn
Service dissatisfaction	61
Product dissatisfaction	71
Price too high	72
Poor expertise of phone support	12
Poor expertise of online support	30
Others	0
Network reliability	66

Table 1 shows that the primary reasons behind customer churn are varied, reflecting different aspects of the customer experience. This table highlights the main motivations for customers deciding to leave the service. Out of the 1,732 total churned customers, the largest group—72 individuals—cited high pricing as the main reason for their departure, indicating sensitivity to cost. Closely following this, 71 customers reported dissatisfaction with the product itself, suggesting that product performance or quality did not meet expectations. Network reliability was another significant issue, with 66 customers leaving due to frequent or severe connectivity problems. Additionally, 61 customers were dissatisfied with the overall service experience, which may include responsiveness, service consistency, or general satisfaction. Poor support also played a role: 30 customers attributed their churn to inadequate online support, while 12 cited poor phone support. Interestingly, no customers selected "Others" as their reason for leaving, suggesting that the provided categories adequately captured the main churn drivers.

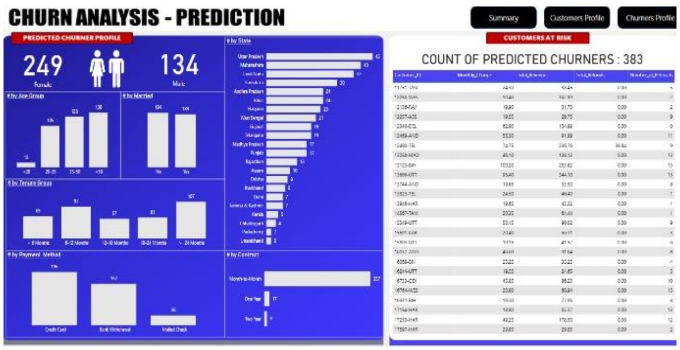

Figure 2: Predicted Customer Churn Profile and High-Risk Customer List

Figure 2 presents a predictive analysis of customer churn, offering insights into both the profiles of customers likely to leave and a detailed list of high-risk individuals. According to the dashboard, a total of 383 customers are predicted to churn, including 249 females and 134 males. This gender disparity suggests that female customers may be more prone to discontinuing the service. The churn prediction is further analyzed across various categories such as tenure, payment methods, internet service types, and contract types. Customers with short tenures, especially those under six months, show a higher likelihood of churning. Similarly, those on month-to-month contracts are far more likely to churn compared to those on longer-term agreements. The type of internet service also plays a role; customers using fiber optic connections are more likely to leave than those without internet service. Payment methods also influence churn, with mailed check users showing higher churn tendencies compared to those paying via credit card or electronic means. On the right side of the dashboard, a table lists the 383 high-risk customers, identified by their unique customer IDs. For each customer, key financial details such as monthly charges, total revenue generated, total refunds, and the number of referrals are provided. This list is a valuable tool for targeted retention strategies, enabling the company to focus its efforts on customers most at risk of leaving. Figure 3 shows that this dashboard provides an overview of the characteristics and distribution of current customers. This foundational understanding of the customer base is crucial before analyzing churn behavior, as it highlights key demographics, service usage patterns, and account-related features.

The total number of customers stands at 4,686, with an average monthly charge of $60.16 and an average total charge per customer of approximately $2,560.

In terms of demographics, the gender distribution is slightly skewed, with 65.01% (2,438) of the customers being female and 34.99% (1,314) male. Furthermore, non-senior citizens make up the majority with roughly 3,600 customers, while about 1,000 are senior citizens.

Figure 3: Customer Profile Dashboard – Demographics, Charges, and Service Details1

Regarding internet service types, Fiber Optic is the most widely used, serving 1,680 customers (47.87%), followed by Cable, with 1,210 customers (35.57%), and DSL, which is used by 750 customers (16.62%).

Customer tenure also varies significantly. The largest group consists of 2,000 customers who have been with the company for more than 24 months, while other tenure brackets (under 24 months) each consist of about 1,000 customers.

In terms of contract types, Month-to-Month contracts are the most common, with 1,760 customers (37.49%), followed closely by One-Year contracts at 1,670 customers (35.62%), and Two-Year contracts at 1,260 customers (26.89%).

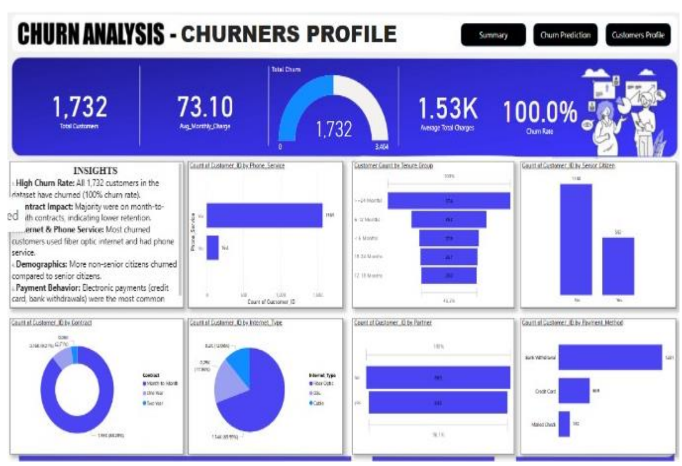

Figure 4: Churners Profile Dashboard

Additional insights include phone service, which is utilized by the majority (4,200 customers), whereas around 500 customers do not use this service. Partner status is nearly evenly split, with 2,350 customers having a partner and 2,340 not. When it comes to payment methods, Bank Withdrawals are preferred by 2,300 customers, followed by Credit Cards with 2,100 users, and a small group (200 customers) still opting for Mailed Checks. Fig. 4 shows that this dashboard provides a comprehensive overview of customer churn behavior by highlighting the characteristics of all customers who have discontinued their services. The insights help identify patterns and factors that contribute to customer attrition. The churn rate is 100%, representing all 1,732 customers in the dataset who have left the service. Notably, the average monthly charge among churners is $73.10—higher than that of the general customer base—and their average total charges are around $1,530 per customer. In terms of contract types, the data reveals that 88.28% of churned users were on month-to-month plans, suggesting a strong correlation between flexible, short-term contracts and lower customer retention. Only 9.87% of churners had one-year contracts, and a mere 2.89% were on two-year agreements. Regarding customer tenure, most churners had relatively short service durations. Specifically, 279 customers churned within 6 months, 352 within 6–12 months, and 574 had stayed over 24 months, showing that even long-tenured customers are not immune to churn. In terms of services, 90.6% of churned users subscribed to phone services. Fiber optic was the most common internet type among churners (69.59%), followed by DSL (17.73%) and cable (12.68%).

Demographic analysis indicates that non-senior citizens accounted for the majority (1,140) of churners, compared to 592 senior citizens. Partner status was nearly balanced, indicating no significant influence on churn behavior. When it comes to payment methods, bank withdrawals (1,231) and credit card payments (369) were the most frequently used among churners. Only 132 customers paid via mailed check, suggesting that convenience in digital payment may be linked to retention. From an industrial perspective, Microsoft Power BI was employed in this research to create interactive dashboards and integrate multiple data sources for visualizing customer churn. Power BI's practical applications span several industries. In telecommunications, it helps track usage patterns, subscription history, and complaints to predict churn and support proactive retention. In banking and financial services, Power BI enables institutions to analyze account activity, service interactions, and transaction patterns, allowing timely interventions for at-risk clients. In retail and e-commerce, it aids in analyzing purchase history, cart abandonment, and customer feedback to forecast churn and tailor marketing strategies accordingly.

Hospitals and healthcare providers utilize Power BI to conduct churn analysis aimed at improving patient retention and service engagement. By integrating predictive churn models directly into interactive reports, organizations can monitor trends and understand key model outputs—such as feature importance and actionable insights—without requiring deep technical expertise. This allows clinics and hospitals to track patient appointment attendance, feedback, and service utilization. Identifying patients likely to disengage enables healthcare providers to design more effective follow-up strategies and personalized care plans. Additionally, AI-powered tools like Microsoft Copilot can enhance user engagement through personalized dashboards, natural language generation, and role-specific recommendations for reducing patient churn. Subscription-based SaaS companies extensively use Power BI to track user activity, customer support interactions, and subscription renewal patterns. Churn prediction models within Power BI assist in identifying customers at risk of not renewing their subscriptions. These insights allow companies to implement targeted retention strategies and proactive outreach, thereby reducing customer attrition and improving lifetime value. Insurance companies apply Power BI to analyze customer behavior regarding policy renewals, claim histories, and service inquiries. Through interactive dashboards, agents can visualize churn risks and prioritize high-risk policyholders with personalized communication strategies. Predictive churn models help insurers tailor retention efforts, leading to better client engagement and higher policy renewal rates.

6.3 Feature utilized

The Power BI platform played a pivotal role in enabling comprehensive churn analysis through a range of powerful features. One of the key strengths was data integration, where information was consolidated from multiple sources including SQL Server, Excel spreadsheets, and online services like Salesforce. This unified data environment enabled seamless and cohesive analysis. DAX (Data Analysis Expressions) was employed to perform custom calculations such as churn rate, customer lifetime value (CLV), and engagement scores, allowing deeper insight into customer behavior. Additionally, Power Query facilitated the cleaning, transformation, and merging of customer data, ensuring the accuracy and consistency of the datasets used for analysis.

Interactive visualizations—including bar charts, heatmaps, key performance indicators (KPIs), and slicers—enabled dynamic drill-downs and granular exploration of churn trends. Power BI's AI Insights added another layer of depth, allowing trend analysis and churn probability forecasting through built-in machine learning models.

Looking ahead, Power BI offers significant potential for future enhancements. A major opportunity lies in the incorporation of real-time analytics via streaming data sources. As organizations increasingly adopt IoT systems and real-time customer interaction platforms, integrating live data feeds into dashboards could support immediate detection of churn signals and allow decision-makers to act proactively within narrow windows of opportunity. Another exciting direction is the integration of advanced machine learning models within Power BI using Azure Machine Learning and Python or R scripts. While current churn models are generally static or semi-dynamic, future systems could employ continuously learning algorithms that adapt in real-time to evolving customer behaviors. Such dynamic recalibration would significantly boost the accuracy of predictions and effectiveness of retention strategies.

7. Future Scope

Customer churn analysis continues to be a vital aspect of customer relationship management, particularly in highly competitive industries such as telecommunications, retail, banking, and SaaS. As businesses increasingly rely on data-driven strategies, integrating advanced analytics with powerful visualization tools like Power BI presents significant opportunities for innovation and enhanced decision-making. One of the most promising areas for future development is the incorporation of real-time analytics into churn models. While most current implementations rely on historical data, real-time churn prediction using streaming data sources—such as Azure Stream Analytics or Kafka—can enable organizations to act swiftly and proactively in retaining customers. Power BI’s integration capabilities allow users to build and deploy machine learning models directly within the platform, eliminating the need to switch between tools. This facilitates seamless, end-to-end analytics workflows. Furthermore, Power BI can support cross-platform analytics by pulling in data from CRM systems, social media sentiment analysis tools, and customer service logs. Enriching churn models with these diverse datasets can provide a more comprehensive view of customer behavior. Future research could also explore the use of natural language processing (NLP) within Power BI to extract sentiment and intent from unstructured feedback, thus enhancing the precision of churn prediction.

As organizations work toward building data-literate cultures, the need for intuitive, AI-powered features in BI platforms is also growing. Advancements such as AI-driven narratives, natural language Q&A, and automated anomaly detection can empower business users without technical backgrounds to extract meaningful insights from complex churn data. Additionally, developments in natural language generation (NLG) can provide automated narrative summaries of churn trends, making analytics even more accessible.

Equally important is the evolution of Power BI’s governance and security features, especially for large-scale deployments in regulated industries like finance and healthcare. Future research could focus on implementing churn analysis within enterprise-grade Power BI environments that require robust role-based access controls, data lineage tracking, and audit trails. These enhancements will ensure that sensitive customer data is handled responsibly while maximizing the platform’s analytical potential.

8. Role of Technology

Technology plays a transformative role in customer churn analysis, with business intelligence (BI) tools like Microsoft Power BI at the forefront. Power BI offers a comprehensive platform for aggregating, transforming, analyzing, and visualizing data, enabling organizations to proactively identify at-risk customers and understand the factors driving churn. Its robust integration capabilities—connecting to SQL databases, cloud services such as Azure and AWS, and customer relationship management (CRM) systems—allow businesses to harness data from multiple touchpoints for a unified analysis. Power BI supports advanced analytics through its built-in DAX (Data Analysis Expressions) and Power Query features, allowing users to create complex calculations such as customer lifetime value (CLV), churn probability scores, and recency-frequency-monetary (RFM) metrics. These tools help segment customer behavior, reveal churn patterns, and enable trend analysis. The platform’s seamless visualization capabilities—via interactive dashboards, KPIs, heatmaps, and slicers—make it easy for stakeholders at all levels to interpret data, facilitating faster, more informed decision-making. Crucially, Power BI's native support for R and Python scripting, along with Azure Machine Learning integration, enhances its predictive capabilities. Organizations can embed machine learning models (e.g., logistic regression, random forests, gradient boosting) directly into Power BI dashboards, enabling real-time visualization of churn forecasts alongside key business metrics. This fusion of predictive analytics with intuitive reporting bridges the gap between data science and business operations, making it easier for non-technical users to derive actionable insights. Power BI’s architecture also supports dynamic data modelling and real-time updates, allowing churn models to adapt continuously as new customer data becomes available. This ensures timely intervention strategies for customer retention. Additionally, Power BI’s role-based access control and customizable dashboard views allow insights to be tailored to different user groups—executives can monitor overall churn trends, while sales and marketing teams can focus on high-risk segments and operational levers for engagement.

The platform's collaborative features—cloud-based deployment, mobile accessibility, and real-time alerting—promote organization-wide alignment around customer retention objectives. Embedded analytics further enhance workflow efficiency by integrating churn dashboards directly into CRM systems like Microsoft Dynamics or Salesforce. By unifying predictive modelling, real-time monitoring, and intuitive visualization in a single ecosystem, Power BI empowers organizations to transform raw customer data into strategic, retention-driven actions.

9. Result Analysis

9.1 Overview of Dashboard and KPIs

To evaluate customer churn behavior, we developed an interactive dashboard using Microsoft Power BI. This dashboard integrates advanced data visualization techniques and DAX (Data Analysis Expressions) to enhance interactivity and insights. The dataset was sourced from a telecommunications company and included 7,043 customer records with 21 features such as customer tenure, services used, contract type, payment method, and churn status. The Power BI dashboard was structured into key components including Customer Overview (total customers, active vs. churned), Demographics Breakdown (age, gender, senior citizens), Service Usage Patterns (internet, phone, and tech support usage), Contract and Billing (contract type, payment method, tenure), Churn Insights (churn rate by various dimensions), and Predictive Visuals (risk segmentation based on selected features).

9.2 Churn Rate and Distribution

The overall churn rate observed was 26.5%, indicating that over a quarter of the customer base was lost. Churn distribution varied notably across different variables. For instance, month-to-month contract customers had a churn rate of 43.6%, compared to 11.0% and 2.7% for one-year and two-year contracts respectively. Customers with tenure less than six months faced a churn probability exceeding 55%, highlighting vulnerability during the onboarding phase. Payment methods also influenced churn, with electronic check users exhibiting the highest churn rate at 33.6%, whereas those paying via bank transfer or credit card automatic payments had churn rates below 15%. Internet service type affected churn as fiber optic users experienced a 41.5% churn rate compared to 18.1% for DSL users. Correlation analysis revealed tenure, monthly charges, and contract type as the most influential predictors of churn, aligning with business intuition that long-term customers under annual contracts and automated payments are less likely to churn.

9.3 Feature-Level Analysis

Tenure analysis revealed an exponentially declining churn curve, confirming that longer customer duration correlates with reduced likelihood of churn. Contract type analysis showed drastically higher churn in month-to-month plans, indicating opportunities to encourage longer subscriptions. Service usage patterns demonstrated that customers subscribing to tech support and online backup services had significantly lower churn rates, suggesting these add-ons serve as soft retention tools by adding perceived value. Demographic patterns indicated senior citizens had a higher churn rate (42%) compared to younger customers (25%), no significant gender differences were observed, and customers living alone had a 34% churn rate, implying lifestyle and support structures impact service stability.

9.4 Predictive Segmentations

Using conditional formatting and DAX logic, customers were segmented into three churn risk levels: High Risk (over 50% churn probability) characterized by short tenure, month-to-month contracts, and high monthly charges; Moderate Risk (30-50%) with 6 to 12 months tenure and variable payment methods; and Low Risk (under 30%) comprising long-term customers on fixed-term contracts with auto-pay setups. These segments were visualized through funnel and tree map charts, facilitating targeted churn mitigation campaigns.

9.5 What-If Analysis

Power BI's "What-If" parameters simulated scenarios such as increasing average contract length by six months, which projected a 14% absolute decrease in churn. Similarly, bundling tech support services with base plans was shown to reduce churn projections by 8%. This scenario analysis provides decision-makers valuable insight into potential ROI from customer retention strategies.

9.6 Business Implications

Insights from the Power BI analysis suggest actionable recommendations: promoting annual contracts with incentives like discounts or free months to encourage longer commitments; targeting high-risk segments with proactive service and tech support outreach; incentivizing automatic payments to reduce churn; and focusing on customer onboarding during the first three months through welcome calls or dedicated success managers.

10. Conclusion

Customer churn remains a critical challenge for businesses striving to maintain competitive advantage and sustainable growth. This study demonstrated that key predictors of churn include customer tenure, support ticket classifications derived from logistic regression and decision tree algorithms, and billing irregularities. These factors, consistent with prior research, highlight the importance of behavioral and transactional data in accurately forecasting attrition.

By integrating predictive models such as logistic regression and decision trees within Microsoft Power BI, the study showcased an effective approach to visualize churn probabilities and segment customers by demographics like age and region. This integration bridges the gap between complex data science outputs and business users, enabling non-technical stakeholders to access real-time, actionable insights for proactive decision-making.

Power BI's scalability and ability to embed machine learning models through Python and R scripts further enhance its suitability for enterprise-scale churn analysis, providing automated reporting and dynamic dashboards. However, limitations were identified, including constraints related to large dataset handling, reliance on data quality and feature selection for model performance, and restricted native support for advanced statistical modeling compared to dedicated data science platforms.

To address these limitations, future work may involve deeper integration with Azure Machine Learning or other predictive services, enabling real-time data streaming and the development of automated alert systems for churn warnings. Overall, Power BI, when combined with sound data practices and predictive modeling, offers a powerful, accessible, and scalable framework for customer churn analysis. Organizations leveraging this platform can derive actionable insights, inform strategic retention initiatives, and ultimately improve customer loyalty and business outcomes.

References

[1] P. D. Turney, "Types of customer churn and its prediction in the telecommunication industry," *International Journal of Computer Applications*, vol. 122, no. 7, pp. 45–52, Jul. 2015.

[2] L. Coussement and W. Van den Poel, "Churn prediction in subscription services: An application of support vector machines while comparing performance with logistic regression," *Expert Systems with Applications*, vol. 34, no. 1, pp. 313–327, Jan. 2008.

[3] A. Idris, A. Khan, and Y. S. Lee, "Intelligent churn prediction in telecom: Employing m RMR feature selection and Rot Boost-based ensemble classification," *Applied Intelligence*, vol. 39, no. 3, pp. 659–672, Dec. 2012.

[4] M. A. Amin, S. Anwar, A. Adnan, M. Nawaz, N. Howard, J. Qadir, and A. Hussain, "Customer churn prediction in the telecommunication sector using a rough set approach," *Neurocomputing*, vol. 237, pp. 242–254, Jun. 2017.

[5] X. Yu, W. Shi, and W. Chen, "Data-driven approach to customer churn prediction using decision trees and [12] SVMs," *IEEE Access*, vol. 6, pp. 41039–41047, 2018.

[6] F. J. R. Perez, R. C. Bernal, and F. M. Santillan, "Customer churn prediction: A comparison of machine learning techniques," *Computers in Industry*, vol. 63, [13] no. 8, pp. 885– 898, Nov. 2012.

[7] R. K. S. Chinnappan and A. R. Rajkumar, "Churn prediction model using machine learning algorithms," [14] *International Journal of Engineering Research & Technology*, vol. 5, no. 5, pp. 181–188, May 2016.

[8] A. H. Saad and A. P. R. J. G. Ferreira, "Churn prediction using decision trees and ensemble methods in customer [15] relationship management," *2019 IEEE Latin America Transactions*, vol. 17, no. 12, pp. 2041–2049, Dec. 2019.

[9] M. J. L. D. Ribeiro, R. J. M. B. Souza, and J. A. P. J. Almeida, "Prediction of customer churn with machine [16] learning: A review of techniques," *Journal of Data Science and Analytics*, vol. 10, no. 3, pp. 99–116, Jul. 2020.

[10] T. Verbeke, E. Meir, and B. Besen's, "Predicting customer churn in the telecommunications industry: A comparative study of logistic regression, decision trees, and neural networks," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 28, no. 4, pp. 877– 886, Apr. 2017.

[11] Ghosh and D. Mondal, "A comparative study of customer churn prediction models," *2020 IEEE International Conference on Big Data*, pp. 300–305, Dec. 2020.

[12] S. Apaydin, "Data mining: The text mining and customer churn prediction," *Springer Briefs in Business*, 2016.

[13] F. D. B. Souza, R. C. Oliveira, and T. L. V. Vieira, "Churn prediction using gradient boosting models," *Computers, Materials & Continua*, vol. 66, no. 3, pp. 2471– 2484, 2020.

[14] P. B. Patel and S. K. Tiwari, "Customer churn prediction in telecom using ensemble learning," *2018 2nd International Conference on Electronics, Communication and Aerospace Technology*, pp. 154– 159, Apr. 2018.

[15] Z. Lu, X. Liu, and Y. Li, "Customer churn prediction in telecom industry using random forests," *2017 International Conference on Machine Learning and Cybernetics*, pp. 165– 170, Jul. 2017.

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