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Visual Analysis of Customer Behavior and Churn Triggers in the Telecommunications Industry: An Implementation of a BI Dashboard

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Abstract

The telecommunications industry faces the challenge of high customer churn rates, which can negatively affect company revenue and long-term business sustainability. This study aims to develop a Business Intelligence (BI)-based dashboard to visualize customer behavior and identify factors contributing to customer churn. A dataset consisting of 7,043 customer records was analyzed to discover churn patterns, develop predictive models, and perform customer segmentation. The proposed dashboard was designed as a user-friendly and interactive web-based platform to support data-driven decision-making. The results showed that 26.5% of customers experienced churn. The main factors influencing churn included monthly contracts, fiber optic service usage, the absence of online security and technical support services, and electronic payment methods. The findings also revealed that customers with higher monthly charges had a greater tendency to discontinue their subscriptions. User evaluation results indicated that the developed dashboard achieved a high level of usability and effectively presented customer information in a clear and understandable format. Therefore, the proposed BI dashboard can assist telecommunications companies in identifying at-risk customers and developing more proactive, targeted, and effective customer retention strategies.

Keywords: *business intelligence; customer analytics; customer churn; data visualization; dashboard*

Introduction

The telecommunications industry has seen a lot of change over the twenty years. It has gotten really big with billions of users around the world and it makes a lot of money. New technology like 5G networks has driven these changes. The 5G networks have given the telecommunications industry chances to make money and they have also made the telecommunications industry more competitive. The telecommunications industry is very competitive now because of the 5G networks. However, the telecommunications industry is also facing some problems. One of the problems the telecommunications industry is facing is that a lot of customers are leaving the telecommunications industry. The customer churn rates are really high, for the telecommunications industry (Saha et al., 2024). Churn refers to the situation where customers cancel their subscriptions or switch to another service provider within a certain period of time. This phenomenon poses a serious threat to telecommunications companies, given that the sustainability of their revenue depends heavily on their ability to retain existing customers (Saha et al., 2024).

Decision-makers and business analysts point out that the cost of acquiring new customers is significantly higher than the cost of retaining existing customers (Al-Sultan & Al-Baltah, 2024). Several studies show that the cost of acquiring new customers can be five to six times higher than the cost of retention (Ullah et al., 2019; Wu et al., 2021a). As a result, current industry strategies are beginning to shift from aggressive acquisition approaches toward more effective and sustainable customer churn management (Seo & Yoo, 2023).

Telecommunications companies generate massive amounts of data from their extensive customer base, including demographic information (Amiri & Hosseini, 2024), service profiles, including usage history (Ullah et al., 2019). When managed effectively, this data can reveal hidden behavioral patterns that are useful for understanding the factors that lead customers to cancel their subscriptions. However, processing large and complex datasets presents a unique challenge for Customer Relationship Management (CRM) analysts (Amin et al., 2016).

The modern CRM concept is divided into two main types of analysis: operational CRM and analytical CRM (Ahn et al., 2020). CRM analysis uses customer data to design marketing strategies. The use of technology for data analysis within a company helps in understanding customer needs (De & Prabu, 2023). Data on customers who have canceled their subscriptions must be managed to improve existing systems. Rather than merely reacting after a problem occurs, the management of customer cancellation data must be proactive (Freire et al., 2024; E. Lee et al., 2020).

With early detection, companies have the opportunity to implement the right retention strategies (Han et al., 2024), such as offering special deals or loyalty programs, to retain customers (Alizadeh et al., 2023).To bridge the gap between complex analytical results and practical decision-making needs, the implementation of a Business Intelligence (BI) system is crucial (Vazquez-Ingelmo et al., 2019). The BI system enables standardization in the data analysis process while integrating various data sources into a single, unified platform. This supports a more efficient flow of information, from the data processing stage through to the delivery of analysis results to management (De & Prabu, 2022). In addition, data visualization through interactive dashboards is an effective way to present Key Performance Indicators (KPIs) in a concise and easy-to-understand manner (Ahn et al., 2020). The BI dashboard also makes it easy for non-technical users, such as managers and marketing professionals, to explore complex data through various visual elements such as charts, heat maps, and flowcharts (Lee-Cultura et al., 2024).

An effective dashboard doesn’t just present data; it also builds a narrative that helps users understand the meaning behind the data in the context of decision-making (Ganesan et al., 2024). Integration of behavioral analysis (N. T. Lee et al., 2024) Dynamic systems with interactive visualizations can result in more responsive decision support systems. Therefore, this study aims to develop a customer analytics framework integrated into a web-based BI dashboard. By using the customer churn dashboard, we can develop customer retention strategies and market trends (Alizadeh et al., 2023).

Previous research has not been able to present a dashboard of behaviors and triggering factors explaining why customers cancel their subscriptions, nor information regarding customers at risk of churning. This would help companies develop strategies to retain customers and increase revenue. The dashboard developed must be capable of displaying the factors influencing customer churn rates as well as the profiles of at-risk customers, thereby helping companies plan strategies to retain their customers.

Methods

This study utilizes data and findings from previous research to develop a customer analytics framework integrated into a Business Intelligence (BI) dashboard, as illustrated in Figure 1. The dashboard was designed to analyze telecommunications customer data, including customer profiles, subscribed services, and usage behavior, to provide meaningful insights for understanding customer patterns and supporting data-driven decision-making.

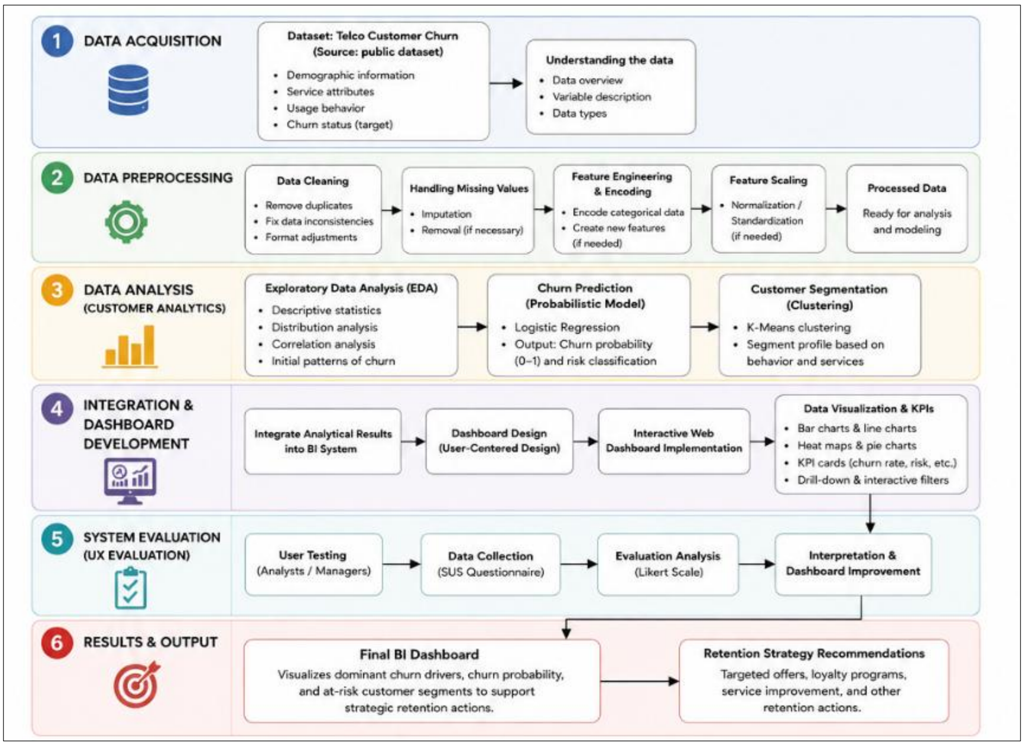

Figure 1. Research Methodology Flowchart

The public dataset used in this study consists of 7,043 customer records with 21 attributes, including 20 independent variables and one dependent variable (BlastChar, 2023). The variables contained in the Telco Customer Churn dataset are presented in Table 1.

Table 1. Variable of Telco Customer Churn

Independent variables		
No	Variable Name	Description
1	customer ID	Unique identity for each customer.
2	gender	Customer gender (Male or Female).
3	Senior Citizen	Indicates whether the customer is a senior citizen (1: Yes, 0: No).
4	Partner	Status whether the customer has a partner.
5	Dependents	Status whether the customer has dependents.
6	tenure	The number of months the customer has subscribed with the company.
7	Phone Service	Status whether the customer is using telephone services.
8	Multiple Lines	Status whether the customer has multiple telephone lines.
9	Internet Service	Customer's internet service provider (DSL, Fiber optic, No).
10	Online Security	Status of use of additional online security services.
11	Online Backup	Additional online backup service usage status.
12	Device Protection	Device protection service usage status.
13	TechSupport	Status of use of additional technical support services.
14	Streaming TV	Status whether the customer is using the TV streaming service.
15	Streaming Movies	Status whether the customer is using the movie streaming service.
16	Contract	Customer contract duration (Month to month, One year, Two years).

17	Paperless Billing	Status of whether the customer is using paperless billing.
18	Payment Method	Payment method used by the customer.
19	Monthly Charges	Fees billed to customers each month.
20	Total Charges	Total costs paid by the customer during the subscription.
Dependent variable		
1	Churn	Status whether the customer has unsubscribed (Yes or No).

A. Data Preprocessing Results

The primary goal of data cleaning is to remove noise and ensure that the data is useful for predictive models, as unclean data can lead to poor results. Handling Missing Values: Datasets often contain empty or "null" values, which must be addressed using two main methods. Feature scaling is performed to ensure that numerical variables have a consistent range of values, thereby speeding up the model training process and preventing variables with large scales from dominating other variables during subsequent processing stages.

B. Data Analysis

The data analysis phase is conducted systematically using a customer analytics framework, beginning with Exploratory Data Analysis (EDA) to understand descriptive statistics and data distributions, as well as to identify initial patterns and relationships among variables related to customers' decisions to cancel their subscriptions. Next, a churn prediction model was developed using the Logistic Regression algorithm, an efficient probabilistic classification approach for calculating the probability of churn (scores ranging from 0 to 1) for each customer based on the contribution of each independent variable (Wu et al., 2021a). The next step is customer segmentation using the K-Means clustering technique to group customers into clusters with similar characteristics and behaviors, in order to help identify high-risk segments (Wu et al., 2021b).

C. Integration & Dashboard Development

The results of the Data Analysis phase—which include churn probabilities from the Logistic Regression model and segment labels (Low, Medium, Risky) from K-Means clustering—were fed into the BI system, as obtained from previous research (Wu et al., 2021a). This integration ensures that the backend dashboard displays not only historical data but also future predictions and statistically processed behavioral profiles. The primary focus of the design is to simplify complex information so that it can be understood at a glance. Visual elements such as KPI Cards are strategically placed to highlight key metrics like Churn Rate and Average Monthly Charges (Froese & Tory, 2016).

Results and Discussion

A. Segmentation of High-Risk Customers

Customer Segmentation: The research results (Wu et al., 2021b), using the K-Means algorithm, were divided into three segments: Low, Medium, and Risky. Based on the results of EDA and probabilistic modeling, several critical factors contributing to a high risk of customer churn were successfully identified (Ahmad et al., 2024). The low segment consists of customers with a Two-Year Contract Subscribers. The medium segment consists of customers with a one-year subscription contracts, while the risky segment consists of customers with a monthly subscription contracts. These segments will be discussed further in the results of the Implementation of BI Dashboards and Visualizations.

B. Implementation of BI Dashboards and Visualizations

The developed dashboard integrates EDA, churn prediction, and customer segmentation results to provide interactive visualizations based on user-centered design principles. Figure 2 illustrates the dashboard interface, which presents key churn factors, customer behavior patterns, and segment profiles to support the identification of potential churn customers.

Figure 2. Dashboard BI

The executive summary dashboard presents several key performance indicators (KPIs), including the total number of customers, churned customers, retained customers, and average monthly charges. Based on the analysis of 7,043 customer records, 1,869 customers (26.5%) were identified as churned customers, while 5,174 customers remained active. The average monthly charge was $64.76, providing insights into customer spending behavior and potential revenue loss associated with customer churn. The churn driver analysis revealed that contract type significantly influenced customer retention. Customers with monthly subscription contracts showed the highest churn tendency, particularly during the early subscription period of less than ten months. In contrast, customers with one-year contracts demonstrated moderate retention levels, representing a transitional stage toward stronger customer loyalty. Meanwhile, two-year contract subscribers showed the highest level of loyalty, indicating that long-term commitments effectively reduced the likelihood of customer churn. The analysis also indicated a relationship between monthly spending and churn behavior, where customers with higher average monthly charges, approximately $74.64, were more likely to discontinue their subscriptions.

Customer demographic analysis was conducted to identify customer groups with higher churn risks based on characteristics such as age, marital status, and number of dependents. Through demographic-based visualization, companies can better understand vulnerable customer segments and develop more personalized retention strategies instead of applying a uniform approach to all customers.

Service and infrastructure segmentation further highlighted important patterns related to customer churn. The analysis showed that customers using fiber optic internet services experienced higher churn rates compared to DSL users. This finding indicates the need for companies to evaluate service reliability, network stability, and pricing strategies within the fiber optic segment. In addition, the analysis of phone service usage provided insights into how different service configurations may influence customer retention and loyalty.

The analysis of value-added services (VAS) demonstrated that additional support features play an important role in reducing customer churn. Customers without online security services and technical support showed a higher tendency to discontinue their subscriptions. Therefore, integrating these additional services into the main subscription package can be considered as a strategic approach to improve customer satisfaction, strengthen customer trust, and enhance long-term retention.

Overall, the dashboard visualization identified several major churn triggers, including short-term contracts, higher monthly charges, fiber optic service issues, limited access to support services, and electronic check payment methods. These findings demonstrate that the developed Business Intelligence dashboard can provide actionable insights to support more targeted and data-driven customer retention strategies.

C. System Evaluation

Based on the System Evaluation phase, which includes the UX Evaluation, the results of the testing conducted on advanced users using the questionnaire in Table 2—specifically, the System Usability Scale (SUS)—indicate a high level of acceptance. The average SUS score of 82.5 falls into the “very good” category.

Table 2. List Of Questions

No	Questions
1.	I think I’ll use this dashboard often for customer data analysis.
2.	I find this dashboard too complex to understand.
3.	I find this dashboard easy to use for finding the information I need.
4.	I need technical assistance to understand how to use this dashboard.
5.	I feel that the visualization features (graphs, charts, etc.) in this dashboard are well-integrated.
6.	I feel that new users can quickly learn how to use this dashboard.
7.	I feel confident using this dashboard to support decision-making.
8.	I need to learn a lot first before I can use this dashboard effectively.

Overall, the BI dashboard developed in this study successfully identified the key factors contributing to churn as well as the profiles of at-risk customers. These findings make a tangible contribution to the development of more effective and targeted customer retention strategies, which have the potential to increase corporate profits in the telecommunications industry.

Conclusion

Through a visual analysis approach, the BI dashboard successfully presents Key Performance Indicators (KPIs) and customer behavior patterns in a concise, informative, and easy-to-understand manner, even for non-technical users. Visualization features such as charts, heat maps, and other interactive elements have proven effective in helping users explore data and understand the key factors influencing customer churn. Furthermore, this study shows that the success of a dashboard is determined not only by its ability to present data, but also by its ability to construct narratives that are relevant to user needs. By integrating dynamic customer behavior analysis into structured visualizations, the resulting system is capable of serving as a responsive and adaptive decision support system. Future research is expected to identify monthly customer churn rates and determine which programs customers prefer most.

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