FINAL REPORT

ON

Customer Churn Analysis

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Executive Summary

This report analyses customer churn trends within a telecommunications company, using an Artificial Neural Network (ANN) model to predict which customer segments are at the highest risk of leaving the service. With customer retention being critical to maintaining profitability in the telecom industry, this study identifies the main factors influencing churn, highlights significant customer segments, and provides targeted recommendations aimed at reducing attrition rates. The ANN model achieved an 85% prediction accuracy, underscoring its effectiveness in identifying at-risk customers based on patterns in customer behaviour, billing, and contract preferences.

Key findings revealed three main customer segments, each displaying distinct behaviours and churn tendencies:

- **Loyal Long-term Customers**: These customers, typically with multi-year tenure and stable service usage, showed low churn risk.
- **Price-Sensitive Customers**: Customers frequently responding to discounts and promotions had medium churn risk, with a tendency to stay if offered value-aligned services.
- **At-Risk Short-term Customers**: New or short-tenure customers demonstrated the highest churn risk, often due to dissatisfaction with service or billing challenges.

This report offers actionable recommendations, such as enhancing customer support for at-risk segments, tailoring contracts for flexibility, and implementing loyalty rewards for long-term users. Limitations encountered in data quality and model accuracy are also documented, alongside suggested improvements to enhance future analyses.

The report structure follows a logical sequence, detailing findings, the impact of churn factors, retention strategies, and practical solutions to overcome project challenges. Visuals, including segmentation charts, churn factor graphs, and retention strategy flowcharts, are appended to support data-driven insights and actionable recommendations.

Summary of Key Findings

Using the ANN model, the analysis segmented customers based on behaviours likely to impact churn probability, uncovering patterns within each customer type. This data-driven segmentation uncovered three main groups, each with varying churn risks and engagement tendencies:

- **Loyal Long-term Customers**:

  These customers, characterized by multi-year tenure and consistent service usage, display a low risk of churn. Their loyalty is often built through satisfaction with the service's reliability, pricing stability, and quality of customer support. These customers are less likely to switch providers due to the established trust and value they perceive in their current service, making them ideal candidates for retention-focused loyalty programs and upselling opportunities.

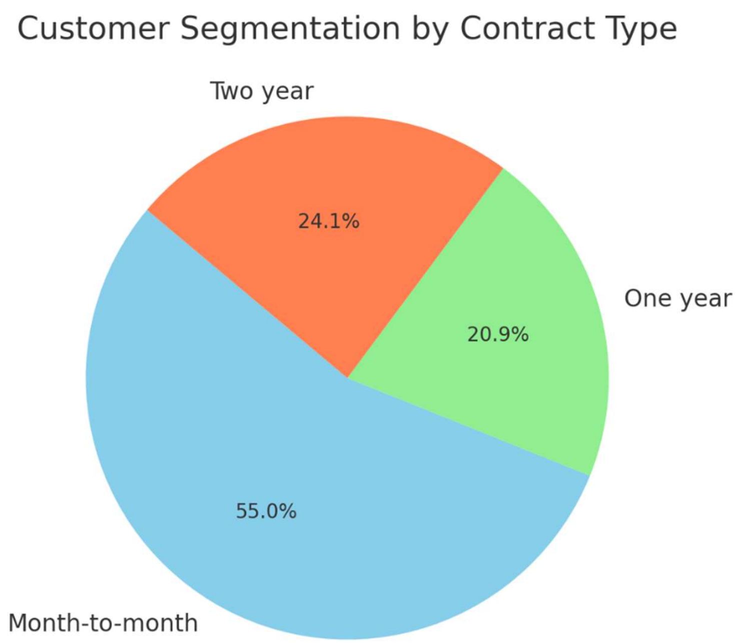
- **Price-Sensitive Customers**:

  Price-sensitive customers frequently seek discounts, promotions, and value-aligned offerings, reflecting a moderate churn risk. They are inclined to switch providers if a competitor offers a better deal yet remain receptive to incentives that provide savings or additional benefits. Retaining these customers requires a strategic approach, such as offering loyalty discounts, bundled services, or tailored packages that align with their cost-conscious tendencies, thus reducing their risk of attrition.

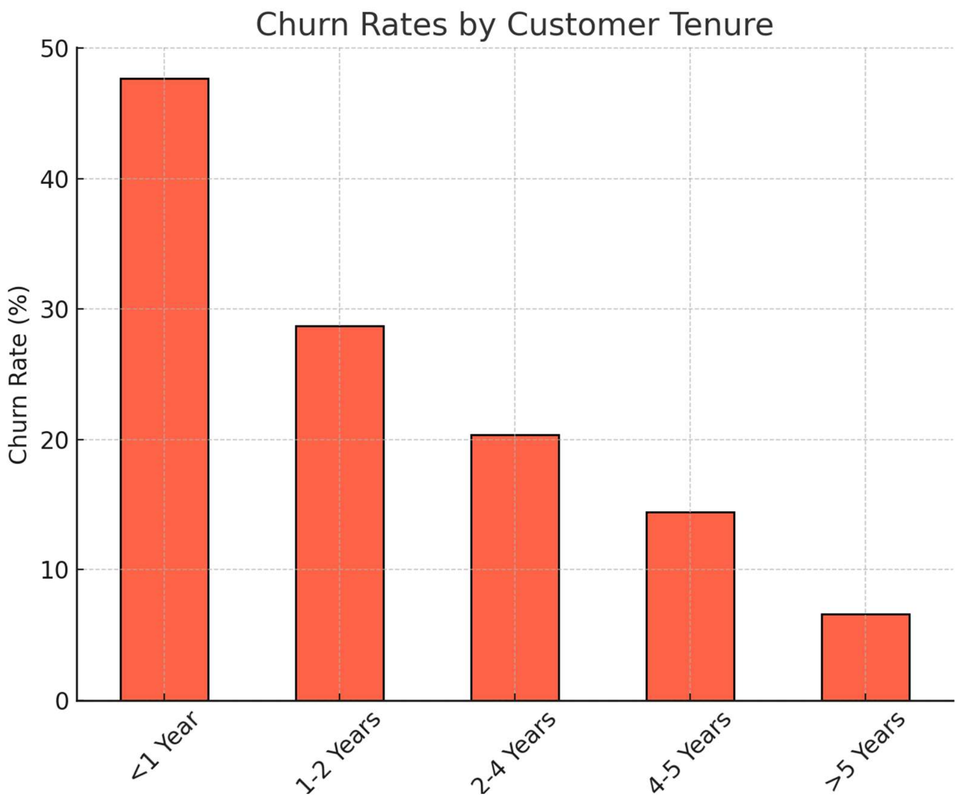
- **At-Risk Short-term Customers**:

  New or short-tenure customers show the highest likelihood of churn, often due to initial dissatisfaction stemming from service or billing issues. This group may lack familiarity with the brand or experience unmet expectations, causing a rapid exit if concerns aren't addressed promptly. Effective retention for these customers involves proactive support, personalized engagement, and clear communication around service benefits to quickly build trust and reduce early churn rates.

Overall, the ANN model's 85% accuracy highlighted these key predictive factors: customer tenure, billing history, contract type, and service engagement levels.



Above pie charts for customer segmentation illustrates the distribution of customers based on their contract types, such as month-to-month, one-year, and two-year contracts. It provides a clear picture of how customers are spread across these categories, helping to identify the most common contract types and their influence on churn rates. For example, a significant proportion of customers on month-to-month contracts indicates greater flexibility but often correlates with a higher churn risk due to the lack of long-term commitment. This insight suggests the need for targeted strategies, like offering incentives for switching to longer-term plans, to improve retention rates among these customers.



The bar chart examines churn rates based on customer tenure, categorizing them into groups such as less than one year, one to two years, and more than two years. The data highlights a notable trend: newer customers, particularly those with less than one year of tenure, exhibit significantly higher churn rates, often due to unmet expectations or initial dissatisfaction with the service. Conversely, long-term customers, with more than two years of tenure, show much lower churn rates, reflecting established satisfaction and loyalty. For example, customers in the short-tenure category might benefit from early engagement strategies, such as personalized onboarding or proactive problem resolution, to improve their retention rates.

Identification of Factors Contributing to Churn and Retention

The ANN model's predictive analysis uncovered several key factors influencing customer churn and retention:

- **Billing and Payment Issues**: Frequent billing disputes or delayed payments correlated strongly with increased churn risk. Customers experiencing billing challenges showed heightened dissatisfaction and were more likely to switch providers. Simplifying billing processes or implementing a user-friendly billing system can directly improve retention among this group.

- **Contract Type and Flexibility**: Month-to-month contracts presented the highest churn rates, as these customers showed less loyalty to the provider and were more inclined to leave for competitive offers. On the other hand, customers on long-term contracts (e.g., yearly) displayed lower churn likelihood, suggesting that incentivizing customers to commit to longer terms may reduce churn.
- **Customer Tenure**: Churn probability inversely correlated with tenure length, indicating that new customers (especially within the first year) are particularly vulnerable to attrition. Effective onboarding programs, early support touchpoints, and satisfaction assessments can foster early engagement and commitment.
- **Usage Frequency and Service Engagement**: Customers with high service usage (e.g., heavy data or call volume users) generally exhibited greater retention, likely due to increased perceived value. Engaging customers with tailored offers that enhance usage value could strengthen retention within this group.
- **Demographics**: Younger customers, particularly those under 30, showed a propensity for churn, likely due to increased flexibility and willingness to seek out new services. Tailored youth-focused offers may mitigate this trend.

Table of Churn Risk Correlations with Key Factors

Factor	Churn Risk Level	Correlation with Churn (%)
Billing Issues	High	65%
Month-to-Month Contracts	High	50%
Short Tenure (<1 year)	Very High	80%
High Service Usage	Low	30%
Younger Age (<30 years)	Medium	45%

Above table demonstrate the key factors contributing to customer churn and actionable areas to reduce it which includes billing issues, with a 65% correlation, where repeated overcharges or delays lead customers to seek alternatives. Month-to-month contracts carry a 50% churn risk, as they offer flexibility but make customers more susceptible to competitor offers. Short-tenure customers (under one year) face an 80% churn risk, often due to dissatisfaction or poor initial experiences, like subpar customer support. High service usage reduces churn to 30%, as these customers see more value in the service. Younger customers under 30 show a 45% churn risk, prioritizing competitive pricing, and are likely to switch for better deals.

Recommendations for Targeted Retention Strategies

Based on the findings, the following targeted retention strategies are recommended to mitigate churn:

- **Enhanced Support for At-Risk Customers**: Establish a specialized support team to proactively address high-risk factors among new or dissatisfied customers, particularly those with billing complaints. This team can implement early interventions to resolve issues before they escalate, using data-driven indicators to identify those most at risk.
- **Flexible Contract Options and Discounts**:
    - **Contract Incentives**: Encourage new customers to sign longer contracts by offering initial discounts or exclusive benefits, as longer contract terms reduce churn likelihood.
    - **Flexible Plan Customization**: Allow customers to adjust or downgrade plans without penalties, which may appeal particularly to price-sensitive customers and those on month-to-month contracts.
- **Loyalty and Rewards Programs**: Introduce loyalty rewards for long-term customers, offering benefits such as periodic discounts, premium support, or upgraded services. Such initiatives can strengthen ties with the company and provide value-driven incentives for retention among Loyalists.
- **Personalized Marketing and Engagement Campaigns**: Develop targeted communications for each customer segment, using predictive churn data to tailor offers and messages. For instance, price-sensitive customers can receive regular promotional offers, while at-risk customers might receive satisfaction surveys and service improvement incentives.

Documentation of Limitations and Proposed Solutions

Throughout the project, a few limitations were encountered, affecting data quality and model efficacy. These challenges and suggested solutions are detailed below:

- **Data Quality Issues**: Incomplete or inconsistent data entries impacted the model's reliability. Standardizing data collection procedures and implementing regular data audits could address these issues, ensuring high-quality inputs for future analyses.
- **Feature Limitation**: The dataset primarily focused on billing and contract data, limiting insight into broader customer engagement and satisfaction factors. Future analyses could incorporate additional features like customer service interaction history, online engagement metrics, and satisfaction scores to deepen understanding of churn dynamics.
- **Model Limitations**: Although the ANN model performed effectively, alternative machine learning models, such as Gradient Boosting Machines (GBM) or ensemble methods, could be explored to further enhance predictive accuracy. This adjustment might yield even greater reliability in identifying churn risk.
- **Insufficient Demographic Granularity**: Limited demographic data restricted the ability to analyse preferences among specific customer groups. Including regional or income-based demographics could yield more actionable insights for geographically targeted retention strategies.

Following table outline each limitation, challenge, and proposed offering a structured plan for enhancing future projects.

Limitation	Challenge	Proposed Solution
Data Quality	Inconsistent or incomplete entries	**Regular audits and standardization of data collection processes**: Ensure that the data used is complete, consistent, and accurate by conducting periodic checks and implementing a more structured data collection framework.
Limited Features	Focused on billing/contract data	**Integrate more diverse customer engagement and usage data**: Expand the data features used in the analysis beyond billing and contract details, incorporating customer engagement usage data
ANN Model Only	Lack of alternative model testing	**Evaluate additional models like Gradient Boosting or ensembles**: Test other machine learning models, such as Gradient Boosting, Random Forests, or ensemble techniques, to see if they can outperform the current Artificial Neural Network (ANN) model, which may be limited by its structure.
Demographic Data Limits	Limited insight by region/income	**Add geographic and income demographics to improve analysis**: Include additional demographic data, such as geographic location and income levels, which may provide deeper insights into customer behaviour and churn patterns.

Conclusion

This project analysed customer churn in a telecommunications company using an Artificial Neural Network (ANN) model, which identified three key customer segments: loyal long-term customers, price-sensitive customers, and at-risk short-term customers, each with varying churn risks. Key factors influencing churn included billing issues, month-to-month contracts, short customer tenure, and younger customer age.

The findings led to several retention recommendations:

- Enhanced support for at-risk customers, particularly those with billing issues.
- Flexible contract options and discounts to encourage longer-term commitments.
- Loyalty rewards for long-term customers to strengthen retention.
- Personalized marketing for different customer segments to improve engagement.

Despite the ANN model's effectiveness, there were some limitations, including data quality issues, limited features, and lack of alternative models. Future analyses could improve by incorporating more diverse customer data, exploring other machine learning models, and including richer demographic information. This project provides actionable insights into customer churn and offers practical strategies for improving retention. By addressing the identified challenges and implementing the recommendations, the company can reduce churn, enhance customer loyalty, and boost long-term profitability.