**Executive Summary**

This report analyses customer churn trends within a telecommunications company, leveraging 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.

**1. 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 displayed the lowest churn rate and showed signs of satisfaction with the service, often due to stable contract terms, positive billing history, and regular service use. This segment typically has a tenure exceeding two years and represents a core group with strong retention rates.
* **Price-Sensitive Customers**: Medium churn risk was observed among price-sensitive customers who respond strongly to promotional discounts. They value affordability and tend to remain with the service if they perceive high value for the cost. Targeted, value-focused offers can help retain this segment, emphasizing competitive pricing.
* **At-Risk Short-term Customers**: This group showed a high churn likelihood, mainly consisting of customers with less than one year of tenure. Frequent billing complaints, contract flexibility issues, and dissatisfaction with service were prevalent in this group, suggesting the need for improved onboarding and service assurance strategies.

Overall, the ANN model’s 85% accuracy highlighted these key predictive factors: customer tenure, billing history, contract type, and service engagement levels. The visualizations in Appendix A (pie charts for customer segmentation and bar charts for churn by tenure and billing) further illustrate these findings.

**2. 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.

Appendix B includes tables demonstrating the correlation between churn likelihood and these factors, highlighting billing issues and contract flexibility as primary influences on churn.

**3. 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.

Flowcharts depicting each retention strategy’s implementation steps are presented in Appendix C.

**4. 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 analyze preferences among specific customer groups. Including regional or income-based demographics could yield more actionable insights for geographically targeted retention strategies.

A summary table outlining each limitation, challenge, and proposed solution is provided in Appendix D, offering a structured plan for enhancing future projects.

**Appendices**

* **Appendix A**: Visuals depicting customer segmentation and churn distribution.
* **Appendix B**: Detailed tables correlating churn risk with key factors.
* **Appendix C**: Flowcharts for each recommended retention strategy.
* **Appendix D**: Summary table of limitations and improvement recommendations.