JIEE Journal of Industrial Engineering and Education

Reducing Customer Churn for XL Axiata Prepaid: Factors and Strategies

Afifa Puspitasari[1]* and Nur Aini Masruroh[1]

[1] Department of Mechanical and Industrial Engineering, Universitas Gadjah Mada, Yogyakarta 55281, Indonesia

ABSTRACT

Understanding and mitigating customer churn is pivotal for companies, especially those operating with subscription models like telecommunications firms. This study focuses on XL Axiata Company, delving into the factors driving customer churn. The data used is from a questionnaire and focuses on consumers who have used prepaid cards and are considered churn customers, while customers who continue to use cards are termed non-churn customers. Using machine learning algorithms such as logistic regression, ANN, and XGBoost, the data is applied in the prediction step of customer churn classification. The best machine learning method's coefficient results will be followed by strategy analysis using the QSPM method and risk analysis of the loss distribution using the CVaR method. According to the findings of this study, ANN is the most accurate machine learning method, and network factors are the most important factors in customer churn, followed by level of interest in VAS products, company services, failed calls, customers who have made calls to call service, package prices that are fairly expensive, and ads that are less attractive. The QSPM strategy study indicated an AI/ML approach to examine the bundling promo with VAS products, taking into account the impact on customer churn and implementation costs. The CVaR risk analysis results reveal that the VAS products that can be prioritized in the VAS promo plan are bundling products in the form of primary quotas and online games, which are more profitable than bundling with video streaming or chatting.

ARTICLE INFO

Received 18 September 2023
Accepted 28 February 2024
Available online 26 April 2024

***Correspondence**

Afifa Puspitasari
afifapuspitasari@mail.ugm.ac.id

Keywords:
Customer churn; CvaR; factor analysis; machine learning; QSPM

1. Introduction

Telecommunications companies are subscription-based enterprises that frequently grapple with the issue of customer churn, or the migration of customers to other service providers. Given the affordability of prepaid SIM cards in the Indonesian market, ranging from Rp 10,000 to Rp 20,000, customers have the ease of switching between telecommunication service providers. The churn rate for cellular phones is estimated to be between 20% to 40% annually due to the relatively low cost of SIM cards in the market (Ahn et al., 2006). Telecommunications companies have employed various strategies such as bundling packages, offering diverse plans to meet customer needs, and providing discounts to foster customer loyalty and attract new customers to boost their sales. Hence, it is crucial to comprehend customer behavior and preferences in order to retain customers, minimize customer churn, and stay competitive in an increasingly fierce market (Shukla et al., 2021)

In retaining existing customers, it is well-established that it is more profitable than acquiring new ones (Lu et al., 2014; Verbeke et al., 2012). This phenomenon arises from the incentives and promotional offers extended to new customers, such as initial-month discounts and other cost-intensive inducements. Consequently, it is no surprise that telecommunications service providers have employed various methods to retain their existing customer base. To achieve this, having an accurate customer churn prediction model becomes paramount in identifying customers who are predisposed to churning. Based on observations within the organization, XL Axiata, in its approach to customer churn strategy, particularly when employing advanced machine learning methods, relies solely on intuitive methods and inter-team discussions. Initial discussions are initiated to generate ideas using the Design Thinking method, beginning with the Empathize stage, where the respective division or business user is given the opportunity to voice their concerns regarding perceived issues. This is followed by the Define stage, wherein machine learning strategies for addressing customer churn issues are defined. These strategies are categorized into four primary focuses for the company: resource optimization, business processes, artificial intelligence maturity, and operational and capital expense saving. Subsequently, a decision maker selects the most beneficial strategy for the company from a range of options originating from various divisions, all related to the issue of customer churn. In practice, the decision maker still employs intuitive methods by prioritizing the operational and capital expense-saving strategy, even though this strategy may not necessarily be mathematically advantageous for the company. Therefore, this study employs a quantitative technique for strategy selection and assessing the risks associated with customer churn to achieve superior results compared to the intuitive method currently employed by the company. The assumptions guiding this research are as follows:

- The data used remains constant throughout the study's duration.
- The product under investigation is a bundled offering consisting of a SIM card and digital value-added services (VAS).
- The research relies on questionnaire data, which addresses various factors such as demographic information, customer usage patterns, service quality, devices used by customers, and previously utilized VAS products. This method ensures that other potential factors influencing customer churn are treated as static.

However, it's important to note certain limitations of this study. Specifically, the questionnaire data focuses solely on products offered by one Indonesian telecommunications company, XL Axiata. Therefore, the findings of this research cannot be generalized to other telecommunications companies in Indonesia.

2. Literature Review

Research on predicting customer churn in the telecommunications industry is not a novel endeavor. For instance, Coussement et al. (2017) conducted research in the telecommunications sector, focusing on the comparative analysis of alternative data preparation techniques. However, this study remained confined to the initial stages, primarily involving data preparation, and did not progress to the stage of developing predictive models for addressing customer churn. Sulikowski & Zdziebko (2021) conducted an analysis of factors contributing to customer churn using statistical analysis in a real-world case study in Poland. Nevertheless, this study was limited to the factors identified without further analysis of their formation. On the other hand, Amin et al. (2019) predicted customer churn based on the accuracy level of existing datasets using a distinct method called the distance factor, which involves analyzing factors related to customer churn based on the proximity of factors. Óskarsdóttir et al. (2018) explored a novel method for analyzing customer churn and behavior by extracting time series data from customer call records. This time series data was then classified using the random forest and logistic regression methods. While this approach accommodated multivariate time series, it was conducted on a weekly time frame, which may not capture the rapid changes in customer behavior. Calzada-Infante et al. (2020) evaluated customer behavior with a specific focus on products like SIM Cards with upfront payment or prepaid customers. They also introduced a novel method for extracting the dynamic relevance of each customer using social network analysis techniques and a binary classification method known as similarity forest Cenggoro et al. (2021) extended deep learning methods into a vector embedding model to analyze customer churn, differentiating between loyal and churning customers. The methodologies employed by Calzada-Infante et al. (2020) and Cenggoro et al. (2021) are particularly noteworthy due to their divergence from the approaches adopted by other researchers in analyzing customer behavior prior to or during churn. Al-Mashraie et al. (2020) conducted research employing various machine learning methods, including logistic regression, support vector machines, random forest, and decision trees, to ascertain the primary factors influencing customer churn. They conducted an advanced analysis using the push-pull-mooring (PPM) framework to study the effects of features on customer churn behavior from push, pull, and mooring perspectives. Three scenarios were explored to investigate the influence of pull factors and analyze their relationship with push and mooring factors: (1) 25% of customer churn influenced by the pull effect; (2) 50% of customer churn influenced by the pull effect; and (3) 75% of customer churn influenced by the pull effect. The rationale behind these scenarios is that pull factors are more quantifiable with available data compared to push and mooring factors, thus the study calculated scenarios based on incremental increases in pull factors. Partial least squares (PLS) regression was employed to analyze PPM. Furthermore, behavior analysis of customer churn and non-churners was conducted using Dependence Analysis. The study results indicate that logistic regression yielded the highest prediction accuracy. Additionally, the study found that the pull effect effectively contributes to reducing customer churn, a hypothesis supported by empirical evidence.

The Quantitative Strategic Planning Matrix (QSPM) is a strategic framework management employs to determine the available alternative choices. Quantitative measurement provides a tangible overview of the steps to be taken in accordance with established plans. Consequently, in formulating management strategies, there is confidence in the expected outcomes Suhardi (2011). The QSPM is a tool recommended by strategy management experts, initially developed by Fred R. David (1997). Numerous research studies on strategy management using the QSPM have been conducted and applied across various fields. However, there is a limited body of research that specifically addresses strategy management in the telecommunications industry. One such study is the research conducted by Abdelmonem & Elgeuoshy (2021), which analyzes strategic management audits in the telecommunications industry in Egypt. This research follows the steps outlined by Fred R. David (1997), involving Strengths, Weaknesses, Opportunities, and Threats (SWOT) in External Factor Analysis and Internal Factor Analysis before inputting data into the QSPM. While these studies mention a comprehensive list of factors, they do not provide detailed data for some of these factors. For instance, one of the external factors mentioned is the inflation rate or Gross domestic product (GDP), but the specific values are not disclosed in the research. Providing such detailed data would enhance the precision of the weighting and QSPM analysis.

Research on risk analysis based on quantified loss calculation using Value at Risk (VaR) has been employed in numerous studies. However, further analysis has revealed that the VaR approach is deemed less effective due to its inability to capture extreme losses at the tail end of the distribution. To address this limitation, the Conditional Value at Risk (CVaR) method has been developed and widely applied in various industries, particularly in resilience-related studies. Yet, within the telecommunications industry, specifically in the context of strategic considerations, CVaR application remains relatively underdeveloped. One study that explored telecommunications strategy using the CVaR method was conducted by Pamungkas (2018), which analyzed the risk of stock returns in the telecommunications sub-sector. In addition to the CVaR method, Pamungkas (2018) employs Auto Regressive Moving Average with eXogenous inputs (ARMAX) and various Generalized Autoregressive Conditional Heteroskedasticity (GARCH) variations. This research is discussed in detail and provides valuable insights into the fluctuations in stock prices within the Indonesian telecommunications sector.

This research endeavors to address a gap in the field of customer churn studies, particularly within the telecommunications industry, building upon the insights gleaned from previous research conducted by the aforementioned scholars. Drawing upon the analysis and hypotheses posited by Al-Mashraie et al. (2020) regarding the Push-Pull-Mooring (PPM) effect, which underscores that customer churn is influenced by factors within the Push-Pull-Mooring framework, this study is grounded in the data referenced by the PPM effect. A key development in this research, as compared to previous studies, lies in its approach to the pull factor. While earlier studies often relied on dummy data due to the absence of pull factor data, this research delves into the pull factor analysis by utilizing data from Value Added Service (VAS) products and advertising efforts, which are instrumental in capturing customer attention. In addition to employing logistic regression, known for its superior predictive accuracy when compared to other methods such as support vector machines, random forest, and decision trees, as demonstrated by Mohammed et al., this study also introduces comparisons with other methodologies, namely Artificial Neural Network (ANN) and XGBoost, both of which serve as alternative approaches for constructing customer churn prediction models. The research scope extends beyond traditional SIM card products to encompass bundled offerings that combine SIM cards with digital products, specifically Value-Added Services (VAS). In this study, a novel facet emerges as it provides an in-depth analysis of the contributing factors, culminating in the generation of alternative strategies to address the primary determinants of customer churn. These strategies are rigorously assessed using the Quantitative Strategic Planning Matrix (QSPM) methodology to identify the most suitable strategy. Lastly, the research advances to a subsequent stage by subjecting the selected strategies to a Conditional Value at Risk (CVaR) risk analysis. This analysis involves quantifying potential losses associated with the chosen strategies, ultimately resulting in the identification of the most optimal strategy.

3. Methodology

3.1 Data Collection

The collection of data required for the creation of predictive models was conducted through a questionnaire. The gathered data encompasses factors influencing customer churn. The analyzed factors include:

- Demographics (age, gender, education, income, marital status, and occupation).
- Customer usage patterns (data plans, billing amounts, and purchased packages).
- Service quality (level of transaction failures, the frequency of customer contact with the company's call center, potential reasons behind these calls, and signal conditions in the user's area).
- Customer device usage (number of mobile devices used).
- Usage of Value-Added Service (VAS) packages.

Data acquisition in this research was performed using a questionnaire that focused on profiling customers who are either current (non-churn) or former (churn) users of XL prepaid SIM cards. This study encompasses 21 independent variables, which represent the causative factors of customer churn within the telecommunications industry. These variables are an adaptation and expansion of the findings from prior research conducted by Al-Mashraie et al. (2020), who conducted a similar examination and categorized the constituent variables of customer churn into three-factor groups: Push-Pull-Mooring factors. In this study, the push factors, which encompass negative factors leading to customer dissatisfaction with the XL operator, include call failures, network quality, call center interactions, package pricing, package variety, package purchase failures, and service quality. The pull factors, which represent positive factors attracting customers to new service providers, were previously modeled using dummy data; however, this study employs data related to advertising quality and VAS product usage. The mooring factors, representing inertia factors that keep individuals with the same operator regardless of push and pull effects, include demographic data such as gender, age, marital status, income, tenure, top-up costs, data plans, monthly data quotas, and the number of devices owned.

From the questionnaires, a total of 303 raw data points were obtained, which have yet to undergo further analysis. Applying the 10-times rule method, the minimum data required from the 21 factors in this research is 210 data points. Therefore, the 303 data points acquired are considered sufficient for the study.

3.2 Data Preprocessing

The data obtained from the questionnaire underwent initial analysis, including descriptive statistics and data visualization techniques. Visual tools such as histograms, scatter plots, and pie charts, along with numeric measures such as mean, median, standard deviation, and skewness, were employed to explore the dataset.

3.3 Data Cleaning

The data acquired from the questionnaire revealed the presence of outliers and missing data points, necessitating their identification and appropriate action. This step aimed to ensure that the data used in the study aligns with the research objectives. Outlier analysis was conducted to identify unrealistic values or data points that significantly deviated from the rest of the dataset, particularly within variables such as age and tenure. All outliers were subjected to scrutiny, with those deemed meaningful retained and the insignificant outliers, totaling three in this study, removed from the dataset.

3.4 Data Balancing

Predictive outcomes can potentially exhibit bias towards the majority class when a substantial imbalance exists between the two target variable classes (James, 2013). This bias can be mitigated through oversampling or undersampling techniques to rebalance the data. The balanced dataset is then utilized to train predictive models. The dataset employed in this study displayed a relatively balanced ratio between churners and non-churners, with 140 non-churners and 160 churners. However, data balancing was still carried out to enhance model accuracy and achieve high specificity, indicating the model's ability to effectively predict churner class. The random undersampling technique was employed to balance the dataset, resulting in an equal distribution of 140 churner and 140 non-churner data points in this research.

3.5 Multicollinearity Test

Multicollinearity is a specific case of collinearity where independent variables or features in machine learning exhibit a linear relationship with two or more other independent variables. Belsley (1991) suggests that multicollinearity can be detected using the Variance Inflation Factor (VIF), which measures the extent to which the variance of regression coefficient estimates increases when independent variables are correlated.

According to Ghozali (2016), the test for multicollinearity can be performed by considering the values of Tolerance and Variance Inflation Factor (VIF) in a regression model. The criteria for determining multicollinearity are as follows:

- If VIF < 10 or Tolerance > 0.01, there is no multicollinearity in the model.
- If VIF > 10 or Tolerance < 0.01, multicollinearity is present in the model.
- If the correlation coefficient between each pair of independent variables is > 0.8, multicollinearity is observed in the model. However, if the correlation coefficient is < 0.8, multicollinearity is not present in the model.

Once a balanced dataset is obtained, the next step involves analyzing the existing factors. These factors are subjected to testing for the presence of multicollinearity through the VIF values generated by SPSS. If multicollinearity is detected among the factors, further analysis is conducted to determine whether a particular factor should be retained or if a choice needs to be made among the involved factors.

3.6 Building Prediction Models

The prediction models utilized in this study include Artificial Neural Networks (ANN), Logistic Regression, and XGBoost. For logistic regression and ANN, model packages from sklearn are employed with default parameters. For XGBoost, an API library with default parameters is used. Once the data and factors have been verified, the data is trained using these three prediction models. After obtaining the highest accuracy, sensitivity, and specificity results, the selected model is fed with data for further training and testing.

3.7 Cross Validation

Cross-validation is conducted by splitting the data into training and testing subsets for each model, with a total of 5 folds. The training data is used to build the regression model, while the testing data is used to validate the regression model.

3.8 Model Performance Evaluation

For the models employed, namely Logistic Regression, Artificial Neural Network (ANN), and XGBoost, performance evaluation is carried out in terms of sensitivity, specificity, and accuracy. The model with the highest sensitivity, specificity, and accuracy values is selected.

3.9 Analysis of Output Results

After identifying the machine learning method with the highest sensitivity, specificity, and accuracy values, an analysis is conducted to determine the factors that have the most significant impact on customer churn. According to Ibrahim (2013), the coefficients for ANN can be computed using methods such as the Connection Weight Algorithm with the following formula:

$$RI_x = \sum_{y=1}^{m} w_{xy} w_{yz} \tag{1}$$

Where RI_x is the relative importance of input neuron $x, \sum_{y=1}^{m} w_{xy} w_{yz}$ is sum of product of final weights of the connection from input neuron to hidden neurons with the connection from hidden neurons to output neuron, y is the total number of hidden neurons, and z is output neurons. Meanwhile, Logistic Regression and XGBoost's coefficients can be directly obtained through the implemented code functions.

3.10 Strategic Analysis

Having identified the most influential factors in customer churn, the next step involved the generation of strategies using the Quantitative Strategic Planning Matrix (QSPM) method. The QPSM aims to determine the best strategy selected from various strategy alternatives obtained from previous stages. Formulating strategies involves the use of the Strengths, Weaknesses, Opportunities, Threats (SWOT) method (David, 2009). This encompassed the creation of the Internal Factor Evaluation Matrix, based on the company's internal Strengths and Weaknesses, and the External Factor Evaluation Matrix, derived from external Opportunities and Threats. Subsequently, these matrices were assigned a weighting based on priority and importance in problem-solving. During the QPSM phase, input from experts or stakeholders, who were decision-makers within the company and obtained through interviews, was utilized to provide an attractive score in the QPSM matrix. The detailed steps of QPSM were as follows (David, 2009):

1. Analysis with SWOT and QSPM: In this step, the External Factor Evaluation Matrix (EFEM) was determined by considering external factors and their weights, including Opportunities and Threats.
2. Determining the Internal Factor Evaluation Matrix (IFEM): Internal factors and their weights, including Strengths and Weaknesses, were determined in this stage.
3. Creating the SWOT matrix: Strategies were generated by combining the EFEM and IFEM.
4. Selecting the preferred strategy resulting from the SWOT analysis with QSPM analysis: Decision-makers could participate in this step to provide Attractive Scores (AS). If a predetermined factor affected the considered alternative strategy, the decision-maker assigned an AS ranging from 1 to 4, with 1 indicating unacceptability, 2 being possibly acceptable, 3 signifying likely acceptability, and 4 representing acceptability. If there was no influence on the alternative strategy being considered, no AS was necessary.
5. Calculating the weighted attractiveness score: This step involves the multiplication of the AS by the weight assigned at the beginning.
6. Calculating the total weighted attractiveness score: This calculation yielded the best strategy with the highest weighted attractiveness score.

3.11 Risk Analysis

The selected strategy outcomes were further developed with uniform parameter patterns for advanced analysis in the form of Risk Analysis using the CVaR method, which assessed risk based on loss distribution. In general, the definition of value-at-risk (VaR) was the minimum loss. To compute VaR, Jorion (2007) suggested five steps: determining the current position, such as the current portfolio; measuring the variability of risk factors; specifying the time horizon; selecting the confidence level; and finally, reporting the worst possible loss by calculating all revenue-affecting information in the form of VaR. CVaR calculations were performed using Palisade's @RISK software. Conditional Value at Risk (CVaR) used a similar methodology to VaR but involved the average of VaR results. VaR had limitations in capturing extreme losses in the tail of the distribution, while the CVaR method could address this limitation (Rockafellar & Uryasev, 2002).

4. Results

4.1 Multicollinearity Result

From the test results presented in Appendix 1, it was evident that the VIF values fell within the range of $1 < VIF < 5$. According to Belsley (1991), values in this range indicate a moderate level of multicollinearity. Additionally, the VIF values were < 10, and the Tolerance values were > 0.01, as per Ghozali (2016) which implied the absence of multicollinearity. Therefore, it could be concluded that there was no multicollinearity among the independent variables. Consequently, the data could proceed to the next step without specific treatment.

4.2 Model Performance Results

Data analysis was conducted using machine learning methods, Logistic Regression, XGBoost, and ANN. In all three methods, K-Fold cross-validation with 5 folds was performed. The purpose of this was to obtain the best combination of data in terms of accuracy, precision, recall, and F1 score. Each fold yielded different results because the testing and training data applied to each fold were distinct. As a result, the data was analyzed evenly across multiple points, rather than relying solely on one specific instance. The outcomes of the 5 K-Fold cross-validation iterations were then averaged to determine the most effective machine learning method.

Table 1. Model Performance Result

Average	Training/Testing	Logistic Regression	ANN	XGBoost
Accuracy	Training Accuracy	93.8%	96.0%	94.8%
	Testing Accuracy	90.4%	92.6%	90.4%
Precision	Training Precision	94.2%	95.8%	94.6%
	Testing Precision	92.4%	93.4%	91.2%
Recall	Training Recall	93%	97%	95%
	Testing Recall	88%	95%	89%
F-1 Score	Training F1-Score	93%	97%	95%
	Testing F1-Score	88%	95%	90%

Based on the results presented in Table 1, it can be concluded that the machine learning method with the highest values for accuracy, precision, recall, and F1 score is the ANN method.

4.3 Model Coefficient Results

Since the machine learning method selected was the ANN method, an analysis of the output coefficients was conducted using Equation 1. The final coefficients' results were presented in Table 2 and Table 3 for each factor, with network quality emerging as the primary factor in this study. However, a threshold was set by the author, stipulating that factors with coefficients greater than 1.5 would still be considered in the determination of the strategies to be implemented. This related to the consideration of the implementation of strategies, taking into account the expected impact on the churn rate and the associated implementation costs. Thus, the factors most strongly considered in the subsequent strategic analysis were presented in Table 2 and Table 3, with network quality as the primary factor, followed by the level of interest in Value Added Services (VAS) products, company services, call failure, customers who had contacted customer service, expensive package prices, and less appealing advertisements.

Table 2. ANN Coefficients Result

Factor	ANN Coefficient (Σ Wxy.Wyz)
Age	0.2546692193
Gender	-1.898368853
Marital Status	0.4496175726
Occupation	-0.2392373071
Income	-0.8596606061
Tenure (Months)	0.2809600196
Call Failures	**3.330841208**
Customer Service Call Frequency	**2.402181173**
Pulse Costs	-0.232408436
Package	0.816223381
Quota	0.04506973056
Number of Devices	-0.3345524655
Previously Used VAS	1.032737838
Attractiveness of VAS	**3.747656213**
Poor Network	**3.83421036**
Expensive Packages	**1.809755642**
Poor Advertising	**1.760283405**

Table 3. ANN Coefficients Result (Cont.)

Factor	ANN Coefficient (Σ Wxy.Wyz)
Limited Variations	2.390660262
Failed Package Purchase	0.7700082273
Failed VAS Purchase	-0.5877664675
Poor XL Service	**3.364483457**

4.4 QSPM Result

From the primary factors identified, the next step involved strategy development using the QSPM method. The QSPM method was constructed from the stages of the Internal Factor Evaluation Matrix based on the Strengths and Weaknesses of the internal aspects of the company and the External Factor Evaluation Matrix based on Opportunities and Threats from the external environment. To obtain a more optimal strategic analysis, additional supporting factors were introduced, adapted from Abdelmonem & Elgeuoshy (2021) research, which analyzed strategies for telecommunications companies in Egypt. Subsequently, these factors were assigned weights based on their priority and significance in problem resolution, taking into account the results of the factor determinations. Therefore, factors included in the highest coefficients carried substantial weights. The weight calculations and justifications can be observed in Appendix 2 and Appendix 3 for the Internal Factor Evaluation Matrix, while for the External Factor Evaluation Matrix, they were presented in Appendix 4 and Appendix 5.

The factors from the IFEM and EFEM tables were subsequently used to filter the results of the Design Thinking stages at XL Axiata, namely Empathize and Define, which were summarized in a workshop. In this workshop, Business Users provided strategies related to customer churn issues, and these strategies were then reviewed by decision-makers. The following are the steps or procedures for selecting strategies from the workshop stage to obtain the final results in line with the factors in the IFEM and EFEM or SWOT. Process for selecting candidate strategies:

1. A workshop was conducted to gain insights and strategies from Business Users.
2. Business Users provided strategies related to customer churn.
3. The Internal Factor Evaluation Matrix was created.
4. The External Factor Evaluation Matrix was created.
5. The selection of strategies in step 2 became the chosen strategy based on the factors in steps 3 and 4 (SWOT).
6. The final strategy was chosen through the QSPM stage.

Appendix 6 presents the strategies obtained from the design thinking stages, with reasons and statements for the selection of the strategy provided on the right side of the table. The development of these strategies was based on the consideration that the company had already implemented measures to reduce the current churn rate. However, it had not yet effectively utilized AI/ML methods, which could provide more real-time and cost-effective results while considering customer patterns. Based on their alignment with IFEM and EFEM, the selected strategies were elaborated upon in detail in Table 4 and 5. During this phase, strategies were selected as solutions based on Strength-Threat, Strength-Opportunity, Weakness-Threat, and Weakness-Opportunity combinations.

Table 4. Strategies Development with SWOT Analysis

SWOT	***Strength*** 1. Significant Market Share. 2. Strong Brand Image (blue) with a Memorable Tagline (XL: A Step Ahead). 3. Popular VAS Packages Among Customers	***Weakness*** 1. Inaccurate Competitor Activity Analysis. 2. Less Interactive Customer Journey on the MyXL Application. 3. Insufficient Active Follow-up on Customer Complaints. 4. Incidents of Call Failures Experienced by Customers.
Opportunities 1. Government's Relocation of the Capital to East Kalimantan. 2. External Events (MotoGP, EPrix, etc.). 3. Social Media Subscriber Count (Total subscribers: 675k from Instagram, YouTube, and LinkedIn). 4. Government Programs (USO & 3T Villages).	1. AI/ML for Analyzing Bundling Promotions with VAS Products (S3; O3; O2; O1).	1. AI/ML for Analyzing Campaigns Tailored to Customer Locations and Competitor Activities (W1; O4; O3; O1; O2)
Threats 1. Merger of Indosat and Tri Operators. 2. Competitors with Superior Networks. 3. Price Competition with Competitors.	1. AI/ML for Analyzing Competitive Potential Areas in Base Transceiver Station (BTS) Infrastructure (S1; T2). 2. AI/ML for Analyzing Dynamic Pricing Strategies to Increase ARPU (Average Revenue Per User) (T3; S1; S2; S3).	1. AI/ML for Analyzing Network Performance and Handling Customer Complaints Using Chatbots (W2; W3; W4; T2).

Table 5. Details of Strategy Selection Based on SWOT

Strategies based on IFEM and EFEM	Alignment of IFEM & EFEM with SWOT
Strategy 1: AI/ML for analyzing bundling promotions with VAS products.	*Strength 3; Opportunities 1; Opportunities 2; Opportunities 3*
Strategy 2: AI/ML for analyzing campaigns tailored to customer regions and competitor activities.	*Weakness 1; Opportunities 1; Opportunities 2; Opportunities 3; Opportunities 4*
Strategy 3: AI/ML for identifying competitive potential areas in BTS infrastructure.	*Strength 1; Threats 2*
Strategy 4: AI/ML for dynamic pricing to increase ARPU (Average Revenue Per User).	*Threats 3; Strength 1; Strength 2; Strength 3*
Strategy 5: AI/ML for analyzing network performance and customer complaints using a chatbox.	*Weakness 2; Weakness 3; Weakness 4; Threats 2*

Next, a QSPM analysis was conducted, which served as an evaluation of the formulated strategies. The evaluation process involved assigning Attractive Scores within a range of 1-4, based on the assessment criteria of impact and the feasibility of strategy implementation. In this context, Impact pertained to the strategy's effectiveness in addressing the existing customer churn issue, specifically whether it could reduce the number of customer churns. Implementation considerations encompassed the cost implications of further implementing these strategies. The Attractive Scores were determined by five decision-makers within the company, each specializing in areas relevant to customer churn strategy analysis. An example calculation of the Quantitative Strategic Planning Matrix (QSPM) is provided in Appendix 7 for Decision Maker 1. This research involves the participation of five decision-makers. For the attractive scores assigned by the other four Decision Makers, please refer to Appendix 8 until Appendix 11, to obtain the final results presented in Table 6. Subsequently, the average scores derived from the QSPM analysis were computed to identify the selected strategy. In Table 6, it was evident that Strategy 1, which involved the use of AI/ML to analyze bundling promotions with VAS products, emerged as the chosen strategy.

Table 6. QSPM Calculation Result

Strategy	QPSM1	QPSM2	QPSM3	QPSM4	QPSM5	Average
Strategy 1: AI/ML for analyzing bundling promotions with VAS products.	4.5	4.9722	4.80556	3.80556	4.3611	4.4889
Strategy 2: AI/ML for analyzing campaigns tailored to customer regions and competitor activities.	4.25	3.9722	4.4722	3.52778	4.111	4.0667
Strategy 3: AI/ML for identifying competitive potential areas in BTS infrastructure.	3.3889	3.5	4.13889	4.0833	3.8611	3.7944
Strategy 4: AI/ML for dynamic pricing to increase ARPU (Average Revenue Per User).	4.02778	3.722	4.33	3.8611	3.778	3.944
Strategy 5: AI/ML for analyzing network performance and customer complaints using a chatbox.	4.13889	3.722	4.556	4.33	4.2778	4.20556

4.5 Risk Analysis Results

Following the selection of the chosen strategy, which involved the use of AI/ML to analyze bundling promotions with VAS products, a profit and loss analysis was conducted using the CVaR method. The VAS product types emphasized in this study were categorized into three types: video streaming, gaming, and chatting, which collectively accounted for the most substantial bandwidth consumption within the telecommunication company's network. This is related to the costs associated with providing bandwidth capacity across the company's networks and the profits the company could generate. When the company focuses on a primary commodity widely used by the public, it could reduce the capacity allocated to less desirable products, thus reallocating it to more popular and profitable products. The author employed an analysis of the VAS product most favored by customers to determine the focus of promotional bundling, resulting in greater profitability for the company. Mathematical calculations for the input variables were conducted using Equation 2, assuming a price of Rp 10,000 per gigabyte for both the primary quota and VAS.

$$\text{Promo Price} = (\text{Primary Quota} + (\text{VAS Type Quota} \times \text{Probability of VAS Type})) * \text{Rp } 10{,}000 \quad (2)$$

The VAS product types were then referred to as input variables, while the promo price was denoted as the output variable in this study. Furthermore, an analysis of the distribution types for the input variables was performed using EasyFit software, and the distribution types obtained were presented in Table 7 below.

Table 7. Distribution Type for CVaR Input

CVaR Input Type	Distribution Type
Package Quota + Netflix/Streaming Video	Uniform
Package Quota + Game	Uniform
Package Quota + Chatting	Uniform
Total Main Quota	Uniform
Total VAS Quota	Uniform

After the distribution types were obtained in EasyFit, the next step involved defining the input variables by entering questionnaire data into the @Risk software. This process resulted in the definition of input variables, as presented in Table 7. Subsequently, simulations were carried out on the output variables, specifically the promotional prices for the three types of VAS products. These simulations were conducted with 1000 replications, and CVaR calculations were performed with α = 90%. The results are displayed in Table 8 below.

Table 8. CVaR Final Result

VAS Promotion Type	CVaR Value (α = 90%)
Package Quota + Netflix	104.720
Package Quota + Game	107.280
Package Quota + Chatting	106.080

From the results presented above, it is evident that the highest profit was obtained from the bundling of Data Quota and Gaming VAS. Consequently, the company can strategically focus its promotional efforts on this specific bundled product.

5. Discussions

As mentioned earlier, the machine learning method with the highest values for accuracy, precision, recall, and F1 score was found to be the ANN method. This result was supported by research conducted by Pendharkar (2009), where the Genetic Algorithm method was combined with Maximum Likelihood, Decision, and ANN methods to analyze features in customer churn data. In that study, the combination of Genetic Algorithm and ANN yielded the most optimal results. This was related to the role of hidden nodes in the neural network's performance in predictive modeling. Having an adequate number, or in this case, a medium number of hidden nodes, which was twice the number of input nodes, led to a well-performed predictive model. In this study, the number of nodes or neurons in the hidden layer was set to 100, while there were 21 inputs, allowing the ANN model to perform effectively. In artificial neural networks, inputs are multiplied by their respective weights, then summed and passed through an activation function. There are high expectations for ANNs to handle intricate, non-linear mappings in multi-dimensional spaces, often seen as versatile function approximators. The sigmoid activation function, characterized by its S-shaped curve ranging from 0 to 1, faces challenges like vanishing gradients and non-zero-centered output, resulting in slow convergence as gradients diverge. In contrast, the hyperbolic tangent function (tanh) is centered at zero, making it more conducive to optimization and surpassing the sigmoid function in effectiveness. Another popular choice is the Rectified Linear Unit (ReLU), which outperforms tanh by sixfold and effectively mitigates the vanishing gradient issue. ReLU is typically utilized in hidden layers of neural networks (Khan et al., 2019). In this research, the ReLU activation function is employed for its benefits in addressing the vanishing gradient problem, leading to faster convergence during training.

In the QSPM results, the selected strategy is Strategy 1, which involves using AI/ML to analyze bundling promotions with VAS products. This choice is supported by research conducted by Wells & Billings (2020), which suggests that the use of AI/ML in determining promotions can mitigate or reduce the churn rate occurring within a company. From the CVaR results, it was obtained that the highest profit for VAS products would be generated by bundling the Data Package and Game. Consequently, the company can focus its promotions on this bundled product. This conclusion aligns with the statement made by one of the decision-makers in the VAS division, who emphasized that VAS or OTT games have a high standing as one of the most sought-after products by customers. Furthermore, these products contribute significantly to the company's profits. In addition to data packages and games, the company also sells VAS products separately, such as in-game diamonds used for online gaming transactions, which proves to be highly lucrative for the company. Therefore, promoting bundled VAS products, particularly games, is deemed to be more advantageous for the company.

To effectively leverage the findings of the study, managerial implications at XL Axiata should prioritize the implementation of Artificial Neural Networks (ANN) for churn prediction due to their superior accuracy. This entails allocating resources for training data scientists or partnering with external experts to develop and deploy ANN models within the company's existing infrastructure. According to the findings of this study, ANN emerges as the most accurate machine learning method, with network factors identified as the primary contributors to customer churn, followed by the level of interest in Value-Added Service (VAS) products, company services, failed calls, customers who have contacted customer service, relatively high package prices, and less engaging advertisements. These factors derived from the ANN results can then be incorporated or considered in the subsequent step of the Quantitative Strategic Planning Matrix (QSPM). While the ANN's machine learning capabilities alone can identify root causes, QSPM aids in facilitating more straightforward actions to address the issues. QSPM incorporates qualitative insights from workshops with Business Users, who contribute to crafting Internal and External matrices, along with quantitative steps like assigning weights based on priority and importance for effective problem-solving. Furthermore, informed by the findings of the QSPM strategy study advocating for an AI/ML approach to evaluate the bundling of promotions with Value-Added Service (VAS) products, managers ought to assess the real-world implications on customer churn and implementation costs. Integrating this insight into the decision-making process is crucial for promotional planning and risk management. Creating streamlined decision-making processes that fuse insights from machine learning models and QSPM, aimed at selecting the best strategy from various alternatives, facilitates more effective strategy formulation by employing SWOT analysis to generate Internal and External Factor Evaluation Matrices, assigning weightings, and integrating input from experts or stakeholders to yield an optimal score in the QSPM matrix. Furthermore, based on CVaR risk analysis, managers should prioritize bundling promotions with VAS products that yield higher profitability and lower risk, focusing on primary quotas and online games over video streaming or chatting services. Cross-functional collaboration between marketing, data analytics, and finance teams is essential to facilitate data-driven decision-making in this regard. Additionally, implementing mechanisms for continuous monitoring and adjustment of promotional strategies based on real-time customer feedback and market dynamics is crucial. Regular evaluation of the performance of machine learning models and updating them as needed will help maintain relevance and effectiveness. Through these actions, XL Axiata can effectively leverage machine learning to analyze customer churn factors, optimize promotional strategies, and mitigate risks, thereby driving sustainable growth and competitiveness in the telecommunications market.

Nevertheless, it's essential to acknowledge some of the constraints of this study. In particular, the survey data is centered exclusively on the offerings of a single Indonesian telecom firm, XL Axiata. Consequently, the conclusions drawn from this investigation may not be applicable to other telecom entities operating in Indonesia.

6. Conclusion

Aligned with the research purpose, this study seeks to diverge from conventional, intuition-based decision-making approaches frequently utilized by decision-makers. Instead, it advocates for the adoption of a quantitative methodology that employs rigorous analysis for both strategy selection and risk evaluation linked to customer churn. This quantitative methodology encompasses various techniques, including machine learning algorithms such as logistic regression, Artificial Neural Networks (ANN), and XGBoost, as well as the Quantitative Strategic Planning Matrix (QSPM) and Conditional Value-at-Risk (CVaR) analysis.

The following are the conclusions drawn from the conducted research. The machine learning method with the highest values for accuracy, precision, recall, and F1-score among logistic regression, ANN, and XGBoost is ANN. The most influential factors causing customer churn in XL Axiata are network-related, followed by the level of interest in VAS products, the company's service quality, call failures, customers who have contacted the call service, relatively expensive package prices, and less appealing advertisements. The selected strategy for addressing customer churn issues, taking into account the impact on reducing churn rates and implementation costs, is the AI/ML strategy for analyzing bundled promotions with VAS products. This choice is based on the consideration that while the company has made efforts to reduce churn rates, the implementation of AI/ML is deemed to be more effective. Further analysis is performed on the selected strategy using CVaR to obtain more specific results regarding profit and loss distribution. This analysis takes into account the cost of providing bandwidth capacity on each network and the company's profit. The study focuses on three types of VAS products: games, video streaming, and chatting. The analysis reveals that the bundling of main data packages with VAS products, specifically games, yields the highest profits for the company. Consequently, the company can concentrate its promotional efforts on this product.

Overall, this research makes a substantial contribution to advancing the theoretical understanding and practical strategies for effectively managing customer churn in the telecommunications industry. By employing a combination of machine learning models, SWOT analysis, and CVaR evaluation, this study provides a comprehensive framework for telecom companies to analyze and optimize their churn reduction strategies. The insights gained from this research offer valuable guidance to organizations seeking to leverage modern technology and data-driven decision-making to enhance customer retention and profitability in a highly competitive industry.

Acknowledgments. I would like to thank all the employees of XL Axiata for the opportunity to conduct research and interview.

Declaration of Conflicting Interests. The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Appendix

Appendix 1 Multicollinearity Result

Coefficients[a]

Model		Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)		
	Usia	.351	2.850
	JenisKelamin	.906	1.104
	StatusPernikahan	.452	2.214
	Pekerjaan	.625	1.600
	Pendapatan	.330	3.028
	Tenure	.595	1.679
	GagalPanggilan	.317	3.157
	CallService	.246	4.058
	BiayaPulsa	.410	2.442
	Paket	.394	2.536
	Kuota	.337	2.967
	JumlahPerangkat	.602	1.662
	PernahVAS	.567	1.763
	VASMenarik	.481	2.078
	JaringanBuruk	.599	1.671
	PaketMahal	.716	1.396
	IklanBuruk	.763	1.310
	VariasiSedikit	.862	1.160
	GagalBeliPaket	.592	1.689
	GagalBeliVAS	.378	2.645
	PelayananXLBuruk	.336	2.977

a. Dependent Variable: Churn

Appendix 2 Internal Factor Evaluation Matrix

Internal Factor	***Weight***
Strength	
Market Share	0.111
Having a Strong Brand Image (Blue) and a Memorable Tagline (XLangkah lebih maju)	0.056
Popular VAS Packages among Customers	0.222
Weakness	
Inaccurate Competitor Activity Analysis	0.056
Less Interactive Customer Journey on the MyXL Application	0.111
Lack of Active Follow-Up on Customer Complaints	0.222
Customers Experiencing Call Failures	0.222
Total	**1.00**

Appendix 3 Internal Factor Evaluation Matrix Justification

Internal Factor	**Justification**
Strength	
Market Share	The number of XL Axiata customers ranks third in Indonesia (Telkomsel 169.7 million; Indosat Ooredoo 60.3 million; XL Axiata 56.7 million).
Having a Strong Brand Image (Blue) and a Memorable Tagline (XLangkah lebih maju)	Source: 2021 Annual Report of the Company
Popular VAS Packages among Customers	Source: XL Axiata Website
Weakness	
Inaccurate Competitor Activity Analysis	Internal Interviews
Less Interactive Customer Journey on the MyXL Application	Internal Interviews
Lack of Active Follow-Up on Customer Complaints	Questionnaire Data & Internal Interviews
Customers Experiencing Call Failures	Questionnaire Data

Appendix 4 External Factor Evaluation Matrix

External Factor	Weight
Opportunities	
Relocation of the Capital City to East Kalimantan	0.08
External Events (MotoGP, EPrix, etc.)	0.08
Social Media Subscribers (Total subscribers: 675k from Instagram, YouTube, and LinkedIn)	0.11
Government Programs (USO & 3T Village Program)	0.06
Threats	
Merger of Indosat and Tri operators	0.11
Competitors with superior networks	0.28
Price competition with competitors	0.28
Total	**1.00**

Appendix 5 External Factor Evaluation Matrix Justification

External Factor	Justification
Opportunities	
Relocation of the Capital City to East Kalimantan	Data from the Ministry of Home Affairs of Indonesia
External Events (MotoGP, EPrix, etc.)	Data from the Ministry of Tourism and Creative Economy of Indonesia
Social Media Subscribers (Total subscribers: 675k from Instagram, YouTube, and LinkedIn)	Total subscribers: 675,000 from Instagram, YouTube, and LinkedIn
Government Programs (USO & 3T Village Program)	Internal interviews and data from the Ministry of Communication and Information Technology of Indonesia
Threats	
Merger of Indosat and Tri operators	Website of Indosat Ooredoo
Competitors with superior networks	Questionnaire and internal interviews
Price competition with competitors	Questionnaire and internal interviews

Appendix 6 Strategy Selection in the Design Thinking Stage

Strategies Related to Customer Churn	Reasons for Not Being Selected
AI/ML for Analyzing Areas with Competitive BTS Infrastructure Potential	Selected
AI/ML for Identifying the Right Products to Offer to Customers Based on Homepass	Product not aligned with the research
AI/ML for Interaction in First Call Resolution (FCR)	Strategy not aligned with the factors in IFEM & EFEM
AI/ML for Analyzing Customer Region-specific Campaigns and Competitor Activities	Selected
AI/ML for Analyzing Specific Areas in Determining Promotion Capacity	Strategy not aligned with the factors in IFEM & EFEM
AI/ML for analyzing multiple promotions and dynamic support programs for Priority products from a marketing perspective	Product not aligned with the research
AI/ML for social media Listening on trending topics related to campaigns	Strategy not aligned with factors in IFEM & EFEM
AI/ML for sentiment analysis related to tNPS	Strategy not aligned with factors in IFEM & EFEM
AI/ML for analyzing bundling promotions with VAS products	Selected
AI/ML for analyzing network performance and handling customer complaints using chatbots	Selected
AI/ML for auto-notifications related to network issues	Strategy not aligned with factors in IFEM & EFEM
AI/ML for measuring customer happiness	Strategy not aligned with factors in IFEM & EFEM
AI/ML for auto-handling complaints and incidents	Strategy not aligned with factors in IFEM & EFEM
AI/ML for capacity planning based on customer service profiles	Strategy not aligned with factors in IFEM & EFEM
AI/ML for validation analysis after bonus promotions are launched in each city	Strategy not aligned with factors in IFEM & EFEM
AI/ML for dynamic pricing analysis to increase ARPU	Selected

Appendix 7 QSPM Calculation for Decision Maker 1

INTERNAL		Strategy 1 (AI/ML for analyzing bundled promotions with VAS products)		Strategy 2 (AI/ML for analyzing campaigns tailored to customer locations and competitor activities)		Strategy 3 (AI/ML for analyzing competitive BTS infrastructure potential areas)		Strategy 4 (AI/ML for analyzing dynamic pricing to increase ARPU)		Strategy 5 (AI/ML for analyzing network performance and customer complaints using chatbots)	
Strengths:	**Weight**	**Attractive Score**	**Weighted Attractive Score**	**Attractive Score**	**Weighted Attractive Score**	**Attractive Score**	**Weighted Attractive Score**	**Attractive Score**	**Weighted Attractive Score**	**Attractive Score**	**Weighted Attractive Score**
Market Share	0.111	3	0.33	3	0.33	2	0.22	3	0.33	1	0.11
Possesses a Strong Brand Image (blue) and a Memorable Tagline (XLangkah lebih maju)	0.056	2	0.11	4	0.22	1	0.0556	1	0.0556	1	0.0556
Popular VAS Packages among Customers	0.22	4	0.889	4	0.889	1	0.22	2	0.444	1	0.22
Weaknesses:											
Inaccurate Analysis of Competitor Activities	0.056	2	0.11	2	0.11	3	0.1667	3	0.1667	1	0.0556
Lack of Interactivity in the Customer Journey on the MyXL Application	0.11	1	0.11	1	0.11	1	0.11	1	0.11	2	0.22
Inadequate Follow-up on Customer Complaints	0.22	1	0.22	1	0.22	1	0.22	2	0.44	3	0.667
Occurrence of Dropped Calls for Customers	0.22	1	0.22	1	0.22	3	0.667	1	0.22	4	0.889
TOTAL (Internal Weight)	1										

External		Strategy 1 (AI/ML for analyzing bundled promotions with VAS products)		Strategy 2 (AI/ML for analyzing campaigns tailored to customer locations and competitor activities)		Strategy 3 (AI/ML for analyzing competitive BTS infrastructure potential areas)		Strategy 4 (AI/ML for analyzing dynamic pricing to increase ARPU)		Strategy 5 (AI/ML for analyzing network performance and customer complaints using chatbots)	
Opportunities	**Weight**	**Attractive Score**	**Weighted Attractive Score**	**Attractive Score**	**Weighted Attractive Score**	**Attractive Score**	**Weighted Attractive Score**	**Attractive Score**	**Weighted Attractive Score**	**Attractive Score**	**Weighted Attractive Score**
Relocation of the Capital to East Kalimantan	0.08	2	0.1667	3	0.25	3	0.25	2	0.1667	2	0.1667
External Events (MotoGP, EPrix, etc.)	0.08	3	0.25	3	0.25	2	0.1667	2	0.1667	2	0.1667
Social Media Subscriber Base (Total subscribers: 675k from Instagram, YouTube, and LinkedIn)	0.11	3	0.33	4	0.44	1	0.11	1	0.11	1	0.11
Government Programs (USO & Desa 3T)	0.06	2	0.11	2	0.11	3	0.1667	1	0.0556	2	0.111
Threats:											
Merger of Indosat and Tri Operators	0.11	1	0.11	1	0.11	1	0.11	1	0.11	1	0.11
Competitors with Superior Networks	0.28	1	0.2778	1	0.2778	4	1.11	1	0.2778	4	1.11
Price Competition with Competitors	0.28	4	1.111	2	0.556	1	0.2778	4	1.11	1	0.2778
TOTAL (External + Internal)	1		4.3611		4.11		3.8611		3.778		4.2778

Appendix 8 Attractive Score for QSPM Calculation from Decision Maker 2

Internal Factors	Strategy 1 (AI/ML for analyzing bundled promotions with VAS products)	Strategy 2 (AI/ML for analyzing campaigns tailored to customer locations and competitor activities)	Strategy 3 (AI/ML for analyzing competitive BTS infrastructure potential areas)	Strategy 4 (AI/ML for analyzing dynamic pricing to increase ARPU)	Strategy 5 (AI/ML for analyzing network performance and customer complaints using chatbots)
Strengths:	**Attractive Score for DM 2**	**Attractive Score for DM 2**	**Attractive Score for DM 2**	**Attractive Score for DM 2**	**Attractive Score for DM 2**
Market Share	2	2	3	2	2
Possesses a Strong Brand Image (blue) and a Memorable Tagline (XLangkah lebih maju)	2	3	1	1	1
Popular VAS Packages among Customers	3	3	1	3	1
Weaknesses:					
Inaccurate Analysis of Competitor Activities	3	2	2	4	1
Lack of Interactivity in the Customer Journey on the MyXL Application	1	1	1	1	2
Inadequate Follow-up on Customer Complaints	1	1	1	1	4
Occurrence of Dropped Calls for Customers	1	1	3	1	4
External Factors:					
Opportunities:					
Relocation of the Capital to East Kalimantan	3	2	4	2	2
External Events (MotoGP, EPrix, etc.)	2	3	3	3	2
Social Media Subscriber Base (Total subscribers: 675k from Instagram, YouTube, and LinkedIn)	3	3	1	1	1
Government Programs (USO & Desa 3T)	2	2	3	2	2
Threats:					
Merger of Indosat and Tri Operators	1	1	1	1	1
Competitors with Superior Networks	1	1	4	1	3
Price Competition with Competitors	3	2	1	4	1

Appendix 9 Attractive Score for QSPM Calculation from Decision Maker 3

Internal Factors	Strategy 1 (AI/ML for analyzing bundled promotions with VAS products)	Strategy 2 (AI/ML for analyzing campaigns tailored to customer locations and competitor activities)	Strategy 3 (AI/ML for analyzing competitive BTS infrastructure potential areas)	Strategy 4 (AI/ML for analyzing dynamic pricing to increase ARPU)	Strategy 5 (AI/ML for analyzing network performance and customer complaints using chatbots)
Strengths:	**Attractive Score for DM 3**	**Attractive Score for DM 3**	**Attractive Score for DM 3**	**Attractive Score for DM 3**	**Attractive Score for DM 3**
Market Share	3	3	3	2	1
Possesses a Strong Brand Image (blue) and a Memorable Tagline (XLangkah lebih maju)	2	2	1	1	1
Popular VAS Packages among Customers	4	4	1	4	1
Weaknesses:					
Inaccurate Analysis of Competitor Activities	4	3	1	3	1
Lack of Interactivity in the Customer Journey on the MyXL Application	1	1	1	1	3
Inadequate Follow-up on Customer Complaints	1	1	1	1	4
Occurrence of Dropped Calls for Customers	1	1	4	1	4
External Factors:					
Opportunities:					
Relocation of the Capital to East Kalimantan	2	3	3	2	3
External Events (MotoGP, EPrix, etc.)	3	4	2	2	3
Social Media Subscriber Base (Total subscribers: 675k from Instagram, YouTube, and LinkedIn)	4	4	1	2	1
Government Programs (USO & Desa 3T)	1	3	4	2	3
Threats:					
Merger of Indosat and Tri Operators	1	1	1	1	1
Competitors with Superior Networks	2	1	4	2	3
Price Competition with Competitors	4	3	1	4	1

Appendix 10 Attractive Score for QSPM Calculation from Decision Maker 4

Internal Factors	**Strategy 1 (AI/ML for analyzing bundled promotions with VAS products)**	**Strategy 2 (AI/ML for analyzing campaigns tailored to customer locations and competitor activities)**	**Strategy 3 (AI/ML for analyzing competitive BTS infrastructure potential areas)**	**Strategy 4 (AI/ML for analyzing dynamic pricing to increase ARPU)**	**Strategy 5 (AI/ML for analyzing network performance and customer complaints using chatbots)**
Strengths:	**Attractive Score for DM 4**	**Attractive Score for DM 4**	**Attractive Score for DM 4**	**Attractive Score for DM 4**	**Attractive Score for DM 4**
Market Share	3	2	1	3	1
Possesses a Strong Brand Image (blue) and a Memorable Tagline (XLangkah lebih maju)	2	3	2	2	1
Popular VAS Packages among Customers	4	3	1	3	1
Weaknesses:					
Inaccurate Analysis of Competitor Activities	3	3	1	3	1
Lack of Interactivity in the Customer Journey on the MyXL Application	1	1	1	1	2
Inadequate Follow-up on Customer Complaints	1	1	1	1	4
Occurrence of Dropped Calls for Customers	1	1	3	1	4
External Factors:					
Opportunities:					
Relocation of the Capital to East Kalimantan	3	2	3	1	3
External Events (MotoGP, EPrix, etc.)	4	3	3	1	2
Social Media Subscriber Base (Total subscribers: 675k from Instagram, YouTube, and LinkedIn)	4	4	1	1	1
Government Programs (USO & Desa 3T)	2	2	3	2	2
Threats:					
Merger of Indosat and Tri Operators	1	1	1	1	1
Competitors with Superior Networks	2	1	3	1	3
Price Competition with Competitors	4	3	1	4	1

Appendix 11 Attractive Score for QSPM Calculation from Decision Maker 5

Internal Factors	**Strategy 1 (AI/ML for analyzing bundled promotions with VAS products)**	**Strategy 2 (AI/ML for analyzing campaigns tailored to customer locations and competitor activities)**	**Strategy 3 (AI/ML for analyzing competitive BTS infrastructure potential areas)**	**Strategy 4 (AI/ML for analyzing dynamic pricing to increase ARPU)**	**Strategy 5 (AI/ML for analyzing network performance and customer complaints using chatbots)**
Strengths:	**Attractive Score for DM 5**	**Attractive Score for DM 5**	**Attractive Score for DM 5**	**Attractive Score for DM 5**	**Attractive Score for DM 5**
Market Share	3	3	1	2	1
Possesses a Strong Brand Image (blue) and a Memorable Tagline (XLangkah lebih maju)	3	3	2	2	1
Popular VAS Packages among Customers	4	2	1	3	1
Weaknesses:					
Inaccurate Analysis of Competitor Activities	1	4	2	2	1
Lack of Interactivity in the Customer Journey on the MyXL Application	1	1	1	1	3
Inadequate Follow-up on Customer Complaints	1	1	1	1	4
Occurrence of Dropped Calls for Customers	1	1	3	1	4
External Factors:					
Opportunities:					
Relocation of the Capital to East Kalimantan	3	3	2	1	3
External Events (MotoGP, EPrix, etc.)	3	4	2	2	2
Social Media Subscriber Base (Total subscribers: 675k from Instagram, YouTube, and LinkedIn)	3	3	1	2	1
Government Programs (USO & Desa 3T)	3	2	3	2	2
Threats:					
Merger of Indosat and Tri Operators	1	1	1	1	1
Competitors with Superior Networks	2	2	3	2	2
Price Competition with Competitors	3	3	1	4	1

References

Abdelmonem, M. S., & Elgeuoshy, O. (2021). *Strategic Management Audit for Orange Egypt for Telecommunications Prepared by*.

Ahn, J. H., Han, S. P., & Lee, Y. S. (2006). Customer churn analysis: Churn determinants and mediation effects of partial defection in the Korean mobile telecommunications service industry. *Telecommunications Policy*, *30*(10–11), 552–568. https://doi.org/10.1016/j.telpol.2006.09.006

Al-Mashraie, M., Chung, S. H., & Jeon, H. W. (2020). Customer switching behavior analysis in the telecommunication industry via push-pull-mooring framework: A machine learning approach. *Computers and Industrial Engineering*, *144*. https://doi.org/10.1016/j.cie.2020.106476

Amin, A., Al-Obeidat, F., Shah, B., Adnan, A., Loo, J., & Anwar, S. (2019). Customer churn prediction in telecommunication industry using data certainty. *Journal of Business Research*, *94*, 290–301. https://doi.org/10.1016/j.jbusres.2018.03.003

Belsley, D. A. (1991). Conditioning diagnostics: Collinearity and weak data in regression. *John Wiley & Sons, Inc.*

Calzada-Infante, L., Óskarsdóttir, M., & Baesens, B. (2020). Evaluation of customer behavior with temporal centrality metrics for churn prediction of prepaid contracts. *Expert Systems with Applications*, *160*. https://doi.org/10.1016/j.eswa.2020.113553

Cenggoro, T. W., Wirastari, R. A., Rudianto, E., Mohadi, M. I., Ratj, D., & Pardamean, B. (2021). Deep Learning as a Vector Embedding Model for Customer Churn. *Procedia Computer Science*, *179*, 624–631. https://doi.org/10.1016/j.procs.2021.01.048

Coussement, K., Lessmann, S., & Verstraeten, G. (2017). A comparative analysis of data preparation algorithms for customer churn prediction: A case study in the telecommunication industry. *Decision Support Systems*, *95*, 27–36. https://doi.org/10.1016/j.dss.2016.11.007

David, M. E., D. F. R., & D. F. R. (2009). the Quantitative Strategic Planning Matrix (Qspm) Applied to a Retail Computer Store. *The Coastal Business Journal*, *8(1)*, 42–52.

Fred R. David. (1997). Strategic Management. *Prentice Hall Inc.*

Ghozali, I. (2016). Aplikasi Analisis Multivariete Dengan Program IBM SPSS 23. *Badan Penerbit Universitas Diponegoro*.

Ibrahim, OM. (2013). A comparison of methods for assessing the relative importance of input variables in artificial neural networks. *Journal of Applied Sciences Research*, *9(11)*, 5692–5700.

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An introduction to statistical learning. *Springer.*, *Vol. 112.*

Jorion, P. (2007). Value at Risk: The New Benchmark for Managing Financial Risk. *3rd Ed., McGraw-Hill, New York.*

Khan, Y., Shafiq, S., Naeem, A., Hussain, S., Ahmed, S., & Safwan, N. (2019). Customers churn prediction using Artificial Neural Networks (ANN) in telecom industry. *International Journal of Advanced Computer Science and Applications*, *10*(9), 132–142. https://doi.org/10.14569/ijacsa.2019.0100918

Lu, N., Lin, H., Lu, J., & Zhang, G. (2014). A customer churn prediction model in telecom industry using boosting. *IEEE Transactions on Industrial Informatics*, *10*(2), 1659–1665. https://doi.org/10.1109/TII.2012.2224355

Óskarsdóttir, M., van Calster, T., Baesens, B., Lemahieu, W., & Vanthienen, J. (2018). Time series for early churn detection: Using similarity-based classification for dynamic networks. *Expert Systems with Applications*, *106*, 55–65. https://doi.org/10.1016/j.eswa.2018.04.003

Pamungkas, N. P. (2018). *Analisis Risiko Return Saham Sub Sektor Telekomunikasi di Indonesia Menggunakan Metode Cvar Dengan Pendekatan Armax Dan Variasi Garchx*. Institut Teknologi Sepuluh Nopember.

Pendharkar, P. C. (2009). Genetic algorithm based neural network approaches for predicting churn in cellular wireless network services. *Expert Systems with Applications*, *36*(3 PART 2), 6714–6720. https://doi.org/10.1016/j.eswa.2008.08.050

Rockafellar, R. T., & Uryasev, S. (2002). Conditional value-at-risk for general loss distributions. *Journal of Banking & Finance, 26*, 1443–1471.

Shukla, V., Prashar, S., & Pandiya, B. (2021). Is price a significant predictor of the churn behavior during the global pandemic? A predictive modeling on the telecom industry. *Journal of Revenue and Pricing Management*. https://doi.org/10.1057/s41272-021-00367-2

Suhardi. (2011). Quantitative Strategic Planning Matrix (QSPM). *STIE Semarang, 3 Number 1*.

Sulikowski, P., & Zdziebko, T. (2021). Churn factors identification from real-world data in the telecommunications industry: Case study. *Procedia Computer Science*, *192*, 4800–4809. https://doi.org/10.1016/j.procs.2021.09.258

Verbeke, W., Dejaeger, K., Martens, D., Hur, J., & Baesens, B. (2012). New insights into churn prediction in the telecommunication sector: A profit driven data mining approach. *European Journal of Operational Research*, *218*(1), 211–229. https://doi.org/10.1016/j.ejor.2011.09.031

Wells, A., & Billings, K. (n.d.). *30 Multichannel.com VIEWPOINT*.

To Cite This Article: Puspitasari, A., Masruroh, N.A. (2024). Reducing Customer Churn for XL Axiata Prepaid: Factors and Strategies. *Journal of Industrial Engineering and Education*, 2(1), 83-107.