Hyper-Segmentation Lapser MyTelkomsel Apps Using K-Means Clustering to Increase Data Package Purchases in Area 3 - East Java, Central Java - DIY, Bali Nusa Tenggara

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Abstract

Telkomsel is currently working to enhance the basis of the digital business by pursuing digital transformation. Given the intense competitiveness in the digital telecommunications industry, this is a crucial task. MyTelkomsel Apps, a self-service digital channel, was introduced by Telkomsel on March 25, 2016, as evidence of the company's digital transformation. MyTelkomsel Apps streamlines the purchasing of credit, data packages, kartuHalo bill payments, and exchange point self-service for Telkomsel customers. However, there is still a low conversion rate in the MyTelkomsel Apps between active users (users of the app) and package users (purchasers of the product). There are active customers who previously actively purchased products but do not currently do so on MyTelkomsel Apps, or what is known as MyTelkomsel Lapser, which is one of the causes of the poor conversion rate. Therefore, the issue at hand today is how to reactivate MyTelkomsel Lapser so they can renew their product to MyTelkomsel Apps. In order for Telkomsel to offer tailored treatment to recover lapsed transactions in MyTelkomsel Apps, the goal of this research is to give Telkomsel knowledge into the precise profile of MyTelkomsel Apps lapsers. 2.206.636 clients are lapsers as of March 2023. The decision tree algorithm is used to predict lapsers who are in the high prospect group to become non lapsers and The K-Means Cluster algorithm is used to create lapser segments from 2.206.636 lapsers based on relevant variables that have been determined, and in one data set with a period of March 2023. There are 70 variables made up of 1 geographic variable, 8 psychographic variables, and 61 behavioral variables. 1.914.232 lapsers are collected from the data cleansing procedure, which may then be processed to separate them into 20% testing data and 80% training data. With a model accuracy of 97.25%, it is predicted that 45,116 (2.35%) consumers will make purchases at MyTelkomsel and 1.869.116 (97.64%) customers will stay lapser after the variables are discovered and the lapser data is processed using the decision tree method. The top 5 significant variables from the model are the number of data package purchases made through the MKIOS channel, the UMB channel, acquisition-type purchases, physical voucher purchases, and transaction-type purchases of data packages. Furthermore, using the K-Means Cluster technique, 45.116 consumers are divided into clusters based on the top 5 important variables. The silhouette index for these 45.116 high-prospect clients is divided into 3 clusters, with n_cluster = 3 having the biggest value (0.78), compared to the other n_cluster. Low Data User (94.89%), Medium Data through UMB Channel (4.14%), and Physical Voucher User with Medium ARPU (0.97%) are the 3 clusters that were formed.
Telkomsel can perform behavioral targeting for the three clusters based on the prediction model & clustering results to give tailored product gimmicks.

Keywords
Market Segmentation, Behavioral Targeting, K-Means Clustering

1. Introduction

Naturally, in the digital age, the telecommunications industry can not only be supported by a broad and robust network coverage, but reliable digital services and apps are one of the crucial factors to address the various needs of customers. To meet customer demand for credit or data package purchases directly from their mobile phones, the three telecom carriers are striving to create self-service digital channels. As a self-service digital channel, XL, Indosat, and Telkomsel all introduced their respective MyXL Apps, MyIm3 Apps, and MyTelkomsel Apps. To grow and keep their market dominance in Indonesia, the three telecom carriers must constantly innovate in digital channels. Telkomsel is the largest telecommunication service provider in Indonesia with cellular subscribers as of December 2021 reached 176 million for prepaid and postpaid subscribers (PT Telekomunikasi Selular, 2021). On March 25, 2016, Telkomsel has commercially launched MyTelkomsel Apps as a digital channel that aims to provide convenience to its customers in online self-service. The service consists of:

1. Check the remaining balance & quota package (data, voice, SMS & international roaming);
2. Check kartuHALO billed & billed history several months in advance;
3. Purchase data package, voice, SMS & international roaming for own number or any other person;
4. Purchase credit for prepaid number alone or any other person;
5. Check the number of TELKOMSEpoints;
6. TELKOMSELPoint merchant info & location;
7. Redeem TELOMSELpoint;

MyTelkomsel Apps is one of Telkomsel's primary areas of focus for application development and is anticipated to be a powerful digital corporation. The creation of MyTelkomsel Apps serves two purposes: first, to meet customer demands; second, to increase consumer adherence to Telkomsel as a telecommunications provider. In Indonesia, MyTelkomsel Apps is only one of several digital channels that participate in the telecommunications sector by offering services to purchase data packages and top up credit for prepaid lines. Other digital channels include Tokopedia, Shopee, Bukalapak, Dana, and others.

Currently MyTelkomsel Apps can be installed in all smartphones both Android and IOS based with the number of active users as of December 2022 reached 7.02 million customers both prepaid and postpaid. MyTelkomsel Apps service has transformed the customer behavior towards a more digital with self-service & online transaction where the package users & revenue of this service during 2022 trend continues to increase by breaking the figure of Rp 345 Billion from 3.99 million package user.

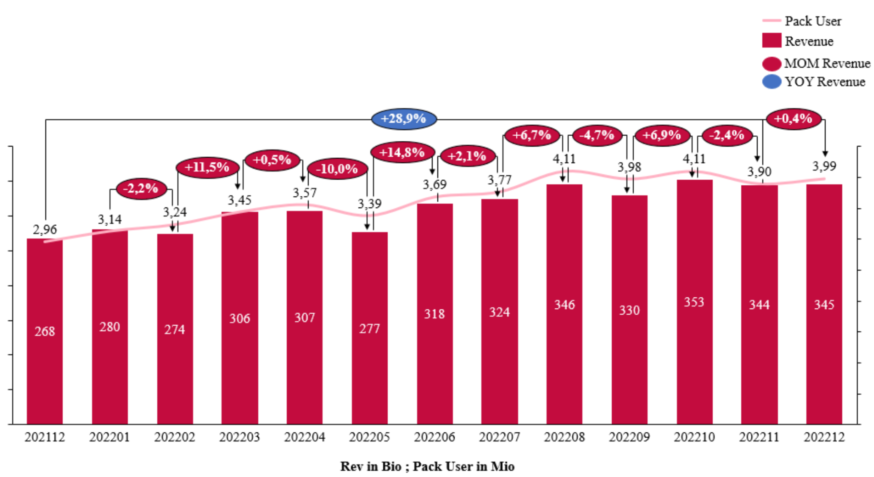

Figure 1. Trend Package User & Revenue MyTelkomsel Apps

Currently Revenue from MyTelkomsel Apps contributes positively, as evidenced by the steady rise in revenue from December 2021 to December 2022. According to Figure 1, MyTelkomsel Apps revenue in December 2022 was 345 Billion, with MOM absolute revenue of 1.23 Billion and YOY absolute revenue of 28.9 Billion. The number of package users has a significant impact on the magnitude of revenue growth and conversion rate. Lapsers are customers who buy data packages through MyTelkomsel Apps but do not repurchase them within a month. More measures are required to prevent lapsers since the more lapsers there are, the lower MyTelkomsel's revenue will be. Figure 2 displays the potential package users and conversion rate in the absence of lappers. If lapsers in December

2022 are converted back to package users, it can be observed that package users will increase with a CR of 88.0% and revenue will reach 405.3 M with a penetration of 96.5% of the objective.

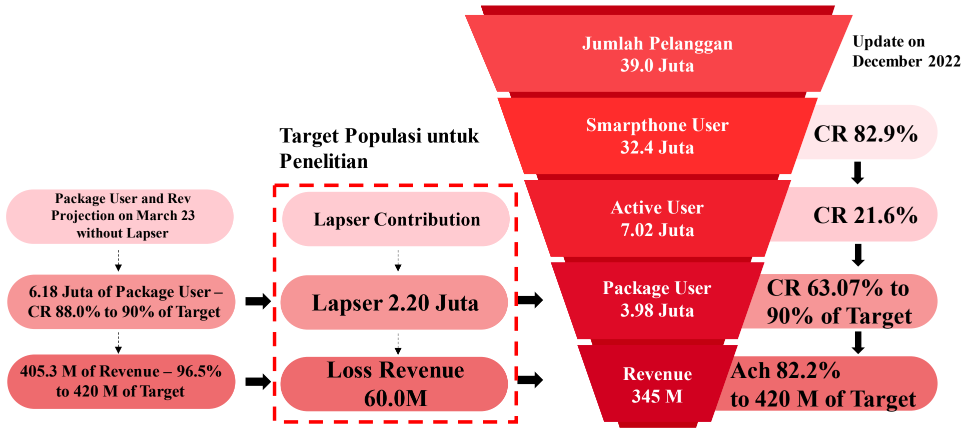

Figure 2. Conversion Rate & Achievement to Target of MyTelkomsel Apps

It is necessary to find a strategy for achieving this goal that focuses on lowering the number of lapsers. To make it simpler to analyze the behavior and preferences of lapsers for each segment so that the action plan taken to reactivate lapsers is on target, MyTelkomsel Apps lapsers who are predicted to make purchases in MyTelkomsel Apps can be divided into several segments according to demographic variables, psychographic variables, and behavioral variables. Focusing on company objectives, making the most of the resources employed for analysis, and offering focused business solutions all depend on this.

1.1. Objectives

This research aims to:

1. Knowing what factors have a substantial impact on lapser decisions to repurchase data packages at MyTelkomsel Apps was one of the research issues that had been raised earlier.
2. Knowing the profile of MyTelkomsel Apps lapser
3. Understanding the characteristics and profile of the segment that is designed to make purchases in MyTelkomsel Apps, and in this case, treatment through product determination in accordance with the lapser segment profile, to determine what sort of treatment is required to return lapsers.

2. Basic Theory

1. Core Marketing Concept

One of the key elements that affects a company's ability to successfully sell products and services is marketing. Marketing seeks to provide clients with value in order for them to be satisfied with their decision to use the goods and services offered. Marketing is more than just the buying and selling of goods and services. According to the book (Kotler, Armstrong, Harris & He, 2020), marketing is a process through which businesses create value for customers and forge close bonds with them in an effort to get value from them in return. To explain this definition, the following important terms in core marketing concept (Kotler, Armstrong, Harris & He, 2020), consist of:

- Needs, wants and demands
- Target Markets, Positioning & Segmentation
- Offering & Brands
- Marketing Channel
- Paid, Own and Earned Media
- Impression and Engagement
- Value and Satisfaction
- Supply Chain
- Competition
- Marketing Environment

2. Marketing Mix

A business must create a strong competitive marketing plan in order to compete in the market. It is feasible for the company's products and services to be positively welcomed by the market by appropriately defining the marketing mix concept. The marketing mix, according to (Kotler, Amstrong, Harris, & He, 2020), is a collection of promotional instruments that can be strategically managed to elicit responses from target markets. Product, pricing, place, and promotion are the four Ps that make up the marketing mix (Kotler, Amstrong, Harris, & He, 2020). The following is a description of the marketing mix (Figure 3):

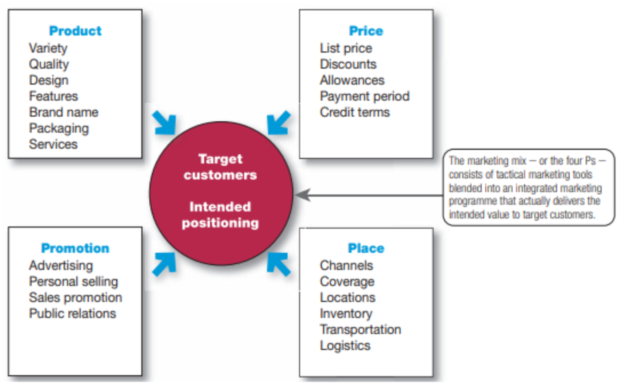

Figure 3 Marketing Mix

3. Personalized Marketing

The goal of personalization is to cater to the specific demands of each consumer when offering products and services. Because of this, management is included as a new component to the marketing mix, and personalization becomes more significant in marketing strategy. The new marketing mix 8Ps are made up of the following: product, price, location, promotion, personnel, tangible assets, and processes (Goldsmith, 1999). Additionally, personalized marketing is the use of technology and consumer data to tailor electronic commerce interactions between organizations and specific clients, according to (Vesanen, 2005). It will be simpler for businesses to supply goods or services in line with client wants if they use information about customer profiles that is valid and obtained in real-time. Even today, tailored marketing enables businesses to offer clients goods or services they are unaware they require. Naturally, data mining techniques are used to manage customer data. As information technology has advanced, businesses are now able to acquire accurate customer data in real time, manage it using descriptive and predictive analysis to provide insights, and then offer customized goods based on those insights.

4. Market Segmentation

A group of customers with comparable wants make up a market segment (Kotler, Armstrong, Harris, & He, 2020). Marketers must decide which consumer segment to focus on for sales. Geographic, demographic, psychographic, and behavioral characteristics are the four key components that go into market segmentation (Kotler, Armstrong, Harris, & He, 2020).

5. Market Segmentation Level

According to (Keith J, 2016) that there are four levels of market segmentation as follows:

- Mass Marketing
- Market Segmentation
- Niche Marketing
- Direct or One to One Segmentation

According to Kotler (Kotler & Keller, Marketing Management -14/E, 2012), there are 5 important factors to consider while doing market segmentation. These are as follows:

- Measurable
- Substantial
- Accessible
- Differentiable
- Actionable

By using customer data to profile customers who fall into the MyTelkomsel Apps lapser category and identifying high prospect lapsers to return and purchase data packages in MyTelkomsel Apps in accordance with the segmentation formed, the author will apply the concept of Direct or One to One Segmentation in this study.

3. Framework

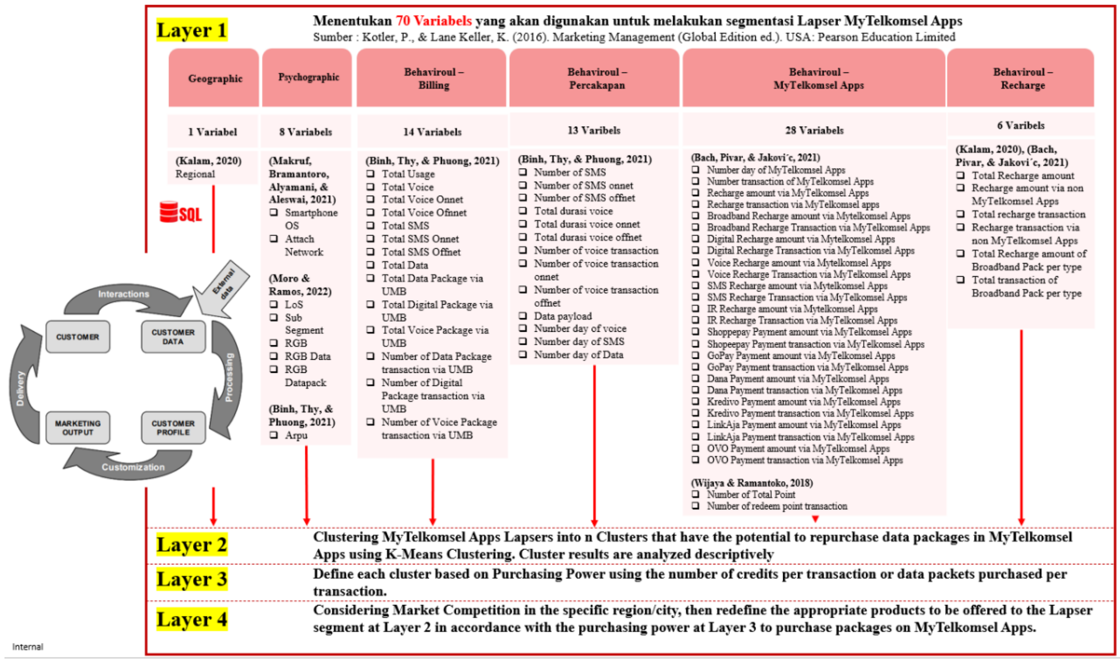

Figure 4. Framework

Layer 1 is where predictor variable that will be used in the segmentation process are identified and gathered. (Kalam, 2020) asserts that knowing the competitive landscape of the telecoms market from a business perspective is the first step in the segmentation process (Figure 4). The three categories of variables used in this study are geographic, psychographic, and behavioral; demographic factors are not used. Demographic variables do not need to be used in research in the telecommunications industry related to customers who are no longer as open to providing personal data like gender, age, career level, occupation, and other preferences, claim (Mirjana Peji'c Bach, Jasmina Pivar, and Boidar Jakovi'c, 2021) and (Tu Van Binh1, Ngo Giang Thy, and Ho Thi Nam Phuong, 2021).

- Layer 2 is a data clustering process using the Data Mining K-Means Cluster algorithm to group lapsers who have the potential to become non-lapsers or make purchases on MyTelkomsel Apps into several segments, with lapsers in the same segment having the same preferences and lapsers in different segments having different preferences from one segment to the next. Currently, the author employs the decision tree algorithm to forecast which lappers may eventually become non-lappers and the k-means algorithm to separate lappers into different groups.
- Layer 3 - Utilizing the quantity of recharges or data packages bought per transaction, purchasing power is calculated. Calculating purchasing power is crucial to understanding how each segment's purchasing power differs from the others. It is anticipated that by figuring out each segment's purchasing power at Layer 2, the products presented would be precisely targeted and bought by MyTelkomsel Apps users through MyTelkomsel Apps.
- Layer 4 - According to the purchasing power created in Layer 3, Layer 4 determines the products that will be made available to MyTelkomsel Apps lapser.

4. Discussion

4.1 Research Flow

In this study, the researcher highlighted data mining based on CRISP-DM (The Cross-Industry Standard Process for Data Mining) where the process is not rigid and the results of one stage will be input for the next stage. According to (Chapman, et al., 2000) that the process in data mining consists of 6 levels as follows (Figure 5):

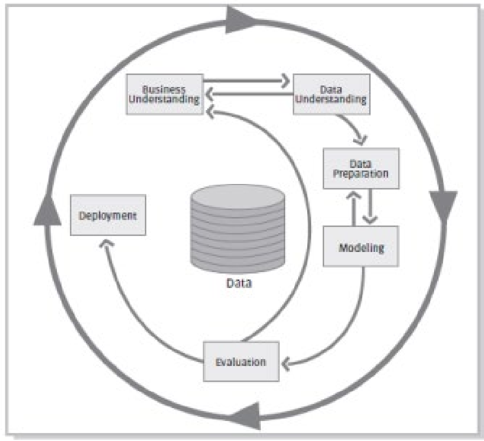

Figure 5. The Cross-Industry Standard Process for Data Mining

Source: (Vesanen, 2005) *What is personalization? A literature review and framework. Helsinki, Finland: HSE Print*

4.1.1 Business Understanding
In this early stage, the activities are focusing on the objectives and business requirement then turn it into data mining problems and initial design to achieve the goals.

4.1.2 Data Understanding
In this stage begins with data collection and proceeds with the activity of data understanding, data quality, discovering the initial insight of the data.

4.1.3 Data Preparation
In this step includes all activities performed to build a data set from raw data. This activity is done many times include making tables, variable selection, cleaning data as an analytics based table for the purposes of making statistical modeling. Data sets were divided into 2 groups randomly in the form of 80% for training data set and 20% for testing data set. Training data set will be used as data source for building model while model formed will be evaluated using testing data set.

4.1.4 Modelling
At this stage, various statistical modeling techniques are selected and applied, and the variables are calibrated optimally. There are usually some statistical modeling techniques for the same type of data mining problem. Some statistical modeling techniques have specific requirements in the form of data. Therefore, returning to the data preparation stage is often necessary. In this study, the researcher use decision tree because it is used to predict the value of the target variable in the form of binary (0 or 1) by using variable input with numeric type. After purchasing score has been formed by using decision tree, the researcher then building customer profile of the customers who likelihood to purchase data package in MyTelkomsel Apps by using clustering technique (K-Means).
model formed will be evaluated using testing data set.

4.1.5 Evaluation & Development
At this stage, statistical modeling has been established with an accuracy that meets the needs of answering business problems that have been defined previously.

4.2 Data Population
The whole population of 2.20 million Telkomsel prepaid subscribers who fall within the MyTelkomsel Apps lapser category as of December 2022 is used in this analysis (Table 1).

Category	Population	%Sample	Pembulatan
Jawa Tengah	886,114	95%	841,809
Jawa Timur	942,456	95%	895,334
Bali Nusa Tenggara	378,066	95%	359,163
Total	2,206,636		2,096,306

Table 1. Population & Sample

4.2.1 Build the Model

The author selected data at random from 500,000 customers who lapser MyTelkomsel Apps and 500,000 users who not lapser. SQL database is used to obtain the data. One million customers' worth of data were randomly selected. The following table uses analytics to create a prediction model using a decision tree algorithm with a total of 1,000,000 consumers. These data are divided into 20% of testing data set and 80% of training data set (Table 2).

Lapser Status	Description	Subs	%Sub
0	*NonLapser*	50.000	50%
1	*Lapser*	50.000	50%
Total		**1.000.000**	**100%**

Table 2. Analytic Based Table

4.3 Predictive Analytics

In analyzing the results of this study using decision tree predictive analytic, the researcher will create a confusion matrix as in Table 3. Each value of the confusion matrix is obtained from the model test results.

		Actual Score	
	Total Population	Purchase	Not Purchase
Predicted Score	Purchase	TP (*True Positive*)	FP (*False Positive*)
	Not Purchase	FN (*False Negative*)	TN (*True Negative*)

Table 3 Confusion Matrix

True positive rate (TPR) or *sensitivity* = $\frac{\text{TP}}{\text{TP+FN}}$

True positive rate (TNR) or *spesificity* = $\frac{\text{TN}}{\text{FP+TN}}$

Accuracy (ACC) = $\frac{\text{TP+TN}}{\text{Population}}$

By applying decision tree equation to 70 numeric variables, below the result of predictive modeling (Table 4):

		Actual	
	Total Population	Non Lapser	Lapser
Prediction Result	Non Lapser	97.035	2.965
	Lapser	2.525	97.475

Table 4. Confusion Matrix of Testing Data

Accuracy : 97.25%
Sensiitivity : 97.04%

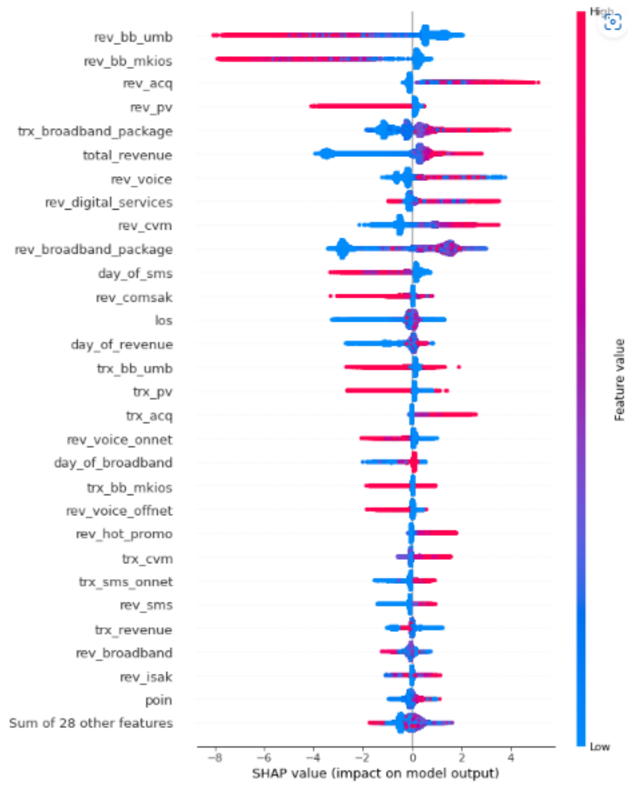

Figure 6. Shap Value of the Variable

The influence of factors on the developed lapser model is shown in Figure 6. The lapser predictions' likelihood of becoming non-lapser increases with increasing shap values, which are represented on the X axis and indicate the influence of variables on prediction outcomes. The Y-axis represents the feature value, and the redder the line, the more strongly the feature influences the outcome of the prediction.s. rev_bb_umb, rev_bb_mkios, rev_acq, rev_pv, and trx_broadband_package are the top 5 variables that are thought to have the greatest influence.

- A variable called rev_bb_umb indicates the dollar amount of data package purchases made via the UMB channel. The blue line points to the right, showing that the likelihood of a MyTelkomsel Apps lapser becoming a non-lapser increases as the value of this variable decreases.
- The amount of rupiah spent on data package purchases made through the MKIOS channel is specified by the rev_bb_mkios variable. The blue line goes to the right, showing that the likelihood of a MyTelkomsel Apps lapser becoming a non-lapser increases with decreasing value of this variable.
- The rev_acq variable is a variable that specifies how much money was spent on acquisition data packages. The red line goes to the right, showing that the likelihood of MyTelkomsel Apps lapsers becoming non-lapsers increases as the value of this variable rises.
- The price of acquiring a physical voucher data package is specified by the variable rev_pv. The red line slopes to the left, showing that the likelihood that a MyTelkomsel Apps lapser will become a non-lapser decreases as the value of this variable increases.
- The number of data package purchase transactions is defined by the variable trx_broadband_package. The red line indicates that the probability that a MyTelkomsel Apps lapser will become a non-lapser increases as the value of this variable increases.

Based on result of confusion matrix, researcher applied it to all populations of lapser MyTelkomsel Apps by 2.206.636 customers. There were identified 45.116 customers as highly likelihood to purchase package in MyTelkomsel Apps based on result of predictive modeling using decision tree.

4.4 Customer Segmentation and Behavioral Targeting

4.4.1 Customer Segmentation

This research uses the elbow-method algorithm, which analyzes the value or percentage of a number of k values (clusters) that have been examined and form an elbow at a location, to ascertain the number of legitimate clusters. The graph of the cluster relationship with decreasing error is represented by the value of k in the elbow combination with k-means. The graph gradually declines as the value of k is increased until the outcome stabilizes. The elbow technique process is shown in phyton in Figure 7. An elbow line is generated at point 2 on the x-axis, as can be seen. Point 2 indicates that there are up to three clusters.

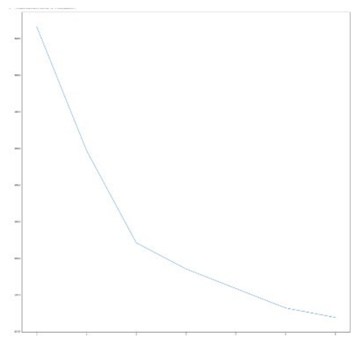

Figure 7. Elbow Method

The Sum of Square Error (SSE) method is used to assess the number of clusters k that emerged from testing with K-means. SSE uses the sum of the squares of each cluster member toward the cluster's center to validate clusters. The following is the SSE in phyton:

```
For n_clusters=2, the silhouette score is 0.7425506074734838
For n_clusters=3, the silhouette score is 0.78569352345261
For n_clusters=4, the silhouette score is 0.7253547947254755
For n_clusters=5, the silhouette score is 0.6583788491126933
For n_clusters=6, the silhouette score is 0.6804607603359694
For n_clusters=7, the silhouette score is 0.68888101119255
For n_clusters=8, the silhouette score is 0.716818847231926
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Figure 8. SSE

The highest silhouette score was found in the analysis shown in Figure 8 at n_cluster = 3 of 0.785. The better the cluster value, or the closer it is to 1, the higher the silhouette score. This silhouette score agrees with the elbow method results, where the elbow method diagram in this study displays an elbow line at n_cluster = 3, the most ideal number of clusters. These the result of K-Means clustering in 45.116 lapsers with 3 clusters.

Cluster	Nama Cluster	Jumlah Lapser	Ukuran Cluster	rev_bb_umb (Rp)	rev_bb_mkios (Rp)	rev_acq (Rp)	rev_pv (Rp)	trx_broadband_package (n)
Cluster-1	*Low Data User*	42,810	94.89%	614	-	-	146	2
Cluster-2	*Medium Data User thru UMB Channel*	1,870	4.14%	68,630	-	-	250	4
Cluster-3	*Physical Voucher User with Medium ARPU*	436	0.97%	1,145	-	-	40,729	7

Figure 9. Result of the Cluster

- Cluster-1: Customers who fall into the category of "Low Data User" are those who transact data packages infrequently, with the lowest rev_bb_umb value and the fewest number of trx_broadband_package transactions per month (Figure 9). To determine whether these consumers are still actively transacting or simply using Telkomsel as a backup card, it is required to examine the overall credit usage for a month in terms of data, digital, phone, and SMS.
- Cluster-2: Customers that actively transact data packages through the UMB channel and have a monthly ARPU of Rp 68,630 are referred to as Medium Data Users through UMB Channel. These consumers are categorized as high impact customers who can be redirected to utilize My Telkomsel Apps. 4 transactions for the purchase of data packages occur per month. Neither Cluster-1 nor Cluster-2 use physical vouchers very frequently.

- Cluster-3: Medium Physical Voucher User With an average consumption of Rp 40,729, the greatest average physical voucher usage among the other clusters. Seven times each month, this cluster performs data package transactions. According to estimates, cluster-3 consumers frequently travel or live far from Telkomsel outlets, making it more common for them to purchase significant quantities of physical vouchers at those places and then use them elsewhere.

4.4.2 Behavioral Targeting

Based on the outcomes of the prediction model and clustering model, Telkomsel can do behavioral targeting in order to deliver more tailored forecasts. An illustration of a gimmick for each cluster in accordance with its profile is given below (Figure 10):

	Profile of Lapser							Offering	
Segment	**Revenue All (Rp)**	**Revenue Data (Rp)**	**Revenue Digital (Rp)**	**Transaksi Voice**	**Poin**	**Payload (GB)**	**Personalized Campaign**	**Product Offer**	**Gimmick**
Low Data User	87	79	4	12	45	11	Low Data User + Free Telp	Rp 89.000,- 29 GB Quota | 29 GB Apps | 39 GB Youtube |	Free Telp 30 minutes
Medium Data User thru UMB Channel	163	150	9	10	74	21	High Data Package + Video OTT	Rp 153.000,- 53 GB Quota | 53 GB Apps | 61 GB Youtube |	Free Disney Subscription + 25 GB Video Quota
Physical Voucher User - Medium ARPU	137	127	7	4	73	14	Medium Data User + Video OTT	Rp 133.000,- 45 GB Quota | 45 GB Apps | 61 GB Youtube |	Free Disney Subscription + 15 GB Video Quota

Figure 10. Behavioral Targeting Design

- The Low Data User Cluster, which has the largest voice transaction compared to the other clusters with an average monthly speech transaction of 12 times and an average payload of 11 GB. Customers in this cluster will have the option of purchasing a Monthly Data Package for Rp 89,000 that includes a total main quota of 29 GB, as well as an additional 29 GB of Apps Quota, 39 GB of Youtube Quota, and a 30-minute call bonus that is only available through MyTelkosmel Apps. Customers are anticipated to be drawn to this offer since it provides a greater data limit at a price that is often not that different from the average history of customers' monthly fees.
- With an average package use of Rp 150,000, an average payload of 21 GB, and an average digital revenue of Rp 9,000, Cluster Medium Data User via UMB Channel has the highest average digital revenue when compared to the other clusters. This cluster will receive a Monthly Data Package offer for Rp 153,000 with a total main allowance of 53 GB, additional 53 GB for apps and 61 GB for Youtube, as well as a bonus of a Free Disney Subscription and 25 GB for videos, both of which are, of course, exclusively available on MyTelkomsel Apps. Customers are anticipated to be drawn in by the value of this promotion to MyTelkomsel Apps purchases. A digital quota is assigned to this cluster customer.
- Physical Voucher User Medium Arpu cluster with an average payload of 14 GB, average data package usage of Rp 127,000, and an average digital revenue of Rp 7,000. This cluster will receive a Monthly Data Package for Rp 133,000 with a total main quota of 45 GB, an extra 45 GB Apps Quota, 61 GB Youtube Quota, as well as a bonus of Free Disney Subscription and 25 GB Video Quota that is, of course, only available at MyTelkomsel Apps. This promotion is meant to entice customers to buy things from MyTelkomsel Apps.

5. Conclusion

Decision Tree addresses the issue of predicting a target variable that may be binary or binomial (such as 1 or 0, yes or no) using predictors or attributes, which may be numeric. By applying it to all populations of lapser MyTelkomsel Apps by 2.206.636 customers. There were identified 45.116 customers as highly likelihood to purchase package in MyTelkomsel Apps and 4.14% of them came from Medium Data Users through UMB Channel segment with average data revenue per user reached IDR 150.000. Top 5 significant variables that affected customers to purchase package in MyTelokmsel Apps are data recharge amount thru UMB and MKIOS Channel, recharge of acquisition pack type and physical voucher type and number of broadband package transaction. Researcher creates design of behavioral targeting based on result from predictive modeling & customer segmentation to offer product based on customer behavior.

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