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Analysis of the impact of Customer Value Management (CVM) on increasing Cellular Packet Telkomsel (Study case: PT Telkomsel)

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Abstract

Purpose: This study aims to analyze the impact of the Customer Value Management (CVM) program supported by machine learning on increasing customer purchases of Telkomsel cellular data packages, as well as identifying the key behavioral factors influencing purchasing decision.

Methodology/approach: This research employs a quantitative explanatory approach using big data analytics. The dataset consists of customer transaction records over a three-month period (January–March 2023), involving 5.7 million customer data points. A supervised machine learning classification model was developed using the CatBoost Gradient Boosting Decision Tree (GBDT) algorithm to predict customer purchasing propensity, supported by Focus Group Discussions (FGD) with subject-matter experts.

Results/findings: The CatBoost model achieved an accuracy of 86% in predicting potential lapsers. The test-and-learn campaign based on CVM personalization resulted in a 6.55% increase in take-up rate and generated a revenue uplift of IDR 141.6 million. The most significant factors influencing purchases were monthly data package revenue, frequency of data usage within specific price ranges, and total monthly data revenue.

Conclusion: The findings confirm that CVM implementation supported by machine learning effectively enhances personalized marketing, improves customer targeting, and increases purchasing performance at PT Telkomsel.

Limitations: This study is limited to a single company, a three-month observation period, and the use of one machine learning algorithm.

Contribution: This study contributes empirical evidence on the effectiveness of integrating CVM and CatBoost-based machine learning in large-scale telecom marketing to optimize customer value and revenue growth.

Keywords: *Behavior, Big Data, Customer Value Management, Machine Learning, Propensity*

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1. Introduction

Marketing is defined as the activity, set of institutions, and processes for creating, communicating, delivering, and exchanging offerings that have value for customers, clients, partners, and society (Wahyudi, Puspita, & Ramadhani, 2021). Marketing is also a process of introducing products or services so that they become known to the public, starting from strategy formulation to consumer perceptions (Suka & Lubis, 2019). Marketing provides value to customers. Marketers communicate these benefits to customers through value propositions, which are market offerings that fairly and accurately summarize the value that customers will realize if they purchase a product (Eggert, Ulaga, Frow, & Payne, 2018).

Customer Value Management (CVM) is a process of managing and maximizing value or benefits at every stage of the customer journey, from the first interaction to the last. One of the main objectives of Customer Value Management is to create the best experience at every customer interaction in accordance with customer needs, so that customers develop a positive perception of the product and the price offered (Kumar & Reinartz, 2016). In contrast, Customer Value Management provides insights into customer interactions on an integrated platform. These insights facilitate business processes to understand customer interests and needs (Wedel & Kannan, 2016). Consequently, the sales process can be accelerated through mutually beneficial value propositions for both buyers and sellers. Buyers obtain products that best suit their needs, allowing them to make purchasing decisions more quickly throughout their buying journeys. This directly affects product sales. CVM specifically focuses on literature that explores the determinants of customer retention, expansion, and lifetime value.

Following recent developments in the marketing literature, customer value is widely recognized as one of the most important metrics in customer management. Moreover, because customers possess different value levels, companies can allocate their resources efficiently among customers (Lemon & Verhoef, 2016). This further emphasizes the importance of Customer Value Management within organizations. CVM requires the optimization of customer-based value within a company. CVM focuses on the individual-level data analysis of prospects and customers. The resulting information is used to acquire customers and influence customer behavior through marketing strategies developed in such a way that the value of all current and future customers can be optimized (Rosário & Dias, 2023).

PT Telkomsel has implemented a Customer Value Management approach in the offers provided to its customers, enabling greater customer benefits by allowing customers to receive package offers that match their needs based on transaction behavior trends. This approach also provides marketing opportunities by increasing purchases among relevant customers using Machine Learning techniques. The MyTelkomsel application is one of the approaches used by PT Telkomsel to implement Customer Value Management by delivering personalized offers based on customer behavior, ultimately increasing purchases of Telkomsel products and boosting the company’s revenue. This personalized marketing process enables the delivery of services or products tailored to individual customer requirements.

Thus, personalization becomes an additional element within the marketing mix, which consists of tools used by organizations to create the desired response among targeted consumers, namely the 4Ps: Product, Place, Price, and Promotion strategies (Padual, Ong, German, & Gumasing, 2024). Consequently, research on user and transaction data can enhance revenue generation through the CVM approach at PT Telkomsel. Customer Value Management has been implemented since 2020, beginning with the Data Management Platform (DMP) program, which produces several data models for behavior-based marketing programs. A DMP is defined as a technology that functions to collect and organize data from various sources and is generally used for digital marketing activities. A DMP is an application used to collect and manage data, create customer profiles, store data, and facilitate various marketing activities (Boch et al., 2022).

Currently, many customers are unable to find products that match their needs and their ability to pay. Consequently, customers adopt a more personal approach by selecting products that most closely align with their preferences. This situation creates the potential for customers to leave without making a purchase if they feel that the available products do not match their needs (Boateng, 2016). From a managerial perspective, limited understanding of customers leads to difficulties in collecting and analyzing relevant customer data to understand their needs, preferences, and behaviors. Without strong customer insights, it is difficult for managers to develop appropriate strategies to increase customer value (Stremersch, Cabooter, Guitart, & Camacho, 2025).

In addition, data and system integration involving customer data from various sources, such as customer databases, customer interactions, and online behavioral data, poses managerial challenges when there are difficulties in integrating data across different systems or when existing systems lack the capability to efficiently collect, manage, and analyze data (Wamba et al., 2017). This condition can hinder CVM program implementation and limit managers' ability to make decisions based on comprehensive information. Therefore, the Customer Value Management (CVM) program performs predictive processes based on transaction data and generates recommended offerings for customers through suitable product combinations that are tailored to their needs. Based on the above background, the research problems are formulated as follows.

1. How does the use of CVM impact the increase in customer purchases of mobile services?
2. What factors most strongly influence customer purchasing behavior in relation to the value received from mobile service providers?
3. How does the application of technology and data analytics in CVM affect the increase in customer purchases of mobile services?

1.1. Research Objectives

Based on the research problems presented above, this study has the following objectives:

1. To analyze the impact of CVM implementation on increasing customer purchases of mobile services.
2. To analyze the factors that most strongly influence customer purchasing behavior in mobile services.

To evaluate the use of technology in data analysis within the CVM program that may affect the increase in customer purchases of mobile services.

2. Literature review

2.1. Understand Consumers' Value Need

Information is the fuel that drives the engine of marketing decision-making, and poor input information generally leads to poor output in the form of ineffective decisions (Purwanti & Lupiana, 2023). By understanding customer needs, marketers can deliver maximum value in accordance with those needs. To understand such needs, marketers must conduct marketing research to identify them. One method of identification is data mining to obtain statistical data that can be analyzed to discover trends and patterns (Atif, Shakir, Nussairi, Mohammed, & Almusawi, 2022). Data mining also opens up opportunities to explore new potential insights into data characteristics. From these data, marketers can interpret, estimate, and even predict customer needs and potential future needs based on customer transaction data. Value-Based Marketing, also referred to as value marketing, is generally understood in two different ways: as a means of communicating values and ethics to customers (an approach more commonly applied in consumer markets) or as a utility-driven marketing approach that emphasizes a unique value proposition for a specific offering (an interpretation more adapted to industrial markets) (Payne, Frow, & Eggert, 2017).

Value-Based Marketing stimulates the perception of ethical dimensions in customer behavior. A specific example of value-oriented marketing is green marketing, which focuses on products and services that provide potential environmental benefits to consumers. The customer value model is based on assessing the costs and benefits of a particular market offering in a given application (Efita, 2023). Depending on conditionssuch as data availability and customer cooperation, suppliers develop value models either for individual customers or for market segments by drawing on data collected from several customers within those segments. This process aims to create a customer perspective that what is being offered is worth what they are paying. This highlights the importance of accurately demonstrating the value of a product or service to customers, as it provides direct solutions to their needs and wants.

2.2. Segmenting, Targeting, and Positioning

According to Homburg, Jozić, and Kuehnl (2017), marketers are responsible for creating value, building relationships with customers, and satisfying their needs. However, in modern societies that are increasingly complex, it is no longer appropriate to assume that everyone has the same need. Understanding customer needs has become more complex due to technological and cultural advancements that have led to market fragmentation. This means that diverse social interests and backgrounds divide consumers into multiple groups with different needs and desires. Because of this diversity, the same product or service does not appeal equally to everyone. This heterogeneity requires marketers to carefully determine the most appropriate strategy to deliver optimal value to their customers. By implementing accurate and highly customized segmentation, marketers can provide the best possible customer experiences. Marketers must balance the efficiency of mass marketing, where the same product is offered to everyone, with the effectiveness that comes from offering each individual what they truly want.

From the firm's perspective, mass marketing is generally less costly, as offering a single product to all customers eliminates the need for separate advertising campaigns and customized product packages. However, customers perceive value differently: from their point of view, the ideal strategy is for firms to offer products that are perfectly tailored to their individual needs even if the offer is not always precise (Bleier & Eisenbeiss, 2015). Segmentation divides a larger market into smaller groups based on one or more value-relevant characteristics. The next step is targeting, in which marketers evaluate the attractiveness of each potential segment and decide which group they will convert into customers. The selected customer group then becomes the target market. The final stage in developing a target marketing strategy is to provide goods or services that meet the unique needs and expectations of consumers within the target segment. Positioning refers to the development of marketing strategies that influence how a specific target segment perceives a product or service compared to competing offerings. To position a brand effectively, marketers must clearly understand the criteria used by target consumers to evaluate competing products and then convince them that their product, service, or organization best fulfills those needs. Moreover, marketers must identify appropriate ways to communicate this positioning to their target markets.

2.3. Customer Value Management

One of the major developments in marketing over the past few years has been the growing importance of customer relationships and the rapid increase in the availability of individual customer data stored in large customer databases (in the form of big data). Companies use customer data to effectively target customers, develop and expand customer relationships, and enhance customer understanding. For example, information obtained through historical customer interactions can be used to learn how to develop more effective customer strategies (Erevelles, Fukawa, & Swayne, 2016). Customer modeling and classification are applied to deliver more specific services tailored to customer needs, with the ultimate goal of creating effective marketing strategies that can increase sales. The increasing availability of customer data has created a highly valuable new research area in marketing science. Customer Value Management (CVM) focuses on analyzing individual-level data on prospects and customers. The information generated is used to acquire customers and to influence customer behavior through marketing strategies developed in such a way that the value of all current and future customers is optimized (Ali & Shabn, 2024). Today, the term "data is the new oil" is widely recognized, and companies rely on data-driven approaches for analysis and decision making.

From a managerial perspective, CVM is a learning system in which customer strategies are continuously improved based on ongoing evaluations of prior strategies. Companies can enhance the value of their customer base by:

1. Acquiring new customers,
2. Increasing customer retention, and
3. Creating customer expansion is the first step.

These three elements must be balanced and coordinated. Companies that focus excessively on customer retention while neglecting customer acquisition at a certain point may encounter difficulties due to the aging of their customer base. In addition, customers' variety-seeking behavior can weaken their customer base.

2.4. Data Mining as a Research Methodology

According to Shu and Ye (2023), data mining is a non-trivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data stored in structured databases. At its most fundamental level, data mining can be defined as the process of discovering or extracting actionable knowledge or information from large amounts of data. Data mining involves the use of statistical, mathematical, and artificial intelligence techniques and algorithms to extract and identify useful information and knowledge (patterns or trends) from large data sets. Data mining represents a new philosophy that encourages the use of data and mathematical models to create and discover new knowledge. It systematically and synergistically integrates capabilities from various disciplines, including statistics, artificial intelligence, machine learning, management science, information systems and databases. By utilizing the collective power of these disciplines, data mining aims to advance the extraction of useful information and knowledge from large repositories. Data mining is the process of transforming data into information and, subsequently, into knowledge. In the context of knowledge management, data mining is the phase in which new knowledge is generated. Knowledge differs significantly from data and information: while data consist of raw facts, measurements, and statistics, information is data that have been properly organized or processed in a timely manner.

Data mining operations employ several specialized computational methods to discover meaningful and useful structures in the data. These computational methods originate from the fields of statistics, machine learning, and artificial intelligence. Data mining coexists and is closely related to several associated fields, such as database systems, data cleansing, visualization, exploratory data analysis (EDA), and performance evaluation (Penta, 2016).

2.4.1. Key Features of Data Mining

Data mining can be further defined by examining its main features and motivations, including the following:

1) Extracting Meaningful Patterns

Knowledge discovery in databases is a nontrivial process for identifying valid, novel, potentially useful, and ultimately understandable patterns or relationships in data to make important decisions. The term "nontrivial process" distinguishes data mining from simple statistical calculations, such as computing averages or standard deviations. Data mining involves hypothesis generation and iterative testing of multiple hypotheses. A key aspect of data mining is the generalization of patterns from datasets. Generalization must be valid not only for the dataset used to observe the patterns but also for new and unknown data. Data mining is also a multi-step process, with each step consisting of a series of tasks that must be performed. The term "novel" indicates that data mining typically involves the discovery of previously unknown patterns. The ultimate goal of data mining is to uncover potentially useful and actionable insights for users.

2) Building Representative Models

In statistics, a model represents the relationships among variables in the data. It illustrates how one or more variables are related to other variables. Modeling involves constructing representative abstractions from observed datasets. For example, a model can be developed using credit scores, income levels, and loan amounts to determine the loan interest rates. To perform this task, we require training data with known values for credit scores, income levels, loan amounts, and interest rates.

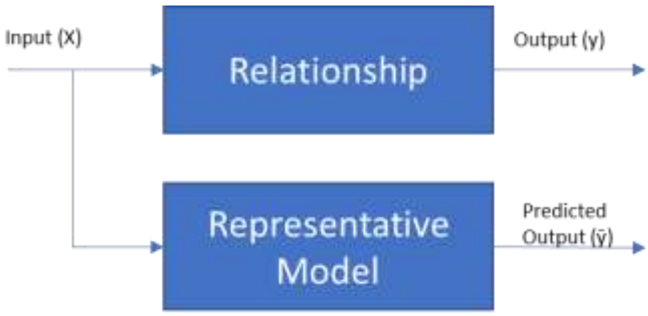

Figure 1. Representative Model of Predictive Analytics

Figure 1 illustrates the inputs and outputs of the representative model. Once a representative model is created, it can be used to predict the interest rate based on all the input values (credit score, income level, and loan amount). In the context of predictive analytics, data mining is the process of building representative models that fit the observed data. These models serve two purposes: first, to predict outputs (interest rates) based on input variables (credit score, income level, and loan amount); and second, to enhance the understanding of the relationships between output variables and all input variables. For example, questions such as whether income level truly matters in determining loan interest rates, whether income is more important than credit score, or what happens when income doubles or credit scores decrease by 10 points can be examined using this data. Model construction in data mining can be used for both predictive and explanatory (descriptive) purposes.

3) A Combination of Statistics, Machine Learning, and Computation

Data mining draws on computational techniques from statistics, artificial intelligence, machine learning, database theory, and pattern recognition to extract useful and relevant information from large datasets. The algorithms used in data mining originate from these disciplines but have since evolved to incorporate more advanced techniques, such as parallel computing, evolutionary computing, linguistics, and behavioral studies. One of the most important prerequisites for successful data mining is substantial prior knowledge of both the data and the business processes that generate the data, known as domain (subject matter) expertise. Similar to many quantitative frameworks, data mining is an iterative process in which practitioners gain deeper insights into patterns and relationships with each cycle of analysis. Data mining combines statistical knowledge, domain expertise, database technologies, and machine learning techniques to extract meaningful and useful information from data. Data mining typically operates on large datasets that must be stored, processed, and computed efficiently. Database techniques combined with parallel and distributed computing play a crucial role in this process.

4) Algorithms

Data mining can also be defined as the process of discovering previously unknown patterns in data using automated, iterative methods. An algorithm is a step-by-step repetitive procedure for transforming inputs into outputs. The application of sophisticated algorithms to extract useful patterns from data distinguishes data mining from traditional analysis techniques. Most of these algorithms have been developed over the past few decades and are widely used in machine learning and artificial intelligence (AI). However, some algorithms are rooted in classical probabilistic Bayesian theory and regression analysis, which originated centuries earlier. These iterative algorithms automatically search for optimal solutions to given data problems. Based on the type of problem, data mining is classified into tasks such as classification, association analysis, clustering, and regression tasks. Each task uses specific algorithms, such as decision trees, neural networks, k-nearest neighbors, k-means clustering, and others. As research in data mining continues to grow, the number of algorithms has increased, although classical algorithms remain the foundation for many data mining applications.

2.4.2. Types of Data Mining

Data mining can be categorized into two main types of learning: supervised and unsupervised learning. Supervised data mining (directed data mining) attempts to infer a function or relationship based on labeled training data and uses this function to map new unlabeled data. Supervised techniques predict the value of an output variable based on a set of input variables. To perform this task, a model was developed from a training dataset in which the values of both the input and output variables were already known. The model generalizes the relationship between the input and output variables and uses this relationship to make predictions on datasets where only the input variables are known. The predicted output variable is also referred to as the class label or target variable. Supervised data mining requires a sufficient number of labeled records for effective model learning. Unsupervised data mining (undirected data mining), on the other hand, uncovers hidden patterns in the unlabeled data. Unsupervised data mining does not involve the prediction of output variables. The objective of this technique is to discover patterns in data based solely on the relationships among the data points themselves. In practical applications, both supervised and unsupervised learning are widely used.

3. Research methods

3.1. Data Collection

To achieve the objectives of this study, the author carried out data collection procedures by submitting a formal request for data usage to the Sub-Directorate responsible for Customer Value Management, namely, the Sub-Directorate of Advanced Analytics and Growth Marketing (AAGM). The data collection steps were as follows:

1. Collecting customer transaction data from billing records.
2. Collecting marketing campaign data through promotional offers made to Telkomsel customers.
3. Interviews and Focus Group Discussions (FGD) were conducted with experts in data processing and marketing from the Business Data Engineering unit to determine appropriate Internet marketing strategies, select machine learning models, and gain insights, supported by literature studies, to serve as a reference in implementing effective marketing strategies through big data–driven offers.
4. Coordinating with the Information Technology department to obtain data on the outputs generated by the analytics tools used.

The available data consist of structured data managed by the IT Directorate under the Subdirectorate of Business Intelligence and Analytics Platforms. The data are stored in a big data infrastructure using Hadoop and several other software systems.

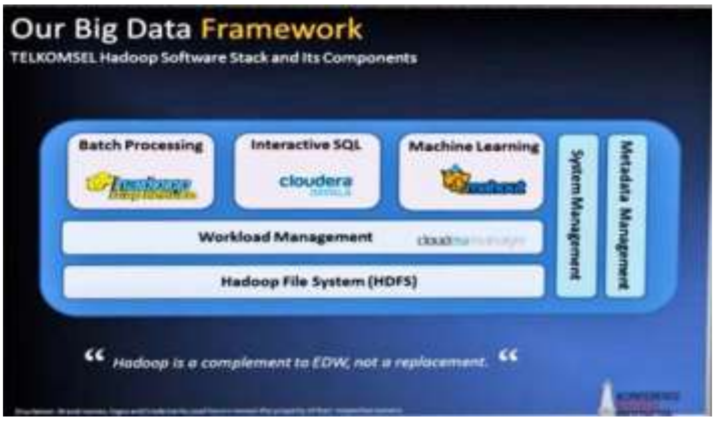

Figure 2. Big Data Framework of PT Telkomsel
Source: Internal Telkomsel, 2023

The data used in this study consist of customer transaction data over a three-month period, from January to March 2023, covering 168 million prepaid (Prabayar) customers of PT Telkomsel (Telkomsel, 2021). These data sufficiently support big data processing for this study using machine learning techniques. Data processing was conducted on PT Telkomsel’s internal servers, and several aggregated results were processed independently by the author for analytical purposes without reducing the essence of the data collected.

3.1.1. Focus Group Discussion (FGD)

Focus Group Discussion (FGD) is a qualitative data collection method used to prepare strategies for quantitative data analysis. According to Bisjoe and Rizal (2018), FGD is defined as “a process of collecting information on a very specific issue through group discussion”. The purpose of the FGD was to explore specific problems efficiently and cost-effectively in relation to the topic under discussion. In this study, the FGD discussed the most effective methods for implementing Customer Value Management at PT Telkomsel. The FGD involved four participants, including the author of this paper. The participants consisted of structural roles, namely one General Manager and two data scientists, who discussed methods, models, and analytical approaches to identify the research problems.

3.1.1.1. FGD Implementation

The FGD was conducted twice, each session lasting 60 minutes, at the PT Telkomsel office on the 15th floor of the Payung Terbuka meeting room. The sessions were held during the stages of strategy formulation and research framework development, as well as during the discussion of the results and conclusion formulation. The FGD was facilitated and moderated by the author, who also participated as a member of the discussion.

3.1.1.2. FGD Layout and Location

Figure 3. FGD Layout and Location
Source: Author's Documentation, 2023

Seating Arrangement:
1. Moderator: Indra Syahputra (Author)
2. General Manager of Business Data Engineering: Umar Fudin
3. Officer of Analytics Dashboard: Dewa Gbs Widnyana
4. Data Scientist: Ngakan Putu Alit Supriyana Putra

3.1.1.3. FGD Questions
The FGD was conducted by preparing several guiding questions to ensure focused and structured discussion. The following questions were prepared before the FGD began:
1. What is the most appropriate method for implementing personalized marketing?
2. What strategies should be applied to implement Customer Value Management within PT Telkomsel?
3. How can the number of takers be increased and lapsers be reduced in the CVM program?
4. What strategies can be implemented to increase revenue using the CVM approach in PT Telkomsel?

3.2. Quantitative Analysis
This study used a quantitative research method. Primary data were obtained by collecting customer transaction data from Telkomsel's database. Quantitative research is often referred to as a traditional, positivistic, scientific, confirmatory method. In contrast, qualitative research is often referred to as a new, post-positivistic, discovery-oriented, interpretive, and qualitative method (Sugiyono, 2017). The two most commonly used research approaches are quantitative and qualitative methods, respectively. The quantitative method is appropriate for studies involving large populations, clearly defined problems, observable and measurable phenomena, and when the researcher aims to test the hypotheses (Ibrahim, Ariyanti, & Iskamto, 2025; Rachman & Ariyanti, 2025). This study uses seven variables: total data usage in monetary value (rupiah), total duration of data usage, total duration of MyTelkomsel application usage, number of campaign offers delivered to customers, number of customers who accepted the offers, and number of customers who rejected the offers. Based on these variables, the researcher developed a learning model using predictive analysis with the CatBoost method to estimate the propensity of customer behavior to purchase a product. This model also identifies variables that significantly increase package sales.

3.3. Data Processing
Data processing in machine learning involves several stages that must be completed before a model can be trained and used for prediction or data classification. The general stages of machine learning data processing are as follows:
1. **Data collection**: The first stage involves Collecting: The relevant data for machine learning. These data may originate from various sources, including databases, text files, sensors, or web scraping.

2. **Data Cleaning**: After data collection, the next step is to clean the data. This process involves the identification and handling of missing values, outliers (data that significantly deviate from the norm), and noise (disturbances in the data). At this stage, data normalization is also performed, such as standardizing date formats, converting measurements into uniform scales, and removing unnecessary special characters.
3. **Data Integration**: If data originate from multiple sources, this stage involves combining data from different sources into a single dataset. This may require adjusting data formats, aligning data schemas, and ensuring consistency among the datasets obtained from different sources.
4. **Feature Selection**: At stage, a subset of the most relevant and significant features or attributes is selected to predict or classify the target data. This process aims to reduce the data dimensionality and eliminate features that do not contribute significantly to the machine learning objectives. Proper feature selection can improve the model performance and help prevent overfitting.
5. Data transformation involves changing the scale of the data or modifying the distribution of the data. For example, if an attribute has a very wide range of values, normalization or standardization is required to ensure that each attribute has a comparable influence on the model.
6. **Dataset Splitting**: The dataset must be divided into training, validation, and testing subsets. The training set was used to train the model, the validation set was used to evaluate and select the best model, and the test set was used to test the performance of the trained model on previously unseen data. Proper dataset splitting is essential to prevent overfitting and obtain an objective estimate of the model performance.

After completing these stages, the data were ready to be used to train the machine learning model.

3.4. Machine Learning

Machine learning is a technology used in the data mining process. Machine learning is a branch of artificial intelligence that focuses on the development of algorithms and statistical models that allow computers to learn from data and experience to perform specific tasks without explicit programming. In machine learning, algorithms and models "learn" from data by identifying patterns and making predictions or classifications based on those patterns. In general, there are three main types of machine learning:

1. Supervised Learning
   In supervised learning, the model is provided with a dataset containing examples that are already labeled or classified. The model learns to associate the input data features with the correct labels or classes. The objective is to learn patterns from the training data so that the model can later make predictions or classifications on the new data.
2. Unsupervised Learning
   In unsupervised learning, the model is provided with an unlabeled dataset. The model attempts to identify patterns and structures in data without external guidance or predefined labels. The objective is to group data into similar clusters or reveal hidden structures within the data.
3. Reinforcement Learning
   In reinforcement learning, the model learns by interacting with its environment. The model receives feedback based on the actions performed in the environment. The objective is to learn to optimize decisions to achieve certain goals by maximizing the rewards provided by the environment.

Machine learning is applied in various fields, including facial recognition, speech recognition, stock price prediction, product recommendation systems, pattern recognition, and sentiment analysis. In practice, machine learning involves data preparation, model training, model performance evaluation, and continuous adjustment to achieve optimal results.

3.5. Catboost

CatBoost is a machine-learning algorithm developed by Yandex. CatBoost stands for "Categorical Boosting," referring to its strong capability to handle categorical or qualitative variables within a dataset. The algorithm is specifically designed to address challenges related to categorical variables and delivers strong performance across various machine learning tasks, including classification and regression tasks. Several key features and advantages of CatBoost are as follows.

1. **Handling of Categorical Variables**: CatBoost automatically processes categorical variables in a dataset without requiring manual conversion or encoding. The algorithm applies techniques such as Target Encoding and Ordered Target Encoding to transform categorical variables into informative numerical representations.
2. **Automatic Handling of Missing Values**: CatBoost automatically manages missing values in the dataset. Users do not need to manually input missing data before training the model.
3. **High Scalability**: CatBoost is designed for high scalability and can efficiently handle large data sets. It includes optimized implementations to accelerate both the model training and inference.
4. **Integrated Regularization**: CatBoost incorporates integrated regularization mechanisms that help reduce overfitting. This allows the model to generalize better, instead of memorizing patterns from the training data.
5. **Support for Parallel Training**: CatBoost supports parallel training across multiple CPUs or GPUs, significantly accelerating the training process for large datasets.

CatBoost has been widely applied in various machine learning tasks, such as customer churn classification, price prediction, and personalized recommendation systems. It has proven to be highly effective and user-friendly because of its strong ability to handle categorical variables and other complex data characteristics.

3.6. Research Implementation

The initial stage of this research involved collecting data from the Telkomsel database, followed by processing these data to enable analysis of the impact of the Customer Value Management (CVM) program on increasing cellular package purchases through the MyTelkomsel application. The research was conducted using Python, with the aid of Python Notebook tools, specifically, a web-based interactive platform used for data processing, modeling, and evaluation within the machine learning workflow.

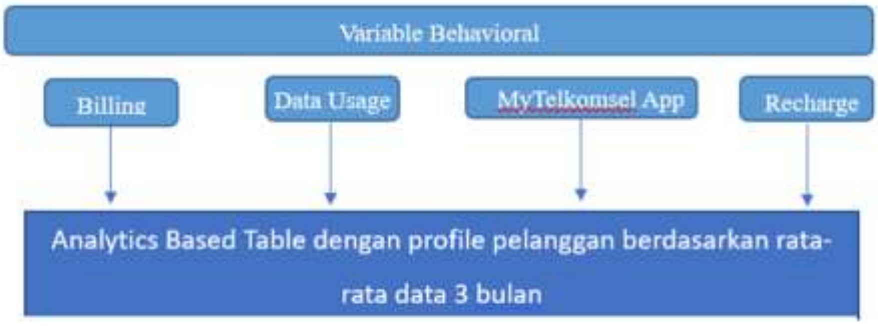

Figure 4. Data Analysis Implementation
Source: Internal Telkomsel, 2023

4. Result and discussion

This chapter provides a general overview of the company and its corporate vision, the implementation of the Focus Group Discussion (FGD), the analysis and discussion of the data processing results, and the presentation of the campaign program outcomes.

4.1. Company Overview and Corporate Vision

PT Telekomunikasi Seluler (Telkomsel) is a cellular operator engaged in mobile telecommunications services. It is a subsidiary of PT Telkom Indonesia (Persero) Tbk (Telkomsel), a State-Owned Enterprise (SOE) operating in the fields of information and communication technology (ICT) services and telecommunications networks in Indonesia, as well as Singapore Telecommunications Limited (SGX: T48, abbreviated as Singtel), the largest telecommunications company in Singapore, which is also largely owned by the state investment company Temasek Holdings. PT Telkom Indonesia (Persero) holds 65% of Telkomsel’s shares, whereas Singapore Telecommunications (Singtel) owns 35% of the shares. Currently, PT Telkomsel holds the largest market share, accounting for nearly 60% of Indonesia’s cellular market. PT Telkomsel serves more than 169 million customers, comprising 162.48

million prepaid and 6.72 million postpaid subscribers. This provides an enormous volume of data and offers significant potential for research. Corporate Vision: "Be a world-class, trusted provider of mobile digital lifestyle services and solutions."

4.2. Focus Group Discussion

The research process and data collection began with interviews and Focus Group Discussions (FGD) involving Subject Matter Experts (SMEs). This process was conducted directly to construct a structured research framework. The FGD was conducted on December 6, 2022. The discussion participants included the following:

1. Moderator: Indra Syahputra (Author)
2. General Manager of Business Data Engineering: Umar Fudin
3. Officer of Analytics Dashboard: Dewa Gbs Widnyana
4. Data Scientist: Ngakan Putu Alit Supriyana Putra

The results of this discussion produced an initial qualitative analysis indicating that there are several customer behavior variables that can be used to build the Customer Value Management (CVM) model. The variables included were as follows:

1. Number of airtime (credit) purchases by customers
2. Total data usage in monetary value (rupiah)
3. Total duration of data usage
4. Total duration of MyTelkomsel application usage
5. Number of campaign offers delivered to customers
6. Number of customers who accepted the offers
7. Number of customers who rejected the offers

The modeling approaches to be applied are as follows.

1. Predictive Analysis: This model is intended to predict lapsers and identify the significance of variables that influence Telkomsel package sales.
2. Using a model that has been tested on the most recent monthly data.

4.3. Data Processing Results

At this stage, all data processing was conducted on PT Telkomsel's internal infrastructure using big data technology (Apache Spark) and machine learning (Python, Scikit-learn, NumPy, SciPy, and Matplotlib). The data used covered a three-month period, from January to March 2023, to develop a customer behavior model for predicting whether customers would accept an offer (taker) or not accept an offer (lapser). The Python libraries used are listed in the following table:

Table 1. Python Libraries

Library	Version
Python	3.6.8
Sckit-learn	0.24.2
Pandas	1.1.5
Numpy	1.19.5
Scipy	1.5.4
Catboost	0.24.4
seaborn	0.11.1

Source: Internal Telkomsel, 2023

4.4. Customer Segmentation and Data Characteristics

Customer segmentation at Telkomsel is based on Average Revenue per User), with revenue intervals of IDR 5,000 per segment, plus additional segments for high ARPU at IDR 25,000 and IDR 50,000. Customer segmentation at Telkomsel is as follows:

1. Zero : Customers with revenue of IDR 0
2. 0–5k : Customers with revenue of IDR 0–5,000
3. 5k–10k : Customers with revenue of IDR 5,000–10,000

4. 10k–15k : Customers with revenue of IDR 10,000–15,000
5. 15k–20k : Customers with revenue of IDR 15,000–20,000
6. 20k–25k : Customers with revenue of IDR 20,000–25,000
7. 25k–50k : Customers with revenue of IDR 25,000–50,000
8. 50k–100k : Customers with revenue of IDR 50,000–100,000
9. ≥ 100k : Customers with revenue above IDR 100,000

Figure 5. Number of Predicted Target Lapsers
Source: Internal Telkomsel Data, 2023

Figure 5 shows that there were 159 million Telkomsel customers in 2022, based on the financial report. Of these 159 million customers, 5.7 million (5,739,154) unique subscriber MSISDNs (mobile customers) were categorized as core-package customers. Core package customers refer to customers with the highest Price Per Megabyte (PPMB), meaning those who incur the highest cost per megabyte of data usage. Transaction data were then collected and processed using a machine learning approach. The available data were subsequently scored to develop a model that can be used to predict which customers are likely to become takers of campaign offers through available channels (SMS, USSD/UMB, and the MyTelkomsel application).

Table 2. Number of MSISDN

Count(msisdn)
5739154

Source: Internal Telkomsel, 2023

From the 5.74 million (5,739,154) core-category customers (core data packages represent the highest PPMB across the entire broadband portfolio), an identification process was conducted to determine how many customers had purchased packages during January and February 2023. It was found that 1.59 million customers became data package lapsers and experienced a decline in Average Revenue per User), with the lowest downgrade originating from core data package lapsers who have the potential to become CVM package users (who will be offered products using the CVM method). These data were used as baseline data for building the propensity model. Therefore, a simulation was conducted to identify customers with a high probability of becoming core data package lapsers by offering packages using Customer Value Management (CVM).

The available data were used to build a propensity model to predict core data package users who are likely to become lapsers in the following month using 100 significant features (including Revenue, Recharge, Data Usage, Customer Profile, and others). The resulting model accuracy was 86%. Based on the model, 1.3 million customers were predicted to become core data package lapsers in the next month. The training dataset consisted of 200,000 numbers that subscribed to core packages within two months and lapsed in the following month, using CatBoost classification.

	precision	recall	f1-score	support
0	0.88	0.94	0.91	36049
1	0.81	0.66	0.73	13951
accuracy			0.86	50000
macro avg	0.84	0.80	0.82	50000
weighted avg	0.86	0.86	0.86	50000

ROCAUC = 0.8004783812372362
Weighted F1 Score = 0.857653152349169
Accuracy = 0.8623

Figure 6. Model Accuracy and Precision
Source: Software Output, 2023

Based on model accuracy, the top three significant variables that contribute to becoming a core data package lapser are:

1. fea_revnew_data_pkg_sum_01m
2. fea_revnew_days_with_data_above_9999_below_50000_sum_01m
3. fea_revnew_data_tot_sum_01m.

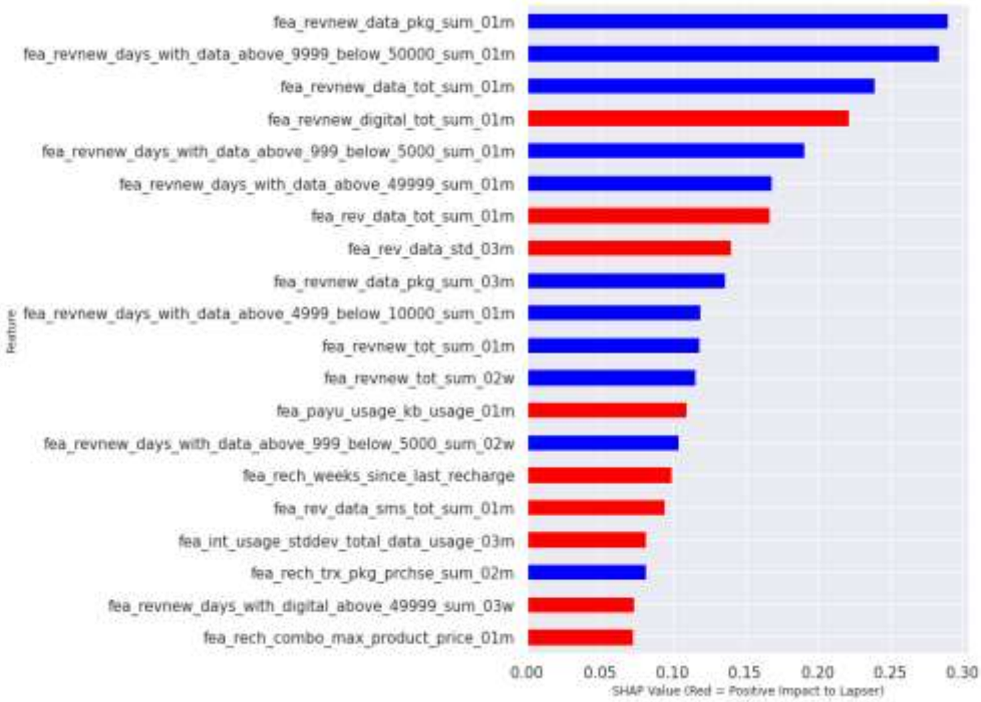

Figure 7. Significant Variables (Features)
Source: Internal Telkomsel, 2023

These results indicate that the lower the data package revenue in the previous month, the lower the number of days with data revenue between IDR 10,000 and IDR 50,000, and the lower the total data revenue in the previous month, the higher the tendency for customers to become lapsers. This model was then applied to 1.3 million customers in the current month to predict the probability of becoming a core data package lapser in the following month by running a test-and-learn campaign targeting ARPU segments with transaction values of IDR 0–100,000 and an average purchase frequency of five sachet data package per month. The results were as follows:

Table 3. Test-and-Learn Results Using CatBoost

ARPU Band Data Pack/Trx	Total Subs ('000)	%Subs	ARPU Total ('000)	ARPU Data ('000)	ARPU Data Pack ('000)	ARPU Data Pack/Trx ('000)	Trx Data Pack	Trx Rech	Total Rech ('000)	Rech/Trx ('000)	Monthly Payload/Subs (GB)	Payload / Data Pack Trx (GB)	RPMB
Zero	20.8	2%	34.6	7.9	0.0	0.0	0.0	1.0	40.0	40.0	5.5	5.5	0.0
0-5k	77.3	6%	50.8	35.3	31.1	3.7	7.4	5.0	50.0	10.0	9.6	1.3	3.2
5k-10k	170.0	13%	91.5	73.8	69.0	7.1	9.8	6.0	90.0	15.0	17.0	1.7	4.0
10k-15k	116.9	9%	99.3	79.5	74.0	12.2	6.1	5.0	90.0	18.0	19.0	3.1	3.8
15k-20k	96.9	7%	98.4	76.3	70.6	17.2	4.1	3.0	90.0	30.0	17.9	4.4	3.9
20k-25k	87.1	7%	104.0	80.2	74.7	22.0	3.4	3.0	90.0	30.0	18.1	5.4	4.0
25k-50k	306.5	23%	125.6	101.4	95.6	37.0	2.7	3.0	110.0	37.0	21.1	7.9	4.4
50k-100k	297.7	23%	163.6	132.1	126.0	67.5	1.9	3.0	150.0	50.0	22.8	12.2	5.4
>= 100k	132.0	10%	221.0	177.0	170.1	132.4	1.3	3.0	210.0	70.0	27.9	21.5	6.0
Grand Total	**1,305.2**	**100%**	**127.8**	**101.8**	**96.1**	**42.5**	**4.0**	**3.0**	**120.0**	**40.0**	**20.1**	**5.1**	**4.7**

Source: Internal Telkomsel, 2023

Based on the test-and-learn results using CatBoost, the following conclusions were drawn:
1. The data package revenue per transaction reflects the customer’s purchasing power.
2. Payload (data usage) per data package transaction is used to regulate customer needs based on the data quota and renewal rate.

Furthermore, from a more detailed data analysis, the most frequently purchased core data package was the Core 3+1 GB package.

Table 4. Detailed Test-and-Learn Results

Product	Total Subs ('000)	Revenue (Bn)	Trx/Subs	Rev/Trx('000)
Core 3+1	111.2	9.2	1.8	46.8
BQSV 1-Day 0.5 GB	97.4	1.5	3.8	4.2
OMG! URP (3.3 GB - 7 GB) + 1 GB	55.3	4.7	1.5	55.0
Core 12+2	48.3	8.0	1.6	106.6
BQSV 3-Day 1 GB	43.0	1.5	2.0	17.8
OMG! URP (4 GB - 13 GB) + 2 GB	34.7	3.6	1.4	75.0
Core 5+2	33.0	3.4	1.4	74.8
Core 3+1+1.5	28.7	2.5	1.8	46.5
Core Combo 17+2	27.5	5.3	1.5	131.1
BQSV 1-Day 3 GB	25.9	0.8	1.9	15.9
Night Data Daily 5 GB	25.1	0.4	2.2	7.0
Night Data Monthly 15 GB	25.0	1.2	1.8	27.5
OMG! URP(7 GB - 23 GB) + 2 GB	24.0	3.7	1.4	110.0

Source: Internal Telkomsel, 2023

Based on the above test-and-learn results, multiple offers are provided simultaneously (multi-offer) as follows:
1. Internet 2GB & 30 minutes Telkomsel calls, 7 days, IDR 6,000
2. Internet 3GB, 7 days, IDR 10,000
3. Internet 3GB, 7 days, IDR 8,000
4. Internet 4GB, 7 days, IDR 11,000
5. Internet 6GB & 30 minutes Telkomsel calls, 7 days, IDR 19,000
6. Internet 9GB, 7 days, IDR 23,000
7. Internet 8GB & 550 minutes Telkomsel calls & 50 minutes all operators, 7 days, IDR35,000
8. Combo 9GB, 150 minutes Telkomsel calls, 400 SMS, 15 days, IDR 44,000
9. 15GB + 2GB OMG!, 30 days, IDR 75,000
10. Monthly HOTPROMO Special 12GB, 30 days, IDR 70,000

4.5. Campaign Program

Based on the results of the test-and-learn process, a campaign in the form of customer offers will be conducted through all available channels using a multi-offer approach with segmentation based on Average Revenue per user (ARPU). The campaign program will be implemented by segmenting customers into the following ARPU categories:

1. Average revenue per user of IDR 0
2. Average revenue per user of IDR 0–5K
3. Average revenue per user of IDR 5–10K
4. Average revenue per user of IDR 10–25K
5. Average revenue per user of IDR 25–50K
6. Average revenue per user of IDR 50–100K

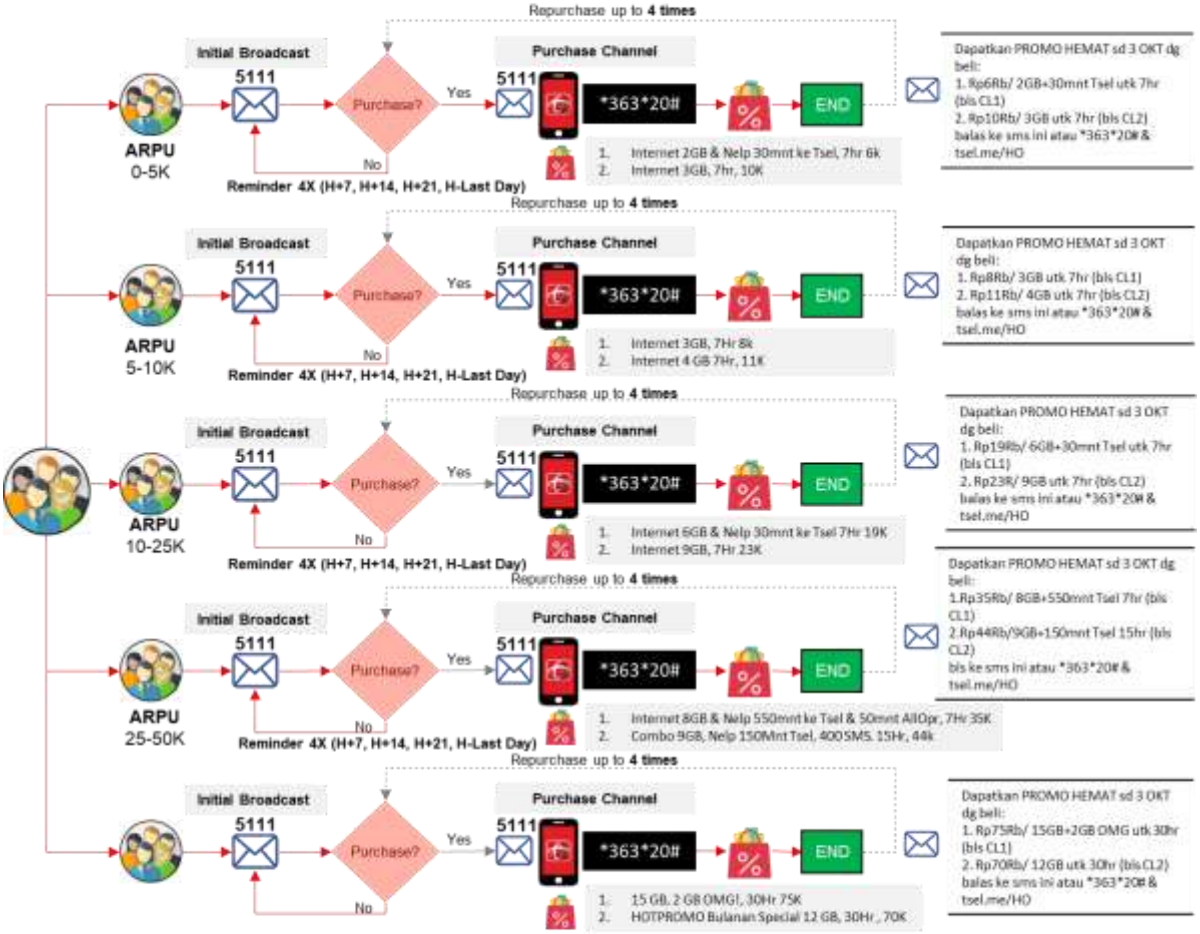

Figure 8. Campaign Program
Source: Internal Telkomsel, 2023

Figure 8 illustrates the campaign method applied to the Customer Value Management program. The campaign is conducted by segmenting customers based on Average Revenue Per User (ARPU) and is delivered through available channels such as Short Message Service (SMS), USSD Menu Browser (UMB), and the MyTelkomsel application. The campaign is implemented massively with repeated reminders up to four times per month for customers who do not make a purchase immediately. The messages contain package offers based on the existing product catalogs.

Table 5. Campaign Results

ARPU Band Data Pack/Trx	Product 1	Product 2	Target ('000)	Taker ('000)	Take Up Rate	Rev Gross (Mn)	Trx /Subs	Rev /Trx('000)	Rev Uplift (Mn)
0-5K	Combo Sakti Special Internet 2GB & 30	Internet 3GB, 7 Days, IDR 10K	40.00	3.36	8.41%	57.14	2.26	7.50	47.80

	Minutes On-Net Calls (Telkomsel), 7 Days, IDR 6K								
5-10K	Combo Sakti Special Internet 3GB, 7 Days, IDR 8K	OMG Special, Internet 4GB, 7 Days, IDR 11K	80.00	8.55	10.68%	202.29	2.53	9.36	42.35
10-25K	Internet 6GB & 30 Minutes On-Net Calls (Telkomsel), 7 Days, IDR 19K	Internet 9GB, 7 Days, IDR 23K	150.00	11.66	7.77%	477.02	1.96	20.85	-160.45
25-50K	Combo Sakti Special Internet 8GB & 550 Minutes On-Net Calls (Telkomsel) & 50 Minutes All Operators, 7 Days, IDR 35K	Combo 9GB, 150 Minutes On-Net Calls (Telkomsel), 400 SMS, 15 Days, IDR 44K	140.00	4.65	3.32%	254.95	1.40	39.11	28.09
50-100K	15GB + 2GB OMG!, 30 Days, IDR 75K	HOT PROMO Monthly Special 12GB, 30 Days, IDR 70K	140.00	9.65	6.89%	810.65	1.13	74.21	183.81
Grand Total			**550.00**	**37.87**	**6.55%**	**1,802.05**	**1.84**	**25.91**	**141.60**

Source: Internal Telkomsel, 2023

Table 5 shows that the campaign results indicate an increase in the uptake rate. The 5–10 K ARPU segment achieved the highest take-up rate at 10.68%. However, the highest gross revenue was recorded in the 50–100 K segment, amounting to IDR 0.81 billion. Most segments made more than one purchase, which contributed to an increase in ARPU among customers who accepted the data-package offers. Therefore, the campaign will continue across all segments. Although the 10–25 K segment experienced a negative uplift (–160) or a decline, the overall campaign performance still showed a positive increase.

5. Conclusions

5.1. Conclusion

Based on this study, several conclusions can be drawn.

1. The impact of personalized offers based on transaction behavior showed a positive result in final purchases after the campaign program was implemented. The campaign resulted in an increase in the take-up rate of 6.5% or an uplift in revenue of IDR 141.6 million.
2. The factors influencing customer purchases in relation to the value received from the mobile service provider (PT Telkomsel) are represented by the top three significant variables as core data package lapsers:
   a. fea_revnew_data_pkg_sum_01m (data package revenue within one month),
   b. fea_revnew_days_with_data_above_9999_below_50000_sum_01m (revenue between IDR 9,999–50,000), and
   c. fea_revnew_data_tot_sum_01m (total monthly data revenue).

   These findings indicate that revenue and time (one month) are the main factors influencing customer purchase. It can be concluded that the lower the data package revenue in the previous month, the lower the number of days with data revenue between IDR 10,000 and 50,000, and the lower the total monthly data revenue, the higher the likelihood of customers becoming lapsers.
3. Data analysis and processing using machine learning with the CatBoost classification method produced a propensity model with an accuracy of 86% for both the training and test data. This demonstrates that CatBoost modelling is effective for high-dimensional and complex categorical datasets. The resulting predictions of lapsers followed by targeted offers led to an overall increase in purchases. Thus, it can be concluded that the Customer Value Management approach supported by machine learning technology facilitates a better understanding of customer needs, preferences, and behavior, leading to a 6.5% increase in the take-up rate of the insurance product.

4. The integration of data and systems involving customer databases, customer interaction data, and online behavioral data provides a solution to managerial challenges related to difficulties in integrating data from different systems and limitations in data collection, management, and analysis capabilities for decision-making based on comprehensive information. The Customer Value Management (CVM) program enables predictions based on transaction data and generates recommended offers with product combinations that match customer needs.

5.2. Managerial Implications
The managerial implications of implementing the Customer Value Management (CVM) program in a cellular company involve several important aspects.

1. Understanding Customer Value: The CVM program aims to increase customer value by identifying, understanding, and fulfilling customer needs and preferences. The managerial implication is that managers must develop a deep understanding of customer value, including customer preferences, behaviors, and expectations toward mobile services.
2. Customer Segmentation: The CVM program requires customer segmentation based on customer characteristics and needs. Managers must identify different customer segments and understand the unique preferences and needs of each segment. This enables the company to design and deliver relevant and attractive service offerings for each customer segment.
3. Personalization and Customer Experience: The CVM program focuses on personalization and superior customer experience. Managers must design strategies and initiatives that enable effective personalization, such as customized products and services, personalized customer interactions, and the use of technology to deliver consistent and satisfying customer experience.
4. Customer Data Analysis: The CVM program utilizes customer data analytics to generate valuable insights into customer behavior, preferences, and needs. Managers must possess strong data analytics capabilities and adequate technological infrastructure to efficiently collect, store, and analyze customer information. This enables the identification of patterns, trends, and opportunities to enhance customer satisfaction and business values.
5. Customer Retention and Loyalty: The CVM program aims to increase customer retention and loyalty. Managers must prioritize effective retention strategies, including delivering superior customer service, building strong relationships with customers, providing incentives and rewards to loyal customers, and identifying and addressing issues that may weaken loyalty.
6. Managerial Commitment and Coordination: The Effective CVM implementation requires strong managerial commitment and coordination in strategy development, resource allocation, employee training, and performance measurement. By addressing these managerial implications, cellular companies can maximize customer satisfaction, strengthen customer relationships, and achieve a competitive advantage in an increasingly competitive market.

5.3. Suggestions
Suggestions for future research include conducting data analysis using alternative algorithms to enrich references related to the methods applied in the Customer Value Management approach. Given that research references in the field of Customer Value Management are still limited, future studies may test other machine learning classification algorithms to compare accuracy and precision in prediction, thereby optimizing results to increase the number of takers and purchase outcomes. Campaign strategies may also be expanded beyond financial incentives to include non-financial or non-monetary approaches, such as differentiated service treatment, enhanced cellular services, and improved customer complaint handling. Managerial Recommendations for PT Telkomsel

1. Customer Segmentation: PT Telkomsel should conduct more in-depth customer segmentation based not only on Average Revenue Per User (ARPU) but also on other data, such as service utilization preferences, usage patterns, spending levels, and more specific needs. This deeper segmentation will enable the development of more targeted strategies to maximize the value of each segment.
2. Lifetime Value (LTV) Analysis: PT Telkomsel should conduct an (LTV) analysis to estimate the long-term value of customers throughout their relationship with the company. By understanding customer LTV, a company can identify high-potential customers who contribute to long-term revenue and strengthen customer retention efforts.

3. Service Personalization: Customer data should be used to provide more personalized and relevant services. Based on customer preferences and behavior, PT Telkomsel can tailor service packages, special promotions, and specific recommendations to enhance customer satisfaction and loyalty.
4. Loyalty Programs: PT Telkomsel should implement attractive and beneficial loyalty programs for loyal customers by providing incentives, discounts, or special rewards for active and loyal users, while continuously monitoring program effectiveness to ensure customers feel valued and motivated to continue using Telkomsel's services.
5. Churn Analysis: PT Telkomsel should perform churn analysis to identify customers who are likely to switch to alternative service providers. By understanding the factors influencing churn, companies can take preventive measures, such as offering special incentives, improving service quality, or strengthening customer interactions to enhance retention.
6. Effective Communication: PT Telkomsel should maintain effective communication with customers through both digital and traditional channels, ensuring that messages are clear, informative, and easy to understand. Communication channels should align with customer preferences, such as text messages, emails, or social media, to maximize communication effectiveness.
7. Customer Experience Enhancement: PT Telkomsel should focus on delivering a superior customer experience by providing user-friendly services, responsive customer support, and efficient operational processes. Regular reviews of operational processes and company policies should ensure that customers feel prioritized and are satisfied.
8. Cross-Sell and Up-Sell Analysis: PT Telkomsel should utilize data analytics to identify cross-sell and up-sell opportunities among existing customers by identifying additional customer needs and offering relevant products or services to increase revenue per customer.

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