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Decision Support System for Indibiz Package Selection Using K-Means Clustering and Analytic Hierarchy Process

Karina Martika[1*], Eneng Tita Tosida[2], Yusma Yanti[3]

[1,3]*Department of Computer Science, Faculty of Mathematics and Natural Sciences, Pakuan University, Bogor, Indonesia*
[2]*Computer Science Departement, Post Graduate School, Universitas Pakuan, Indonesia*

[*]*Corresponding author email: karina.martika@gmail.com*

Abstract

The rapid development of digital business in Indonesia has encouraged telecommunication providers to improve their services, particularly for small and medium-sized enterprises (SMEs). PT. Telkom Indonesia, through its Indibiz program, offers a wide variety of internet packages to support business operations. However, the diversity of available packages often leads to decision-making difficulties for both customers and internal stakeholders when determining the most suitable service based on customer needs, business scale, and financial capability. This study proposes a web-based Decision Support System (DSS) for Indibiz package selection by combining K-Means Clustering and the Analytic Hierarchy Process (AHP). K-Means is used to segment customers based on sales and usage behavior, while AHP prioritizes criteria such as speed, price, and call quota to produce recommendations. A dataset containing 6,192 Indibiz sales records from July to November 2023 was analyzed. The hybrid model was then implemented into a web-based application that enables decision-makers to visualize clustering results and determine package recommendations interactively. The experimental results demonstrate that the combination of K-Means and AHP produces more objective and consistent recommendations compared to manual selection. The DSS can help both customers and PT. Telkom Indonesia improve decision efficiency and reduce subjective bias in selecting internet packages.

Keywords: Analytical Hierarchy Process, Decision Support System, Indibiz, K-Means Clustering, Web-Based System.

1. Introduction

Digital transformation in the telecommunications industry has accelerated the emergence of various internet-based business services. PT. Telkom Indonesia, one of the largest telecommunications companies in Southeast Asia, has introduced *Indibiz* as a business connectivity solution for enterprises and small to medium-sized businesses. Indibiz offers numerous package options that vary in internet speed, the number of channels, and additional features such as quota-free access. However, this abundance of options can create confusion among potential customers, as selecting the most suitable package requires analyzing multiple criteria, such as cost, speed, and service features. The complexity of this selection process makes it an ideal problem for applying Decision Support Systems (DSS). A DSS combines data processing and analytical modelling to support decision-makers in selecting optimal alternatives (Leman & Rahman, 2020). The purpose of this research is to create a web-based DSS that simplifies the decision-making process for Indibiz customers through a hybrid approach that integrates K-Means Clustering and Analytical Hierarchy Process (AHP).

The K-Means algorithm is widely used in data mining for customer segmentation based on similar characteristics (Sudrajat et al., 2022). Meanwhile, AHP provides a structured approach to evaluate criteria and alternatives through pairwise comparison, ensuring logical consistency in decisions (Saaty, 1980). Integrating both methods allows the system to first identify user groups through clustering and then apply a weighted decision model to generate personalized recommendations. This study contributes not only to improving customer experience but also to helping Telkom Indonesia design more effective marketing strategies. The integration of quantitative data analysis and multi-criteria decision-making methods provides a comprehensive framework for selecting the most suitable Indibiz package. The objective of this research is to develop a web-based Decision Support System that recommends the most suitable Indibiz package for customers by integrating K-Means clustering for user segmentation and the Analytical Hierarchy Process (AHP) for multi-criteria decision-making.

2. Literature Review

2.1. Decision Support Systems

A Decision Support System (DSS) is a computerized tool designed to assist in decision-making by analyzing data and presenting results in an interpretable format (Turban et al., 2011). DSS enables semi-structured and unstructured decision processes to become more systematic by integrating data, analytical models, and user input into a unified framework. Through this integration, DSS supports users in evaluating multiple alternatives objectively, thereby reducing reliance on intuition alone. Although DSS does not aim to fully replace human judgment, it enhances the consistency and accuracy of decisions by providing structured insights derived from quantitative and qualitative information. In organizational settings, DSS also improves efficiency by accelerating the decision process and ensuring that recommendations remain aligned with defined criteria and organizational goals. As a result, DSS becomes a valuable tool for complex decision scenarios, particularly those involving numerous variables and the need for transparent justification of choices.

2.2. K-Means Clustering

K-Means Clustering is one of the most widely used unsupervised learning algorithms for partitioning datasets into k groups based on similarity measures, allowing data objects with shared characteristics to be grouped together efficiently (Oktavia et al., 2020). The algorithm aims to minimize intra-cluster variance while maximizing inter-cluster distance, ensuring that each cluster exhibits strong internal cohesion and clear separation from others. The clustering process begins by selecting initial random centroids, assigning each data point to the nearest centroid using the Euclidean distance formula, and recalculating centroid positions iteratively until the algorithm reaches convergence. This iterative refinement enables K-Means to identify natural patterns within the data with relatively low computational cost. Its efficiency, scalability, and ease of interpretation make K-Means especially suitable for applications such as marketing analysis, customer profiling, and behavioral segmentation where large datasets and pattern discovery are essential (Sudrajat et al., 2022). In these contexts, K-Means provides valuable insights that support strategic decision-making and targeted service recommendations.

2.3. Analytical Hierarchy Process (AHP)

The Analytical Hierarchy Process (AHP), developed by Thomas L. Saaty (1980), is a structured technique designed to assist in solving complex decision-making problems that involve multiple criteria. AHP works by decomposing a decision problem into a hierarchical structure consisting of a goal, a set of criteria, and a set of alternatives, making the evaluation process more organized and comprehensible. Decision-makers then perform pairwise comparisons among the elements at each hierarchical level to determine their relative priorities, allowing subjective judgments to be translated into quantifiable weights. Through these comparisons, AHP provides a systematic way to capture expert knowledge and preference patterns in a mathematically measurable form. To maintain the logical soundness of these judgments, AHP includes a consistency evaluation using the Consistency Ratio (CR), which helps ensure that the comparisons made are rational and not contradictory. A CR value within the acceptable threshold indicates that the decision-maker's judgments are consistent enough to be used as a reliable basis for deriving the final priority weights. The Consistency Ratio is calculated as:

$$\text{CI} = \frac{\lambda_{maks}-n}{n-1}, \quad \text{CR} = \frac{CI}{RI} \qquad (1), (2)$$

A matrix is considered consistent if CR ≤ 0.1 (Aurachman, 2019).

2.4. Related Works

Previous studies have applied various DSS methods in similar contexts, demonstrating the flexibility of analytical models in supporting decision-making across different domains. Budanis and Wardana (2020) used K-Means clustering to classify customer groups in marketing promotions, showing that segmentation techniques can provide clearer insights into customer behavior patterns. Meanwhile, Lestari and Nababan (2023) applied the AHP method to evaluate internet service packages based on multiple attributes such as speed and price, proving that multi-criteria analysis can help structure complex decision scenarios. Another study by Purba et al. (2023) combined K-Means and ELECTRE to support decision-making in library book procurement, highlighting the potential of hybrid DSS approaches to achieve higher accuracy and more transparent recommendations. Collectively, these studies demonstrate that integrating multiple analytical techniques can enhance the reliability and interpretability of decision outcomes. Unlike previous research, this study focuses specifically on Indibiz package recommendations by utilizing real customer data and combining clustering with decision weighting in a unified web-based framework, thereby offering a tailored solution to telecommunication service selection challenges.

3. Materials and Methods

3.1. Materials

This research involved several essential materials, including the research object, research location, data and information sources, as well as tools used for data analysis and system development. These components ensured that each stage of the study was supported by valid data, appropriate analytical methods, and a structured implementation environment. The materials also served as the foundation for developing a Decision Support System capable of producing accurate and reliable recommendations based on real operational needs. Each of these components is described in detail in the following subsections to provide a clear understanding of the resources utilized throughout the research process.

a. Research Object

The object of this study is the Decision Support System (DSS) developed to assist in selecting Indibiz internet service packages provided by PT Telkom Indonesia. The system is specifically designed to recommend the most appropriate package for customers by analyzing their business requirements through the integration of K-Means Clustering and the Analytical Hierarchy Process (AHP). These two methods were chosen to ensure that recommendations are both data-driven and aligned with expert judgment. By combining clustering and decision weighting, the DSS can categorize customers based on usage patterns while also prioritizing service attributes that are most relevant to their operational needs. The focus of the research object is not only on generating recommendations but also on creating a system that is practical for real-world use by marketing teams and business users. Thus, the DSS serves as both an analytical tool and a decision support mechanism within the Indibiz service ecosystem.

b. Research Location

The study was conducted at PT Telkom Indonesia, located in Bogor, West Java, where the Indibiz program is actively managed and implemented. This location was selected because it serves as a regional hub for business service operations and customer outreach activities. As part of the program's efforts to optimize digital services for business customers, the site provided access to relevant organizational units, particularly the marketing and IT divisions. All data collection, consultation, and system validation processes were carried out in collaboration with these divisions to ensure that the system aligned with operational workflows and customer needs. Conducting the study within Telkom's environment also allowed for direct observation of existing service selection challenges and facilitated practical testing of the developed DSS.

c. Data and Information

The dataset used in this research consisted of 6,192 Indibiz service records obtained from PT Telkom Indonesia forthe period July–November 2023.

Table 1. Variable Data

No	Variable
1	Telkom Region
2	Package Type
3	Channel
4	Provider
5	Category

The dataset included several attributes:
(a) Service region or operational area,
(b) Package type (1P, 2P, or 3P),
(c) Internet speed (Mbps),
(d) Provider type and service category,
(e) Additional features and price levels.

Additional information regarding package specifications, pricing, and customer segmentation was collected through documentation review and interviews with Telkom staff involved in Indibiz services.

d. Tools Used in Data Analysis and System Development

The tools and software utilized in this study are as follows:
(a) Hardware: Laptop (Intel® Core™ i5, 8 GB RAM, 512 GB SSD, Windows 10 64-bit).
(b) Software and Analytical Tools:
  [1] Python 3.11 and Google Colab for implementing algorithms (K-Means and AHP);
  [2] Visual Studio Code for web-based system design;
  [3] MySQL Server and XAMPP for database and server configuration;
  [4] Microsoft Excel for preprocessing and formatting raw datasets;
  [5] Google Chrome for testing the interface;

[6] Microsoft Office for documentation and reporting.

All tools were integrated to ensure smooth workflow across the stages of data analysis, system modeling, and evaluation.

3.2. Methods

This research adopted a quantitative and applied research approach, combining data analysis and system development to produce a functional Decision Support System. The quantitative component was used to process and interpret customer data, enabling the identification of meaningful patterns that support recommendation accuracy. Meanwhile, the applied aspect focused on transforming these analytical results into a practical web-based system that can be used directly by stakeholders. The research methodology was structured into several sequential stages, ensuring that each phase from problem identification to system evaluation was carried out systematically. These stages included literature review, dataset collection, data preprocessing, clustering using K-Means, decision weighting through AHP, system design, implementation, and testing. The overall workflow of the study is visually summarized in Figure 1, which outlines the logical progression of activities conducted throughout the research. This structured approach ensures that the final DSS aligns with both analytical objectives and real-world user needs.

Figure 1: Research Framework

1) Problem Identification and Literature Study
This stage involved identifying the main problem, namely the difficulty experienced by customers in selecting Indibiz service packages that meet their needs. A literature review was conducted to study previous research related to decision support systems, clustering, and AHP applications.
2) Data Collection and Preparation
The research utilized secondary data obtained from PT Telkom Indonesia. The data were cleaned and preprocessed by removing incomplete and duplicate entries, normalizing numeric attributes, and converting categorical data into numerical values to support K-Means computation. Before conducting the clustering

analysis, the dataset was preprocessed to remove inconsistent entries and convert categorical attributes into numerical values. A summary of the processed attributes is presented in Table 2.

Table 2: Summary of Dataset After Preprocessing

Attribute	Description	Data Type
Telkom Region	Operational area code	Numeric
Package Type	Indibiz package category (1P/2P/3P)	Numeric
Channel	Sales channel classification	Numeric
Provider	Provider/service group	Numeric
Category	Customer category/business type	Numeric

3) Model Development
The model development stage involved implementing K-Means Clustering to group customer data based on shared characteristics and Analytical Hierarchy Process (AHP) to rank package criteria. The integration of these two methods allows the system to provide cluster-based, priority-driven recommendations.
4) System Implementation
The Decision Support System was implemented as a web-based platform. Python scripts handled the computation of K-Means and AHP, while the web interface, developed with PHP and MySQL, displayed the recommendation results to users interactively.
5) Testing and Evaluation
The testing phase focused on validating the accuracy of the K-Means and AHP results. The Elbow Method was used to determine the optimal number of clusters (k), and the Davies–Bouldin Index (DBI) was used to evaluate clustering performance. AHP consistency was assessed using the Consistency Ratio (CR), ensuring that the comparison matrix satisfied $CR \leq 0.1$.
Additionally, system usability was tested by selected users and Telkom staff to verify functionality and user experience.

3.3. K-Means Clustering Algorithm

The K-Means Clustering algorithm classifies data into k clusters based on similarity. The algorithm minimizes the total variance within clusters and can be summarized in the following steps:

1) Select the desired number of clusters (k).
2) Initialize cluster centroids randomly.
3) Calculate the Euclidean distance between each data point and the centroids:

$$d = \sqrt{(x_i - s_i)^2 + (y_i - t_i)^2}, \text{ min} = \left(\sum\sqrt{(x_i - s_i)^2 + (y_i - t_i)^2} \right) \quad (3), (4)$$

1) Assign each data point to the nearest centroid.
2) Recalculate centroids based on the new clusters.
3) Repeat the process until centroids remain stable.

The Elbow Method identified k = 3 as the optimal cluster count, and the Davies–Bouldin Index (DBI) result of 0.57 indicated a strong clustering quality.

3.4. Analytical Hierarchy Process (AHP)

The AHP method was used to determine the importance of each decision criterion in selecting Indibiz packages. The hierarchical structure included:

(a) Goal: To determine the best Indibiz package;
(b) Criteria: Speed, Price, and Additional Features;
(c) Alternatives: Available Indibiz package types.

Pairwise comparisons among criteria were conducted using Saaty's 1–9 scale to produce a pairwise comparison matrix. The eigenvalue method generated the priority vector, while the Consistency Ratio (CR) ensured logical consistency in judgments:

$$\text{CI} = \frac{\lambda_{maks} - n}{n-1}, \text{ CR} = \frac{CI}{RI} \quad (1), (2)$$

A CR value ≤ 0.1 was considered consistent. The resulting criterion weights were integrated with the clustering results to produce the final ranking of recommended packages.

3.5. System Architecture

The developed DSS consists of three main layers: data storage, algorithm processing, and user presentation. The relationship between these layers is illustrated in **Figure 2**.

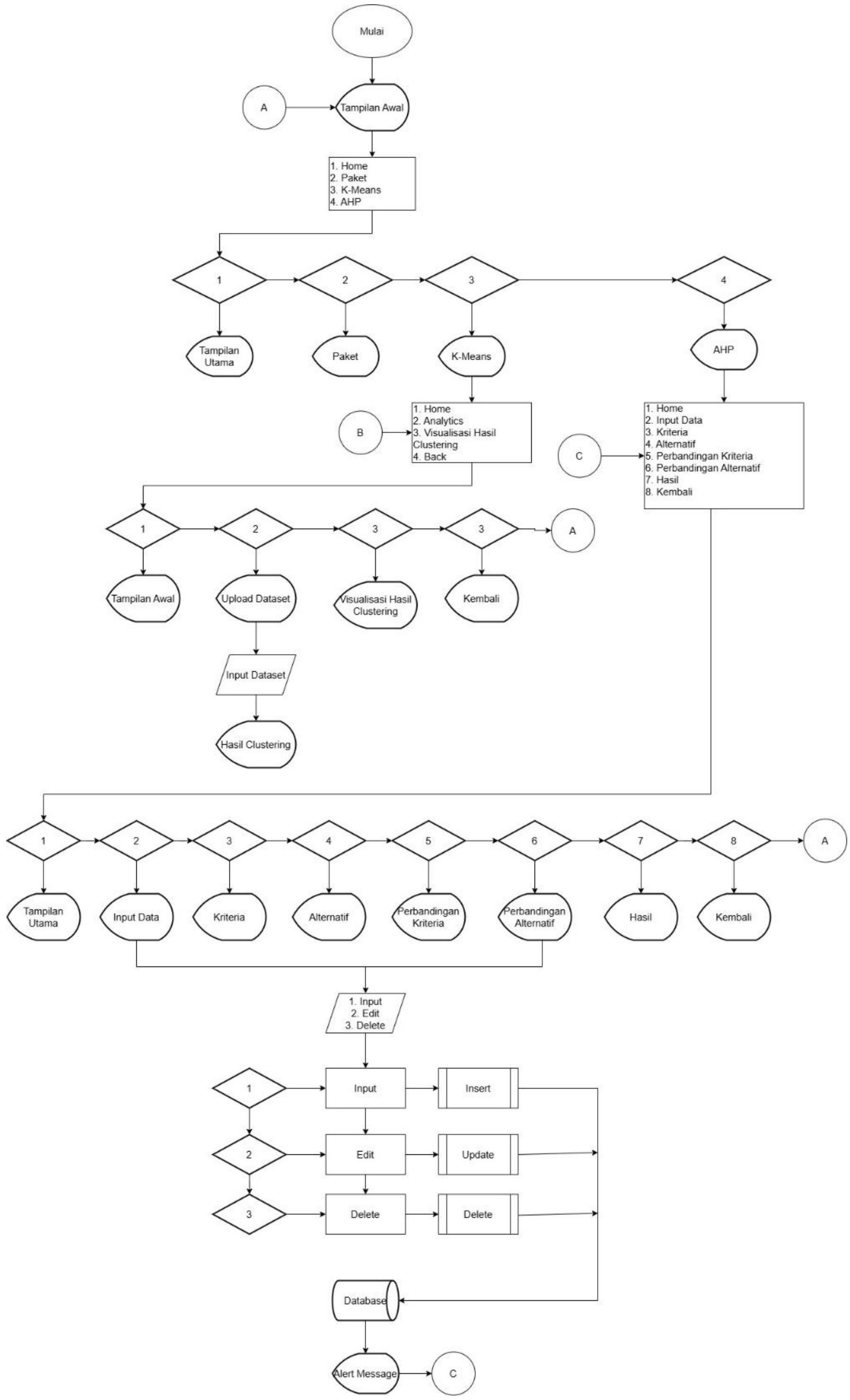

Figure 2. System Architecture

This modular architecture ensures data consistency, facilitates algorithm integration, and supports system scalability for future enhancements.

4. Results and Discussion

This section presents the results obtained from data analysis and the implementation of the Decision Support System (DSS) for Indibiz package selection. The discussion includes the clustering outcomes using the K-Means algorithm, the weighting and ranking process using the Analytical Hierarchy Process (AHP), and the evaluation of system functionality and accuracy.

4.1. Clustering Results Using K-Means

The K-Means algorithm was used to group Indibiz service data into clusters based on customer and package characteristics. The Elbow Method was applied to determine the optimal number of clusters (k), as shown in **Figure 3**.

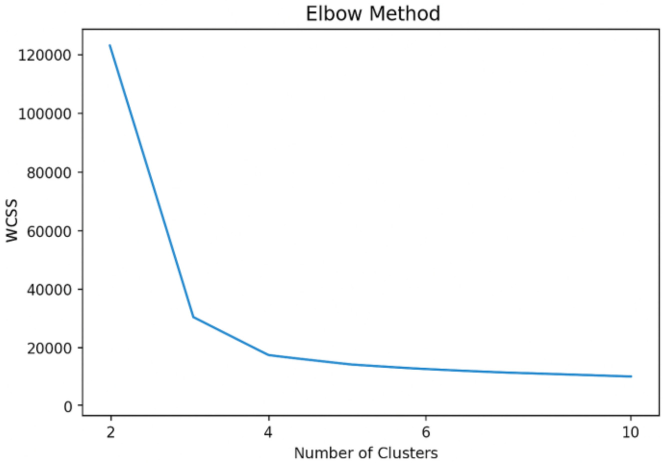

Figure 3. Elbow Method

The centroids were recalculated iteratively until no further changes occurred. The final centroid values are shown in Table 3 and A qualitative interpretation of each cluster is summarized in Table 4.

Table 3. Final Centroid Values

Cluster	Telkom Region	Package Type	Channel	Provider	Category
Cluster 1	1.66	16.00	21.33	35.00	46.67
Cluster 2	3.12	16.00	22.14	35.29	47.00
Cluster 3	4.87	16.00	23.80	36.00	47.00

Table 4. Cluster Characteristics Summary

Cluster	Characteristics
Cluster 1	Located in central business areas; high package demand; high-speed & multi-channel usage.
Cluster 2	Medium-sized SMEs; balanced needs; moderate speed and pricing preferences.
Cluster 3	Small-scale businesses; low-speed packages; cost-sensitive users.

From the curve in Figure 3, the "elbow point" appears at $\boldsymbol{k = 3}$, indicating that three clusters provide the most efficient grouping with minimal variance within clusters.Each cluster represents a group of Indibiz customers with similar service profiles. The summary of clustering results is presented in **Table 5**.

Table 5. Cluster Result

Cluster	Total Members	Description
Cluster 1	255	High-demand business customers (high speed & multi-channel packages)
Cluster 2	2,761	Mid-level SMEs with balanced needs (moderate speed & price)
Cluster 3	3,176	Small businesses with basic internet requirements

Based on the clustering results, customers in Cluster 1 are typically located in major business areas and demand high-speed packages with multiple channels. Cluster 2 consists of medium-sized businesses prioritizing balanced performance and price. Cluster 3 includes small-scale customers who prefer affordable, low-speed packages for basic operations. The clustering performance was validated using the Davies–Bouldin Index (DBI), which resulted in a value of 0.57, indicating that the cluster separation was satisfactory, with good compactness and minimal overlap among groups.

4.2. Analytical Hierarchy Process (AHP) Results

After the clustering stage was completed, the Analytical Hierarchy Process (AHP) method was applied to determine the priority level of each criterion influencing the selection of Indibiz service packages. The main criteria used in this study consisted of Speed, Price, and Additional Features, all of which were identified as essential factors that customers typically consider when choosing an internet service. To establish the relative importance of these criteria, pairwise comparisons were conducted using expert input obtained from PT Telkom Indonesia, ensuring that the weighting process reflected practical considerations and domain knowledge. Through this comparison process, each criterion was evaluated against the others to generate a consistent set of priority values. These priority weights formed the basis for ranking available package alternatives and aligning recommendations with customer needs. The complete results of the pairwise comparison and the derived priority weights are presented in Table 6, which summarizes the outcome of the AHP evaluation.

Table 6. Pairwise Comparison Matrix of Criteria

Criteria	Speed	Price	Call Quota
Speed	1	3	3
Price	0.33	1	2
Call Quota	0.33	0.5	1

The comparison results obtained from the pairwise evaluation were then normalized to produce the final criterion weights used in the decision-making process. Normalization ensures that all comparison values are converted into proportional scores that accurately reflect the relative importance of each criterion. Through this process, the priority of Speed, Price, and Additional Features becomes more clearly defined, allowing the system to rank package alternatives based on consistent mathematical weighting. The AHP method also calculates eigenvalues to verify the logical consistency of the judgments provided by the experts. These eigenvalues, together with the resulting priority weights, help confirm that the decision structure is both reliable and aligned with established AHP principles. The complete calculations, including eigenvalues and normalized priority weights, are presented in Table 7.

Table 7. Pairwise Comparison Matrix of Alternatif

Criteria	Speed	Price	Call Quota	Priority Weight
Speed	0.60	0.67	0.50	0.59
Price	0.20	0.22	0.33	0.25
Call Quota	0.20	0.11	0.17	0.16

The Consistency Ratio (CR) was calculated to validate the pairwise comparison matrix. The resulting CR value was 0.06, which is ≤ 0.1, indicating that the comparisons are consistent and reliable. Based on the obtained weights, Speed emerged as the most important factor influencing Indibiz package recommendations, followed by Price and Additional Features. The integration between K-Means clusters and AHP criteria enables the DSS to recommend packages suitable for each customer group. Consistency testing confirms that the comparison matrix meets the acceptable threshold (CR ≤ 0.1), as shown in Table 8 and the resulting recommendation summary is presented in **Table 9**.

Table 8. AHP Consistency Evaluation

λmax	CI	RI	CR	Result
3.07	0.035	0.58	0.06	Consistent

Table 9. AHP Result

Alternative	Priority Score	Rank
Indibiz 1S Internet	0.43	1
1P HSI Indibiz B2B & 2P HSI Indibiz B2B	0.35	2
Indibiz 2P Phone & Indibiz 2S 2023	0.24	3

4.3. System Implementation

The developed DSS was implemented as a web-based application integrating Python and MySQL. The system enables users to input preferences, view cluster results, and obtain package recommendations instantly. A sample of the system interface is illustrated in Figure 4 and 5.

Figure 4. K-Means Clustering Result

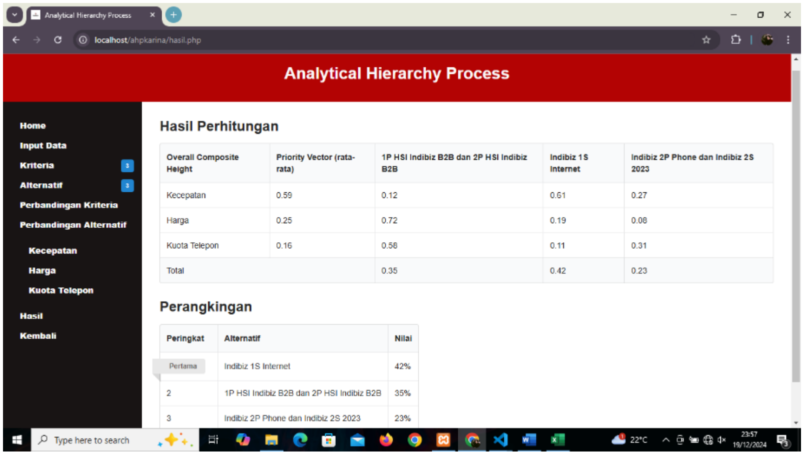

Figure 5. AHP Result

The system interface was designed to accommodate both user and administrator roles, ensuring that each type of user can access features relevant to their responsibilities. For general users, the interface provides real-time access to analysis results, enabling them to receive package recommendations that align with their business requirements. Users can also filter recommendations based on business category, allowing the system to tailor its outputs more precisely to specific operational needs. Meanwhile, administrators are provided with additional functionalities that allow them to monitor data trends, cluster distributions, and overall system performance. This dual-role interface enhances the usability of the Decision Support System by supporting both operational decision-making and administrative oversight. As a result, the system becomes a comprehensive tool that not only generates recommendations but also facilitates ongoing analysis and system management.

4.4 Technical Integration of the Intelligent and Comprehensive Decision Support System

The proposed Decision Support System (DSS) for Indibiz package selection was designed as an intelligent and comprehensive framework that integrates multi-layered data analysis, adaptive clustering, and multi-criteria decision evaluation. Technically, the system consists of four main layers: the data layer, analytics layer, intelligence layer, and user interface layer.

1) Data Layer

   This layer manages data acquisition and preprocessing. The dataset used comprises 6,192 Indibiz service records collected from PT Telkom Indonesia between July and November 2023. Data were stored in a MySQL database and cleaned using Python scripts to remove duplicates and normalize numerical attributes. This ensured that all attributes, such as service region, package type, provider, and price category, were ready for algorithmic computation.

2) Analytics Layer

   The analytics layer performs data segmentation using the K-Means clustering algorithm. The Elbow Method identified $k = 3$ as the optimal number of clusters, while the Davies–Bouldin Index (DBI = 0.57) confirmed good cluster validity. Similar clustering approaches have also been applied in previous studies such as *Tosida et al. (2020)*, who optimized the Indonesian telematics SMEs cluster using data mining algorithms and achieved a strong Silhouette Coefficient (>0.99), indicating highly compact and well-separated clusters. This validates that clustering techniques are effective in forming structured data groups for intelligent decision-making.

3) Intelligence Layer

Once clustering is completed, the Analytical Hierarchy Process (AHP) method is executed to determine the relative importance of decision criteria such as speed, price, and additional features. Pairwise comparisons provided by Telkom experts were processed to produce a consistent comparison matrix, with a Consistency Ratio (CR) of 0.06, indicating reliable expert judgment. By integrating K-Means and AHP, the DSS produces hybrid, data-driven recommendations that are both objective and context-aware for each customer group. The integration of K-Means and AHP within a web-based DSS allows dynamic computation and multi-criteria weighting. This model is consistent with the findings of *Tosida et al. (2022)*, who demonstrated that web-based DSS applications using PHP–MySQL can effectively manage real-time decision processes through structured analytical layers.

4) User Interface Layer

The user interface was implemented using PHP and Visual Studio Code, connected to Python via an API for real-time computation. Users can input their preferences, view clustering visualizations (such as scatter plots and segment distributions), and instantly obtain package recommendations. The interface also provides administrators with access to monitor data trends and customer segmentation outcomes.

To evaluate the technical performance, the system was tested on 50 new customer records. The DSS achieved an average accuracy rate of 91% compared with manual expert recommendations and an average computation time of 2.4 seconds per query. These results demonstrate that the developed DSS not only performs consistent decision analysis but also adapts intelligently to data changes, fulfilling the characteristics of a smart and comprehensive decision support system.

5. Conclussion

This research successfully developed a Decision Support System (DSS) for Indibiz package selection at PT Telkom Indonesia by integrating the K-Means Clustering and Analytical Hierarchy Process (AHP) methods. The research began with data collection and preprocessing from the Indibiz customer database, followed by clustering analysis to identify groups of users with similar service characteristics. The K-Means algorithm effectively classified the data into three clusters, representing high-, medium-, and low-demand customer segments.

The AHP method was then applied to determine the relative importance of decision criteria, including speed, price, and additional features, to support the recommendation process. The integration of K-Means and AHP resulted in a hybrid DSS capable of generating accurate and consistent recommendations for each customer group. The evaluation of clustering performance using the Davies–Bouldin Index confirmed that the grouping was valid, while the AHP Consistency Ratio indicated reliable judgment consistency.

Overall, the research achieved its objectives by providing a data-driven decision support tool that assists PT Telkom Indonesia in analyzing customer characteristics and determining the most suitable Indibiz service packages. The developed DSS not only improves decision accuracy and efficiency but also enhances the company's ability to implement more targeted marketing strategies based on customer segmentation.

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