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A Hybrid K-Means and AHP-Based Decision Support System for Dormitory Monitoring

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Abstract

Dormitory management at the Human Resources Development Center for Transportation Apparatus (PPSDMAP) encounters challenges in room allocation, facility monitoring, and decision-making due to reliance on manual systems. This study develops an intelligent decision support system (DSS) that integrates K-Means clustering and the Analytical Hierarchy Process (AHP) to improve management efficiency. A quantitative methodology was employed, encompassing planning, data collection, analysis, design, implementation, and testing. Data collected through observation and interviews at PPSDMAP were processed using K-Means for clustering dormitory room data and AHP for prioritizing facility improvements. The results show that the system successfully grouped data into three clusters, achieving a Davies Bouldin Index validity value of 0.52, and generated priority decisions based on service, facility, and security criteria. Improving internet connectivity was identified as the top alternative with a weight of 49.25%, followed by CCTV installation and laundry services. The system enables managers to make faster and more accurate data-driven decisions, offering practical benefits for facility management efficiency and enhancing the comfort of dormitory occupants.

Keywords: analytical hierarchy process, decision making, decision support system, dormitory management, facility management, K-Means clustering, PPSDMAP

INTRODUCTION

Dormitory management at the Transportation Human Resources Development Center (PPSDMAP) is essential for supporting training and competency development programs for government officials. Dormitories serve as critical facilities that must effectively address participants' needs, including room availability, equitable placement, and suitability of the facilities. The current manual management process presents several challenges, such as mismatches between participant requirements and room availability, uneven room allocation, and delays in facility maintenance. These issues highlight the necessity for a system that delivers accurate, real-time information to facilitate data-driven decision-making. Previous studies, such as Salsabila's (2020) survey on apartment selection in Tangerang City using the Fuzzy Analytical Hierarchy Process (F-AHP) method, demonstrate that multi-criteria decision-making methods can identify user preferences by priority factors. The study identified legality as the most influential factor in apartment selection. This finding confirms that analytical approaches, including F-AHP and related methods, can yield more objective results in facility and housing decision-making.

The primary challenge in managing PPSDMAP dormitories is the lack of an effective monitoring and decision-support system to track occupancy data, room capacity, occupancy rates, and facility conditions. Dependence on manual recording increases the risk of administrative errors and diminishes management efficiency. To address these challenges, this study aims to develop a Decision Support System (DSS) that integrates the K-Means clustering method for data grouping and the Analytical Hierarchy Process (AHP) for prioritizing facility improvements based on relevant criteria (Hou *et al*. 2020)

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This study addresses the following research question: How can an intelligent decision support system be designed and implemented to assist PPSDMAP dormitory managers in monitoring facility conditions, efficiently grouping room data, and determining repair priorities based on predetermined criteria? The objective is to develop a DSS that combines K-Means and AHP to enhance decision-making accuracy and speed in the management of PPSDMAP dormitories (Haekal & Mu'min 2024). This system is expected to produce structured analyses of room and facility conditions, thereby supporting more objective and efficient managerial decisions. From an academic perspective, this research advances the application of data mining and multi-criteria decision-making (MCDM) methods in public facility management. The results of this study can also serve as a reference for the development of decision-support systems for asset management and infrastructure maintenance in government agencies. By integrating innovative technology into managerial processes, this research also strengthens efforts to improve the efficiency of public-sector resource management.

METHODS

This research methodology outlines the study's stages. Methods are described in the planning, system development, and implementation sections. The workflow of this study is illustrated in Figure 1.

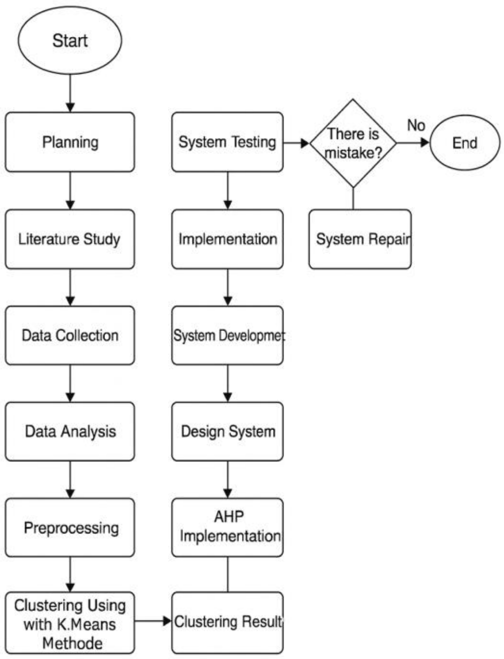

Figure 1 Research stages

This study follows a structured research process based on the System Development Life Cycle (SDLC), encompassing planning, data analysis, system design, development, testing, and maintenance.

1. Planning: In the planning stage, dormitory data were collected using the Analytical Hierarchy Process (AHP) and K-Means clustering. This phase included observation, direct interviews, and data collection at the research site.
2. Data Analysis: Data collected during fieldwork through direct interviews with experts were processed and subsequently clustered using the K-Means method.
3. Preprocessing: In this stage, collected data are cleaned by removing duplicates and inconsistencies, correcting errors, and ensuring accuracy. In K-Means clustering, categorical and textual data are converted to numerical values before processing.

4. System Design and Development: In this stage, the system is designed to recommend dormitory facilities to guests based on their stated preferences. Room selection decisions are informed by guest needs and the results of the Analytical Hierarchy Process (AHP).
5. Implementation: This implementation stage is the stage for realizing the results of the design analysis that has been carried out or created previously, so that it becomes an information system that can be used. At this stage, Visual Studio Code and MySQL software are used to implement the web.
6. Testing: In this testing stage, the elbow method was used to determine the optimal cluster and visualize it in the form of a graph, where the results are shown in the form of an elbow, and values that show a drastic decrease are the optimal clusters. Next, the Analytical Hierarchy Process (AHP) test was conducted by calculating the Consistency Ratio, a parameter used to assess paired comparisons; a good value is CR<0.1. If it exceeds this value, the weighting needs to be corrected (Maori 2023).
7. Maintenance: At this stage, several activities must be carried out, including performing regular system maintenance to ensure that the system continues to run smoothly. In addition, the system also needs to be developed by adding new features to improve its performance.

K-Means Clustering

The clustering process using the K-Means method involves the following steps, as outlined by Oktavia *et al.* (2020):

1. Determine the number of clusters (k) within the dataset.
2. Determine the centroid values. The initial centroid values are chosen randomly or can be set using the maximum value for high clusters and the minimum value for low clusters.
3. Determine the distance of the data closest to the centroid using the Euclidean Distance formula, which is:

$$D = \sqrt{(x_i - s_i)^2 + (y_i - t_i)^2} \tag{1}$$

Explanation:
D = Euclidean distance
i = Number of objects
(x, y) = Coordinates of the object
(s, t) = Coordinates of the centroid

4. Group the objects based on the nearest centroid distance to create a new centroid. The new centroid is calculated by summing the values weighted by the distances from the previous iteration, then dividing by the total number of objects in each cluster, using the formula in Equation 2.

$$C(x,y) = \frac{\Sigma xy}{n} \tag{2}$$

5. Repeat steps 2, 3, and 4 and iterate until the centroids reach their optimal values.

Analytical Hierarchy Process (AHP)

The following is the AHP calculation to obtain a consistent scale:

1. Normalize the data in the pairwise matrix for each criterion by dividing each element in column i and column j by the sum of column i. Alternatively, it can be calculated using the formula in Equation 3.

$$a_{ij} = \frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}} \tag{3}$$

2. Calculate the row averages (weights) for each criterion in the pairwise matrix.
3. Compute the maximum eigenvalue using the formula in Equation 4.

$$\lambda\text{max} = (A1 \times Y1 + B1 \times Y2 + C1 \times Y3 \ldots .n \tag{4}$$

Explanation:
A = Sum of each column (before normalization)

Y = Row average (weight) for each criterion

4. Calculate the Consistency Index (CI) to determine the consistency of the responses, which affects the validity of the results. The formula is in Equation 5 below.

$$CI = \frac{\lambda max - n}{n-1} \tag{5}$$

Explanation:
CI = Consistency Index
λmax = Maximum eigenvalue
n = Order of the matrix

5. To check if a CI is valid, compute the Consistency Ratio (CR). The matrix is considered consistent if CR≤0.1. The formula is in Equation 6 below.

$$CR = \frac{CI}{RI} \tag{6}$$

Explanation:
CR = Consistency Ratio
CI = Consistency Index
RI = Random Index

The table of random index values is shown in Table 1.

Table 1 Random index values (Saaty 2013)

n	1	2	3	4	5	6	7	8	9	10	11	12	13
RI	0.0	0.0	0.5	0.9	1.1	1.2	1.32	1.41	1.45	1.49	1.51	1.48	1.56

6. Prioritization of alternatives can be calculated by computing the eigenvalue for each criterion and its alternatives using the Formula in Equation 7.

$$\Sigma\ eigen\ value = (A1 \times Y1) + (B1 \times Y2) + \ldots n \tag{7}$$

Explanation:
A = Criterion weight
Y = Alternative weight under the criterion

RESULT AND DISCUSSION

An Intelligent Decision Support System (IDSS) is an evolution of conventional DSSs that applies intelligent algorithms (AI-based reasoning) to enhance analysis, learning, and prediction capabilities in the decision-making process. A Decision Support System (DSS) is a computer-based system that assists decision makers in complex situations by combining data, analytical models, and interactive user interfaces. DSS utilizes quantitative approaches, intelligent algorithms, and information technology to provide faster, more accurate, and adaptive decision alternatives. In their research, Tosida *et al.* (2023) developed the concepts of Smart Village and Smart Economy using Fuzzy C-Means (FCM), GIS spatial analysis, and Causal Loop Diagram (CLD) for data-driven decision-making and community participation in Kabandungan and Bogor regions. This connection shows that intelligent decision-making systems initially applied to micro-facility management (dormitories) can be adapted to macro contexts, such as managing village economic potential and spatial-based tourism.

An intelligent DSS not only presents raw data but also interprets patterns, anticipates future decisions, and provides adaptive recommendations that adapt to changing contexts. In the era of Industry 5.0, decision-making systems are no longer limited to data-driven analytics; they must also support intelligent reasoning, adaptive learning, and autonomous decision-making. In the context of this study, the dormitory monitoring decision support system represents a transitional stage from a conventional DSS to an Intelligent DSS (IDSS), as it combines two complementary approaches (analytical decisioning and machine-based learning). Generating recommendations based on a combination of expert knowledge and analysis of actual data patterns has independent validation capabilities through the Consistency Ratio (Antoniadi *et al*. 2021).

The development of an intelligent decision-support system for dormitory management at PPSDMAP aligns closely with the broader smart city and innovative village frameworks, which emphasize the use of digital technologies, data analytics, and intelligent systems to enhance the quality, efficiency, and sustainability of public services. Within the Smart City domain, the proposed system reflects the principles of smart living and innovative governance, leveraging data-driven tools to optimize resource allocation and enhance service responsiveness. By integrating K-Means clustering for data segmentation and the Analytical Hierarchy Process for multi-criteria prioritization, the system enables automated identification of dormitory conditions. It generates evidence-based recommendations for facility improvements, such as enhancing internet connectivity, installing CCTV, and upgrading supporting services. Such capabilities mirror the technological components commonly found in innovative facility management systems, particularly their ability to monitor conditions, classify needs, and support real-time, informed decision-making.

In parallel, the system also embodies the core values of innovative village initiatives, which aim to leverage digital innovation to strengthen governance, service delivery, and community welfare in rural or semi-urban contexts. Given that PPSDMAP operates in a training and residential environment, the introduction of a data-driven management platform demonstrates how analytical technologies can modernize local infrastructure and reduce reliance on manual administrative processes. This contributes to creating an adaptive, efficient living environment that enhances residents' comfort and well-being, attributes central to innovative village development. Furthermore, the implementation of the DSS provides a scalable model that can be extended to other rural facilities, such as community centers, dormitory complexes, or educational institutions seeking to adopt intelligent management practices.

Overall, this study not only improves dormitory management efficiency but also provides empirical evidence of how analytical decision support technologies can reinforce the operational dimensions of smart city and innovative village ecosystems. By enabling transparent, efficient, and responsive facility management, the system supports the transformation of residential and institutional environments into smarter, more connected, and more sustainable spaces. Integration of K-Means and AHP in an intelligent decision support system is shown in Table 2.

Table 2 Integration of K-Means and AHP in intelligent decision support systems

Component	Role in Intelligent Decision Support Systems	Types of intelligence
K-Means Clustering	Detecting hidden patterns and grouping objects based on similar attributes.	Unsupervised Learning
Analytical Hierarchy Process (AHP)	Evaluate alternatives based on structured criteria through pairwise comparisons.	Expert-driven Decision Intelligence

The integration of these two methods demonstrates the defining features of an intelligent DSS in several key aspects:

1. This system combines exploratory analysis through K-Means clustering and multi-criteria decision making via AHP.
2. This approach results in an adaptive, data-driven system that updates recommendations in response to evolving conditions.
   The system demonstrates high consistency and accuracy, objectively evaluating the physical attributes of dormitories.

K-Means Clustering Results

According to Tita Tosida *et al.* (2024), the initial step in determining cluster centers is to designate the average location of each cluster. As the initial centers are typically imprecise, the cluster centers and membership values are iteratively refined, and the cluster centers converge toward optimal locations. K-means is the algorithm that uses a non-hierarchical approach (Ramadhan *et al.* 2023). Effective dormitory management at PPSDMAP necessitates the application of both K-Means Clustering and the Analytic Hierarchy Process. The implementation steps are described below. The K-Means flowchart can be seen in Figure 2.

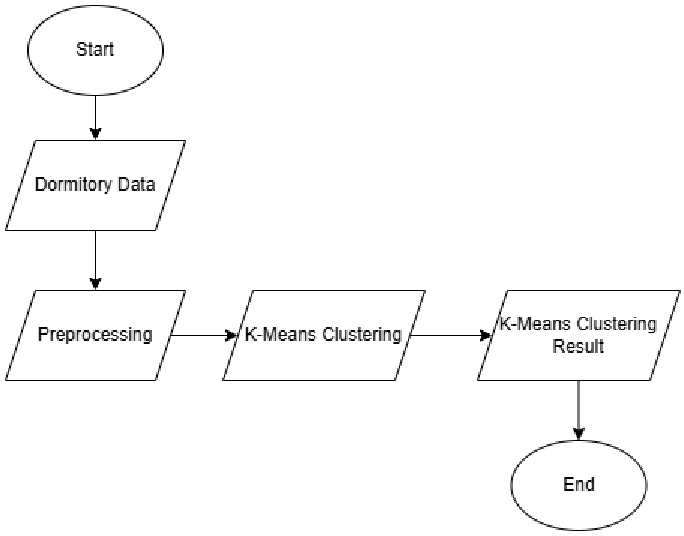

Figure 2 K-Means clustering flow

Based on Table 3, the initial centroid in the K-Means method is randomly determined as the starting point for the dormitory data clustering process. This centroid represents the initial value of each variable used before iteration is performed to obtain the optimal centroid.

Table 3 Centroid random

Centroid	Room Number	Dormitory Type	Area	Exposed to the Sun (Y/T)	Direction	Dormitory Building (B/C)
1	15	1	3	5	10	11
2	40	2	4	5	10	11
3	45	1	3	5	9	12

The calculations for determining distance using the Euclidean Distance method, as defined by Equation 1, are:

$$CI\ No\ 2 = \sqrt{(15-15)^2 + (1-1)^2 + (3-3)^2 + (5-5)^2 + (10-10)^2 + (11-11)^2} = 0$$

$$CI\ No\ 2 = \sqrt{(15-40)^2 + (1-2)^2 + (3-4)^2 + (5-5)^2 + (10-10)^2 + (11-11)^2} = 25.03$$

$$C1\ No\ 3 = \sqrt{(15-45)^2 + (1-1)^2 + (3-3)^2 + (5-5)^2 + (10-9)^2 + (11-12)^2} = 330.03$$

Table 4 presents the initial results of K-Means clustering; however, further iterations are required until the results stabilize. Equation 1 determines the centroid. Subsequently, since cluster 1 contains 4 members, each member is subdivided accordingly. The implementation of K-Means clustering has been implemented, producing 3 clusters, as detailed in Table 5.

Table 4 Result of iteration 1

Area	**Exposed to the sun**	**Area**	**Dormitory Type**	**C1**	**C2**	**C3**	**Minimum**	**Cluster**
3	5	10	11	0	25.04	30.03	0	1
3	5	10	11	1	24.04	29.03	1	1
3	5	10	11	2	23.04	28.03	2	1
3	5	10	11	3	22.04	27.03	3	1
3	5	9	11	13.03	12.12	17.02	11.12	2
3	5	9	11	14.03	11.13	16.03	11.13	2
3	5	9	11	15.03	10.14	15.03	10.14	2
3	5	10	12	44.01	19.07	14.03	14.03	3
3	5	7	12	45.11	20.29	15.13	15.13	3
3	5	7	12	46.10	21.28	16.12	16.12	3

Table 5 Clustering result analysis

Cluster	Number of Members	Dominant Direction	Dominant Building
Cluster 1	13	East	Building C
Cluster 2	14	West	Building C
Cluster 3	26	South	Building B

Table 5 shows that cluster 1 has 13 buildings, cluster 2 has 14, and cluster 3 has 26. Evaluation using the Davies Bouldin Index resulted in a value of 0.52, indicating relatively good clustering quality, as lower DBI values indicate more optimal clustering. The scatter plot visualization demonstrates clear separation among clusters, indicating that the K-Means method is effective for dormitory data segmentation.

Figure 3 presents a dormitory cluster scatter plot that visualizes the K-Means clustering results, with clusters clearly separated by color: Cluster 1 is green, Cluster 2 is red, and Cluster 3 is blue. Cluster 1 includes dorm rooms C301–B101, which predominantly face east. Cluster 2, comprising rooms C314–B102, primarily faces west. Cluster 3 consists of rooms B103–B218, most of which face south and are mainly located in dormitory B.

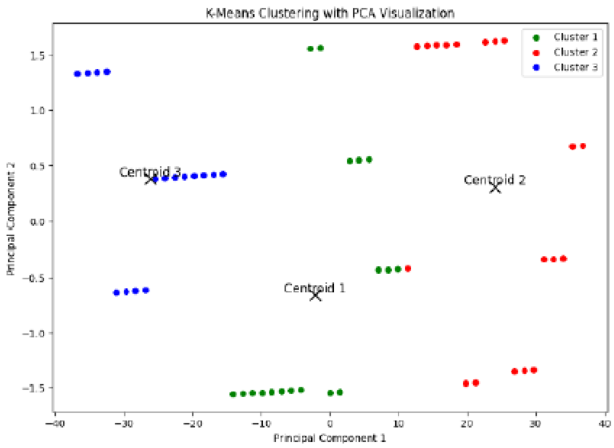

Figure 3 Scatter plot of dormitory cluster

Figure 4 shows the cluster results and room numbers as percentages for the first diagram: cluster 1 (34.0%), cluster 2 (35.8%), and cluster 3 (30.2%). These percentages indicate that cluster 2 has the highest proportion.

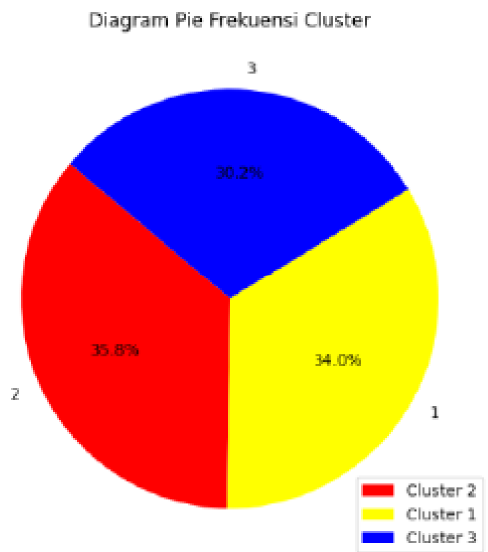

Figure 4 Cluster percentage

Analytical Hierarchy Process (AHP) Results

Duruka *et al.* (2023) define the Analytical Hierarchy Process (AHP) as a general measurement theory for deriving ratio scales from both discrete and continuous pairwise comparisons. This approach facilitates ad hoc data analysis and decision modeling for future planning (Tsaqila *et al.* 2024). The stages of AHP implementation are illustrated in Figure 5.

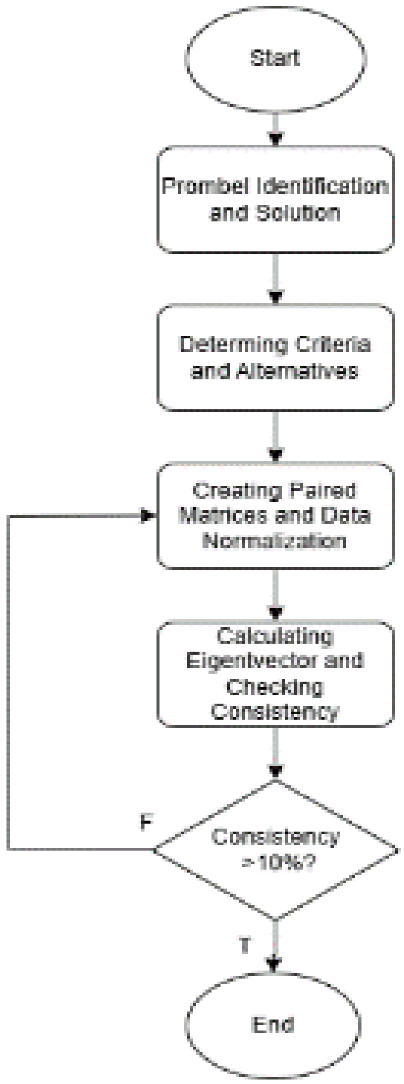

Figure 5 AHP implementation flow

The application of AHP in managing dormitory buildings at the Transportation Human Resources Development Center (PPSDMAP) requires interview data related to criteria and alternatives. The AHP research flow is shown in Figure 5.

1. Building a hierarchy starts with the primary goal

Figure 6 shows the hierarchy of plans to be implemented in managing dormitory monitoring. This hierarchy structures the dormitory management process, making it easier for decision-makers to determine the next steps. The results of implementing this hierarchy are shown in Figure 5, which presents the plan, structure, and relationships among processes in dormitory management.

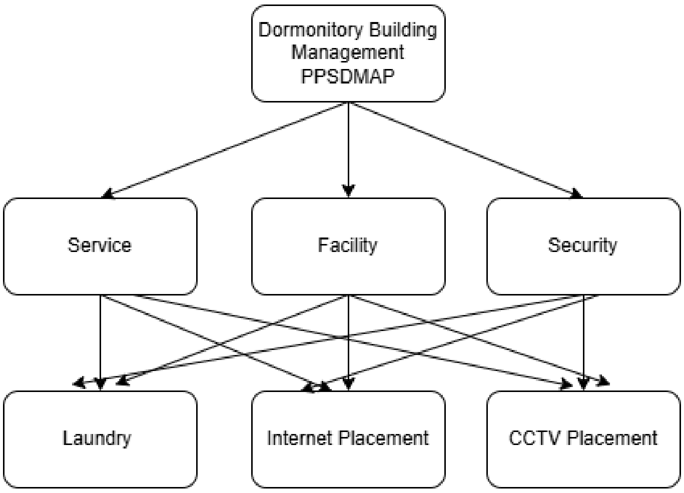

Figure 6 Dormitory management hierarchy

2. Comparative Values

Based on Table 6, the AHP comparison scale is used to assess the relative importance of criteria in pairs. This scale allows expert qualitative assessments to be converted into structured numerical values as a basis for calculating priority weights.

Table 6 Comparative values AHP

Value	Description
1	Both elements are equally important.
3	One element is slightly more important than the other elements.
5	One element is more important than the other elements.
7	One element is clearly more important than the other elements.
9	One element is more important than the other elements.
2,4,6,8	Values between the two closest consideration values
1/ (1-9)	If an activity receives a score relative to a comparative activity, then the comparison has the opposite value.

3. Creating a Pairwise Comparison Matrix

A pairwise comparison matrix is a table used to compare each criterion (or alternative) with every other criterion (or alternative) in pairs, based on their levels of importance. It is used in AHP to determine priority weights, measure assessment consistency, and convert subjective assessments into structured numerical values.

Based on Table 7, the Location criterion has a higher level of importance than Facilities and Security. Facilities are considered more important than Security in decision-making regarding the management of the PPSDMAP dormitory.

Table 7 Criteria comparison matrix

Criteria	Location	Facilities	Security
Location	1	3	3
Facility	0.33	1	2
Security	0,2	0.5	1
Total	1.53	4.5	8

4. Normalize the data by dividing each matching matrix element by the sum of each column's values.

After filling in the comparison matrix, calculate the normalization value of the sum of the criteria comparisons with the criteria column and the average value in the normalization row.

LK/NLK = 1/1,53 = 0,65 LK/NF = 3/4,5 = 0,6 LK/NK = 3/8 = 0,37
F/NLK = 0,33/1,53 = 0,21 F/NF = 1/4,5 = 0,2 F/NK = 2/8 = 0,25
K/NLK = 0,2/1,53 = 0,13 K/NF = 0,5/4,5 = 0,1 K/NK = 1/8 = 0,12

5. Calculate the eigenvector values and check their consistency

The eigenvalue is taken from the average row column multiplied by the sum of the values in the column using Equation 4.

$$\begin{aligned} \text{Eigenvalue} \quad &= \text{AvgrowK} * \text{TotalColumnK} = 0.647 * 1{,}53 = 0{,}99 \\ &= \text{AvgrowF} * \text{TotalColumnF} = 0{,}229 * 4{,}5 = 1{,}035 \\ &= \text{AvgrowK} * \text{TotalColumnK} = 0{,}122 * 8 = 0{,}976 \\ &= 0.99 + 1.035 + 0.976 = 3.00 \end{aligned}$$

6. Calculating the Consistency Index (CI)

Measuring consistency ratios in the AHP method requires consistency index values. The results matrix from the criteria comparison is shown in Table 8.

Table 8 Criteria comparison metrics

Criteria	Normalization			Amount	Priority/Avg	Eigenvalue
	Location	Facility	Security			
Location	0.65	0.67	0.63	1.9	0.64	0.99
Facility	0.22	0.22	0.25	0.68	0.22	1.03
Security	0.13	0.11	0.13	0.36	0.12	0.97
Total	1	1	1	1	1	3.005

After obtaining the eigenvalue, the next step is to find the CI (Consistency Index) values using the formula in Equation 5.

$$CI = (\lambda max - n)/(n - 1) = (3.005 - 3)/(3 - 1) = 0.0025$$

7. Measuring Consistency Ratio

The consistency ratio (CR) is the ratio of the consistency index (CI) to the random index (RI) and measures the level of consistency in a pairwise comparison matrix. If the CR is 0.10 or less (10%), the assessment is considered consistent and acceptable; otherwise, it must be repeated. After finding CI, the next step is to find the CR value using Equation 6. The random index value is based on the number of criteria. If there are three criteria, then the random index value is 0.58.

$$CR = CI/RI = 0.0025/0.58 = 0.0043$$

The Consistency Ratio (CR) is 0.0043, which is below 0.1 (10%). Therefore, 0.0042 is considered consistent. The next step is to calculate the alternative comparison matrix for each criterion using the same method as in calculating the requirements comparison table. The criteria comparison results table is shown in Table 8. After calculating the criterion comparison matrix and the alternative comparison matrix for each criterion, the ranking results are shown in Table 9.

Table 9 AHP Ranking result

Alternative	Number of Hierarchies	Ranking
Internet Connection	49.25%	1
CCTV Placement	26.19%	2
Laundry	2.57%	3

In this study, the Decision Support System uses K-Means Clustering and Analytical Hierarchy Process (AHP). The data used is sourced from the Transportation Human Resources Development Center (PPSDMAP). The K-Means Clustering algorithm helps group data. The next step is to select suitable dormitory rooms using the AHP with three criteria and three alternatives.

System Implementation

The home page is the first page displayed when users open the system. On this page, users are greeted with a simple yet informative interface, which displays a dashboard with menus for all facilities, used facilities, available facilities, and dirty facilities. The results of the dashboard page implementation are shown in Figure 7.

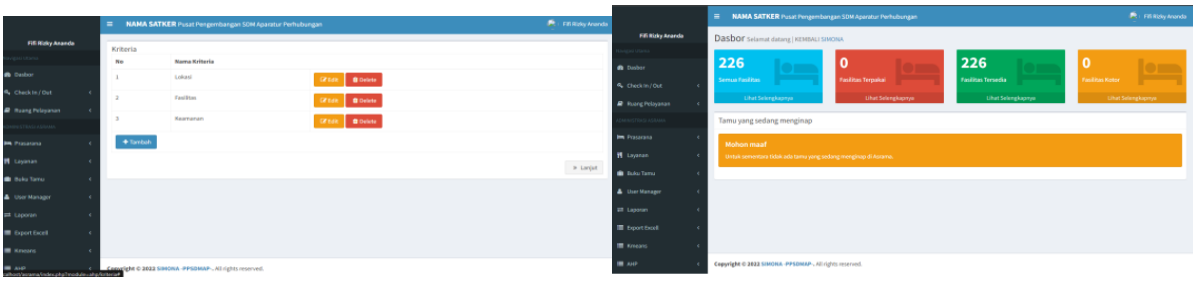

Figure 7 Dashboard and criteria page

The results page for comparing criteria and alternatives is one of the most important in the system, helping users prioritize or assign weights to each available criterion. This page contains numbers, criterion names, edit and delete buttons, and an add icon for entering any necessary criteria.

The comparison table shows that service has the highest priority (0.647), followed by facilities (0.229) and security (0.122). The Consistency Ratio (CR) of 0.0046 < 0.1 indicates consistency in the experts' assessments. Results page: the page displayed when the user has finished filling in all the weighting values, from the criteria weighting to the alternatives. The results of the results page implementation are shown in Figure 8. This means that improving internet connectivity is a top priority for dormitory management.

Figure 8 AHP results

The implementation of the developed web system has two main modules:

1. Clustering Module: uploads dormitory data and automatically displays room segmentation results based on K-Means results.
2. AHP Module: provides an interface for inputting criteria and alternatives to generate priority rankings in table and graph form.

Black-Box Testing results show that all main functions are functioning as specified.

CONCLUSION

The Dormitory Monitoring Decision Support System uses K-Means clustering and AHP with data sourced from the Transportation Human Resources Development Center (PPSDMAP). This dataset consists of 53 data points, with 26 for dormitory C and 27 for dormitory B. The attributes used are room number, dormitory type, area, sun exposure (Y/T), direction, and dormitory building (C/B). The data used was sourced from interviews and direct observation by experts. K-Means Clustering was used with K=3 or Three Clusters. K-Means produced 3 clusters, which were categorized as medium clusters (34.0%) with rooms facing south, north, west, and east. Good clusters (35.8%) with rooms facing east, west, and south. Low cluster (30.2%) with rooms facing east, north, south, and west. In the AHP, three priority sequences were generated from the clustering results and the weighting calculations for the alternatives and criteria. The priority was internet connection (49.25%), CCTV placement (24.57%), and laundry (26.19%).

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