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Article

Implementation and verification of a SAW-based decision support system for culinary MSME ranking

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***Abstract*—This study aims to develop a Decision Support System (DSS) using the Simple Additive Weighting (SAW) method to determine the most preferred culinary Micro, Small, and Medium Enterprises (MSMEs) in the Dracik Campus area of Batang. The system incorporates four primary criteria—price, location, service, and food quality—each supported by structured sub-criteria and weights derived from customer assessments. Data were collected via questionnaires administered to MSME customers, and the results were normalized and weighted to generate objective rankings. The system architecture was developed using the SDLC model, with MySQL utilized for database management and automated SAW computation. The results indicate that the system successfully generated rankings, and the preference values produced by the automated SAW computation were identical to those from manual SAW calculations, with no numerical deviation, proving the algorithmic correctness of the system. The study confirms that DSS with SAW enhances transparency, reduces subjective bias, and provides actionable insights for MSME development. Overall, this study validates the successful functional implementation of a SAW-based DSS and demonstrates that the system can be used as a reliable computational tool for multi-criteria decision-making.**

Keywords—culinary msme; decision support system; simple additive weighting.

1. Introduction

Micro, Small, and Medium Enterprises (MSMEs) serve as a fundamental pillar of local economic development in many regions of Indonesia, including the culinary clusters surrounding Dracik Field in South Proyonanggan, Batang. Their presence stimulates local income, creates employment opportunities, and supports the daily needs of students, residents, and visitors who frequent the area. The abundance of culinary MSMEs—ranging from rice stalls and porridge vendors to beverage carts and snack sellers—illustrates the vibrancy of the local micro-economy. As highlighted by Hanny et al (2020), MSMEs play a crucial role as an economic backbone at the household and regional levels. Similarly, Gunawan et al (2021) emphasize their strategic importance as micro to medium-scale enterprises that contribute substantially to social and economic welfare.

Beyond their economic influence, culinary MSMEs hold cultural and commercial significance by shaping consumer attraction and preserving local food traditions. Studies have shown that innovation and uniqueness in culinary products, such as the popular Ice Cream Alpukat Al-Fathir in Medan, enhance consumer engagement and enable MSMEs to compete in broader markets (Agustini et al., 2025). Culinary MSMEs also strengthen cultural identity and tourism appeal by promoting local flavors, as evidenced in Jambi's traditional food enterprises (Kurniawan & Nuringsih, 2022). The increasing

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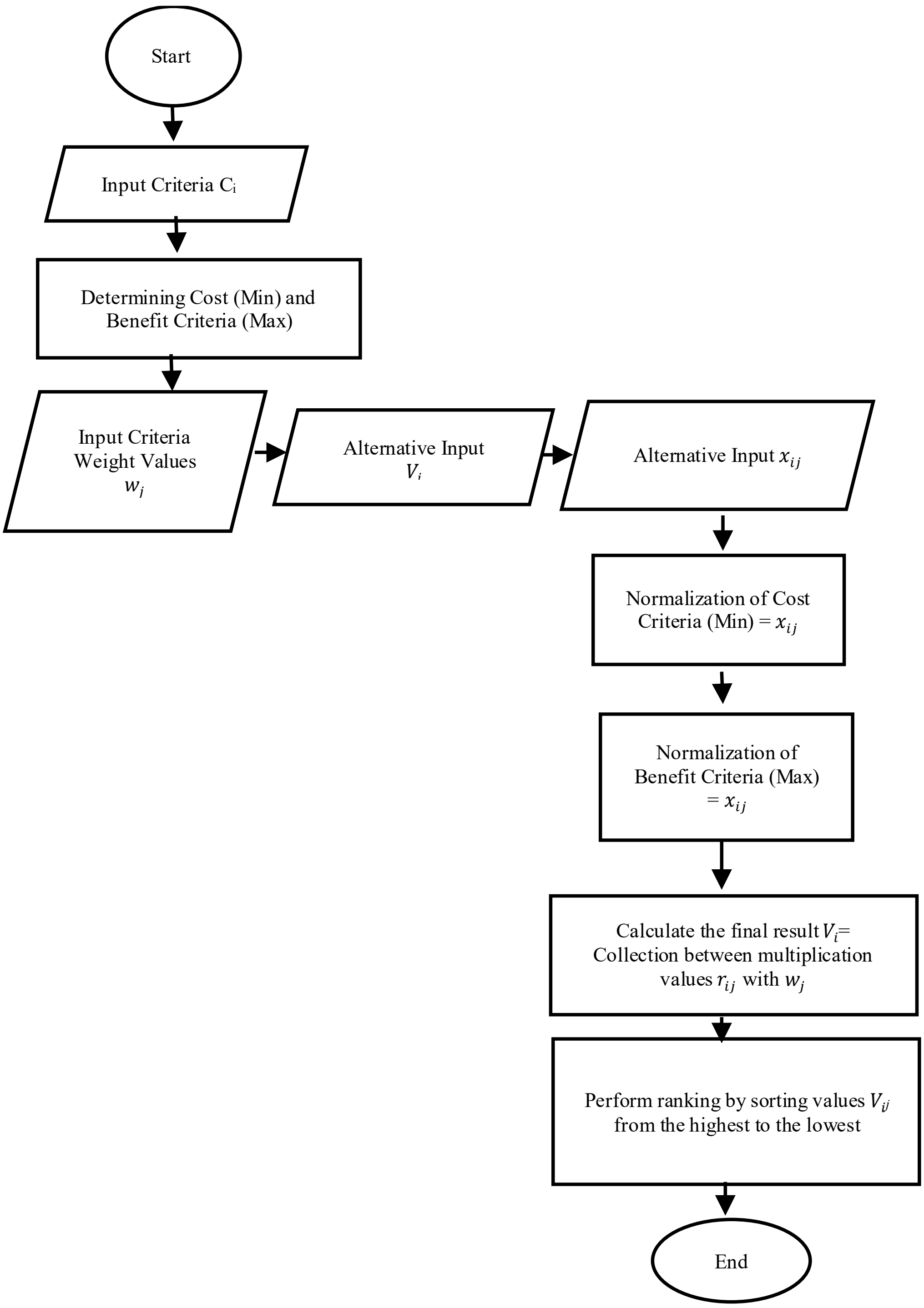


Fig. 1. SAW Calculation Stage

adoption of digital platforms has further expanded market access and competitiveness, supported by digital marketing practices that improve visibility and consumer interaction (Fitrianti et al., 2024; Sulistyowati et al., 2024; Yeni et al., 2025). These developments affirm that culinary MSMEs are not only economic actors but also cultural agents within local communities (Subagyo et al., 2024).

Despite their potential, determining which culinary MSMEs are most favored by consumers remains a challenge due to subjective biases and inefficient manual assessment processes. Customers typically rely on varied, individualized considerations—such as taste, price, service quality, store cleanliness, and menu uniqueness—when choosing where to eat. Without structured data collection and systematic evaluation, MSMEs lack the ability to understand their relative market position, analyze performance, or develop targeted strategies for product and service improvement. This challenge is compounded by the absence of platforms that can transform subjective impressions into objective, analyzable insights. As research on decision-making methods such as FAHP and AHP demonstrates, subjective assessments require structured criteria and weighted evaluation frameworks to reduce ambiguity and bias (Alyamani et al., 2021; Surya & Farizal, 2023).

To address these limitations, data-driven systems have become increasingly necessary to facilitate more transparent and accurate decision-making for MSMEs. Digital financial management tools and analytic systems enable real-time insights that reduce human error and improve operational intelligence (Nwangele et al., 2022; Okeke et al., 2024). Studies further emphasize that integrating data-driven mechanisms into MSME assessment helps minimize subjective biases and enhance the reliability of business decisions (Al-Amin et al., 2024). In selecting the most popular culinary MSMEs, an objective, computational approach is therefore essential to accommodate the multidimensional nature of consumer preferences and to yield valid, actionable outcomes.

In this regard, Decision Support Systems (DSS) emerge as a critical tool capable of organizing complex information and generating structured recommendations. DSS provides interactive and analytical workflows that support decision-makers in evaluating alternatives across diverse criteria (Karyaningsih, 2023; Sagala & Hasugian, 2023; Supriadi et al., 2021). Techniques frequently applied in DSS—such as the Analytical Hierarchy Process (AHP), TOPSIS, and Simple Additive Weighting (SAW)—allow for systematic weighting, comparison, and ranking of alternatives across defined variables (Casildo et al., 2023; Mundzir et al., 2023). The flexibility of DSS has enabled its adoption across sectors, including education, agriculture, and public administration, demonstrating its effectiveness in both structured and semi-structured decision contexts (Sridevy et al., 2023; Suryani et al., 2024).

Among various DSS techniques, the Simple Additive Weighting (SAW) method is widely recognized for its simplicity, efficiency, and reliability in multi-criteria evaluation. SAW operates by normalizing decision matrices, assigning weights to each criterion, and calculating aggregate preference scores for each alternative (Handayani & Hariyanti, 2022; Soleh & Supatman, 2024). Research shows that SAW's transparent weighting mechanism makes it highly effective for ranking alternatives in domains such as student admission, cooperative evaluation, and micro-business prioritization (Amanda et al., 2023; Hamsinar et al., 2021; Machfiroh et al., 2023). Its widespread use further underscores its practical advantages over more complex MCDM approaches, particularly when decision-makers require straightforward yet accurate evaluation tools (Puška et al., 2023; Zulkarnain & Helma, 2023).

In response to these challenges and opportunities, the present study implements a Decision Support System using the SAW method to identify the most popular culinary MSMEs in the Dracik Field area. The system utilizes MySQL as its primary database to store information on MSMEs, relevant criteria, consumer evaluations, normalization results, and final rankings. Customer assessments collected through structured questionnaires are processed into quantitative data that enable objective preference scoring. The resulting DSS not only supports consumers in selecting dining options but also assists MSME owners and area managers in conducting targeted business development, empowerment programs, and strategic planning based on real, data-driven insights. Thus, this study aims to validate the functional capability of a Decision Support System to execute multi-criteria ranking using the SAW method by ensuring that the computational process produces mathematically correct output. This study does not attempt to generalize consumer behavior; the dataset is used only as test data to verify system functionality and algorithmic correctness.

2. Metode

2.1. System use case diagram

To describe the functional interactions between users and the developed Decision Support System, a use case diagram was designed. The system involves two primary actors: Administrator and Decision Maker. The Administrator is responsible for managing system data, including MSME records, criteria, sub-criteria, and assessment input. The Decision Maker utilizes the system to generate and review ranking reports based on the SAW computation.

The main use cases for the Administrator include: (1) managing MSME data (create, update, delete MSME records), (2) managing criteria and sub-criteria, (3) inputting or importing assessment data, and (4) triggering SAW computation to generate rankings. For the Decision Maker, the main use cases are: (1) viewing normalized data, (2) viewing ranking results, and (3) printing or exporting the final report.

These interactions are summarized in the system use case diagram shown in Fig. 1, which illustrates how each actor interacts with the system boundaries and how the DSS supports the end-to-end decision-making workflow for multi-criteria ranking.

2.2. SAW algorithm activity diagram

To clarify the internal logic of the SAW implementation in the DSS, an activity diagram was created to represent the sequence of computational steps executed by the system. The process begins when the Administrator completes input of criteria, weights, and alternative scores. The system then constructs the decision matrix and proceeds with the following activities: 1) Read Input Data: The system retrieves criteria, weights, and alternative scores from the database; 2) Build Decision Matrix: A decision matrix is constructed where each row represents an alternative and each column corresponds to a criterion; 3) Normalize Criterion Values: For each criterion, the system determines whether it is a benefit or cost attribute and applies the corresponding normalization formula; 4) Apply Weights: The normalized values are multiplied by their respective criterion weights; 5) Compute Preference Scores: The system sums the weighted normalized values for each alternative to produce a final preference score; 6) Sort Alternatives: Alternatives are ranked in descending order of their preference scores; and 6) Display and Store Results: The final ranking is displayed to the user and stored in the calculation results table for reporting.

2.3. SAW implementation pseudocode (controller logic)

The SAW method was implemented in the application controller layer using PHP within the Laravel framework. To ensure clarity and reproducibility of the algorithmic logic, the core computation is expressed in the pseudocode below. The pseudocode abstracts from specific syntax and focuses on the main steps of reading data, normalizing values, applying weights, and generating final rankings.

In the actual Laravel implementation, the criteria and alternative scores are loaded from the corresponding database tables, and the normalized and final preference values are stored back into the normalization and calculation tables. The

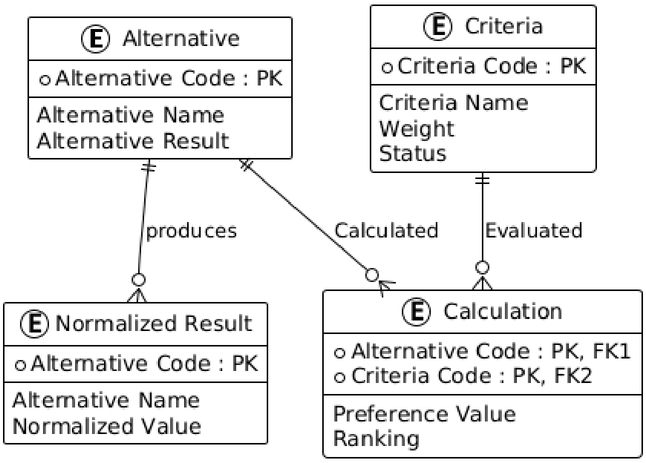


Fig. 2. Relationships Between Tables

pseudocode confirms that the implementation strictly follows the SAW formulation reported in related literature and provides a clear view of the algorithmic flow for other researchers who wish to replicate or extend this work.

3. Result

3.1.1. Planning model

According to Honggo et al (2014), relationships between tables are interconnected and governed by specific rules. The planning model created contains four interconnected tables: criteria, alternatives, normalization results, and calculations, as shown in Fig. 2.

3.1.2. Determining criteria, sub-criteria, and weights

Criteria are needed because they are important factors in the Decision Support System for determining the most popular culinary MSMEs. Sub-criteria and weights are used for sub-selection within each criterion and weight for each sub-criterion. The criteria table is shown in Table 1. Subsequently, Table 2 to Table 5 show sub-criteria for respondents to use to determine the most popular culinary MSMEs.

3.1.3. Determining culinary MSMEs

The culinary MSMEs selected for this study were those most frequently visited by customers. This culinary MSME table will be used as a determinant in the Alternative table. The culinary

Table 1. Images/tables within textboxes so they can be moved around dynamically

Criteria Code	Criteria Name	Weight	Status
C1	Price	40	Cost
C2	Location	30	Benefit
C3	Service	20	Benefit
C4	Food Quality	10	Benefit

Table 2. Price Sub-Criteria

Criteria Name	Criteria Code	Sub-Criteria	Weight	Status
Price	C1	≤ 15,000	2	Cost
		15,000 – 25,000	3	Cost
		25,000 – 35,000	4	Cost
		≥ 35,000	5	Cost

Table 3. Place Sub-Criteria

Criteria Name	Criteria Code	Sub-Criteria	Weight	Status
Location	C2	Poor	2	Benefit
		Fair	3	Benefit
		Good	4	Benefit
		Very Good	5	Benefit

Table 4. Service Sub-Criteria

Criteria Name	Criteria Code	Sub-Criteria	Weight	Status
Service	C3	Poor	2	Benefit
		Fair	3	Benefit
		Good	4	Benefit
		Very Good	5	Benefit

Table 5. Food Quality Sub-Criteria

Criteria Name	Criteria Code	Sub-Criteria	Weight	Status
Food Quality	C4	Poor	2	Benefit
		Fair	3	Benefit
		Good	4	Benefit
		Very Good	5	Benefit

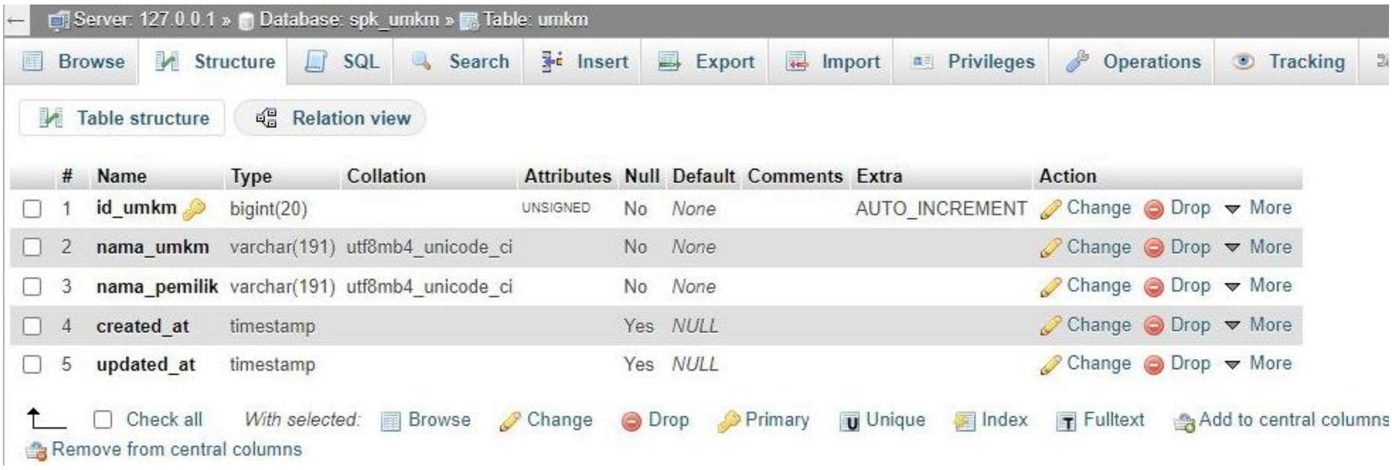


Fig. 3. MSME Table Structure

MSME table is shown in Table 6.

3.1.4. SAW calculation

In this calculation, we determine the decision matrix based on the criteria. Next, the normalization process is performed using the decision matrix, as shown on Table 7. The normalization calculation uses the following formulas:

$$X = [x_{ij}], \quad i = 1,2,\ldots,m, \quad j = 1,2,\ldots,n \tag{1}$$

Where:
x_{ij} = the value of the third alternative on the criteria j,
m = number of alternatives,
n = number of criteria.

The following formulas are used to determine attributes classified as benefits.

- Benefit criteria:

$$r_{ij} = \frac{x_{ij}}{\max(x_{ij})} \tag{2}$$

- Cost criteria:

$$r_{ij} = \frac{\min(x_{ij})}{x_{ij}} \tag{3}$$

Where:
r_{ij} = The value of the element in the normalized matrix,
x_{ij} = The attribute value of each criterion,
$\max(x_{ij})$ = The maximum value of each criterion,
$\min(x_{ij})$ = The minimum value of each criterion.

After applying the normalization formulas, the normalized matrix R is obtained as shown in Table 8. Next, the calculation process will be carried out to determine the final value (V value), which is obtained by adding the total results of the calculation of the preference weights W applied to the normalized matrix R. This calculation will determine the Alternative with the largest value as the superior Alternative, as follows:

Table 6. Culinary MSMEs

UMKM ID	UMKM Name	Owner Name
1	Chicken Porridge	Mrs. Beti
2	Food Stall	Mrs. Rukeni
3	Pecel Stall	Mrs. Arofah
4	Bakso Bang Ali	Mr. Ali
5	Es Teler	Mr. Edo

Table 7. Decision matrix data

Alternative	C1	C2	C3	C4
A1	2	4	4	5
A2	3	3	4	3
A3	2	5	3	4

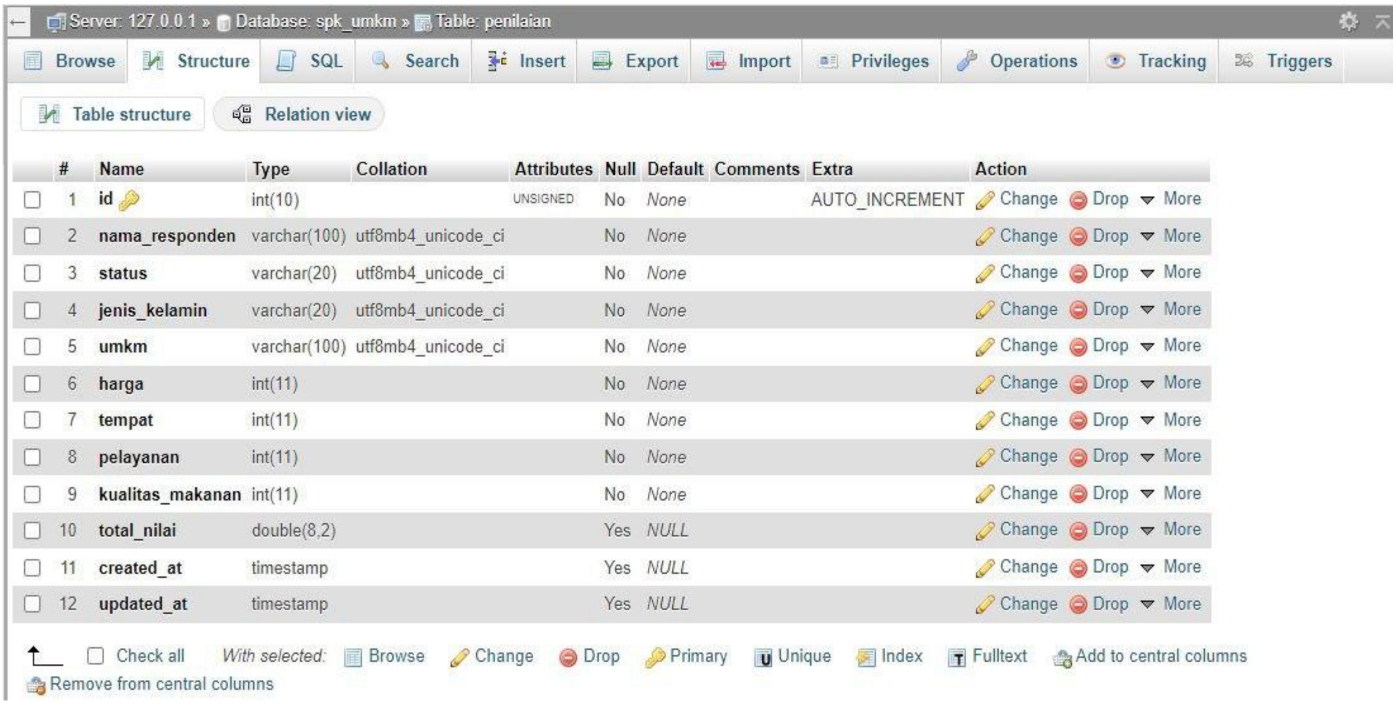
Table 8. Normalized Data

Alternative	Criteria			
	C1	C2	C3	C4
A1	1	0.8	1	1
A2	0.7	0.6	1	0.6
A3	1	1	0.75	0.8

$$V_i = \sum_{j=1}^{n} w_j \cdot r_{ij} \tag{4}$$

where:
V_i = alternative preference value to i,
w_j = weight of criteria to j,
r_{ij} = normalization value.

The example of calculation after the formula, as follows:



#	Name	Type	Collation	Attributes	Null	Default	Comments	Extra	Action
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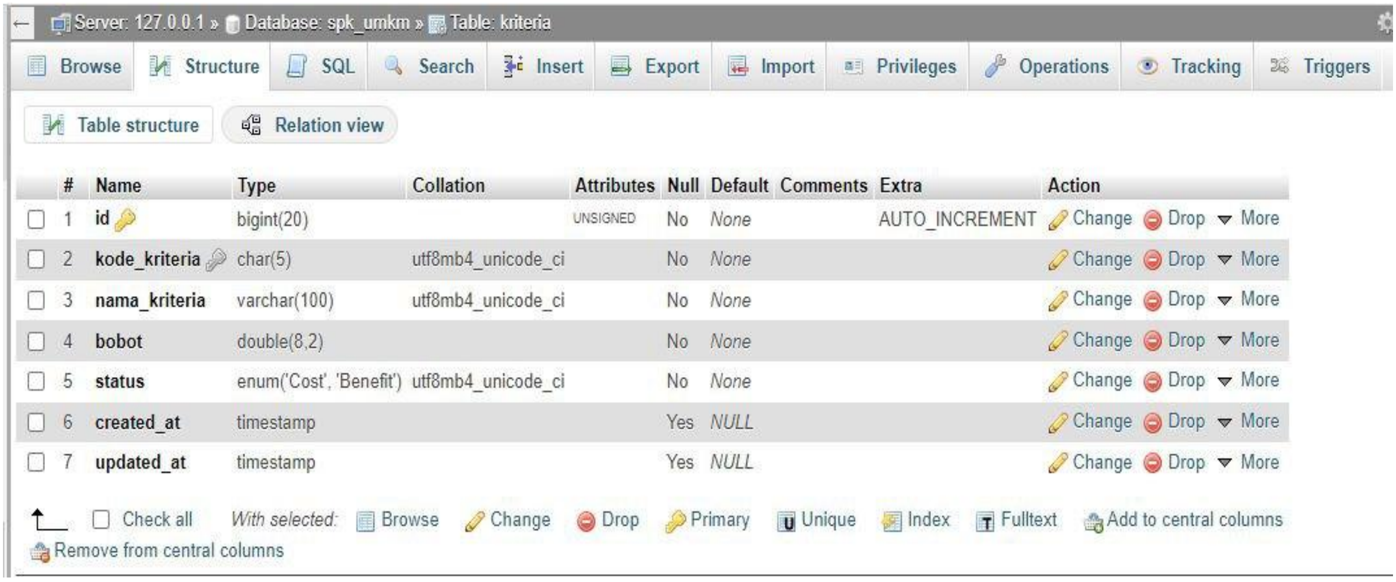
2	nama_responden	varchar(100)	utf8mb4_unicode_ci		No	None			Change Drop More
3	status	varchar(20)	utf8mb4_unicode_ci		No	None			Change Drop More
4	jenis_kelamin	varchar(20)	utf8mb4_unicode_ci		No	None			Change Drop More
5	umkm	varchar(100)	utf8mb4_unicode_ci		No	None			Change Drop More
6	harga	int(11)			No	None			Change Drop More
7	tempat	int(11)			No	None			Change Drop More
8	pelayanan	int(11)			No	None			Change Drop More
9	kualitas_makanan	int(11)			No	None			Change Drop More
10	total_nilai	double(8,2)			Yes	NULL			Change Drop More
11	created_at	timestamp			Yes	NULL			Change Drop More
12	updated_at	timestamp			Yes	NULL			Change Drop More

Fig. 4. Assessment Table Structure



#	Name	Type	Collation	Attributes	Null	Default	Comments	Extra	Action
1	id	bigint(20)		UNSIGNED	No	None		AUTO_INCREMENT	Change Drop More
2	kode_kriteria	char(5)	utf8mb4_unicode_ci		No	None			Change Drop More
3	nama_kriteria	varchar(100)	utf8mb4_unicode_ci		No	None			Change Drop More
4	bobot	double(8,2)			No	None			Change Drop More
5	status	enum('Cost', 'Benefit')	utf8mb4_unicode_ci		No	None			Change Drop More
6	created_at	timestamp			Yes	NULL			Change Drop More
7	updated_at	timestamp			Yes	NULL			Change Drop More

Fig. 5. Criteria Table Structure

$$r_{12} = \frac{x_{12}}{\max(x_{12}, x_{22}, x_{32}, x_{42})} \quad (5)$$

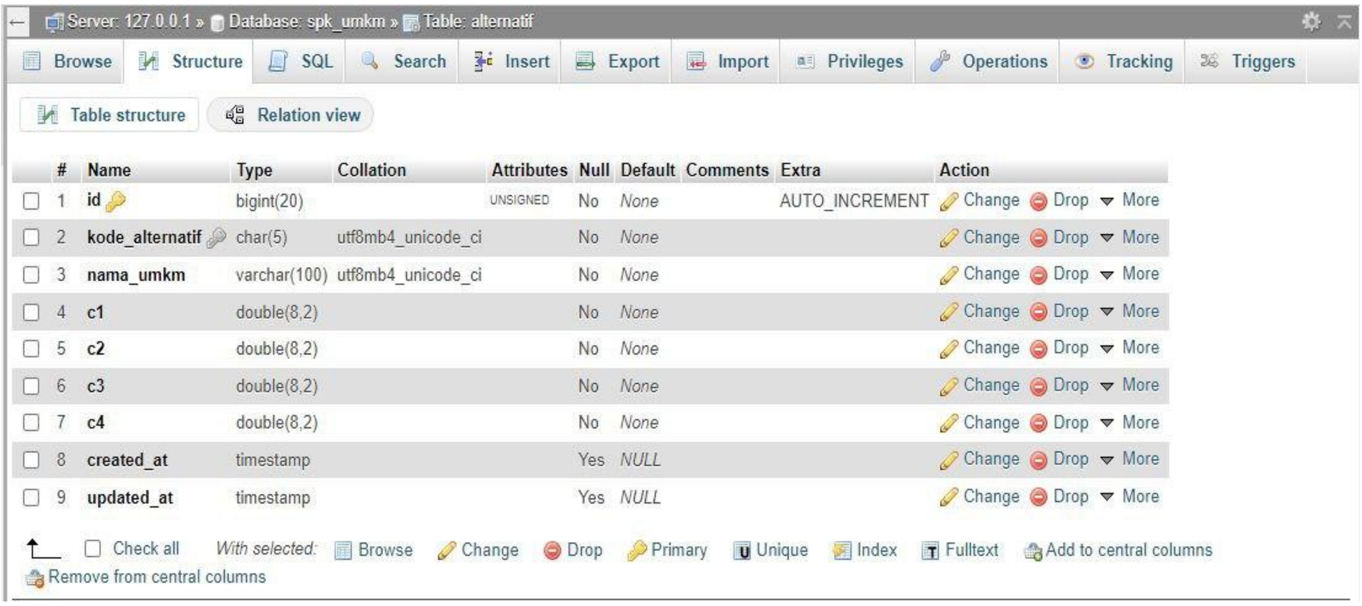
$$r_{12} = \frac{\min(x_{12}, x_{22}, x_{32}, x_{42})}{x_{12}}. \quad (6)$$

Based on the provided multiplication and addition formulas, the formulas are applied to the normalized results in Table 8. Using the criteria as shown in Table 1, the calculation results are presented in Table 9 and Table 10.

3.1.5. Database implementation in MySQL

MySQL will be used to store the DSS database that identifies the most popular culinary MSMEs. The MSME table structure is shown in Fig. 3. The MSME table structure has only three columns: ID, MSME Name, and Owner Name. The MSME table structure has a primary key, id_umkm. The assessment table structure is shown in Fig. 4.

The assessment table has 10 columns: ID, Respondent Name, Status, Gender, MSME, Price, Place, Service, Food



Server: 127.0.0.1 » Database: spk_umkm » Table: alternatif

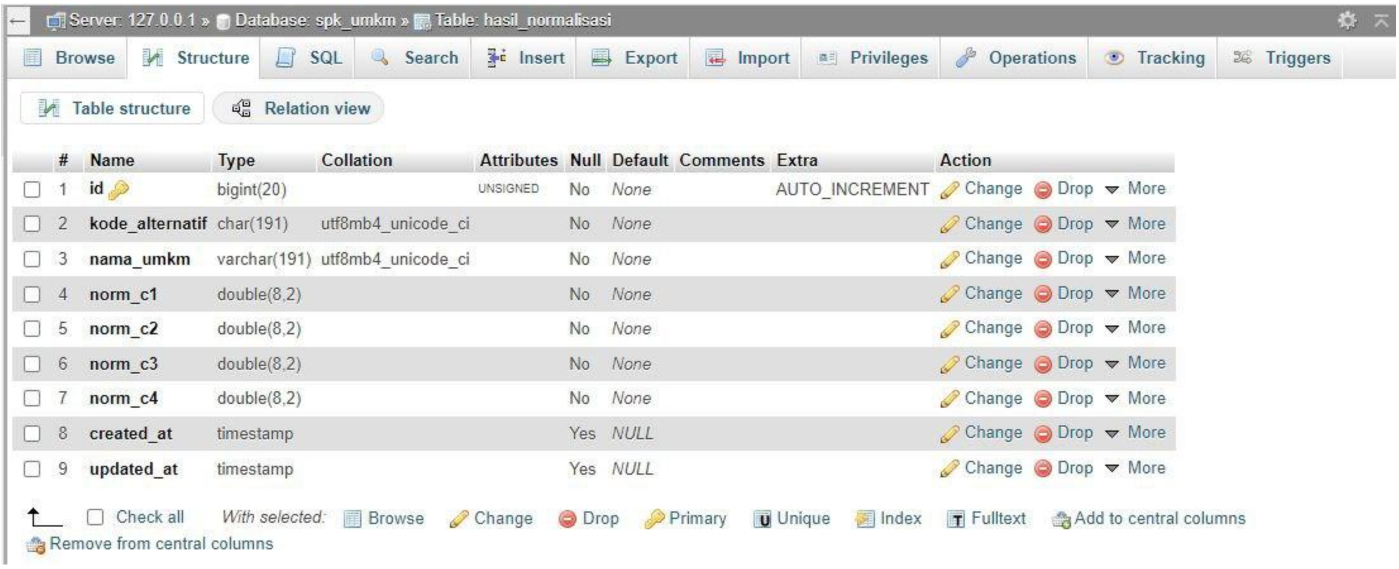
Browse | Structure | SQL | Search | Insert | Export | Import | Privileges | Operations | Tracking | Triggers

Table structure | Relation view

#	Name	Type	Collation	Attributes	Null	Default	Comments	Extra	Action
1	id	bigint(20)		UNSIGNED	No	None		AUTO_INCREMENT	Change Drop More
2	kode_alternatif	char(5)	utf8mb4_unicode_ci		No	None			Change Drop More
3	nama_umkm	varchar(100)	utf8mb4_unicode_ci		No	None			Change Drop More
4	c1	double(8,2)			No	None			Change Drop More
5	c2	double(8,2)			No	None			Change Drop More
6	c3	double(8,2)			No	None			Change Drop More
7	c4	double(8,2)			No	None			Change Drop More
8	created_at	timestamp			Yes	NULL			Change Drop More
9	updated_at	timestamp			Yes	NULL			Change Drop More

Check all With selected: Browse Change Drop Primary Unique Index Fulltext Add to central columns Remove from central columns

Fig. 6. Alternative Table Structure



Server: 127.0.0.1 » Database: spk_umkm » Table: hasil_normalisasi

Browse | Structure | SQL | Search | Insert | Export | Import | Privileges | Operations | Tracking | Triggers

Table structure | Relation view

#	Name	Type	Collation	Attributes	Null	Default	Comments	Extra	Action
1	id	bigint(20)		UNSIGNED	No	None		AUTO_INCREMENT	Change Drop More
2	kode_alternatif	char(191)	utf8mb4_unicode_ci		No	None			Change Drop More
3	nama_umkm	varchar(191)	utf8mb4_unicode_ci		No	None			Change Drop More
4	norm_c1	double(8,2)			No	None			Change Drop More
5	norm_c2	double(8,2)			No	None			Change Drop More
6	norm_c3	double(8,2)			No	None			Change Drop More
7	norm_c4	double(8,2)			No	None			Change Drop More
8	created_at	timestamp			Yes	NULL			Change Drop More
9	updated_at	timestamp			Yes	NULL			Change Drop More

Check all With selected: Browse Change Drop Primary Unique Index Fulltext Add to central columns Remove from central columns

Fig. 7. Structure of the Normalization Results Table

Quality, and Total Score. The primary key is in the ID column. This table stores assessment data from respondents via questionnaires, which will later be averaged to produce a total score. Then the Criteria Table Structure is shown in Fig. 5.

The criteria table structure contains five columns: ID, Criteria Code, Criteria Name, Weight, and Status. The primary key is the ID, while the criteria code is the foreign key. This table will be linked to the calculation results table. The structure of the Alternative table is shown in Fig. 6.

This table structure consists of seven columns: ID, Alternative Code, Alternative Name, C1, C2, C3, and C4. The alternative table structure has a primary key on the ID and a foreign key on the alternative code. The Normalized Table Structure is shown in Fig. 7.

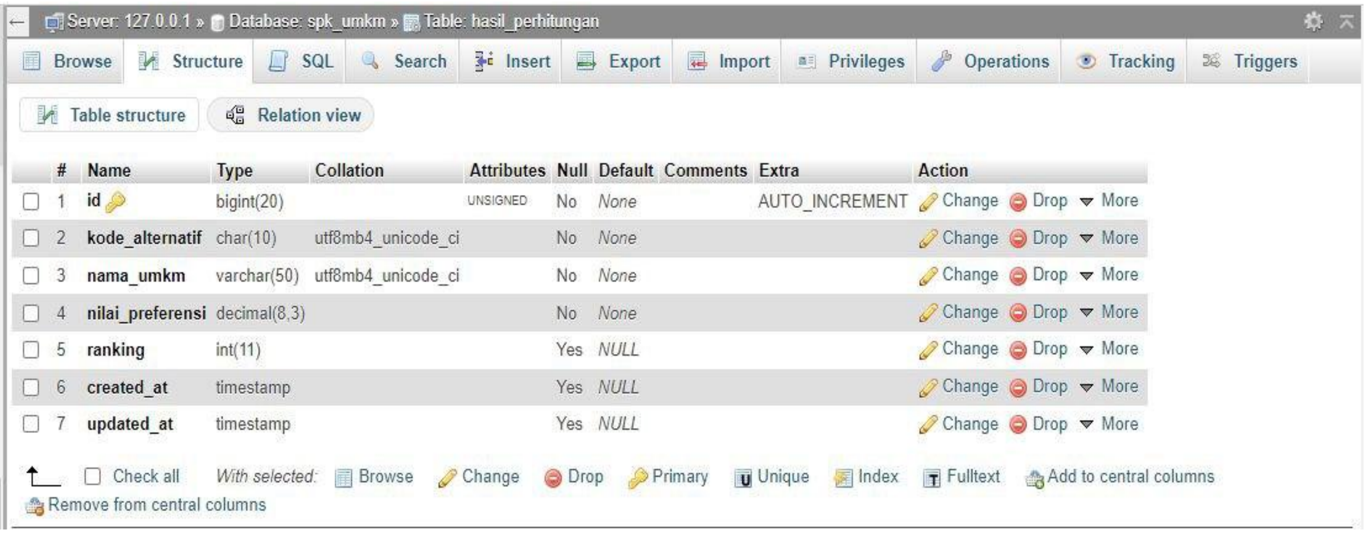
The normalized table structure consists of seven columns: ID, Alternative Code, Alternative Name, C1, C2, C3, and C4. The

Table 9. Preference Calculation

Alternative	Criteria				Results
	C1	C2	C3	C4	
A1	0.4	0.24	0.2	0.1	0.94
A2	0.268	0.18	0.2	0.06	0.708
A3	0.4	0.3	0.15	0.08	0.93

Table 10. Ranking

Alternative	Preference Value	Ranking
A1	0.94	1
A3	0.93	2
A2	0.708	3


Server: 127.0.0.1 » Database: spk_umkm » Table: hasil_perhitungan

Browse | Structure | SQL | Search | Insert | Export | Import | Privileges | Operations | Tracking | Triggers

Table structure | Relation view

#	Name	Type	Collation	Attributes	Null	Default	Comments	Extra	Action
1	id	bigint(20)		UNSIGNED	No	None		AUTO_INCREMENT	Change Drop More
2	kode_alternatif	char(10)	utf8mb4_unicode_ci		No	None			Change Drop More
3	nama_umkm	varchar(50)	utf8mb4_unicode_ci		No	None			Change Drop More
4	nilai_preferensi	decimal(8,3)			No	None			Change Drop More
5	ranking	int(11)			Yes	NULL			Change Drop More
6	created_at	timestamp			Yes	NULL			Change Drop More
7	updated_at	timestamp			Yes	NULL			Change Drop More

Check all With selected: Browse Change Drop Primary Unique Index Fulltext Add to central columns Remove from central columns

Fig. 8. Calculation Results Table Structure

normalized table structure has a primary key in ID. The calculation table structure is shown in Fig. 8.

The calculation results table structure consists of seven columns: ID, Alternative Code, Alternative Name, C1, C2, C3, and C4. This table will later be linked to the criteria table. This table has a primary key of ID.

3.1.6. System evaluation (comparison between system output and manual SAW calculation)

To ensure the accuracy and reliability of the implemented Decision Support System, an evaluation was carried out by comparing system-generated ranking results with manual SAW calculations. The manual calculation followed three stages: (1) constructing the decision matrix based on the criteria values for each alternative, (2) performing normalization according to the attribute type (benefit or cost), and (3) calculating the preference value (Vi) by multiplying the normalized values by their respective weights and summing the results. The summary of the comparison between the system results and the manual SAW calculations is presented in Table 11.

Table 11. The Comparison Between the System Results and the Manual SAW Calculations

Alternative	Preference Value (System)	Preference Value (Manual)	Difference
Es Teler	0.988	0.988	0.000
Warung Pecel	0.967	0.967	0.000
Chicken Porridge	0.934	0.934	0.000
Warung Makan	0.910	0.910	0.000
Bakso Bang Ali	0.872	0.872	0.000

The comparison results show that the system's preference values are identical to those obtained manually, with zero difference across all alternatives. This confirms that the SAW calculation embedded in the system—covering normalization and weighted aggregation—works correctly, consistently, and in accordance with the expected computational logic. Thus, the DSS developed in this study has been validated through manual verification and proven to perform SAW computations accurately.

3.1.7. System verification and testing

To ensure that the Decision Support System functions correctly beyond the mathematical validation of the SAW calculations, system verification and software testing were performed. The objective of this stage was not to evaluate consumer behavior but to assess whether the system processes input vectors accurately and generates consistent output without computational or functional errors. The verification was carried out using two complementary approaches.

3.1.7.1. Algorithm verification

The system output for the SAW preference values was compared against manual SAW calculations using Microsoft Excel. The Mean Absolute Error (MAE) was computed across all alternatives and resulted in = 0.000, which confirms that the SAW algorithm embedded in the system was executed without numerical deviation.

3.1.7.2. Functional testing

Functional testing was performed using input–process–output validation. For each change in criteria weight, sub-criterion selection, and alternative scoring, the system dynamically recomputed the normalized values and updated the final ranking without delay or runtime failure. No interruptions, crashes, or incorrect data flow were found during testing.

The combined results of algorithm verification and functional testing demonstrate that the developed system fully satisfies the expected operational requirements. The system consistently computes preference values, handles recalculation logic in real time when data changes, and produces output that is mathematically equivalent to manual SAW calculations. Therefore, the result of this research is the successful

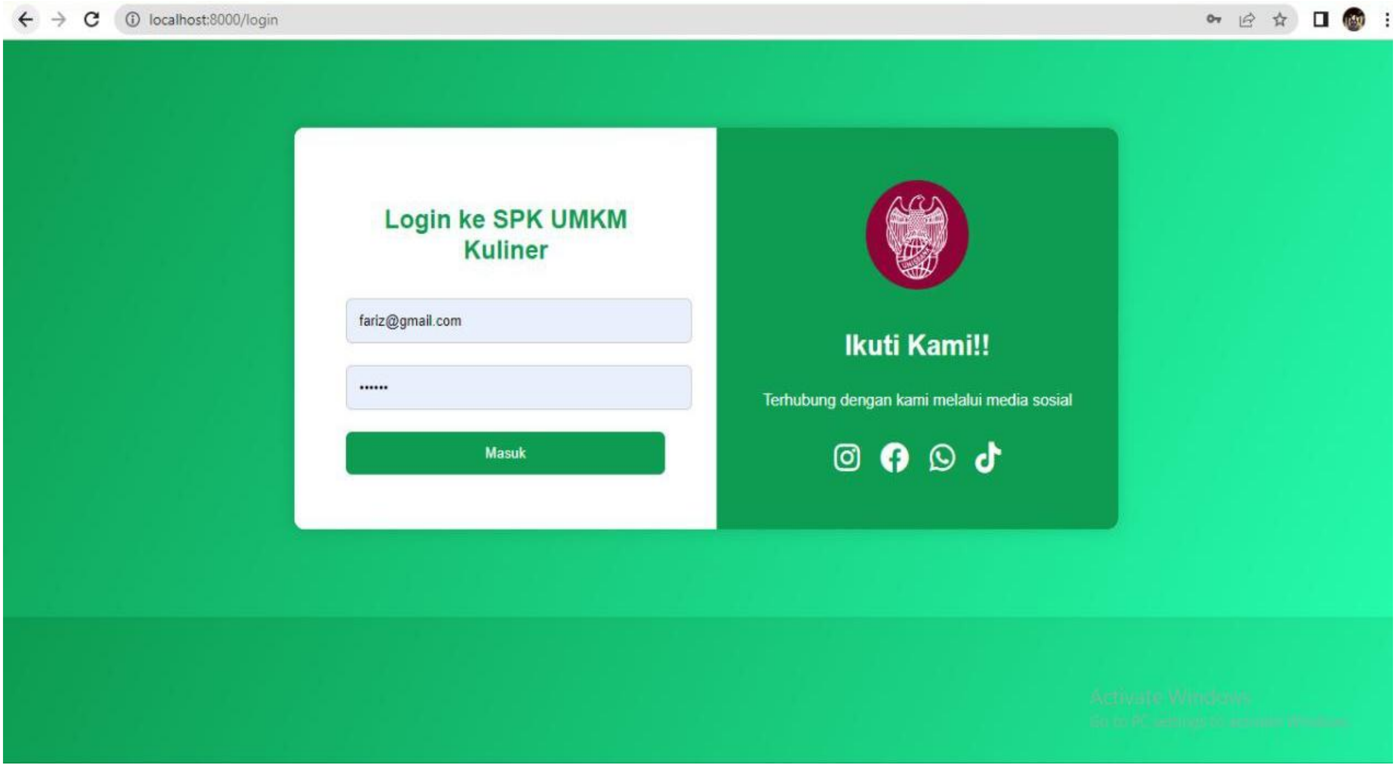


Fig. 9. Culinary UMKM DSS Login Form

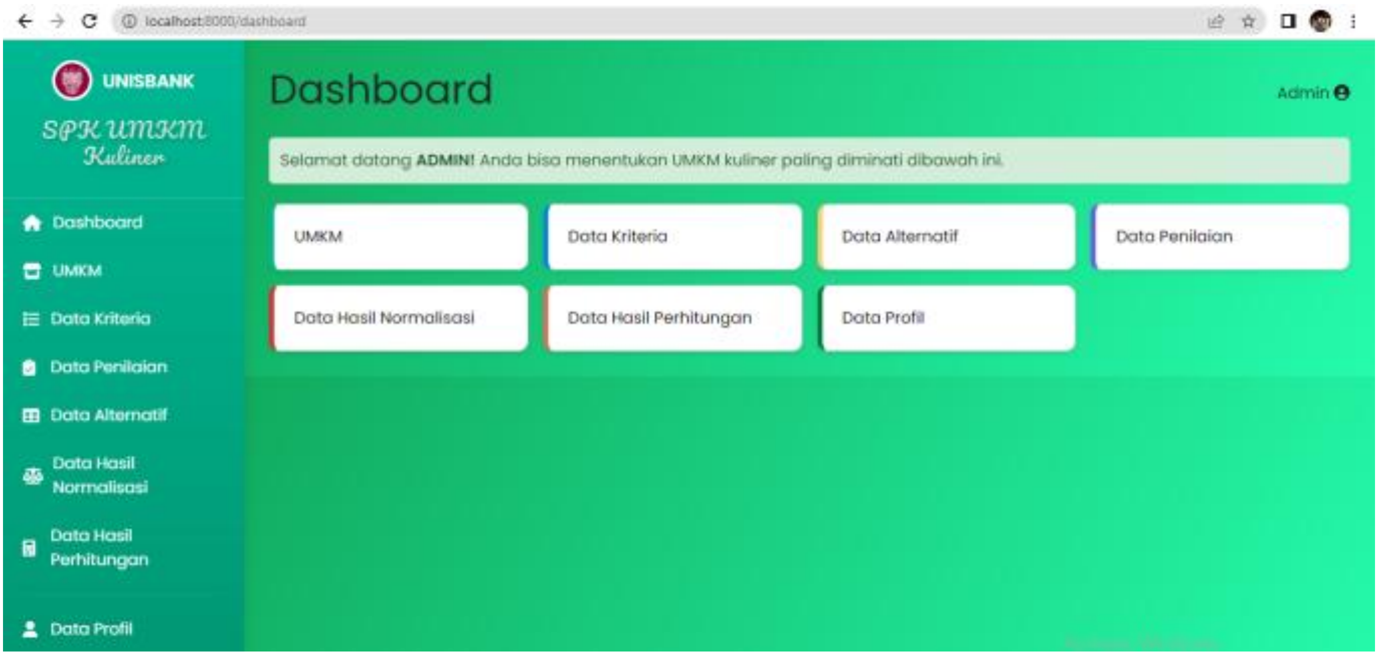


Fig. 10. Culinary UMKM DSS Dashboard

verification of a working DSS implementation rather than the identification of the most popular MSME.

3.1.8. System view

The system display will explain the Decision Support System for determining the desired culinary MSMEs, using the SDLC system development life cycle. This system can only be accessed by users and administrators. First, the administrator will log in with their registered username and password. The login form is shown in Fig. 9.

After logging in with the correct username and password, the system will automatically redirect you to the dashboard, as show in Fig. 10. The dashboard contains several features, including MSME data, criteria data, assessment data, alternative data, normalization data, calculation data, and profile data.

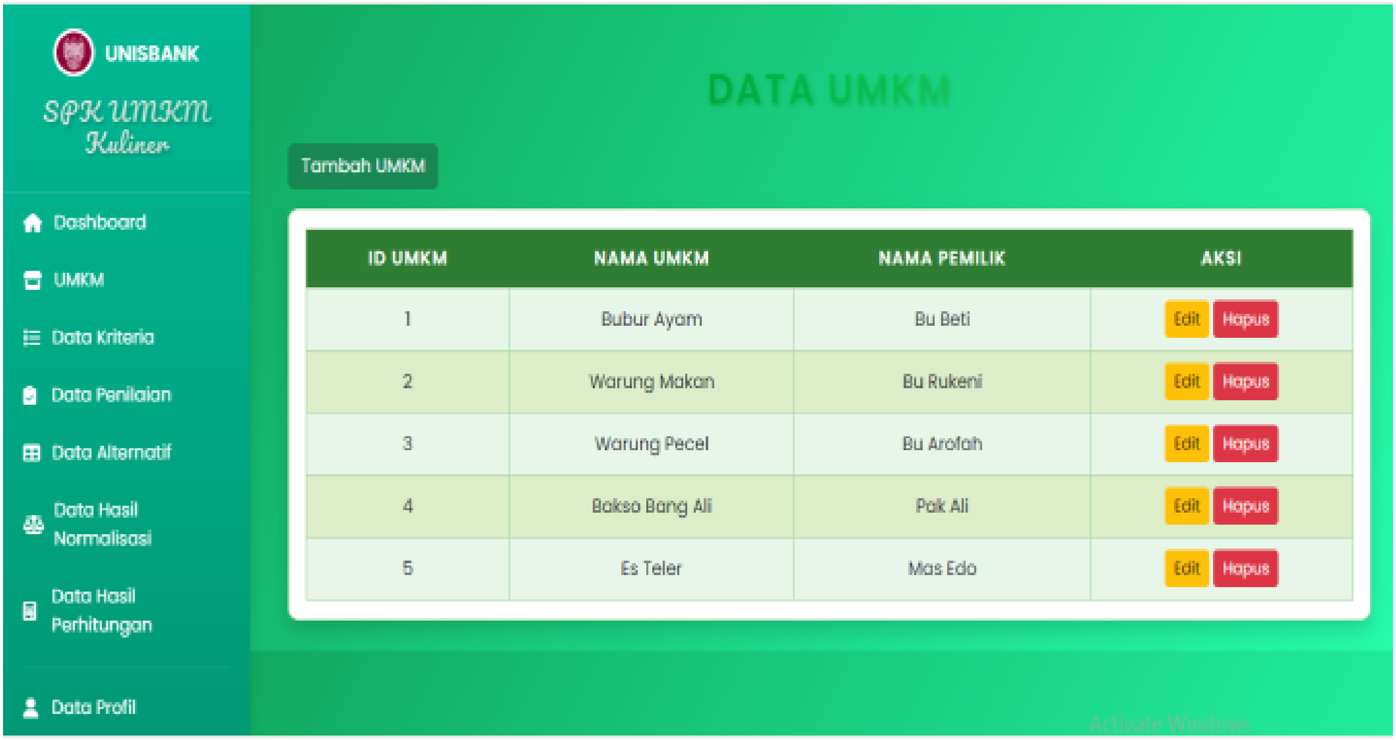


Fig. 11. Culinary MSME Data

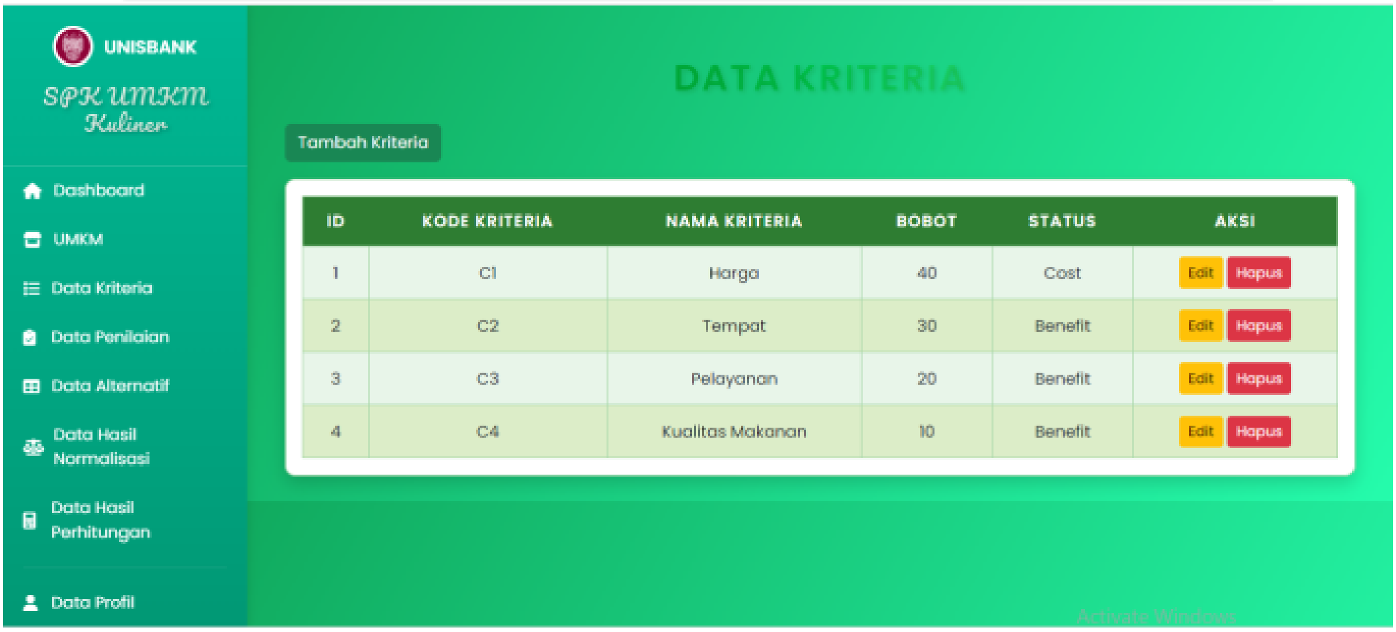


Fig. 12. Criteria Data

After navigating to the dashboard, the admin will input data for the culinary MSMEs located at the Dracik field on the Batang campus. The MSME data is shown in Fig. 11.

The input MSME data represent the 65 MSMEs most frequently visited by customers at the Dracik field on the Batang campus. This MSME data will be used to select respondents through a questionnaire to determine the most popular culinary MSMEs. The system then fills in the Criteria Data. A graphical representation of the Criteria Data is shown in Fig. 12.

The input criteria can be adjusted to meet user needs. Each criterion has a different weighting value, and sub-criteria will be used to determine the value of the MSME of interest. which is contained in the assessment data. The assessment data is found in Fig. 13.

This assessment data was obtained through a customer questionnaire. The researchers selected only 10 respondents to select the MSMEs they were interested in. Respondents were free to choose their own weighting for each sub-criterion, and then the average of all the sub-criterion scores was calculated based on the culinary MSME name. The average assessment data

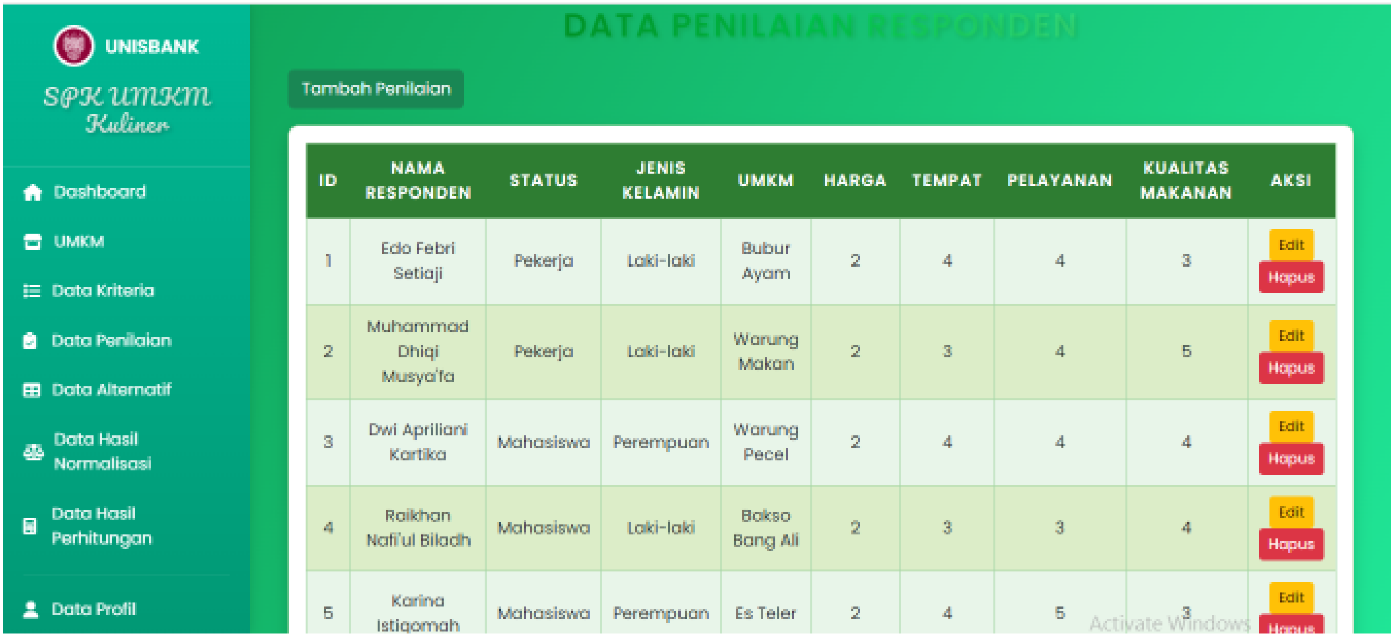


Fig. 13. Assessment Data

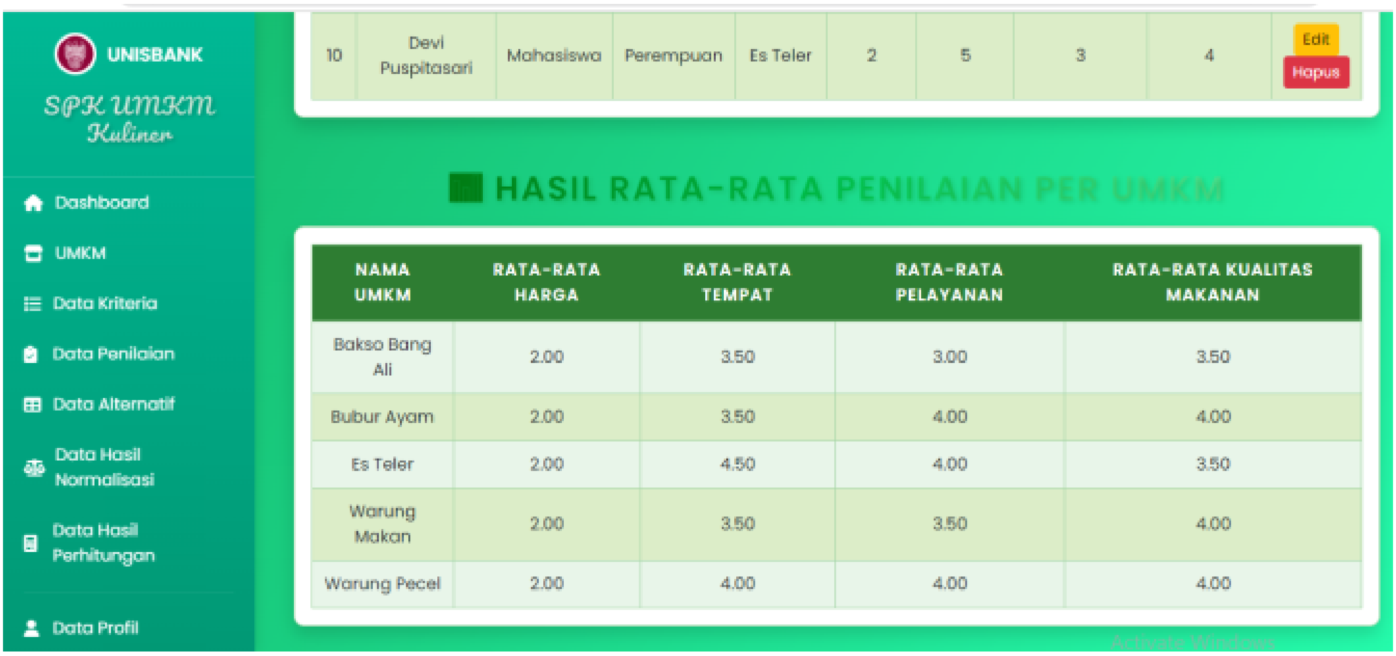


Fig. 14. Average Assessment Data

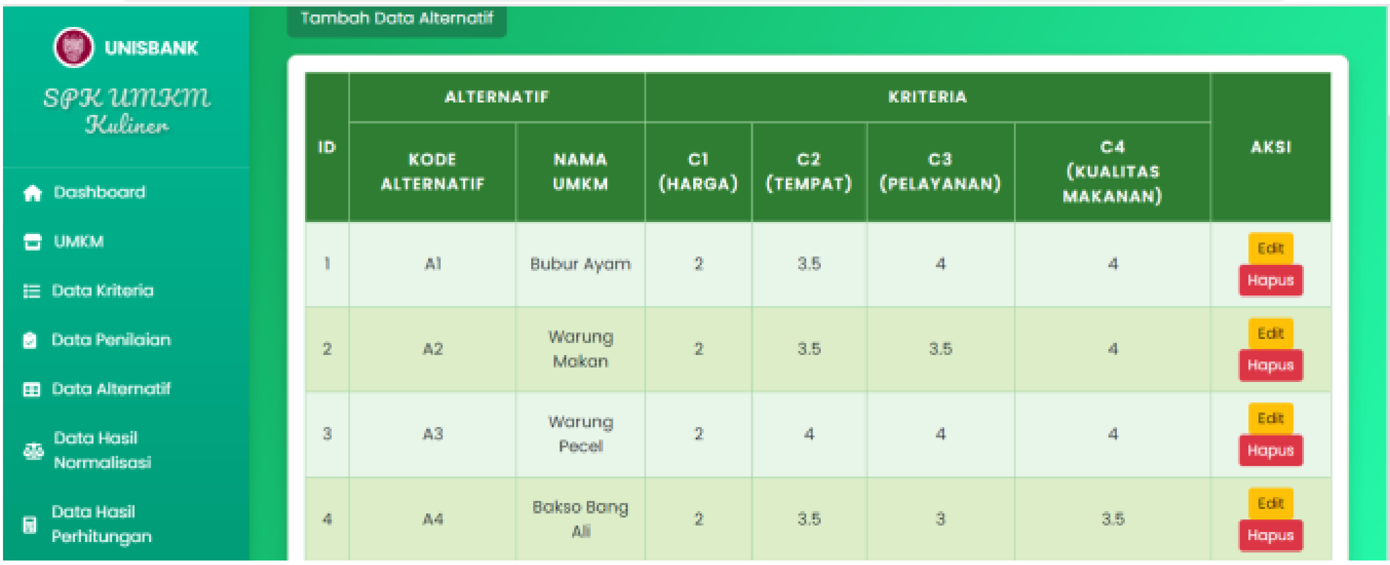
results are shown in Fig. 14.

The average results are then input into alternative data, which will determine the decision matrix based on the criteria. The alternative data is shown in Fig. 15.

Alternative Data will then perform a SAW calculation to determine the normalized values for each criterion. These values will form the normalized matrix. The normalized data results are shown in Fig. 16.

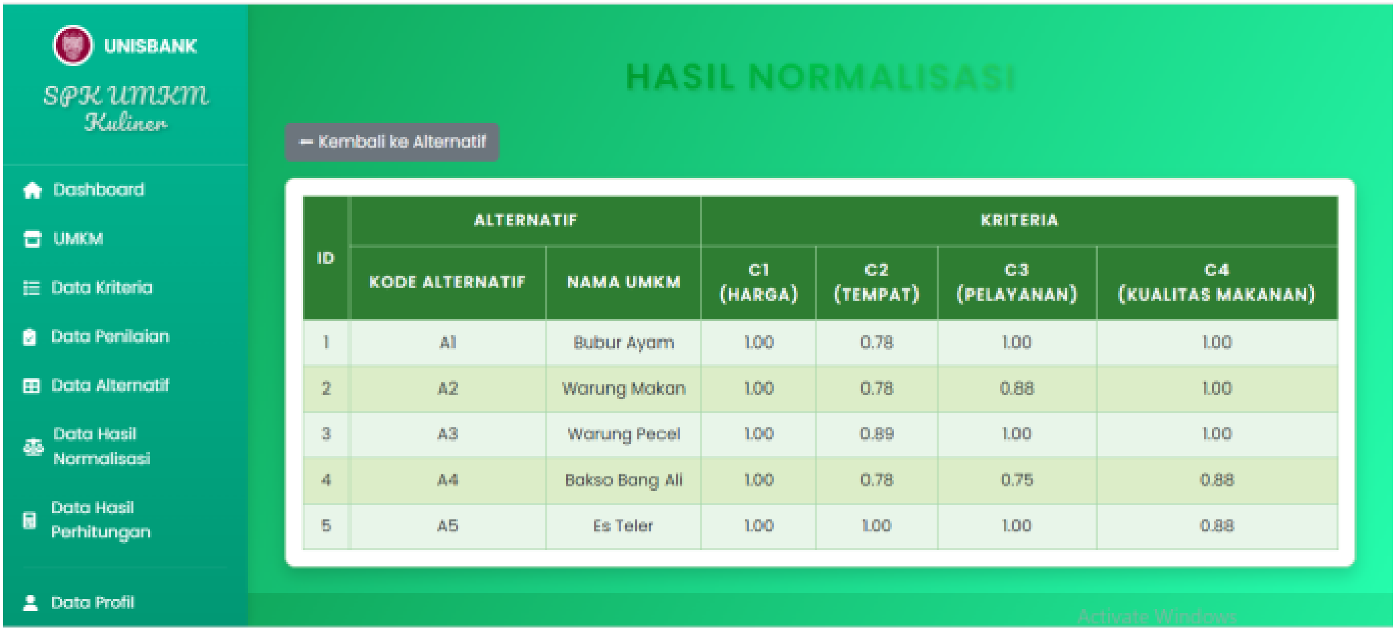
In this section, the admin cannot change, delete, or add because the Normalized Data Results in the Decision Support System, which determines the most popular MSMEs, are automatically calculated using the SAW method based on the alternative data added. Therefore, every time the alternative data changes, the normalized results section will also change. Then, calculations will be performed on the normalized results to determine the preference values and rankings for the popular culinary MSMEs. The calculation data is shown in Fig. 17.

The system successfully generated ranking results using the weighted SAW computation, and all calculated preference values matched the manual SAW results with zero error, demonstrating the correct execution of the SAW algorithm. This calculation data will be printed as a report result and then given



ID	ALTERNATIF		KRITERIA				AKSI
	KODE ALTERNATIF	NAMA UMKM	C1 (HARGA)	C2 (TEMPAT)	C3 (PELAYANAN)	C4 (KUALITAS MAKANAN)	
1	A1	Bubur Ayam	2	3.5	4	4	Edit Hapus
2	A2	Warung Makan	2	3.5	3.5	4	Edit Hapus
3	A3	Warung Pecel	2	4	4	4	Edit Hapus
4	A4	Bakso Bang Ali	2	3.5	3	3.5	Edit Hapus

Fig. 15. Alternative Data



ID	ALTERNATIF		KRITERIA			
	KODE ALTERNATIF	NAMA UMKM	C1 (HARGA)	C2 (TEMPAT)	C3 (PELAYANAN)	C4 (KUALITAS MAKANAN)
1	A1	Bubur Ayam	1.00	0.78	1.00	1.00
2	A2	Warung Makan	1.00	0.78	0.88	1.00
3	A3	Warung Pecel	1.00	0.89	1.00	1.00
4	A4	Bakso Bang Ali	1.00	0.78	0.75	0.88
5	A5	Es Teler	1.00	1.00	1.00	0.88

Fig. 16. Normalization Result Data

to the MSME owner, with the aim of providing further development direction for MSMEs based on the criteria values provided by customers. The report results are in Fig. 18.

4. Discussion

The discussion in this chapter focuses on evaluating the performance, functionality, and correctness of the implemented Decision Support System (DSS) rather than interpreting the ranking results as indicators of culinary preferences. Since the dataset used in this study served as test input rather than population representation, the primary contribution of this system lies in validating its technical reliability, algorithmic precision, and consistency in executing SAW computations.

The first point of discussion concerns the accuracy of the SAW algorithm embedded in the DSS. The comparison between the automated preference values and the manual SAW calculation yielded a Mean Absolute Error (MAE) of 0.000, demonstrating that the system's computational process strictly follows the mathematical formulation of the SAW method. This confirms that the normalization and weighted aggregation procedures operate without numerical deviation and ensure deterministic ranking outcomes under any combination of criteria and weights. These results support the view in Hak et al (2023), Hamsinar et al (2021), and Meidelfi et al (2021) that SAW remains effective in multi-criteria evaluation when the computational model is executed accurately.

The second aspect concerns the system's functional

Fig. 17. Calculation Data

REPORT ON THE RESULTS OF THE DECISION SUPPORT SYSTEM
MOST PREFERRED MSMEs USING THE SAW METHOD
AT THE DRACIK KAMPUS FIELD, BATANG

Prepared by: Muhammad Fariz

Alternative Code	MSME Name	Final Score	Rank
A5	Es Teler	0.988	1
A3	Warung Pecel	0.967	2
A1	Bubur Ayam	0.934	3
A2	Warung Makan	0.910	4
A4	Bakso Bang Ali	0.872	5

Based on the results of the Decision Support System using the SAW (Simple Additive Weighting) method, it can be concluded that **Es Teler** achieved the first rank with a score of 0.988. **Warung Pecel** ranked second with a score of 0.967, followed by **Bubur Ayam** in third place with a score of 0.934. **Warung Makan** ranked fourth with a score of 0.910, and **Bakso Bang Ali** ranked fifth with a score of 0.872. Thus, it can be concluded that **Es Teler** is the most preferred MSME with the highest score among all alternatives.

Fig. 18. Results of the Culinary UMKM DSS Report

robustness during dynamic recalculation. When input values, criteria weights, and alternative scores were modified during testing, the system immediately recomputed all normalized values and updated the final ranking without delay or runtime failure. This indicates that the system's relational structure—supported by four core tables (criteria, alternatives, normalization, and calculations)—successfully preserves data integrity throughout the decision flow. This aligns with the argument of Honggo et al (2014), who emphasized that DSS performance is highly dependent on consistent relational mapping to prevent disruptions in computation and data traceability.

Third, the system demonstrates practical interpretability of algorithmic output through a user-oriented interface. Rather than emphasizing the user interface as a standalone contribution, the system design prioritizes clarity of score breakdown and transparency of SAW calculation results. This ensures that non-technical decision-makers can understand how the final ranking is generated, thereby improving the DSS's usability in real decision-making environments. This is consistent with Supriadi et al (2021) and Teixeira et al (2022), who assert that interface clarity plays a functional role in ensuring the accessibility of computational decision-making tools.

Finally, the results highlight the practical benefit of integrating DSS and multi-criteria decision models to eliminate subjective inconsistencies commonly found in manual decision-making processes. The system delivers stable and repeatable outcomes across repeated trials, which aligns with Alyamani et al (2021) and Surya & Farizal (2023), who emphasize determinism as a key success indicator in DSS development. While this work successfully validates the SAW implementation, further enhancement may incorporate alternative weighting methods—such as AHP, FAHP, or ROC—to support cross-validation of weight assignments and sensitivity analysis.

Overall, the findings affirm that the contribution of this study lies in the successful development and verification of a SAW-based DSS capable of accurately, consistently, and transparently computing multi-criteria rankings. The DSS is therefore positioned not as a behavioral prediction tool, but as a reliable computational framework to support data-driven decision-making.

5. Conclusion

The implementation of the Simple Additive Weighting (SAW) method within the Decision Support System (DSS) successfully demonstrates the system's capability to execute multi-criteria ranking accurately and consistently. By integrating clearly defined criteria, automated normalization, and weighted preference calculations, the system ensures the ranking process operates without computational errors and eliminates the ambiguity commonly found in manual decision-making. The automated ranking results generated by the system matched the manual SAW calculations with zero numerical deviation, providing strong evidence of algorithmic correctness and functional reliability.

This study is positioned as a system development paper rather than an empirical investigation of consumer behavior. Accordingly, the ranking data used in the system served as test input for validating software performance rather than representing real market tendencies. The primary contribution of this research is to verify that the DSS performs the SAW computation correctly and processes user-defined criteria and weights dynamically and consistently. Future work may extend the system by incorporating additional weighting techniques such as AHP or ROC, integrating usability evaluation, or benchmarking runtime performance against other DSS frameworks.

Data availability

All data produced and analyzed during this study are included within this published article. The datasets were used solely as test data to verify the functional correctness and computational accuracy of the implemented Decision Support System and are sufficient to support the findings of this research.

Declaration of competing interest

The authors declare that they have no known financial or personal competing interests that could have influenced the work reported in this paper.

Authors' contributions

Muhammad Fariz Nugroho was responsible for system design, data collection, algorithm implementation, experimental analysis, and drafting the original manuscript. Edy Supriyanto contributed to conceptualization, methodology validation, supervision, critical revision of the manuscript, and overall research guidance. All authors have read and approved the final manuscript.

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