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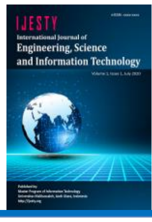

Implementation of the Simple Additive Weighting Algorithm for Café Recommendations in Lhokseumawe City

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Abstract

The selection of cafés that match customer preferences is a challenge, especially in the city of Lhokseumawe, which has 30 cafés with different characteristics. This research implements the Simple Additive Weighting (SAW) algorithm to provide recommendations for the best café based on six criteria, namely price (weight 0.25), menu (0.2), order duration (0.15), service (0.2), facilities (0.15), and discounts & promotions (0.05). The recommendation system was developed using a combination of Laravel PHP and Python, where Laravel is used to build an interactive web interface. Python also plays a role in data processing and complex mathematical calculations. The results showed that the system was able to provide optimal recommendations, with Petrodollar Coffeeatery & Roastery as the top choice based on the calculation of the highest preference values (3.28 for price, 2.48 for menu, 3.16 for order duration, 2.88 for service, 2.96 for facilities, and 2.8 for discounts & promotions). TR Coffee and Platinum Coffee occupy the following positions. In addition, this study found that the weight of the criteria and the number of datasets (150 reviewers) significantly influence the quality of recommendations. The more representative the weights used and the larger the dataset analyzed, the more accurate the system will produce recommendations based on user preferences. Thus, weight optimization and dataset expansion are essential factors in improving the effectiveness of SAW-based recommendation systems.

Keywords: *Café Recommendation, Simple Additive Weighting, Laravel, Python, Decision Support System.*

1. Introduction

Lhokseumawe is a city that attracts many students from outside the region who want to pursue higher education. Students often look for comfortable places such as cafés to study, have discussions, or unwind to support their academic and social activities. The number of cafés in the city has skyrocketed due to the increasing demand from students for environments that support their daily routines. With so many café options available, students require specific criteria, such as facilities, location, and ambiance, to determine the ideal café. Therefore, a decision support system is needed to assist students in selecting a café that best suits their needs.

A decision support system can rank values from highest to lowest in a selection process, thus enabling faster problem-solving [1]. This system combines data with analytical models to support semi-structured or unstructured decision-making [2]. Decision-making is the result of choosing among various alternatives using specific mechanisms to generate optimal outcomes.

The decision support system assesses the quality of cafés, with students acting as the decision-makers. This system implements the Simple Additive Weighting (SAW) method, which calculates the total weight of performance ratings for each alternative across all attributes [3]. The basic concept of the SAW method is to compute the weighted total value of performance for each alternative across all criteria. The SAW method is considered adequate and efficient, as it saves time and effort while minimizing the risk of errors in decision-making [4]. Therefore, this method is highly suitable for determining the ideal café for students in Lhokseumawe.

A study by Nurdin titled *"Implementation of Simple Additive Weighting and Profile Matching Methods to Determine Outstanding Students at Universitas Malikussaleh"* combined the SAW method with Profile Matching to identify outstanding students more objectively and measurably. SAW was used to assign weights to various criteria such as academic grades and extracurricular activities, while Profile Matching compared students' profiles against the expected achievement standards. This combination resulted in a more comprehensive and practical decision support system for academic environments, although its success heavily depends on accurate data and effective integration between the two methods [5].

This research aims to develop a system that can automatically provide café recommendations to users based on predefined criteria. This system can help users select the café that best fits their preferences based on factors such as price, menu variety, ordering duration, and reviews from other users. One of the simplest yet most effective multi-criteria decision-making methods is Simple Additive Weighting (SAW). SAW allows for the combination of various criteria to generate optimal recommendations that align with user needs.

This system allows users to easily access and choose cafés that best suit their preferences, thereby improving decision-making efficiency and quality. This research is also expected to contribute significantly to developing more responsive, effective, and user-friendly web-based services.

2. Literature Review

2.1. Data Mining

Data mining is a process through which knowledge or patterns can be discovered from large datasets. It involves the extraction of implicit, previously unknown, and potentially useful information from data [6]. Data is often imperfect in practice: some parts may be noisy, and some may be missing. Anything discovered will rarely be exact—there will be exceptions to every rule and cases not covered by any rule at all. Algorithms must be robust enough to handle imperfect data and to extract patterns that are imprecise yet still useful [7].

2.2. Decision Support System

The concept of a Decision Support System (DSS) was first introduced in the early 1970s by Michael S. Scott Morton under the term *Management Decision System*. It is a computer-based system designed to support decision-making by utilizing specific data and models to solve various unstructured problems [8]. According to Dicky Nofriansyah [9], a decision support system is a computer-based information system that generates multiple decision-making alternatives to assist management in handling both structured and unstructured problems using data and models. This definition implies that a problem must first be explored thoroughly to identify the core issues, distinguishing whether it is a matter that truly requires a decision or choice [10].

2.3. Simple Additive Weighting

The Simple Additive Weighting (SAW) method is one of the multi-criteria decision-making methods used to assign weights or importance values to each recommended criterion [11]. The SAW method is also known as the weighted summation method. The basic concept of SAW is to calculate the weighted sum of performance ratings for each alternative across all attributes [12]. The SAW method is used in multi-criteria decision-making to determine the best alternative based on each criterion's weighted sum of values [13]. The process includes:

1. Normalization of the Decision Matrix – Transforming the values into a uniform scale depending on the type of criterion (benefit or cost).
   a. For Benefit Criteria (where higher values are better), the original value of the criterion is normalized by dividing it by the maximum value of that criterion

$$r_{ij} = \frac{x_{ij}}{\max(x_{ij})} \quad \text{(1)}$$

   b. For Cost Criteria (where lower values are better): Therefore, the original value of the criterion is normalized by dividing it by the minimum value of that criterion

$$r_{ij} = \frac{\min(x_{ij})}{x_{ij}} \quad \text{(2)}$$

Explanation:
r_{ij} : Normalized value for criterion *j* and alternative *i*
x_{ij} : Original value of criterion *j* for alternative *i*
$\max(x_{ij})$: Maximum value of criterion *j* among all alternatives
$\min(x_{ij})$: Minimum value of criterion *j* among all alternatives

2. Calculation of Weighted Values – Calculating the weighted value for each alternative based on the importance (weight) of each criterion:

$$v_{ij} = w_j \times r_{ij} \quad \text{(3)}$$

Explanation:
v_{ij} : Weighted value for criterion *j* and alternative *i*
w_j : Weight of criterion *j*, where $\sum wj = 1$ (the total weight of all criteria must be equal to 1)
r_{ij} : Normalized value for criterion *j* and alternative *i*

3. Total Score Summation – Summing all the weighted values for each alternative to obtain a final score, which will be used to rank the alternatives:

$$S_i = \sum_{j=1}^{n} v_{ij} \quad \text{(4)}$$

Explanation:
S_i: Total score for alternative *i*
n: Number of criteria used in the decision-making process
v_{ij}: Weighted value for criterion *j* and alternative *i*

2.4. Recommedation System

A recommendation system is a system that can provide information and suggestions to assist users in making decisions based on the available information up to the present time [14]. A recommendation system is designed to offer alternative considerations that are useful in supporting users' decisions. In the study by Utomo and Anggriawan [15], it is stated that a recommendation system is an application model derived from observations of users' living conditions and desires.

3. Research Method

In preparation for implementing the SAW method in this study, it is necessary to collect café data including name, location, and category (e.g., study, leisure, or social cafés)—as the foundation for recommendations; primary evaluation criteria for each café, namely average menu price, menu variety (food, beverages, or special items), order processing time, service quality (staff friendliness and speed), and customer reviews regarding taste, comfort, and atmosphere; and additional criteria data such as available facilities (e.g., Wi-Fi, comfortable seating, parking) and any discounts or promotions, enabling the system to generate recommendations that best match user preferences.

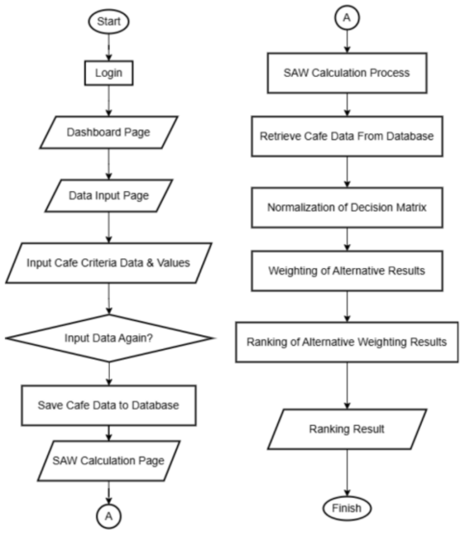

Fig 1. System Schema

4. Results and Discussion

The implementation of the SAW algorithm for the café recommendation case study in Lhokseumawe—considering café variables such as price (cost type, weight 0.25), menu (benefit type, weight 0.20), order duration (cost type, weight 0.15), service (benefit type, weight 0.20), facilities (benefit type, weight 0.15), and discounts & promotions (benefit type, weight 0.05)—using a dataset of 30 cafés and 150 reviewers, showed that Petrodollar Coffeeatery & Roastery emerged as the top recommendation. Based on the final scores, the results were as follows: price scored 0.19 (in the "expensive" interval), menu scored 0.13 (in the "varied" interval), order duration scored 0.12 (in the "long" interval), service scored 0.16 (in the "good" interval), facilities scored 0.12 (in the "good" interval), and discounts & promotions scored 0.04 (in the "frequent promotions" interval). TR Coffee and Platinum Coffee ranked second and third, respectively.
The following is the manual calculation process of the SAW (Simple Additive Weighting) algorithm in determining the best café recommendation to visit, along with the table of criteria and weights used:

Table 1. Criteria And Weight

Price	Menu	Order Duration	Service	Fasilities	Discount & Promotion
C1	C2	C3	C4	C5	C6
Cost	*Benefit*	*Cost*	*Benefit*	*Benefit*	*Benefit*
0.25	0.2	0.15	0.2	0.15	0.05

Each criterion has sub-criteria with their respective weights. The sub-criteria and their weights can be seen in the following table:

Table 2. Subcriteria

Criteria	Subcriteria	Weight
Price	Very Expensive	1
	Expensive	2
	Moderate	3
	Cheap	4
	Very Cheap	5
Menu	Very Limited	1
	Limited	2
	Fairly Diverse	3
	Diverse	4
	Very Diverse	5
Oder Duration	Very Slow (>30 minutes)	1

	Slow (21–30 minutes)	2
	Moderate (11–20 minutes)	3
	Fast (1–10 minutes)	4
	Very Fast (<5 minutes)	5
Service	Very Poor	1
	Poor	2
	Fair	3
	Good	4
	Very Good	5
Fasilities	Very Minimal (slow Wi-Fi, no parking, uncomfortable seating)	1
	Minimal (slow Wi-Fi, small parking area, average seating)	2
	Fairly Good (stable Wi-Fi, limited parking, comfortable seating)	3
	Good (fast Wi-Fi, adequate parking, comfortable seating)	4
	Excellent (very fast Wi-Fi, spacious parking, very comfortable seating)	5
Discount & Promotion	No Promotions/Discounts	1
	Very Rare Promotions (once a month)	2
	Limited Promotions (2–3 times per month)	3
	Frequent Promotions (4–5 times per month)	4
	Very Frequent Promotions (more than 5 times per month)	5

The following dataset contains the average ratings from all reviewers for each café:

Table 3. Average Café Ratings

Café	C1	C2	C3	C4	C5	C6
Petrodollar Coffeeatery & Roastery	3.28	2.48	3.16	2.88	2.96	2.8
Platinum Coffee	3.24	2.84	3.44	2.84	3.56	2.88
D'royal Coffee Reborn	2.6	3.16	3.16	3.08	2.92	2.8
Mensa	2.8	2.8	3.24	2.96	2.88	3.08
Fun's Café	2.76	3.08	2.6	3.4	3	3.12
Bi Coffee	2.52	3.68	2.88	3	3.24	3.08
Bagi Bagi Coffee & Pastry	2.76	2.88	2.64	2.6	2.68	3.28
Ruma Coffee & Eatery	3.28	3.12	2.88	3.24	3.16	2.8
Ocean Coffee	3.08	3.08	2.8	3.68	3.2	2.84
Achek Coffee	2.6	2.72	2.84	3.16	3.24	2.8
Tr Coffee	3.24	2.84	3.52	2.96	2.92	2.64
The Breeze Coffee	3	2.84	2.84	2.96	2.96	2.64
Master Cafe Lhokseumawe	2.68	3.36	2.84	2.72	3.32	3.12
Koffiepedia Roastery	2.88	3.52	2.72	2.84	2.68	2.76
Sudut Temu	2.96	2.64	2.96	3.08	3.08	3.48
Bara Kopi	2.84	3.2	2.88	2.96	3.4	3
Qahwa Coffee Lhokseumawe	3.24	3.12	3.04	2.8	3.28	2.92
Pesona Point Lhokseumawe	2.96	3.32	3.08	3.24	3.36	2.96
Legend Reborn Coffee & Beans	2.48	2.6	2.76	2.56	2.96	3.04

Table 3. Average Café Ratings (continuation)

Café	C1	C2	C3	C4	C5	C6
R2 Coffee	2.64	3.16	2.6	2.8	2.88	3.12
Dapue Dlegend Atjeh Coffee Roastery & Coffee Beans	3.08	2.68	2.68	2.8	3.4	2.8
Kaduskafe	2.84	3.32	2.8	3	3.08	3
Beeje Coffee	2.96	2.8	2.72	2.72	3.28	2.72
Assembly Point Lhokseumawe	2.64	3.28	2.96	2.84	3.36	2.92
Dr. Kupi Espresso	3.28	2.72	2.88	2.88	2.64	2.8
Kafe An Coffee	3.2	2.96	3.04	3.24	3.2	3.16

Pakwen Coffee	2.72	2.88	2.84	3.08	2.88	3.04
Taurus Coffee & Resto	3.16	3.28	2.92	2.76	3.56	3.04
Harvies Coffee Lhokseumawe	3	2.84	2.92	3.36	3.2	2.36
Lava Choco Drink. Lhokseumawe	3.16	3.32	2.68	3.52	2.96	2.84
Dapue Dlegend Atjeh Coffee Roastery & Coffee Beans	3.08	2.68	2.68	2.8	3.4	2.8
Kaduskafe	2.84	3.32	2.8	3	3.08	3
Beeje Coffee	2.96	2.8	2.72	2.72	3.28	2.72
Assembly Point Lhokseumawe	2.64	3.28	2.96	2.84	3.36	2.92
Dr. Kupi Espresso	3.28	2.72	2.88	2.88	2.64	2.8
Kafe An Coffee	3.2	2.96	3.04	3.24	3.2	3.16
Pakwen Coffee	2.72	2.88	2.84	3.08	2.88	3.04
Taurus Coffee & Resto	3.16	3.28	2.92	2.76	3.56	3.04
Harvies Coffee Lhokseumawe	3	2.84	2.92	3.36	3.2	2.36
Lava Choco Drink. Lhokseumawe	3.16	3.32	2.68	3.52	2.96	2.84

After calculating the average scores for each café based on the criteria, the next step is the normalization process using formulas (1) and (2). The following is the result of the manual normalization calculation:

Table 4. Normalization

Café	Normalisasi					
	C1	C2	C3	C4	C5	C6
Petrodollar Coffeeatery & Roastery	0.76	0.67	0.82	0.78	0.83	0.80
Platinum Coffee	0.77	0.77	0.76	0.77	1.00	0.83
D'royal Coffee Reborn	0.95	0.86	0.82	0.84	0.82	0.80
Mensa	0.89	0.76	0.80	0.80	0.81	0.89
Fun's Café	0.90	0.84	1.00	0.92	0.84	0.90
Bi Coffee	0.98	1.00	0.90	0.82	0.91	0.89
Bagi Bagi Coffee & Pastry	0.90	0.78	0.98	0.71	0.75	0.94
Ruma Coffee & Eatery	0.76	0.85	0.90	0.88	0.89	0.80
Ocean Coffee	0.81	0.84	0.93	1.00	0.90	0.82
Achek Coffee	0.95	0.74	0.92	0.86	0.91	0.80
Tr Coffee	0.77	0.77	0.74	0.80	0.82	0.76
The Breeze Coffee	0.83	0.77	0.92	0.80	0.83	0.76
Master Cafe Lhokseumawe	0.93	0.91	0.92	0.74	0.93	0.90
Koffiepedia Roastery	0.86	0.96	0.96	0.77	0.75	0.79
Sudut Temu	0.84	0.72	0.88	0.84	0.87	1.00
Bara Kopi	0.87	0.87	0.90	0.80	0.96	0.86
Qahwa Coffee Lhokseumawe	0.77	0.85	0.86	0.76	0.92	0.84

Table 4. Normalization (continuation)

Café	Normalisasi					
	C1	C2	C3	C4	C5	C6
Pesona Point Lhokseumawe	0.84	0.90	0.84	0.88	0.94	0.85
Legend Reborn Coffee & Beans	1.00	0.71	0.94	0.70	0.83	0.87
R2 Coffee	0.94	0.86	1.00	0.76	0.81	0.90
Dapue Dlegend Atjeh Coffee Roastery & Coffee Beans	0.81	0.73	0.97	0.76	0.96	0.80
Kaduskafe	0.87	0.90	0.93	0.82	0.87	0.86
Beeje Coffee	0.84	0.76	0.96	0.74	0.92	0.78

Assembly Point Lhokseumawe	0.94	0.89	0.88	0.77	0.94	0.84
Dr. Kupi Espresso	0.76	0.74	0.90	0.78	0.74	0.80
Kafe An Coffee	0.78	0.80	0.86	0.88	0.90	0.91
Pakwen Coffee	0.91	0.78	0.92	0.84	0.81	0.87
Taurus Coffee & Resto	0.78	0.89	0.89	0.75	1.00	0.87
Harvies Coffee Lhokseumawe	0.83	0.77	0.89	0.91	0.90	0.68
Lava Choco Drink. Lhokseumawe	0.78	0.90	0.97	0.96	0.83	0.82

The same method is applied to the remaining cafés until all are processed. After normalization, the next step is calculating the preference values or final scores using formula (3). The following is the result of the manual calculation for all cafés:

Table 5. Preference Values

Café	Nilai Preferensi						TTo-tal	RRank
	C1	C2	C3	C4	C5	C6		
Petrodollar Coffeeatery & Roastery	0.19	0.13	0.12	0.16	0.12	0.04	0.77	1
Platinum Coffee	0.19	0.15	0.11	0.15	0.15	0.04	0.80	4
D'royal Coffee Reborn	0.24	0.17	0.12	0.17	0.12	0.04	0.86	19
Mensa	0.22	0.15	0.12	0.16	0.12	0.04	0.82	5
Fun's Café	0.22	0.17	0.15	0.18	0.13	0.04	0.90	29
Bi Coffee	0.25	0.20	0.14	0.16	0.14	0.04	0.93	30
Bagi Bagi Coffee & Pastry	0.22	0.16	0.15	0.14	0.11	0.05	0.83	10
Ruma Coffee & Eatery	0.19	0.17	0.14	0.18	0.13	0.04	0.84	14
Ocean Coffee	0.20	0.17	0.14	0.20	0.13	0.04	0.88	27
Achek Coffee	0.24	0.15	0.14	0.17	0.14	0.04	0.87	20
Tr Coffee	0.19	0.15	0.11	0.16	0.12	0.04	0.78	2
The Breeze Coffee	0.21	0.15	0.14	0.16	0.12	0.04	0.82	7
Master Cafe Lhokseumawe	0.23	0.18	0.14	0.15	0.14	0.04	0.88	28
Koffiepedia Roastery	0.22	0.19	0.14	0.15	0.11	0.04	0.86	18
Sudut Temu	0.21	0.14	0.13	0.17	0.13	0.05	0.83	11
Bara Kopi	0.22	0.17	0.14	0.16	0.14	0.04	0.87	22
Qahwa Coffee Lhokseumawe	0.19	0.17	0.13	0.15	0.14	0.04	0.82	6
Pesona Point Lhokseumawe	0.21	0.18	0.13	0.18	0.14	0.04	0.88	24
Legend Reborn Coffee & Beans	0.25	0.14	0.14	0.14	0.12	0.04	0.84	13
R2 Coffee	0.23	0.17	0.15	0.15	0.12	0.04	0.87	23
Dapue Dlegend Atjeh Coffee Roastery & Coffee Beans	0.20	0.15	0.15	0.15	0.14	0.04	0.83	8
Kaduskafe	0.22	0.18	0.14	0.16	0.13	0.04	0.87	21

Table 5. Preference Values (continuation)

Café	Nilai Preferensi						TTo-tal	RRank
	C1	C2	C3	C4	C5	C6		
Beeje Coffee	0.21	0.15	0.14	0.15	0.14	0.04	0.83	9
Assembly Point Lhokseumawe	0.23	0.18	0.13	0.15	0.14	0.04	0.88	26
Dr. Kupi Espresso	0.19	0.15	0.14	0.16	0.11	0.04	0.78	3
Kafe An Coffee	0.19	0.16	0.13	0.18	0.13	0.05	0.84	12
Pakwen Coffee	0.23	0.16	0.14	0.17	0.12	0.04	0.85	17
Taurus Coffee & Resto	0.20	0.18	0.13	0.15	0.15	0.04	0.85	16
Harvies Coffee Lhokseumawe	0.21	0.15	0.13	0.18	0.13	0.03	0.85	15

Lava Choco Drink. Lhokseumawe	0.20	0.18	0.15	0.19	0.12	0.04	0.88	25

Based on the SAW algorithm calculation results shown in the table above, *Petrodollar Coffeeatery & Roastery* is the most recommended café, while *Bi Coffee* is the least recommended. This conclusion is based on the ranking order, which refers to the preference scores.

Fig 2. Café Recommendation System Page

5. Conclusion

The study titled "Implementation of the Simple Additive Weighting (SAW) Algorithm for Café Recommendations in Lhokseumawe City" concludes that the implementation of the SAW algorithm, utilizing a combination of Laravel PHP and Python, has proven to be effective in developing a café recommendation system. Laravel facilitates web interface development, while Python supports data processing and complex mathematical calculations. This integration enhances both the efficiency and accuracy of the normalization process and final score computation, resulting in more optimal recommendations. Additionally, the influence of criterion weights and dataset size on the recommendation outcomes is significant. Accurate weight assignment ensures that the results align closely with user preferences, while a larger dataset improves the system's ability to make precise comparisons between alternatives. Therefore, optimizing both the weights and using a representative dataset are crucial for enhancing the performance of SAW-based decision support systems.

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