

A Multi-Criteria Decision Support System for Product Selling Price Determination: A Comparative Analysis of Weighted Product and Simple Additive Weighting Methods

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Article Info

Abstract

Article history:

Received
16 June 2026

Accepted
18 October 2026

Keywords:

Decision Support System,
Multi-Criteria Decision
Makin, Product Selling
Pric, Weighted Produc,
Simple Additive Weighting,
Retail Business.

Determining an appropriate product selling price is a critical decision in retail business because it directly affects profitability, market competitiveness, and business sustainability. However, small retail businesses often rely on subjective judgment and manual calculations, which can lead to inconsistent pricing decisions when multiple factors must be considered simultaneously. This study develops a Multi-Criteria Decision Support System to determine product selling prices by comparatively applying the Simple Additive Weighting (SAW) and Weighted Product (WP) methods. Five decision criteria were considered: Product Acquisition Cost, Product Quality, Market Demand, Operational Cost, and Expected Profit. The proposed approach was implemented at the Yeni Mode Retail Store, with five product alternatives evaluated using identical criteria and weighting schemes. The results show that both methods produced an identical ranking order, with Jeans (A3) achieving the highest priority, followed by Shirt (A2), Blouse (A5), Muslim Dress (A1), and Women's Skirt (A4). The SAW method yielded a preference score of 0.868 for the highest-ranked alternative, whereas WP yielded 0.220. Despite differences in their additive and multiplicative aggregation mechanisms, both methods demonstrated consistent decision outcomes. SAW offers advantages in computational simplicity and ease of interpretation, whereas WP provides an alternative mechanism for representing proportional relationships among criterion values. The proposed system provides a systematic, transparent, and data-driven approach to supporting product pricing decisions and can help retail business owners reduce reliance on subjective judgment when evaluating multiple pricing factors.

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1. INTRODUCTION

Product pricing is one of the most strategic decisions in retail business management because it directly influences sales performance, profitability, and competitive positioning. An appropriate selling price should cover not only product acquisition and operational costs but also factors such as product quality, market demand, customer purchasing power, and expected profit. In practice, however, pricing decisions in small retail businesses may still rely heavily on managerial experience, intuition, or conventional cost-based considerations. Such approaches can become less effective when several pricing factors, each with varying importance, must be considered simultaneously (Kotler *et al.*, 2022).

Increasing competition in the retail sector has made pricing decisions more complex. Retailers must simultaneously consider multiple economic, product-related, and market factors to establish prices that remain competitive while supporting profitability (Dhurkari, 2022). Because these factors may differ in importance and may involve conflicting objectives, product pricing can be formulated as a Multi-Criteria Decision Making (MCDM)

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problem. MCDM provides a structured approach for evaluating alternatives across multiple weighted criteria and is therefore suitable for decision problems in which a single factor is insufficient to represent the overall decision context.

Decision Support Systems (DSS) provide a systematic means of assisting decision-makers in complex problems by integrating data, decision models, and analytical procedures. In multi-criteria environments, DSS can reduce reliance on purely subjective judgment by providing a structured mechanism for evaluating and ranking alternatives (Phillips-Wren *et al.*, 2021). Analytics, data science, and artificial intelligence provide a strong foundation for implementing Decision Support Systems (DSS), enabling organizations to make more accurate, efficient, and informed decisions (Sharda *et al.*, 2020). According to Kovari (2024), AI-based decision support systems offer practical benefits for improving decision quality and gaining user confidence. A study found that Decision Support Systems (DSS) have been widely adopted as effective tools for decision-making across a wide range of application domains (Ali *et al.*, 2023; Kostopoulos *et al.*, 2024; Poonguzhali, 2026). The study further emphasizes the need to integrate artificial intelligence into decision-making frameworks in a manner consistent with ethical standards. Among the various MCDM techniques, Simple Additive Weighting (SAW) and Weighted Product (WP) are widely used for their relatively straightforward computational procedures and ability to incorporate multiple weighted criteria. SAW determines the overall preference of an alternative through weighted additive aggregation of normalized criterion values, whereas WP employs multiplicative aggregation by raising criterion values to the power of their corresponding weights (Hamdan *et al.*, 2022). A study found that the SAW method excels in terms of simplicity, the Weighted Product (WP) method provides greater discrimination among alternative scores, and the TOPSIS method offers a more comprehensive approach by considering the ideal and negative-ideal solutions. These three methods can serve as effective decision-support tools to facilitate objective, rational vendor selection processes and provide a foundation for developing decision-support systems (Wahyuddin *et al.*, 2025).

Previous studies have demonstrated the applicability of SAW and WP in various decision-support problems. Simanungkalit *et al.* (2023), for example, applied SAW to evaluate university alternatives based on multiple criteria, demonstrating its applicability to structured multi-criteria selection problems. Comparative research has also investigated the performance of SAW and WP within the same decision environment. Sazaki *et al.* (2023) compared WP and SAW using 200 test data and highlighted differences in their weighting and ranking processes. These studies demonstrate that both methods can support systematic alternative evaluation and that comparative analysis is useful when more than one MCDM technique is applicable to the same decision problem.

Despite the extensive application of SAW and WP in decision-support studies, their comparative implementation for determining product selling prices in small retail businesses remains underexplored (Alosta *et al.*, 2021). Existing applications more commonly focus on selection and ranking problems in areas such as education, personnel evaluation, and other decision-support contexts rather than retail pricing. Furthermore, applying different MCDM methods independently makes it difficult to determine whether the resulting decisions remain consistent when identical alternatives, criteria, and weights are evaluated using different aggregation mechanisms. This provides an opportunity to investigate SAW and WP comparatively within the same retail pricing decision environment. Other research demonstrated that the developed hybrid method serves as a reliable decision-support tool for

site selection, facilitating the achievement of sustainable coastal management objectives (Abdell-Basset *et al.*, 2021).

To address this gap, this study develops a Multi-Criteria Decision Support System to determine product selling prices by applying the SAW and WP methods in a comparative manner (Sutoyo, 2024). Five decision criteria are considered: Product Acquisition Cost, Product Quality, Market Demand, Operational Cost, and Expected Profit. Both methods are applied to the same product alternatives, decision criteria, and weighting scheme, thereby providing a consistent basis for comparing their resulting preference scores and rankings.

The primary contribution of this study is the development of a comparative MCDM-based decision-support framework for retail product pricing. Rather than relying on a single decision-making method, the proposed approach assesses the consistency of product priorities produced by two distinct aggregation mechanisms. The comparison focuses on ranking outcomes, computational characteristics, and practical interpretability. The resulting framework is expected to provide retail business owners with a more systematic, transparent, and data-driven basis for evaluating product pricing decisions while contributing to the practical application of MCDM techniques in small retail business management.

2. METHODOLOGY

2.1 Research Design

This study employed a quantitative research approach to develop a Decision Support System (DSS) for determining product selling prices using Multi-Criteria Decision Making (MCDM) techniques. The proposed DSS comparatively evaluates two widely used MCDM methods, namely Weighted Product (WP) and Simple Additive Weighting (SAW), to identify the most appropriate approach to support retail pricing decisions. The system was developed and evaluated using product data collected from Yeni Mode Retail Store, with both methods applied under identical decision criteria and weighting schemes to ensure a fair and objective comparison.

2.2 Research Framework

To conduct the study systematically, a structured research framework was developed to describe the overall process of the proposed Decision Support System (DSS). The research process begins with problem identification and data collection, followed by determining decision criteria, establishing measurement scales, assigning criterion weights, and constructing the decision matrix. The same decision matrix is subsequently processed independently using the Simple Additive Weighting (SAW) and Weighted Product (WP) methods. The results from both methods are then evaluated to determine the most appropriate approach for supporting product selling price decisions. The overall research process is illustrated in Figure 1

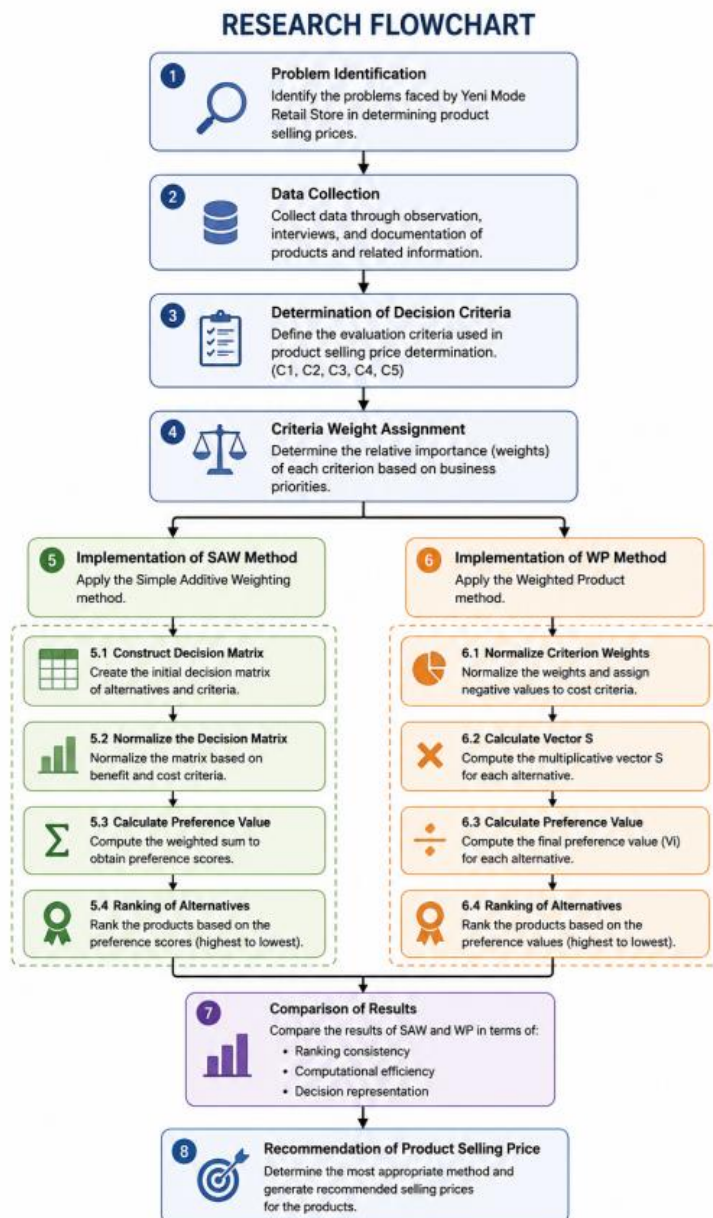


Figure 1.
Research Flowchart

As illustrated in Figure 1, the initial stages establish the decision components required for the MCDM analysis, including product alternatives, evaluation criteria, measurement scales, criterion weights, and the decision matrix. The SAW and WP methods are then applied independently to the same input data, allowing each method to generate preference scores and rankings under identical decision conditions. The resulting rankings are subsequently compared for ranking consistency, computational efficiency, and decision representation. The final stage uses the comparative results to identify the most suitable MCDM method and to generate an objective, data-driven recommendation for determining the product selling price.

2.3 Data Collection

This study was conducted at Yeni Mode Retail Store, a retail business specializing in fashion products. The store was selected as the research subject because its product selling prices were primarily determined by manual calculations and managerial judgment, without

a structured decision-making approach. Such practices may lead to inconsistent pricing decisions, particularly when multiple pricing factors must be considered simultaneously.

Primary data were collected directly from the retail store using three data collection techniques: observation, interviews, and documentation. An observation was conducted to understand the existing pricing process and to identify the factors influencing the determination of selling prices. Semi-structured interviews were conducted with the store owner to obtain information on business priorities, pricing strategies, and the relative importance of each evaluation criterion. Documentation was used to collect historical product data, including acquisition costs, operational expenses, and selling price records.

Five representative fashion products were selected as decision alternatives for evaluation. Each product was assessed using five decision criteria: product acquisition cost, product quality, market demand, operational cost, and expected profit. These criteria were selected based on the store owner's expertise and relevant literature on retail pricing and multi-criteria decision-making. The collected data served as the input for both the Simple Additive Weighting (SAW) and Weighted Product (WP) methods, ensuring that the comparative analysis was performed using identical datasets and evaluation criteria.

The product alternatives evaluated in this study are presented in Table 1.

Table 1.

Product Alternatives

Code	Product Name
A1	Muslim Dress
A2	Shirt
A3	Jeans
A4	Women's Skirt
A5	Blouse

These five products were selected because they represent the major product categories sold at the Yeni Mode Retail Store and exhibit varying characteristics in acquisition cost, product quality, customer demand, operational cost, and expected profit. Evaluating products with different characteristics enables a comprehensive assessment of the proposed decision support system and facilitates an objective comparison between the SAW and WP methods.

2.4 Decision Criteria

Determining an appropriate product selling price requires consideration of multiple factors that influence business profitability and market competitiveness. Based on interviews with the owner of Yeni Mode Retail Store and a review of relevant literature on retail pricing and Multi-Criteria Decision Making (MCDM), five decision criteria were selected to evaluate product alternatives. These criteria represent the most influential factors in determining selling price while ensuring that the evaluation process remains objective and systematic.

The selected decision criteria are classified into cost and benefit attributes. Cost criteria are factors to be minimized, whereas benefit criteria are factors to be maximized to obtain the most appropriate pricing recommendation. The decision criteria used in this study are presented in Table 2.

Table 2.
Decision Criteria

Code	Criterion	Attribute	Description	Measurement
C1	Product Acquisition Cost	Cost	The purchase cost incurred by the retailer to acquire the product from the supplier. Lower acquisition costs generally allow greater pricing flexibility and higher profit margins.	Monetary value (IDR)
C2	Product Quality	Benefit	The overall quality of the product is based on material, durability, finishing, and customer perception. Higher-quality products generally justify higher selling prices.	Assessment scale (1–5)
C3	Market Demand	Benefit	The level of customer demand for a product in the market. Products with stronger demand have greater potential to support competitive selling prices.	Assessment scale (1–5)
C4	Operational Cost	Cost	Additional costs associated with product handling, storage, packaging, and daily retail operations. Lower operational costs contribute to improved pricing efficiency.	Monetary value (IDR)
C5	Expected Profit	Benefit	The desired profit margin established by the retailer for each product. Higher expected profits contribute to improved business profitability while maintaining market competitiveness.	Assessment scale (1–5)

The selected criteria collectively represent the economic and market factors that influence the determination of product selling price. By incorporating both cost and benefit attributes into the evaluation process, the proposed Decision Support System provides more balanced, objective, and data-driven pricing recommendations than conventional manual pricing practices.

Table 3.
Assessment Scale for Product Quality (C2)

Assessment Score	
Very Good	5
Good	4
Moderate	3
Poor	2
Very Poor	1

Product Quality (C2) represents the overall quality of each product based on the assessment conducted at Yeni Mode Retail Store. A higher score indicates better product quality and therefore represents a more favorable condition in the decision-making process.

Table 4.
Assessment Scale for Market Demand (C3)

Assessment Score	
Very High	5
High	4
Moderate	3
Low	2
Very Low	1

Market Demand (C3) represents the level of consumer need and interest in each product. Products with higher levels of demand receive higher scores, indicating greater market potential.

Table 5.

Assessment Scale for Expected Profit (C5)

Assessment Score	
Very High	5
High	4
Moderate	3
Low	2
Very Low	1

Expected Profit (C5) represents the level of profit expected by the retailer from each product. A higher assessment score indicates a greater expected contribution to business profitability.

The use of these assessment scales transforms qualitative evaluations into quantitative scores that can be incorporated into the decision matrix. Consequently, all alternatives can be systematically evaluated using the same measurement framework before normalization and preference calculation are performed with the SAW and WP methods.

2.6 Criteria Weighting

After determining the evaluation criteria, each criterion was assigned a weight to reflect its relative importance in determining the product's selling price. The weighting process was conducted through interviews with the owner of Yeni Mode Retail Store, who possesses practical experience in pricing strategies and retail business management. The assigned weights reflect the business priorities considered in determining competitive and profitable selling prices.

To ensure consistency in the decision-making process, the weights were normalized so that their total value equals one. A higher weight indicates that the corresponding criterion has a greater influence on the final pricing decision. The normalized criterion weights used in this study are presented in Table 6.

Table 6.

Criteria Weights

Code	Criterion	Weight
C1	Product Acquisition Cost	0.30
C2	Product Quality	0.20
C3	Market Demand	0.20
C4	Operational Cost	0.10
C5	Expected Profit	0.20
	Total	1.00

As shown in Table 3, Product Acquisition Cost (C1) was assigned the highest weight (0.30) because it directly determines the minimum feasible selling price and significantly influences business profitability. Product Quality (C2), Market Demand (C3), and Expected Profit (C5) each received a weight of 0.20, reflecting their comparable importance in establishing competitive and profitable selling prices. Meanwhile, Operational Cost (C4) was assigned the lowest weight (0.10) because its variation across products is relatively small compared with the other evaluation criteria.

The normalized weights serve as the basis for calculating the preference values in both the Simple Additive Weighting (SAW) and Weighted Product (WP) methods. Using the same weighting scheme for both methods ensures that any differences in the final rankings result from the characteristics of the MCDM algorithms rather than differences in criterion importance.

2.7 Decision Matrix

After defining the decision criteria, measurement scales, and criterion weights, a decision matrix was constructed to represent each product alternative's performance across all evaluation criteria. The decision matrix serves as the primary input for the Simple Additive Weighting (SAW) and Weighted Product (WP) methods. Each row represents a product alternative, while each column represents an evaluation criterion.

The matrix incorporates both quantitative and converted qualitative data. Product Acquisition Cost (C1) and Operational Cost (C4) are expressed in Indonesian Rupiah (IDR), whereas Product Quality (C2), Market Demand (C3), and Expected Profit (C5) are represented using the five-point assessment scales described in the previous subsection. The same decision matrix is used for both MCDM methods to ensure a consistent and fair comparison.

Mathematically, the decision matrix can be represented as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} \\ \vdots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} \end{bmatrix} \dots\dots\dots (1)$$

where x_{ij} represents the performance value of alternative A_i with respect to criterion C_j . The initial decision matrix used in this study is presented in Table 7.

Table 7.

Initial Decision Matrix

Code	Product	C1 (IDR)	C2	C3	C4 (IDR)	C5
A1	Muslim Dress	[actual value]	[1–5]	[1–5]	[actual value]	[1–5]
A2	Shirt	[actual value]	[1–5]	[1–5]	[actual value]	[1–5]
A3	Jeans	[actual value]	[1–5]	[1–5]	[actual value]	[1–5]
A4	Women's Skirt	[actual value]	[1–5]	[1–5]	[actual value]	[1–5]
A5	Blouse	[actual value]	[1–5]	[1–5]	[actual value]	[1–5]

Note: C1 = Product Acquisition Cost; C2 = Product Quality; C3 = Market Demand; C4 = Operational Cost; C5 = Expected Profit.

The values in Table 7 constitute the raw decision data before normalization and preference calculation. Since the criteria have different measurement units and attribute characteristics, appropriate transformations are required before aggregation. C1 and C4 are classified as cost criteria, where lower values are preferred, whereas C2, C3, and C5 are classified as benefit criteria, where higher values indicate more favorable conditions. These attribute classifications are subsequently incorporated into the normalization and preference calculation procedures of the SAW and WP methods.

2.8 Simple Additive Weighting (SAW) Method

The Simple Additive Weighting (SAW) method is one of the most widely used Multi-Criteria Decision Making (MCDM) techniques because of its simplicity, computational efficiency, and ease of implementation. The SAW method determines the preference value

of each alternative by calculating the weighted sum of normalized criterion values. The alternative with the highest preference value is considered the most suitable for determining the product's recommended selling price.

The implementation of the SAW method in this study consists of four sequential steps.

a. Step 1. Construct the Decision Matrix

The first step is to construct the decision matrix containing the performance values of each product alternative with respect to every evaluation criterion. The decision matrix is expressed as

$$X=[x_{ij}]$$

where

X represents the decision matrix;

x_{ij} denotes the performance value of alternative I on criterion j

b. Step 2. Normalize the Decision Matrix

Since the decision criteria consist of both benefit and cost attributes, normalization is performed to transform all criterion values into comparable scales.

For benefit criteria, the normalization is calculated as

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

For cost criteria, the normalization is calculated as

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

Where

r_{ij} = normalized value;

x_{ij} = original criterion value.

c. Step 3. Calculate the Preference Value

After normalization, the preference value of each alternative is obtained by multiplying every normalized criterion value by its corresponding weight and then summing the results.

$$V_i = \sum_{j=1}^n w_j r_{ij} \dots\dots\dots (4)$$

where

- V_i = preference value of alternative i ;
- w_j = weight of criterion j ;
- r_{ij} = normalized criterion value.

The resulting preference value represents the overall performance of each alternative after considering all evaluation criteria simultaneously.

d. Step 4. Ranking the Alternatives

Alternatives are ranked in descending order by V_i/V_i . The highest value indicates the most appropriate selling price recommendation. The final step is to rank all product alternatives according to their preference values. Alternatives with higher preference values receive higher rankings and are considered more suitable for determining the product's recommended selling price.

The ranking generated by the SAW method is then compared with that produced by the Weighted Product method to evaluate the effectiveness of both methods in supporting retail pricing decisions.

The preference scores obtained from the SAW method provide the basis for comparing ranking performance with that of the Weighted Product method, which is described in the following subsection.

2.9 Weighted Product (WP) Method

The Weighted Product (WP) method is a Multi-Criteria Decision Making (MCDM) technique that evaluates alternatives using a multiplicative aggregation model. Unlike the Simple Additive Weighting (SAW) method, which employs additive aggregation after normalization, the WP method directly uses criterion weights as exponents in the calculation. This approach enables the method to better represent the proportional influence of each criterion while preserving the relative differences among alternative values. Consequently, the WP method is considered suitable for decision-making problems involving multiple criteria with varying levels of importance.

The implementation of the WP method in this study consists of four sequential steps.

a. Step 1. Normalize the Criterion Weights

Before calculating the preference values, the criterion weights are normalized to ensure that their total equals one. The normalized weight of each criterion is calculated as

$$w_j = \frac{w_j}{\sum w_j} \dots\dots\dots (5)$$

where

- w_j = normalized weight of criterion j ;
- n = total number of evaluation criteria.

For cost criteria, the normalized weights are assigned negative values to represent the inverse relationship between criterion values and preference scores, whereas benefit criteria retain positive weights.

b. Step 2. Calculate the Vector SSS

The performance score of each alternative is calculated by multiplying the criterion values raised to the power of their respective weights.

$$S_i = \prod_{j=1}^n x_{ij}^{w_j} \dots\dots\dots (6)$$

where

- S_i = vector value of alternative i ;
- x_{ij} = performance value of alternative iii on criterion j ;
- w_j = normalized criterion weight.

The vector SSS represents the overall performance of each alternative before normalization.

c. Step 3. Calculate the Preference Value

The preference value of each alternative is obtained by normalizing the vector S.

$$V_i = \frac{S_i}{\sum_{i=1}^m S_i} \dots\dots\dots (7)$$

Where

- V_i = preference value of alternative i ;
- S_i = vector value of alternative i ;
- m = total number of alternatives.

The preference value represents the relative priority of each product alternative after considering all evaluation criteria simultaneously.

d. Step 4. Rank the Alternatives

The final ranking is obtained by sorting the alternatives in descending order of their preference values. The alternative with the highest preference value is considered the most suitable recommendation for determining the product selling price.

The ranking results from the WP method are then compared with those from the SAW method to identify the most appropriate MCDM technique for supporting retail pricing decisions.

2.10 Comparative Evaluation

To objectively evaluate the performance of the proposed decision support system, the ranking results from the SAW and WP methods were compared using the same dataset, evaluation criteria, and criterion weights. Employing identical input data ensures that any differences in the results are attributable to the computational characteristics of the two MCDM methods rather than variations in the decision variables.

The comparison focused on three evaluation aspects:

1. Ranking Consistency, which examines the similarity and stability of the rankings generated by both methods for the evaluated product alternatives.
2. Computational Efficiency, which evaluates the computational procedures required by each method, including normalization, preference score calculation, and ranking generation.
3. Decision Representation, which assesses how effectively each method reflects the relative importance of evaluation criteria in determining product selling prices. The additive aggregation mechanism of the SAW method is compared with the multiplicative aggregation employed by the WP method to determine their suitability for retail pricing applications.

The comparative analysis provides a comprehensive evaluation of the strengths and limitations of both methods. The findings are expected to identify the most appropriate MCDM approach for supporting objective, transparent, and data-driven product selling price determination in retail businesses.

3. RESULT

This section presents the results obtained from implementing the Simple Additive Weighting (SAW) and Weighted Product (WP) methods to determine product selling prices at Yeni Mode Retail Store. Both methods were applied using the same product alternatives, decision criteria, criterion weights, and decision matrix to ensure a fair comparison. The analysis includes calculating preference scores, ranking product alternatives, comparing the results from both methods, and interpreting their suitability for supporting retail pricing decisions.

3.1 Initial Decision Matrix

The initial decision matrix represents the performance of each product alternative across the five evaluation criteria. Product Acquisition Cost (C1) and Operational Cost (C4) were obtained from the store's recorded monetary values, whereas Product Quality (C2), Market Demand (C3), and Expected Profit (C5) were converted into numerical scores using the five-point assessment scales described in the Method section. The resulting decision matrix is presented in Table 8.

Table 8.

Initial Decision Matrix

Code	Product	C1 (IDR)	C2	C3	C4 (IDR)	C5
A1	Muslim Dress	180,000	5	4	20,000	4
A2	Shirt	120,000	4	5	18,000	3
A3	Jeans	150,000	5	5	22,000	5
A4	Women's Skirt	100,000	3	3	15,000	2
A5	Blouse	130,000	4	4	17,000	4

Note: C1 = Product Acquisition Cost; C2 = Product Quality; C3 = Market Demand; C4 = Operational Cost; C5 = Expected Profit.

As presented in Table 8, the five product alternatives exhibit different performance characteristics across the evaluation criteria. Product Acquisition Cost (C1) ranges from IDR 100,000 to IDR 180,000, while Operational Cost (C4) ranges from IDR 15,000 to IDR 22,000. Meanwhile, Product Quality (C2), Market Demand (C3), and Expected Profit (C5) are represented using the five-point assessment scale defined in the methodology. C1 and C4 are classified as cost criteria, whereas C2, C3, and C5 are classified as benefit criteria. These values constitute the initial decision matrix used as the common input for both the SAW and WP calculations.

3.2 Results of the SAW Method

The SAW method was applied to the initial decision matrix presented in Table 8. The calculation process begins by normalizing each criterion according to its attribute type. Product Acquisition Cost (C1) and Operational Cost (C4) are classified as cost criteria; therefore, lower values are preferred. In contrast, Product Quality (C2), Market Demand (C3), and Expected Profit (C5) are classified as benefit criteria, where higher values indicate better performance.

For example, the normalized value of Product Acquisition Cost (C1) for alternative A1 was calculated as:

$$R_{11} = \min(C1)/x_{11} = 100.000/180.000 = 0,556$$

Meanwhile, Product Quality (C2) is a benefit criterion; therefore, its normalized value for A1 was calculated as:

$$r_{12} = x_{12}/\max(C2) = 5/5 = 1.000$$

The same normalization procedure was applied to all alternatives and criteria. The resulting normalized decision matrix is presented in Table 9.

Table 9.

Normalized Decision Matrix Using SAW

Alternative	C1	C2	C3	C4	C5
A1	0.556	1.000	0.800	0.750	0.800
A2	0.833	0.800	1.000	0.833	0.600
A3	0.667	1.000	1.000	0.682	1.000
A4	1.000	0.600	0.600	1.000	0.400
A5	0.769	0.800	0.800	0.882	0.800

The normalized values indicate the relative performance of each alternative after accounting for differences in criterion scales and attribute types. A value closer to 1 indicates better performance for the corresponding criterion. For example, A4 obtains the maximum normalized score for C1 and C4 because it has the lowest acquisition and operational costs, whereas A3 obtains the maximum scores for C2, C3, and C5 because of its high product quality, market demand, and expected profit.

Calculation of SAW Preference Scores After normalization, the final preference score of each alternative was calculated by multiplying the normalized criterion values by their corresponding weights:

$$W = (0,30, 0,20, 0,20, 0,10, 0,20)$$

For alternative A1:

$$V1 = (0,30)(0,556)+(0,20)(1,000)+(0,20)(0,800)+(0,10)(0,750)+(0,20)(0,800) = 0,762$$

Using the same procedure, the preference scores for the remaining alternatives were obtained. The results are presented in Table 10.

Table 10.

SAW Preference Scores and Rankings

Alternative	Product	Preference Score	Rank
A1	Muslim Dress	0.762	4
A2	Shirt	0.813	2
A3	Jeans	0.868	1
A4	Women's Skirt	0.720	5
A5	Blouse	0.799	3

As shown in Table 10, A3 (Jeans) achieved the highest SAW preference score of 0.868, making it the highest-ranked alternative. A2 (Shirt) ranked second with a score of 0.813, followed by A5 (Blouse) with 0.799. A1 (Muslim Dress) ranked fourth with a preference score of 0.762, while A4 (Women's Skirt) had the lowest preference score of 0.720.

Although A4 has the lowest acquisition and operational costs, its relatively low scores for product quality, market demand, and expected profit reduce its overall preference value. Conversely, A3 has relatively higher costs but achieves the maximum scores for all three benefit criteria. This indicates that the SAW method balances cost and benefit factors through weighted additive aggregation rather than selecting alternatives solely on the basis of lower costs.

3.3 Results of the Weighted Product (WP) Method

The WP method was subsequently applied to the same decision matrix and criterion weights used in the SAW calculation. Unlike SAW, which uses additive aggregation, WP evaluates each alternative through multiplicative aggregation. The normalized weights for the benefit criteria remain positive, whereas the weights for the cost criteria are negative. Therefore, the weight vector used in the WP calculation is:

$$W = (-0.30, 0.20, 0.20, -0.10, 0.20)$$

The vector S_i for each alternative was calculated using:

$$S_i = \prod_{j=1}^n x_{ij}^{w_j} \quad \dots\dots\dots (8)$$

Using the values from Table 8, the calculated S_i values are approximately:

Tabel 11.

Weighted Product (WP) Preference Scores and Rankings

Alternative	Product	Vector S
A1	Muslim Dress	0.01052
A2	Shirt	0.01159
A3	Jeans	0.01228
A4	Women's Skirt	0.00956
A5	Blouse	0.01136

The preference value of each alternative is then obtained by normalizing the vector S:

$$V_i = \frac{S_i}{\sum_{i=1}^m S_i} \quad \dots\dots\dots (9)$$

The resulting WP preference values and rankings are presented in Table 12.

Table 12.

WP Preference Scores and Rankings

Alternative	Product	Vector S	Preference (V_i)	Rank
A1	Muslim Dress	0.023656	0.192	4
A2	Shirt	0.025489	0.207	2
A3	Jeans	0.027059	0.220	1
A4	Women's Skirt	0.021550	0.175	5
A5	Blouse	0.025352	0.206	3

The WP method produces the same ranking order as the SAW method, with A3 (Jeans) ranked first, followed by A2 (Shirt), A5 (Blouse), A1 (Muslim Dress), and A4 (Women's Skirt). However, the preference scores generated by WP differ from those produced by SAW because WP uses multiplicative aggregation and incorporates criterion weights as exponents.

3.4 Comparative Analysis of SAW and WP Methods

The comparative analysis was conducted to evaluate the performance of the SAW and WP methods in determining product priorities based on the same alternatives, criteria, and weighting scheme. Although both methods use different aggregation mechanisms, their ranking results can be directly compared to assess the consistency of the resulting decisions. The comparison of preference scores and rankings is presented in Table 13.

Table 13.

Comparison of SAW and WP Results

Alternative	Product	SAW Score	SAW Rank	WP Score	WP Rank
A1	Muslim Dress	0.762	4	0.192	4
A2	Shirt	0.813	2	0.207	2
A3	Jeans	0.868	1	0.220	1
A4	Women's Skirt	0.720	5	0.175	5
A5	Blouse	0.799	3	0.206	3

As shown in Table 12, both methods produced identical rankings despite differences in their preference score scales. A3 (Jeans) was consistently ranked as the highest-priority alternative, followed by A2 (Shirt), A5 (Blouse), A1 (Muslim Dress), and A4 (Women's Skirt). The identical ordering indicates a high degree of consistency between the two MCDM methods for the dataset evaluated in this study.

The absolute preference scores generated by SAW and WP should not be interpreted as equivalent, as the two methods employ different mathematical aggregation mechanisms. SAW generates preference scores through weighted additive aggregation of normalized criterion values, whereas WP applies multiplicative aggregation in which criterion values are raised to the power of their respective weights. Therefore, the comparison should primarily focus on the resulting ranking order rather than the numerical magnitude of the preference scores.

3.4.1 Ranking Consistency

The ranking consistency analysis indicates that SAW and WP produced the same priority order for all five alternatives. The ranking sequence generated by both methods was: A3>A2>A5>A1>A4

This complete agreement suggests that selecting the highest-priority alternative is robust across the two aggregation approaches for the evaluated dataset. In particular, A3 remained the best-performing alternative despite differences between SAW's additive mechanism and WP's multiplicative mechanism.

For a more explicit representation of ranking agreement, the results are summarized in Table 14.

Table 14.

Ranking Consistency between SAW and WP

Alternative	SAW Rank	WP Rank	Rank Difference
A1	4	4	0
A2	2	2	0
A3	1	1	0
A4	5	5	0
A5	3	3	0

All alternatives show a rank difference of zero, indicating complete agreement between the two methods for this dataset. This finding suggests that the decision outcome is not sensitive to the choice between additive and multiplicative aggregation under the specified criteria and weighting scheme.

3.4.2 Computational Characteristics

Although both methods produced identical rankings, their computational procedures differ. SAW requires normalization of the initial decision matrix followed by weighted summation. This procedure is relatively straightforward and easy to interpret, making SAW particularly suitable for applications where computational simplicity and transparency are important.

In contrast, WP uses multiplicative aggregation and exponential weighting. Cost criteria are represented by negative exponents, while benefit criteria are represented by positive exponents. This mechanism allows WP to preserve proportional relationships among criterion values, but its computational procedure is slightly more complex than SAW's.

The computational characteristics of both methods are summarized in Table 15.

Table 15.

Comparative Characteristics of SAW and WP

Aspect	SAW	WP
Aggregation mechanism	Additive	Multiplicative
Normalization	Explicit normalization	Weight-based exponentiation
Cost treatment	Minimum/value	Negative exponent
Benefit treatment	Value/maximum	Positive exponent
Computation	Relatively simple	Relatively more complex
Interpretation	Easy	Moderate
Ranking result	$A3 > A2 > A5 > A1 > A4$	$A3 > A2 > A5 > A1 > A4$

The results indicate that SAW offers advantages in terms of simplicity and interpretability, whereas WP provides a multiplicative decision model that emphasizes proportional differences among criterion values. Nevertheless, for the current dataset, these methodological differences did not alter the final ranking of the alternatives.

3.4.3 Decision Interpretation

Both methods identified **A3 (Jeans)** as the highest-priority alternative. This result can be explained by A3's strong performance across the benefit criteria. A3 obtained the maximum assessment scores for Product Quality (C2), Market Demand (C3), and Expected Profit (C5). Although A3 did not have the lowest acquisition or operational costs, its superior benefit performance compensated for the higher costs in both decision models.

Conversely, A4 (Women's Skirt) achieved the lowest acquisition and operational costs but ranked last under both methods. This result demonstrates that low cost alone does not necessarily yield the highest overall priority when product quality, market demand, and expected profit are considered simultaneously. The proposed multi-criteria approach, therefore, provides a more comprehensive basis for pricing decisions than a conventional strategy based primarily on acquisition cost.

4. DISCUSSION

The results demonstrate that both the Simple Additive Weighting (SAW) and Weighted Product (WP) methods can provide systematic decision support for determining product selling prices. Although the two methods employ different aggregation mechanisms, they produced the same ranking order: $A3 > A2 > A5 > A1 > A4$. This consistency indicates that the prioritization of product alternatives remains stable across both additive and multiplicative MCDM approaches, given the criteria and weighting scheme used in this study.

A3 (Jeans) was consistently identified as the highest-priority alternative by both methods. This result is primarily attributable to its strong performance on the benefit criteria, particularly Product Quality (C2), Market Demand (C3), and Expected Profit (C5). Although A3 does not have the lowest Product Acquisition Cost (C1) or Operational Cost (C4), its superior performance on the benefit criteria compensates for its relatively higher costs. In contrast, A4 (Women's Skirt) has the lowest acquisition and operational costs but receives relatively lower evaluations for product quality, market demand, and expected profit, resulting in the lowest overall ranking. These findings demonstrate that relying solely on low product costs may not necessarily lead to the most favorable pricing decision when other important business factors are simultaneously considered.

From a methodological perspective, the consistency of the ranking results is noteworthy because SAW and WP process criterion values differently. SAW employs an additive aggregation mechanism in which normalized criterion values are multiplied by their respective weights and subsequently summed. This mechanism makes SAW relatively straightforward to calculate and interpret. In contrast, WP applies multiplicative aggregation by raising criterion values to the power of their corresponding weights, with negative exponents used for cost criteria. This mechanism preserves proportional relationships among criterion values and provides an alternative representation of the trade-offs between cost and benefit criteria. Despite these computational differences, both methods yielded the same priority order in this case, indicating that the final decision was not substantially affected by the choice of aggregation mechanism.

The findings also support the broader application of MCDM techniques to decision problems involving multiple, potentially conflicting criteria. Previous studies have demonstrated the applicability of SAW and WP in various decision-support contexts, particularly when alternatives must be evaluated simultaneously against several weighted criteria. The present study extends this application to retail product pricing by implementing both methods under identical decision conditions. Unlike an approach based on a single MCDM method, the comparative framework used in this study provides additional evidence on the consistency of the resulting product priorities and helps decision-makers understand the computational characteristics of each method.

From a practical perspective, SAW offers advantages in computational simplicity and ease of interpretation, which may be particularly useful for small retail businesses that require a straightforward decision-support mechanism. WP provides an alternative multiplicative evaluation mechanism that considers proportional differences among criterion values. Since both methods produced identical rankings in this study, either method can support the pricing decision process. However, SAW may be more practical when simplicity and transparency are prioritized, whereas WP may be considered when a multiplicative representation of criterion performance is preferred. Therefore, the selection of an MCDM method should consider not only the resulting ranking but also the decision-maker's computational and interpretative requirements.

For Yeni Mode Retail Store, the proposed Decision Support System provides a structured alternative to conventional pricing practices that rely heavily on managerial judgment. By simultaneously considering acquisition cost, product quality, market demand, operational cost, and expected profit, the system enables evaluation of product alternatives from both cost and benefit perspectives. The resulting recommendations can therefore provide a more transparent and consistent basis for supporting selling price decisions while still allowing the store owner to incorporate managerial considerations and changing market conditions into the final decision.

Nevertheless, the findings should be interpreted within the scope of the study. The evaluation was conducted with a limited set of product alternatives and five decision criteria, and the criterion weights reflect the business priorities of a single retail store. Consequently, the results should not be generalized to all retail businesses without further evaluation. Future studies could involve a larger number of product alternatives, multiple retail businesses, additional criteria such as competitor prices and customer purchasing power, and alternative weighting techniques. Further comparisons with other MCDM methods could also provide a broader understanding of their suitability for retail pricing decision support.

5. CONCLUSION

This study developed a Multi-Criteria Decision Support System for determining product selling prices by comparatively implementing the Simple Additive Weighting (SAW) and Weighted Product (WP) methods. Five decision criteria were considered, namely Product Acquisition Cost, Product Quality, Market Demand, Operational Cost, and Expected Profit. Both methods were applied to the same product alternatives, decision criteria, and weighting scheme to ensure a consistent and objective comparison.

The results demonstrate that both SAW and WP can provide systematic, consistent decision support for product pricing. The two methods produced identical rankings, with A3 (Jeans) identified as the highest-priority alternative, followed by A2 (Shirt), A5 (Blouse), A1 (Muslim Dress), and A4 (Women's Skirt). Although the preference scores generated by the two methods differ because of their respective additive and multiplicative aggregation mechanisms, these computational differences did not affect the final ranking of the evaluated alternatives. The findings indicate that both methods are suitable for supporting decisions on product selling prices under the criteria and weighting scheme used in this study.

From a practical perspective, the proposed system provides retail business owners with a more structured and transparent approach to pricing decisions by simultaneously considering cost, product quality, market demand, operational expenses, and expected profit. SAW offers advantages in terms of computational simplicity and ease of interpretation, whereas WP provides an alternative multiplicative mechanism for representing the relative performance of product alternatives. Therefore, the choice between the two methods may be determined by the decision-maker's computational and interpretative requirements rather than by ranking performance alone.

The present study is limited by the number of product alternatives, evaluation criteria, and its application to a single retail business. Future research should evaluate the proposed approach using larger and more diverse datasets, incorporate additional criteria such as competitor prices and customer purchasing power, and investigate alternative weighting or MCDM techniques. Such extensions may improve the adaptability and applicability of the decision support system across different retail business environments.

Author Contributions: The authors are Yaslinda Lizar (Y.L.), Maysa Suwandi Putri (M.S.P.), and Asriwan Guci (A.G.). Conceptualization, Y.L.; methodology, Y.L and M.S.P.; validation, A.G.; formal analysis, Y.L., M.S.P., A.G.; investigation, A.G.; resources, Y.L.; data curation, M.S.P; writing—original draft preparation, Y.L., M.S.P.; writing—review and editing, A.G.; visualization, M.S.P.; supervision, Y.L.; project administration, M.S.P., A.G. All authors have read and agreed to the published version of the manuscript.

Funding: The authors did not receive any financial support or sponsorship from any institution, company, or organization to conduct this research.

Conflicts of Interest: The authors declare no conflict of interest.

Declaration of Generative AI Statement: During the preparation of this article, the authors used ChatGPT to check grammar. Following the use of this tool/service, the authors reviewed and edited the content as necessary and take full responsibility for the content of this publication.

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