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Decision Support System for Determining Signature Menus Using the Integration of BMW, MOORA, and Copeland Scores

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Abstract−Menu optimisation is a crucial yet challenging challenge for business sustainability because the speciality coffee sector is marked by dynamic consumer tastes and a high degree of product diversity. This study tackles a basic operational issue at Inti Coffee, where a subjective, intuition-based method is currently used to identify "signature offerings"the important menu items that ought to be given priority for promotion, inventory, and resource allocation. This current process, which mainly depends on the owner, operational manager, and lead barista's intuition, is intrinsically vulnerable to individual cognitive biases, personal taste preferences, and inconsistent evaluation, which frequently results in less than ideal menu performance and lost revenue opportunities. The main goal of this research is to develop and deploy an online Decision Support System (DSS) that offers a transparent, data-driven, and organised framework for objectively ranking menu items in order to get around these restrictions. A hybrid multi-criteria decision-making (MCDM) technique is included into the suggested system to guarantee group unanimity and robustness. In order to minimise pairwise comparison inconsistencies and capture the knowledge of the three primary decision-makers, the Best-Worst Method (BWM) is first used to systematically extract the relative relevance weights of six different evaluation criteria. Second, a thorough dataset of 500 real sales transactions is used to assess and rank 51 menu alternatives using the MOORA (Multi-Objective Optimisation on the basis of Ratio Analysis) method. Both financial parameters (total items sold, HPP or cost of goods sold, and profit margin) and operational characteristics (uniqueness of taste score, preparation time, and ingredient lifetime) are included in the evaluation criteria. In order to successfully resolve any potential conflicts between decision-makers, the Copeland Score is finally used to combine the individual preference rankings into a single, collective group score. This study makes three main contributions: first, it develops a novel integrated DSS framework that integrates BWM, MOORA, and Copeland Score into a single unified workflow specifically designed for signature menu selection; second, it involves three different stakeholders (owner, operational manager, and head barista) in the group decision-making process, ensuring that the final recommendation reflects a balanced consensus rather than individual bias; and third, it creates a fully functional web-based system with statistical validation tools that empirically verify the accuracy and dependability of the recommendations using Spearman correlation, RMSE, and overlap ratio against actual customer preferences. The creation of a useful, web-based DSS that turns menu curating from an art to a science and offers a reproducible model for other food and beverage businesses is the main contribution of this research. With a MOORA score of 0.249180 and a Copeland Score of 50, the interim results show that the system is able to identify "Kopi Susu Aren" as the best-performing signature item. A poll involving 130 participants was carried out to verify the system's output against human judgement in the actual world. In addition to a low Root Mean Square Error (RMSE) of 5.5734 and an overlap ratio of 66.7%, the results show a strong positive correlation (Spearman's rho = 0.9238) between the system's ranks and participant feedback, proving the system's high accuracy and practical applicability. In order to provide scalability and usability for continuous operational choices, the DSS is implemented using a combination of PHP Native, Python, MySQL, and a testing dashboard based on Streamlit.

Keywords: Decision Support System; BWM; MOORA; Signature Menu; Copeland Score

1. INTRODUCTION

In Indonesia, the food and beverage business is now expanding quickly, especially the café sector. Owners of businesses are forced by this expansion to use competitive methods that work in order to draw in and keep clients. For Inti Coffee, determining the Signature Menu, the main product that characterises the brandis a crucial part of management strategy. In addition to serving as a major draw for customers and a symbol of the business, a signature menu may be used strategically to increase profit margins, lower HPP (cost of goods sold), and effectively manage raw materials to avoid having too much inventory that could spoil [1]. Signature menus are essential to coffee companies' sales strategies, brand identity, and product difference [2]. But popularity is not the only factor to consider while choosing a distinctive menu at Inti Coffee. Sales success, cost effectiveness, profit margins, unique flavour, fair preparation time, and good ingredient durability are all factors that must be integrated into an ideal signature item. This choice is categorised as semi-structured since it incorporates both quantitative data and expert opinions [3]. At the moment, intuition plays a major role in the choosing process.

The proprietor might highlight sales volume [4], While the head barista might emphasise taste distinctiveness, the operational manager might place more emphasis on profit and cost effectiveness. These differing viewpoints are common, but in order to moderate them, a clear decision model is necessary [5]. Without such a model, a seemingly popular menu item might be selected even though it has high HPP, takes a long time to prepare, or contains perishable products, which would ultimately impair the sustainability of the firm [6]. Transaction data, criteria, weights, rankings, decision aggregation, and reports must all be managed by a decision support system [7].

This study uses Multi-Criteria Decision Making (MCDM) techniques through a hybrid approach that integrates three complementary methods: the Best-Worst Method (BWM) to derive consistent, pairwise-comparison-based criteria weights from multiple decision-makers while minimising inconsistency; MOORA (Multi-Objective

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Optimisation on the basis of Ratio Analysis) for ratio-based normalisation and scoring of menu alternatives to enable clear ranking based on weighted criteria; and the Copeland Score to combine individual rankings from multiple decision-makers into a single group preference using a pairwise head-to-head voting mechanism to ensure a more equitable final result [8], [9]. A thorough analysis of earlier research on menu selection and food recommendation systems identifies a number of noteworthy studies that help place this study within the body of existing literature. Firstly, prior research on food product selection often used a single ranking method, such as SAW, WP, TOPSIS, AHP, or MOORA, which usually produced a final ranking but lacked mechanisms for group decision-making or validation [10]. Second, the practical reliability of some DSS implementations for menu recommendation was limited because they were only validated through functional or black-box testing without statistical correlation against actual consumer or expert feedback. Third, other studies relied on a single decision-maker (such as the owner or a chef) to provide criteria weights, which introduces individual bias and fails to capture the variety of operational perspectives required for balanced menu decisions [11]. Prior research has demonstrated that the weighting procedure in group decision support systems is still based on the subjective findings of interviews and has not been computed quantitatively [12]. Fifth, it was challenging to evaluate the accuracy of the system because other studies compared several MCDM approaches without incorporating a group aggregation method like Copeland Score or offering statistical validation against survey data like Spearman correlation, RMSE, or overlap ratio [13]. This study introduces an online Decision Support System that combines the Best-Worst Method, MOORA, and Copeland Score for selecting the signature menu [14]. The process initiates when the administrator uploads transaction data of the menu, which the system then transforms into a decision matrix reflecting each menu option. Next, three decision-makers, including the owner, operational manager, and head barista, deliver their preference assessments employing the BWM method, allowing the system to ascertain the ideal weights for each individual [15]. These weights are subsequently analyzed using the MOORA technique to calculate scores for the menus and produce preliminary rankings based on the weighted criteria values. In order to form a final collective decision, the Copeland Score method consolidates the individual rankings from all three decision-makers into a single group preference [16]. Ultimately, the system displays the detailed results via an interactive ranking dashboard, which includes validation metrics compared to customer survey data, and offers downloadable PDF reports and Excel spreadsheets to facilitate decision verification and business record-keeping [17].

A thorough analysis of earlier research reveals that the majority of studies still have serious shortcomings. It was discovered that a study on the best employee selection utilising a single MOORA technique lacked statistical validation against user preferences and structured criterion weighting, which led to suggestions that were not empirically evaluated for accuracy. The final results were descriptive and lacked quantifiable priority recommendations because another study that used BWM to determine development priorities for UMKM products did not proceed with alternative ranking using quantitative methods like MOORA. Another study that tried to combine BWM with TOPSIS only used functional testing for system validation; statistical tests were not yet used to compare the results with actual customer preferences. A single decision-maker was used in a study that applied MOORA to restaurant menu selection, and group aggregation techniques were not incorporated, leaving the decisions susceptible to individual bias. Therefore, the primary gaps found in earlier research are: the lack of a fully integrated web-based system with report export features and interactive dashboards to support transparency and decision auditing; the dominance of single decision-maker usage that ignores the diverse perspectives of owners, managers, and head baristas; the lack of comprehensive statistical validation using Spearman correlation, RMSE, and overlap ratio to measure the accuracy of system recommendations against actual customer preferences; and the absence of integration of three methods BWM, MOORA, and Copeland Score within the context of signature menu selection. The development of an integrated DSS framework that incorporates BWM for quantitative weighting with measurable consistency, MOORA for ratio-based ranking, and Copeland Score for group decision aggregationall of which have never been used concurrently in the café industryas well as the participation of three distinct stakeholdersthe owner, operational manager, and head baristain the group decision-making process to produce a more representative and balanced consensus; the creation of an online system with statistical validation tools that can be used by managers and owners for systematic menu optimisation. This combination facilitates a more thorough and organized evaluation method that integrates expert preference weighting, quantitative rankings, and group preference aggregation into a single workflow. Additionally, this research tackles a major drawback of traditional single decision-maker models by involving group decision-making from three different stakeholders within the cafe: the owner, the operational manager, and the head barista. By including the various viewpoints and priorities of these important individuals, the proposed framework guarantees that the ultimate decision represents a more balanced and inclusive consensus rather than the bias of one person. Furthermore, the research introduces a fully operational online system that enables data-driven menu choices, complete with statistical validation tools that confirm the dependability and precision of the recommendations provided. The system not only simplifies the decision-making process but also enhances transparency through comprehensive result presentations and downloadable reports. Lastly, the study delivers a clear, reproducible, and verifiable decision-making process that cafe owners and managers can use when looking for a methodical approach to optimizing their menus. By linking rigorous mathematical techniques with practical system usage, this research offers both theoretical knowledge and practical tools that can improve operational effectiveness and competitiveness in the food service sector. Based on this review, five critical research gaps are identified: most prior studies use a single MCDM method without combining expert weighting, scoring, and group aggregation into

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one unified workflow; validation is often limited to functional testing without statistical validation against actual customer or expert preferences; weights are frequently derived from subjective interviews without using a quantitative, consistency-checked method like BWM; most systems rely on a single decision-maker, ignoring the diverse perspectives of owners, operational managers, and baristas; and prior research does not incorporate a group aggregation method like Copeland Score to resolve conflicts between multiple decision-makers' rankings.

To address these gaps, this study introduces several significant advancements: it merges three recognized MCDM techniques, BWM, MOORA, and Copeland Score, into a unified DSS framework tailored for signature menu selection, facilitating a more thorough and organized evaluation that integrates expert preference weighting, quantitative rankings, and group preference aggregation into a single workflow; it tackles the major drawback of single decision-maker models by involving group decision-making from three different stakeholders (the owner, operational manager, and head barista), ensuring that the ultimate decision represents a balanced and inclusive consensus rather than individual bias; it develops a fully operational online system that enables data-driven menu choices complete with statistical validation tools (Spearman correlation, RMSE, and overlap ratio) that confirm the reliability and precision of the recommendations, while also enhancing transparency through interactive ranking dashboards, downloadable PDF reports, and Excel spreadsheets for decision verification and business record-keeping; and finally, it delivers a clear, reproducible, and verifiable decision making process that café owners and managers can adopt for systematic menu optimization. The primary objectives of this research are therefore to design and develop an online DSS that integrates BWM, MOORA, and Copeland Score for selecting signature menu items at Inti Coffee; to quantitatively determine optimal criteria weights from three decision-makers using BWM while ensuring consistency and reducing subjective bias; to rank 51 menu options based on 500 sales transactions and six evaluation criteria (total items sold, HPP, profit margin, uniqueness of taste score, preparation duration, and ingredient longevity) using MOORA; to consolidate individual rankings from the three decision-makers into a single group preference using Copeland Score; to validate the system's recommendations through statistical comparison against feedback from 130 survey participants, measuring correlation (Spearman), error (RMSE), and agreement (overlap ratio); and to provide a reproducible, transparent, and practical DSS framework that café owners and managers can adopt for systematic menu optimization, thereby improving operational efficiency and competitiveness in the food service sector while contributing both theoretical knowledge and practical tools that link rigorous mathematical techniques with practical system usage.

2. RESEARCH METHODOLOGY

2.1 Research Framework

The research framework consists of problem identification, alternative and criteria identification, expert preference collection, BWM weighting, MOORA ranking, Copeland Score ranking aggregation, model validation, web implementation, and system testing. The process starts with gathering transaction information which includes 500 records along with 51 different menu items. This information acts as the essential base for the overall decision-making procedure. The initial analytical phase employs the Best-Worst Method (BWM) to ascertain the significance of each evaluation criterion. In this context, BWM serves to methodically allocate levels of importance to various criteria relying on expert insights, making sure that the weighting is both consistent and trustworthy. Once the weights for the criteria are defined, the following phase utilizes the MOORA (Multi-Objective Optimization on the Basis of Ratio Analysis) technique to rank the 51 menu options. MOORA assesses each menu according to the weighted criteria and generates a performance score for every alternative, enabling a ranking from highest to lowest based on overall performance.

After deriving the individual rankings through MOORA, the next step involves applying the Copeland Score method to combine the rankings into a collective consensus. This approach evaluates each menu against all others in a pairwise fashion, tallying how many times one menu excels over another, and ultimately yields a single, consolidated ranking that represents the shared preferences of the decision-makers. The framework next moves on to the model validation stage, which is essential for guaranteeing the dependability and usefulness of the system's suggestions. This stage involves comparing the final rankings produced by the integrated BWM, MOORA, and Copeland Score model with the actual preferences stated by 130 survey participants who were asked to list their top Inti Coffee menu items. The agreement between the system-generated ranks and the survey findings is measured using a variety of statistical metrics, such as the overlap ratio, Kendall's Tau, Root Mean Square Error (RMSE), and Spearman's rank correlation coefficient. These metrics offer a thorough evaluation of the model's accuracy; tighter alignment between the system's recommendations and actual client preferences is indicated by higher correlation values and lower error values. The suggested DSS's validity is then verified and any possible areas for improvement are found using the validation findings. The final conclusion of this entire approach is a set of recommended menu alternatives. Based on an integrated multi-criteria evaluation procedure, this set of menu items was determined to be the best. These suggestions are the outcome of an organized, visible, and repeatable analytical methodology that incorporates weighing, ranking, and cluster aggregation rather than being purely dependent on raw data. As seen in Figure 1, this guarantees that the final menu choice is both data driven and in line with the preferences of the parties involved.

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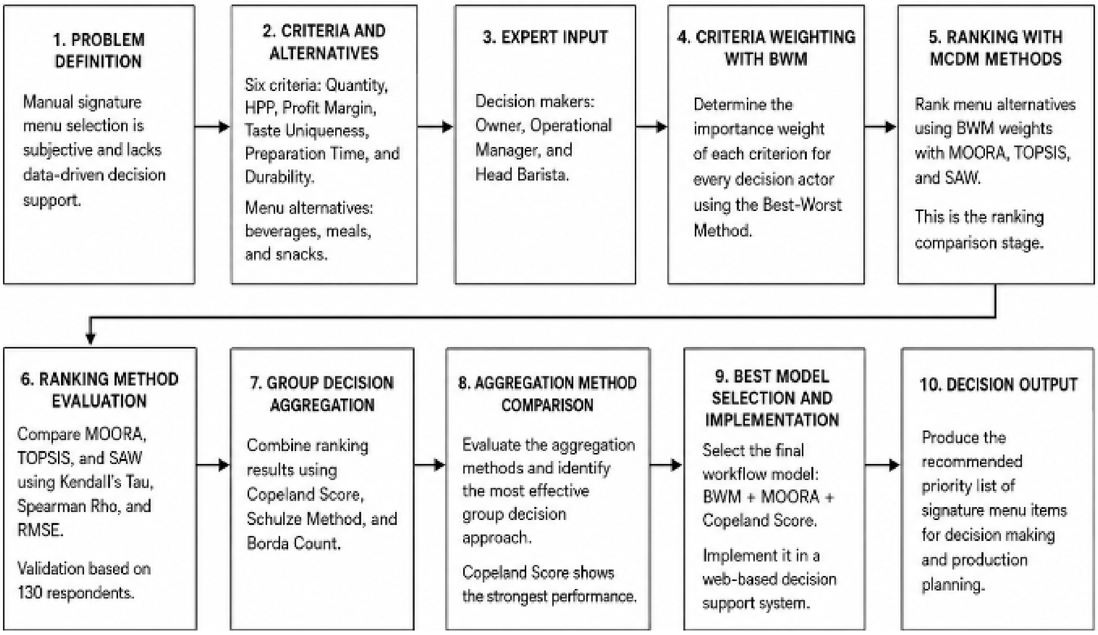

Figure 1. Research workflow for the integrated BWM, MOORA and Copeland Score Model

2.2 Research Object and Data Sources

Inti Coffee, situated at Jl. Besito- Gebog No. 39, RT.2/RW.05, Besito Kulon, Besito, Kecamatan Gebog, Kabupaten Kudus, Jawa Tengah, is the subject of the study. 500 transactions from March 19, 2026, to April 10, 2026, are included in the transaction dataset. 51 menus in four categoriesbeverages, snacks, meals, and dessertsare included in the dataset. The head barista, operations manager, and owner are the experienced actors utilized. According to the research data description in Table 1.

Table 1. Research Data Description

Item	Description
Total transactions	500 transaction lines
Number of alternatives	51 menus
Number of criteria	6 criteria
Menu categories	Beverages, Snack, Meals, Dessert
Decision makers	Owner, Manager, Head Barista
Validation respondents	130 questionnaire respondents
System platform	PHP Native, Python, MySQL, Bootstrap, Streamlit

2.3 Alternatives and Criteria

Every Inti Coffee menu that appears in the transaction data is one of the research options. Six criteria are used to evaluate each menu. C1, C3, C4, and C6 are shown as advantages. C2 and C5 are listed as expenses. Because there is less chance of inventory loss when ingredients stay longer, ingredient durability is seen as an advantage, as shown in Table 2.

Table 2. Evaluation Criteria for Signature Menu Determination

Code	Criteria	Unit/Scale	Attribute	Description
C1	Total Quantity Sold	Unit	Benefit	Total products sold during observation period. Higher sales indicate stronger market acceptance.
C2	HPP	Rupiah	Cost	Production cost per unit. Lower HPP is more cost-efficient.
C3	Profit Margin	%	Benefit	Percentage of profit per product after deducting HPP from selling price.
C4	Taste Uniqueness Score	Scale 1-10	Benefit	Expert assessment of taste uniqueness and appeal compared to competitors.
C5	Preparation Time	Minutes	Cost	Average time needed to prepare one serving. Faster service is more operationally efficient.
C6	Ingredient Durability	Days	Benefit	Shelf life of main ingredients. Longer durability minimizes waste risk.

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2.4 BWM Criteria Weighting

Based on pairwise comparisons supplied by each decision-maker, the Best-Worst Method (BWM) is utilised to ascertain the relative relevance weights of the six evaluation criteria. The first step in the formal mathematical definition of BWM is to define the collection of evaluation criteria. The conditions are expressed as follows:

$$C = \{C_1, C_2, \dots, C_n\} \tag{1}$$

This equation establishes the collection of all criteria considered in the decision process, where n represents the total number of criteria used to evaluate the menu alternatives. Next, each decision-maker identifies the best (most important) criterion and the worst (least important) criterion from the set. The decision-maker then expresses their preference for the best criterion over all other criteria using a scale from 1 to 9. The Best-to-Others vector is written as:

$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn}) \tag{2}$$

In this vector, each element a_{Bj} represents the degree of preference of the best criterion B over criterion j, where a higher value indicates that the best criterion is strongly more important than criterion j. Similarly, the decision-maker expresses their preference for all other criteria over the worst criterion. The Others-to-Worst vector is written as:

$$A_W = (a_{1W}, a_{2W}, \dots, a_{nW}) \tag{3}$$

Here, each element a_{jw} represents the degree of preference of criterion j over the worst criterion w, with higher values indicating that criterion j is strongly more important than the worst criterion. To derive the optimal weights, BWM minimizes the maximum absolute difference between the actual weight ratios and the stated preferences. The BWM objective function minimizes the inconsistency value [18]:

$$\min_{w,\xi} \xi \tag{4}$$

This objective function seeks to find the weight vector w and a non-negative scalar ξ that represents the maximum deviation from the ideal pairwise comparisons, effectively minimizing the overall inconsistency in the decision-maker's judgments. The first constraint controls deviation between the best criterion and others:

$$\left|w_B - a_{Bj} w_j\right| \le \xi \tag{5}$$

This constraint ensures that for every criterion j, the ratio of the best criterion's weight w_B to the weight of criterion j w_j does not deviate from the stated preference a_{Bj} by more than the inconsistency level ξ. The second constraint controls deviation between other criteria and the worst criterion:

$$\left|w_j - a_{jW} w_W\right| \le \xi \tag{6}$$

This constraint ensures that for every criterion j, the ratio of the weight of criterion j w_j to the weight of the worst criterion w_w does not deviate from the stated preference a_{jw} by more than the inconsistency level ξ. To produce a valid set of weights, the sum of all individual criterion weights must equal one. The sum of all weights must equal one:

$$\textstyle\sum_{j=1}^{n} w_j = 1 \tag{7}$$

This normalization constraint guarantees that the resulting weights form a proper probability distribution, where each weight represents the relative importance of its corresponding criterion. Additionally, each weight must be non-negative to ensure mathematical and logical validity. Each weight must be non-negative:

$$w_j \ge 0 \tag{8}$$

This non-negativity constraint prevents any criterion from receiving a negative weight, which would be meaningless in a practical decision-making context. Since this study involves three decision-makers (the owner, operational manager, and head barista), individual BWM weights are computed for each expert and then aggregated to obtain a consensus set of weights. The average weight from multiple decision-makers is calculated as:

$$\bar{w}_j = \tfrac{1}{K} \textstyle\sum_{k=1}^{K} w_{jk} \tag{9}$$

In this equation, $\bar{w}_j$ represents the average weight for criterion j across all K decision-makers, where w_{jk} is the weight assigned to criterion j by the k-th decision-maker. This averaging step ensures that the final weights reflect a balanced consensus among all stakeholders.

2.5 MOORA Menu Ranking

The MOORA (Multi-Objective Optimization on the Basis of Ratio Analysis) method is used to rank menu alternatives. the decision matrix is written as:

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$$X = [x_{ij}]_{m\times n} \tag{10}$$

In this matrix, x_{ij} represents the performance value of alternative i (menu item) with respect to criterion j, where m is the total number of menu alternatives and n is the total number of evaluation criteria. Each row corresponds to a specific menu, and each column corresponds to a specific criterion. Because the criteria are measured on different scales (e.g., Rupiah, percentage, minutes, days), a normalization step is necessary to make the values comparable. MOORA uses vector normalization to transform all values into dimensionless ratios. MOORA ratio normalization is calculated as [19]:

$$\tilde{x}_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{11}$$

This equation normalizes each value x_{ij} by dividing it by the square root of the sum of squares of all values in the same criterion column. The resulting normalized value $\tilde{x}_{ij}$ lies between 0 and 1, and the sum of squares of all normalized values for a given criterion equals one, preserving the relative differences between alternatives. After normalization, the criteria weights derived from BWM are applied to each normalized value to reflect the relative importance of each criterion. The normalized weighted value is calculated as:

$$v_{ij} = w_j\tilde{x}_{ij} \tag{12}$$

Here, v_{ij} is the weighted normalized value for alternative i under criterion j, obtained by multiplying the normalized value $\tilde{x}_{ij}$ by the average weight w_j of criterion j. This step ensures that criteria with higher importance contribute more significantly to the final score. MOORA distinguishes between benefit criteria (where higher values are preferred) and cost criteria (where lower values are preferred). For each alternative, the benefit score aggregates all weighted normalized values belonging to benefit attributes. The benefit score is calculated as:

$$B_i = \sum_{j\in G} v_{ij} \tag{13}$$

In this equation, B_i represents the total benefit score for alternative i, obtained by summing the weighted normalized values v_{ij} for all criteria j that belong to the benefit set G. For this study, benefit criteria include Total Quantity Sold (C1), Profit Margin (C3), Taste Uniqueness Score (C4), and Ingredient Durability (C6). Similarly, the cost score aggregates all weighted normalized values belonging to cost attributes. The cost score is calculated as:

$$C_i = \sum_{j\in H} v_{ij} \tag{14}$$

Here, C_i represents the total cost score for alternative i, obtained by summing the weighted normalized values v_{ij} for all criteria j that belong to the cost set H. For this study, cost criteria include HPP (C2) and Preparation Time (C5). The overall performance of each menu alternative is determined by subtracting the total cost score from the total benefit score. The MOORA preference score is calculated as:

$$y_i = B_i - C_i \tag{15}$$

This equation computes the final MOORA score y_i for alternative i. A higher score indicates better overall performance, as it reflects a combination of high benefit values and low cost values. The score can be positive, negative, or zero, and it provides a single quantitative measure for ranking purposes. Finally, all menu alternatives are ranked in descending order based on their MOORA scores. Alternatives are sorted from highest to lowest:

$$A_i \succ A_l \quad \text{jika} \quad y_i > y_l \tag{16}$$

This ranking rule states that alternative i is preferred over alternative l if its MOORA score y_i is greater than the MOORA score y_l of alternative l. The alternative with the highest MOORA score is considered the best-performing menu item based on the weighted criteria.

2.6 Rank Aggregation Methods

The following rank aggregation methods are tested: Copeland Score, Schulze Method, Borda Count, and Average Rank.

2.6.1 Copeland Score

The Copeland Score method aggregates individual rankings by conducting a pairwise comparison between all alternatives based on the preferences expressed by each decision-maker. For each pair of alternatives, the method counts how many decision-makers prefer one alternative over the other and determines a winner based on majority support. The first step is to define a binary preference indicator for each decision-maker. Decision-maker preference for two alternatives is written as:

$$P_{ij}^{(k)} = 1 \tag{17}$$

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This equation defines that $P_{ij}^{(k)} = 1$ applies if decision-maker k prefers alternative i over alternative j in their individual ranking. This binary indicator is used to tally preferences across all decision-makers.

$$P_{ij}^{(k)} = 0 \tag{18}$$

Conversely, this equation defines that $P_{ij}^{(k)} = 0$ applies if the opposite condition occursthat is, if decision-maker k does not prefer alternative i over alternative j (meaning they prefer j over i or are indifferent). These binary values form the basis for computing majority support. The total majority support for alternative i against alternative j is then calculated by summing the preference indicators across all decision-makers. The majority support for alternative i against alternative j is calculated as:

$$D_{ij} = \sum_{k=1}^{K} P_{ij}^{(k)} \tag{19}$$

in this equation, D_{ij} represents the total number of decision-makers who prefer alternative i over alternative j, where K is the total number of decision-makers (in this study, K = 3). Similarly, D_{ji} would represent the total number who prefer j over i. Alternative i is declared the winner over alternative j if the number of decision-makers supporting i is greater than those supporting j. Alternative i wins over alternative j if support for i is greater than support for j:

$$M_{ij} = 1 \quad \text{jika} \quad D_{ij} > D_{ji} \tag{20}$$

This equation establishes a pairwise win indicator M_{ij}, which equals 1 if alternative i receives majority support over alternative j. If $D_{ij} < D_{ji}$, then $M_{ij} = 0$ and alternative j wins the pairwise comparison. Once all pairwise comparisons are completed, the total number of wins for each alternative is calculated by summing all pairwise victories. Total wins are calculated as:

$$W_i = \sum_{j=1}^{m} M_{ij} \tag{21}$$

Here, W_i represents the total number of pairwise victories achieved by alternative i against all other m alternatives in the comparison set. A higher number of wins indicates that the alternative is preferred over many other options. Similarly, the total number of losses for each alternative is calculated by summing all pairwise defeats. Total losses are calculated as:

$$L_i = \sum_{j=1}^{m} M_{ji} \tag{22}$$

In this equation, L_i represents the total number of pairwise defeats suffered by alternative i, where M_{ji} equals 1 when alternative j wins over alternative i. This value captures how many times alternative i loses to other alternatives. The final Copeland Score for each alternative is obtained by subtracting total losses from total wins. The final Copeland Score is calculated as:

$$CS_i = W_i - L_i \tag{23}$$

This equation computes the final Copeland Score CS_i for alternative i. A higher Copeland Score indicates that the alternative wins more pairwise comparisons than it loses, reflecting stronger group consensus in favor of that alternative. The alternative with the highest Copeland Score is selected as the top-ranked option in the aggregated group decision.

2.6.2 Schulze Method

The Schulze Method works by determining the strongest paths in a directed graph of pairwise preferences. For each pair of alternatives (i, j), the strength of the path is determined. The Schulze winner is the alternative that has a stronger path to every other alternative than they have to it.

2.6.3 Borda Count

In Borda Count, each alternative receives points based on its position in each voter's ranking. If there are m alternatives, first place gets m-1 points, second place gets m-2 points, and so on. The alternative with the highest total Borda points wins.

2.6.4 Average Rank

Average Rank simply calculates the arithmetic mean of each menu's rank across all three decision-makers. Menus are sorted based on this average rank.

2.7 Model Evaluation

To validate the accuracy and reliability of the proposed Decision Support System, the system-generated rankings are compared against the actual preferences expressed by 130 survey respondents who were asked to indicate their favorite Inti Coffee menu items. Model validation uses data from 130 questionnaire respondents on their preferences for the Inti Coffee menu. Several statistical measures are employed to quantify the agreement between the system's recommendations and the survey results. The first validation metric is the Spearman correlation coefficient, which measures the monotonic relationship between two ranked lists. Spearman correlation is calculated as:

$$\rho = 1 - \frac{6\sum_{i=1}^{N} d_i^2}{N(N^2-1)} \tag{24}$$

In this equation, ρ represents the Spearman rank correlation coefficient, d_i is the difference between the ranks assigned to menu item i by the system and by the survey respondents, and N is the total number of menu items compared. A value of ρ close to +1 indicates a strong positive correlation, meaning the system's ranking closely matches the respondents' preferences, while a value near 0 indicates no correlation. The second validation metric is Kendall's Tau, which also measures rank correlation but is based on the number of concordant and discordant pairs rather than squared rank differences. Kendall's Tau is calculated as:

$$\tau = \frac{n_c - n_d}{\frac{1}{2}N(N-1)} \tag{25}$$

Here, τ represents Kendall's Tau coefficient, n_c is the number of concordant pairs (where both rankings agree on the relative order of two items), and n_d is the number of discordant pairs (where the rankings disagree on the relative order). The denominator $\frac{1}{2}N(N-1)$ represents the total number of possible pairs. Similar to Spearman's rho, a value of τ close to +1 indicates strong agreement between the two rankings. The third validation metric is the Root Mean Square Error (RMSE), which measures the average magnitude of the difference between the system's assigned ranks and the survey-based ranks. RMSE is calculated as:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(r_i - \hat{r}_i)^2} \tag{26}$$

In this equation, r_i represents the survey-based rank of menu item i, $\hat{r}_i$ represents the system-generated rank of menu item i, and N is the total number of menu items. A lower RMSE value indicates that the system's predictions are closer to the actual survey preferences, with an RMSE of 0 representing perfect prediction accuracy. Finally, to provide a single comprehensive measure of validation performance, a performance score is calculated by averaging the Kendall's Tau and Spearman's Rho correlation coefficients and converting the result to a percentage. Performance score is calculated using the formula:

$$Performance\ Score = \left(\frac{Kendall's\ Tau + Spearman's\ Rho}{2}\right) \times 100 \tag{27}$$

This equation computes a unified performance score by taking the arithmetic mean of Kendall's Tau and Spearman's Rho and multiplying by 100 to express the result as a percentage. A higher performance score indicates better overall agreement between the system's recommendations and the survey respondents' actual preferences, confirming the validity and practical usefulness of the decision support system.

2.8 Web-Based DSS Development

Using PHP Native and a MySQL database, the primary system is constructed as an online application [19]. The computation backend for BWM, MOORA, Copeland Score, and report exports is Python. Admin, Owner, Manager, and Head Barista positions are available in the system. Login, transaction data management, criterion management, decision-maker management, BWM preference input, computation processing, ranking outcomes, validation, reporting, PDF printing, and Excel export are among the system modules. Administrator, Owner, Manager, and Head Barista are the four different user roles that are defined by the system's extensive role-based access control mechanism. Each role has access levels and permissions that are specific to their roles in the decision-making process. With the highest level of access, the Administrator is in charge of controlling the complete system setup, which includes creating and maintaining user accounts, uploading and maintaining transaction data, defining and updating criteria, and supervising the full computation procedure. In addition, the Administrator can execute system backups, confirm system outputs against survey data, and create and export reports. The final ranking results, analytical reports, and validation summaries are accessible to the Owner, who is the principal strategic decision maker.

2.9 System Testing

Streamlit is used in the method testing system. Eighteen approaches totalsix weighing, six ranking, and six aggregation, are tested by this system. The objective is to demonstrate the methodological justification and technological functionality of the BWM, MOORA, Copeland Score combo [20]. Functional testing, which confirms that every system module functions as intended, and methodological testing, which contrasts the performance of the chosen integrated model with alternative MCDM configurations to show its superiority and practical relevance, are the two complementary aspects of testing.

The Inti Coffee Decision Support System login screen is shown in Figure 2. The system name "INTI COFFEE" appears at the top, followed by the tagline "Decision Support System." A login panel with two necessary input fields, one for the username and another for the password, is located in the middle of the screen. Users can access the system

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by clicking the Login button located beneath the password form. The phrase "Login with Coffee Expert," which appears beneath the login button, indicates that the system is intended for users who are coffee experts. The warm brown color scheme complements the coffee motif, and the entire design is simple and uncomplicated.

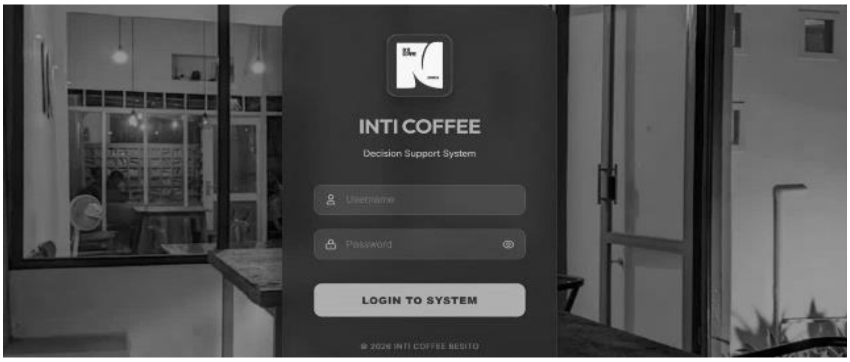

Figure 2. Login Page

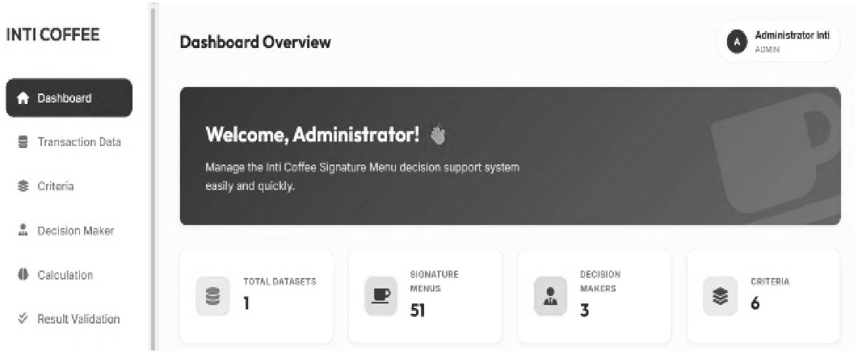

Figure 3. Admin Dashboard

Figure 3 illustrates the primary dashboard of the same system, which is shown following a successful login. The dashboard greets the administrator with a welcome message and a short explanation that emphasizes the system's role in overseeing the selection process of signature menus for Inti Coffee. To the left, a primary navigation menu grants access to vital modules such as Transaction Data, Criteria, Decision Maker, Calculation, Result Validation, User Management, and My Profile. The main area of the dashboard contains a "System Readiness" section that indicates the successful upload of the CSV dataset. Additionally, there is a "Quick Actions" area for expedited task completion. At the lower part of the dashboard, four summary cards present essential statistics: Total Datasets, Signature Menus, Decision Makers, and Centers. This dashboard is crafted to provide administrators with a clear, intuitive, and effective overview of the system's condition and other critical metrics, allowing them to oversee and manage the complete decision-making process from a single consolidated interface.

3. RESULT AND DISCUSSION

3.1 Dataset Description

The transaction dataset comprises 500 rows and 51 distinct menus. There are 325 transactions in the beverage category, 97 in the snack category, 53 in the meal category, and 25 in the dessert category. The total quantity sold, average HPP, profit margin, taste originality score, preparation time, and ingredient durability are then calculated by aggregating data by menu.

3.2 Decision Matrix

The multi-criteria decision-making approach in this study is based on a decision matrix. In order to facilitate methodical comparison and analysis, it arranges the evaluation data for every menu option across the six preset criteria. A sample of the decision matrix is shown in Table 3, which shows the top 10 menus according to their overall performance ranking.

Table 3. Decision Matrix Sample (Top 10 Menus)

Rank	Menu	Quantity Sold	HPP (Rp)	Profit Margin (%)	Taste Score	Prep Time (min)	Ingredient Durability (days)
1	Kopi Susu Aren	52	8,500	58.82	9	3	30

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Rank	Menu	Quantity Sold	HPP (Rp)	Profit Margin (%)	Taste Score	Prep Time (min)	Ingredient Durability (days)
2	Matcha	42	10,200	51.43	9	4	30
3	Mix Platter	28	19,500	48.72	8	10	14
4	Kopi Susu Butterscotch	24	10,500	48.78	9	4	30
5	Americano	22	5,800	61.33	7	2	60
6	Kentang	18	7,000	58.82	8	8	14
7	Udang Keju	16	15,000	45.45	9	8	14
8	Dimsum	15	12,000	50.00	8	7	14
9	Red Velvet	12	13,500	42.55	8	5	14
10	Nasi Ayam Katsu	12	16,500	48.43	8	10	7

The decision matrix depicted in Table 3 outlines the leading 10 options out of 51 menu choices assessed based on six factors: Quantity Sold, HPP, Profit Margin, Taste Score, Preparation Time, and Ingredient Durability. These factors are categorized into benefit attributes, specifically Quantity Sold, Profit Margin, Taste Score, and Ingredient Durability, which are aimed to be maximized, and cost attributes, HPP and Preparation Time, which are intended to be minimized in the MOORA analysis. The findings indicate that drink items, especially Kopi Susu Aren and Matcha, generally achieve greater sales figures and better taste ratings, while food options such as Mix Platter and Nasi Ayam Katsu frequently encounter compromises, including elevated production costs, extended preparation durations, or limited ingredient lifespan. Noteworthy is Kopi Susu Aren, which shows a strong overall performance by ranking first in sales with 52 units sold, a high profit margin of 58.82%, a perfect taste score of 9, a quick preparation time of 3 minutes, and a satisfactory ingredient shelf life of 30 days. On the other hand, Americano stands out in terms of cost and efficiency, possessing the lowest HPP at Rp 5,800, the highest profit margin at 61.33%, the briefest preparation time of 2 minutes, and the longest durability lasting 60 days; however, its comparatively lower taste rating of 7 hinders its suitability as a leading choice. These observations highlight the essential compromises involved in menu selection, as no single option excels in all aspects. Therefore, a systematic multi-criteria method employing BWM-weighted factors and MOORA ranking is crucial for effectively balancing these competing elements and determining the best signature menu that satisfies both customer desires and operational business objectives.

3.3 BWM Criteria Weighting Results

BWM results show that each decision-maker has different priorities. The owner gives the highest weight to Total Qty at 0.4468. The manager gives the highest weight to Profit Margin at 0.4443. The Head Barista gives the highest weight to Taste Uniqueness Score at 0.4249. This pattern aligns with the role of each decision-maker, as shown in Table 4.

Table 4. BWM Weighting Results from Three Decision Makers

Criteria	Owner	Manager	Head Barista	Average
Total Qty	0.4468	0.1958	0.2419	0.2948
HPP (Rp)	0.0896	0.1045	0.0704	0.0882
Profit Margin (%)	0.1470	0.4443	0.1242	0.2385
Taste Uniqueness Score	0.2261	0.1446	0.4249	0.2652
Preparation Time	0.0396	0.0368	0.0392	0.0385
Ingredient Durability	0.0509	0.0741	0.0994	0.0748

BWM consistency values are Owner 0.0905, Manager 0.1131, and Head Barista 0.0719. These values indicate that the preferences can be used in the ranking stage.

3.4 MOORA Ranking Results

Based on the weighted criteria acquired via the BWM process, preference scores (Yi) are generated for each of the 51 menu options using the MOORA (Multi-Objective Optimization on the Basis of Ratio Analysis) approach. A clear quantitative foundation for analyzing each menu's overall performance is provided by Table 5, which lists the top 10 menus based on their MOORA scores.

Table 5. MOORA Ranking Results (Top 10 Menus)

Rank	Menu	MOORA (Yi)
1	Kopi Susu Aren	0.24918
2	Mix Platter	0.14654
3	Matcha	0.14579
4	Kopi Susu Butterscotch	0.13554
5	Americano	0.13320
6	Udang Keju	0.11925
7	Kentang	0.11828

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Rank	Menu	MOORA (Yi)
8	Dimsum	0.11437
9	Nasi Ayam Katsu	0.10758
10	Red Velvet	0.10719

3.5 Rank Aggregation Results

The Copeland Score and the Average Rank are two aggregated measures that show how the rank aggregation findings, as shown in Table 6, integrate the separate ranks from the three decision-makersthe Owner, Manager, and Head Barista.

Table 6. Rank Aggregation Results (Top 10 Menus)

Rank	Menu	Owner	Manager	Head Barista	Copeland Score	Average Rank
1	Kopi Susu Aren	1	1	2	50	1.33
2	Matcha	2	3	1	48	2.00
3	Mix Platter	4	2	3	46	3.00
4	Kopi Susu Butterscotch	5	4	4	44	4.33
5	Americano	3	5	5	42	4.33
6	Kentang	7	6	6	40	6.33
7	Udang Keju	6	8	7	38	7.00
8	Dimsum	9	7	8	36	8.00
9	Red Velvet	8	9	9	34	8.67
10	Nasi Ayam Katsu	10	10	10	32	10.00

3.6 Evaluation Results Using Spearman, Kendall's Tau, and RMSE

By contrasting the outputs of the suggested Decision Support System with the preferences stated by 130 survey participants, the system validation findings, as shown in Table 7, show the efficacy and dependability of the proposed system. The BWM-MOORA-Copeland Score integration's correctness and practical application are confirmed by the validation procedure, which is crucial to ensuring that the system-generated suggestions match actual client preferences.

Table 7. System Validation Results Against 130 Respondents

Indicator	Result
Number of respondents	130
Validation status	VALID
Spearman correlation	0.9238
RMSE	5.5734
Overlap ratio	66.7%
Highest beverages menu	Kopi Susu Aren, 76 votes, 58.46%
Highest meals menu	Nasi Ayam Katsu, 46 votes, 35.38%
Highest snacks menu	Mix Platter, 39 votes, 30.00%

3.7 Best Model Selection

The optimal model selection procedure compares the group decision aggregation strategies used to combine individual preferences with the ranking methods used in the MOORA computation. Three ranking techniques, MOORA, TOPSIS, and SAW, are compared in Table 8 based on how well they correlate with survey data, and three aggregation techniques, Copeland Score, Schulze Method, and Borda Count, are compared in Table 9 based on how well they generate representative and accurate group decisions. To support the choice of the best techniques for the signature menu decision support system, these comparisons are crucial. This comparative analysis is crucial because the final recommendations can be greatly impacted by the selection of both the ranking technique and the aggregation method.

Table 8. Comparison of Ranking Method Performance

Method	Kendall's Tau	Spearman Rho	RMSE	Performance Score
MOORA	0.9357	0.9891	2.1693	96.24%
TOPSIS	0.8949	0.9814	2.8354	93.82%
SAW	0.8871	0.9762	3.2115	93.16%

Table 9. Comparison of Group Decision Aggregation Methods

Method	Function	Score	Interpretation
Copeland Score	Pairwise majority comparison	98.10%	Very strong and realistic
Schulze Method	Strongest preference path	97.50%	Strong but more complex
Borda Count	Position-based scoring	85.00%	Easy but prone to manipulation

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3.8 Web-Based DSS Implementation

The online Decision Support System utilizes PHP Native for the user interface on the front end, MySQL for managing the database, and Python for processing backend calculations related to BWM weighting, MOORA ranking, and aggregating the Copeland Score. Users interact with the system via a web browser, beginning at the Login Page where each individual is verified based on their assigned role, which can be Administrator, Owner, Manager, or Head Barista. After logging in, the Admin Dashboard delivers a thorough overview of the system, showcasing essential performance indicators, the status of system readiness, and quick action buttons for streamlined navigation. The system includes several key management modules, such as Transaction Data Management, which enables users to upload, modify, and remove transaction data related to the menu; Criteria Management for adding, changing, or deleting evaluation criteria; and Decision Maker Management to supervise user accounts and their preferences. A specialized BWM Preference Input page permits each decision-maker to provide their pairwise comparison evaluations, which the system then processes to compute individual and average weights for the criteria. The Calculation and Results Page showcases all analytical outputs, such as BWM weighting findings, MOORA ranking results, and the final ranking compiled using the Copeland Score method. Lastly, the Validation Results Page shows the performance metrics of the system in relation to survey data, offering statistical proof of the model’s accuracy and reliability. This cohesive interface guarantees that the entire decision-making process from uploading data to presenting the final recommendations occurs smoothly, transparently, and effectively within a unified digital platform.

Figure 4 illustrates the concluding ranking results page of the Inti Coffee Decision Support System. On the left side, the layout features a navigation menu containing essential sections such as Dashboard, Transaction Data, Criteria, Decision Maker, Calculation, Result Validation, Manage Users, My Profile, and Logout. The main body of the page is labeled "Final Ranking Results" and showcases the Signature Menu Ranking, which is produced through the combination of BWM, MOORA, and Copeland Score methodologies. The ranking table includes six menu options along with their corresponding MOORA scores (Y1) and Copeland Scores. At the top of the list is Kopi Susu Aren, represented by a green icon, followed by Matcha, Mix Platter, Kopi Susu Butterscotch, Americano, and Kentang, which are ordered from second to sixth place. This ranking establishes a clear, data-supported hierarchy of menu preferences stemming from the multi-criteria assessment procedure. Beneath the ranking table, there is a section headed "Criteria Weights (BWM)" that enumerates the evaluation criteria applied during the decision-making phase, comprising Taste, Price Margin, Skin Resistance, and additional relevant factors [21]. Ultimately, the page features an "Export Report" button, granting users the ability to download the calculation outcomes in a document format, which aids in further analysis and record-keeping. This interface offers administrators a clear, organized, and user-friendly method to review and confirm the final recommendations.

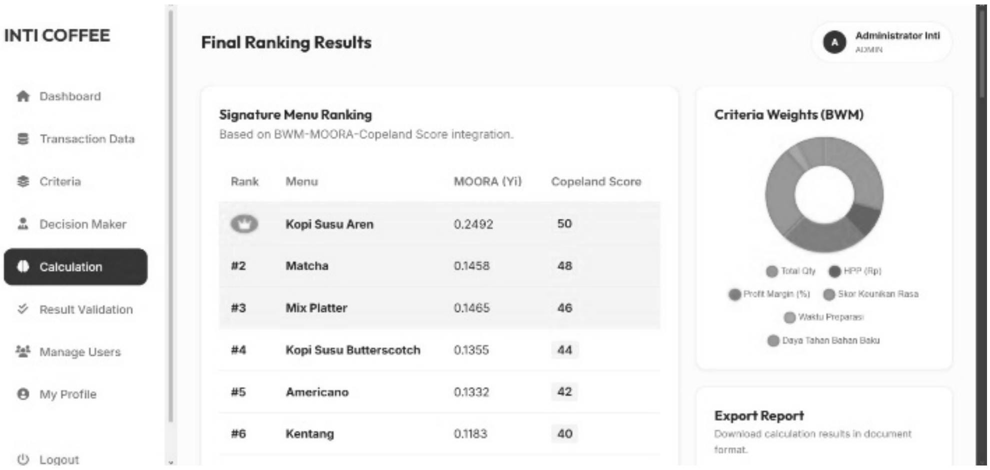

Figure 4. Calculation results pages for BWM, Moora, and CopelandScore

3.9 System Testing Results

A number of ranking techniques are compared to the consensus rating by the method testing system. According to the results, MOORA have the best accuracy. MOORA is still preferred marginally superior correlation metrics since it is easier to use, requires less computing power, and is more stable against extreme values thanks to vector normalization. The following comparison of ranking method performance is shown in Table 10.

Table 10. System Functional Testing Results

Test Case	Expected Result	Actual Result	Status
User login with valid credentials	Access granted, redirect to dashboard	Access granted, dashboard displayed	✓ PASS
User login with invalid credentials	Access denied, error message shown	Access denied, error shown	✓ PASS

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Test Case	Expected Result	Actual Result	Status
Upload CSV transaction data	Data imported and stored in database	Data imported successfully	✓ PASS
Input BWM preferences	Preferences saved and weighted	Preferences saved, weights computed	✓ PASS
Calculate MOORA scores	Scores computed and displayed	Scores computed correctly	✓ PASS
Apply Copeland Score aggregation	Rank aggregation displayed	Aggregation displayed correctly	✓ PASS
Generate PDF report	Report downloaded in PDF format	PDF generated and downloaded	✓ PASS
Export Excel report	Report downloaded in Excel format	Excel generated and downloaded	✓ PASS

According to aggregation testing, but its NP-Hard complexity makes it unfeasible for 51-menu implementation. Because it can generate fair, quick aggregation that is challenging for a single decision-maker to influence, the Copeland Score is selected as the best practical model. Table 11 presents a comparison of group decision aggregating techniques.

Table 11. Comparison of Group Decision Aggregation Methods

Method	Function	Score	Interpretation
Copeland Score	Pairwise majority comparison	98.10%	Very strong and realistic
Schulze Method	Strongest preference path	97.50%	Strong but more complex
Borda Count	Position-based scoring	85.00%	Easy but prone to position manipulation

3.10 Discussion

A thorough analysis of earlier research reveals that the majority of studies still have serious flaws. Only one MOORA approach was employed in the study on the optimal staff selection; structured criterion weighting and statistical validation against user preferences were not included [22]. Another study used BWM to identify development priorities for UMKM products, but it did not proceed with the process of rating alternatives using quantitative techniques like MOORA. As a result, the final results were descriptive and lacked quantifiable priority recommendations [23]. This study established a group-based MOORA DSS for supplier selection, however it relied on simple averages from expert assessments rather than a consistency-based weighting approach like BWM, which may have resulted in less accurate weights in the absence of consistency testing [24]. The Copeland Score was used in a multi-criteria setting, however this study was independent of weighting and ranking techniques, therefore the process of establishing alternative scores and criteria weights was still done independently and subjectively [25]. In the meantime, another study tried to combine BWM with TOPSIS; however, system validation was restricted to functional testing and had not yet included statistical testing to compare with real customer preferences [26]. Although MOORA was also used for restaurant menu selection, this study only included one decision-maker and did not incorporate group aggregation techniques, thus individual bias could still affect the choices [27]. BWM weighting outcomes reveal variations in managerial focus. The proprietor prioritizes total sales as a standout menu should resonate with the market. The supervisor highlights profit margins as a prominent menu must enhance the overall financial health of the business. The chief barista stresses the importance of unique flavors since a distinguished menu is essential for developing brand identity. The average weights indicate that Total Quantity, Taste Uniqueness Score, and Profit Margin are the top three influential factors. The findings from MOORA and the Copeland Score indicate that Kopi Susu Aren successfully balances appeal, flavor, and operational success. The Copeland Score bolsters the conclusion as this menu prevails in most comparisons against other options. Therefore, the ultimate outcome relies not solely on one numeric evaluation but also on the agreement among the preferences of those making decisions. The implementation of the web system enhances the documentation of the decision-making process. The administrator can oversee transaction information alongside BWM preferences. The owner has access to view rankings and analytical reports. Decision-makers can confirm the weights applied. Features allowing exports to Excel and PDF printing facilitate decision audits and business record-keeping.

4. CONCLUSION

This study effectively developed an online decision support system tailored for selecting the signature menu at Inti Coffee. The framework incorporates six factors, which include sales figures, costs, profit margins, uniqueness of flavors, time needed for preparation, and durability of ingredients. The Best-Worst Method derived weightings for the criteria based on input from the owner, manager, and lead barista. The Multi-Objective Optimization by Ratio Analysis generated scores and rankings for the menu items. The Copeland Score compiled the outcomes of the group decision-making process. The ultimate outcome identified Kopi Susu Aren as the signature menu option, achieving a MOORA score of 0.249180 and a Copeland Score of 50. Validation with 130 participants yielded a Spearman correlation of

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0.9238, a root mean square error of 5.5734, an overlap ratio of 66.7%, confirming validity. This system serves as an impartial, clear decision support mechanism that aligns with the operational requirements of Inti Coffee. Future studies may explore real-time integration of the system with point-of-sale systems, incorporate customer feedback, broaden the metrics for promotional costs, and analyze ranking variations over different sales periods. Additionally, the system could be enhanced with forecasting capabilities to ensure that signature menu choices adapt to evolving customer preferences. It is advisable to prioritize the Copeland Score as the main model due to its alignment with voting principles and its simplicity in explanation to business owners. Nonetheless, the Borda Count method should be contemplated in subsequent studies, as the evaluation of survey subsets indicates marginally improved RMSE figures.

5. DECLARATIONS

5.1 Author Contributions

Conceptualization: M.A.S., A.W., and N.L.;
Methodology: M.A.S., A.W., and N.L.;
Software: M.A.S.;
Validation: M.A.S., A.W., and N.L.;
Formal Analysis: M.A.S., A.W., and N.L.;
Investigation: M.A.S.;
Resources: M.A.S., and A.W.;
Data Curation: M.A.S.;
Writing Original Draft Preparation: M.A.S.;
Writing Review and Editing: A.W., and N.L.;
Visualization: M.A.S.;
All authors have read and agreed to the published version of the manuscript.

5.2 Data Availability

The corresponding author can provide the data used in this study upon request. Due to privacy and confidentiality agreements with Inti Coffee, the transaction dataset, survey responses, and computation results used to support the research conclusions are not publicly available; however, they can be obtained from the corresponding author upon reasonable request.

5.3 Funding

No particular grant from governmental, private, or nonprofit funding organisations was received for this study. The authors personally paid all of the publication and manuscript processing costs related to the production and release of this scholarly work.

5.4 Institutional Review Board Statement

Not relevant. There were no human or animal subjects in this study that needed institutional review board ethical approval. Expert preferences and transactional data from business operations were the main sources used in the study.

5.5 Informed Consent Statement

Not relevant. Human subjects in clinical trials or investigations requiring informed permission were not involved in this study. For validation purposes, all survey respondents voluntarily and anonymously submitted their answers.

5.6 Declaration of Competing Interest

The authors affirm that the work described in this publication was not influenced by any known competing financial interests or personal ties. Without any financial or commercial engagement that might be interpreted as a potential conflict of interest, the research was carried out independently.

5.7 Generative AI and AI-assisted Technologies in The Writing Process

The writers employed generative AI methods to enhance the paper's readability, grammar, and writing clarity. These tools were used to organise the manuscript and refine the language. All AI-assisted work was manually checked and revised by the writers, who assume full responsibility for the final published version's correctness, integrity, and originality.

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