A Comparison Between FAHP-TOPSIS and FAHP-FTOPSIS Methods for Selecting the Best Products for Home-Based Sellers: A Performance Analysis

Selvia Lorena Br Ginting[1]*, Zulaiha Ali Othman[2]
Center for Artificial Intelligence Technology (CAIT)-Faculty of Information Science and Technology,
University Kebangsaan Malaysia, Bangi 43600, Malaysia[1, 2]
Computer System Study Program-Faculty of Engineering and Computer Science,
Universitas Komputer Indonesia, Bandung, Indonesia[1]

***Abstract*—This study discusses common problems faced by home-based sellers in determining the right product ideas to sell. To overcome this problem, a method is needed that can help home-based sellers to choose the right product. Therefore, a decision support system using a multi-criteria decision-making technique with a hybrid approach was applied, which integrates the FAHP-TOPSIS and FAHP-FTOPSIS methods in the product selection process. The analysis results show that the FAHP-TOPSIS method is more effective in producing product rankings, with alternative A5948 ranking first with a score of 0.946. Meanwhile, the FAHP-FTOPSIS method also placed the same alternative in first place with a score of 0.679. The findings in the ranking analysis showed that the addition of fuzzy did not affect the rankings but did affect the score value of the alternatives. Sensitivity Analysis using Mean Absolute Deviation (MAD), Mean Square Error (MSE), and Spearman Correlation (SC) was conducted. FAHP-TOPSIS performed best at Weight 1 (MAD 89, MSE 18.486, SC 0.972) and excelled at Weight 3 (MAD 144, MSE 51.791, SC 0.997), though more volatile at other weights. Overall, at the base weight (Weight 1), TOPSIS shows the best ranking stability (low MAD/MSE, high SC), while with shifted weights (especially Weight 3), FTOPSIS better maintains ordering (SC ≈ 1) despite higher error at Weight 2. Practically, TOPSIS suits baseline scenarios; FTOPSIS is more robust under weight variations, with error variance control still necessary. These findings provide a practical guideline: use FAHP-FTOPSIS when preferences are uncertain, and use FAHP-TOPSIS when preferences are clear. The resulting rankings can be directly adopted by sellers to prioritize and select products with confidence.**

***Keywords*—Home-based sellers; product selection; FAHP-TOPSIS; FAHP-FTOPSIS; sensitivity analysis**

I. INTRODUCTION

The rapid growth in internet availability and improvements in the quality of high-speed internet services have created significant opportunities for the development of electronic commerce (e-commerce) systems. Home-based sellers use this technology to increase operational efficiency, reach a wider market, and make money from home through e-commerce platforms [1, 2]. However, home-based sellers face particular difficulties due to the wide range of products and many competitors on e-commerce platforms. Often, sellers new to online commerce do not adequately consider the selection of truly profitable products [3]. Therefore, if a company or seller achieves very high profits, it can be categorized as having good performance [4]. Consequently, a method is needed to assist home-based sellers in determining the most profitable products, both for the present and the future.

One commonly used approach is the Decision Support System, which helps decision makers choose the best alternative based on a number of criteria [5-7]. In this context, the concept of fuzzy logic becomes relevant because it can represent uncertainty and subjectivity in assessments. Introduced by Lotfi A. Zadeh in 1965, fuzzy logic is not strictly binary (true/false) but rather permits a value to exist within a range of 0 to 1 [8-10]. When making decisions involving information that is frequently unclear, ambiguous, or imprecise, this method is highly effective. The decision-making model's accuracy and realism can be enhanced by more flexibly describing the degree of importance or preference when criterion values are represented as fuzzy numbers, such as triangular fuzzy numbers (TFN) [9-12].

This study proposes two hybrid methods: FAHP-TOPSIS and FAHP-FTOPSIS. The FAHP-FTOPSIS method is an MCDM approach in which the Fuzzy Analytical Hierarchy Process (FAHP) is used to determine the relative weights of each criterion more flexibly by considering the uncertainty of the assessment [13-15]. Meanwhile, Fuzzy TOPSIS is used to rank alternatives based on their proximity to positive and negative ideal solutions in fuzzy space [16, 17]. As a comparison, the FAHP-TOPSIS method is used, which employs FAHP for weight determination and conventional TOPSIS for ranking, thereby enabling the evaluation of the feasibility and accuracy of the main method. Based on the research by Okfalisa et al. [18], five criteria are used in recommending online store products. The final results of this study will identify the method that produces the best ranking and determine the most suitable products to recommend to home-based sellers as a reference for selecting products to sell [19].

*Corresponding author.

II. Literature Review

A. Related Works

Previous studies have utilized fuzzy methods within the framework of Multi-Criteria Decision Making (MCDM).

A study by Ceren Erdin and Halil Emre Akba (2019) entitled "A Comparative Analysis of Fuzzy TOPSIS and Geographic Information Systems (GIS) for the Location Selection of Shopping Malls: A Case Study from Turkey", aimed to select strategic shopping mall locations in Turkey using the MCDM method with the Fuzzy TOPSIS and GIS approaches, and to compare the accuracy of each method [13]. In general, this study shows that combining fuzzy-based MCDM methods (e.g., Fuzzy-TOPSIS) with spatial analysis (e.g., GIS) makes location and alternative selection decisions more robust: ambiguous expert assessments can be handled, objective data is taken into account, and the results are more consistent and easier to visualize. As a result, the risk of wrong decisions is reduced, the planning process becomes more transparent and traceable, and this framework can be easily applied to other contexts (retail, logistics, energy, health).

In the study "Selection of Software Requirements using TOPSIS under Fuzzy Environment" by Mohd. Sadiq (2020), a method for selecting software requirements using Fuzzy TOPSIS was developed to address uncertainty and complexity in decision making [20]. In general, this research provides a structured and uncertainty-resistant method for prioritizing and selecting software requirements: linguistic expert assessments are converted into quantitative ratings using Fuzzy-TOPSIS (closeness coefficient), resulting in more objective and transparent decisions. This method is suitable for multi-stakeholders, addresses information ambiguity, and is relatively simple to calculate compared to several other techniques, as well as known to have minimal rank-reversal issues. The end result makes it easier for teams to select the most valuable "top-n" requirements and reduces the risk of misprioritization in development.

In a study conducted by Shamsuzzoha et al. [21] entitled "Application of the fuzzy TOPSIS framework for selecting complex projects", it offers a Fuzzy-TOPSIS-based selection framework to quickly identify the most complex projects, using eleven factors as a practical checklist, so that team allocation, budgeting, and support can be more targeted. The ranking results are proven to be stable through sensitivity testing, so decisions are not easily changed simply due to weight variations. As a result, the selection process becomes more objective, the risk of misplaced priorities is reduced, and project portfolio productivity increases while also filling a research gap due to its specific focus on selecting complex projects, rather than simply selecting general projects.

Previous studies have concluded that a research gap exists because studies on product selection with multiple criteria in e-commerce have not specifically addressed home-based sellers in Indonesia with large amounts of real data. The focus on indicators closely related to sellers (price, rating, sales, discounts, chat responses) is also still rare, as is a direct comparison between TOPSIS and Fuzzy TOPSIS with the same weighting basis and testing whether the results remain stable when there are small changes or when the criteria weights are shifted.

B. Product Selection

A crucial decision-making process is product selection: a process in which a variety of qualities and standards are evaluated to identify the best possible product. The application of cutting-edge techniques to deal with complexity and uncertainty in decision-making is emphasized in research on product selection. Fuzzy logic, hierarchical decision making, online reviews, multi-criteria analysis, and consumer expectations are some of the methods used [12, 22-25]. By taking consumer preferences, production efficiency, environmental impact, and technical viability into account, the objective is to maximize product selection [22]. The optimization method in the study by Tan et al. [23] focuses on determining the best product design that incorporates individual customer preferences and manufacturing constraints. Several studies on product selection show two main perspectives. First, the research by Gultom et al. [24] focuses on comprehending consumer preferences and using fuzzy sets to assist in decision-making, such as when prospective students are choosing a university. Second, the research by Aznag et al. [25] highlights how sellers should maximize revenue by optimizing product combinations while considering resource constraints.

C. MCDM

Multi-criteria decision-making (MCDM) is a method for evaluating and selecting the best choice from a number of options based on a number of factors. This approach is commonly used in areas such as selecting equipment, choosing technology, and evaluating service providers to improve performance, cost-efficiency, and other related aspects [26-28]. For these types of situations, multi-criteria decision methods (MCDMs) have been developed. These methods are also known for their formal structure and their ability to handle multiple conflicting goals and include different stakeholders in the decision-making process. Due to the wide range of problems they address, many multi-criteria decision methods have been created. One example is the Characteristic Objects METhod (COMET), which does not require the use of weights and is suitable for problems where rank reversal cannot happen [26]. Several MCDM methods can offer different solutions to the same problem. Variations in outcomes when using different computational approaches may result from factors such as the use of different weights for criteria, differences in the algorithms used, and the way targets are scaled [27, 29]. These observations highlight the importance of using a multi-method approach and techniques to fairly compare results in MCDM studies. Analyzing different MCDM methods shows that selecting the appropriate method and normalization technique is crucial. Almost any combination of a method and its parameters can lead to varied results [28]. Moreover, the increasing number of MCDM methods has created a need to compare the results they produce.

D. Home-Based Sellers

A home-based seller is typically a small-scale operation carried out from an individual's residence. These businesses contribute to household income and have a significant impact on the economy by using available resources, increasing national output, generating employment opportunities, and supporting the livelihoods of individuals in urban areas. Despite these benefits, home-based sellers encounter challenges such as intense competition and limited sales [30-34]. Furthermore, various studies highlight that online home-based sellers offer a broad array of products and services, including food items, beauty products, clothing, artwork, handmade crafts, accounting services, consulting, freelance writing, virtual assistance, marketing, design, translation, web development, dropshipping, and caregiving [35-40].

There is a growing trend of home-based sellers participating in the digital marketplace or e-commerce, with a substantial portion of their revenue generated through online sales. The different categories of home-based sellers include: 1) home-based family businesses [35], 2) e-commerce home-based firms [37], 3) home-based sellers that focus on work-life balance [36], 4) diverse home-based sellers [37], and 5) women-owned home-based sellers [38].

In addition, several studies suggest that online home-based sellers sell a variety of products and services, such as food items, beauty products, clothing, artwork, homemade crafts, accountancy, consulting, freelance writing, virtual assistance, marketing, design, translation, web development, dropshipping, and caregiving [35-39].

E. FAHP

The fuzzy analytic hierarchy process (FAHP) is based on Zadeh's fuzzy set theory and Saaty's analytic hierarchy process (AHP) method for multi-criteria decision making (MCDM) [14, 41, 42]. The Hierarchy Analysis Process, or AHP, is the most commonly used. There are two main steps to using AHP in real life. The first step is to break a complicated problem down into a structured hierarchy. The second step is to determine the priority of each criterion to establish their importance at each level. The final stage involves evaluating the hierarchy based on the decision maker's preferences, where the weights from each matrix are calculated and normalized [28, 42]. One of the major advantages of this process is that it reduces a multi-dimensional problem to an equivalent unidimensional problem. This also facilitates producing a standard solution, which can be fused across several experts to come to a single agreed output. The method is flexible, and inconsistencies can be detected. It also provides tools for achieving consensus among experts. However, as noted in [43], the traditional AHP does not effectively address uncertainty in the evaluation of criterion importance. Because of this limitation, a fuzzy version of the method was adopted. This version enables the use of AHP in uncertain or ambiguous situations and has become increasingly accepted. It has been widely accepted and applied to address decision-making problems in various fields [44].

F. Fuzzy TOPSIS

The TOPSIS technique was proposed in 1981 by Hwang and Yoon and has been widely applied during the past several years. This strategy is beneficial for making decisions by comparison of alternative measures as a function of how close they are to an ideal point [28].

Fuzzy numbers are employed to handle uncertainty and subjective judgments in real-life situations. Intuitionistic Fuzzy Sets provide a more accurate representation of decision-makers' approvals, rejections, and uncertain or hesitant opinions [45].

G. Sesitivity Analysis

Sensitivity analysis aims to measure the accuracy of the validation values obtained in the case study and demonstrate the robustness of the hybrid model [46]. The determination of this sensitivity analysis is based on several smallest value ranges and a regression process. The following are various ways to determine sensitivity analysis [47]:

1) Mean Absolute Deviation (MAD): Mean Absolute Deviation (MAD) is a statistical measure that calculates the average absolute deviation of data from the central value, and is used to assess the extent of variation or instability in a system [48, 49].

2) Mean Squared Error (MSE): Mean Squared Error (MSE) is the bias (systematic deviation) of an estimate plus, statistically independent components that account for its variation [50], and thus can be used to indicate general accuracy levels of a predictive model.

3) Spearman's Correlation (SC): Spearman's Rank Correlation Coefficient is a non-parametric statistical measure used to assess the degree of monotonic relationship between two variables, especially when the data is expressed in the form of ranks or orders [51]. This coefficient measures the extent to which the relationship between two sets of ranks is consistent (rising or falling simultaneously) [52].

III. METHODOLOGY

A. Research Framework

A flowchart of this study is illustrated in Fig. 1.

The following is an explanation of the flowchart shown in Fig. 1:

1) Criteria and data setup

- Identify Criteria → Criteria Data: define the evaluation criteria (e.g., rating, price, sold, etc.) and prepare the criterion dataset.
- Alternative Data Identification / Collection / Processing → Alternative Data: identify the alternatives (products), collect raw data, clean/normalize as needed, and produce a ready-to-use alternatives dataset.

2) Weighting with FAHP (two parallel tracks)

- Establishing a Decision-Making Hierarchy → Compiling a Pair-Wise Matrix: build the decision hierarchy and create the pairwise comparison matrix of criteria.
- Determining the Level of Importance → CR ≤ 0.1: perform the consistency check (Consistency Ratio). If CR > 0.1, revise judgments; if CR ≤ 0.1, continue.
- Matrix Fuzzification → Weight Calculation → Weight Data: fuzzify judgments (e.g., triangular fuzzy numbers), compute criterion weights (defuzzify/normalize), and store them as Weight Data.

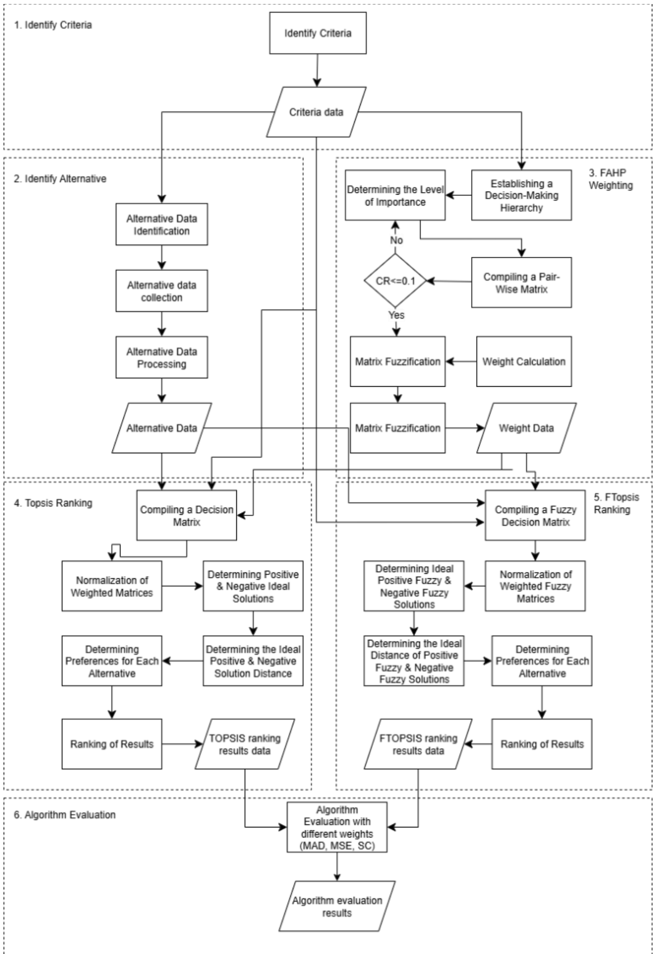

Fig. 1. Research method flowchart.

3) Decision matrix construction

- Compiling a Decision Matrix / Compiling a Fuzzy Decision Matrix: build the decision matrix (crisp for classical TOPSIS; fuzzy for FTOPSIS) that contains each alternative's performance on each criterion.

4) Ranking with TOPSIS (left branch)

- Normalizing the Weighted Matrices: normalize and apply weights to obtain the weighted normalized matrix.
- Determining the Positive and Negative Ideal Solutions: define the positive and negative ideal solutions.
- Determining the Ideal Positive and Negative Solution Distance: compute each alternative's distance to the positive and negative ideals.
- Determining the Preferences for Each Alternative → Ranking of Results → TOPSIS ranking results data: compute the preference score, rank the alternatives, and output TOPSIS ranking results.

5) Ranking with FTOPSIS (right branch)

- Normalizing the Weighted Fuzzy Matrices: perform fuzzy normalization and apply fuzzy weights.
- Determining the Ideal Positive and Negative Fuzzy Solutions: set the fuzzy positive/negative ideals.
- Determining the Ideal Distance of Positive Fuzzy and Negative Fuzzy Solutions: calculate distances in the fuzzy space (e.g., TFN distance).
- Determining the Preferences for Each Alternative → Ranking of Results → FTOPSIS ranking results data: (de)fuzzify preference scores, rank the alternatives, and output FTOPSIS ranking results.

6) Sensitivity evaluation across weight sets

- Algorithm evaluation with different weights (MAD, MSE, SC): test the stability of both algorithms under weight changes using three metrics:
  - MAD (Mean Absolute Deviation): average absolute rank difference vs. the baseline (smaller = more stable).
  - MSE (Mean Square Error): average squared rank difference (more sensitive to large shifts).
  - SC (Spearman Correlation): rank-order consistency (closer to 1 = highly consistent).
- Algorithm evaluation results: summarize which algorithm is more stable/robust under the tested weight profiles.

B. Data Collection and Criteria

1) Dataset source: This study uses data on food and beverage products from various stores on the Shopee Indonesia e-marketplace, collected using web scraping methods, amounting to 10,000 data points.

The criteria used in the study were obtained from the questionnaire results to determine the importance of each criterion. Referring to previous studies and adding two new criteria, which are subscribers and followers. The criteria used can be seen in Table I.

TABLE I. CRITERIA FOR SELECTING THE BEST PRODUCTS

Criteria	Description	Type
Rating	Product evaluation by consumers	Benefit
Price	Selling price of products	Cost
Sold	Number of units sold of a product	Benefit
Discount	Discounts on products	Benefit
Response Chat	Percentage of conversations responded to by sellers	Benefit

C. Fuzzy Analytic Hierarchy Process (FAHP

Here are the steps for weighting FAHP:

1) Conversion of multi-criteria decision-making problems into hierarchical models.

2) Identification of the importance of the pair-wise comparison matrix in determining the importance of criteria on the Saaty comparison scale is given in Table II.

TABLE II. INTENSITY OF INTEREST

Verbal scale	Numerical scale
1	Both elements are equal
3	A little more important
5	Most important
7	Much more important
9	Absolutely more important
2,4,6, and 8	Intermediate value
invers	$aij = 1/aij$

3) Normalization of the weight of each criterion importance value and find its eigenvector value.

4) Calculation of the consistency ratio using the index ratio to check the consistency of the weight values is given in Eq. (1):

$$CI = \frac{\lambda max - n}{RI*(n-1)} \tag{1}$$

If the CR value is ≤ (less than or equal to) 0.1, then the criteria values are consistent. However, if not, a re-evaluation is necessary to ensure the consistency of the criteria values.

5) Fuzzification of Pair-Wise Comparison Matrix into TFN Fuzzy Scale is given in Table III.

TABLE III. PAIR-WISE FUZZY SCALE

Intensity of importance	Fuzzy Scale (l,m,u)
1	(1,1,1)
2	(1,2,3)
3	(2,3,4)
4	(3,4,5)
5	(4,5,6)
6	(5,6,7)
7	(6,7,8)
8	(7,8,9)
9	(8,9,10)
invers	$(l,m,u)_{ij} = (1/u, 1/m, 1/l)_{ij}$

6) Fuzzy weight calculation using Fuzzy Geometrix Mean [Eq. (2)]:

$$\widetilde{w}_i = \tilde{r}_i \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \dots \oplus \tilde{r}_n)^{\frac{1}{n}} \tag{2}$$

7) Defuzzification of fuzzy weights using the Center Of Area method [Eq. (3)]:

$$w_i = (lw_i + mw_i + uw_i)/3 \tag{3}$$

8) Weight normalization [Eq. (4)]:

$$w_r = \frac{w_i}{\sum_{i=1}^{n} w_i} \tag{4}$$

D. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

The steps of TOPSIS are as follows:

1) Determination of the normalization of the decision matrix.

The normalized weight value rij is calculated using the following Eq. (5):

$$r_{ij} = \frac{Xij}{\sqrt{\sum_{i=1}^{m} X_{ij}^2}} \tag{5}$$

2) Determination of the normalized weights of the decision matrix.

The normalized weight value yij is calculated using the following Eq. (6):

$$yij = Wij \, x \, rij \tag{6}$$

provided that:

$$A+ = (y_1^+, y_2^+, \dots, Y_N^+)$$
$$A- = (y_1^-, y_2^-, \dots, Y_N^-)$$

Description:

$y+ = (max\ _i y_{ij}$; if j is an alternative category of benefits)

$y- = (min\ _i y_{ij}$; if j is an alternative category of Costs)

With a value of j = 1, 2, …n

3) Calculation of the distance between the Ai alternative and the positive ideal solution using the following Eq. (7):

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (y_j^+ - y_{ij})^2} \tag{7}$$

4) Calculation of the distance between the Ai alternative and the ideal solution using Eq. (8):

$$D_i^- = \sqrt{\sum_{j=1}^{n} (y_{ij} + y_j^-)^2} \tag{8}$$

5) Calculation of the preference value for each alternative (Vi) using Eq. (9):

$$V_i = \frac{D_I^-}{D_I^- + D_I^+} \tag{9}$$

E. Fuzzy Technique for Order Preference by Similarity to Ideal Solution (FTOPSIS)

The steps of Fuzzy TOPSIS are as follows:

1) Fuzzyfication of the decision matrix into TFN fuzzy values becomes three values: low, medium, and upper.

2) Determination of the normalization of the decision matrix. The normalized weight values rij are calculated using the following equation:

Benefit Criteria [Eq. (10)]:

$$\check{r}_{ij} = \left(\frac{a_{ij}}{c_i^{\text{MAX}}} + \frac{b_{ij}}{b_i^{\text{MAX}}} + \frac{c_{ij}}{a_i^{\text{MAX}}}\right) \tag{10}$$

Cost Criteria [Eq. (11)]:

$$\check{r}_{ij} = \left(\frac{c_i^{\text{MAX}}}{a_{ij}} + \frac{b_i^{\text{MAX}}}{b_{ij}} + \frac{a_i^{\text{MAX}}}{c_{ij}}\right) \tag{11}$$

provided that:

$$A+ = \left(\max a_{ij} \max b_{ij}, \max c_{ij}\right)$$

$$A- = \left(\min a_{ij} \min b_{ij}, \min c_{ij}\right)$$

3) Calculation of the distance between the Ai alternative and the positive ideal solution using Eq. (12):

$$D_i^+ = \sum_{i=j}^{n} \sqrt{\frac{1}{3}\{(a_{\tilde{ij}} - A_i^+) + \left(b_{\tilde{ij}} - A_i^+\right) + (c_{\tilde{ij}} - A_i^+)\}} \quad (12)$$

4) Calculation of the distance between the Ai alternative and the negative ideal solution using Eq. (13):

$$D_i^- = \sum_{i=j}^{n} \sqrt{\frac{1}{3}\{(a_{\tilde{ij}} - A_i^-) + \left(b_{\tilde{ij}} - A_i^-\right) + (c_{\tilde{ij}} - A_i^-)\}} \quad (13)$$

5) Calculation of the preference value for each alternative (Vi) using Eq. (14):

$$V_i = \frac{D_1^-}{D_1^- + D_I^+} \quad (14)$$

F. Sensitivity Analysis

The following are the equations for sensitivity analysis.

1) Mean Absolute Deviation (MAD)

The following is the equation for MAD [Eq. (15)]:

$$MAD = \frac{1}{n}\sum_{i=1}^{n} |xij - \text{YJ}| \quad (15)$$

2) Mean Squared Error (MSE)

The following is the equation for MSE [Eq. (16)]:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (xij - yj)^2 \quad (16)$$

3) Spearman's Correlation (SC)

The following is the equation for SC [Eq. (17)]:

$$SC = r_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \quad (17)$$

IV. Results and Discussion

A. Criteria Weight Calculation Using FAHP

The first step is to convert the multi-criteria decision-making problem into a hierarchical model consisting of objectives, criteria, sub-criteria (if any), and alternatives. The following is a decision hierarchy illustrated in Fig. 2.

The hierarchical model in this study consists of three levels: objectives, criteria, and alternatives. The first level is the objective, which is to determine the most potential product to sell for home-based sellers. The second level consists of five criteria: rating, price, sold, discount, and chat response. The third level contains product alternatives to be evaluated: Product 1 to Product N.

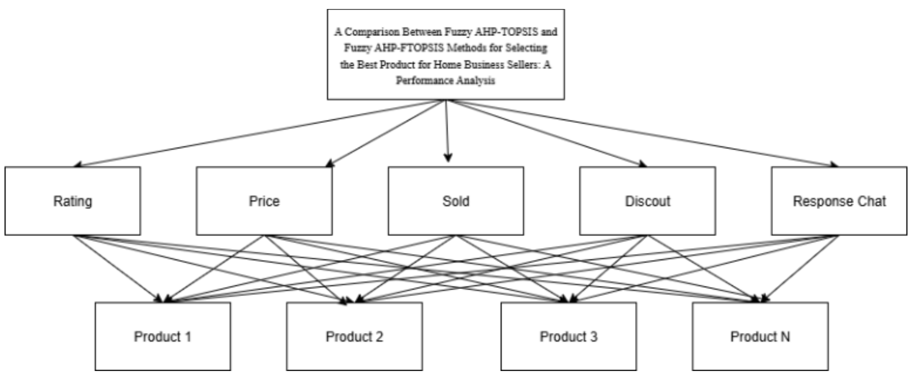

Fig. 2. Decision hierarchy.

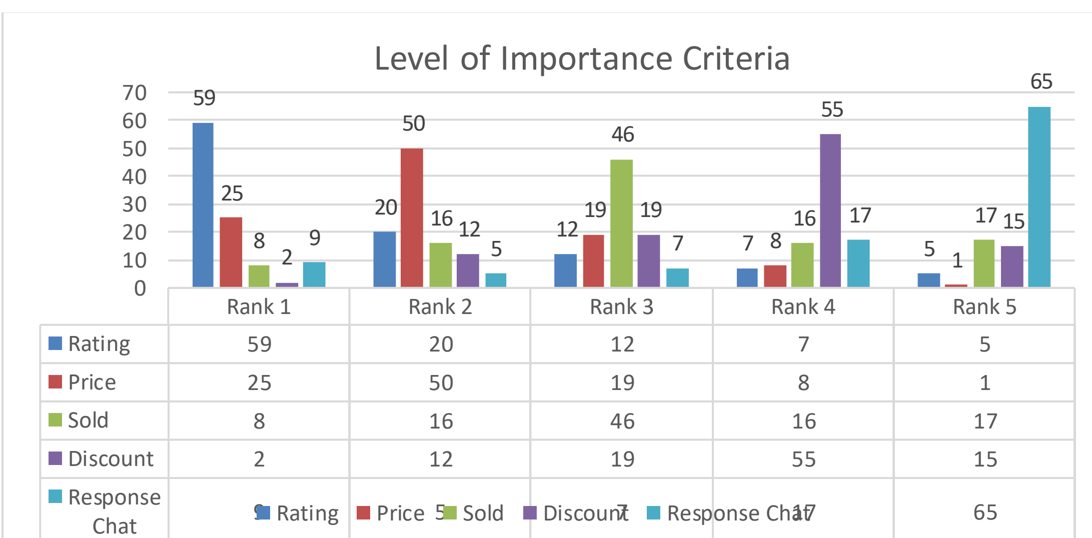

Fig. 3. Level of importance criteria.

After establishing the hierarchy, the next step was to determine the level of importance of each criterion. This was done by distributing questionnaires to sellers and successfully obtaining 103 respondents. The results of determining the level of importance are shown in Fig. 3.

Once the criteria were known, pair-wise comparisons were then conducted for each criterion, as in Table IV.

TABLE IV. MATRIX PAIR-WISE COMPARISON

	Rating	Price	Sold	Discount	Response Chat
Rating	1	2	3	4	5
Price	$\frac{1}{2}$	1	2	3	4
Sold	$\frac{1}{3}$	$\frac{1}{2}$	1	2	3
Discount	$\frac{1}{4}$	$\frac{1}{3}$	$\frac{1}{2}$	1	2
Response Chat	$\frac{1}{5}$	$\frac{1}{4}$	$\frac{1}{3}$	$\frac{1}{2}$	1

The results of the weights (eigenvectors) of each criterion from the pair-wise comparison results can be used to calculate the best product selection, as shown in Table V.

TABLE V. EIGENVECTOR

Criteria	Eigenvector
Rating	0.416
Price	0.262
Sold	0.161
Discount	0.099
Response Chat	0.062

Then, the eigenvector is evaluated by determining the Consistency Ratio (CR) using Eq. (1). The Consistency Ratio obtained is 0.022, which is less than 0.1, so the matrix obtained previously is consistent and does not need to be corrected.

After the matrix is consistent, fuzzification is performed on the pair-wise matrix according to the FAHP matrix scale, as in Table III. The following are the fuzzification results as shown in Table VI.

TABLE VI. FUZZY MATRIX PAIR-WISE

	Rating	Price	Sold	Discount	RC
Rating	(1;1;1)	(1;2;3)	(2;3;4)	(3;4;5)	(4;5;6)
Price	$\left(\frac{1}{3};\frac{1}{2};1\right)$	(1;1;1)	(1;2;3)	(2;3;4)	(3;4;5)
Sold	$\left(\frac{1}{4};\frac{1}{3};\frac{1}{2}\right)$	$\left(\frac{1}{3};\frac{1}{2};1\right)$	(1;1;1)	(1;2;3)	(2;3;4)
Discount	$\left(\frac{1}{5};\frac{1}{4};\frac{1}{3}\right)$	$\left(\frac{1}{4};\frac{1}{3};\frac{1}{2}\right)$	$\left(\frac{1}{3};\frac{1}{2};1\right)$	(1;1;1)	(1;2;3)
RC	$\left(\frac{1}{6};\frac{1}{5};\frac{1}{4}\right)$	$\left(\frac{1}{5};\frac{1}{4};\frac{1}{3}\right)$	$\left(\frac{1}{4};\frac{1}{3};\frac{1}{2}\right)$	$\left(\frac{1}{3};\frac{1}{2};1\right)$	(1;1;1)

After the matrix has been fuzzified, the fuzzy weight will be calculated using Eq. (2), and the results of the calculation are shown in Table VII.

TABLE VII. FUZZY WEIGHT

Criteria	L	M	U
Rating	0,421	0,417	0,389
Price	0,256	0,263	0,272
Sold	0,156	0,160	0,171
Discount	0,098	0,097	0,104
Response Chat	0,069	0,062	0,063

Next, defuzzification of the fuzzy weights from the fuzzy weight calculations performed using Eq. (3), and the weights were normalized using Eq. (4). The results can be seen in Table VIII.

TABLE VIII. CRIPS WEIGHT

Criteria	Weight
Rating	0.409
Price	0.264
Sold	0.163
Discount	0.100
Response Chat	0.065
CR	0.015

B. Product Ranking using TOPSIS

After obtaining the weight of each criterion, the calculation of the best product ranking was carried out using 10,000 (ten thousand) alternatives obtained from the Shopee Indonesia website, as shown in Table IX.

TABLE IX. DATASET TOPSIS

A/C	C1	C2	C3	C4	C5
A1	2	5000	10	0	14
A2	4	55000	5	0	82
A3	3	88000	2	5	50
A4	5	11000	9	0	79
A5	5	17999	10	0	41
A6	5	18900	31	0	38
A7	5	9500	2	0	96
A8	5	75900	64	0	91
A9	5	39999	125	0	66
A10	4	13000	83	30	94
………..					
A10000	5	4750	8	0	89

Next, calculations were performed using the TOPSIS method with Eq. (6) for weight normalization, Eq. (7) and Eq. (8) for negative and positive ideal values, and Eq. (9) to find the utility value of each alternative, as in Table X.

After that, the scores were calculated and ranked from the highest to the lowest. The following are the top 10 rankings as shown in Table XI.

TABLE X. UTILITY VALUE

A/C	C1	C2	C3	C4	C5
A1	0,00029	0,00128	0,00007	0,00000	0,00013
A2	0,00322	0,00256	0,00003	0,00000	0,00074
A3	0,00515	0,00192	0,00001	0,00043	0,00045
A4	0,00064	0,00320	0,00006	0,00000	0,00071
A5	0,00105	0,00301	0,00007	0,00000	0,00037
A6	0,00111	0,00308	0,00021	0,00000	0,00034
A7	0,00056	0,00320	0,00001	0,00000	0,00087
A8	0,00444	0,00308	0,00044	0,00000	0,00082
A9	0,00234	0,00308	0,00085	0,00000	0,00060
A10	0,00076	0,00282	0,00057	0,00258	0,00085
…………					
A10000	0,00028	0,00320	0,00005	0,00000	0,00080

TABLE XI. TOPSIS RANKING RESULTS

Rank	Alternative	Score
1	A5948	0,945977
2	A5950	0,897357
3	A6375	0,775835
4	A6625	0,705012
5	A3358	0,668346
6	A2667	0,649551
7	A3930	0,563599
8	A5312	0,498368
9	A776	0,423548
10	A6521	0,415185

C. Product Ranking Using FTOPSIS

The calculation using the FTOPSIS method was performed using fuzzy weights with three values from FAHP. The dataset used the data in Table IX, which was converted into Fuzzy TFN form in Table XII.

Next, calculations were performed using the FTOPSIS method with Eq. (10) for normalization if the criterion was Benefit and Eq. (11) if the criterion was Cost, as well as Eq. (12) and Eq. (13) for negative Fuzzy and positive Fuzzy ideal values. Then, the score was calculated using Eq. (14). The final results can be seen in Table XIII.

D. Graph of Ranking Changes

To evaluate the impact of weight variations on the ranking results, a comparative analysis was conducted using both Fuzzy TOPSIS and classical TOPSIS methods. The results are presented in the following figures, which illustrate how the rankings of alternatives change under different weight scenarios.

The first graph in Fig. 4 shows the ranking changes of alternatives under different weight scenarios using the Fuzzy TOPSIS method. Most alternatives show relatively stable rankings with minor shifts, but A919 and A5774 demonstrate sharp fluctuations, especially under the Second Weight scenario, where their ranks rise drastically. This indicates that Fuzzy TOPSIS is more sensitive to weight variations, particularly for certain alternatives, and may produce significant rank changes when the weights are adjusted.

TABLE XII. DATA FTOPSIS

A/C	C1	C2	C3	C4	C5
A1	(1.8;2.0;2.2)	(4500;5000;5500)	(9.0;10;11)	(0;0;0)	(12.6;14;15.4)
A2	(3.6;4.0;4.4)	(49500;55000;60500)	(4.5;5;5.5)	(0;0;0)	(73.8;82;90.2)
A3	(2.7;3.0;3.3)	(79200;88000;96800)	(1.8;2;2.2)	(4.5;5;5.5)	(45;50;55)
A4	(4.5;5.0;5.5)	(9900;11000;12100)	(8.1;9;9.9)	(0;0;0)	(71.1;79;86.9)
A5	(4.2;4.7;5.2)	(16199;17999;19799)	(9.0;10;11)	(0;0;0)	(36.9;41;45.1)
A6	(4.3;4.8;5.3)	(17010;18900;20790)	(27.9;31;34.1)	(0;0;0)	(34.2;38;41.8)
A7	(4.5;5.0;5.5)	(8550;9500;10450)	(1.8;2;2.2)	(0;0;0)	(86.4;96;106)
A8	(4.3;4.8;5.3)	(68310;75900;83490)	(57.6;64;70.4)	(0;0;0)	(81.9;91;100)
A9	(4.3;4.8;5.3)	(35999;39999;43999)	(112.5;125;138)	(0;0;0)	(59.4;66;72.6)
A10	(4.0;4.4;4.8)	(11700;13000;14300)	(74.7;83;91.3)	(27;30;33)	(84.6;94;103)
………..					
A10000	(4.5;5.0;5.5)	(4275;4750;5225)	(7.2;8;8.8)	(0;0;0)	(80.1;89;97.9)

TABLE XIII. FTOPSIS RANKING RESULTS

Rank	Alternative	Score
1	A5948	0,67910
2	A5950	0,63945
3	A6375	0,60883
4	A771	0,56562
5	A2667	0,56104
6	A2025	0,52758
7	A2384	0,52582
8	A5774	0,52290
9	A919	0,52283
10	A1623	0,52274

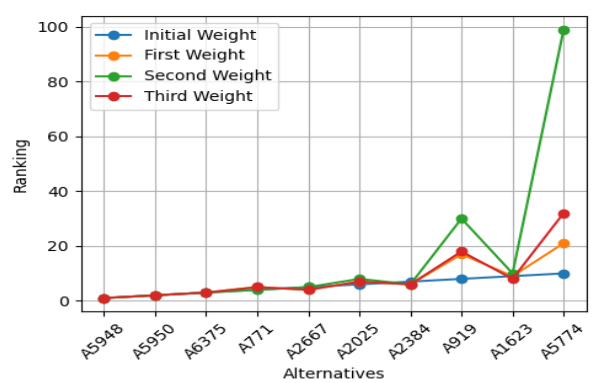

Fig. 4. FTOPSIS ranking change chart.

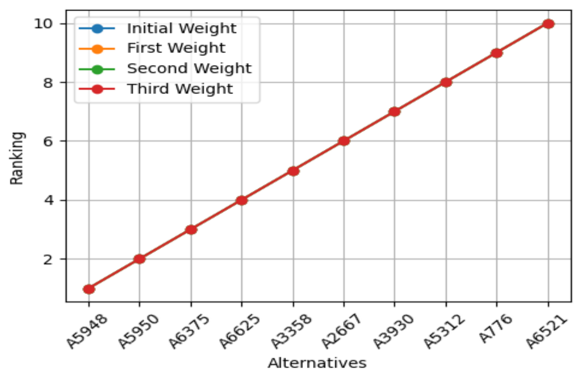

Fig. 5. TOPSIS ranking change chart.

The second graph in Fig. 5 displays the ranking results under different weight scenarios using the classical TOPSIS method. In this case, the rankings remain perfectly consistent across all scenarios, with all lines overlapping into a straight diagonal pattern. This demonstrates that TOPSIS yields a highly stable ranking outcome that is unaffected by weight modifications, showing robustness in preserving rank order despite changes in weights.

Together, the two graphs highlight a contrast: Fuzzy TOPSIS provides more flexibility but introduces higher sensitivity to weight changes, while TOPSIS delivers more stable and robust results, maintaining the same ranking across different scenarios.

E. Sensitivity Analysis

Sensitivity analysis was conducted by re-ranking alternatives using three different FAHP weight datasets and comparing the rankings from the main weights with those from the experimental weights to assess the impact of weight changes on alternative rankings, using Mean Absolute Deviation (MAD), Mean Square Error (MSE), and Spearman Correlation (SC).

1) MAD: The following are the MAD results of the two methods used, as shown in Fig. 6.

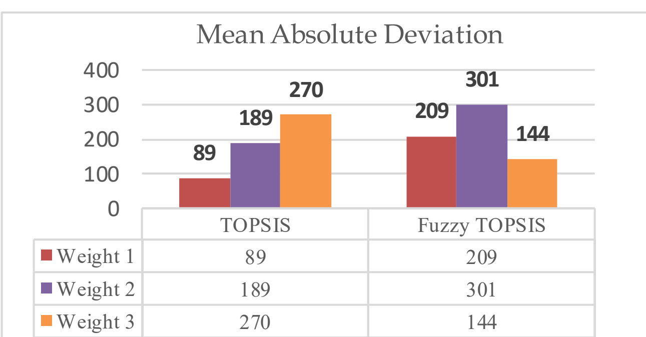

Fig. 6. Mean absolute deviation graph.

The results of the Mean Absolute Deviation (MAD) calculation in Fig. 6 show that TOPSIS has the highest ranking stability in Weight 1 (89) but is sensitive in Weight 3 (270). Conversely, Fuzzy TOPSIS is relatively unstable in Weight 1 (209) and most sensitive in Weight 2 (301), but shows the best stability in Weight 3 (144). In general, TOPSIS is more stable in the initial weights, while Fuzzy TOPSIS performs better in certain weights, but with greater fluctuations.

2) MSE: The following are the MSE results of the two methods used, as shown in Fig. 7.

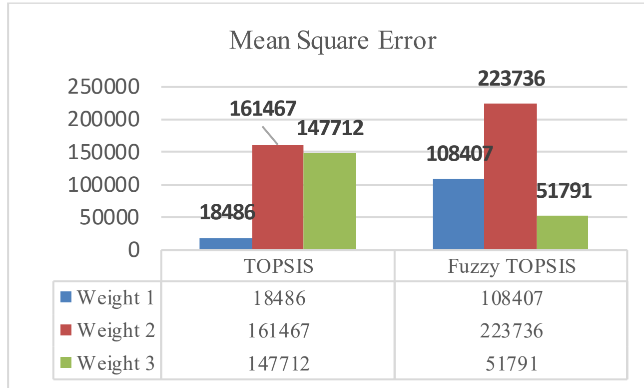

Fig. 7. Mean square error graph.

The Mean Square Error (MSE) results in Fig. 5 show that TOPSIS has the smallest error in Weight 1 (18.486) and increases significantly in Weight 2 (161.467) and Weight 3 (147.712). Conversely, Fuzzy TOPSIS has the lowest MSE for Weight 3 (51.791) but the highest for Weight 2 (223.736). In general, TOPSIS is more stable at the initial weights, while Fuzzy TOPSIS performs better for Weight 3, despite having larger error fluctuations.

3) SC: The following are the SC results of the two methods used, as shown in Fig. 8.

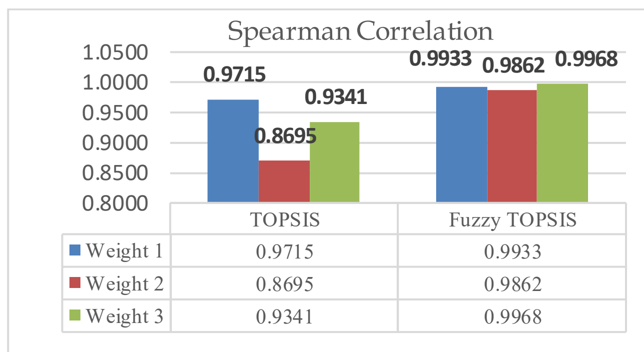

Fig. 8. Spearman correlation graph.

The Spearman Correlation results in Fig. 8 show that Fuzzy TOPSIS has a very high and consistent correlation in all weight scenarios: 0.9933 (Weight 1), 0.9862 (Weight 2), and 0.9968 (Weight 3). Meanwhile, TOPSIS recorded the highest correlation in Weight 1 (0.9715) and the lowest in Weight 2 (0.8695), with a moderate value in Weight 3 (0.9341). Overall, Fuzzy TOPSIS demonstrated better ranking stability compared to TOPSIS across all weight scenarios. Overall, Fuzzy TOPSIS demonstrated better ranking stability compared to TOPSIS across all weight scenarios.

Based on the results of testing using three evaluation metrics, namely Mean Absolute Deviation (MAD), Mean Square Error (MSE), and Spearman Correlation (SC), it was found that TOPSIS showed the best stability at the initial weight (MAD = 89; MSE = 18.486; SC = 0.9715), while Fuzzy TOPSIS outperformed it at Weight 3 (MAD = 144; MSE = 51.791; SC = 0.9968) and maintained consistently high correlation values across all weight scenarios. However, Fuzzy TOPSIS tends to experience greater error fluctuations in Weight 2. These findings indicate that the selection of the appropriate method and weight settings significantly influences the stability and accuracy of the ranking results.

Based on sensitivity analysis using MAD, MSE, and Spearman's Correlation (SC), it can be concluded that at the base weight (Weight 1), TOPSIS shows the best ranking stability—characterized by relatively low mean absolute deviation and mean square error as well as high ranking correlation with the reference. However, when the weights are shifted (particularly in the Weight 3 pattern), Fuzzy TOPSIS (FTOPSIS) is superior in maintaining consistency in the order, as reflected in the SC value that is very close to 1, even though the error profile increased in the Weight 2 configuration.

V. Conclusion

This study fills the gap by constructing a simple, field data-based model, comparing two approaches (FAHP–TOPSIS and FAHP–FTOPSIS), and then testing the stability of the results in scenarios of minor changes and significant weight changes. From this, practical guidelines that are easy to follow are compiled: Fuzzy TOPSIS is more appropriate when the data tends to be vague but the changes are small, while TOPSIS is more suitable when the focus of the assessment shifts significantly. The process is easy to repeat, and the consistent peak results in both approaches show that the recommendations produced are reliable.

The results of the comparative ranking analysis using the FAHP-TOPSIS and FAHP-FTOPSIS hybrid methods to support decision making in selecting potential products for home-based sellers. The alternative ranking results show that the first-ranked alternative is the same in both the FAHP-TOPSIS and FAHP-FTOPSIS methods: alternative A5948; however, the scores are different. In the FAHP-TOPSIS results, the score for this alternative is 0.945977, while in the FAHP-FTOPSIS results, this alternative receives a score of 0.67910. This proves that the addition of the Fuzzy approach to TOPSIS does not affect the product ranking results but does affect the score values of the product alternatives.

The sensitivity test results show that, FAHP-TOPSIS is stronger in dealing with changes in criterion weights, with the best results for weight one. Mean Absolute Deviation 89, Mean Square Error 18.486, and Spearman Correlation 0.972. Conversely, FAHP-FTOPSIS shows superiority at weight three—Mean Absolute Deviation 144, Mean Square Error 51.791, and Spearman Correlation 0.997, though its performance is more fluctuating at other weights. Practically, for baseline weighting scenarios in product selection, TOPSIS is the most stable choice; while for scenarios with weight variations (e.g., shifting seller preferences), FTOPSIS offers better ranking robustness, with the caveat that controlling error variance at certain weights remains necessary.

In short, FAHP-FTOPSIS is the safer choice for messy, real-world settings with uncertain or shifting preferences because it keeps rankings more stable. FAHP-TOPSIS can be attractive when decision makers have crisp, well-defined weights and you mainly care about minimizing numerical error. So, use FAHP-FTOPSIS as the default under ambiguity; switch to FAHP-TOPSIS when preferences are clear and consistency is less of a concern.

These findings can serve as a practical guideline for sellers. When preferences are uncertain or may shift over time as is common in dynamic marketplaces, FAHP-FTOPSIS should be the default because it keeps rankings stable and reliable under ambiguity. When priorities are crisp and well agreed upon, FAHP-TOPSIS can be used to emphasize minimal numerical error. In both cases, the resulting rankings are actionable: sellers can use them to shortlist products, allocate budget, and schedule promotions with greater confidence. We also recommend reviewing weights periodically (e.g., when market conditions or campaign goals change) and re-running the analysis so that the ranking continues to reflect current strategy and risk tolerance.

References

[1] D. Reuschke and C. Mason, "The engagement of home-based businesses in the digital economy," Futures, vol. 135, p. 102542, 2022.

[2] R. J. Nathan, V. Victor, C. L. Gan, and S. Kot, "Electronic commerce for home-based businesses in emerging and developed economy," Eurasian Business Review, vol. 9, no. 4, pp. 463-483, 2019.

[3] X. Pu, S. Sun, and J. Shao, "Direct selling, reselling, or agency selling? Manufacturer’s online distribution strategies and their impact," International Journal of Electronic Commerce, vol. 24, no. 2, pp. 232-254, 2020.

[4] B. Cuellar-Fernández, Y. Fuertes-Callén, and C. Serrano-Cinca, "Survival of e-commerce entrepreneurs: The importance of brick-and-click and internationalization strategies," Electronic Commerce Research and Applications, vol. 46, p. 101035, 2021/03/01/ 2021, doi: https://doi.org/10.1016/j.elerap.2021.101035.

[5] M. Hosoya, H. Yamaura, S. Nakamura, M. Nakamura, E. Takamatsu, and Y. Kitaide, "Does the pop-out make an effect in the product selection of signage vending machine?," in Human-Computer Interaction–INTERACT 2019: 17th IFIP TC 13 International Conference, Paphos, Cyprus, September 2–6, 2019, Proceedings, Part II 17, 2019: Springer, pp. 24-32.

[6] S. Ma and Y. Liang, "Human Resource Management Decision System University Based on Decision Model," Mathematical Problems in Engineering, vol. 2023, no. 1, p. 6212569, 2023.

[7] A. Bączkiewicz, B. Kizielewicz, A. Shekhovtsov, J. Wątróbski, and W. Sałabun, "Methodical aspects of MCDM based E-commerce recommender system," Journal of Theoretical and Applied Electronic Commerce Research, vol. 16, no. 6, pp. 2192-2229, 2021.

[8] D. Jhodkar, A. Khan, and K. Gupta, "Fuzzy-MOORA based optimization of machining parameters for machinability enhancement of titanium," 2021.

[9] G. Chen, T. Pham, and N. Boustany, "Introduction to Fuzzy Sets, Fuzzy Logic, and Fuzzy Control Systems," Applied Mechanics Reviews - APPL MECH REV, vol. 54, 11/01 2001, doi: 10.1115/1.1421114.

[10] A.-T. Nguyen, T. Taniguchi, L. Eciolaza, V. Campos, R. Palhares, and M. Sugeno, "Fuzzy control systems: Past, present and future," IEEE Computational Intelligence Magazine, vol. 14, no. 1, pp. 56-68, 2019.

[11] F. Wang, "Preference degree of triangular fuzzy numbers and its application to multi-attribute group decision making," Expert Systems with Applications, vol. 178, p. 114982, 2021/09/15/ 2021, doi: https://doi.org/10.1016/j.eswa.2021.114982.

[12] M. Borza and A. S. Rambely, "A new method to solve multi-objective linear fractional problems," Fuzzy information and engineering, vol. 13, no. 3, pp. 323-334, 2021.

[13] C. Erdin and H. E. Akbaş, "A comparative analysis of fuzzy TOPSIS and geographic information systems (GIS) for the location selection of shopping malls: a case study from Turkey," Sustainability, vol. 11, no. 14, p. 3837, 2019.

[14] P. Data, "Fuzzy analytical hierarchy process (FAHP) using geometric mean method to select best processing framework adequate to big data," Journal of Theoretical and Applied Information Technology, vol. 99, no. 1, pp. 207-226, 2021.

[15] Y. Liu and X. Zhang, "Evaluating the Undergraduate Course based on a Fuzzy AHP-FIS Model," International Journal of Modern Education & Computer Science, vol. 12, no. 6, 2020.

[16] F. Kutlu Gündoğdu and C. Kahraman, "A novel fuzzy TOPSIS method using emerging interval-valued spherical fuzzy sets," Engineering Applications of Artificial Intelligence, vol. 85, pp. 307-323, 2019/10/01/ 2019, doi: https://doi.org/10.1016/j.engappai.2019.06.003.

[17] A. Memari, A. Dargi, M. R. A. Jokar, R. Ahmad, and A. R. A. Rahim, "Sustainable supplier selection: A multi-criteria intuitionistic fuzzy TOPSIS method," Journal of manufacturing systems, vol. 50, pp. 9-24, 2019.

[18] D. U. Iswavigra, "Online Shop Recommendations: Decision Support System Based on Multi-Objective Optimization on the Basis of Ratio Analysis," in 2020 8th International Conference on Cyber and IT Service Management (CITSM), 2020: IEEE, pp. 1-6.

[19] S. M. AL-Ghuribi, S. A. Mohd Noah, S. Tiun, M. A. Mohammed, and N. I. Y. Saat, "Combining review elements for modelling various multi-criteria collaborative recommendation models," Journal of Big Data, vol. 12, no. 1, p. 160, 2025.

[20] M. Sadiq, K. Shadab, and C. W. and Mohammad, "Selection of software requirements using TOPSIS under fuzzy environment," International Journal of Computers and Applications, vol. 44, no. 6, pp. 503-512, 2022/06/03 2022, doi: 10.1080/1206212X.2020.1820689.

[21] A. Shamsuzzoha, S. Piya, and M. Shamsuzzaman, "Application of fuzzy TOPSIS framework for selecting complex project in a case company. J Glob Oper Strateg 14 (3): 528–566," ed, 2021.

[22] G. Zhang and H. Qiu, "Competitive product identification and sales forecast based on consumer reviews," Mathematical Problems in Engineering, vol. 2021, no. 1, p. 2370692, 2021.

[23] C. Tan, H. Chung, K. Barton, S. J. Hu, and T. Freiheit, "Incorporating customer personalization preferences in open product architecture design," Journal of Manufacturing Systems, vol. 56, pp. 72-83, 2020.

[24] P. Gultom and H. Mulyono, "Fuzzy Sets Applied for Product Selection based on Customer Preferences," 2022.

[25] A. Aznag, V. Goyal, and N. Perivier, "MNL-Bandit with Knapsacks: a near-optimal algorithm," arXiv preprint arXiv:2106.01135, 2021.

[26] R. Robina-Ramírez, A. Chamorro-Mera, and L. Moreno-Luna, "Organic and online attributes for buying and selling agricultural products in the e-marketplace in Spain," Electronic Commerce Research and Applications, vol. 42, p. 100992, 2020.

[27] B. Agarski, M. Hadzistevic, I. Budak, S. Moraca, and D. Vukelic, "Comparison of approaches to weighting of multiple criteria for selecting equipment to optimize performance and safety," International Journal of Occupational Safety and Ergonomics, vol. 25, no. 2, pp. 228-240, 2019.

[28] O. Boutkhoum, M. Hanine, T. Agouti, and A. Tikniouine, "A decision-making approach based on fuzzy AHP-TOPSIS methodology for selecting the appropriate cloud solution to manage big data projects," International Journal of System Assurance Engineering and Management, vol. 8, no. Suppl 2, pp. 1237-1253, 2017.

[29] M. Shantal, Z. Othman, and A. A. Bakar, "A novel approach for data feature weighting using correlation coefficients and min–max normalization," Symmetry, vol. 15, no. 12, p. 2185, 2023.

[30] G. Haynes et al., "Family business research: Reviewing the past, contemplating the future," Journal of Family and Economic Issues, vol. 42, no. Suppl 1, pp. 70-83, 2021.

[31] M. N. Anwar and E. Daniel, "The role of entrepreneur-venture fit in online home-based entrepreneurship: A systematic literature review," Journal of Enterprising Culture, vol. 24, no. 04, pp. 419-451, 2016.

[32] K. Kane and W. A. Clark, "Mapping the landscape of urban work: Home-based businesses and the built environment," Environment and Planning A: Economy and Space, vol. 51, no. 2, pp. 323-350, 2019.

[33] A. Ekhlassi, F. Fazli, and E. Alinaghian, "Marketing and Branding for Iranian Home-Based Businesses," in Iranian Entrepreneurship: Deciphering the Entrepreneurial Ecosystem in Iran and in the Iranian Diaspora: Springer, 2017, pp. 343-359.

[34] W. Tyas and J. Hutama, "Strategy and innovation of home based enterprises for local development in the 4.0 era: a bibliographic study," in IOP Conference Series: Earth and Environmental Science, 2021, vol. 673, no. 1: IOP Publishing, p. 012054.

[35] M. Madanoglu, E. Memili, and A. De Massis, "Home-based family firms, spousal ownership and business exit: a transaction cost perspective," Small business economics, vol. 54, no. 4, pp. 991-1006, 2020.

[36] R. Gorjifard and J. Crawford, "Working from home: Impact on wellbeing and work-life balance," New Zealand Journal of Employment Relations, vol. 46, no. 2, pp. 64-78, 2021.

[37] L. Philip and F. Williams, "Remote rural home based businesses and digital inequalities: Understanding needs and expectations in a digitally underserved community," Journal of Rural Studies, vol. 68, pp. 306-318, 2019.

[38] H. A. Seshie-Nasser and A. D. Oduro, "Women-owned businesses and household welfare," International Journal of Gender and Entrepreneurship, vol. 10, no. 4, pp. 310-331, 2018.

[39] T. M. Osaili, A. A. Al-Nabulsi, and T. M. Al-Jaberi, "Food safety knowledge, attitudes, and practices among female food handlers engaged in home-based online food businesses in Jordan during the COVID-19 pandemic," Heliyon, vol. 8, no. 8, 2022.

[40] A. N. Azmi, A. A. Bakar, Z. A. Othman, and N. S. Sani, "Mining Association Rules to Determine the Overspending Behavior Among Low Income Households in Malaysia," Asia-Pacific Journal of Information Technology & Multimedia, vol. 14, no. 1, 2025.

[41] T. L. Saaty, "Optimization by the analytic hierarchy process," 1979.

[42] M. Bakır and Ö. Atalık, "Application of Fuzzy AHP and Fuzzy MARCOS Approach for the Evaluation of E-Service Quality in the Airline Industry," Decision Making: Applications in Management and Engineering, vol. 4, no. 1, pp. 127-152, 03/13 2021, doi: 10.31181/dmame2104127b.

[43] M. T. Al Fozaie and H. Wahid, "A guide to integrating expert opinion and fuzzy AHP when generating weights for composite indices," Advances in Fuzzy Systems, vol. 2022, no. 1, p. 3396862, 2022.

[44] J. Franek and A. Kresta, "Judgment scales and consistency measure in AHP," Procedia economics and finance, vol. 12, pp. 164-173, 2014.

[45] B. D. Rouyendegh, A. Yildizbasi, and P. Üstünyer, "Intuitionistic fuzzy TOPSIS method for green supplier selection problem," Soft computing, vol. 24, no. 3, pp. 2215-2228, 2020.

[46] J. Y. Yap, C. C. Ho, and C.-Y. Ting, "Aggregating multiple decision makers' judgement," in Intelligent and Interactive Computing: Proceedings of IIC 2018: Springer, 2019, pp. 13-21.

[47] A. Naumann, S. Rieser, S. Musow, J. Hochweber, and J. Hartig, "Sensitivity of test items to teaching quality," Learning and Instruction, vol. 60, pp. 41-53, 2019.

[48] B. Gładysz and A. Kasperski, "Computing mean absolute deviation under uncertainty," Applied Soft Computing, vol. 10, no. 2, pp. 361-366, 2010.

[49] K. Elsayed, "Mean absolute deviation: analysis and applications," International Journal of Business and Statistical Analysis, vol. 2, no. 02, 2015.

[50] T. O. Hodson, T. M. Over, and S. S. Foks, "Mean squared error, deconstructed," Journal of Advances in Modeling Earth Systems, vol. 13, no. 12, p. e2021MS002681, 2021.

[51] G. W. Corder and D. I. Foreman, Nonparametric statistics: A step-by-step approach. John Wiley & Sons, 2014.

[52] Ž. Stević, M. Baydaş, M. Kavacık, E. Ayhan, and D. Marinković, "Selection of data conversion technique via sensitivity-performance matching: ranking of small e-vans with PROBID method," Facta Universitatis, Series: Mechanical Engineering, pp. 643-671, 2024.