8C SPS Model: A Seller Product Selection Model for Home-Based Business Sellers Using a Multi-Criteria Decision-Making Approach

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Abstract—**Home-based businesses are becoming a necessary tool for sellers of home-based businesses to determine which products they might be able to sell well. Otherwise, most of the sellers still choose products by trial and error, which may bring low demand as well as stock that doesn't sell, resulting in wasted capital. This study proposes an extended Seller Product Selection model from the seller perspective by enlarging the five-criterion benchmark customer-oriented model into eight criteria: Rating, Price, Sold, Discount, Response Chat, Repurchase, Favorite, and Followers. The data utilized in this study are records of food and beverage products from Shopee Indonesia, amounting to 150,000 products. The criteria relevance was tested with Forward Stepwise Multiple Linear Regression, which is additionally supported by the questionnaire given to 30 marketplace sellers online. Regression results for Sold are presented, indicating that all selected criteria were significantly related to the final model, achieving R = 0.953, R Square = 0.908, Adjusted R Squared = 0.908 with a Durbin-Watson of 1.863 (P<.0005) as shown in the table… The ANOVA result also indicates that the total model is statistically significant, F = 206961.417, p < 0.001. Repurchase had the highest statistical correlation with Sold (β = 0.758) among predictors, followed by Favorite (β = 0.299). Questionnaire results illustrate the following: Sold was ranked number one with a mean rank of 2.40 and Borda Weight of 0.183; Repurchase followed closely in position two with a mean rank of 3.63 and Borda Weight of 0.149. In order to validate whether dyads were able to agree on their RfD, Kendall's coefficient of concordance was obtained as follows: W = 0.236 (P < 0001), suggesting a moderate level of agreement among respondents. We conducted product ranking experiments for MOORA, SMART, PSI and TOPSIS under different combinations of criteria and weight assignments based on AHP. The results indicate that the eight-criterion Seller Product Selection model achieves substantially improved ranking stability and consistency compared with the five-state benchmark model presented in the relevant literature. While considering the eight-criterion model, MOORA performed the best in terms of obtaining the lowest MAD value (1,093), MSE value (4,969,891), and the highest Spearman's Rank Correlation value (0.99868). The results demonstrate that the proposed eight-criterion Seller Product Selection model can be an actionable decision aid to guide home-based business sellers in selecting products that have a better potential in the marketplace using MOORA.**

Keywords—Seller product selection; home-based business; online marketplace; multi-criteria decision-making; multi-objective optimization based on ratio analysis; analytic hierarchy process; product ranking

I. Introduction

Home-based businesses (HBBs) have become an increasingly important source of household and supplementary income, particularly for people seeking flexible and low-cost business opportunities that can be run from home. Besides supporting the welfare of families, HBBs also contribute towards employment generation, local economic activity, resource mobilization, and national economic development [1-6]. The rapid growth of digital marketplaces and e-commerce platforms has facilitated many HBB sellers to have access to wider markets and an extensive range of products and services online [1] [7] [8-13]. Among these, food and beverage products are one of the most common and promising categories due to their continuous demand and large consumer base [14]. However, despite these opportunities, HBB sellers face many serious challenges in sustaining their businesses, especially in highly competitive online environments [15]. One of the main problems is deciding what the best product to sell is. Many sellers, especially those new to business, choose products without researching the market well. This leads to low demand, unsold products, wasted money, and repeated trial-and-error decisions. These conditions not only decrease profitability but also endanger business survival and long-term sustainability [11, 16-18]. Therefore, the HBB sellers need practical support to identify product ideas with strong market potential, so that they can offer products that are more likely to sell, generate profit, and strengthen their competitiveness against other sellers. This assistance to HBB sellers is not only important for their own welfare, but also for the broader economy, as good and sustainable HBB performance can bring about wider social and economic benefits. In this context, providing a ranked list of promising products can serve as a useful decision support mechanism for HBB sellers in determining which products should be prioritized for sale. To achieve this objective, Multi-Criteria Decision-Making (MCDM) is considered an appropriate approach because it enables product alternatives to be systematically evaluated and ranked based on multiple relevant criteria, thereby helping sellers make more informed, rational, and competitive product selection decisions [18-25].

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Previous research by Okfalisa et al (2021) has addressed a related marketplace decision problem by applying the MOORA algorithm in a decision support system to recommend online shops based on five criteria, namely price, rating, discount, sold, and response chat, and showed that these criteria could be used to generate ranked recommendations effectively [23]. However, that study was mainly designed from the customer perspective and was limited to five evaluation criteria and a specific product context [23]. Building on this foundation, the present study extends the evaluation framework to eight criteria to better capture the needs of seller product selection, particularly for home-based business sellers who require broader market signals in selecting products with stronger selling potential [26, 27]. Moreover, the problem is evaluated with several MCDM algorithms, such as MOORA, SMART, PSI, and TOPSIS, to prove the robustness of product ranking under the extended criteria set. This extension aims to provide a comprehensive and practical ranking approach to identify the best products to sell in a competitive online marketplace.

The rest of this study is organized as follows. Section II reviews the literature on product selection, seller-related marketplace criteria, statistical analysis, and measures of robustness of rankings. Section III presents the proposed 8C SPS model and the dataset collection and preprocessing, questionnaire analysis, regression procedure, AHP weighting, MCDM algorithms, and evaluation measures. Section IV presents and discusses the results of the questionnaire, regression, product-ranking, criterion-removal and robustness. Finally, Section V presents a summary of the main findings, practical implications, limitations and directions for future research.

II. Literature Review

A. Product Selection

Product selection is another decision-making issue extensively examined by many scholars in diverse research contexts. Examples range from online shopping, supplier selection, material selection, transportation, business studies, to various sales applications. The ubiquity of applications highlights that the issue of product selection is relevant for both the business and industrial communities. As summarized in Table I, previous research has addressed product selection in different contexts by using various datasets, analytical approaches, and evaluation methods to identify the most suitable alternatives. These studies show that product selection is not limited to choosing a single item, but also involves determining the most appropriate alternative among several competing options under different decision environments.

TABLE I. Summary of Existing Selection-Based Decision Studies, Criteria, Algorithms, and Evaluation Measures

Author, Year, Ref	Selection Problem	Criteria								Dataset	Algorithms					Evaluation Measures
		Rating	Price	Discount	Sold	Response Chat	Repurchase	Favorite	Followers		MOORA	SMART	PSI	TOPSIS	OTHERS	
Okfalisa *et al.*, 2021 [23]	Best online shop for shirts	✓	✓	✓	✓	✓	-	-	-	Shirt products	✓	-	-	-	-	CM
Liu *et al.*, 2021, [28]	E-commerce selection	✓	-	-	-	-	✓	-	-	Feedback from buyers	-	-	-	-	NE	RT
Jain *et al.*, 2018, [29]	Automotive Supplier Selection	-	✓	-	-	-	-	-	-	India's automotive company	-	-	-	✓	AHP	SA
Memari *et al.*, 2019, [30]	Automotive Supplier Selection	✓	✓	-	-	-	-	-	-	Automotive parts in Iran	-	-	-	✓	-	SA
Jain & Upadhyay, 2020 [31]	Iron and steel supplier Selection	✓	✓	-	-	-	-	-	-	Iron and steel industry of India	-	-	-	✓	AHP	SPI
Emovon & Oghenenyerovwho, 2020 [19]	Various kinds of material selection	-	✓	-	-	-	-	-	-	Material criteria data	✓	-	✓	✓	AHP, VIKOR, PROMETHEE, ELECTRE	SA
Ulutas *et al.*, 2021 [32]	Transportation company selection	✓	✓	-	-	-	-	-	-	Transportation capacity	✓	-	✓	-	PIPRECIA	SA
Yadav *et al.*, 2019, [33]	Material selection	-	✓	-	-	-	-	-	-	Hybrid aluminium composite	-	-	✓	✓	-	CI
Amin *et al.*, 2021, [34]	Baby cream selection	✓	✓	-	-	-	-	-	-	Baby cream products	-	-	✓	✓	-	-
Cabeza-Ramírez *et al.*, 2022, [35]	Selection of fashion products	-	-	-	-	-	-	✓	✓	Influencer followers on social media	-	-	-	-	PLS-SEM	CA, R, Q

Liu *et al*., 2018, [36]	Product supplier selection	-	✓	-	-	✓	✓	-	-	Green fresh product supplier	-	-	-	✓	F-MULTIMOORA	SA
Abdel-Basset *et al*., 2019, [37]	Medical service efficiency	✓	-	-	-	-	-	-	-	Smart medical device data	✓	-	-	✓	AHP	SC
Chawla & Singari, 2021 [38]	Material selection	✓	-	-	-	-	-	-	-	Six aluminum alloys	✓	-	-	✓	AHP	ARP
Raju *et al*., 2020, [22]	Ranking of Al-CSA composite	✓	-	-	-	-	-	-	-	Aluminum-Coconut shell ash (Al-CSA) composite	✓	-	-	✓	AHP	_
Dorfeshan *et al*., 2018 [39]	Selecting the project-critical path	✓	✓	-	-	-	-	-	-	Aircraft Component Development Project	-	-	-	-	MULTIMOORA & TPOP	SA & CoA
Ulutaş *et al.,* 2021 [40]	Textile Supplier Selection	✓	✓	✓	-	-	-	-	-	Suppliers from three companies	✓	-	-	-	MULTIMOOSRAL	CoA
Çakır, 2016, [41]	Machine selection	✓	✓	-	-	-	-	-	-	Continuous fluid bed tea dryer	-	✓	-	-	F-SMART	LSDM
Bera *et al*., 2019 [42]	Manufacturing supplier selection	✓	✓	✓	-	-	-	-	-	Supplier data	✓	-	-	✓	IT2F TOPSIS, & IT2F MOORA	SA
Poongavanam *et al*., 2021 [21]	Best refrigerants selection	-	✓	-	-	-	-	-	-	14 Types of refrigerant	✓	-	-	✓	EDAS	SA
Liu *et al*., 2020, [43]	Car model selection	-	-	-	-	-	-	✓	-	car model data	-	-	-	-	SBDP	CS
Petcharat & Leelasantitham, 2021 [44]	Commerce selection	-	✓	-	✓	-	✓	✓	-	Online shop user respondents	-	-	-	-	SEM	CA
Kutela et al., 2022, [45]	Influence of language use	-	-	-	✓	-	-	✓	✓	Tweets from Tanzanian airlines	-	-	-	-	NBR	-
Wong & Wei, 2023 [46]	Influence of users and influencers on sales		-	-	✓	-	-	✓	✓	Followers of beauty influencers in China	-	-	-	-	PLS - SEM	MA
Farivar et al., 2022 [47]	The problem with followers and influencers	✓	-	-	-	-	-	-	✓	Instagram influencer followers in North America	-	-	-	-	SEM	CFA
Jin & Youn, 2022 [48]	Selection of sales performance	-	-	-	✓	-	-	✓	✓	Social media users in America	-	-	-	-	PLS-SEM	CA & CR

Note Algorithm: NE =Nash Equilibrium, AHP = Analytical Hierarchy Process, ELECTRE = Elimination and Choice Expressing Reality, QFD = Quality Function Deployment, ALFM = aspect-aware latent factor model, E = Entropy, AMB = Ambidextrous, PIPRECIA = Pragmatic Idealized Process for Risk Evaluation, Combined Influence Analysis, F = Fuzzy, IT2F = Interval Type-2 Fuzzy, EDAS = Evaluation based on Distance from Average Solution , PROMETHEE = Preference Ranking Organization Method for Enrichment of Evaluations, PLS = Partial Least Squares, SEM = Structural Equation. Modeling, TPOP = Technique of Precise Order Preference, VIKOR = VIšekriterijumsko Kompromisno Rangiranje(Multi-criteria Compromise Ranking), SBDP = Sparse Biterm-based Dirichlet process, NBR = Negative Binomial Regression.

Note Measurements : CM = Confusion Matrix, SA = Sensitivity Analysis, RT = Robustness Test, RMSE = Root Mean Square Error, T-T =T-Test, SPI = Sustainability Performance Index, CI = Closeness Index, CA = Cronbach's Alpha, R = R-squared, Q = Q-squared, CR = Composite Reliability, CS = Coherence Score, SC = Spearman correlation, ARP = Approach Reference Point, CoA = Comparative Analysis, LSDM = Least Squares Distance Method, CFA = Confirmatory Factor Analysis, MA = Mediation Analysis..

1) Product selection in previous studies: In the online marketplace context, product selection has been examined to support better choices among available alternatives and to reduce uncertainty in decision-making. For example, Okfalisa et al. [23] explored online shop recommendations for shirt products, while Liu et al. [28] investigated e-commerce selection using buyer-related information. In other contexts, product selection has been extended to supplier selection in the automotive, iron and steel, textile, and manufacturing sectors [29]-[31], [40], [42], as well as to material and component selection in engineering applications [19], [33], [22, 38, 39], [21]. Lately, several studies have explored the product selection decision problem, which is no longer confined to business and engineering disciplines, but has expanded to digital commerce, social media, and human consumer behaviors with different research focuses.

For example, recent research investigates product selection issues in fashion e-Commerce, modeling of cars, digital commerce, as well as studies on influencer marketing impact on product sales [35], [43-48]. The findings of this research literature show that digital experience, social factors, internet presentation, and market behaviors dominate product-related decision-making. However, to the best of the author's knowledge, the body of related work has remained fragmented due to the varied nature and focal points of disparate domains investigated.

2) MCDM: From a methodology viewpoint, in addition to other decision-making techniques applied previously to address the problem under study (selection of products), it can be noted that the use of the TOPSIS method is among the most prevalent in the area of decision-making, as it addresses issues related to the selection of suppliers, materials, and evaluation in product-related tasks [19, 29-31], [33], [34], [22, 36-38], [42], [21]. This wide application shows its recognition due to the high suitability for evaluating solutions based on their respective proximity to ideal solutions. Also prevalent in the academic context is the application of the MOORA method in research studies in relation to the recommendations for online stores, the selection of suppliers, material, and evaluation of service [23], [19], [32], [22, 37, 38], [40], [42], [21]. This can also indicate a high degree of applicability in a variety of problems involving evaluation.

In contrast, PSI and SMART are mentioned less widely in the documents obtained. However, they are important as other MCDM methods for ranking purposes. PSI was used in Emovon and Oghenenyerovwho [19], Ulutas et al. [32], Yadav et al.[33], and Amin et al. [34], while SMART was identified in Çakır [41]. Apart from the basic MCDM methods mentioned above, others were found combined with different techniques or with other MCDM methods such as AHP, VIKOR, PROMETHEE, ELECTRE, SEM, PLS-SEM, NBR and FMULTIMOORA [29], [31], [19], [35], [36], [44-48]. This richness means that product selection itself can be interpreted as a complex problem with approaches in terms of rankings and explanations. Nonetheless, most of the previous works have just tested either two or a single algorithm in a particular context. A comparative study that contains MOORA, SMART, PSI, and TOPSIS within the framework of product selection should be done systematically. A comparative study with a larger number of seller-related criteria will help the sellers to choose the most suitable products, especially for sellers related to online home-based business.

3) Criteria used in previous studies: It has been observed that the product selection criterion used may consist of a range of factors that are decided by the problem in the decision-making context and that can also be affected by the set of attributes used in a particular dataset and study motivation. As summarized in Table I, it can be seen that rating and price are the main selection attributes used in previous studies.[23], [29]-[32], [34], [22, 37-42]. Two criteria are frequently applied because they refer to central dimensions in product assessment, and they are easy to understand; ranking indicates rating on subjective perception of quality, satisfaction, or performance, and price indicates economic accessibility and good buy. Usually, in a decision problem, the above criteria form the center part, upon which alternatives could be selected, like those selected from the research area of supplier selection, material selection, or online shop selection problems.

Among all considered marketplace dimensions apart from rating and price, some research also paid attention to: discount, sold, and response chat [23], [36], [44]. Discount denotes commercial attractiveness and attracts shoppers; it may have a positive effect on consumers' intention. Sold refers to the sale volume of items in the marketplaces and is the proxy of customer preferences; it denotes that items' desirability is already proven by actual consumers' demand. Response chat measures both the speed of the seller's reply, interaction level, and service, and so is relevant particularly at marketplaces, which are the environment where there is a need to give information quickly, and can improve consumer experience and influence buying intentions. These criteria have to be taken into account, especially in digital commerce, not only for a cost/quality reason, but also related to market and service success.

Besides, more recent papers have emphasized the necessity of applying behavioral and engagement criteria which represent purchasing intention and loyalty, such as repurchase, favorite, and followers [28], [35], [36], [43-48]. Repurchase represents customers' re-purchasing the item, representing overall customer satisfaction, overall product quality, and the long-term product's appeal; Favorite represents customers' like or collection behavior, meaning that the customer noted this item but has not even purchased it, let alone repurchased it. Follower represents the seller's audience value. These criteria are increasingly important because online product selection is now shaped not only by transactional performance but also by social signals and customer engagement.

B. Statistical Test

1) Stepwise multiple linear regression: Stepwise multiple linear regression is commonly used to identify relevant predictors from a larger set of candidate variables. Liu et al. (2021) applied forward stepwise regression, VIF analysis, and significance testing to 115 explanatory variables and obtained a final model explaining 95% of crop yield variation[28], Muazam et al. (2024) used stepwise multiple regression to determine the agronomic variables affecting sorghum production. From ten candidate variables, the model selected only two significant predictors, namely panicle weight and days to harvesting, with an R^2 value of 0.754 [49]. These studies show that stepwise multiple linear regression is useful not only for prediction but also for screening and validating important variables before they are used in a decision model.

Therefore, in this study, Forward Stepwise Multiple Linear Regression was selected because the candidate predictors had been identified in advance from the literature and the proposed SPS framework. Therefore, the procedure was not intended to explore an unrestricted set of variables, but to examine the order and incremental statistical contribution of seven predefined marketplace variables to the observed Sold variable. The method also provides an interpretable sequence showing whether each additional predictor contributes to the explanatory capacity of the model. Nevertheless, stepwise regression may be sensitive to sample characteristics and may produce statistically significant results for predictors with small practical contributions, particularly when applied to a large dataset. Therefore, the results were interpreted using not only significance values, but also Adjusted R Square, changes in R

Square, standardized coefficients, multicollinearity statistics, residual diagnostics, and the magnitude of the additional contribution of each predictor.

C. Measurement

Measurement was used to evaluate the stability and consistency of the ranking results under changes in criteria weights. MAD, MSE, and Spearman's Rank Correlation were chosen as all these indices are commonly used in MCDM literature and measure the disparate yet complementary aspects of ranking stability [50–53]. MAD represents the mean absolute displacement of values between rankings and gives an indication of the average shift of an alternative. MSE is designed to disproportionately penalize greater displacements than those associated with MAD; and Spearman's rank correlation reflects a measure of concordance with respect to the orders being compared. Therefore, a combination is provided of mean rank displacement, evidence of substantial change in the rankings, and agreement in rank order.

III. Methodology

A. Proposed Method

1) Current model and its limitations: The current model suggested by Okfalisa et al. Has been a reference for marketplace decision support since using the MOORA method as an alternative to rank online shops to be the best by using 5 criteria: Rating, Price, Sold, Discount, and Response Chat. However, the benchmark has three distinct limitations in relation to the present study.

First, it has a perspective limitation. The benchmark was developed from the Customer's Perspective to help buyers select an online shop, whereas the present study addresses Seller Product Selection from the Seller's Perspective. These decision problems involve different users and different decision objectives.

Second, it has an empirical-domain limitation. The benchmark was demonstrated using men's shirt products and 50 marketplace alternatives. Therefore, its findings cannot automatically be generalized to broader product categories or substantially larger marketplace datasets.

Third, it has a criteria-structure limitation. The five benchmark criteria do not include indicators of repeated purchasing behavior, product interest, and shop visibility. Specifically, Repurchase, Favorite, and Followers are not represented in the benchmark structure.

The proposed 8C SPS model directly addresses the perspective and criteria-structure limitations by adopting the Seller's Perspective and incorporating Repurchase, Favorite, and Followers. However, the present study remains limited to Shopee Indonesia food and beverage products. Validation in other product categories and marketplace environments is therefore still required.

2) Proposed seller product selection model: In an effort to bridge this gap, this research extends the benchmark on the SPS Model from 5 dimensions to 8 dimensions, namely: Repurchase (Repeat-purchase behavior and customer-retention), Favorite (Product interest and favorability), and Follower (Visibility of shop and social connections' effectiveness in the online environment). Consequently, the model builds the customer's perspective on SPS to the seller's perspective on SPS by considering 8 dimensions: transactional effectiveness, repeated potential purchases, appraisal customers have, the quality of promotions, interaction quality, visibility of transactions and promotions, audience attention of the market, and visibility of the shop. Compared to the SPS model with the 5 criteria of Okfalisa et al. The SPS model with 8Cs enhances its completeness in making an appropriate decision of selecting the best-suited product for sellers.

B. Research Framework and Practical Application Workflow

A framework is suggested that increases the benchmark 5C model by factors - Repurchase, Favorite, and Followers- leading to the model represented by the 8C SPS as described above. Both the Regression analysis investigate empirical effects of 7 independent variables on Sold and seller's perceived criteria weights as perceived through a survey based on Importance. Borda Weights explain seller preferences, and AHP will provide weights computed based on the selection of 4 'MCDMs'(MOORA, SMART, TOPSIS, PSI) for 150,000 product evaluations on five different configurations of these 8 factors based on performance metrics like 'MAD', 'MSE ', and 'Spearman's Rank Correlation '. A visualization of the framework is shown in Fig. 1.

In real-time deployment, sellers need to supply the values for these eight factors in relation to candidate products and run the weights derived by AHP using any of the discussed MCDM approaches to produce a list of items in rank order of their marketability potential. Based on the current experiment in the given context, MOORA achieved the strongest overall robustness in the 8C model, with the lowest MAD and MSE and the highest Spearman's Rank Correlation. In contrast, TOPSIS showed greater consistency in maintaining the same first-ranked alternative across the weight conditions. Therefore, MOORA is recommended as the primary ranking algorithm, while the leading alternatives identified by TOPSIS may be used as additional candidates for seller assessment.

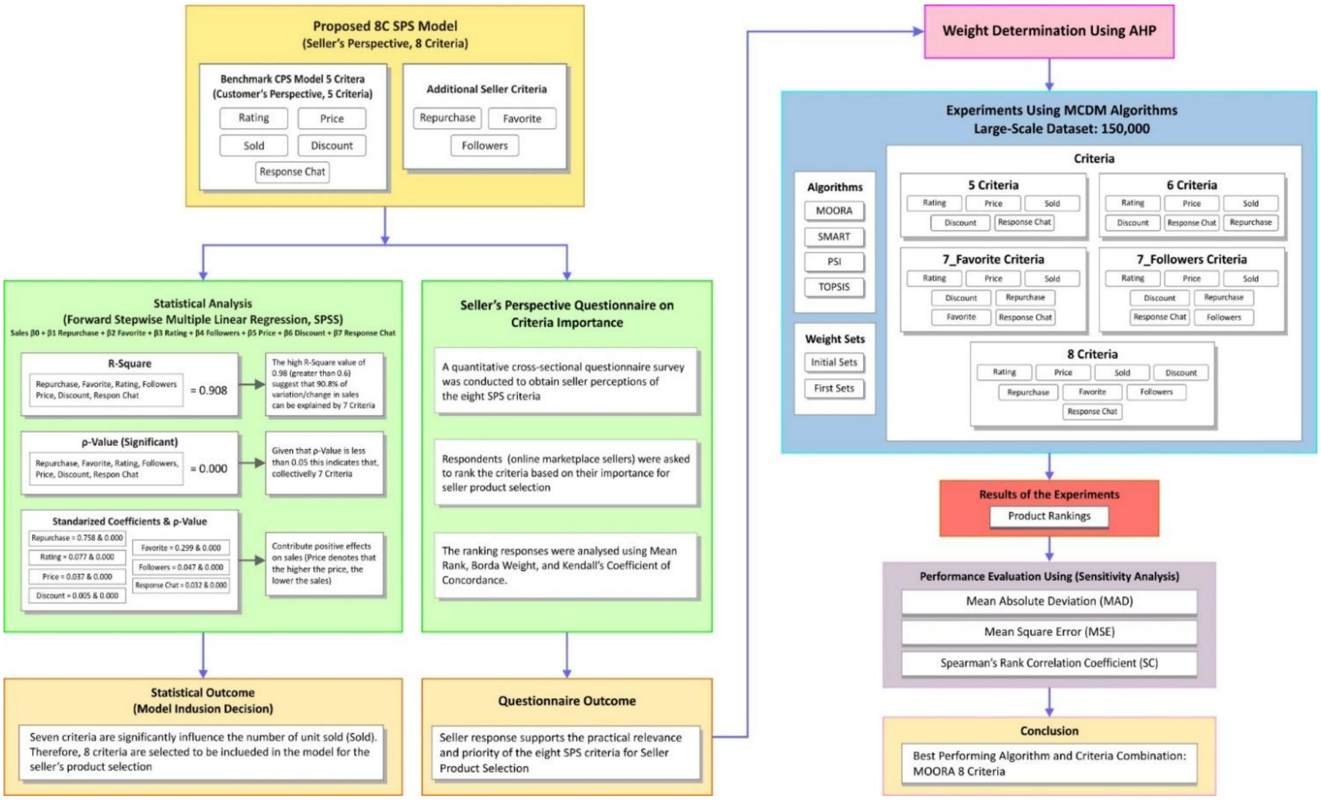

Fig. 1. Research method framework.

C. Dataset and Criteria Description

1) Data collection, preprocessing, and ethical considerations: The dataset was obtained using a Google Chrome extension to perform the crawling activity through several categories of Food and Beverage products available publicly from the Shopee Indonesia website during the research data collection stages. A total number of variables used that are publicly listed on both the product level (product name and URL) and shop level (name of the shop, Rating, Price, Sold, Discount, Response Chat, Repurchase, Favorite, Followers) were captured. The scraping metadata for the page and the order were also extracted so as to retrieve a source document used to identify origin pages and scraping order. The downloaded records were exported in the format of a raw file, and further processing for statistical analysis and MCDM experiments was conducted at this stage.

For standardization of the marketplace records for consistency, the following steps of data preprocessing were performed: Scraping Metadata columns to discard. Rows with product names missing/not available and Rows without pricing Information discarded, based on (unique based on product names), duplicates rows found, attribute Name standardized on basis of categorization, empty numerical value were replaced by zero value, (Rating, Discount, Sold, Favorite, Repurchase, Response Chat and Followers), where regular price not available discounted Price assumed final Price of the products, The text based marketplace values in their numerical presentation were removed currency symbol, thousand separator, percentage symbol, and other such characters to remove non numerical label then used as normalized to match the marketplace abbreviation like “RB”, “+”, then convert to numerical data types.

The issue of ethics has been handled by constraining the data extraction to information presented openly and publicly through the Shopee Indonesia product and shop pages. Data privacy has ensured that account numbers, private conversation message data, financial transaction data, and other personal information were not harvested. The product identification or name of the shop and seller was not revealed in the results, and each item was assigned an identifier code which served in the place of the product ID for the purpose of experimentation, and the dataset was not to be reused again in its original format that was identifiable.

2) Criteria description: The attributes dataset in this study is selected to be two criteria frames: Customers' Product Selection (CPS) and Sellers' Product Selection (SPS). We propose CPS as a benchmark model with five criteria: Rating, Price, Sold, Discount, Response Chat, following the literature on customer choice based on Okfalisa et al. SPS model is an extension of CPS to eight criteria by adding the other three criteria, namely Repurchase, Favorite, and Followers, to CPS, which reflect customers' loyalty, customers' interest in products that are not immediately purchased, and shop reputation, respectively, all of which are considered to increase product sales. Based on this framework, the mapping of Shopee dataset attributes to CPS and SPS criteria is presented in Table II.

TABLE II. OPERATIONAL DEFINITION OF CRITERIA IN CPS AND FAHP SPS MODELS

No	Criterion	Description	Criterion Type	Model
1	Rating	Average user rating score for a product	Benefit	CPS & SPS
2	Price	Product price listed on the product page	Cost	CPS & SPS
3	Sold	Number of units sold during the observation period	Benefit	CPS & SPS
4	Discount	Discount percentage offered for the product	Benefit	CPS & SPS
5	Response Chat	Seller responsiveness percentage to buyer chats	Benefit	CPS & SPS
6	Repurchase	Repeat-purchase indicator reflecting customer loyalty	Benefit	SPS
7	Favorite	Number of users who mark the product as a favorite/wishlist	Benefit	SPS
8	Followers	Number of shop followers as an indicator of shop reputation	Benefit	SPS

D. Analytical Statistic Method

The relevance of Rating, Price, Discount, Favorite, Repurchase, Response Chat, and Followers was examined using Forward Stepwise Multiple Linear Regression in SPSS. Sold was treated as the dependent variable, while the seven remaining criteria were entered as candidate predictors. The candidate variables were defined before the regression analysis based on the literature and the proposed SPS framework. Therefore, the regression was used as an exploratory criterion-screening procedure rather than as a forecasting model. The stepwise procedure examined the incremental statistical association of each predictor with Sold, while the standardized coefficients were used to compare their relative contributions. Model reliability was examined using Adjusted R Square, changes in R Square, tolerance, Variance Inflation Factor, the Durbin-Watson statistic, and residual diagnostics.

1) Forward stepwise multiple linear regression: The general regression model is expressed as shown in Eq. (1).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon \qquad (1)$$

where, Y is the dependent variable, $X_1, X_2, \ldots, X_n$ are the independent variables, β_0 is the constant, $\beta_1, \beta_2, \ldots, \beta_n$ are regression coefficients, and ε is the error term. The forward stepwise procedure adds predictors iteratively, starting from the strongest predictor, until no additional variable significantly improves the model.

The use of forward selection was considered appropriate for the present study because the analysis aimed to determine the order in which the predefined predictors contributed additional explanatory information. However, because the dataset contains a large number of observations, statistical significance alone was not considered sufficient evidence of practical importance. The interpretation, therefore, considered the magnitude of the standardized coefficients and the increase in R-squared produced at each step.

2) The standardized coefficients (beta): The Standardized Coefficients (Beta) were taken into consideration to show the relative contribution of each selected predictor in the regression models developed. The standardized coefficient is represented in Eq. (2).

$$\beta_j^* = b_j \left(\frac{s_{X_j}}{s_Y}\right) \qquad (2)$$

where, β_j^* is the standardized coefficient, b_j is the unstandardized coefficient, s_{X_j} is the standard deviation of the predictor X_j, and s_Y is the standard deviation of the dependent variable. A higher value of an absolute Beta refers to a higher contribution towards Sales. Thus, supported empirically in the case of retaining variables that are good for the analysis of selecting a product.

E. Questionnaire Outcome

A quantitative cross-sectional questionnaire survey was used in this study to get the criteria importance from the seller's point of view. The questionnaire asked the respondent to rank the 8 SPS criteria - namely Sold, Discount, Repurchase, Rating, Favorite, Price, Response Chat, and Followers according to the rank from the most important to the least important. The questionnaire was thus utilized to provide evidence of the buyer based on the seller, the practicability and prioritization of the SPS criteria, prior to carrying out computational weighing.

The forced ranking exercise forced each participant to give a rank value to each criterion, varying from rank 1 (highest priority) to rank 8 (lowest priority). Since the obtained data were ordinal in nature, the analysis of such data concerned rank aggregation and the level of agreement between participants. The data gathered through the use of the questionnaire were analyzed through descriptive analysis, with summary statistics of the data presented through Mean Rank, Borda Weight, and Kendall's coefficient of concordance. Mean Ranks were employed in order to provide an overall ranking of priorities of each item, with the lowest mean rank being assigned to the highest priorities. The ranking data was then converted into numerical weight via the use of the Borda Weight. The Borda score is calculated as shown in Eq. (3)

$$b_{ij} = n - r_{ij} + 1 \qquad (3)$$

where, b_{ij} is the Borda score of the criterion j assigned by the respondent i, r_{ij} is the rank given by the respondent i to criterion j, and n is the number of criteria. The normalized Borda Weight for each criterion is calculated as shown in Eq. (4).

$$w_j = \frac{\sum_{i=1}^{m} b_{ij}}{\sum_{j=1}^{n} \sum_{i=1}^{m} b_{ij}} \qquad (4)$$

where, w_j is the normalized Borda Weight of the criterion j, m is the number of respondents, and n is the number of criteria.

Kendall's coefficient of concordance was used to examine the level of agreement among respondents because the questionnaire involved ranking the same set of criteria. Kendall's W is calculated as follows: Eq. (5)

$$W = \frac{12S}{m^2(n^3-n)} \quad (5)$$

where, S is the sum of squared deviations of the total ranks for each criterion from the mean total rank, m is the number of respondents, and n is the number of ranked criteria. A higher value of W indicates stronger agreement among respondents.

Methodologically, the questionnaire complements the statistical validation and experimental evaluation of the proposed SPS model. This result not only adds evidence towards AHP weighting but would also make it possible to show that the chosen eight criteria actually matter to a seller's product range. The response to the seller questionnaire also indicated that there is a practical application for and, in fact, a practical priority among the eight SPS criteria for sellers' product range.

F. Research Setup

1) Weight setup: The weight configurations for two weight options, Initial Weights and First Weight, were generated for ranking stability testing. First Weight adjusted the original weight structure to evaluate the susceptibility of each decision-making algorithm to any variations in criterion weight configurations. A graphical representation is generated showing the criterion weight distribution of various criterion combinations examined within the scope of this project. The weight of each criterion combination for this exercise is achieved through the Analytical Hierarchy Process (AHP) by building criteria from a given problem, creating a pairwise comparison matrix, calculating criterion priority vectors, and then normalizing weights to equal 1 for each combination.

- 8 criteria: Pairwise comparison assessments were collected through a questionnaire for all criteria, and their weights were then calculated using AHP.
- 6 criteria: Two criteria were removed (Favorite/Wishlist and Followers), and the weights for the remaining six criteria were then recalculated using AHP and normalized.
- 7 criteria (Favorite): The Followers criterion was removed, leaving 7 criteria (including Favorite/Wishlist); the weights were then recalculated using AHP and normalized.
- 7 criteria (Followers): The Favorite/Wishlist criterion was removed, leaving 7 criteria (including Followers); the weights were then recalculated using AHP and normalized.
- 5 criteria (benchmark): weights are determined based on the reference weights (benchmarks) for five basic criteria, then used as a comparison in the evaluation of the method's performance.

The weight settings in this experiment were set under two conditions to test the stability of the ranking results when decision-making preferences change. The weight settings are as follows:

- Initial weight (Baseline): obtained from the AHP calculation, where pairwise comparison assessments were collected through a questionnaire for all criteria, then calculated into priority weights and normalized.
- First Weight: obtained from adding 1 point to the pairwise comparison by pairs; we will be able to obtain an alternative weight arrangement pairwise by pairwise to study rank modifications in this alternative weighing.

2) AHP: The Analytic Hierarchy Process (AHP) was applied to derive the relative weights of the SPS criteria through pairwise comparisons. The criteria were compared using Saaty's 1–9 scale, where 1 represents equal importance, and 9 represents absolute importance. The pairwise comparison matrix was normalized, and the priority vector was calculated to obtain the criteria weights. This procedure was conducted separately for the 5C, 6C, 7C Favorite, 7C Followers, and 8C configurations because each configuration contained a different set of criteria. The consistency of the pairwise judgments was evaluated using the Consistency Index and Consistency Ratio, as expressed in Eq. (6) and (7).

$$CI = \frac{\lambda max - n}{RI*(n-1)} \quad (6)$$

$$CR = \frac{CI}{RI} \quad (7)$$

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.

3) Comparative MCDM algorithms: Four established MCDM algorithms, namely MOORA, SMART, PSI, and TOPSIS, were applied to rank the product alternatives. These algorithms were selected because they represent different ranking mechanisms and enable the robustness of the proposed criteria configurations to be compared under the same dataset and weight conditions. Price was treated as a cost criterion, while Rating, Sold, Discount, Response Chat, Repurchase, Favorite, and Followers were treated as benefit criteria.

a) MOORA: The Multi-Objective Optimization based on Ratio Analysis (MOORA) ranks alternatives by normalizing the decision matrix and combining the weighted benefit and cost criteria. The final assessment value is obtained by subtracting the weighted cost values from the weighted benefit values. An alternative with a higher final value receives a higher ranking. (8).

$$y_i = \sum_{j=1}^{g} w_j\, x_{ij}^* - \sum_{j=g+1}^{n} w_j\, x_{ij}^* \quad (8)$$

where, w_j denotes the weight of the criterion j. A higher y_i indicates a better alternative.

b) SMART: The Simple Multi-Attribute Rating Technique (SMART) determines the overall performance of each alternative by aggregating its weighted utility values. Each criterion value is transformed into a utility value according to its benefit or cost orientation, and the alternatives are ranked according to their total utility scores. The overall score of each alternative is then obtained by Eq. (9).

$$S_i = \sum_{j=1}^{n} w_j\, 'u_{ij} \quad (9)$$

where, u_{ij} is the utility value of the alternative i on criterion j. Alternatives with higher S_i values are ranked higher.

c) PSI: The Preference Selection Index (PSI) evaluates alternatives using normalized criterion values and preference indices derived from the variation of each criterion. Unlike the other evaluated methods, PSI can determine criterion preferences from the decision matrix. The alternative with the highest total preference score is assigned the highest rank.

The final PSI score is calculated as shown in Eq. (10).

$$PSI_i = \sum_{j=1}^{n} N_{ij}\, \Omega_j \tag{10}$$

where, Ω_j denotes the preference value of the criterion j. A higher PSI_i indicates a more preferred alternative.

d) TOPSIS: The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) ranks alternatives according to their relative closeness to the positive ideal solution and their distance from the negative ideal solution. An alternative is considered preferable when it is closer to the positive ideal solution and farther from the negative ideal solution. The relative closeness of each alternative is then determined by Eq. (11).

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{11}$$

where, D_i^+ and D_i^- are the distances from the positive and negative ideal solutions, respectively. A higher C_i indicates a better alternative.

4) Measurement: In this study, the Initial Weight ranking was treated as the baseline, while the First Weight ranking represented the modified preference condition. A lower MAD value indicates that alternatives move fewer ranking positions on average. A lower MSE value indicates that large or extreme rank changes are less pronounced. A Spearman coefficient closer to 1 indicates that the overall ordering of the alternatives remains consistent after the weight modification. Accordingly, an algorithm is considered more robust when it simultaneously produces lower MAD and MSE and higher Spearman's Rank Correlation.

a) Mean Absolute Deviation (MAD): The following is the equation for MAD shown in Eq. (12).

$$MAD = \frac{1}{n}\sum_{i=1}^{n} |xij - \mathrm{yj}| \tag{12}$$

b) Mean Squared Error (MSE): The following is the equation for MSE shown in Eq. (13).

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (xij - yj)^2 \tag{13}$$

c) Spearman's Correlation (SC): The following is the equation for SC shown in Eq. (14).

$$SC = r_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{14}$$

IV. Results and Discussion

A. Results of Questionnaire

The questionnaire was administered to 30 online marketplace sellers from 22 September 2025 to 2 October 2025. Table III presents the criterion priorities obtained from the seller questionnaire.

TABLE III. RESULT OF CRITERIA PRIORITY

Criteria	Mean Rank	Borda Weight	Priority
Sold	2.40	0.183	1
Repurchase	3.63	0.149	2
Rating	4.00	0.139	3
Response Chat	4.30	0.131	4
Price	4.57	0.123	5
Favorite	5.53	0.096	6
Discount	5.57	0.095	7
Followers	6.00	0.083	8

As can be seen from Table III, Sold had shown a value of the most important factor as low as 2.40 in rank mean; also, it possessed a value of the highest in Bordas Weight for 0.183. Hence, Sold shows more importance to sellers to prioritize the products for sales as they perform well.

Overall, the ranking result suggests that the responders perceived Sold, Repurchase, and Rating to be the top three criteria that have the highest priority. As for the criteria Favourite, Discount, and Followers, the priorities received are not high; however, it still exists as the other supportive SPS criteria for the Seller's Perspective. As the Kendall's Coefficient of Concordance W was 0.236 and there are 30 responders, we shall view the questionnaire results as the potential evidence from the sellers' view on the practical relevance and priority of these 8 SPS criteria. The potential priority that responders perceived does not weaken the priority obtained via regression and computationally assigned with the weighting factors with AHP and ranked by the result of the algorithms using MCDM.

B. Statistical Test

1) Stepwise multiple linear regression: The following are the statistical results of the test using Stepwise Multiple Linear Regression, which are shown in Table IV.

The change in explanatory power across the steps is evident in Table IV. Entering Repurchase alone explained 0.811 R-square. The addition of Favorite over and above Repurchase helped the R-square improve by 0.084 with a total explanation of 0.895 (0.811 + 0.084).

The addition of Rating yielded yet another increase in explained variance to 0.094, while Followers increased the R-square by an additional 0.003.

Each of Price, Response Chat, and Discount increased R-square by 0.001, respectively. Based on the changes across steps, Repurchases and Favorite had greater explanatory influence among the set. Price, Response Chat, and Discount added the lowest amount to the explanation of buying.

The last iteration (Model 7), as shown in Table V, shows that the R-square value is 0.908. It suggests that 90.8 percent of the variability in Sales is explained by Repurchase, Favorite, Rating, Follower, Price, Response Chat, and Discount as a group.

Meanwhile, the remaining 9.2 percent is explained by other factors. In other words, these seven variables collectively correlate strongly with Sales.

TABLE IV. MODEL SUMMARY

Model	R	R Square	Adjusted R-Square	Std. Error of the Estimate	Durbin-Watson
1	0.900[a]	0.811	0.811	28.035	
2	0.946[b]	0.895	0.895	20.857	
3	0.950[c]	0.902	0.902	20.129	
4	0.951[d]	0.905	0.905	19.847	
5	0.952[e]	0.906	0.906	19.718	
6	0.953[f]	0.907	0.907	19.610	
7	0.953[g]	0.908	0.908	19.585	1.863
a. Predictors: (Constant), Repurchase					
b. Predictors: (Constant), Repurchase, Favorite					
c. Predictors: (Constant), Repurchase, Favorite, Rating					
d. Predictors: (Constant), Repurchase, Favorite, Rating, Follower					
e. Predictors: (Constant), Repurchase, Favorite, Rating, Follower, Price					
f. Predictors: (Constant), Repurchase, Favorite, Rating, Follower, Price, Response_Chat					
g. Predictors: (Constant), Repurchase, Favorite, Rating, Follower, Price, Response_Chat, Discount					
h. Dependent Variable: Sales					

TABLE V. ANOVA[A]

Model		Sum of Squares	df	Mean Square	F	Sig.
7	Regression	555699114.195	7	79385587.742	206961.417	.000[h]
	Residual	56589845.238	147532	383.577		
	Total	612288959.433	147539			
a. Dependent Variable: Sales						
h. Predictors: (Constant), Repurchase, Favorite, Rating, Follower, Price, Response Chat, Discount						

Furthermore, despite a strong correlation between independent and dependent variables, it is important to examine whether this correlation is statistically significant. Table VI reveals that the F test results in a p-value (Sig.) of 0.000, much less than 5 percent or 0.05 of the significance level. It indicates that the correlation between all seven independent variables of Repurchase, Favorite, Rating, Follower, Price, Response Chat, and Discount as a group with Sales is statistically significant.

2) The standardized coefficients (beta): After assessing the correlation between dependent and independent variables and their significance in collective terms, Table VI explains the correlation or the influence of each independent variable on the dependent variables separately.

Table VI presents the individual statistical association of each independent variable with Sold. All predictors were statistically significant at $p < 0.001$. Repurchase had the largest standardized coefficient (β=0.758), followed by Favorite (β=0.299), Rating (β=0.077), Followers (β=0.047), Price (β=−0.037), Response Chat (β=0.032), and Discount (β=0.016). Repurchase and Favorite therefore showed the strongest statistical associations with Sold. Price had a negative coefficient, indicating that higher product prices were associated with lower observed sales, while the other predictors showed positive associations. Because the data are observational, these coefficients represent statistical associations rather than causal effects.

TABLE VI. COEFFICIENTS[A.]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
7	(Constant)	-2.190	0.159		-13.763	.000		
	Repurchase	7.025	0.008	0.758	867.811	.000	0.820	1.219
	Favorite	0.904	0.003	0.299	336.990	.000	0.794	1.259
	Rating	2.359	0.025	0.077	94.660	.000	0.940	1.063
	Follower	.000	0.000	0.047	57.889	.000	0.935	1.070
	Price	-3.239E-5	0.000	-0.037	-45.961	.000	0.992	1.008
	Response Chat	.0077	0.002	0.032	39.698	.000	0.955	1.047
	Discount	0.106	0.005	0.016	19.508	.000	0.973	1.028
a. Dependent Variable: Sales								

3) Regression diagnostics and model reliability: Final regression model fitting proceeded, and the diagnostics for the final model were computed. The model resulted in an R^2 value of 0.908, while the Adj. R^2 value is 0.908. The explanatory power does not appear to be seriously distorted by the addition of extra predictors. Multicollinearity among predictors did not seem to be serious; all tolerance values were between 0.794 and 0.992, and VIF values did not exceed 1.259. The Durbin-Watson value is 1.863, which also suggests no serious serial autocorrelation among residuals. The normality of residuals has also been explored through the Normal P-P plot (Fig. 2) and the Histogram of residuals (Fig. 3).

With reference to Fig. 2, the cumulative probabilities have systematic deviations from the reference diagonal line at probabilities from the lower and higher ends. This means that the distribution of residuals does not fall on a normal distribution.

Fig. 3 displays standard normal residuals that are centered at zero but follow an uneven, positively skewed distribution. This again accords with the results of the P-P plots indicating less-than-ideal normal residuals; however, considering the massive nature of the dataset (150,000 records), this suggests that the regression should be used solely for investigation of statistical associations between the sampled data points only, rather than to establish causalities or as a tool to validate external predictions of future Sold values.

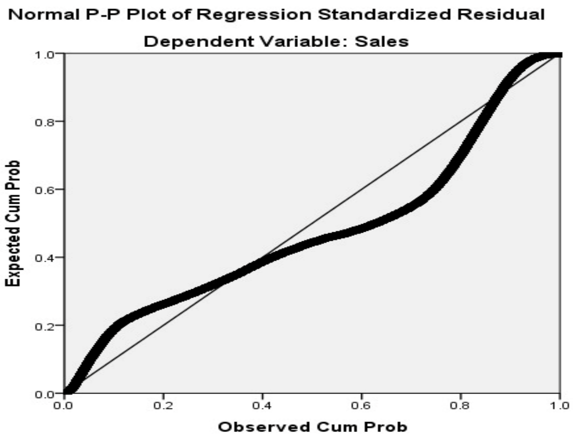

Fig. 2. Normal P-P plot of regression standardized residuals.

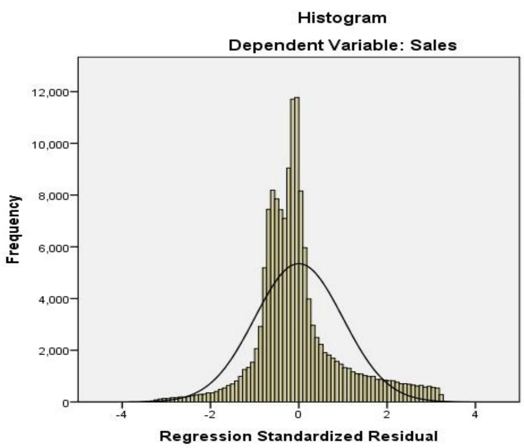

Fig. 3. Histogram of regression standardized residuals. (Note: “Sales” in the SPSS output represents the Sold variable used in this study.)

4) Relationship between questionnaire and regression results: Questionnaire and regression results perform different yet complementary functions. The questionnaire reports that all eight factors of SPS (including the Sold factor) are considered important to sellers. Hence, the questionnaires tell which factors a seller considers to be most important when he selects products to sell. The regression does the opposite: taking Sold as the dependent variable and analyzing the statistical relationship between the other seven factors and the Sold performance observed in the marketplace.

The results from the questionnaires and the regression should not therefore be in the same order of priority. Sold was found to be in the first order because it was considered most important, as it represents the most direct feedback on product marketability to the sellers. Repurchase was found to be in the first order in terms of standardized regression coefficient due to having the strongest statistical correlation with the Sold observed in the marketplace data. Questionnaires, therefore, measure subjective importance; regression measures the importance observed in market data.

C. Weight Determination Using AHP

Based upon the AHP determining result, two different weight combinations were generated for each criterion combination scenario. Initial weight indicated the base preferences scenario, and First weight represented a variation in a preference scenario used for ranking sensibility analysis. Table VII lists weight configurations for five-, six-, seven-, and eight-criteria combinations.

TABLE VII. INITIAL AND FIRST WEIGHT RESULTS

Criterion	5C I/F	6C I/F	7C Fav I/F	7C Foll I/F	8C I/F
Rating	0.417/ 0.482	0.160/ 0.150	0.160/ 0.153	0.160/ 0.153	0.159/ 0.155
Price	0.263/ 0.235	0.101/ 0.088	0.104/ 0.094	0.104 /0.094	0.107/ 0.099
Sold	0.160/ 0.149	0.381/ 0.424	0.352 /0.388	0.352/ 0.389	0.328/ 0.360
Discount	0.097/ 0.082	0.042/ 0.031	0.031/ 0.023	0.045/ 0.036	0.033/ 0.026
Response Chat	0.062/ 0.053	0.064/ 0.052	0.068/ 0.059	0.068/ 0.058	0.071/ 0.063
Repurchase	–	0.252/ 0.255	0.241/ 0.246	0.241/ 0.247	0.232/ 0.238
Favorite	–	–	0.045/ 0.036	–	0.048/ 0.041
Followers	–	–	–	0.031/ 0.023	0.023/ 0.018
CR	0.02/ 0.07	0.02/0.08	0.02/0.08	0.03/0.08	0.03/0.09
Note: I/F denotes Initial Weight/First Weight; 5C = five criteria; 6C = six criteria; 7C Fav = seven criteria including Favorite; 7C Foll = seven criteria including Followers; and CR = Consistency Ratio.					

Table VI shows that CR values were within the required level of consistency, less than 0.10 for all of the weight sets. Table VII shows that all the calculated CR values were less than 0.10. Therefore, the weight sets show acceptable consistency. Those sets were applied for MOORA, SMART, PSI, and TOPSIS methods in order to view the product ranking in the change conditions.

D. Ranking Result for all Criteria

The result of rankings for all criteria shows the final scores of alternatives as produced by MOORA, SMART, PSI, and TOPSIS along with their orderings in ranking. The tables below show all of the combinations for evaluating the alternatives among different criteria to show the results of ordering the product according to different MCDM approaches.

For the five-criteria model in Table VIII, the proposed alternative number, A107137, obtained the first position by any algorithm for both criteria types, Initial Weight and First Weight. By using the evaluation from only benchmark criteria, the proposed alternative A107137 obtained the highest marks among the five benchmark alternative selections from any one of these criteria (MOORA, SMART, PSI, and TOPSIS. The consistent ranking by A107137 with any four criteria suggested that the proposed alternative possesses a relatively stable advantage in the selection from the five original criteria. For example, the benchmarks: A82978, A143588, A108358, A11740, A99974, and A133019 still seem to have better selection for a structure of benchmark criterion.

TABLE VIII. RANKING RESULT 5 CRITERIA

Rank	Algorithm															
	Moora				Smart				PSI				Topsis			
	Initial Weight		First Weight		Initial Weight		First Weight		Initial Weight		First Weight		Initial Weight		First Weight	
	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score
1	A107137	0.06290	A107137	0.05829	A107137	6.23673	A107137	6.24027	A107137	0.66850	A107137	0.69148	A107137	0.72179	A107137	0.73848
2	A82978	0.05912	A82978	0.05507	A82978	6.21868	A82978	6.23373	A82978	0.64910	A82978	0.68361	A143588	0.70519	A143588	0.72262
3	A143588	0.05867	A143588	0.05469	A108358	6.19245	A108358	6.21827	A108358	0.61511	A108358	0.66048	A82978	0.69141	A82978	0.70930
4	A108358	0.05743	A108358	0.05365	A133019	6.15530	A133019	6.18784	A133019	0.59415	A133019	0.64604	A11740	0.68676	A11740	0.70486
5	A11740	0.05658	A11740	0.05291	A99974	6.13161	A99974	6.16924	A99974	0.56256	A99974	0.61964	A99974	0.68673	A99974	0.70484
6	A99974	0.05654	A99974	0.05288	A11740	6.12682	A11740	6.16262	A11740	0.55421	A11740	0.60950	A108358	0.68292	A108358	0.70112
7	A133019	0.05647	A133019	0.05282	A143588	6.12521	A143588	6.15692	A143588	0.55089	A143588	0.60212	A133019	0.68188	A133019	0.70013
8	A44595	0.03166	A44595	0.02781	A141367	6.08252	A141367	6.12492	A141358	0.51574	A7532	0.56856	A44595	0.35031	A44595	0.33248
9	A149486	0.03052	A149486	0.02686	A141358	6.08163	A82112	6.12200	A7532	0.50663	A141367	0.56856	A149486	0.32891	A149486	0.31202
10	A17363	0.02313	A17363	0.02052	A82112	6.07897	A42946	6.11906	A141367	0.50663	A42946	0.56855	A17363	0.26012	A136643	0.25992

TABLE IX. RANKING RESULT 6 CRITERIA

Rank	Algorithm															
	Moora				Smart				PSI				Topsis			
	Initial Weight		First Weight		Initial Weight		First Weight		Initial Weight		First Weight		Initial Weight		First Weight	
	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score
1	A107137	0.17439	A107137	0.18841	A107137	5.24992	A107137	5.10647	A107137	0.64828	A107137	0.69544	A45290	0.56609	A107137	0.55299
2	A45290	0.17056	A45290	0.17375	A82978	5.18319	A82978	5.04408	A82978	0.58103	A82978	0.63270	A107137	0.52966	A45290	0.54558
3	A143588	0.13926	A143588	0.15350	A108358	5.17250	A108358	5.03816	A108358	0.56736	A108358	0.62475	A108358	0.46086	A108358	0.48583
4	A108358	0.13762	A108358	0.15223	A133019	5.15177	A133019	5.02258	A133019	0.55284	A133019	0.61341	A143588	0.46082	A143588	0.48551
5	A82978	0.13743	A82978	0.15174	A143588	5.14785	A143588	5.01988	A143588	0.54387	A143588	0.60726	A82978	0.45865	A82978	0.48350
6	A11740	0.13566	A11740	0.15028	A11740	5.14286	A11740	5.01638	A11740	0.53953	A11740	0.60421	A11740	0.45778	A11740	0.48267
7	A133019	0.13385	A133019	0.14852	A99974	5.13997	A99974	5.01347	A99974	0.53801	A99974	0.60223	A133019	0.45536	A133019	0.48029
8	A99974	0.13271	A99974	0.14730	A45290	5.06574	A45290	4.86350	A45290	0.46257	A45290	0.45143	A99974	0.45308	A99974	0.47792
9	A19305	0.10309	A19305	0.10316	A19305	4.94899	A19305	4.74085	A19305	0.34917	A19305	0.33108	A19305	0.35811	A19305	0.34295
10	A45286	0.07217	A45286	0.07410	A149486	4.90443	A45286	4.69289	A149486	0.30132	A45286	0.28054	A45286	0.27507	A45286	0.26575

Considering Table IX, where the combination of criteria grows to six, A107137 still holds more than half of the ranking results. Its rank position is highest for all methods MOORA, SMART, and PSI under Initial Weight and First Weight except for TOPSIS, which lists A45290 first for Initial Weight and A107137 first for First Weight. This suggests that with the consideration of Repurchase, a shift happened in the ranking pattern of a couple of methods (in this case, TOPSIS), where A45290 achieved the first position under this methodology, and this implies it's favored due to the seller view-based ranking methods considered.

Similar ranking outcome patterns occur in seven-criteria models with Favorite Table X. A107137 still has rank 1 from MOORA, SMART, and PSI under both weighted setting while TOPSIS always suggests A45290 as the first alternative. Thus, there is an implication of the favorite effect in the ranking result, especially with the TOPSIS technique, in which each alternative is assessed according to its distances to ideal and anti-ideal solutions. This can be seen as a positive assessment of A45290 relative position compared to other alternatives.

TABLE X. RANKING RESULT 7 FAVORITE CRITERIA

Rank	Algorithm															
	Moora				Smart				PSI				Topsis			
	Initial Weight		First Weight		Initial Weight		First Weight		Initial Weight		First Weight		Initial Weight		First Weight	
	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score
1	A107137	0.16322	A107137	0.17535	A107137	5.23159	A107137	5.16225	A107137	0.61270	A107137	0.64995	A45290	0.57258	A45290	0.55679
2	A45290	0.16305	A45290	0.16720	A82978	5.16888	A82978	5.10194	A82978	0.54945	A82978	0.58921	A107137	0.52077	A107137	0.53979
3	A143588	0.12965	A143588	0.14160	A108358	5.16113	A108358	5.09874	A108358	0.53864	A108358	0.58347	A143588	0.45157	A108358	0.47174
4	A108358	0.12769	A108358	0.13992	A133019	5.14254	A143588	5.08484	A133019	0.52644	A133019	0.57398	A108358	0.45142	A143588	0.47162
5	A82978	0.12756	A82978	0.13955	A143588	5.14172	A133019	5.08396	A143588	0.52042	A143588	0.57056	A82978	0.44929	A82978	0.46949
6	A11740	0.12602	A11740	0.13824	A11740	5.13734	A11740	5.08124	A11740	0.51671	A11740	0.56752	A11740	0.44841	A11740	0.46865
7	A133019	0.12411	A133019	0.13635	A99974	5.13266	A99974	5.07702	A99974	0.51344	A99974	0.56446	A133019	0.44596	A133019	0.46623
8	A99974	0.12308	A99974	0.13526	A45290	5.07181	A45290	4.96198	A45290	0.45135	A45290	0.44839	A99974	0.44375	A99974	0.46392
9	A19305	0.09951	A19305	0.10054	A19305	4.95993	A19305	4.84458	A19305	0.34291	A19305	0.33384	A19305	0.36360	A19305	0.35150
10	A45286	0.06910	A45286	0.07123	A149486	4.92366	A45286	4.79772	A149486	0.30326	A45286	0.28376	A45286	0.27798	A45286	0.27088

TABLE XI. RANKING RESULT 7 FOLLOWERS CRITERIA

Rank	Algorithm															
	Moora				Smart				PSI				Topsis			
	Initial Weight		First Weight		Initial Weight		First Weight		Initial Weight		First Weight		Initial Weight		First Weight	
	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score
1	A107137	0.16453	A107137	0.17679	A107137	5.24720	A107137	5.18015	A107137	0.62830	A107137	0.66242	A45290	0.57249	A45290	0.55730
2	A45290	0.16376	A45290	0.16838	A82978	5.18412	A82978	5.11907	A82978	0.56469	A82978	0.60089	A107137	0.52072	A107137	0.53957
3	A143588	0.12956	A143588	0.14183	A108358	5.16254	A108358	5.10668	A108358	0.54004	A108358	0.58594	A143588	0.45148	A108358	0.47146
4	A82978	0.12917	A82978	0.14112	A133019	5.14143	A133019	5.08960	A133019	0.52533	A133019	0.57421	A108358	0.45133	A143588	0.47131
5	A108358	0.12766	A108358	0.14028	A143588	5.13755	A143588	5.08760	A143588	0.51626	A143588	0.56786	A82978	0.44929	A82978	0.46925
6	A11740	0.12568	A11740	0.13831	A99974	5.13118	A11740	5.08282	A99974	0.51196	A11740	0.56364	A11740	0.44831	A11740	0.46835
7	A133019	0.12405	A133019	0.13665	A11740	5.13108	A99974	5.08155	A11740	0.51046	A99974	0.56355	A133019	0.44587	A133019	0.46595
8	A99974	0.12331	A99974	0.13575	A45290	5.07586	A45290	4.97089	A45290	0.45539	A45290	0.45185	A99974	0.44368	A99974	0.46364
9	A19305	0.09948	A19305	0.10066	A19305	4.95937	A19305	4.84981	A19305	0.34235	A19305	0.33365	A19305	0.36349	A19305	0.35161
10	A45286	0.06875	A45286	0.07120	A149486	4.93225	A149486	4.80223	A149486	0.31184	A149486	0.28324	A45286	0.27789	A45286	0.27108

With regard to Table XI, similar behavior was found in the seven-criteria model with Followers. A107137 is again the best alternative by MOORA, SMART, PSI, and again TOPSIS indicates A45290 as the first alternative by applying both weight configurations. This shows that Followers is one of the factors contributing to the A107137 and A45290 rank exchange. In conclusion, the seller-perspective awareness and involvement-oriented attributes do have some impact on moving A45290 to become a competitor, although A107137 continues to be very stable with almost all alternatives.

In the eight-criteria model, referring to Table XII, A45290 has gained first place again using the MOORA method with Initial Weight and by the TOPSIS method with two weight settings, but A107137 with MOORA First Weight, SMART, and PSI, so it becomes that a total SPS criterion changes the ranking results obtained. Another aspect of the results is that an increased consideration of sellers (which comprises those five items) not only follows the previous result but produces a wider view on the possible purchase outcomes from the different alternatives of the product by taking into account the achieved sales performance of the sellers as well as their customers' feedback in addition to repurchase rates, store visitors, favorites and interested individuals.

However, when introducing the SPS model from the seller's point of view, A45290 becomes significant at some combinations and even at the top when the number of criteria is eight, and it uses TOPSIS. Thus, the eight-criterion expanded SPS has shown a broader alternative arrangement than the six-criterion-based one by the combination of customer aspects and seller aspects in the online market environment. Although the rankings of the primary alternative are different from the four techniques, the rankings cannot be judged as wrong, as they use different normalization, aggregation, and distance techniques. For example, with the eight-criterion-based configuration, MOORA ranked A45290 first at the Initial Weight, and A107137 first at the First Weight; however, A45290 remained at the top under both Initial Weight and First Weight by use of TOPSIS. Therefore, algorithm selection was not based solely on the identity of the first-ranked alternative.

TABLE XII. RANKING RESULT 8 CRITERIA

Rank	Algorithm															
	Moora				Smart				PSI				Topsis			
	Initial Weight		First Weight		Initial Weight		First Weight		Initial Weight		First Weight		Initial Weight		First Weight	
	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score	Alt	Score
1	A45290	0.15742	A107137	0.16576	A107137	5.23171	A107137	5.18210	A107137	0.59496	A107137	0.62811	A45290	0.57846	A45290	0.56539
2	A107137	0.15495	A45290	0.16193	A82978	5.17185	A82978	5.12287	A82978	0.53455	A82978	0.56841	A107137	0.51242	A107137	0.52934
3	A143588	0.12160	A143588	0.13223	A108358	5.15607	A108358	5.11355	A108358	0.51562	A108358	0.55634	A143588	0.44285	A143588	0.46062
4	A82978	0.12058	A82978	0.13100	A133019	5.13718	A143588	5.09820	A133019	0.50331	A133019	0.54618	A108358	0.44253	A108358	0.46059
5	A108358	0.11946	A108358	0.13035	A143588	5.13654	A133019	5.09767	A143588	0.49732	A143588	0.54206	A82978	0.44052	A82978	0.45843
6	A11740	0.11779	A11740	0.12867	A11740	5.13109	A11740	5.09379	A11740	0.49256	A11740	0.53826	A11740	0.43957	A11740	0.45754
7	A133019	0.11600	A133019	0.12687	A99974	5.12848	A99974	5.09084	A99974	0.49139	A99974	0.53656	A133019	0.43711	A133019	0.45510
8	A99974	0.11527	A99974	0.12603	A45290	5.08299	A45290	5.00420	A45290	0.44463	A45290	0.44880	A99974	0.43496	A99974	0.45285
9	A19305	0.09650	A19305	0.09789	A19305	4.97134	A19305	4.88697	A19305	0.33652	A19305	0.33466	A19305	0.36861	A19305	0.35810
10	A45286	0.06631	A45286	0.06857	A149486	4.94867	A149486	4.84532	A149486	0.31037	A149486	0.28998	A45286	0.28056	A45286	0.27475

E. Measurement

Evaluation of the results obtained from MOORA, SMART, PSI, and TOPSIS regarding the sensitivity of the results due to criterion variations by applying measured values for the ranking outcomes. Three measurement indicators were applied, namely Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Spearman's Rank Correlation Coefficient (SC).

TABLE XIII. RESULT OF MEAN ABSOLUTE DEVIATION

Combined Criteria	Algorithm			
	MOORA	SMART	PSI	TOPSIS
5 Criteria	1,894	2,189	1,730	4,694
6 Criteria	1,674	1,662	1,463	1,783
7_Favorite Criteria	1,169	1,680	1,861	1,308
7_Followers Criteria	1,452	1,284	1,529	1,409
8 Criteria	1,093	1,474	1,616	1,221

The MAD results are further illustrated graphically in Fig. 4.

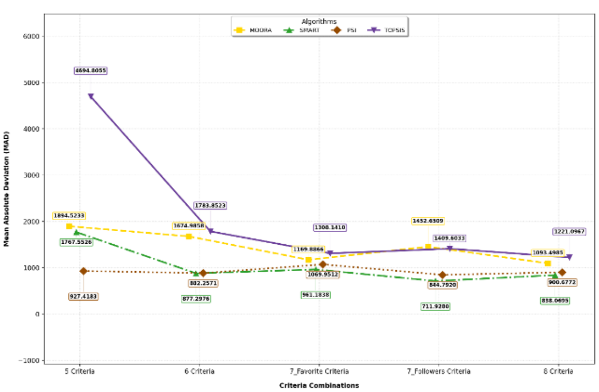

Fig. 4. Graph result of mean absolute deviation.

As presented in Table XIII and illustrated in the MAD graph in Fig. 4, the five-criteria model produces higher ranking deviation for several algorithms, especially TOPSIS, with a MAD value of 4,694. This indicates that the benchmark five-criteria model is more sensitive to changes in weight settings. When the criteria are expanded, the MAD values generally decrease.

The lowest MAD value is achieved by MOORA in the eight-criteria model, with a value of 1,093, followed by TOPSIS in the eight-criteria model with 1,221. This shows that the expanded seller-perspective criteria improve ranking stability, particularly for MOORA and TOPSIS.

TABLE XIV. RESULT OF MEAN SQUARED ERROR

Combined Criteria	Algorithms			
	MOORA	SMART	PSI	TOPSIS
5 Criteria	16,268,119	19,935,786	45,773,915	43,139,503
6 Criteria	12,544,343	9,776,007	24,513,668	12,965,720
7_Favorite Criteria	5,698,679	12,558,361	36,354,826	6,334,756
7_Followers Criteria	9,143,235	8,871,743	23,495,285	8,752,934
8 Criteria	4,969,891	9,287,339	29,247,850	5,023,281

The MSE results are further illustrated graphically in Fig. 5.

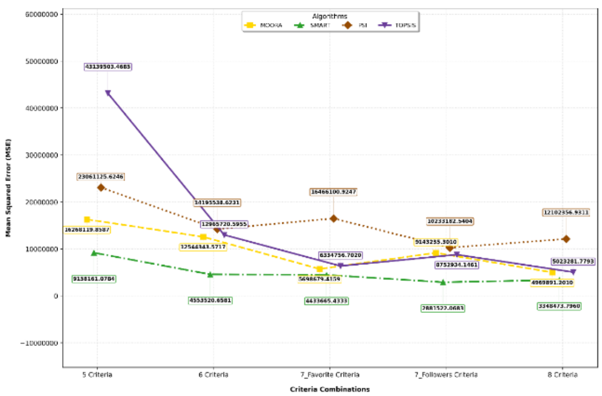

Fig. 5. Graph result of mean square error.

As presented in Table XIV and illustrated in the MSE graph in Fig. 5, the highest MSE values are found in the five-criteria model, especially PSI with 45,773,915 and TOPSIS with 43,139,503. In contrast, the eight-criteria model produces the lowest MSE for MOORA, with 4,969,891, and TOPSIS, with 5,023,281. This indicates that the eight-criteria SPS model reduces ranking error more effectively than the benchmark five-criteria model.

TABLE XV. RESULT OF SPEARMAN'S RANK CORRELATION COEFFICIENT

Combined Criteria	Algorithms			
	MOORA	SMART	PSI	TOPSIS
5 Criteria	0.99566	0.99468	0.98779	0.98850
6 Criteria	0.99666	0.99739	0.99346	0.99654
7_Favorite Criteria	0.99848	0.99665	0.99031	0.99831
7_Followers Criteria	0.99756	0.99763	0.99374	0.99767
8 Criteria	0.99868	0.99752	0.99220	0.99866

The SC results are further illustrated graphically in Fig. 6.

As presented in Table XV and the SC graph in Fig. 6, all algorithms produce very high rank correlation values, with SC values above 0.987. This means that the ranking orders remain highly consistent across different criteria combinations and weight settings. However, the eight-criterion model gives the strongest SC result for MOORA, with 0.99868, and TOPSIS, with 0.99866. These values indicate that both algorithms produce highly stable and consistent ranking patterns when the complete SPS criteria are applied.

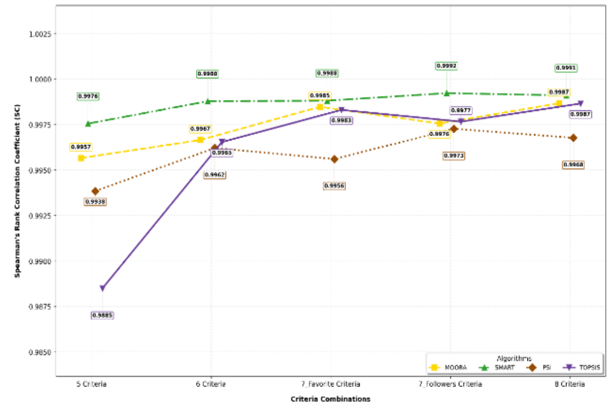

Fig. 6. Graph result of Spearman's rank correlation coefficient.

MOORA performed the best for combined robustness under 8C, achieving the lowest MAD (1,093), the lowest MSE (4,969,891), and the highest Spearman's Rank Correlation (0.99868). The result of TOPSIS was similar; however, MAD and MSE were higher at 1,221 and 5,023,281, respectively, and the Spearman coefficient was 0.99866. Hence, we chose MOORA as the optimal algorithm for the dataset under analysis as it afforded the best overall combined stability and robustness to a change in the weight values.

Each of the three can be interpreted practically. MAD shows the average degree to which ranks were shifted, MSE shows drastic ranking shifts, and Spearman's Rank Correlation assesses whether the overall relative ordering remains. Consequently, a small disparity between the Spearman correlation measures could still be important when MAD and MSE were reduced.

F. *Criterion-Removal Analysis of Followers*

A criterion-removal analysis was conducted to examine the added contribution of Followers. The 7_Favorite Criteria configuration contains Rating, Price, Sold, Discount, Response Chat, Repurchase, and Favorite, but excludes Followers. The 8 Criteria configuration includes the same criteria with the addition of Followers. Both configurations were evaluated using the same 150,000 product alternatives, four MCDM algorithms, two weight conditions, and three robustness measures.

The inclusion of Followers improved the robustness results across all four algorithms. Compared with the 7_Favorite Criteria configuration, the 8 Criteria configuration reduced MAD by 6.50% for MOORA, 12.26% for SMART, 13.16% for PSI, and 6.65% for TOPSIS. MSE was reduced by 12.79%, 26.05%, 19.55%, and 20.70%, respectively. Spearman's Rank Correlation also went up for all four algorithms.

These findings indicate that Followers provides complementary information related to shop visibility and audience reach. Its effect is more of a small addition rather than a major one because its standardized regression coefficient is smaller compared to that of Repurchase and Favorite. Nevertheless, when combined with the other seller-related criteria, Followers contributes to more stable and consistent product rankings.

G. Direct Comparison Between the 5C Benchmark and the 8C SPS Model

To provide a controlled comparison, the 5C benchmark and the proposed 8C SPS model were evaluated using the same 150,000 product alternatives, the same MOORA, SMART, PSI, and TOPSIS algorithms, the same Initial and First Weight conditions, and the same MAD, MSE, and Spearman evaluation procedures.

The 8C SPS model produced lower MAD and MSE and higher Spearman's Rank Correlation than the 5C benchmark for all four algorithms. For MOORA, MAD decreased by 42.29%, and MSE decreased by 69.45%, while Spearman's Rank Correlation increased from 0.99566 to 0.99868. For SMART, MAD decreased by 32.66%, and MSE decreased by 53.41%, while Spearman's Rank Correlation increased from 0.99468 to 0.99752. For PSI, MAD decreased by 6.59%, and MSE decreased by 36.10%, while Spearman's Rank Correlation increased from 0.98779 to 0.99220. For TOPSIS, MAD decreased by 73.99%, and MSE decreased by 88.36%, while Spearman's Rank Correlation increased from 0.98850 to 0.99866.

These results demonstrate that the improved robustness of the 8C model was obtained under the same experimental and evaluation procedures as the benchmark. Therefore, the improvement cannot be attributed to differences in the number of alternatives, algorithms, or evaluation measures.

V. CONCLUSION

This study proposed an 8C Seller Product Selection model by extending the five-criteria Customer's Perspective benchmark with Repurchase, Favorite, and Followers. Regression and questionnaire analyses provided complementary support for the proposed criteria, with regression examining their empirical associations with Sold and the questionnaire capturing sellers' perceived importance. Using the same alternatives, algorithms, weight settings, and evaluation procedures, the 8C model produced lower MAD and MSE and higher Spearman's Rank Correlation than the 5C benchmark. The addition of the Followers made continuous smaller improvements in most of the above algorithms. Of all the algorithms tested with the 8C model, MOORA gave the highest level of robustness, i.e MAD = 1,093, MSE = 4,969,891, SC= 0.99868.

However, the findings must be interpreted within the empirical context of Shopee Indonesia food and beverage items and in the context of the time frame from which the data comes. Marketplace aspects, customer characteristics, seller attributes, product demand trends, and the availability or specifications of the criteria may vary from one platform to another country, between product categories, or from one time period to another. More so, as regression results represent observed statistical correlation of data, they are not indicative of cause-and-effect or externally validated sales prediction and future. Hence, even though the 8C SPS could conceptually be transferable, the criteria definitions, the AHP weights, and the ranking performance need to be reinvented before their implementation to another dataset. Further studies need to assess the models by using data sets from different points in time, from other marketplaces, and across different item categories, and by using a wider seller sample.

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