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Case Study

A Framework for Sustainable Supplier Selection Integrating Grey Forecasting and F-MCDM Methods: A Case Study

Enty Nur Hayati [1,*], Wakhid Ahmad Jauhari [2], Retno Wulan Damayanti [2], Cucuk Nur Rosyidi [2], Muhammad Hafidz Fazli Bin Md Fauadi [3]

[1] Doctoral Program of Industrial Engineering, Universitas Sebelas Maret, Surakarta, Indonesia
[2] Department of Industrial Engineering, Universitas Sebelas Maret, Surakarta, Indonesia
[3] Faculty of Artificial Intelligence and Cyber Security, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia

*Corresponding Author: enty@student.uns.ac.id

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ABSTRACT

Selecting appropriate suppliers is critical for healthcare organizations to ensure high-quality, reliable, and sustainable patient care services. In an increasingly competitive environment, hospitals must optimize supplier selection not only based on economic factors but also by integrating environmental and social sustainability considerations. This study aims to create a strong system for choosing sustainable suppliers in healthcare by combining fuzzy-based multi-criteria decision-making (MCDM) methods with Grey Forecasting GM(1,1) to handle uncertainty and changes in performance over time. The proposed framework applies the Fuzzy Best-Worst Method (F-BWM) to determine the relative importance of sustainability criteria, while the Fuzzy Additive Ratio Assessment (F-ARAS) method is used to rank suppliers based on these weighted criteria. Grey Forecasting GM(1,1) is employed to predict supplier performance for future periods, with forecasting accuracy evaluated through Mean Absolute Percentage Error (MAPE). All supplier forecasts achieved MAPE values below 5%, indicating very high prediction reliability. Empirical results from a case study at a general hospital in Indonesia confirm that social aspects, such as patient safety and reputation, are prioritized over economic and environmental considerations. Practically, the proposed framework enables healthcare institutions to holistically evaluate suppliers, specifically reducing risks related to supply disruptions and quality inconsistencies. The model performs best under conditions of limited or uncertain data availability, where supplier historical performance trends can be leveraged to forecast future reliability and sustainability outcomes. The prioritization of sustainability criteria yields social criteria (weight = 0.3703) as the most important, followed by economic (0.3609) and environmental (0.2688) criteria.

Keywords: fuzzy ARAS, fuzzy BWM, grey forecasting, multi-criteria decision-making, sustainable supplier selection

INTRODUCTION

Sustainable procurement in healthcare supply chains has become increasingly critical as global health systems face heightened pressure to ensure reliable access to essential medicines and medical equipment while simultaneously meeting environmental and social responsibility standards. The COVID-19 pandemic, regulatory tightening, and growing public expectations for sustainability have exposed vulnerabilities in conventional supplier selection practices. In this context, hospitals must not only ensure cost-effective procurement but also prioritize resilience, ethical sourcing, and long-term sustainability within their supply networks. Consequently, developing robust, sustainability-oriented supplier selection frameworks tailored to the unique complexities of the healthcare sector is a pressing academic and practical challenge. A critical consideration in healthcare organizations is the availability of essential facilities and resources, particularly the consistent provision of comprehensive pharmaceutical products and medical equipment to support the delivery of patient care. The quality of drugs is determined by the composition of the drug, while the availability of drugs is closely related to the quality of the supplier. Therefore, in an effort to improve the quality of service to consumers, especially in the provision and service of patient drugs, supplier selection is one of the factors that must be considered [1]. Supplier selection is important decisions in every organization because they have a direct impact on the profitability of the company's competitive position [2].

As sustainability concerns have intensified globally, numerous studies have proposed frameworks for sustainable supplier selection across industries. Hosseini et al. [3] emphasized the importance of integrating social and environmental factors into procurement decisions to mitigate reputational and operational risks. Similarly, Franco and Alfonso-Lizarazo [4] identified the strategic benefits of sustainable sourcing in enhancing long-term competitiveness. Bai and Sarkis [5] argued that sustainability-driven supplier selection supports broader corporate responsibility initiatives, while Ageron et al. [6] highlighted how neglecting sustainability dimensions can expose organizations to regulatory penalties and supply chain disruptions. Although these studies collectively underscore the necessity of sustainability in supplier selection, they predominantly focus on the manufacturing and retail sectors, with limited attention to the healthcare industry.

Incorporating various aspects of social and environmental sustainability into supply chain management is known as sustainable supply chain management, or SSCM. Through the triple-bottom-line idea, which integrates environmental, social, and economic factors into organizational decision-making, sustainability can be characterized as an intergenerational philosophy that uses resources from today without compromising the requirements of future generations [7]. Choosing the correct supplier for a manufacturer is a crucial component of SSCM since it will significantly lower purchasing costs, boost customer satisfaction, and improve competitiveness. One of the most important procedures is the sustainable supplier selection process, which is generally seen as a crucial management duty. Selecting appropriate suppliers is challenging because it requires the simultaneous evaluation of quantitative and qualitative factors, which often present conflicting priorities. The performance and adaptability of each link in a supply chain determine its overall efficiency. To reduce costs and improve competitive advantage, businesses should not only choose the finest suppliers but also distribute demand among them as efficiently as possible [8].

The selection, development, and maintenance of suppliers a process frequently referred to as supplier performance management (SPM) are among the purchasing function's most crucial goals. In order to achieve this goal, purchasing must also collaborate closely with suppliers to improve current capabilities and create new ones. After a contract is awarded, monitoring performance is one method to find the best vendors. Supplier measurement and management is an important part of the purchasing cycle. Continuous measurement is needed to identify opportunities for improvement or suppliers that are not performing well [9]. Supplier performance needs to be monitored regularly to ensure the company is able to maintain long-term relationships with suppliers.

Goren [10] has created decision-making frameworks for choosing sustainable suppliers by employing the Fuzzy Decision-Making Trial and Evaluation Laboratory (F-DEMATEL) approach and ranking the computation results using weights as input from the Taguchi loss function. Using the Fuzzy Delphi approach to choose appropriate evaluation criteria for VMI supplier selection, the Fuzzy Step-wise Weight Assessment Ratio Analysis (SWARA) method to determine the relative importance weights of the evaluation criteria, and the Fuzzy Complex Proportional Assessment of Alternatives (COPRAS) method to compare, rank, and choose the best supplier, Sumrit's study [11] created an MCDM framework. Nayeri [12] suggested three key ideas for supplier selection: resilience, sustainability,

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and responsiveness. To do so, the current study developed a Multi-Stage Decision-Making Framework (MSDMF) to select potential suppliers.

Rezaei [13] introduced the Best Worst Method (BWM), a new multi-criteria decision-making technique that uses pairwise comparisons to determine the weights of criterion and alternatives with regard to various criteria while requiring less data. Pairwise comparison errors can be successfully corrected by BWM [13]. Supplier selection is often an MCDM problem where a small number of suppliers are evaluated using a small number of criteria. Sustainable supplier selection, in particular, entails identifying and using a number of criteria, many of which are incompatible with one another. In addition, supplier selection problems and processes often involve ambiguity and uncertainty because the exact values for all criteria used in the supplier selection process may not be available or accessible.

Zadeh's fuzzy set theory has been incorporated into a number of MCDM techniques [14]. The benefit of applying fuzzy set theory to the supplier selection process is its ability to minimize subjective, ambiguous, and imprecise information that shapes human opinions, attitudes, and actions [15]. Most of the methods proposed to achieve economical and sustainable supplier selection over the past two decades are MCDM models defined in a fuzzy or grey environment [16].

Although previous studies have advanced sustainable supplier selection models, several critical gaps remain. First, existing frameworks predominantly evaluate supplier performance at a single point in time, overlooking the dynamic nature of supplier capabilities across multiple periods. In reality, supplier attributes such as quality, reliability, and compliance may evolve over time, necessitating an approach that can accommodate such variability. Second, research specifically addressing sustainable supplier selection within the healthcare sector is limited, despite its unique challenges related to regulatory requirements, product criticality, and supply chain volatility.

To address these gaps, this study poses the following central research question: How can a sustainable supplier selection framework be developed for the healthcare sector that integrates multi-period performance evaluation under conditions of uncertainty? Accordingly, the objective of this study is to develop and validate a comprehensive framework that integrates fuzzy-based multi-criteria decision-making (MCDM) methods and Grey Forecasting GM(1,1) to support sustainable supplier selection in healthcare supply chains.

This study proposes a comprehensive framework that integrates grey forecasting and fuzzy MCDM methods for measuring supplier performances based on sustainable criteria. Criteria and sub-criteria of sustainability are identified in the early stages of the evaluation process based on a literature review and judgment of the DMs. In previous research, F-BWM has been successfully applied in complex decision-making environments, such as airport selection, where multiple conflicting criteria must be evaluated with limited and uncertain data (Tanrıverdi et al., 2022). Inspired by its effectiveness in handling similar multi-criteria problems, this study adopts F-BWM to prioritize sustainable supplier selection criteria in the healthcare sector. The F-BWM is considered better than the analytical hierarchy process (AHP) with fewer pairs of comparisons. Suppliers are subsequently assessed using the fuzzy additive ratio assessment (F-ARAS) method, a structured methodology, created by Heidary Dahooie et al. (2022) to assess the influence of high-performance human resource practices on the success of innovation in SMEs. These two newly developed methods are becoming popular due to their effective problem-solving abilities [18].

The main contributions of this paper are as follows:

a. Creating a comprehensive evaluation framework for sustainable supplier selection requires an integration of the three pillars of sustainability: economic, environmental, and social dimensions. The economic pillar encompasses considerations such as price, quality, reliability, and logistics efficiency. The environmental pillar focuses on green practices and effective waste management, while the social pillar emphasizes reputation, transparency, training, and both occupational and patient safety. Together, these elements provide a holistic approach to selecting healthcare suppliers.

b. Extending the application of sustainable supplier selection frameworks to the healthcare sector, addressing sector-specific challenges such as regulatory compliance, product criticality, and inventory volatility. The framework is tailored to the healthcare context by incorporating key industry-specific challenges, including strict regulatory requirements, the critical nature of medical supplies, and fluctuating inventory demands.
c. Incorporating supplier performance trends over multiple periods to predict future reliability and sustainability outcomes. Rather than relying solely on current data, the model integrates historical performance trends to provide a more accurate prediction of future supplier reliability and sustainability.
d. Enhancing decision-making under uncertainty by integrating the Fuzzy Best-Worst Method (F-BWM) for criteria weighting and the Fuzzy Additive Ratio Assessment (F-ARAS) for supplier ranking. F-BWM generates criteria weights consistently by considering expert opinions, while F-ARAS evaluates supplier performance based on these weights. The integration of these two methods has never been used before in the context of sustainable supplier selection in the healthcare sector.
e. The integration of F-BWM and F-ARAS methods with Grey Forecasting GM(1,1) in a case study at UNS Hospital significantly enhances the accuracy of decision-making in the selection of drug suppliers on an ongoing basis. This approach facilitates the objective assessment of criteria weights and supplier rankings amid data uncertainty while also enabling predictions of future supplier performance based on historical data. Beyond improving the accuracy and stability of procurement decisions, this model represents a methodological innovation, as it has not been previously applied in an integrated manner for supplier selection within the healthcare sector.

METHODS

The framework proposed in this study integrates the Fuzzy Multi Criteria Decision Making (F-MCDM) approach with Grey Forecasting GM(1,1) to support sustainable supplier selection based on criteria determined by decision-makers and supplier performance data across multiple periods (see Figure 1). The F-MCDM component consists of two core methods: the Fuzzy Best-Worst Method (F-BWM) for criteria weighting and the Fuzzy Additive Ratio Assessment (F-ARAS) for evaluating supplier performance. F-BWM was selected over conventional methods such as AHP or ANP due to its ability to reduce the number of pairwise comparisons to 2n−3, ensure higher consistency in decision matrices, and effectively incorporate uncertainty through fuzzy logic an advantage especially useful in environments where judgments are expressed linguistically or imprecisely. Unlike ANP, F-BWM does not assume interdependence among criteria, which suits the structure of this study. After the criteria weights are derived via F-BWM, supplier alternatives are evaluated using F-ARAS, which was chosen over more common MCDM methods like TOPSIS or VIKOR due to its computational simplicity, intuitive score-based logic, and compatibility with fuzzy assessments without relying on distance measures to an ideal solution. Based on the historical fuzzy evaluations of supplier performance using F-ARAS, annual performance scores are generated for each supplier. These annual scores then form the time series input for the Grey Forecasting model GM(1,1), which is employed to predict future supplier performance trends. The output of GM(1,1) does not modify the original scores or weights but provides forecasted scores that inform long term strategic decisions. Hence, this integrated approach allows for both short term evaluation and future oriented selection, ensuring robustness and sustainability in supplier decision making. Supplier performance uncertainty over several periods is predicted using the Grey Forecasting GM(1,1) method. This method can provide good predictions even with limited or incomplete data [19], so it can be used in situations where the available historical data is limited, is relatively easy to understand and implement, can handle a variety of types of data, and has adaptive properties that allow it to quickly respond to changes in data trends or patterns.

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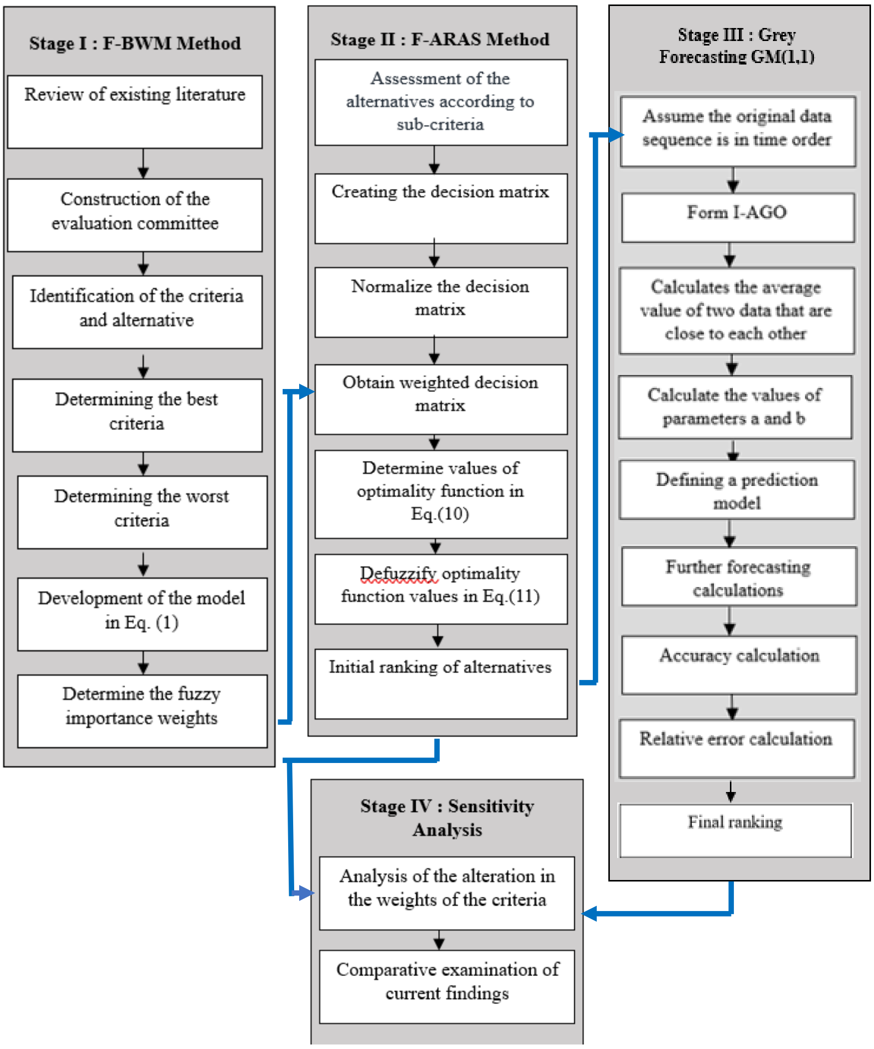

Figure 1. Proposed Integrated Grey Forecasting and F-MCDM Framework

Weighting Criteria with Fuzzy BWM

Rezaei [13] introduced the best-worst method (BWM) as an efficient means of solving MCDM problems. Compared to full pairwise comparison, the basic idea behind this approach is to simplify the process by reducing the number of comparisons from n^2 to $2n-3$. Traditional BWM only handles crisp values. BWM is capable of dealing with MCDM problems in fuzzy environments [20]. The results are significantly closer to the actual views of decision-makers when the comparison criteria are described as linguistic labels with triangular fuzzy numbers used to represent linguistic words.

The principal steps of F-BWM are as follows [21]:

Step 1: Identify a set of criteria $\{C_1, C_2, \ldots, C_n\}$

Step 2: Among the set of criteria from Step 1, determine which criterion is best (most important) and worst (least important).

Step 3: For the best criterion, conduct a fuzzy reference comparison. The best-to-others (BO) fuzzy vector will fuzzy preference of the best criterion over the criteria (j = 1, 2, …, n), and it is proven that $\tilde{a}_{BB}$ = (1, 1, 1).

Step 4: Conduct a fuzzy reference comparison for the worst criterion, do a fuzzy reference comparison. The others-to-worst (OW) fuzzy vector is $\tilde{A}_W = (\tilde{a}_{1W}, \tilde{a}_{2W}, \ldots, \tilde{a}_{nW})^T$, where $\tilde{a}_{jW}$ shows the preference of criteria (j = 1, 2, .., n) over the worst and proven criteria, and $\tilde{a}_{WW}$ = (1, 1, 1).

Step 5: Determine the ideal fuzzy weight for the criteria. According to Guo and Zhao [20], vector members BO and OW can be used to construct the following nonlinear programming models:
Equation (1) formulates the nonlinear programming model of the Fuzzy Best-Worst Method (Fuzzy BWM), which is designed to determine the optimal fuzzy weights of evaluation criteria. This model seeks to minimize the maximum deviation ($\tilde{\varsigma}$) between the fuzzy preference ratios provided by the decision-maker and the actual ratios of fuzzy weights. The constraints ensure the consistency of the fuzzy pairwise comparisons.

$$\min \tilde{\varsigma} * \tag{1}$$

$$s.t. \begin{cases} \left| \frac{(l_B^w, m_B^w, u_B^w)}{(l_j^w, m_j^w, u_j^w)} - (l_{Bj}, m_{Bj}, u_{Bj}) \right| \leq (k^*, k^*, k^*) \\ \left| \frac{(l_j^w, m_j^w, u_j^w)}{(l_W^w, m_W^w, u_W^w)} - (l_{jW}, m_{jW}, u_{jW}) \right| \leq (k^*, k^*, k^*) \\ \sum_{j=1}^{n} R(\widetilde{W}_j) = 1 \\ l_j^w \leq m_j^w \leq u_j^w \\ l_j^w \geq 0 \\ j = 1,2, \dots, n \end{cases}$$

Roles and Interpretation of parameters:

(l_B^w, m_B^w, u_B^w)	: the fuzzy weight of the best criterion
(l_W^w, m_W^w, u_W^w)	: the fuzzy weight of the worst criterion
(l_j^w, m_j^w, u_j^w)	: the fuzzy weight of criterion j, which is to be determined
(l_{Bj}, m_{Bj}, u_{Bj})	: the fuzzy preference of the best criterion over criterion j, provided by the decision maker
(l_{jW}, m_{jW}, u_{jW})	: the fuzzy preference of criterion j over the worst criterion
$\tilde{\varsigma} *$	: the upper bound of allowable deviation to maintain consistency
$R(\widetilde{W}_j)$	: a defuzzification function used to normalize fuzzy weights such that their sum equal 1

where $\tilde{\varsigma} = (l^{\tilde{\varsigma}}, m^{\tilde{\varsigma}}, u^{\tilde{\varsigma}}); l^{\tilde{\varsigma}} \leq m^{\tilde{\varsigma}} \leq u^{\tilde{\varsigma}}$, $\tilde{\varsigma}^* = (k^*, k^*, k^*); k^* \leq l^{\tilde{\varsigma}}$. By solving Equation (1), the optimal weights $(w_1^*, w_2^*, \dots, w_n^*)$ and optimal consistency index (CI), $\tilde{\varsigma}^*$, can be obtained. The consistency ratio (CR) can be calculated according to the formula $CR = \tilde{\varsigma}^* / CI$. The fuzzy weights are then defuzzified using Equation (2) [20]:

$$R(w_j) = \frac{w_j^L + 4w_j^M + w_j^u}{6} \tag{2}$$

F-ARAS for Alternative Evaluation

The F-ARAS approach was first introduced in the literature by [22]. Based on a fundamental relative comparison between alternative and optimal values, the method is simple to implement. The steps of the procedure are as follows:
Step 1: Make a fuzzy decision-making matrix using Equation (3). The columns contain criteria while the rows represent m alternatives.

$$\bar{X} = [\tilde{x}_{01} \dots \tilde{x}_{0n} \vdots \ddots \vdots \tilde{x}_{m1} \dots \tilde{x}_{mn}]; i = 0, m; \;\; j = 1, n \tag{3}$$

where $\tilde{x}_{ij}$ is the performance value of the fuzzy value of the *ith* alternative in terms of criteria *j*, and $\tilde{x}_{0j}$ is the optimal value of criterion *j*. If the optimal value of criterion *j* is not known, then:

$$\tilde{x}_{0j} = \underbrace{\max}_{i} \tilde{x}_{ij}, \;\; if \;\;\; \underbrace{\max}_{i} \tilde{x}_{ij} \;\;\; \text{is better, and}$$

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$$\tilde{x}_{0j} = \underbrace{\min}_{i} \tilde{x}_{ij}, \quad \text{if} \quad \underbrace{\min}_{i} \tilde{x}_{ij} \quad \text{is better} \tag{4}$$

Step 2: Determine the normalized decision-making matrix using Equation (5):

$$\underline{\bar{X}} = \left[\underline{\tilde{x}_{01}} \dots \underline{\tilde{x}_{0n}} \vdots \ddots \vdots\ \underline{\tilde{x}_{m1}} \dots \underline{\tilde{x}_{mn}}\right]; i = \underline{0, m}; \;\; j = \underline{1, n} \tag{5}$$

The criteria where the maximum value is preferred are normalized as follows (Equation 6) :

$$\underline{\tilde{x}_{ij}} = \frac{\tilde{x}_{ij}}{\sum_{i=0}^{m} \tilde{x}_{ij}} \tag{6}$$

The criteria where a minimum value is desired are normalized using a two-step process using Equation (7) :

$$\tilde{x}_{ij} = 1/\ \underline{\tilde{x}_{ij}} \tag{7}$$

Equation (7) describes the normalization process for criteria where lower values are preferred, typically referred to as cost-type criteria.

$\underline{\tilde{x}_{ij}}$: the original fuzzy evaluation of alternative *i* under criterion *j*, represented as a triangular fuzzy number (TFN) with lower (l), middle (m), and upper (u) value.

$\tilde{x}_{ij}$: the normalized fuzzy value obtained by applying the reciprocal transformation to each component of TFN.

Step 3: Calculate the weighted normalized matrix using Equation (8).

$$\sum_{j=1}^{n} w_j = 1 \tag{8}$$

All criterion-weighted normalized values are determined as follows (Equation (9)) :

$$\tilde{x}_{ij} = \underline{\tilde{x}_{ij}} \widetilde{w}_j \;; \qquad i = \underline{0, m}; \tag{9}$$

Step 4: Calculate the value of the optimality function using Equation (10).

$$\tilde{S}_l = \sum_{j=1}^{n} \widetilde{x_{ıȷ}} \qquad ; i =, m \tag{10}$$

where $\tilde{S}_l$ is the value of the optimality function of the ith alternative. Defuzzification utilizing Equation (11) is necessary because the values found are not clear.

$$S_i = \frac{1}{3}\left(S_{i\alpha} + S_{i\beta} + S_{i\beta}\right) \tag{11}$$

Equation (12) is used to determine alternative utility rates Equation (12).

$$K_i = \frac{S_i}{S_0} \qquad i = \underline{0, m}; \tag{12}$$

where the ideal criteria values are S_i and S_0. K_i is calculated as [0, 1]. Therefore, the values can be sorted in ascending order.

Grey Forecasting GM(1,1) Method

The GM(1,1) Grey Forecasting model has been widely used to solve prediction problems with small data. The following steps are used to obtain GM(1,1) [23]:

Step 1 : Define the non-negative original data sequence as shown in Equation (13).

$$x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)) \tag{13}$$

The accumulated generation operation (AGO) is then used to generate the sequence $x^{(1)}$, using Equation (14) and Equation (15).

$$x^{(1)} = (x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n)) \tag{14}$$

where $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(k)\,, k = 1,2,\dots,n$ (15)

Step 2: The sequence $z^{(1)}$ is obtained by applying the mean consecutive neighbor's operator on $x^{(1)}$.

$$z^{(1)} = \{z^{(1)}(2), z^{(1)}(3), \dots, z^{(1)}(n)\} \tag{16}$$

where $z^{(1)}(k) = 0{,}5x^{(1)}(k) + 0{,}5x^{(1)}(k-1), \quad k = 2,3,\dots,n$ (17)

Step 3: To determine the rate of change in the accumulated data sequence with respect to time, a first-order differential equation can be used to construct the grey GM(1,1) model over $x^{(1)}$.

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = b \tag{18}$$

The developmental coefficient is named after parameter a, which reflects the improvement in the trend of the sequence. The coordination parameter, b, indicates the change in relationships.

Step 4: Based on Equation (18), the original form of GM(1,1) for discrete values can be defined in Equation (19), and the basic form of the model based on z is given in Equation (20).

$$x^{(0)}(k) + ax^{(1)}(k) = b \tag{19}$$

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{20}$$

Step 5: The parameters a and b in Equation (19) and Equation (20) = must be estimated by minimizing squared errors, i.e., least squares estimation, as shown in Equation (21).

$$\binom{\hat{a}}{\hat{b}} = [B^T B]^{-1} B^T Y \tag{21}$$

where : $$B = \begin{bmatrix} -[x^{(1)}(1) + x^{(1)}(2)]/2 & 1 \\ -[x^{(1)}(2) + x^{(1)}(3)]/2 & 1 \\ \dots & \dots \\ -[x^{(1)}(n-1) + x^{(1)}(n)]/2 & 1 \end{bmatrix}$$

$Y = [x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(n)]^{\,T}$.

In Equation (21), B and Y denote the accumulated matrix and constant vector, respectively.

The temporal response function can be calculated by solving Equation (22), as illustrated below:

$$\hat{x}^{(1)}(k+1) = \left[x^{(1)}(1) - \frac{\hat{b}}{\hat{a}}\right] e^{-ak} + \frac{\hat{b}}{\hat{a}} \tag{22}$$

Step 6: This model can be used to forecast the value of the original data sequence in the future. The model's initial condition is $x^{(0)}(1) = \hat{x}^{(0)}(1)$. Because $\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k)$, the expected value after h periods can be computed using the following Equation (23):

$$\hat{x}^{(0)}(n+h) = (1 - e^{\hat{a}}) \left[x^{(0)}(1) - \frac{\hat{b}}{\hat{a}}\right] e^{-\hat{a}(n+h)} \tag{23}$$

Case Study

Sustainable supplier selection is an important step in ensuring that healthcare services are not only medically effective but also socially and environmentally responsible. One way of providing optimal health services to the community is through good-quality medicines. To get good-quality medicines, hospitals must purchase medicines

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from the best suppliers. This case study analyzes drug purchasing at one of the general hospitals in Surakarta, Central Java, Indonesia. The hospital, which is located in an eight-story building and is a Type C general hospital, has ten polyclinic specialists, 63 specialist doctors, 33 general practitioners, one general dentist, and more than 300 non-medical personnel. There are over 190 treatment beds within the hospital.

Drug purchasing decisions are made by the Hospital Procurement Section, which consists of three decision-makers (DMs), namely the head of the Goods and Services Division with 3 years of experience (DM 1), the head of the General and Engineering Department with 26 years of experience (DM 2), and the head of the Procurement Department with 3 years of experience (DM 3). The criteria and sub-criteria were initially identified through a review of relevant literature and subsequently refined through consultations with decision-makers. Consensus was reached through iterative discussions and decision makers' reviews, ensuring that all selected criteria were contextually appropriate and comprehensible for the intended analysis. They agreed on the items shown in Table 1. The DMs consider 14 potential companies as medication suppliers. Due to hospital and company data privacy reasons, these suppliers are anonymous and identified using codes S1–S14. About a quarter of these suppliers are domestic companies that produce and supply various types of medicines. The main criteria and sub-criteria for

Table 1. Sustainable Supplier Selection Criteria

Criteria	Sub-criteria	Description	References
Economy (K1)	Price (C1)	Affordable products	[24], [25], [26], [27]
	Quality (C2)	Standard of products and services provided	[24], [28], [25], [26], [29], [27], [30]
	Reliability (C3)	Relationship of trust between purchaser and supplier	[24], [27]
	Payment terms (C4)	Financial convenience related to payments	[24], [29]
	Production capacity (C5)	Existing human, financial, and material resource capabilities related to product manufacturing	[31]
	Lead time (C6)	Timely delivery	[32]
	Supplier location (C7)	Location of suppliers who provide supply materials (related to transportation costs)	[33]
Environment (K2)	Green design and purchasing (C8)	Eco-friendly practices incorporated at the design and purchasing stage	[34], [35], [29], [16], [27]
	Environmental management system (C9)	Structure, planning, and implementation of supplier policies for environmental protection.	[25], [26], [29], [16]
	Green packaging and Labelling (C10)	Supplier's ability to incorporate environmental considerations into packaging and labelling.	[29], [31], [2], [27]
	Environmental pollution and waste management (C11)	Raw materials are such that wastage and pollution are minimized when producing the product	[30], [31]
	Pollution control (C12)	Efforts to prevent pollution	[24], [26], [31], [16], [2], [27], [36]
Social (K3)	Reputation (C13)	Perception of the supplier in the work environment. Is it viewed as trustworthy or not?	[24], [31], [16]
	Information disclosure (C14)	Important details regarding procedures and goods are shared by suppliers.	[24], [25], [29], [31], [27]

Table 1. (cont.)

Criteria	Sub-criteria	Description	References
Social (K3)	Training after purchase (C15)	Medical staff education regarding the unique items provided.	[24], [26], [29]
	Work safety (C16)	The requirements for occupational health are part of the company's procurement procedure.	[24], [25], [26], [29], [27], [16], [2]
	Patient safety guarantee (C17)	Efforts to prevent dangers to patients	[31]

Table 2. Fuzzy Linguistic Scale [21],[37]

Linguistic Terms	Membership Function	Consistency Index (CI)
Equally important (EI)	(1,1,1)	3.00
Weakly important (WI)	(2/3,1,3/2)	3.80
Fairly important (FI)	(3/2,2,5/2)	5.29
Very important (VI)	(5/2.3,7/2)	6.69
Absolutely important (AI)	(7/2,4,9/2)	8.04

Table 3. Fuzzy Linguistic Assessments by Decision-Makers

	Best Criterion	Worst Criterion	Economy	Environment	Social
DM1	Economy		EI	FI	FI
		Social	FI	FI	Ei
DM2	Social		VI	VI	Ei
		Economy	EI	FI	VI
DM3	Economy		EI	FI	WI
		Environment	FI	EI	WI

Table 4. Fuzzy And Crisp Criterion Weights

	K1	K2	K3
DM1	(0.4653;0.4653;0.5607)	(0.2720;0.2980;0.4383)	(0.1908;0.1908;0.2562)
DM2	(0.1767;0.1767;0.1767)	(0.1584;0.2468;0.2893)	(0.5485;0.5913;0.5913)
DM3	(0.3391;0.4418;0.4418)	(0.1998;0.2603;0.2603)	(0.2451;0.3391;0.3486)
Fuzzy Weight	.3270;0.3613;0.3931)	(0.2101;0.2684;0.3293)	(0.3281;0.3737;0.3987)
Crips Weight	.3609	0.2688	0.3703

RESULT AND DISCUSSION

F-BWM Result

F-BWM was used to weight the main criteria and sub-criteria. The DMs were asked to identify the best and worst criteria in their opinion and to express their best-to-others and others-to-worst choices using the linguistic scale presented in Table 2. The values presented in Table 3 were then translated into triangular fuzzy numbers. These numbers were then used to generate the F-BWM model shown in Equation (24) using LINGO 18.0 software. The fuzzy weights of the criteria were calculated and are shown in Table 4, along with the crisp weights after the fuzzy weights were defuzzified.

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$$\text{Min } k^* \tag{1}$$

$$s.t.\begin{cases}
l_1 - u_1 \leq k^*u_1 \,;\, l_1 - u_1 \geq -k^*u_1 \\
m_1 - m_1 \leq k^*m_1 \,;\, m_1 - m_1 \geq -k^*m_1 \\
u_1 - l_1 \leq k^*l_1 \,;\, u_1 - l_1 \geq -k^*l_1 \\
l_1 - 1{,}5u_2 \leq k^*u_2 \,;\, l_1 - 1{,}5u_2 \geq -k^*u_2 \\
m_1 - 2m_2 \leq k^*m_2 \,;\, m_1 - 2m_2 \geq -k^*m_2 \\
u_1 - 2{,}5l_2 \leq k^*l_2 \,;\, u_1 - 2,5l_2 \geq -k^*l_2 \\
l_1 - 1{,}5u_3 \leq k^*u_3 \,;\, l_1 - 1{,}5u_3 \geq -k^*u_3 \\
m_1 - 2m_3 \leq k^*m_3 \,;\, m_1 - 2m_3 \geq -k^*m_3 \\
u_1 - 2{,}5l_3 \leq k^*l_3 \,;\, u_1 - 2,5l_3 \geq -k^*l_3 \\
l_1 - 1{,}5u_3 \leq k^*u_3 \,;\, l_1 - 1{,}5u_3 \geq -k^*u_3 \\
m_1 - 2m_3 \leq k^*m_3 \,;\, m_1 - 2m_3 \geq -k^*m_3 \\
u_1 - 2{,}5l_3 \leq k^*l_3 \,;\, u_1 - 2{,}5l_3 \geq -k^*l_3 \\
l_2 - 1{,}5u_3 \leq k^*u_3 \,;\, l_2 - 1{,}5u_3 \geq -k^*u_3 \\
m_2 - 2m_3 \leq k^*m_3 \,;\, m_2 - 2m_3 \geq -k^*m_3 \\
u_2 - 2{,}5l_3 \leq k^*l_3 \,;\, u_2 - 2{,}5l_3 \geq -k^*l_3 \\
l_3 - u_3 \leq k^*u_3 \,;\, l_3 - u_3 \geq -k^*u_3 \\
m_3 - m_3 \leq k^*m_3 \,;\, m_3 - m_3 \geq -k^*m_3 \\
u_3 - l_3 \leq k^*l_3 \,;\, u_3 - l_3 \geq -k^*l_3 \\
\frac{1}{6} * l_1 + \frac{1}{6} * 4 * m_1 + \frac{1}{6} * u_1 + \frac{1}{6} * l_2 + \frac{1}{6} * 4 * m_2 + \frac{1}{6} * u_2 + \\
\frac{1}{6} * l_3 + \frac{1}{6} * 4 * m_3 + \frac{1}{6} * u_3 = 1 \\
l_1 \leq m_1 \leq u_1 \\
l_2 \leq m_2 \leq u_2 \\
l_3 \leq m_3 \leq u_3 \\
l_1 > 0 \\
l_2 > 0 \\
l_3 > 0 \\
k \geq 0
\end{cases}$$

Table 5. Priority Weights of The SSS Criteria

Criteria	Fuzzy Weight	Sub-criteria	Local Fuzzy Weight	Global Fuzzy Weight	Global Crisp Weight
Economy (K1)	(0.3270;0.3613;0.3931)	C1	(0.1705;0.2152;0.2315)	(0.0558;0.0778;0.0910)	0.0763
		C2	(0.1674;0.1684;0.1751)	(0.0547;0.0608;0.0688)	0.0612
		C3	(0.1002;0.1406;0.1407)	(0.0328;0.0508;0.0553)	0.0485
		C4	(0.0879;0.1406;0.1407)	(0.0288;0.0508;0.0553)	0.0479
		C5	(0.1054;0.1046;0.1110)	(0,0345;0,0378;0,0436)	0.0382
		C6	(0.0779;0.1219;0.1323)	(0.0255;0.0440;0.0520)	0.0423
		C7	(0.1003;0.1407;0.1407)	(0.0328;0.0508;0.0553)	0.0486
Environment (K2)	(0.2101;0.2684;0.3293)	C8	(0.0206;0.1726;0.0341)	(0.0260;0.0695;0.0673)	0.0619
		C9	(0.1179;0.1581;0.1741)	(0.0248;0.0424;0.0573)	0.0420
		C10	(0.2006;0.2579;0.2830)	(0.0421;0.0692;0.0932)	0.0687
		C11	(0.1676;0.2173;0.2616)	(0.0352;0.0583;0.0862)	0.0591
		C12	(0.2119;0.2303;0.2409)	(0.0445;0.0618;0.0793)	0.0618
Social (K3)	(0.3281;0.3737;0.3987)	C13	(0.1867;0.2027;0.2167)	(0.0613;0.0758;0.0144)	0.0631
		C14	(0.1821;0.2035;0.2154)	(0.0598;0.0760;0.0143)	0.0630
		C15	(0.1208;0.1988;0.2209)	(0.0396;0.0743;0.0147)	0.0586
		C16	(0.1354;0.2096;0.2363)	(0.0444;0.0783;0.0157)	0.0622
		C17	(0.1673;0.2082;0.2268)	(0.0549;0.0778;0.0151)	0.0635

A similar technique was used to assess the sub-criteria and calculate their relative weights. The weights of the main criteria were then multiplied by those of the sub-criteria to produce the global subcriterion weights. The relative and global weights of the main criteria and sub-criteria are shown in Table 5.

The F-BWM criterion weighting indicates that (S12 ranked first) with a global crisp weight of 0.0763, followed by Green Packaging and Labeling (C10) and Patient Safety Assurance (C17) at 0.0687 and 0.0635, respectively. The criteria of Waiting Time (C6), Environmental Management System (C9), and Production Capacity (C5) had the lowest weights of 0.0423, 0.0420, and 0.0382, respectively. Supplier 12 consistently ranks highest; it demonstrates a strong implementation of patient safety protocols, an active and transparent incident reporting system, well trained and responsive staff, and effective communication with patients. These strengths contribute to high performance across multiple subcriteria, particularly in areas such as patient safety, process efficiency, and service reliability, justifying its top overall ranking.

F-ARAS Result

The matrix of alternative ratings was generated using the language rating scale as shown in Table 6. Decision makers (DMs) first evaluate each supplier by considering various established criteria. After all suppliers have been evaluated based on all relevant criteria, the next step is to compile a decision matrix. This decision matrix serves as the basis for further analysis in supplier selection.

Table 6. Linguistic Scale And Fuzzy Numbers [21]

Linguistic Term	Fuzzy Numbers
Very Poor (VP)	(0,1,2)
Poor (P)	(1,2,3)
Medium Poor (MP)	(2,3.5,5)
Fair (F)	(4,5,6)
Medium Good (MG)	(5,6.5,8)
Good (G)	(7,8,9)
Very Good (VG)	(8,9,10)

Table 7. Supplier Ranking Using The F-ARAS Method

Supplier	Si	Qi	Rank
S1	0.1662	0.8981	14
S2	0.1812	0.9791	3
S3	0.1719	0.9290	10
S4	0.1814	0.9804	2
S5	0.1778	0.9607	6
S6	0.1810	0.9782	4
S7	0.1751	0.9463	7
S8	0.1730	0.9351	9
S9	0.1783	0.9634	5
S10	0.1709	0.9234	11
S11	0.1678	0.9066	13
S12	0.1815	0.9805	1
S13	0.1703	0.9201	12
S14	0.1740	0.9402	8

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Furthermore, the Fuzzy Additive Ratio Assessment System (F-ARAS) method is applied to process the data in the decision matrix and produce the final ranking of each supplier. The results of the calculation using the F-ARAS method are then presented in Table 7, which displays the order of suppliers based on their performance according to the established criteria.

Comparison of Ranking Using Different MCDM Methods

In order to evaluate the stability of the employed method, the results of the F-ARAS method were compared with the results of other common decision-making methods, such as MARCOS, CODAS, and EDAS. Table 8 displays the comparative result of applying these alternative methods.

The F-ARAS and MARCOS methods generated the same primary ranking, with S12 in first place. The CODAS method produced a different order of suppliers, with S10 in first place and S12 in second place; likewise, the EDAS method results in a very different order than the F-ARAS method, with S1 in first place and S12 in sixth place. Thank you for the feedback. MARCOS, CODAS, and EDAS were selected because they offer methodological strengths relevant to the decision context. MARCOS considers both ideal and anti-ideal solutions for balanced evaluation, CODAS uses Euclidean and Taxicab distances to enhance discrimination among closely ranked alternatives, and EDAS evaluates alternatives based on their distance from the average solution, providing a realistic performance baseline. These methods were chosen over more established ones like TOPSIS or VIKOR to explore more recent approaches that address limitations such as sensitivity to normalization and rank reversal, and to provide more nuanced comparative insights. MARCOS, CODAS, and EDAS were chosen because they offer methodological strengths relevant to the decision context. MARCOS considers both ideal and anti-ideal solutions for balanced evaluation, CODAS uses Euclidean distance to improve discrimination among closely ranked alternatives, and EDAS evaluates alternatives based on their distance from the mean solution, thus providing a realistic baseline of performance. These methods were chosen over more established methods such as TOPSIS or VIKOR to explore newer approaches that address limitations such as sensitivity to normalization and rank reversal and to provide more nuanced comparative insights.

Table 8. Supplier Scores And Ranks Using Other Mcdm Methods

	F-ARAS		MARCOS		CODAS		EDAS	
	Utility	**Rank**	**Utility**	**Rank**	**Utility**	**Rank**	**Utility**	**Rank**
S1	0.8981	14	0.6595	13	0.0305	5	0.8893	1
S2	0.9791	3	0.6796	3	0.0117	6	0.5788	7
S3	0.9290	10	0.6704	7	-0.0063	8	0.4723	10
S4	0.9804	2	0.6702	8	0.0062	7	0.7159	2
S5	0.9607	6	0.6617	12	-0.0691	14	0.4811	9
S6	0.9782	4	0.6817	2	0.0384	4	0.6213	5
S7	0.9463	7	0.6766	4	0.0454	3	0.4568	11
S8	0.9351	9	0.6653	10	-0.0655	13	0.4093	12
S9	0.9634	5	0.6699	9	-0.0407	12	0.4027	13
S10	0.9234	11	0.6709	6	0.0495	1	0.6427	4
S11	0.9066	13	0.6588	14	-0.0242	11	0.6548	3
S12	0.9805	1	0.6832	1	0.0473	2	0.6115	6
S13	0.9201	12	0.6630	11	-0.0122	10	0.4882	8
S14	0.9402	8	0.6726	5	-0.0109	9	0.3511	14

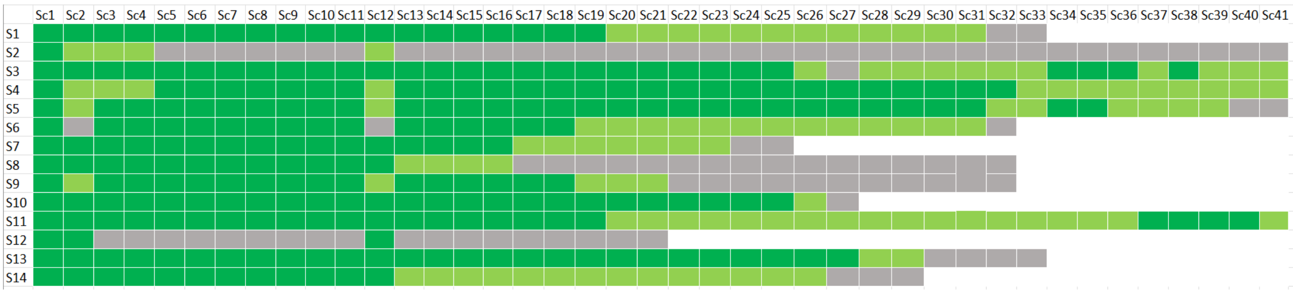

Figure 2. Sensitivity Analysis Conducted by Changing the Weight of Criteria K3.

Sensitivity Analysis no change in ranking occurred or the supplier following

A sensitivity analysis was conducted to examine the impact of various rankings on the outcomes of the proposed integrated fuzzy model. During the process of changing the scenarios (Sc), the weight assigned to the most effective (and important) criterion was altered. The weight of criterion K3 was systematically decreased at a rate of 2% to simulate a total of 41 scenarios [21]. Figure 2 shows the updated supplier rankings across the scenarios.

In Figure 2, dark green bars indicate that no change in ranking occurred; light green bars represent a net change of one rank; grey bars represent a net change of two ranks; and white bars represent a net change of three or more ranks [17]. Suppliers S2, S4, andf S12 are very sensitive to changes in criterion weights. Meanwhile, suppliers S3, S10, and maintain a relatively similar position across all 41 scenarios, indicating that they are not easily affected by changes in criterion weight.

GM(1,1) Result

Grey Forecasting is a method that does not require complete historical data, only a minimum of four historical data points within the same interval. This method focuses on overcoming issues relating to the operational systems such as uncertainty, multiple inputs, discrete data, and incomplete data when forecasting with small data sets. The GM(1,1) model is easy to implement, works quite well with small sample sizes, can effectively handle nonlinear and nonstationary data, and can accommodate incomplete or uncertain information, making it suitable for forecasting in real-world scenarios where data quality may vary.
Supplier performance assessments from 2019 to2023 were provided by decision-makers by considering supplier performance using economic, environmental, and social criteria (Table 9). Grey Forecasting GM(1,1) method was performed as follow:

Step 1: $X^{(1)} = (0.1718, 0.3162, 0.4781, 0.6293, 0.6293, 0.7955\}$
Step 2: $Z^{(1)} = \{0.2440, 0.3972, 0.5537, 0.7124\}$
Steps 3 to 5: The parameters of the GM(1,1) are calculated using Equation (22) as $\left[\hat{a} \quad \hat{b}\right] = [0.0350 \quad 0.1393]$.
Step 6: Based on Equation (22) and the calculated parameters, the prediction model gives the expression

$$\hat{X}^{(1)}(k+1) = \left[x^{(1)}(1) - \left(\frac{0.1393}{0.0350}\right)\right] e^{-0.0350(k)} + \left(\frac{0.1393}{0.0350}\right).$$

Table 10 present the prediction value of X(0). After obtaining the prediction for the other tribe, the residual error is calculated as the difference between the observed value and the predicted value. The first quarter prediction value is identified as the tribe's starting observation value. The consistent top ranking of Supplier S12 across all three forecasting periods indicates a stable and reliable performance, making it a strong candidate for long-term strategic partnerships. In contrast, Supplier S5 shows a notable improvement, rising from rank 5 to 2, which suggests positive

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Table 9. Historical Supplier Performance Data (2019 to 2023)

Supplier	Year				
	2019	2020	2021	2022	023
S1	0.17	0.14	0.16	0.15	0.17
S2	0.17	0.18	0.19	0.18	0.18
S3	0.17	0.17	0.18	0.17	0.17
S4	0.17	0.18	0.17	0.18	0.18
S5	0.18	0.17	0.17	0.17	0.18
S6	0.18	0.18	0.19	0.18	0.18
S7	0.17	0.17	0.18	0.17	0.18
S8	0.17	0.17	0.17	0.17	0.17
S9	0.17	0.18	0.17	0.18	0.18
S10	0.17	0.17	0.18	0.17	0.19
S11	0.16	0.16	0.16	0.17	0.17
S12	0.18	0.17	0.18	0.18	0.18
S13	0.16	0.17	0.17	0.10	0.17
S14	0.17	0.17	0.17	0.17	0.17

Table 10. Supplier Performance Forecasting Result and Supplier Rating

Supplier	Period					
	2023	Rank	2024	Rank	2025	Rank
S1	0.164	14	0.170	14	0.176	8
S2	0.181	3	0.181	3	0.180	4
S3	0.172	10	0.172	9	0.173	11
S4	0.182	2	0.182	2	0.182	3
S5	0.178	5	0.181	3	0.184	2
S6	0.180	4	0.179	5	0.178	5
S7	0.175	7	0.176	7	0.178	6
S8	0.172	10	0.172	11	0.173	13
S9	0.177	6	0.177	6	0.177	7
S10	0.172	9	0.172	9	0.173	12
S11	0.169	13	0.172	12	0.175	9
S12	0.183	1	0.187	1	0.191	1
S13	0.171	12	0.172	12	0.173	14
S14	0.172	8	0.173	8	0.174	10

developments in its performance. Meanwhile, the minor declines observed in other suppliers' rankings may indicate the impact of shifting priorities. These insights are critical for strategic sourcing decisions, as they highlight not only current performance but also future potential and risk exposure associated with each supplier. Based on processing supplier performance forecasts, the mean absolute percentage errors (MAPE) are well under 5%, which is considered "very good." The level of accuracy of the supplier forecasts is close to 100%, as shown in Table 11.

Discussion

This study examined how supplier performance uncertainty is incorporated into the process of selecting sustainable suppliers in the healthcare industry. Healthcare institutions prioritize social sustainability when choosing medicine

Table 11. Average Residual Errors (MAPE)

Supplier	Error rate (MAPE) %	Level of accuracy (%)
S1	1.17	98.83
S2	1.03	98.97
S3	1.41	98.59
S4	1.11	98.89
S5	0.40	99.60
S6	1.04	98.96
S7	2.22	97.78
S8	0.98	99.02
S9	1.06	98.94
S10	0.80	99.20
S11	0.49	99.51
S12	1.05	98.95
S13	0.70	99.30
S14	1.17	98.83

providers, as social sustainability issues were ranked by decision-makers as the most important factor. Previous studies across various sectors such as manufacturing, construction, and logistics [38] have often emphasized economic or environmental dimensions as dominant. Conversely, the current findings highlight a sector-specific subtlety, with social sustainability being the most significant decision-making criterion in healthcare institutions.

This divergence can be interpreted through the lens of stakeholder theory, which posits that organizations are influenced by the expectations and interests of a wide range of stakeholders, including patients, healthcare workers, regulators, and the broader community. In healthcare, where service quality, patient safety, labour well-being, and equitable access are critical, the prominence of social aspects is both expected and justified. Similarly, institutional theory suggests that normative pressures in the healthcare industry such as professional standards, public accountability, and ethical obligations may lead organizations to prioritize social dimensions to maintain legitimacy and trust.

Comparative literature in the healthcare domain also supports the view that social responsibility, employee welfare, and community health impact are central to sustainability initiatives in this sector. However, the importance shown in this study, especially the high ranking of employee related factors, may indicate changing priorities and expectations from stakeholders after the pandemic.

Healthcare suppliers may derive substantial advantages from comprehending the level of ethical standards they should maintain, identifying safety and welfare considerations to incorporate in the procurement process, and acknowledging the essential human factors for achieving success in healthcare supply chain management. These findings offer valuable insights for healthcare supply chain managers who are interested in employing socially sustainable methods when choosing suppliers. Economic sustainability was the second-most important factor for decision-makers. The findings imply that healthcare supply chain professionals mostly prioritize economic criteria such as on-time delivery and competitive pricing. A significant consequence of these findings is that suppliers with environmentally conscious practices might help mitigate adverse effects on the environment and promote sustainability initiatives. The caliber of products and services offered by suppliers directly influences patient safety. Selecting a reputable provider helps decrease the likelihood of receiving faulty or hazardous products. The efficacy of products and services offered by suppliers can have an impact on patient treatment outcomes.

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This study is limited by the fact that the sample only considers the healthcare industry. The findings are also limited in that historical assessments of supplier performance were based on the opinions of drug-purchasing decision-makers and a limited amount of historical data. Future research could focus on other industries, as well as samples from other countries, to further validate these findings and assess their generalizability. In addition, future research can use other grey forecasting methods using more historical data to predict future supplier performance in order to select the best suppliers. Ultimately, the model and measurements presented in this paper can be further refined through interviews with supply chain practitioners rather than relying solely on questionnaire surveys as the primary data collection instrument.

CONCLUSION

Sustainability considerations have become a top research priority in recent years. This study has identified specific factors that are considered important by healthcare decision-makers when selecting sustainable suppliers. This paper proposed a framework for sustainable supplier selection using F-BWM and F-ARAS techniques to determine criteria weights and supplier rankings. Grey forecasting GM(1,1) was used to predict the performance of each supplier. The application of the framework to a hospital case study showed that social criteria are prioritized by decision makers in the healthcare sector because of the nature of healthcare that is closely related to human well-being, social justice, and patient safety. External pressures such as societal expectations, media attention, and demands from patient advocacy groups are driving healthcare organizations to pay greater attention to social aspects in their procurement practices. Hospitals and health care providers have responsibilities to multiple stakeholders, including patients, healthcare professionals, governments, and the wider community, so their decisions reflect a complex balance of social interests.

Procurement decision-makers in the study hospital do not place much emphasis on environmental sustainability in their supplier selection decisions, which reflects broader challenges commonly observed in the healthcare sector. This trend can be attributed to several factors. First, cost constraints often take precedence, with environmental initiatives perceived as adding a financial burden without immediate operational returns. Second, there is a lack of regulatory pressure specific to green procurement in healthcare, especially in regions where environmental guidelines are either voluntary or poorly enforced. Third, limited awareness and technical capacity to evaluate suppliers' environmental performance can hinder the integration of sustainability criteria.

Additionally, healthcare organizations may prioritize immediate patient outcomes and service reliability over long term ecological impacts. To better integrate environmental considerations in the future, targeted policy interventions, incentives for green suppliers, training programs, and standardized. Social criteria are the main consideration for decision-makers when choosing drug suppliers, followed by economic criteria. Healthcare decision-makers should begin to actively consider environmentally friendly suppliers in their supplier selection activities. Balancing the three sustainability pillars of economic, environmental, and social criteria will increase sustainable activities in the health service sector. Integrating the grey forecasting GM(1,1) method will help decision-makers choose the best suppliers for future drug purchases. The proposed model can be practically adopted by decision makers as a structured framework to enhance healthcare procurement strategies through the integration of sustainability criteria. To facilitate its implementation, the model can be embedded into procurement policies by incorporating sustainability metrics particularly social, environmental, and economic dimensions into supplier evaluation guidelines. Additionally, organizations can utilize computational tools such as MATLAB, Python, or Excel based applications to operationalize the fuzzy MCDM approach, enabling systematic analysis and ranking of suppliers. Capacity building efforts, including workshops and training sessions, are recommended to familiarize procurement officers and stakeholders with the fuzzy logic framework and its practical applications. Furthermore, integrating the model into digital decision support systems can enable real time supplier assessment, scenario analysis, and sustainability driven decision making. These approaches collectively support the institutionalization of sustainability oriented procurement practices in the healthcare sector.

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DECLARATION OF AI TOOL USAGE

During the preparation of this manuscript, the authors used ChatGPT (GPT-4, OpenAI) for generating text of selected paragraphs to improve academic tone and clarity, explaining the main contributions of this paper, and simplifying the language used to describe theoretical frameworks about Fuzzy-MCDM Theory. All AI-generated outputs were critically reviewed and thoroughly edited by the authors to ensure factual accuracy, clarity of expression, and compliance with academic standards. The authors take full responsibility for the integrity and content of this manuscript.

CONFLICT OF INTEREST

The authors declare no conflict of interest regarding the publication of this paper.

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AUTHORS BIOGRAPHY

Enty Nur Hayati is a doctoral student in the Industrial Engineering program at SebelasMaret University, Surakarta. She is a lecturer in Industrial Engineering, Faculty of Engineering at Universitas Stikubank Semarang. She obtained her Bachelor's Degree in the Industrial Engineering Department, Faculty of Engineering, Universitas Atma Jaya Yogyakarta, in 1998. She completed a Master's program in the Department of Industrial Engineering, Faculty of Engineering, Pembangunan Nasional “Veteran” University, Yogyakarta, in 2011.

Wakhid Ahmad Jauhari is a lecturer and researcher in the Industrial Engineering Study Program, Faculty of Engineering, Sebelas Maret University (UNS). He completed his Bachelor and Masters in Industrial Engineering at the Sepuluh Nopember Institute of Technology (ITS), Surabaya, and earned a Doctorate in Industrial Engineering from the same institution in 2022. His expertise and research interests focus on inventory management and production systems. With a Scopus H-index of 21, Dr. Wakhid Ahmad Jauhari is widely recognized for his significant contributions to the field of industrial engineering, both nationally and internationally.

Retno Wulan Damayanti is a Professor in the Industrial Engineering Study Program, Faculty of Engineering, at Universitas Sebelas Maret (UNS). She is a lecturer in Industrial Engineering. She obtained a Bachelor's degree in the Department of Industrial Engineering, Faculty of Engineering, Sebelas Maret University, in 2003. She obtained her Master’s degree in Industrial Engineering from Bandung Institute of Technology, Bandung, in 2006. She earned a Doctorate in Industrial Engineering from Gadjah Mada University, Yogyakarta in 2021. Her areas of expertise include Project and Megaproject Management, Complexity Management, Leadership, and Quality Management and Engineering.

Cucuk Nur Rosyidi was born in Lumajang in 1971. He completed his undergraduate studies in Industrial Engineering at the Institut Teknologi Sepuluh Nopember (ITS) and later pursued his Master’s and Doctoral degrees in Industrial Engineering at the Institut Teknologi Bandung (ITB). Currently, he is a Professor in the Industrial Engineering Study Program, Faculty of Engineering, at Universitas Sebelas Maret (UNS). He also actively involves in the Center for Research in Manufacturing Systems. His areas of expertise include Supply Chain Modelling and Quality Engineering.

Muhammad Hafidz Fazli Bin Md Fauadi is an Associate Professor and the Dean of the Faculty of Artificial Intelligence and Cyber Security (FAIX) at Universiti Teknikal Malaysia Melaka (UTeM), Malaysia. He received his Bachelor’s degree in Industrial Computing from Universiti Kebangsaan Malaysia (UKM) in 2004. In 2006, he earned a Master of Engineering in Mechanical Engineering (Advanced Manufacturing Technology) from Universiti Teknologi Malaysia (UTM). He completed his Doctor of Engineering in Information, Production, and Systems Engineering at Waseda University, Japan, in 2012. His research interests encompass applied artificial intelligence, smart manufacturing systems, simulation and optimization, and the Internet of Things.