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ELECTROCARDIOGRAM MONITOR SUPPLIER SELECTION BASED ON FUZZY MCDM EVALUATION METHOD

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Abstract. *The superior electrocardiogram (EKG) monitors can help doctors to discover abnormalities during the early stages of heart disease, and they are considered to be indispensable clinical medical instruments. The ability of a medical institution to select a superior EKG monitor can have a major impact on the quality of its medical care. However, the selection of an EKG monitor for a medical institution is not an easy decision, involving a host of complex considerations. Decision-making information is hard to come by and often vague. In view of the need to boost healthcare quality while controlling costs, an evaluation to select a suitable EKG monitor is therefore an important research topic for medical institutions. This article proposes the utilization of the fundamental principles encompassed in the fuzzy set theory to analyze and consider a multiplicity of complex criteria and determines the most suitable EKG monitor among the feasible suppliers. In light of this, the main purpose of this article is to propose a fuzzy MCDM evaluation method and to perform the selection of a best EKG monitor supplier for a regional hospital in Taiwan. The results showed that 1) the 'quality' constitutes the most important assessment dimension for EKG monitor suppliers; 2) among the assessment influence criteria, the 'product quality certification', 'product stability', and 'maintenance technology capabilities' are the most three determinants about the selection of EKG suppliers for the regional hospital in Taiwan; 3) Brand N was the best EKG monitor supplier for the regional hospital in Taiwan. Furthermore, some discussions concerning the case study are provided in this article. The main contribution of this article is that the definition, conversion, and treatment of vague and complex multi-layer criteria as set memberships under the fuzzy set theory are employed to develop a practical model for business purpose.*
Keywords: Fuzzy evaluation, MCDM, AHP, TOPSIS, EKG monitor, Supplier selection

1. Introduction.

According to a report issued by the World Health Organization (WHO) [1], heart disease has remained a major cause of death throughout the past 20 years. Since 2000, more than 2 million people have died from heart disease worldwide every year, and roughly 9 million people died of this cause in 2019, which indicates that deaths due to heart disease have been increasing steadily on a global basis. In addition, in accordance with the results of the WHO's survey, heart disease accounts for approximately 16% of all causes of death worldwide, which implies that roughly one out of six persons will die from heart disease. This further indicates that heart disease is a deadly killer and a severe threat to human life and health.

Among cardiovascular diseases, myocardial infarction is the most dangerous; when an acute myocardial infarction occurs, saving the patient's life requires taking advantage of

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the “golden first 12 hours”. The patient must be quickly transported to a hospital, where the first step will be electrocardiogram (EKG) monitoring. This is typically followed by emergency cardiac catheterization to clear the heart’s congested blood vessels and save the myocardium before necrosis occurs and causes heart failure or even death. EKG monitors are vital life-saving devices in the event of acute myocardial infarction [2,3], and physicians can use effective EKG monitors to quickly determine the location of the problem in cases of heart disease. As a consequence, EKG monitors are extremely important medical instruments during the diagnosis and treatment of heart disease.

While effective EKG monitors are extremely important life-saving devices [4], the quality of EKG instruments can have a major impact on the effectiveness of testing [5]. Furthermore, the quality of an EKG monitor will directly affect heart disease examination results and the timeliness of lifesaving treatments [6]. Because of this, the choice of EKG monitor will have tremendous influence on the quality of diagnosis and treatment at a medical institution. There are numerous EKG monitor brands, however, and it can be difficult to match the varying needs of medical institutions, physicians, and medical technologists with the functions provided by EKG devices. What functions and services provided by EKG monitor suppliers are truly needed by a hospital’s doctors or medical technologists? What methods and standards should medical institutions use to select EKG monitor brands or suppliers best meeting their needs? The evaluation and selection of EKG monitor brands or suppliers has undeniably become one of the most important procurement decision-making problems facing medical institutions today.

The EKG monitor supplier decision is a critical process involving conflicting qualitative and quantitative criteria. The evaluation process of EKG monitor supplier’s selection is strongly characterized by the multiple criteria decision making (MCDM) [7] problem. The MCDM method is used as a powerful analytical tool to overcome this complex selection process. Due to group decision-making and environmental variability, the relationships between the various criteria and their relative importance tend to be uncertain and variable [8]. As a result, conventional decision-making approaches have difficulty dealing with the fuzziness of criteria weights and conveying the imprecision inherent in decision-making information. These approaches evidently cannot fully express the implicit information in the various alternatives and decision-making criteria. Furthermore, it is also necessary to appropriately integrate the opinions of medical institutions’ decision-making groups or committees consisting of doctors and purchasing departments to provide a basis for the scoring and ranking of EKG monitor brands or suppliers, and thereby find a suitable EKG monitor supplier. This study consequently used fuzzy set theory [8] and MCDM to establish a fuzzy MCDM evaluation method for selecting the EKG monitor suppliers.

Selecting an appropriate supplier is vital to professional growth. Many researchers have investigated the topic of supplier evaluation. For example, Dickson [9] was the first to explore the supplier selection system and decision-making. Wetzstein et al. [10] reviewed 221 journal articles on supplier evaluation. Luthra et al. [11] established a sustainable comprehensive framework for supplier selection and evaluation. Ocampo et al. [12] conducted a literature analysis on supplier evaluation methods from 2006 to 2016. Taherdoost and Brard [13] analyzed the supplier evaluation process and the MCDM method. Chai and Ngai [14] illustrated the latest results and the future development direction. In addition, the selection of medical equipment suppliers is also prevalent in many relevant learned periodicals. For example, Beşkese and Evecen [15] examined supplier selection in the healthcare field. Osiro et al. [16] employed the fuzzy logic method to evaluate the medical equipment supplier selection process. Sabbaghi and Allahyari [17] probed into the supplier selection model of medical production. In addition, Forghani et al. [18] explored the supplier selection model of the medical supply chain. Liu et al. [19] discussed sustainable medical supplier selection. Therefore, it is evident that supplier selection in the health and medical fields is an important research topic recognized by many learned periodicals.

Based on the above literature, it is evident that many medical suppliers have been evaluated by the fuzzy MCDM methods. Osiro et al. [16] used fuzzy inference with the simple fuzzy grid method to evaluate the medical equipment supplier selection. Sabbaghi and Allahyari [17] used the technique for order preference by similarity to ideal solution (TOPSIS) to discuss the selection of medical production suppliers. Forghani et al. [18] investigated the selection process for medicine chain suppliers using principal component analysis (PCA) to combine the TOPSIS (Z-TOPSIS) method based on Z-numbers and the mixed integer linear programming (MILP) method. Cho and Kim [20] adopted the analytic hierarchy process (AHP) method to assess Korean medical equipment and materials. Barrios et al. [21] used AHP-TOPSIS to examine the process of how hospitals selected the most appropriate Tomography equipment. Pamucar et al. [22] used the fuzzy rough decision-making approach to investigate supplier selection in healthcare supply chain management. Finally, Khan et al. [23] reviewed 158 pieces of literature on supplier evaluation methods and found that AHP is the most widely used method, followed by TOPSIS. Therefore, this study constructed a fuzzy MCDM evaluation method for the selection of EKG monitor suppliers, which took the form of an AHP-TOPSIS evaluation method.

More specifically, the MCDM evaluation process typically involves several elements [7], mainly including the feasible alternative set, criteria set, criteria weights, performance matrix of all alternatives versus all criteria, comprehensive evaluation values and the decision ranking rule. In the course of this study, the fuzzy AHP method [24,25] was first used to obtain the relative weights of the assessment dimensions and criteria. The selection process involved many subjective and objective criteria, and these subjective/objective criteria included some benefit criteria (the larger the performance value, the greater the utility preference) and cost criteria (the larger the performance value, the lower the utility preference) [26]. To ensure that the utility preference had a consistent assessment direction, this study applied the basic concept of the TOPSIS method [26-28] – that the chosen alternative should have the shortest distance to the positive ideal solution and simultaneously the longest distance from the negative ideal solution – as a basis for ranking the alternatives in order of superiority.

In summary, experience has shown that the problem of ranking alternatives is not an easy task. It involves a multiplicity of complex considerations. Moreover, particularly regarding potential EKG suppliers, the linguistic terms and information to facilitate such suppliers are difficult to collect and evaluate. The fuzzy set theory is ideal for sorting through ambiguous data and at times conflicting information. Hence, the main purpose of this article is to propose a fuzzy AHP-TOPSIS evaluation method and perform the empirical selection of a best EKG monitor supplier for a regional hospital in Taiwan. This article contains five sections. Apart from the current section, the second section introduces the research method employed, the third section constructs a fuzzy AHP-TOPSIS model for selecting EKG monitor suppliers, the fourth section relies on empirical research to investigate the model's operating process, and the fifth section presents this study's conclusions.

2. **Research Method.** The following is a brief introduction to the research method employed in this study.

2.1. **Triangular fuzzy numbers and their algebraic operations.** Fuzzy set theory [8] treats vague data as possibility distributions that can be described employing set memberships. Once determined and defined, the sets of memberships in possibility distributions can be effectively used in logical reasoning. Because the triangular fuzzy numbers (TFNs) are easy to use and easy to interpret, TFNs are applied throughout this article.

A fuzzy number $\widetilde{A}$ [29] in real line $\Re$ is a TFN if its membership function $f_{\widetilde{A}} : \Re \to [0,1]$ is

$$f_{\widetilde{A}}(x) = \begin{cases} (x-a)/(b-a), & a \le x \le b \\ (x-c)/(b-c), & b \le x \le c \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

with $-\infty < a \le b \le c < \infty$. The TFN can be expressed as (a, b, c), and denoted by $\widetilde{A} = (a, b, c)$.

Assuming $\widetilde{A}_1 = (a_1, b_1, c_1)$ and $\widetilde{A}_2 = (a_2, b_2, c_2)$, in accordance with Zadeh's extension principle [8], the following fuzzy expressions are always true:

1) Fuzzy addition: $\widetilde{A}_1 \oplus \widetilde{A}_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2)$,

2) Fuzzy subtraction: $\widetilde{A}_1 \ominus \widetilde{A}_2 = (a_1 - c_2, b_1 - b_2, c_1 - a_2)$,

3) Fuzzy multiplication: $k \otimes \widetilde{A} = (ka, kb, kc)$, $k \ge 0$, $k \in R$; $\widetilde{A}_1 \otimes \widetilde{A}_2 \cong (a_1a_2, b_1b_2, c_1c_2)$, if $a_1 \ge 0$, $a_2 \ge 0$,

4) Fuzzy division: $\left(\widetilde{A}_1\right)^{-1} \cong \left(\frac{1}{c_1}, \frac{1}{b_1}, \frac{1}{a_1}\right)$, $a_1 > 0$; $\widetilde{A}_1 \oslash \widetilde{A}_2 \cong (a_1/c_2, b_1/b_2, c_1/a_2)$, if $a_1 \ge 0$, $a_2 > 0$.

2.2. **Linguistic variables.** Linguistic variables [30-32] facilitate expression of complex terms or poorly defined descriptions using a quantitative syntax. Linguistic variables consist of variables that are expressed using words or sentences in natural language. Linguistic values allow the approximate reasoning of fuzzy set theory to be expressed in a rational manner. In a fuzzy decision-making environment, two types of preference scale [33] can be used to assess the comparison scale of each alternative under each criterion; one such scale consists of a TFN, and the other consists of linguistic values represented as TFNs. Decision-makers or decision-making groups can opt to use one scale, or use both scales simultaneously. This study employed "degree of superiority" to assess the performance values of alternatives relative to the assessment criteria. In addition, TFNs were used as linguistic values conveying degree of superiority. For instance, the linguistic variable set $S = \{\text{very poor, poor, fair, good, very good}\}$ was used to convey degree of superiority in this study. The membership functions of the linguistic variables in set S could be subjectively defined by decision-makers as very poor $(VP) = (0, 0, 0.25)$, poor $(P) = (0, 0.25, 0.5)$, fair $(F) = (0.25, 0.5, 0.75)$, good $(G) = (0.5, 0.75, 1)$, and very good $(VG) = (0.75, 1, 1)$. These TFNs are referred to in Ghyym [34].

2.3. **Distance method.** The mean distance and geometrical distance methods proposed by Heilpern [35] are the well-known distance methods. In order to improve Heilpern's geometrical distance formula, Hsieh and Chen [36] proposed a modified geometrical distance formula. Using the modified geometrical distance formula proposed by Hsieh and Chen [36], the two-dimensional distance between TFN $\widetilde{A}_i = (a_i, b_i, c_i)$ and $\widetilde{A}_j = (a_j, b_j, c_j)$ can be obtained, and is expressed as $GD_m\left(\widetilde{A}_i, \widetilde{A}_j\right)$. This distance is

$$GD_m\left(\widetilde{A}_i, \widetilde{A}_j\right) = \left\{\frac{1}{4}\left[(a_i - a_j)^2 + 2(b_i - b_j)^2 + (c_i - c_j)^2\right]\right\}^{1/2} \tag{2}$$

Based on the modified geometrical distance method, which can be considered an expanded form of conventional precise directional distance, this study used the distance formula in Equation (2) as a basis for deriving the distance between the two TFNs.

2.4. **Ranking method.** In a fuzzy decision-making environment, ranking the alternatives under consideration is essential. For matching the fuzzy MCDM method developed in this article, and solving the problem powerfully, this study adopts the graded mean integration representation (GMIR) proposed by Chen and Hsieh [37] after comparing the various ranking methods. The GMIR method is used here to perform the defuzzification of TFNs and assess the fuzzy rankings of alternatives.

Letting $\widetilde{A}_i = (a_i, b_i, c_i)$, $i = 1, 2, \ldots, n$ represent n TFNs, the GMIR value of TFN $\widetilde{A}_i$ after defuzzification is expressed as

$$G\left(\widetilde{A}_i\right) = (a_i + 4b_i + c_i)/6 \tag{3}$$

This study defines the ranking rules for the two fuzzy numbers $\widetilde{A}_i$ and $\widetilde{A}_j$ as

$$\begin{aligned} &\widetilde{A}_i > \widetilde{A}_j \Leftrightarrow G\left(\widetilde{A}_i\right) > G\left(\widetilde{A}_j\right); \\ &\widetilde{A}_i < \widetilde{A}_j \Leftrightarrow G\left(\widetilde{A}_i\right) < G\left(\widetilde{A}_j\right); \\ &\widetilde{A}_i = \widetilde{A}_j \Leftrightarrow G\left(\widetilde{A}_i\right) = G\left(\widetilde{A}_j\right). \end{aligned}$$

3. **Procedure for the Fuzzy AHP-TOPSIS Evaluation Method.** This section constructs a fuzzy MCDM assessment model, which took the form of an AHP-TOPSIS evaluation method for selecting the best EKG monitor supplier. We hope that this systematic model will be objective and easy to use. The steps in this evaluation method are as follows.

Step 1: Forming an assessment committee.

Step 2: Aggregating assessment criteria for selection of EKG monitor suppliers.

Step 3: Establishment of a hierarchical structure.

Step 4: Use of the fuzzy AHP method to obtain the weights of the assessment criteria on each layer.

Step 5: Assessment of the fuzzy superiority of all alternatives versus all assessment criteria.

Step 6: Derivation of the ideal solution and negative ideal solution for all assessment criteria versus alternatives layer.

Step 7: Use of the distance formula to derive the distance from each alternative to the ideal solution and negative ideal solution.

Step 8: Derivation of the relative closeness of each alternative to the ideal solution, and thereby select the optimal EKG monitor supplier.

To be easy to understand the proposed model, the flow chart of the fuzzy AHP-TOPSIS method in this article can be shown as Figure 1.

3.1. **Forming an assessment committee.** Decision-making surrounding the MCDM problem should consider the goals, criteria, and alternatives. Researchers should also consider the following questions: "How should the performance values be measured?" "How is a trade-off conducted when the criteria are conflicted?" and "Should the focus be on single-person decision-making or group decision-making?" Decision-making topics, such as the decision-makers' preferences and the relative importance of the criteria, should also be considered. The above MCDM problem has been developed regarding single-person decision-making. Its decision-making situation and results are simple because only one person is making the decision. However, in group decision-making, since the decision-makers involve a decision-making group or committee, the decision-making process is characterized by dynamic bias and strong bargaining characteristics. Therefore, the result of decision-making is typically comprised of composite or trade-off solutions.

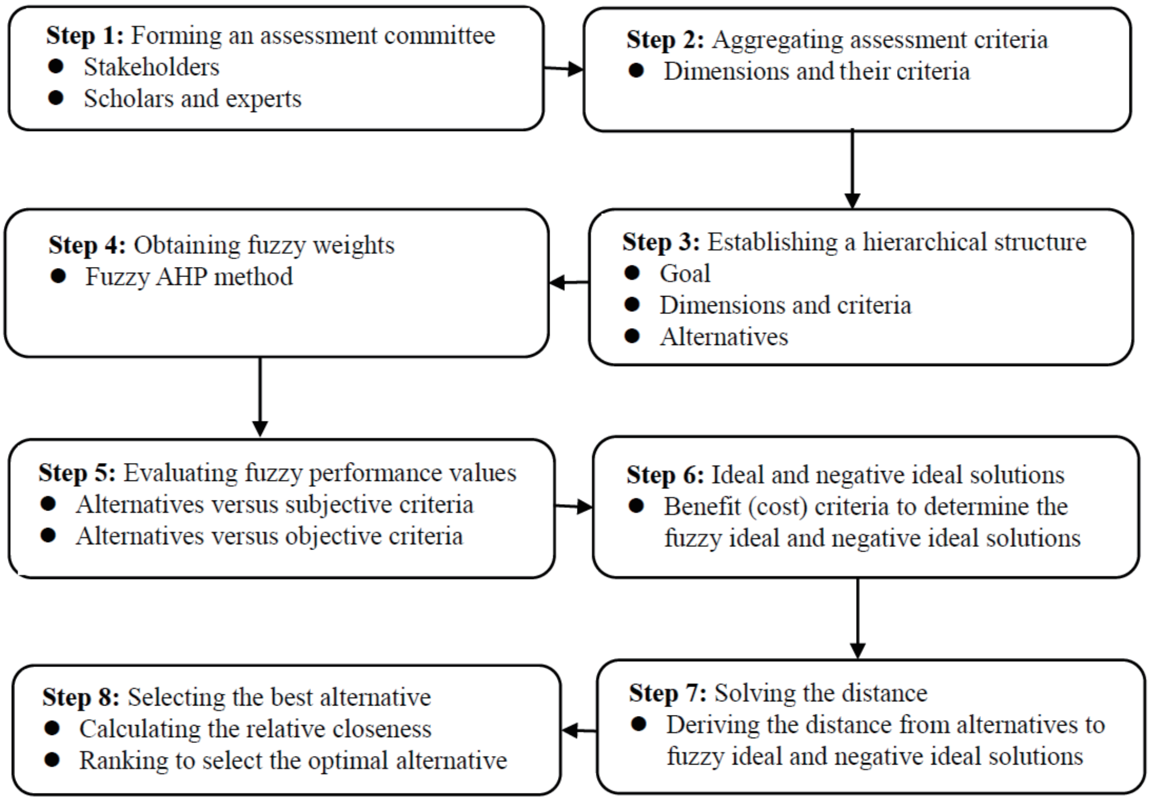

FIGURE 1. Flow chart of the fuzzy AHP-TOPSIS method

Group decision-making of a committee should rely on the professional experience, intuition, and value judgment of experts to make effective decisions. The committee composition should comprise a panel of experts with 10-15 members [38], researching and making decisions on the specific MCDM problem from multiple expert perspectives from different fields. In addition, when MCDM problems become increasingly complex, the evaluation system and factors should be widened. Then, it will become necessary to rely on professionals in different fields to provide professional judgment to obtain a higher quality of decision-making.

This study examines how hospitals can evaluate and select the best EKG monitor supplier. The first task of hospitals is to establish an EKG purchasing committee to evaluate and select the best EKG monitor supplier to purchase EKG monitors appropriate for doctors and patients. This study suggests that the stakeholders suitable to serve as the selection commissioners comprise the following expert groups: university professors engaged in medical equipment research, hospital cardiologists, cardiac medical technologists, and hospital procurement personnel.

3.2. **Selecting assessment criteria.** Factors that may influence the selection of EKG monitor suppliers are complex and far-ranging. To obtain preliminary assessment criteria for selecting EKG monitor suppliers, this study first summarized supplier selection content proposed by the relevant literature, as shown in Table 1.

To obtain the factors influencing the selection of an EKG monitor supplier, the assessment criteria in Table 1 were reviewed and discussed by 10 experts: three university professor performing medical equipment research, three cardiologists, three cardiac medical technologists, and one person responsible for procurement at a hospital. Five major assessment dimensions of ‘quality’, ‘service level’, ‘cost and price’, ‘delivery speed’, and ‘technological

Table 1. Preliminary assessment criteria of EKG monitor suppliers

Assessment factors \ Authors	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**	**M**	**N**	**O**
Product quality has reliability	√	√		√	√	√	√	√		√	√	√	√	√	√
Product has good brand reputation	√	√		√	√				√		√				
Product quality is certified	√	√		√	√	√		√	√		√		√		√
Product has good stability	√	√			√	√	√				√	√	√	√	√
Have good after-sales service	√	√	√	√	√	√				√			√	√	
Have the ability to deal with customer complaints immediately	√	√		√	√	√									
Have perfect and good communication channels	√	√		√	√	√									
Have perfect product education and training	√			√			√							√	
Provide hospitals with reasonable transaction prices	√	√	√	√	√	√	√	√		√			√	√	
Instant price response capability			√	√	√		√						√		
Logistics and transportation costs	√	√	√	√	√	√	√	√		√			√		
Accuracy of delivery	√	√	√	√	√	√	√	√					√		
Stable supply	√	√	√		√	√	√	√					√		
Supply ability with emergency response			√	√	√		√	√		√			√		
Have the ability to research and develop innovation	√			√	√	√	√				√	√		√	√
Have the ability to maintain technology	√	√	√	√	√	√	√		√		√	√		√	√
Have the ability to respond quickly to order changes	√		√	√	√				√				√		
Note: A: [9]; **B**: [13]; **C**: [15]; **D**: [16]; **E**: [17]; **F**: [18]; **G**: [19]; **H**: [39]; **I**: [40]; **J**: [41]; **K**: [42]; **L**: [43]; **M**: [44]; **N**: [45]; **O**: [46]															

capability' were then obtained. The 17 assessment criteria under these assessment dimensions are as follows.

1) Quality (C_1): This assessment dimension included the 4 assessment criteria of "reliable outgoing quality (C_{11})", "excellent brand reputation (C_{12})", "product quality certification (C_{13})", and "product stability (C_{14})".
2) Service level (C_2): This assessment dimension included the 4 assessment criteria of "excellent after-sales service (C_{21})", "ability to immediately respond to customer complaints (C_{22})", "excellent channels of communication (C_{23})", and "excellent product education and training (C_{24})".
3) Cost and price (C_3): This assessment dimension included the 3 assessment criteria of "reasonable price (C_{31})", "rapid price response ability (C_{32})", and "shipping cost (C_{33})".
4) Delivery speed (C_4): This assessment dimension included the 3 assessment criteria of "accuracy of delivery time (C_{41})", "able to make correct, stable deliveries (C_{42})", and "emergency response delivery capability (C_{43})".
5) Technological capability (C_5): This assessment dimension included the 3 assessment criteria of "R&D and innovation capabilities (C_{51})", "maintenance technology capabilities (C_{52})", and "ability to respond quickly to order changes (C_{53})".

3.3. **Establishing a hierarchical structure.** A hierarchical structure [33] representing the system framework was used to research the interaction of key factors at each level and their impact on the system as a whole. The number of hierarchical layers [24] also reveals a system's complexity and analytical needs. This study employed the hierarchical structure shown in Figure 2 as the basis for selecting EKG monitor suppliers. In this structure, the first layer consisted of the objective, which was to select the best EKG monitor supplier, the second layer contained k assessment dimensions of selecting EKG monitor supplier, the third layer contained the $n_1 + \cdots + n_t + \cdots + n_k$ assessment criteria under all assessment dimensions, and the fourth layer contained the m alternatives.

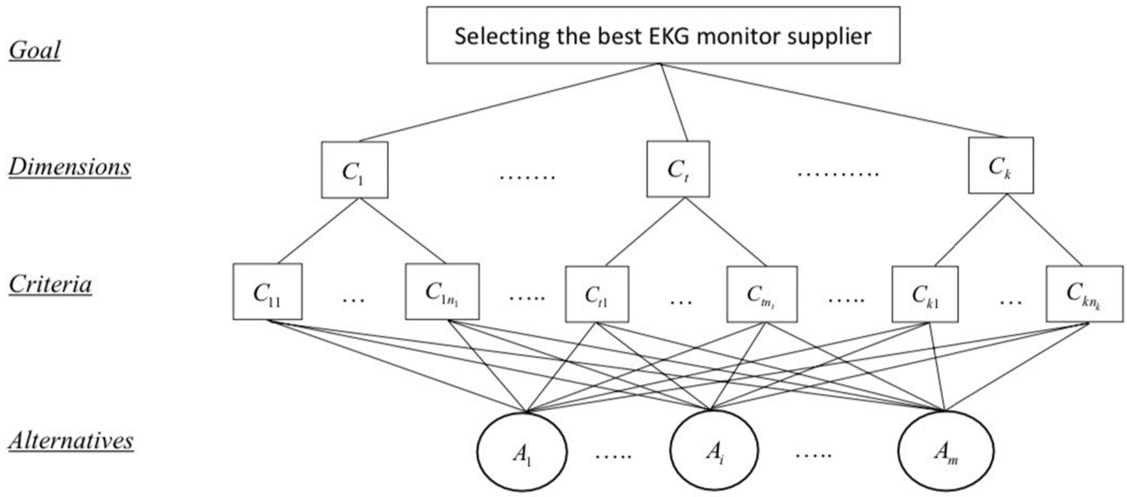

FIGURE 2. Hierarchical structure diagram

3.4. **Using the fuzzy AHP method to obtain the weights for all assessment dimensions and criteria.** This study used the fuzzy AHP method to derive the weights of all assessment dimensions and criteria. The following is a summary of the steps in the fuzzy AHP method [24,25,47].

3.4.1. *Pairwise comparison of crisp values.* A pairwise comparison questionnaire was used to obtain the experts' opinions concerning the relative importance of pairs of both assessment dimensions and assessment criteria.

1) Set l_{ij}^E as the opinion of expert E, where $E = 1, 2, \ldots, e$, concerning the relative importance of any two assessment dimensions i and j on the second layer (dimension layer), so that the pairwise comparison matrix for the second layer is $\left[l_{ij}^E\right]_{k\times k}$.
2) Set l_{uv}^E as the opinion of expert E, where $E = 1, 2, \ldots, e$, concerning the relative importance of any two assessment criteria u and v on the third layer (criteria layer) under a certain assessment dimension of $C_1, \ldots, C_t, \ldots, C_k$ on the second layer. Then the pairwise comparison matrices of any two assessment criteria u and v on the third layer are consequently expressed as $\left[l_{uv}^E\right]_{n_1\times n_1}, \ldots, \left[l_{uv}^E\right]_{n_t\times n_t}, \ldots$, and $\left[l_{uv}^E\right]_{n_k\times n_k}$.

3.4.2. *Establishment of TFNs.* To integrate the consensus of experts [24,48], Hsu [49] took the decision-makers' lowest assessment value of any assessment criterion as the lower bound of the TFN, took the highest assessment value as the upper bound of the TFN, and took the geometric mean of all assessment values as the value when the grade of membership of the TFN is 1.

Accordingly, set $l_{ij}^E \in \left[\frac{1}{9}, \frac{1}{8}, \ldots, \frac{1}{2}, 1\right] \cup [1, 2, \ldots, 8, 9]$, as the opinion of expert E, where $E = 1, 2, \ldots, e$, concerning the relative importance of any two assessment dimensions i and j on the second layer, where $\forall i, j = 1, 2, \ldots, k$. Then let $\widetilde{D}_{ij} = (a_{ij}, b_{ij}, c_{ij})$ be a

TFN integrating the opinions of all e experts concerning the assessment dimensions on the second layer; in this equation:

$$a_{ij} = \min\left\{l_{ij}^1, l_{ij}^2, \ldots, l_{ij}^e\right\}, \quad b_{ij} = \left(\prod_{E=1}^{e} l_{ij}^E\right)^{1/e}, \quad c_{ij} = \max\left\{l_{ij}^1, l_{ij}^2, \ldots, l_{ij}^e\right\}.$$

Similarly, the TFN integrating the experts' opinions in the third layer is $\widetilde{C}_{uv} = (a_{uv}, b_{uv}, c_{uv})$, $\forall u, v = 1, \ldots, n_1; \ldots; \forall u, v = 1, \ldots, n_t; \ldots; \forall u, v = 1, \ldots, n_k$, where

$$a_{uv} = \min\left\{l_{uv}^1, l_{uv}^2, \ldots, l_{uv}^e\right\}, \quad b_{uv} = \left(\prod_{E=1}^{e} l_{uv}^E\right)^{1/e}, \quad c_{uv} = \max\left\{l_{uv}^1, l_{uv}^2, \ldots, l_{uv}^e\right\}.$$

3.4.3. *Establishment of a fuzzy positive reciprocal matrix for each layer.* A fuzzy positive reciprocal matrix was then established employing the resulting fuzzy numbers after the experts performed pairwise comparison for each layer. In the case of the second layer, the fuzzy positive reciprocal matrix is

$$D = \left[\widetilde{D}_{ij}\right] = \begin{bmatrix} \widetilde{1} & \widetilde{D}_{12} & \cdots & \widetilde{D}_{1k} \\ \widetilde{D}_{21} & \widetilde{1} & \cdots & \widetilde{D}_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{D}_{k1} & \widetilde{D}_{k2} & \cdots & \widetilde{1} \end{bmatrix}, \text{ where } \widetilde{D}_{ij} \otimes \widetilde{D}_{ji} \cong 1, \ \ \forall i, j = 1, 2, \ldots, k.$$

To save space, the equations of fuzzy positive reciprocal matrices are omitted by reason of analogy on the third layer.

3.4.4. *Calculating the fuzzy weights of the fuzzy positive reciprocal matrix for each layer.* In the case of the second layer, setting $\widetilde{G}_i \cong \left(\widetilde{D}_{i1} \otimes \widetilde{D}_{i2} \otimes \cdots \otimes \widetilde{D}_{ik}\right)^{1/k}$, $\forall i = 1, 2, \ldots, k$, as the geometric mean of the TFN for the ith assessment dimension, the fuzzy weight of the ith assessment dimensions can be expressed as

$$\widetilde{w}_i \cong \widetilde{G}_i \otimes \left(\widetilde{G}_1 \oplus \widetilde{G}_2 \oplus \cdots \oplus \widetilde{G}_k\right)^{-1}.$$

For convenience, the TFN is expressed as $\widetilde{w}_i = (a_i^w, b_i^w, c_i^w)$.

To save space, the equations of fuzzy weights are omitted by reason of analogy on the third layer.

3.4.5. *Defuzzification of the fuzzy weights.* Because the defuzzification process in the GMIR method proposed by Chen and Hsieh [37] is very effective and convenient, this study used Formula (3) in Section 2.4 to perform defuzzification.

Letting $\widetilde{w}_i = (a_i^w, b_i^w, c_i^w)$, $\forall i = 1, 2, \ldots, k$, for k triangular fuzzy weights, the k crisp weights after defuzzification are

$$G(\widetilde{w}_i) = (a_i^w + 4b_i^w + c_i^w)/6, \ \ \forall i = 1, 2, \ldots, k.$$

To save space, the defuzzifications of fuzzy weights are omitted by reason of analogy on the third layer.

3.4.6. *Normalization.* To facilitate comparison of the relative importance of each assessment dimension and criteria at each layer, the k crisp weights resulting from the foregoing defuzzification process were then normalized as

$$\eta_i = G(\widetilde{w}_i) \Big/ \sum_{i=1}^{k} G(\widetilde{w}_i).$$

3.4.7. *Integrated weights of the assessment dimensions and criteria on each layer.* Expressing the normalized crisp weights on the second and third layers as η_i ($\forall i = 1, 2, \ldots, k$) and η_u ($\forall u = 1, \ldots, n_1; \ldots; \forall u = 1, \ldots, n_t; \ldots; \forall u = 1, \ldots, n_k$), then

1) The integrated weight ξ_i of each assessment dimension on the second layer is still η_i, namely

$$\xi_i = \eta_i, \quad \forall i = 1, 2, \ldots, k.$$

2) The integrated weight ξ_u of each assessment criteria on the third layer is

$$\xi_u = \eta_i \times \eta_u, \quad \forall i = 1, 2, \ldots, k; \ \forall u = 1, \ldots, n_1; \ldots; \forall u = 1, \ldots, n_t; \ldots; \forall u = 1, \ldots, n_k.$$

3.5. **Estimating fuzzy superiority of all alternatives versus all assessment criteria.** This step consisted of assessing the superiority (performance value) of all alternatives versus all assessment criteria, and then using the resulting performance values as a basis for decision-making judgments, which is one of the most important processes in MCDM assessment [7,50]. In the real world, assessment criteria can generally be classified as two types [33]:

1) Subjective criteria: Can have linguistic or qualitative definitions; examples include "reliable outgoing quality (C_{11})" and "excellent brand reputation (C_{12})", etc.
2) Objective criteria: Can be defined in monetary or quantitative terms; examples include "reasonable price (C_{31})" and "shipping cost (C_{33})", etc.

Let $SC = \{s_1, \ldots, s_t, \ldots, s_p\}$ and $OC = \{o_1, \ldots, o_r, \ldots, o_q\}$ express all p subjective criteria and q objective criteria above the alternatives layer.

3.5.1. *Subjective (qualitative) sub-criteria.* The first step was to assess the superiority of all assessment criteria above the alternatives layer. The linguistic variables shown in Section 2.2 were used, and the results of assessment of these linguistic variables were converted to TFNs. For instance, when one expert assessed EKG monitor supplier A_1 relative to subjective criterion "reliable outgoing quality (C_{11})", the assessment result was "good (G)", which we could convert to the TFN as $(0.5, 0.75, 1)$.

Next, the fuzzy superiority values are derived using the arithmetic mean [50]. Letting $\widetilde{\gamma}_{it}^E = \left(a_{it}^E, b_{it}^E, c_{it}^E\right)$, $i = 1, 2, \ldots, m$; $t = 1, 2, \ldots, p$; $E = 1, 2, \ldots, e$, be the fuzzy superiority value of the ith EKG monitor supplier relative to the tth subjective criterion as assessed by the Eth expert, the arithmetic mean is then taken to obtain the mean superiority, which can be expressed as

$$\pi_{it} = \left(\frac{\sum_{E=1}^{e} a_{it}^E}{e}, \frac{\sum_{E=1}^{e} b_{it}^E}{e}, \frac{\sum_{E=1}^{e} c_{it}^E}{e} \right).$$

3.5.2. *Objective (quantitative) sub-criteria.* In the case of objective criteria, the fuzzy superiority value of each alternative can be handled using one of the following two methods [33]:

1) If the value cannot be precisely assessed numerically, the researchers or decision-making group can use objective data to perform assessment. For instance, in the case of "reasonable price (C_{31})", if each EKG monitor costs approximately US$10,000, we can express this with a TFN such as $(8900, 10000, 11250)$ or $(9200, 10000, 10890)$.
2) Using multi-period historical data, conversion is performed using the following method: Letting $x_1, \ldots, x_z, \ldots, x_d$, $z = 1, 2, \ldots, d$, be the price during past period d, the fuzzy assessment value can be expressed as $\left(\min_z\{x_z\}, \left(\prod_{z=1}^{d} x_z\right)^{1/d}, \max_z\{x_z\}\right)$.

3.6. **Deriving the ideal solution and negative ideal solution for all assessment criteria versus all alternatives.** This study used the ideal solution and negative ideal solution concept to derive an optimal alternative [26]. This concept involves the relative closeness between the assessed alternatives and the ideal solution. The closer the assessment criterion is to the ideal solution, and the greater their distance from the negative ideal solution, the more that solution approaches an optimal alternative.

Assuming that there are m alternatives and $n_1 + \cdots + n_t + \cdots + n_k = N$ assessment criteria. Let $\widetilde{\pi}_{ij} = (a_{ij}, b_{ij}, c_{ij})$, $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, N$, be the mean fuzzy superiority value of the ith alternative relative to the jth assessment criterion. Because the assessment criteria include both positive (or benefit) criteria and negative (or cost) criteria, the ideal solution constitutes either the maximum value of the benefit criteria or the minimum value of the cost criteria, and the negative ideal solution constitutes either the maximum value of the cost criteria or the minimum value of the benefit criteria. In this situation, to ensure that there is a consistent basis for assessing the performance value, all benefit criteria and cost criteria must be normalized.

To perform normalization, let $\sigma_j = \max_i\{c_{ij}\}$ and $\rho_j = \min_i\{a_{ij}\}$, and then the normalized fuzzy superiority value $\widetilde{\alpha}_{ij}$ of the ith alternative relative to the jth assessment criterion is defined as follows.

1) For benefit assessment criterion j: The greater the value, the greater the positive contribution made by criterion j to the performance value

$$\widetilde{\alpha}_{ij} = (f_{ij}, g_{ij}, h_{ij}) = \left(\frac{a_{ij}}{\sigma_j}, \frac{b_{ij}}{\sigma_j}, \frac{c_{ij}}{\sigma_j}\right)$$

2) For cost assessment criterion j: The smaller the value, the greater the negative contribution made by criterion j to the performance value

$$\widetilde{\alpha}_{ij} = (f_{ij}, g_{ij}, h_{ij}) = \left(\frac{\rho_j}{c_{ij}}, \frac{\rho_j}{b_{ij}}, \frac{\rho_j}{a_{ij}}\right)$$

We used the GMIR method [37] to compute the representative value of $\widetilde{\alpha}_{ij}$ as $G(\widetilde{\alpha}_{ij})$. A comparison of these GMIR values allowed the fuzzy ideal value $\widetilde{\psi}_j^+$ and fuzzy negative ideal value $\widetilde{\phi}_j^-$ to be determined as follows:

1) For benefit assessment criterion j:
   (i) If $G(\widetilde{\alpha}_{kj}) = \max_i G(\widetilde{\alpha}_{ij})$, then the fuzzy ideal value is $\widetilde{\psi}_j^+ = \widetilde{\alpha}_{kj}$.
   (ii) If $G(\widetilde{\alpha}_{tj}) = \min_i G(\widetilde{\alpha}_{ij})$, then the fuzzy negative ideal value is $\widetilde{\phi}_j^- = \widetilde{\alpha}_{tj}$.
2) For cost assessment criterion j:
   (i) If $G(\widetilde{\alpha}_{kj}) = \min_i G(\widetilde{\alpha}_{ij})$, then the fuzzy ideal value is $\widetilde{\psi}_j^+ = \widetilde{\alpha}_{kj}$.
   (ii) If $G(\widetilde{\alpha}_{tj}) = \max_i G(\widetilde{\alpha}_{ij})$, then the fuzzy negative ideal value is $\widetilde{\phi}_j^- = \widetilde{\alpha}_{tj}$.

Finally, the fuzzy ideal solution $\widetilde{\Psi}^+$ and the fuzzy negative ideal solution $\widetilde{\Phi}^-$ can be defined as

$$\widetilde{\Psi}^+ = \left(\widetilde{\psi}_1^+, \widetilde{\psi}_2^+, \ldots, \widetilde{\psi}_j^+, \ldots, \widetilde{\psi}_N^+\right)$$

and

$$\widetilde{\Phi}^- = \left(\widetilde{\phi}_1^-, \widetilde{\phi}_2^-, \ldots, \widetilde{\phi}_j^-, \ldots, \widetilde{\phi}_N^-\right).$$

3.7. **Solving the distance from each alternative to the ideal solution and negative ideal solution.** Letting ξ_j^*, $j = 1, 2, \ldots, N$, be the integrated weight of assessment criterion j obtained from the fuzzy AHP method in Section 3.4, the distance from the alternatives to fuzzy ideal solution $\widetilde{\Psi}^+$ and to fuzzy negative ideal solution $\widetilde{\Phi}^-$ can be expressed as Δ_i^+ and Δ_i^-, which are defined as

$$\Delta_i^+ = \sqrt{\sum_{j=1}^{N} \left\{ \left(\xi_j^*\right)^2 \times \left[GD_m \left(\widetilde{\psi}_j^+, \widetilde{\alpha}_{ij} \right) \right]^2 \right\}}$$

and

$$\Delta_i^- = \sqrt{\sum_{j=1}^{N} \left\{ \left(\xi_j^*\right)^2 \times \left[GD_m \left(\widetilde{\phi}_j^-, \widetilde{\alpha}_{ij} \right) \right]^2 \right\}}, \quad i = 1, 2, \ldots, m.$$

Here Formula (2) in Section 2.3 can be used to obtain $GD_m(\bullet)$.

3.8. **Calculating the relative closeness of each alternative to the ideal solution and performing ranking.** This study used the distance between each alternative A_i and the ideal solution to assess the superiority of that alternative, which involved use of the relative closeness index RC_i^* to assess the superiority of each alternative. This was defined as

$$RC_i^* = \frac{\Delta_i^-}{\Delta_i^+ + \Delta_i^-}, \quad i = 1, 2, \ldots, m.$$

This formula reveals that when $0 \leq RC_i^* \leq 1$, the larger RC_i^*, the greater the value of Δ_i^-. This indicates that the greater the distance between alternative A_i and the negative ideal solution (which also implies the nearer alternative A_i is to the ideal solution), the higher the rank of alternative A_i. Accordingly, we ranked the m alternatives on the basis of their RC_i^* values, which allowed us to select the optimal alternative.

4. **Case Study.** We employed the proposed fuzzy AHP-TOPSIS method to perform the selection of an optimal EKG monitor supplier from among three major suppliers by a regional hospital in Taiwan. The analytical process and its content are stated as follows.

4.1. **Forming an assessment committee to determine the hierarchical structure.** The case examined in this study involved the selection of an optimal EKG monitor from among three EKG monitor suppliers (i.e., G, N, P) by the procurement unit at a regional hospital in Taiwan for use by the hospital's cardiologists and cardiac medical technologists. The following is a summary of information concerning the three EKG monitor suppliers.

- Supplier G is an American transnational healthcare system conglomerate. This company provides innovative medical technologies and services meeting the needs of global customers and consumers, and it seeks to help more people around the world obtain better and more affordable medical services. The company currently relies on its superior solutions in such areas as medical imaging, software and information technology, patient monitoring and diagnosis, drug R&D, and biopharmaceutical technology to help medical professionals provide patients with high-quality healthcare services.
- Supplier N is a leading Japanese developer, manufacturer, and distributor of medical electronic equipment. This company's mission is to use advanced technology to enhance people's quality of life, and the focal areas of its developmental efforts include emergency care, home care, and health promotion. It dedicated to using cutting-edge technology to fight disease and improve people's health. This company's optoelectronic EKG monitors are widely used in medical centers and emergency rooms worldwide, and it is a leading brand of EKG monitors.

- Supplier P is a leading European healthcare technology firm. This company possesses advanced technology, abundant clinical experience, and extensive consumer recognition, and also has the ability to develop innovative integrated solutions. In addition, this company is also a leading name in the fields of diagnostic imaging, image-guided therapies, patient monitoring, medical informatization, consumer health, and home care.

This study first assembled an EKG monitor procurement assessment committee. The 12 experts forming this committee consisted of five cardiologists, five cardiac medical technologists, and two procurement department personnel, including a manager. We then constructed the hierarchical structure shown in Figure 3 on the basis of the 5 assessment dimensions, 17 assessment criteria, and 3 EKG monitor suppliers. Lastly, the 12 expert committee members assessed the importance of each assessment criterion in this hierarchical structure, and determined the superiority (performance value) of each EKG monitor supplier relative to all assessment criteria.

4.2. **Evaluating weights for all criteria using fuzzy AHP method.** The AHP expert questionnaire was issued to 12 experts to obtain their views concerning the relative importance of the assessment dimensions and assessment criteria. The results of the questionnaire were used as a basis for the pairwise comparison matrices containing the 5 major assessment dimensions and 17 assessment criteria in Figure 3. All twelve of the distributed questionnaires were recovered, for a recovery rate of 100%. The empirical process of this case study is based on Hsu and Ding's article [25], the questionnaire had a consistency index value of less than 0.1, which indicates that the pairwise comparison matrices met the consistency requirement. The consistency among the experts' judgments indicates that the questionnaire can be considered a valid expert questionnaire. In view of Robbins' suggestion [51] that the number of experts engaged in group decision-making cases should require at least 5-7. Hence, the views expressed on the 12 recovered valid AHP expert questionnaires in this study were sufficient to provide representative opinions.

We used the fuzzy AHP method, the integrated weights and rank of each assessment dimension and assessment criterion are provided. The final results are shown in Table 2.

4.3. **Assessing fuzzy superiority values of three alternatives relative to all assessment criteria.** This study designed a questionnaire assessing the performance values of three EKG monitor suppliers, and asked 12 experts to rate the superiority of the three suppliers with regard to all assessment criteria. We can be seen that the two criteria – "reasonable price (C_{31})" and "shipping cost (C_{33})" – were objective criteria and also cost criteria, while the remaining 15 criteria were all subjective criteria and also benefit criteria. This study used the concepts in Section 3.5 to integrate the fuzzy superiority values of the 15 subjective criteria and 2 objective criteria as suggested by the 12 experts, which yielded the results shown in Table 3 and Table 4.

4.4. **Calculating the ideal solution and negative ideal solution.** This case study contained 15 subjective criteria and 2 objective criteria, and also contained 15 benefit criteria and 2 cost criteria. To ensure that performance values could be assessed on a consistent basis, we used the concepts in Section 3.6 to normalize all benefit criteria and cost criteria, which yielded normalized fuzzy superiority values $\widetilde{\alpha}_{ij}$, and then obtained the $G(\widetilde{\alpha}_{ij})$ values, as shown in Table 5.

We next used the data in Table 5 to compare the GMIR values of all criteria relative to the three EKG monitor suppliers, which allowed us to determine the fuzzy ideal values $\widetilde{\psi}_j^+$ and fuzzy negative ideal values $\widetilde{\phi}_j^-$, which are shown in Table 6.

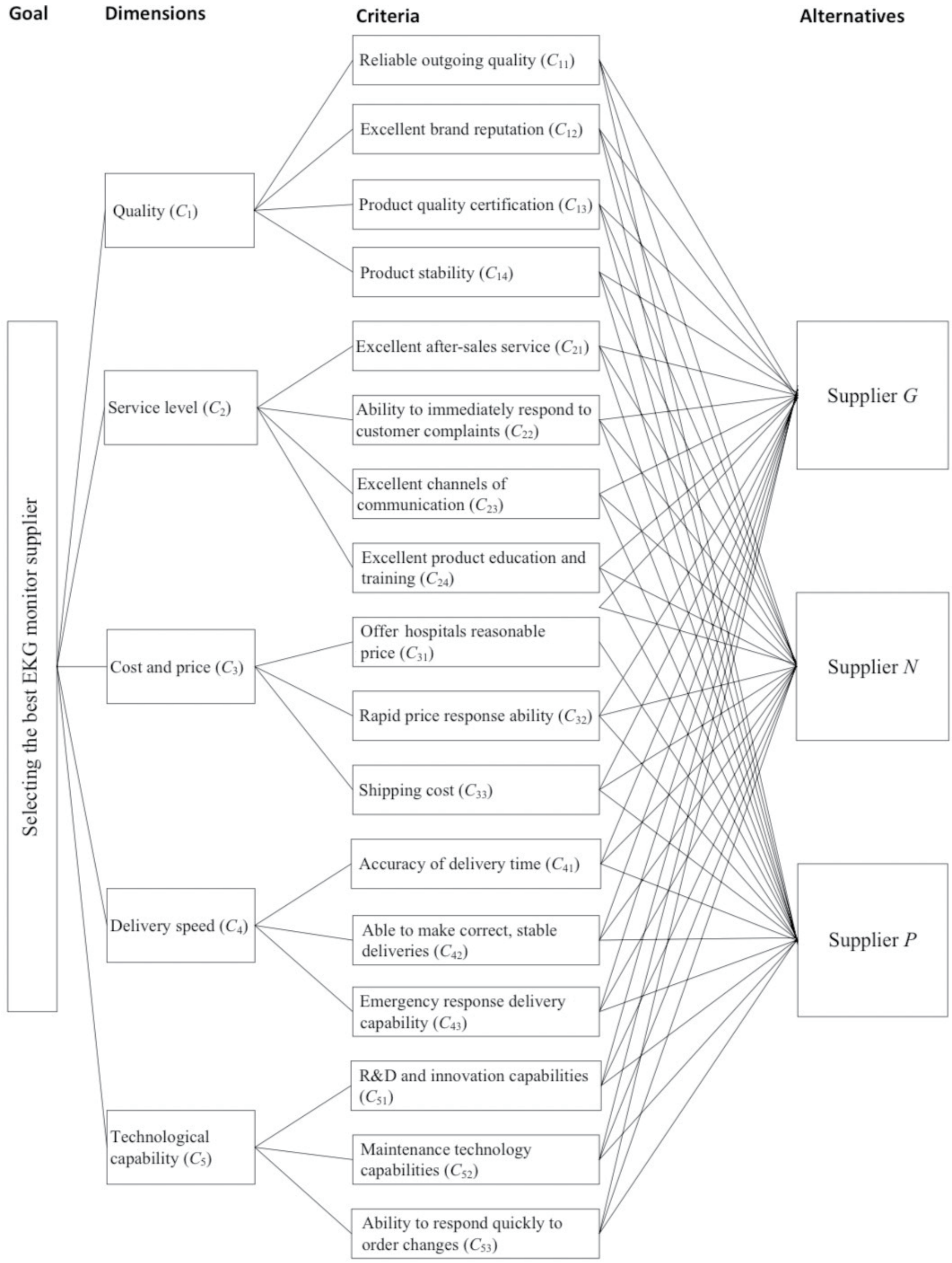

FIGURE 3. Hierarchical structure for selecting the EKG monitor supplier

We then used the data in Table 6 to determine the fuzzy ideal solution $\widetilde{\Psi}^+$ and fuzzy negative ideal solution $\widetilde{\Phi}^-$, which are

$$\widetilde{\Psi}^+ = [(0.708, 0.958, 1), (0.667, 0.917, 1), \ldots, (0.750, 1, 1), (0.583, 0.833, 1)]$$

and

$$\widetilde{\Phi}^- = [(0.458, 0.708, 0.917), (0.333, 0.583, 0.833), \ldots, (0.417, 0.667, 0.917), (0.333, 0.583, 0.833)].$$

TABLE 2. The integration weights of evaluation dimensions and assessment criteria

Dimensions	**Local weight (A)**	**Criteria**	**Local weight (B)**	**Integration weight (C) = (A)∗(B)**
C_1	0.341 (1)	C_{11}	0.218 (3)	0.0743 (6)
		C_{12}	0.20 (4)	0.0682 (7)
		C_{13}	0.295 (1)	0.1006 (1)
		C_{14}	0.287 (2)	0.0979 (2)
C_2	0.217 (3)	C_{21}	0.298 (2)	0.0647 (10)
		C_{22}	0.107 (4)	0.0232 (15)
		C_{23}	0.246 (3)	0.0534 (11)
		C_{24}	0.349 (1)	0.0757 (5)
C_3	0.127 (4)	C_{31}	0.525 (1)	0.0667 (9)
		C_{32}	0.346 (2)	0.0439 (12)
		C_{33}	0.129 (3)	0.0164 (17)
C_4	0.080 (5)	C_{41}	0.247 (3)	0.0198 (16)
		C_{42}	0.375 (2)	0.030 (14)
		C_{43}	0.378 (1)	0.0302 (13)
C_5	0.235 (2)	C_{51}	0.338 (2)	0.0794 (4)
		C_{52}	0.372 (1)	0.0874 (3)
		C_{53}	0.290 (3)	0.0682 (8)

Note: The number in the parentheses after the weight number means the ranking.

TABLE 3. The fuzzy superiority values of 15 subjective criteria

Criteria	Fuzzy superiority values		
	Supplier G	Supplier N	Supplier P
C_{11}	$(0.458, 0.708, 0.917)$	$(0.708, 0.958, 1)$	$(0.583, 0.833, 1)$
C_{12}	$(0.333, 0.583, 0.833)$	$(0.667, 0.917, 1)$	$(0.583, 0.833, 1)$
C_{13}	$(0.333, 0.583, 0.833)$	$(0.667, 0.917, 1)$	$(0.583, 0.833, 1)$
C_{14}	$(0.50, 0.750, 1)$	$(0.750, 1, 1)$	$(0.667, 0.917, 1)$
C_{21}	$(0.333, 0.583, 0.833)$	$(0.667, 0.917, 1)$	$(0.50, 0.750, 0.917)$
C_{22}	$(0.333, 0.583, 0.833)$	$(0.667, 0.917, 1)$	$(0.250, 0.50, 0.750)$
C_{23}	$(0.083, 0.333, 0.583)$	$(0.583, 0.833, 1)$	$(0.333, 0.583, 0.833)$
C_{24}	$(0.250, 0.50, 0.750)$	$(0.50, 0.750, 1)$	$(0.333, 0.583, 0.833)$
C_{32}	$(0.333, 0.583, 0.833)$	$(0.50, 0.750, 0.917)$	$(0.250, 0.50, 0.750)$
C_{41}	$(0.417, 0.667, 0.917)$	$(0.667, 0.917, 1)$	$(0.50, 0.750, 1)$
C_{42}	$(0.333, 0.583, 0.833)$	$(0.583, 0.833, 1)$	$(0.417, 0.667, 0.917)$
C_{43}	$(0.417, 0.667, 0.833)$	$(0.583, 0.833, 1)$	$(0.50, 0.750, 0.917)$
C_{51}	$(0.417, 0.667, 0.833)$	$(0.750, 1, 1)$	$(0.50, 0.750, 1)$
C_{52}	$(0.417, 0.667, 0.917)$	$(0.750, 1, 1)$	$(0.50, 0.750, 1)$
C_{53}	$(0.333, 0.583, 0.833)$	$(0.583, 0.833, 1)$	$(0.417, 0.667, 0.833)$

TABLE 4. The fuzzy superiority values of the two objective criteria

Criteria	Fuzzy superiority values		
	Supplier G	Supplier N	Supplier P
C_{31}	$(280, 284.90, 300)$	$(220, 229.68, 250)$	$(330, 339.90, 350)$
C_{33}	$(4.40, 4.425, 4.50)$	$(3.40, 3.474, 3.60)$	$(4.90, 5.023, 5.20)$

TABLE 5. Normalized fuzzy superiority values and GMIR values for all criteria

Criteria	Supplier G		Supplier N		Supplier P	
	$\widetilde{\alpha}_{ij}$	$G(\widetilde{\alpha}_{ij})$	$\widetilde{\alpha}_{ij}$	$G(\widetilde{\alpha}_{ij})$	$\widetilde{\alpha}_{ij}$	$G(\widetilde{\alpha}_{ij})$
C_{11}	$(0.458, 0.708, 0.917)$	0.701	$(0.708, 0.958, 1)$	0.924	$(0.583, 0.833, 1)$	0.819
C_{12}	$(0.333, 0.583, 0.833)$	0.583	$(0.667, 0.917, 1)$	0.889	$(0.583, 0.833, 1)$	0.819
C_{13}	$(0.333, 0.583, 0.833)$	0.583	$(0.667, 0.917, 1)$	0.889	$(0.583, 0.833, 1)$	0.819
C_{14}	$(0.50, 0.750, 1)$	0.750	$(0.750, 1, 1)$	0.958	$(0.667, 0.917, 1)$	0.889
C_{21}	$(0.333, 0.583, 0.833)$	0.583	$(0.667, 0.917, 1)$	0.889	$(0.50, 0.750, 0.917)$	0.736
C_{22}	$(0.333, 0.583, 0.833)$	0.583	$(0.667, 0.917, 1)$	0.889	$(0.250, 0.50, 0.750)$	0.50
C_{23}	$(0.083, 0.333, 0.583)$	0.333	$(0.583, 0.833, 1)$	0.819	$(0.333, 0.583, 0.833)$	0.583
C_{24}	$(0.250, 0.50, 0.750)$	0.50	$(0.50, 0.750, 1)$	0.750	$(0.333, 0.583, 0.833)$	0.583
C_{31}	$(0.733, 0.772, 0.786)$	0.768	$(0.880, 0.958, 1)$	0.952	$(0.629, 0.647, 0.667)$	0.647
C_{32}	$(0.364, 0.636, 0.909)$	0.636	$(0.545, 0.818, 1)$	0.803	$(0.273, 0.545, 0.818)$	0.545
C_{33}	$(0.756, 0.768, 0.773)$	0.767	$(0.944, 0.979, 1)$	0.977	$(0.654, 0.677, 0.694)$	0.676
C_{41}	$(0.417, 0.667, 0.917)$	0.667	$(0.667, 0.917, 1)$	0.889	$(0.50, 0.750, 1)$	0.750
C_{42}	$(0.333, 0.583, 0.833)$	0.583	$(0.583, 0.833, 1)$	0.819	$(0.417, 0.667, 0.917)$	0.667
C_{43}	$(0.417, 0.667, 0.833)$	0.653	$(0.583, 0.833, 1)$	0.819	$(0.50, 0.750, 0.917)$	0.736
C_{51}	$(0.417, 0.667, 0.833)$	0.653	$(0.750, 1, 1)$	0.958	$(0.50, 0.750, 1)$	0.750
C_{52}	$(0.417, 0.667, 0.917)$	0.667	$(0.750, 1, 1)$	0.958	$(0.50, 0.750, 1)$	0.750
C_{53}	$(0.333, 0.583, 0.833)$	0.583	$(0.583, 0.833, 1)$	0.819	$(0.417, 0.667, 0.833)$	0.653

TABLE 6. The fuzzy ideal value $\widetilde{\psi}_j^+$ and fuzzy negative ideal value $\widetilde{\phi}_j^-$ for all criteria

Criteria	Fuzzy ideal value $\widetilde{\psi}_j^+$	Fuzzy negative ideal value $\widetilde{\phi}_j^-$
C_{11}	$(0.708, 0.958, 1)$	$(0.458, 0.708, 0.917)$
C_{12}	$(0.667, 0.917, 1)$	$(0.333, 0.583, 0.833)$
C_{13}	$(0.667, 0.917, 1)$	$(0.333, 0.583, 0.833)$
C_{14}	$(0.750, 1, 1)$	$(0.50, 0.750, 1)$
C_{21}	$(0.667, 0.917, 1)$	$(0.333, 0.583, 0.833)$
C_{22}	$(0.667, 0.917, 1)$	$(0.250, 0.50, 0.750)$
C_{23}	$(0.583, 0.833, 1)$	$(0.083, 0.333, 0.583)$
C_{24}	$(0.50, 0.750, 1)$	$(0.250, 0.50, 0.750)$
C_{31}	$(0.880, 0.958, 1)$	$(0.629, 0.647, 0.667)$
C_{32}	$(0.545, 0.818, 1)$	$(0.273, 0.545, 0.818)$
C_{33}	$(0.944, 0.979, 1)$	$(0.654, 0.677, 0.694)$
C_{41}	$(0.667, 0.917, 1)$	$(0.417, 0.667, 0.917)$
C_{42}	$(0.583, 0.833, 1)$	$(0.333, 0.583, 0.833)$
C_{43}	$(0.583, 0.833, 1)$	$(0.417, 0.667, 0.833)$
C_{51}	$(0.750, 1, 1)$	$(0.417, 0.667, 0.833)$
C_{52}	$(0.750, 1, 1)$	$(0.417, 0.667, 0.917)$
C_{53}	$(0.583, 0.833, 1)$	$(0.333, 0.583, 0.833)$

4.5. **Calculating the distance between each alternative to the ideal solution and the negative ideal solution.** The data in Tables 2, 5, and 6 was used in conjunction with the formula in Section 3.7 to calculate the distances from the three alternatives to the ideal solution and negative ideal solution, which yielded the results shown in Table 7.

Table 7. Distance of three alternatives versus ideal and negative ideal solutions

Alternatives	Δ_i^+	Δ_i^-
Supplier G	0.005277	0.000084
Supplier N	0	0.005647
Supplier P	0.002052	0.001552

4.6. **Calculating the relative closeness of three alternatives and ranking to select the best EKG monitor supplier.** The data in Table 7 was used in conjunction with the formula in Section 3.8 to obtain the relative closeness of each alternative, which yielded the results of $RC_G^* = 0.0157$, $RC_N^* = 1$, and $RC_P^* = 0.4306$. Because $RC_N^* > RC_P^* > RC_G^*$, the Brand N was determined by the assessment committee to be the optimal EKG monitor supplier, and it was recommended that the hospital's procurement department purchase the EKG monitor of Brand N.

4.7. **Summary and management implications.** In this case, we can see from Table 2 that 'quality (C_1)' is the most important assessment dimension in the selection of an EKG monitor supplier, and is followed by the dimensions of 'technological capability (C_5)', 'service level (C_2)', 'cost and price (C_3)', and 'delivery speed (C_4)'.

According to Daniel [52], firms must possess two to six key factors determining success, and firms that wish to be successful must ensure that these key factors are fully present. Consequently, the 6 key assessment criteria selected in this study were taken as the key factors used to assess EKG monitor suppliers. The sum of the weights of these 6 key factors was 51.53%, which was more than one-half of the total weight. Our case study results indicated that the 6 most important factors in the selection of EKG monitor suppliers are "product quality certification (C_{13}) (0.1006)", "product stability (C_{14}) (0.0979)", "maintenance technology capabilities (C_{52}) (0.0874)", "R&D and innovation capabilities (C_{51}) (0.0794)", "excellent product education and training (C_{24}) (0.0757)", and "reliable outgoing quality (0.0743) (C_{11})".

In addition, we believe that it is necessary to explain why the hospital's procurement department should select the EKG monitor of Brand N. Because Brand N is a leading international medical equipment developer and manufacturer, and the products developed by Company N include EKG monitoring, neural electrophysiology, first aid, clinical testing, and laboratory equipment, as well as clinical information systems and home care systems. Company N's R&D centers, production facilities, and sales locations can be found in many countries and regions in the United States, Asia, and Europe. It is an international medical company with a long history. Furthermore, Brand N holds technological patents to numerous innovative medical devices and instruments. It has spent many years engaging in the development of medical technology, and has established rigorous quality targets. The company has also developed production, sales, and after-sales service operations, and its industry supply chain can provide extremely thoroughgoing service to customers. In line with these facts, the results of the expert questionnaire in this study indicated a preference for an EKG monitor supplied by Company N.

Furthermore, some of the management implications are provided in this study.

1) Management implication to medical institutions: Good-quality medical instruments play important roles in lifesaving care. Accordingly, hospitals must strive to purchase medical devices that can satisfy healthcare quality needs. However, to date, many studies have largely focused on the safety of medical instruments and pharmaceuticals, and there has been very little research addressing the selection of medical equipment suppliers. This study's selection model and empirical results can consequently be

provided to medical institutions' procurement departments to serve as a reference basis for the procurement of EKG monitors. We believe that our findings can provide real practical benefit to medical institutions.

2) Management implication to medical equipment suppliers: EKG technology has helped boost the overall diagnostic and treatment effectiveness of clinical medicine. However, because medical devices are evolving rapidly, the results of this study can provide EKG monitor suppliers with demand information giving them a better understanding of true emergency care needs at the current point in time. In addition, our results can also prompt suppliers to boost their technological capabilities and expertise in an effort to improve their service quality and obtain quality certification, which will help them to strengthen their competitiveness. We hope that the results of this study can provide a useful reference to the industry's managers.
3) Management implication to university education: This study's selection process and results can improve understanding of medical equipment supplier selection among university students in medical management or medical testing departments. By improving their equipment supplier selection knowledge and skills, this study can provide students with practical abilities for their future work in the medical system.

5. **Concluding Remarks.** Due to the need to improve healthcare quality while controlling costs, hospital procurement management and selection of equipment suppliers are extremely important management topics. As a consequence, establishing a selection system for medical equipment suppliers can affect a hospital's profitability and long-term competitiveness. The key indicators used in the selection of medical equipment suppliers are thus an important research topic. Hence, this article proposed a fuzzy AHP-TOPSIS assessment model to select the optimal supplier of EKG monitors for a medical institution, and performed an empirical study of the selection of a EKG monitor supplier by a regional hospital's procurement department. A review of the literature and collection of expert opinions enabled us to determine 5 major assessment dimensions and 17 assessment criteria based on important selection factors. This study then issued an AHP expert questionnaire to obtain the relative weights of each assessment dimension and assessment criterion. Empirical analysis led to the discovery that 1) 'quality' constitutes the most important assessment dimension for EKG monitor suppliers, and 2) the most important assessment criteria in the selection of EKG suppliers are "product quality certification", "product stability", "maintenance technology capabilities", "R&D and innovation capabilities", "excellent product education and training", and "reliable outgoing quality", respectively. In addition, this study also asked experts to assess the performance values of three suppliers, and used the resulting superiority values in conjunction with the assessment model to derive empirical results. This led to the finding that the optimal EKG monitor supplier was Brand N.

This fuzzy AHP-TOPSIS assessment model proposed in this study has the following advantages. 1) The assessment criteria included both qualitative and quantitative criteria, which helped objectivize the decision-making problem. 2) In order to assess the superiority value of each alternative relative to all criteria, this study combined benefit criteria and cost criteria, which enabled a closer approach to the real situation. 3) The proposed model escaped the limitations of working with precise values, but can also be easily implemented as a computer-based decision support system for selecting the best EKG monitor supplier in a fuzzy environment.

However, there are many hybrid methodologies addressing MCDM problems at present [38]. These include 1) multicriteria scoring methods (e.g., the multiple factor, weighted, and Delphi scoring methods); 2) quantitative multicriteria evaluation methods (e.g., the simple additive weighting method, generalized concordance analysis, permutation method, and TOPSIS); 3) qualitative multicriteria evaluation methods (e.g., the ordinal position evaluation method, qualitative concordance analysis, qualitative permutation method, and regime method); 4) multicriteria evaluation methods with qualitative and quantitative data (e.g., the multicriteria EVAluation with MIXed qualitative and quantitative data (EVAMIX) and Group Decision-making with Multiple Qualitative Criteria (GDMQC)); 5) outranking methods (e.g., ELECTRE I and II, and PROMETHEE I, II, III, and IV); and 6) multiple objective mathematical programming (MOMP). Our study examined how to prove the effectiveness of the proposed fuzzy MCDM evaluation method. We investigated whether there is any comparison with state-of-the-art research. Based on our findings, we suggest that there are numerous methods and skills included in the above MCDM; the appropriate moments for applying these methods and skills rely on the complexity of problems, decision-making process, nature of data, and evaluation results. In recent years, many new MCDM methods have been proposed and compared to other similar methodologies to improve the evaluation methods and quality of decision-making problems. The fuzzy AHP-TOPSIS proposed in this study displays the above three advantages. We expect that the model can be applied to similar decision-making evaluation topics and can effectively acquire better selection alternatives.

In many MCDM evaluation methods, we assumed that every decision-maker had a set of fixed weight values after making their own evaluation. The human thinking process has the characteristic of impression, and there is a fuzzy relationship when reflecting on things. Therefore, it is challenging to accurately describe criteria preference. Further research should explore whether there is a set of fixed weight values for decision-makers. These weight values may vary across time and environments. Voogd [53] pointed out that criteria weight usually changes following the different evaluation alternatives. This indicates that the weight is only a calculating medium in the evaluation process; it has no inherent meaning otherwise. Based on the above, we can conclude that the result will vary if a different hospital is chosen as the study sample. Therefore, if medical institutions wish to adopt this model for the selection of medical equipment suppliers, it can be readily systematized and computerized in a form that can reflect different numbers of experts, suppliers, and selection criteria. When the model has been computerized, it will only be necessary to enter relevant data to automatically derive optimal medical equipment suppliers, which can serve as a reference for actual decision-making.

Furthermore, the fuzzy evaluation model proposed in this study can be applied to similar evaluation problems [54-56] in the future, such as the selection of the hospital's strategic partners, the hospital location selection, medical personnel evaluation, and medical equipment evaluation. The researchers can re-evaluate and re-select different types of alternatives according to various questions to further establish the reliability and validity of this selection method.

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