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A new fuzzy approach based on BWM and fuzzy preference programming for hospital performance evaluation: A case study

Maghsoud Amiri [a], Mohammad Hashemi-Tabatabaei [a], Mohammad Ghahremanloo [b], Mehdi Keshavarz-Ghorabaee [c,*], Edmundas Kazimieras Zavadskas [d], Jurgita Antucheviciene [d]

[a] Department of Industrial Management, Faculty of Management and Accounting, Allameh Tabataba'i University, 14348-63111 Tehran, Iran
[b] Department of Management, Faculty of Industrial Engineering and Management, Shahrood University of Technology, 36199-95161, Shahrood, Iran
[c] Department of Management, Faculty of Humanities (Azadshahr Branch), Gonbad Kavous University, 49717-99151 Gonbad Kavous, Iran
[d] Department of Construction Management and Real Estate, Vilnius Gediminas Technical University, Sauletekio al. 11, LT-10223, Vilnius, Lithuania

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ABSTRACT

Hospital performance evaluation (HPE) has a major role in improving the quality, safety, and effectiveness of health care services, so it is indispensable for proper and continuous operation of hospitals. Although several studies have been performed on HPE, few have used group decision-making (GDM). This study presents a comprehensive multi-criteria GDM model for HPE under uncertain conditions. In this model, we have combined the group best–worst method (GBWM) and fuzzy preference programming (FPP) method to create an applicable framework for GDM in which members of a decision-making group including decision-makers (DMs) have different expertise and the importance of criteria and DMs opinions are determined by a supervisor. The advantages of the proposed method include the integration of the GDM process in the form of a single model and there is no need to calculate separately the consistency of the decisions of the decision-making team members. Finally, a case study conducted on 5 hospitals in Tehran is presented to demonstrate the applicability and effectiveness of the proposed method. The results show that Sina Hospital, Baharloo Hospital, and Tehran Heart Center were ranked first to third, respectively. Also, we can conclude from this study that the proposed integrated framework is capable to address the HPE problem by using a GDM and considering the uncertainty of the comparisons made by decision-making team members.

1. Introduction

Hospitals are complex and multipurpose organizations that utilize many up-to-date technologies. Complexity of healthcare organizations, high costs of treatments, emphasis on specialization, and the importance of efficiency and effectiveness of customer service are factors that have increased the importance of performance evaluation in these types of organizations. Therefore, these organizations need a performance evaluation framework to monitor their activities and move towards sustainable development. High performance and precision tools are needed for hospital performance evaluation (HPE) so that managers can select and execute the right strategies to increase performance in their organizations based on the results of performance evaluation.

Hospitals are the main units in the health system; they consume the majority of a country's health care budget, play an important role in providing health care services, and greatly affect the efficiency of the health care system [1]. Health centers are directly responsible for saving lives. Since human health and life are very important, one of the measures proposed for developing countries is to improve the performance of these centers [2]. Despite major and undeniable advances in science and technology, healthcare systems still face many challenges [3].

Performance evaluation is an effective tool used by hospital management to evaluate and monitor hospital activities [4]. Recently, hospital evaluation has received more attention due to the increasing demand for health services, increasing number of jobs in the health system, resource constraints, and high costs of treatment. Measuring and managing the performance of health systems, which include hospitals, medical centers, etc., has become more complex than ever. Therefore, managers should adopt appropriate strategies for managing, improving, and developing current systems based on the existing conditions [5,6]. By evaluating hospitals' performance, the management team can take more effective measures to improve and increase the level of hospital performance and efficiency. Health systems are generally

* Corresponding author.
E-mail address: m.keshavarz@gonbad.ac.ir (M. Keshavarz-Ghorabaee).

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service-oriented organizations that their success depends on the quality of services. The quality of service is closely related to the level of customer satisfaction and can be one of the key success factors for this type of organizations. HPE can help maintain public welfare, improve the quality of health care, and ensure the sustainable development of hospitals [7].

Developing a powerful and effective tool for identifying and ranking factors affecting hospital performance can greatly help the management team to accurately evaluate and improve the current situation. Multi-criteria decision-making (MCDM) techniques can be used for HPE. These techniques help decision-makers (DMs) make proper decisions when they deal with a wide range of data and decision criteria. Many studies have been conducted on HPE based on MCDM techniques including Analytical Hierarchy Process (AHP) [8,9], Data Envelopment Analysis (DEA) [1,10,11], and best–worst method (BWM) [7,12], and many more.

BWM is one of the new methods of MCDM introduced by Rezaei [13]. This method yields better results than the AHP method and requires less pairwise comparisons for decision-making. In this method, the best and worst criteria are chosen by DMs and then other criteria are compared with the best and worst criteria. The BWM-based group decision-making (GDM) method has been developed in a study [14]. In their method, opinions of the manager and expert team are combined into an integrated model to determine the final weights. Also, the Consistency Ratio (CR) is calculated separately for the manager and each expert so that inconsistent decisions of an expert do not adversely affect the group final decision. The proposed method in this study is a combination of group best–worst method (GBWM) and fuzzy preference programming (FPP), which forms an integrated GBWM-FPP approach. In this study, by combining the above methods, a new fuzzy approach is presented for HPE to determine the importance of each criterion and thus to select the best alternative among the other alternatives. Summary of important points in this article are as follows: Using the new MCDM method to create HPE framework, using the logic of BWM because it includes less pairwise comparisons than other methods, and using the GBWM method to build a GDM platform and increase the reliability of the decisions.

Given the importance of the HPE and the important role that health centers play in community health, hospital assessment based on a GDM approach can enhance the accuracy of assessment and help managers to identify hospital strengths and weaknesses. On the other hand, today's real-world decision-making conditions are often faced with uncertainty. As the literature review section illustrates, the existing literature does not address a GDM approach that includes uncertainty.

A new fuzzy method for evaluating the performance of treatment units is provided using a combination of GBWM and FPP (GBWM-FPP) so that by using the advantages of the BWM and fuzzy relationships in FPP method, a new framework is created for the accurate evaluation of hospital performance.

The performance of real cases in Tehran, including several hospitals, is evaluated by developing an appropriate questionnaire for collecting related data from health and treatment experts, as well as using the proposed method in the form of an integrated mathematical model and comparing and analyzing the results.

The rest of this paper is organized as follows: Section 2 reviews the literature and describes MCDM-based HPE methods and models. In Section 3, the research methodology is described. In Section 4, actual HPE cases are used to evaluate the proposed method. The results of the research and suggestions for future research are provided in Section 5.

2. Literature review

This section reviews previous related studies to the BWM method and different models offered for HPE. Various methods have been used for HPE in different countries and environments. A summary of the research literature is provided in Table 1.

Bannick & Ozcan [15] was one of the studies evaluating the performance and effectiveness of health care centers that used the DEA model to compare hospital performance under the Department of Health and Department of Defense in US; It had six inputs and two outputs; their studies showed that Department of Defense hospitals were significantly more efficient.

Ersoy et al. [1] examined the technical efficiency of Turkish hospitals using the DEA method. Their results showed that less than 10 percent of hospitals were more efficient than their counterparts.

Ouellette & Vierstraete [16] investigated the impact of semi-fixed inputs on performance measurement and technology change in the emergency department of a hospital in Montreal; they proposed a modified DEA method with semi-fixed inputs.

Another study presented a performance evaluation model based on the DEA method in which the inputs and outputs were selected based on local environment and classified in more detail [17].

In another study, outsourcing of the hospital information system was investigated using the combined entropy method and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). They point out that establishing specific criteria for evaluating contractors can encourage hospital managers to outsource their IT-related activities to contractors [18].

Window analysis was used by Weng et al. [19] and the DEA model was extended accordingly. This model enabled HPE over multiple time periods and also reduced the errors of hospital evaluation over a given time period.

In study Yawe [10], hospitals were rated and analyzed using the Super-Efficiency Model in the DEA and combined it with the BSC method to perform HPE.

Tsai et al. [20] proposed a Fuzzy Analytic Hierarchy Process (FAHP) and a fuzzy sensitive analysis-based approach to reduce the uncertainty and make the evaluation process more transparent.

Chuang et al. [21] used a combination DEA-artificial neural network and DEA-assurance region model to analyze hospital data for HPE and then discussed efficiency and inefficiency of the hospitals using regression. Ajami & Ketabi [8] and Gholamzadeh Nikjoo et al. [9] evaluated the performance of hospital units using AHP. Davis et al. [22] evaluated public sector hospitals in New Zealand between 2001 and 2009; they conducted their research on three dimensions: efficiency, effectiveness, and equity.

Akdag et al. [23] used the fuzzy hybrid MCDM method to evaluate the quality of Turkish hospital services. Chang [24] used the VIKOR method to evaluate the quality of service in Taiwan's public and private hospitals under a fuzzy environment with triangular fuzzy variables. It concluded that the quality of private hospital services was better than public hospitals because private hospitals were rarely subsidized by the government and had to retain existing patients or attract new patients in order to survive.

Another study examined the impact of organizational, technological, environmental, and human factors on selecting the hospital information systems in Malaysia. 13 sub-criteria were selected for the four main criteria and their effects were measured using MCDM based on Analytic Network Process (ANP) and Decision-making Trial and Evaluation Laboratory (DEMATEL). They showed that, according to experts' judgments, perceived technical competence was the most important among the human factors; comparative advantage was more important among the technological factors; hospital size was more important among the organizational factors; and government policy was more important among the environmental factors [25].

Gholami et al. [26] examined the impact of IT investment on hospitals' performance and quality. Using the double-bootstrap DEA and two-year data of 187 hospitals in the United States, they demonstrated the impact of IT investment on quality and operational efficiency of the hospitals.

Rouyendegh et al. [27] proposed a hybrid model based on DEA and fuzzy Analytic Hierarchy Process (FAHP) for HPE. They showed that the proposed model can help improve decision-making by determining appropriate weights.

Chowdhury & Zelenyuk [28] evaluated the performance of hospital services in Ontario Canada using the DEA method with bootstrap approach and regression. They first estimated the efficiency using the DEA method, then calculated the distribution of efficiency based on different geographic and educational conditions and different sizes of hospitals using the double bootstrap method. They found that many organizational factors such as employment rate, outpatient treatment, geographic location, size, and training status were determinants of hospital performance.

Supeekit et al. [29] proposed a modified DEMATEL-ANP method for hospital internal supply chain assessment. They used this method to examine the relationship between groups and calculate the weights of the performance criteria. They used the DEMATEL method to investigate the causal relationships between groups and performance criteria in each group, and then used these causal relationships to determine the criteria weights using the modified ANP method.

Nilashi et al. [30] examined importance of influencing factors in the hospital information system using the ANP method. They examined four main criteria (technology, environment, human, organization) with 17 sub-criteria introduced in the previous literature and used ANP technique to determine the most important criteria. The decisions were made by 20 experts who were familiar with the hospital information system and the hospital decision-making process. Their results showed that hospitals that want to adapt themselves, reduce their complexity, and support customers should pay more attention to the hospital information system.

Lobo et al. [31] used the dynamic DEA method to evaluate the performance of university hospitals. Dynamic DEA evaluates performance across different years using the variable of "boundary change". They stated that determining scores for performance, monitoring the changes of overall performance and performance of each segment, and defining clear goals for performance improvement are some advantages of the proposed model.

Pasqualini Blass et al. [32] used a scientific approach to measure environmental performance in hospitals. They point out that measuring environmental performance results in reduced environmental impacts and improved quality of results and processes. They conducted field studies on 10 hospitals in the southern region of Brazil and concluded that there was no framework for measuring, monitoring, improving, and reporting the environmental performance. Their framework and process provided a systematic approach for monitoring and reporting hospitals performance.

Johannessen et al. [33] used the DEA method to evaluate physicians at a Norwegian hospital. Their study highlighted the need to pay attention to multifunctional staff.

Chen et al. [11] examined the impact of a major economic recession on hospital performance using the DEA method; they pointed out that the cost of medical care usually comprises a relatively large portion of the budget of the advanced countries, and as a result, hospital performance declines during recession.

In another study, service quality of three hospitals in Indonesia was assessed using a combination of TOPSIS and AHP; they used the AHP method to measure criteria weights and the TOPSIS method to rank hospitals [34].

Haghighi & Torabi [12] evaluated hospital information system as one of the most important factors affecting patient satisfaction. They used the BWM to calculate the criteria weights and then evaluated the performance of each unit using the DEA method.

Giménez et al. [35] performed HPE by combining static and dynamic evaluation. They used the Malmquist–Luenberger global index and bipartite decomposition.

Torkzad & Beheshtinia [36] evaluated hospital performance using four hybrid models including modified digital logic-TOPSIS, AHP-TOPSIS, AHP-ELECTRE, and modified digital logic-ELECTRE.

Li et al. [37] used DEA based on variable returns to scale to evaluate non-homogenous hospitals in Hong Kong. Their approach was based on the assumption that hospitals do not necessarily have similar inputs and outputs. They suggested that their proposed approach could be applied to other organizations as well.

Liao et al. [7] performed HPE using the hesitant fuzzy linguistic BWM. They analyzed the proposed method using a case study and compared the results with the fuzzy BWM and the interval BWM.

Jiang et al. [38] used a large group linguistic Z-DEMATEL to determine key performance indicators (KPIs) in hospital performance management. Their approach included a similarity-based clustering approach. They stated that their approach could help managers to identify systematically a limited number of indicators for performance evaluation.

With regard to the above literature review and Table 1, it can be seen that many models have been proposed for HPE. But most of the research and models presented have been done in a deterministic environment, the decision makers' preferences have been described imprecisely, and we also rarely see group HPE models. For this reason, in this paper, we intend to present a new method based on the fuzzy GBWM for accurate evaluation of hospitals.

Hospitals are organizations consisting of various units and departments that deal directly with community members. Managers always consider the level of client satisfaction as a key factor in the success of hospitals and take steps to increase client satisfaction. This requires a rigorous performance evaluation system to assist hospital managers in achieving this goal and identify important and influential factors for improving performance.

By reviewing the literature, we found that few studies have been conducted in the field of HPE in fuzzy environment. This paper proposes a new method for evaluating HPE in fuzzy environment using GDM, in order to increase the reliability of the decisions and to cover the gaps in previous studies.

In studying the HPE and health centers, choosing the right set of indicators is crucial. In this study, based on the research literature and experts' opinions, the following criteria were selected for performance evaluation: patient average length of stay, number of patient beds, bed occupancy rate, bed turnover rate, and number of hospitalized patients. It is obvious that DMs do not consider equal importance for all criteria and therefore the weights of the criteria will be calculated using the proposed method. The evaluation criteria are described in Table 2. The evaluation criteria based on the research literature and experts' opinions.

As mentioned earlier, the purpose of this study was to introduce fuzzy group decision making based on FPP and BWM. BWM is one of the new MCDM techniques developed by Rezaei [13]. BWM is based on pairwise comparisons of criteria with the best and worst criteria, known as reference comparisons. Then a programming model is developed based on the reference comparisons. The criteria weights are obtained by solving the model.

Table 1
Summary of the HPE techniques.

Reference	Technique(s) used	Uncertainty	Application
Bannick & Ozcan [15]	DEA		The Department of Defense hospitals of USA
Ersoy et al. [1]	DEA		Turkish acute general hospitals
Ouellette & Vierstraete [16]	DEA		hospital emergency services in Montreal
O'Neill et al. [17]	DEA		systematic review of previous studies
Hsu & Hsu [18]	Entropy and TOPSIS		Taiwan's hospital
Weng et al. [19]	DEA		Iowa Hospital Association (IHA)
Yawe [10]	DEA		HPE in Uganda
Tsai et al. [20]	FAHP and Delphi	√	Taiwan's hospital
Chuang et al. [21]	DEA and regression tree		Taiwan's hospital
Ajami & Ketabi [8]	AHP		Medical Records Departments in iran
Gholamzadeh Nikjoo et al. [9]	AHP		Hospital performance indicators
Davis et al. [22]	BSC-Correlations and comparisons		New Zealand public hospital sector
Akdag et al. [23]	AHP And TOPSIS	√	Some Turkish hospitals
Chang [24]	VIKOR	√	Medical centers in Taiwan
Ahmadi et al. [25]	ANP and DEMATEL		Malaysian public hospitals
Gholami et al. [26]	DEA		Hospitals in USA
Rouyendegh et al. [27]	DEA-FAHP	√	Hospitals in turkey
Chowdhury & Zelenyuk [28]	DEA with truncated regression		Hospital services in Ontario
Supeekit et al. [29]	DEMATEL-modified ANP		Hospital supply chain performance
Nilashi et al. [30]	FANP	√	Malaysian public hospitals
Lobo et al. [31]	DEA		Brazilian hospitals
Pasqualini Blass et al. [32]	Meaningful framework		hospitals in the Southern region of Brazil
Johannessen et al. [33]	DEA and panel analysis		Norwegian hospitals
Chen et al. [11]	DEA		Pennsylvania hospitals
Ulkhaq et al. [34]	AHP and TOPSIS		Hospitals in Semarang, Indonesia
Haghighi & Torabi [12]	BWM and DEA		A real general hospital
Giménez et al. [35]	Mamlquist Luenberger index and Bipartite decomposition		Colombian hospitals
Torkzad & Beheshtinia [36]	Hybrid MCDM		Iranian public hospitals
Li et al. [37]	DEA		Hong Kong hospitals
Liao et al. [7]	HFL-BWM	√	Hospitals performance evaluation in china
Jiang et al. [38]	Large group linguistic Z-DEMATEL		Determination of KPI in hospitals
This Study	**New fuzzy MCGDM**	√	**Educational hospitals of Tehran University of Medical Sciences**

The BWM requires fewer pairwise comparisons than the AHP method and provides more consistent results. Therefore, several researchers have used it in decision-making. In the following we review the application of the BWM method in a number of studies.

Rezaei et al. [43] used BWM to classify suppliers into different groups based on selected criteria. This classification made it possible to allocate scarce resources more efficiently. Torabi et al. [44] proposed an advanced risk assessment framework for business continuity management systems. They used BWM to evaluate risk analysis sub-factors. These sub-factors were used to measure the impact of the identified risks. Gupta and Barua [45] applied BWM to identify and rank the key players in the innovation of Micro-Small and Medium Enterprises (MSMEs) in India. Their proposed approach was focused on some key factors to maintain the global competitiveness of MSMEs.

Salimi and Rezaei [46] used BWM to evaluate the effectiveness of projects undertaken as a type of collaboration between industry and university by Ph.D. students. Examples of their studied projects were the projects of graduate students at Eindhoven University of technology. The results of their study showed that projects performed by Ph.D. students inside universities are more efficient than joint university and industry projects.

Van de Kaa et al. [47] used BWM to weigh the factors of biomass thermo-chemical conversion technology selection in the Netherlands. The weights were then used to evaluate and rank technologies. Moktadir et al. [48] identified a set of challenges and barriers to the implementation of Industry 4.0 in the Bangladeshi

Table 2
Hospitals evaluation criteria in this study.

Criteria	Description	Reference
Number of patients (C_1)	Number of patients who are hospitalized simultaneously in a hospital or a treatment center in a given time period	Rahimi et al. [39]
Length of stay (C_2)	The length of time a patient has been hospitalized in a given time period, which is calculated by subtracting the reception date from discharge date.	Masoumi et al. [40]
Bed occupancy rate (C_3)	It is defined as the number of hospital bed days divided by the number of available hospital beds, multiplied by the number of days in a year.	Zhijun et al. [41]
Bed turnover rate (C_4)	Number of discharges (including deaths) in a given time period Divided by Number of beds in the hospital during that time period.	Zhijun et al. [41]
Number of patient beds (C_5)	Numbers of bed specially designed for hospitalized patients or others in need of some form of health care.	Wang et al. [42]

leather industry and evaluated them by BWM. According to the results, the "lack of technology infrastructure" was identified as the most important challenge for implementing Industry 4.0.

Liu et al. [49] used BWM to weight the indicators and sub-indicators of environmental impact of power grid projects in high altitude areas. Salimi and Rezaei [50] used BWM to weigh and evaluate performance of R&D efforts. They examined R&D performance of 50 high-tech small-to-medium sized enterprises (SMEs) in the Netherlands using a questionnaire. Rezaei et al. [51] used the BWM to weight airline baggage handling systems indicators. Results of their study showed that reliability was the most important indicator.

Van de Kaa et al. [52] used BWM to identify major factors of business reporting standards. These standards are used by businesses for reporting data to the government. Their results showed that the main factors were overall commitment of key stakeholders, timing of entry, and installed base. Ren [53] used BWM to determine and prioritize criteria weights to select ballast water treatment technologies. The results showed that the economic criterion was the most important.

Rezaei et al. [54] used BWM to examine performance indicators of ports and showed that shipping cost and shipping time are important factors for competition in the ports. Their results also showed that the availability of certain options could influence the port situation. Kheybari et al. [55] used BWM to determine weights of criteria and sub-criteria for selecting Bioethanol facility location. Then they ranked the locations (provinces of Iran) and showed that Khuzestan province was the most suitable place for Bioethanol production in Iran. Kumar et al. [56] ranked green airports which are less harmful to the environment. They used BWM to measure criteria and sub-criteria of Indian airports.

The abovementioned studies show that BWM is a very applicable method in real-world decision-making problems.

3. Methodology

This section includes the following sub-sections: Section 3.1 introduces BWM; Section 3.2 describes the FPP method; in Section 3.3, an integrated decision-making method is developed by combining BWM and FPP; Section 3.4 describes the GBWM method; and finally in Section 3.5 a combination of GBWM and FPP is developed for an integrated GDM.

3.1. Best–Worst Method (BWM)

BWM is a multi-criteria decision-making technique. An important advantage of this method is that it requires less DM input to calculate the weights of the variables and save DM time and facilitates the required computations [13]. In this method, all the criteria (alternatives) are compared with the best and worst criteria in a manner shown in Fig. 1. The complexity of pairwise comparisons and the low CR in the AHP method have made BWM more widely used recently.

BWM includes the following steps:

Step 1: Defining the decision criteria as $\{c_1, c_2, \ldots, c_n\}$.

Step 2: Identifying the best and worst criteria.

Step 3: determining the priority of the best criterion over each of other criteria as a number between 1 and 9, which is expressed as $A_{Bj} = (a_{B1}, a_{B2}, \ldots, a_{Bn})$, where a_{Bj} is the priority of the best criterion over jth criterion and $a_{BB} = 1$.

Step 4: determining the priority of each criterion over the worst criterion as a number between 1 and 9, which is expressed as $A_{jW} = (a_{1W}, a_{2W}, \ldots, a_{nW})$, where a_{jW} is the priority of j-th criterion over the worst criterion and $a_{WW} = 1$.

Step 5: Calculating the optimal weights of the criteria $(w_1^*, w_2^*, \ldots, w_n^*)$: To obtain the optimal weight of each criterion, we form the pairs $w_B/w_j - a_{Bj}$ and $w_j/w_W - a_{jW}$ then we try to minimize the maximum of $\left|w_B/w_j - a_{Bj}\right|$ and $\left|w_j/w_W - a_{jW}\right|$ for each j.

Given that the weights are non-negative, BWM can be written as follows:

$$\min_j \max\left\{\left|\frac{w_B}{w_j} - a_{Bj}\right|, \left|\frac{w_j}{w_W} - a_{jW}\right|\right\}$$
$$\boldsymbol{st}: \left\{ \sum_j w_j = 1,\ w_j \geq 0 \right. \tag{1}$$

Expression (1) can be rewritten as Expression (2):

$$\min \xi$$
$$st: \begin{cases} \left|\frac{w_B}{w_j} - a_{Bj}\right| \leq \xi, \forall j \\ \left|\frac{w_j}{w_W} - a_{jW}\right| \leq \xi, \forall j \\ \sum_j w_j = 1,\ w_j \geq 0 \end{cases} \tag{2}$$

The linear BWM has been presented in [44] as follows:

$$\min \xi$$
$$\boldsymbol{st}: \begin{cases} \left|w_B - a_{Bj}w_j\right| \leq \xi, \forall j \\ \left|w_j - a_{jW}w_W\right| \leq \xi, \forall j \\ \sum_j w_j = 1,\ w_j \geq 0 \end{cases} \tag{3}$$

Calculating the CR in the BWM Method: Using the value of ξ^*obtained from Expression (2) or (3) and the Consistency Index (CI) presented in Table 3 which is calculated based on the priority of the best criterion over the worst criterion, the CR is calculated

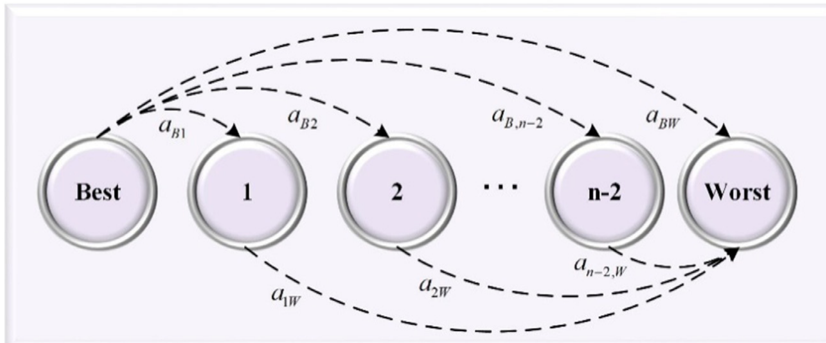

Fig. 1. Reference comparisons in BWM.

Table 3
CI in BWM.

a_{BW}	1	2	3	4	5	6	7	8	9
CI	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

using the Expression (4).

$$\text{Consistency Ratio} = \frac{\xi^*}{\text{Consistency Index}} \tag{4}$$

3.2. Fuzzy Preference Programming (FPP)

Mikhailov [57] introduced the FPP method to derive weight vector from a pairwise comparison set. Suppose that the DM makes his decisions based on the fuzzy comparison matrix instead of the definitive pairwise comparisons. For example, it is likely that ith criterion is more important than jth criterion by coefficient of m_{ij}, where the value of m_{ij} is between l_{ij} and u_{ij}; therefore, the pairwise comparison matrix is defined as follows:

$$\widetilde{A} = (\widetilde{a}_{ij})_{n\times n} = \begin{bmatrix} 1 & (l_{12}, m_{12}, u_{12}) & \dots & (l_{1n}, m_{1n}, u_{1n}) \\ (l_{21}, m_{21}, u_{21}) & 1 & \dots & (l_{2n}, m_{2n}, u_{2n}) \\ \vdots & \vdots & \vdots & \vdots \\ (\ln 1, m_{n1}, u_{n1}) & (\ln 2, m_{n2}, u_{n2}) & \dots & 1 \end{bmatrix} \tag{5}$$

where $0 < l_{ij} \leq m_{ij} \leq u_{ij}$, and we have $u_{ij} = 1/l_{ji}$, $m_{ij} = 1/m_{ji}$, and $l_{ij} = 1/u_{ji}$ for all $i, j = 1, \dots, n$ $(i \neq j)$. Also the crisp priority vector is $w = (w_1, \dots, w_n)^T > 0$ which is derived from $\tilde{A}$ and in which $\sum_{i=1}^{n} w_i = 1$. Mikhailov [58] proposed a membership function for $\tilde{A}$ in the form of Expression (6).

$$\mu_{ij}\left(\frac{w_i}{w_j}\right) = \begin{cases} \dfrac{(w_i/w_j) - l_{ij}}{m_{ij} - l_{ij}}, & \dfrac{w_i}{w_j} \leq m_{ij} \\ \dfrac{u_{ij} - (w_i/w_j)}{u_{ij} - m_{ij}}, & \dfrac{w_i}{w_j} \geq m_{ij} \end{cases} \tag{6}$$

In the fuzzy preference programming, the variable λ is defined to calculate CR of the comparisons. Also, the significance vector with the highest membership degree can be described as follows.

$$\min\left\{\mu_{ij}\left(\frac{w_i}{w_j}\right)\right\} = \lambda, i = 1, \dots, n-1; j = i+1, \dots, n \tag{7}$$

Therefore, calculation of priorities can be formulated as an optimization problem (Expression (18)).

$$\max \lambda$$
$$\boldsymbol{st}: \begin{cases} \mu_{ij}\left(w_i/w_j\right) \geq \lambda, i = 1, \dots, n-1; j = i+1, \dots, n \\ \sum_j w_j = 1, w_j \geq 0 \\ \lambda, \text{ free variable} \end{cases} \tag{8}$$

By substituting the membership function (Expression (6)) in the optimization problem (Expression (8)), the FPP model can be rewritten as Expression (9).

$$\max \lambda$$
$$\boldsymbol{st}: \begin{cases} \frac{(w_i/w_j) - l_{ij}}{m_{ij} - l_{ij}} \geq \lambda, i = 1, \dots, n-1; j = i+1, \dots, n \\ \frac{u_{ij} - (w_i/w_j)}{u_{ij} - m_{ij}} \geq \lambda, i = 1, \dots, n-1; j = i+1, \dots, n \\ \sum_j w_j = 1, w_j \geq 0 \\ \lambda, \text{free variable} \end{cases} \tag{9}$$

The model presented in Expression (9) can also be rewritten as a nonlinear optimization problem in the form of Expression (10).

$$\max \lambda$$
$$\boldsymbol{st}: \begin{cases} -w_i + l_{ij} w_j + \lambda(m_{ij} - l_{ij}) w_j \leq 0, i = 1, \dots, n-1; \\ j = i+1, \dots, n \\ w_i - u_{ij} w_j + \lambda(u_{ij} - m_{ij}) w_j \leq 0, i = 1, \dots, n-1; \\ j = i+1, \dots, n \\ \sum_j w_j = 1, w_j \geq 0 \\ \lambda, \text{free variable} \end{cases} \tag{10}$$

By solving the above nonlinear programming problem, the w^* vector is obtained, which indicates the highest membership function in the fuzzy domain. λ^* also indicates the degree of consistency; $\lambda \geq 0$ indicates that the comparisons are consistence; $\lambda = 1$ indicates that the comparisons are fully consistent; other values of λ indicate that there is inconsistency between the fuzzy judgments and the obtained solution is not optimal.

3.3. Hybrid MCDM based on BWM and FPP

In this section, a new model is developed by combining the FPP and BWM methods for weighting the criteria or alternatives in decision-making process; the mathematical relationships of this model are adapted from the FPP model, but, like the BWM method, all criteria or alternatives are compared to the best and worst criteria to produce a set of reference comparisons. Suppose that the DM wants to compare the criteria or alternatives with the best and worst ones instead of using the AHP pairwise comparisons matrix. For example, it is likely that the best criterion is more important than jth criterion by coefficient of m_{Bj}, where the value of m_{Bj} is between l_{Bj} and u_{Bj}; also it is likely that jth criterion is more important than the worst criterion by coefficient of m_{jW}, where the value of m_{jW} is between l_{jW} and u_{jW}; Therefore, the comparisons are expressed as Expression (11).

$$\tilde{A} = \begin{cases} \tilde{a}_{Bj} = (l_{B1}, m_{B1}, u_{B1}), \dots, (l_{Bn}, m_{Bn}, u_{Bn}) \\ \tilde{a}_{jW} = (l_{1W}, m_{1W}, u_{1W}), \dots, (l_{nW}, m_{nW}, u_{nW}) \end{cases} \tag{11}$$

where $0 < l_{Bj} \leq m_{Bj} \leq u_{Bj}$ and $0 < l_{jW} \leq m_{jW} \leq u_{jW}$; also the crisp priority vector is $w = (w_1, \ldots, w_n)^T > 0$ which is derived from $\tilde{A}$ and in which $\sum_{j=1}^{n} w_j = 1$.

The membership functions presented in Expressions (12) and (13) can be proposed to determine the priority of the best criterion over the jth criterion and the priority of each criterion over the worst criterion for $\tilde{A}$.

$$\mu_{Bj}\left(\frac{w_B}{w_j}\right) = \begin{cases} \dfrac{\left(w_B/w_j\right) - l_{Bj}}{m_{Bj} - l_{Bj}}, & \dfrac{w_B}{w_j} \leq m_{Bj} \\ \dfrac{u_{Bj} - \left(w_B/w_j\right)}{u_{Bj} - m_{Bj}}, & \dfrac{w_B}{w_j} \geq m_{Bj} \end{cases} \tag{12}$$

$$\mu_{jW}\left(\frac{w_j}{w_W}\right) = \begin{cases} \dfrac{\left(w_j/w_W\right) - l_{jW}}{m_{jW} - l_{jW}}, & \dfrac{w_j}{w_W} \leq m_{Bj} \\ \dfrac{u_{jW} - \left(w_j/w_W\right)}{u_{jW} - m_{jW}}, & \dfrac{w_j}{w_W} \geq m_{Bj} \end{cases} \tag{13}$$

To calculate the consistency of the comparisons, the variable λ is defined (similar to its definition in BMW) and its value can be calculated using Expression (14) following the calculation of the weight vector $w = (w_1^*, \ldots, w_n^*)$.

$$\max\min\left\{\mu_{Bj}\left(\frac{w_B}{w_j}\right), \mu_{jW}\left(\frac{w_j}{w_W}\right)\right\} = \lambda \tag{14}$$

Therefore, evaluation of priorities can be formulated as an optimization problem (Expression (15)).

$$\max \lambda$$
$$\textbf{st}: \begin{cases} \mu_{Bj}\left(w_B/w_j\right) \geq \lambda, \forall j \\ \mu_{jW}\left(w_j/w_W\right) \geq \lambda, \forall j \\ \sum_j w_j = 1, w_j \geq 0 \\ \lambda, \text{free variable} \end{cases} \tag{15}$$

By substituting the membership functions presented in Expressions (12) and (13) into Expression (15), the developed model can be rewritten as Expression (16):

$$\max \lambda$$
$$\textbf{st}: \begin{cases} \dfrac{\left(w_B/w_j\right) - l_{Bj}}{m_{Bj} - l_{Bj}} \geq \lambda; \dfrac{u_{Bj} - \left(w_B/w_j\right)}{u_{Bj} - m_{Bj}} \geq \lambda; \forall j \\ \dfrac{\left(w_j/w_W\right) - l_{jW}}{m_{jW} - l_{jW}} \geq \lambda; \dfrac{u_{jW} - \left(w_j/w_W\right)}{u_{jW} - m_{jW}} \geq \lambda; \forall j \\ \sum_j w_j = 1, w_j \geq 0 \\ \lambda, \text{free variable} \end{cases} \tag{16}$$

Expression (16) can be rewritten as Expression (17):

$$\max \lambda$$
$$\textbf{st}: \begin{cases} -w_B + l_{Bj} w_j + \lambda\left(m_{Bj} - l_{Bj}\right) w_j \leq 0, \forall j \\ w_B - u_{Bj} w_j + \lambda\left(u_{Bj} - m_{Bj}\right) w_j \leq 0, \forall j \\ -w_j + l_{jW} w_W + \lambda(m_{jW} - l_{jW}) w_W \leq 0, \forall j \\ w_j - u_{jW} w_W + \lambda\left(u_{jW} - m_{jW}\right) w_W \leq 0, \forall j \\ \sum_j w_j = 1, w_j \geq 0 \\ \lambda, \text{free variable} \end{cases} \tag{17}$$

By solving the above nonlinear programming problem, the vector w^* is obtained which represents the weights of the criteria or alternatives. Also, unlike BWM which requires calculation of consistency rate, the proposed model does not need to calculate it separately and λ^* plays the role of the consistency component; $\lambda \geq 0$ indicates that the comparisons are consistent.

3.4. Group Best–Worst Method (GBWM)

Today, in most organizations, decisions are made by groups, meaning that several people examine different dimensions of a particular issue or problem and try to find the most appropriate solution by evaluating the alternatives. In many organizations, decisions are made by a special "group" or "technical committee"; for example, specialized groups or teams are formed to analyze specific issues. In this section we will review the GDM method presented by Tabatabaei et al. [14]. Their proposed method is based on BWM and it is applicable when a decision-making group includes a group supervisor and DMs. One of the advantages of their model is that the model detects inconsistent comparisons of each member, so these inconsistent comparisons will not adversely affect the decisions of the whole group.

The group best–worst method includes the following steps:

Step 1: Defining the decision criteria as $\{c_1, c_2, \ldots, c_n\}$.

Step 2: evaluating the DMs by the group supervisor.

Step 2.1: Identifying the best and the worst DMs by the supervisor based on their expertise level in the problem.

Step 2.2: determining the priority of the best DM over each of the other DMs by the supervisor through assigning a number between 1 and 9, which is expressed as $A_{Bi} = (a_{B1}, a_{B2}, \ldots, a_{Bd})$, where a_{Bi} is the priority of the best DM over the ith DM and $a_{BB} = 1$.

Step 2.3: determining the priority of each DM over the worst DM by the supervisor through assigning a number between 1 and 9, which is expressed as $A_{iW} = (a_{1W}, a_{2W}, \ldots, a_{dW})$, where a_{iW} is the priority of the ith DM over the worst DM and $a_{WW} = 1$.

Step 3: evaluating the decision criteria by the group supervisor.

Step 3.1: Identifying the best and worst criteria by the supervisor.

Step 3.2: determining the priority of the best criterion over each of the other criteria by the supervisor through assigning a number between 1 and 9, which is expressed as $A_{Bj} = (a_{B1}, a_{B2}, \ldots, a_{Bn})$, where a_{Bj} is the priority of the best criterion over the jth criterion and $a_{BB} = 1$.

Step 3.3: determining the priority of each criteria over the worst criterion by the supervisor through assigning a number between 1 and 9, which is expressed as $A_{jW} = (a_{1W}, a_{2W}, \ldots, a_{nW})$, where a_{jW} is the priority of the jth criterion over the worst criterion and $a_{WW} = 1$.

Step 4: evaluating the decision criteria by the DMs.

Step 4.1: Identifying the best and worst criteria by the DMs.

Step 4.2: determining the priority of the best criterion over each of the other criteria by each DM through assigning a number between 1 and 9, which is expressed as $A_{Bj}^i = (a_{B1}^i, a_{B2}^i, \ldots, a_{Bn}^i)$, where a_{Bj}^i is the priority of the best criterion over the jth criterion determined by the ith DM, and $a_{BB}^i = 1$.

Step 4.3: determining the priority of each criterion over the worst criterion by each DM through assigning a number between 1 and 9, which is expressed as $A_{jW}^i = (a_{1W}^i, a_{2W}^i, \ldots, a_{nW}^i)$, where a_{jW}^i is the priority of the jth criterion over the worst criterion determined by the ith DM, and $a_{WW}^i = 1$.

Step 5: determining the value of α: the parameter α indicates the importance of the supervisor's opinions and $(1-\alpha)$ represents the importance of the opinions of all DMs and its value is between 0 and 1.

Step 6: the DMs weights assigned by the supervisor $(\lambda_1^*, \lambda_2^*, \ldots, \lambda_d^*)$, the criteria optimal weights assigned by the supervisor $(w_1^*, w_2^*, \ldots, w_n^*)$, the criteria weights assigned by the DMs $(w_1^{i*}, w_2^{i*}, \ldots, w_n^{i*})$, and the final weights of the criteria $(\mu_1^*, \mu_2^*, \ldots, \mu_n^*)$ are obtained by executing the group best–worst method.

Given that the weights and the sum of the weights are non-negative, the model can be formulated as Expression (18):

$$\min \xi + \xi' + \sum_i \xi_i$$
$$st: \begin{cases} \left|\frac{\lambda_B}{\lambda_i} - a_{Bi}\right| \le \xi; \left|\frac{\lambda_i}{\lambda_W} - a_{iW}\right| \le \xi; \forall i \\ \left|\frac{w_B}{w_j} - a_{Bj}\right| \le \xi'; \left|\frac{w_j}{w_W} - a_{jW}\right| \le \xi';\ \forall j \\ \left|\frac{w^i_B}{w^i_j} - a^i_{Bj}\right| \le \xi_i; \left|\frac{w^i_j}{w^i_W} - a^i_{jW}\right| \le \xi_i;\ ;\ \forall\, \mathrm{i}, \forall j \\ \mu_j = a w_j + (1-a)\sum_i w^i_j \lambda_i \\ \sum_i \lambda_i = 1, \lambda_i \ge 0 \\ \sum_j w_j = 1, w_j \ge 0 \\ \sum_j w^i_j = 1, w^i_j \ge 0 \end{cases} \tag{18}$$

Assuming that there are a number of equally important DMs to decide on an issue, the group best–worst model changes as follows:

$$\min \sum_i \xi_i$$
$$st: \begin{cases} \left|\frac{w^i_B}{w^i_j} - a^i_{Bj}\right| \le \xi_i; \left|\frac{w^i_j}{w^i_W} - a^i_{jW}\right| \le \xi_i;\ , \forall\, \mathrm{i}, \forall j \\ \mu_j = \frac{\sum_i w^i_j}{d}, \forall\, \mathrm{j} \\ \sum_j w^i_j = 1, w^i_j \ge 0 \end{cases} \tag{19}$$

After calculating the Expressions (18) and (19), we can calculate the CR of the decisions of the supervisor and each of the DMs separately using the Expression (4).

3.5. Hybrid MCGDM based on GBWM and FPP

The proposed method in this study is a combination of GBWM and FPP, which forms an integrated GBWM-FPP approach to determine criteria weights in GDM problems. The mathematical relationships of the model are derived from the FPP method but its comparisons are performed in a manner similar to GBWM. The proposed fuzzy approach is used when there is a need for group decision-making in an organization and the decision-making group includes a supervisor and a number of DMs. The GBWM is a group performance evaluation technique based on best–worst method that can help decision makers to achieve an agreed joint decision. The FPP technique is used to obtain the vector of the criteria weights. The output of both methods is the significance vector or the weight vector of the criteria. In the group best–worst method, each expert (team member) assigns a weight for each criterion based on his viewpoint. Then a combined weight is calculated for each criterion by combining the views of the decision-making team members. But the fuzzy preference programming technique has not a capability to consider the fuzzy preference vector for several experts. Therefore, the proposed approach in this study, which is based on a combination of GBWM and FPP, allows the experts to evaluate criteria or alternatives in a fuzzy group decision making framework. Also, the proposed approach does not require experts to calculate the consistency of their decisions separately, because if the objective function value is positive it means that the decisions of experts are consistent.

The proposed method includes the following steps**:**

Step 1: Defining the decision criteria as $\{c_1, c_2, \ldots, c_n\}$.

Step 2: Identifying the best and the worst DMs, determining the priority of the best DM over each of the other DMs, and determining the priority of each DM over the worst DM by the supervisor through assigning fuzzy numbers provided in Table 4, which is expressed as Expression (20):

$$\begin{aligned} \tilde{a}_{Bi} &= (l_{B1}, m_{B1}, u_{B1}), \ldots, (l_{Bd}, m_{Bd}, u_{Bd}) \\ \tilde{a}_{iW} &= (l_{1W}, m_{1W}, u_{1W}), \ldots, (l_{dW}, m_{dW}, u_{dW}) \end{aligned} \tag{20}$$

where $\tilde{a}_{BB} = 1$ and $\tilde{a}_{WW} = 1$.

Step 3: Identifying the best and worst criteria, determining the priority of the best criterion over each of the other criteria, and determining the priority of each criterion over the worst criterion by the supervisor through assigning fuzzy numbers provided in Table 4, which is expressed as Expression (21):

$$\begin{aligned} \tilde{a}_{Bj} &= (l_{B1}, m_{B1}, u_{B1}), \ldots, (l_{Bn}, m_{Bn}, u_{Bn}) \\ \tilde{a}_{jW} &= (l_{1W}, m_{1W}, u_{1W}), \ldots, (l_{nW}, m_{nW}, u_{nW}) \end{aligned} \tag{21}$$

where $\tilde{a}_{BB} = 1$ and $\tilde{a}_{WW} = 1$.

Step 4: Identifying the best and worst criteria, determining the priority of the best criterion over each of the other criteria, and determining the priority of each criterion over the worst criterion by each DM through assigning fuzzy numbers provided in Table 4, which is expressed as Expression (22):

$$\begin{aligned} \tilde{a}^i_{Bj} &= \left(l^i_{B1}, m^i_{B1}, u^i_{B1}\right), \ldots, \left(l^i_{Bn}, m^i_{Bn}, u^i_{Bn}\right) \\ \tilde{a}^i_{jW} &= \left(l^i_{1W}, m^i_{1W}, u^i_{1W}\right), \ldots, \left(l^i_{nW}, m^i_{nW}, u^i_{nW}\right) \end{aligned} \tag{22}$$

Where $\tilde{a}^i_{BB} = 1$ and $\tilde{a}^i_{WW} = 1$.

Step 5: determining the value of α: the value of this parameter is between 0 and 1 and it indicates the importance of the opinions of the supervisor and DMs. Its value can be determined by the supervisor or by agreement of the members of the decision-making group. The closer the value of α to 1, the greater the importance of the supervisor's opinions, and the closer the value of α to 0, the greater the importance of the DMs' opinions in determining final weights of the criteria.

Step 6: the DMs' weights assigned by the supervisor ($\lambda^*_1, \lambda^*_2, \ldots, \lambda^*_d$), the criteria weights assigned by the supervisor ($w^*_1, w^*_2, \ldots, w^*_n$), the criteria weights assigned by the DMs ($w^{i*}_1, w^{i*}_2, \ldots, w^{i*}_n$) are obtained by executing the hybrid model GBWM-FPP shown in Expression (23).

Acceptability of the proposed model solution can be evaluated by considering the following conditions:

1. If $\xi \ge 0$, the comparisons made by the supervisor to evaluate the DMs are consistent; if $\xi = 1$, the comparisons made by the

Table 4
Linguistic terms for criteria comparison.

Linguistic terms	Fuzzy scales
Equally importance (EI)	(1,1,1)
Weakly important (WI)	(1,2,3)
Moderate importance (MI)	(2,3,4)
Moderate plus importance (MP)	(3,4,5)
Strong importance (SI)	(4,5,6)
Strong plus importance (SP)	(5,6,7)
Very strong importance (VS)	(6,7,8)
Extreme importance (EX)	(7,8,9)

Table 5
Prioritization of DMs by the group supervisor.

Decision maker	Best DM	Worst DM	DM_S		
			DM_1	DM_2	DM_3
Group supervisor	DM_2	–	(1,2,3)	(1,1,1)	(4,5,6)
	–	DM_3	(3,4,5)	(4,5,6)	(1,1,1)

Table 6
Prioritization of the criteria by the DMs.

Decision makers	Best criterion	Worst criterion	C_1	C_2	C_3	C_4	C_5
Group Supervisor	C_3	–	(3,4,5)	(1,2,3)	(1,1,1)	(6,7,8)	(4,5,6)
	–	C_4	(2,3,4)	(5,6,7)	(6,7,8)	(1,1,1)	(1,2,3)
DM_1	C_2	–	(4,5,6)	(1,1,1)	(3,4,5)	(7,8,9)	(2,3,4)
	–	C_4	(2,3,4)	(7,8,9)	(2,3,4)	(1,1,1)	(4,5,6)
DM_2	C_1	–	(1,1,1)	(2,3,4)	(4,5,6)	(1,2,3)	(5,6,7)
	–	C_5	(5,6,7)	(2,3,4)	(1,2,3)	(3,4,5)	(1,1,1)
DM_3	C_3	–	(3,4,5)	(6,7,8)	(1,1,1)	(1,2,3)	(1,2,3)
	–	C_2	(2,3,4)	(1,1,1)	(6,7,8)	(4,5,6)	(4,5,6)

Table 7
Optimal weights of the HPE criteria, determined by the group supervisor and DMs.

Decision makers	Optimal weights of criteria				
	w_1	w_2	w_3	w_4	w_5
Group Supervisor	0.148	0.212	0.490	0.064	0.086
DM1	0.117	0.484	0.117	0.055	0.226
DM2	0.438	0.165	0.098	0.232	0.067
DM3	0.118	0.051	0.391	0.220	0.220

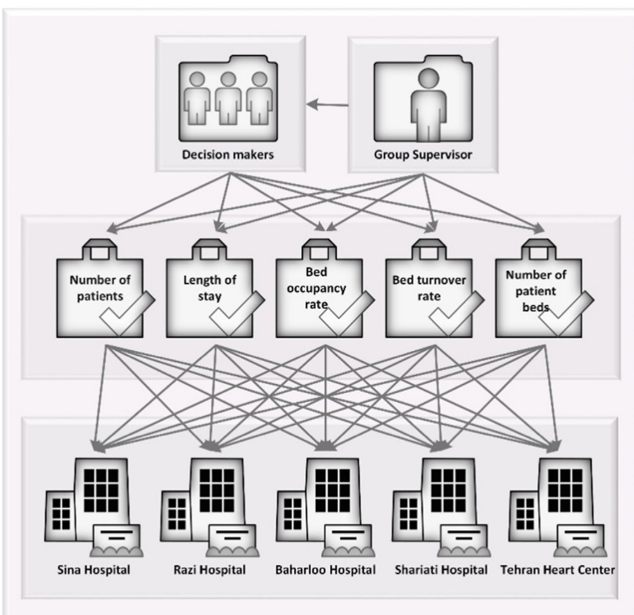

Fig. 2. Hierarchical structure of group decision-making problem for HPE.

Table 8
Optimal weights of DMs, determined by the group supervisor.

Decision maker	Optimal weights of Decision makers		
	DM_1	DM_2	DM_3
Group Supervisor	0.354	0.546	0.100

supervisor to evaluate the DMs are fully consistent; otherwise, there are some inconsistencies in the supervisor's decisions.

2. If $\xi' \geq 0$, the comparisons made by the supervisor to evaluate the criteria are consistent; if $\xi' = 1$, the comparisons made by the supervisor to evaluate the criteria are fully consistent; otherwise, there are some inconsistencies in the supervisor's decisions.

3. If $\xi_i \geq 0$ for DMi (ith DM), the comparisons made by the DMi to evaluate the criteria are consistent; if $\xi_i = 1$, the comparisons made by the DMi to evaluate the criteria are fully consistent; otherwise, there are some inconsistencies in the DMs' decisions.

$$\max \xi + \xi' + \sum_i \xi_i$$
$$st: \begin{cases} \frac{(\lambda_B/\lambda_i)-l_{Bi}}{m_{Bi}-l_{Bi}} \geq \xi;\ \frac{u_{Bi}-(\lambda_B/\lambda_i)}{u_{Bi}-m_{Bi}} \geq \xi;\ \forall j \\ \frac{(\lambda_i/\lambda_W)-l_{iW}}{m_{iW}-l_{iW}} \geq \xi;\ \frac{u_{iW}-(\lambda_i/\lambda_W)}{u_{iW}-m_{iW}} \geq \xi;\ \forall j \\ \frac{(w_B/w_j)-l_{Bj}}{m_{Bj}-l_{Bj}} \geq \xi';\ \frac{u_{Bj}-(w_B/w_j)}{u_{Bj}-m_{Bj}} \geq \xi';\ \forall j \\ \frac{(w_j/w_W)-l_{jW}}{m_{jW}-l_{jW}} \geq \xi';\ \frac{u_{jW}-(w_j/w_W)}{u_{jW}-m_{jW}} \geq \xi';\ \forall j \\ \frac{\left(w^i_B/w^i_j\right)-l^i_{Bj}}{m^i_{Bj}-l^i_{Bj}} \geq \xi_i;\ \frac{u^i_{Bj}-\left(w^i_B/w^i_j\right)}{u^i_{Bj}-m^i_{Bj}} \geq \xi_i;\ \forall\, i\,,\forall j \\ \frac{\left(w^i_j/w^i_W\right)-l^i_{jW}}{m^i_{jW}-l^i_{jW}} \geq \xi_i;\ \frac{u^i_{jW}-\left(w^i_j/w^i_W\right)}{u^i_{jW}-m^i_{jW}} \geq \xi_i;\ \forall\, i\,,\forall j \\ \sum_i \lambda_i = 1 \\ \sum_j w_j = 1 \\ \sum_j w^i_j = 1 \\ \lambda_i \geq 0,\ w_j \geq 0,\ w^i_j \geq 0 \\ \xi, \xi', \xi_i \text{ free variable} \end{cases} \tag{23}$$

Expression (24) is the nonlinear form of the programming problem (23):

$$\max \xi + \xi' + \sum_i \xi_i$$
$$st: \begin{cases} -\lambda_B + l_{Bi}\lambda_i + \xi\,(m_{Bi} - l_{Bi})\,\lambda_i \leq 0, \forall i \\ \lambda_B - u_{Bi}\lambda_i + \xi\,(u_{Bi} - m_{Bi})\,\lambda_i \leq 0, \forall i \\ -\lambda_i + l_{iW}\lambda_W + \xi\,(m_{iW} - l_{iW})\,\lambda_W \leq 0, \forall i \\ \lambda_i - u_{iW}\lambda_W + \xi\,(u_{iW} - m_{iW})\,\lambda_W \leq 0, \forall i \\ -w_B + l_{Bj}w_j + \xi'\left(m_{Bj} - l_{Bj}\right) w_j \leq 0, \forall j \\ w_B - u_{Bj}w_j + \xi'\left(u_{Bj} - m_{Bj}\right) w_j \leq 0, \forall j \\ -w_j + l_{jW}w_W + \xi'\left(m_{jW} - l_{jW}\right) w_W \leq 0, \forall j \\ w_j - u_{jW}w_W + \xi'\left(u_{jW} - m_{jW}\right) w_W \leq 0, \forall j \\ -w^i_B + l^i_{Bj}w^i_j + \xi_i\left(m^i_{Bj} - l^i_{Bj}\right) w^i_j \leq 0, \forall i\,, \forall j \\ w^i_B - u^i_{Bj}w^i_j + \xi_i\left(u^i_{Bj} - m^i_{Bj}\right) w^i_j \leq 0, \forall i\,, \forall j \\ -w^i_j + l^i_{jW}w^i_W + \xi_i\left(m^i_{jW} - l^i_{jW}\right) w^i_W \leq 0, \forall i\,, \forall j \\ w^i_j - u^i_{jW}w^i_W + \xi_i\left(u^i_{jW} - m^i_{jW}\right) w^i_W \leq 0, \forall i\,, \forall j \\ \sum_i \lambda_i = 1 \\ \sum_j w_j = 1 \\ \sum_j w^i_j = 1 \\ \lambda_i \geq 0,\ w_j \geq 0,\ w^i_j \geq 0 \\ \xi, \xi', \xi_i \text{ free variable} \end{cases} \tag{24}$$

Table 9
The merged weights of criteria for different values of α.

Criteria	*Alpha*										
	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
μ_1	0.292	0.278	0.263	0.249	0.235	0.220	0.206	0.191	0.177	0.162	0.148
μ_2	0.266	0.261	0.256	0.250	0.245	0.239	0.234	0.228	0.223	0.217	0.212
μ_3	0.134	0.170	0.205	0.241	0.276	0.312	0.134	0.383	0.419	0.454	0.490
μ_4	0.168	0.158	0.147	0.137	0.126	0.116	0.106	0.095	0.085	0.074	0.064
μ_5	0.138	0.133	0.128	0.123	0.117	0.112	0.107	0.102	0.096	0.091	0.086

Unlike the model presented in Section 3.3 (Expression (17)), which only can be used with one decision-maker, the proposed model in this section (Expression (24)) is useful when we have a group of decision-makers.

The combined weight of experts and group supervisor is calculated by Expression (25).

$$\mu_j = aw_j + (1-a)\sum_i w_j^i \lambda_i \tag{25}$$

We use Expression (26) for ranking the alternatives, where μ_j represents the weight obtained by combining the alternatives determined by the group supervisor and DMs for the criterion j, and p_{kj} is the normalized data value of the alternatives k for the criterion j. Also, the normalized data values of the positive and negative criteria are obtained using Expressions (27) and (28), respectively, where x_{kj} represents the normalized data value of the alternative k for the criterion j [55].

$$V_k = \sum_{j=1}^{n} \mu_j p_{kj}, \text{ for all } k \tag{26}$$

$$p_{kj} = \frac{x_{kj}}{\sum_j x_{kj}}, \text{ for positive criteria} \tag{27}$$

$$p_{kj} = \frac{1/x_{kj}}{\sum_j 1/x_{kj}}, \text{ for negative criteria} \tag{28}$$

4. Case study

In this study, the performance of 5 hospitals in Tehran was evaluated in order to identify the hospital providing the highest quality medical and health services. Proper resource allocation, proper spending of resource, proper service delivery, proper control, accurate and systematic evaluations, etc. can all be the results of successful implementation of a performance evaluation model.

The selected hospitals for performance evaluation included: Sina Hospital, Razi Hospital, Baharloo Hospital, Shariati Hospital, and Tehran Heart Center. The decision-making group consisted of 4 persons, including the group supervisor and three experts; all of them were professors and experts in the medical sciences and had extensive experience in the field of health care. More precisely, the group supervisor was the head of the department of supervision over medical centers, two of the selected experts were supervisors and performance evaluator in the field of health care and another expert was technical director of medical equipment at one of the health centers. The selected criteria for performing the evaluations are shown in Table 2. Data related to these criteria were collected for five hospitals for the year 2018.

First, the members of the decision-making team compare the criteria using the Hybrid MCGDM based on the GBWM and FPP methods presented in Section 3.5. Then, hospitals are ranked using the data and weights obtained for the criteria by the decision-making team. Fig. 2 shows the hierarchical structure of the GDM method used in this study, in which the decision-maker first evaluates the three DMs using the proposed method; the criteria are then evaluated by the group supervisor and DMs; finally, the final weights of the criteria are calculated based on combination of the opinions of the group supervisor and the DMs.

Table 10
Data of hospitals in 2018.

Hospitals	C_1	C_2	C_3	C_4	C_5
Sina Hospital	27452	3.78	83.15	59.58	461
Razi Hospital	4960	2.38	48.26	71.88	69
Baharloo Hospital	22454	3.69	76.26	75.29	298
Shariati Hospital	22124	6.73	84.07	45.38	487
Tehran Heart Center	19268	6.55	84.65	42.68	451

Table 11
The normalized decision matrix of hospitals.

Hospitals	C_1	C_2	C_3	C_4	C_5
Sina Hospital	0.285	0.210	0.221	0.202	0.261
Razi Hospital	0.051	0.334	0.128	0.244	0.039
Baharloo Hospital	0.233	0.215	0.200	0.255	0.169
Shariati Hospital	0.230	0.118	0.120	0.154	0.276
Tehran Heart Center	0.200	0.121	0.225	0.145	0.255

Table 5 shows the comparisons made by the group supervisor, in which the priority of the best DM over the rest of the DMs and the priority of each DM over the worst DM are determined using fuzzy numbers provided in Table 4.

Table 6 shows the comparisons made by the group supervisor and DMs, in which the priority of the best criterion over the rest of the criteria and the priority of each criterion over the worst criterion are determined using fuzzy numbers provided in Table 4.

By substituting the fuzzy comparisons made by the group supervisors and DMs into Expression (23) or (24) and solving the model, the weights of the HPE criteria are obtained. The weights were calculated using LINGO 17.0 software. Table 7 shows the weights of the HPE criteria, determined by the group supervisor and DMs. Table 8 shows the weights of DMs, determined by the group supervisor.

The proposed method includes a parameter called α that regulates bureaucratic and democratic decisions of the decision-making group. An α value close to 1 indicates that the obtained weights of the hospital evaluation criteria are the results of relatively bureaucratic decisions in which the group supervisors plays the most important role. On the other hand, an α value close to 0 indicates that the obtained weights are the results of relatively democratic decisions. Table 9 shows the merged weights of criteria obtained from the model for different values of α; These weights are calculated using the Expression (25). Also, variations of the merged weights for different values of α are shown in Fig. 3.

Table 10 shows the criteria data for the hospitals under study in 2018; this table also referred to as the decision matrix. Expressions (27) and (28) are used to normalize the positive and negative data, respectively and the results of the normalization are shown in Table 11.

Table 12 shows the weighted normalized decision matrix for different values of alpha as well as the hospital rankings obtained using the Expression (26). The effect of group supervisor on the

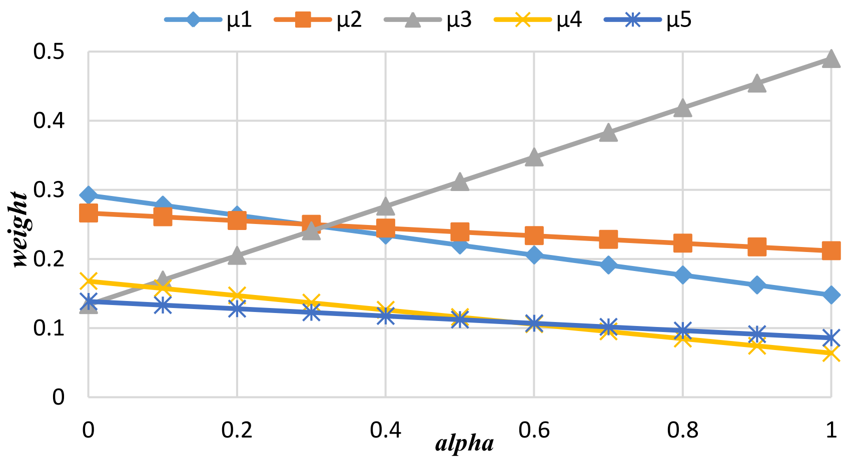

Fig. 3. The merged weights of the HPE criteria in different values of alpha.

Table 12
The weighted normalized decision matrix for alpha values of 0.2, 0.5 and 0.8.

Hospitals	Alpha	C_1	C_2	C_3	C_4	C_5	Sum	Rank
Sina Hospital		0.075	0.054	0.045	0.030	0.033	0.237	1
Razi Hospital		0.014	0.086	0.026	0.036	0.005	0.166	5
Baharloo Hospital	0.2	0.061	0.055	0.041	0.038	0.022	0.217	2
Shariati Hospital		0.060	0.030	0.025	0.023	0.035	0.173	4
Tehran Heart Center		0.053	0.031	0.046	0.021	0.033	0.184	3
Sina Hospital		0.063	0.050	0.069	0.023	0.029	0.235	1
Razi Hospital		0.011	0.080	0.040	0.028	0.004	0.164	5
Baharloo Hospital	0.5	0.051	0.052	0.062	0.030	0.019	0.214	2
Shariati Hospital		0.051	0.028	0.038	0.018	0.031	0.165	4
Tehran Heart Center		0.044	0.029	0.070	0.017	0.029	0.189	3
Sina Hospital		0.050	0.047	0.093	0.017	0.025	0.232	1
Razi Hospital		0.009	0.075	0.054	0.021	0.004	0.162	4
Baharloo Hospital	0.8	0.041	0.048	0.084	0.022	0.016	0.211	2
Shariati Hospital		0.041	0.026	0.051	0.013	0.026	0.157	5
Tehran Heart Center		0.035	0.027	0.094	0.012	0.025	0.194	3

weights was maximum for $\alpha = 0.2$, and it was minimal for $\alpha = 0.8$. As can be seen, Sina Hospital, Baharloo Hospital, and Tehran Heart Center ranked first to third, respectively, for all three values of alpha.

Proper hospital management involves proper allocation and utilization of hospital resources. Performance evaluation and decision making are useful tools for managing resources in hospitals. In general, hospital performance evaluation is performed based on specific indicators. Considering the same importance for these indicators can cause these centers to be mistakenly ranked, because performance evaluation indicators are not of equal importance. To address this problem, a new approach has been developed in this study that helps to evaluate and weight the evaluation indicators. The proposed approach, which is based on agreement between members of a decision-making team (consisting of a group supervisor and three experts), seeks to weight evaluation indicators by combining the weights assigned by each member of the team for each indicator. By examining the results of hospital evaluations, the managers of these centers can identify which aspects of hospitals need improvement in order to meet medical standards.

As mentioned earlier, the alpha parameter with a value between 0 and 1 has been used to determine the effect of opinions of experts and group supervisor on the final results. After pairwise comparisons using linguistic terms, the decision-making team determined the optimal alpha level. For example, for alpha value of 0.5, the following results have been obtained; Bed occupancy rate has been ranked as the most important indicator. Therefore it can be recognized as one of the most important and applicable indicators for measuring hospital performance. Considering the need to pay attention to the equitable distribution of hospital beds and health facilities throughout Iran, and to avoid lack of specialist human resources and wide coverage of health services, efforts should be made to plan for better utilization of existing hospital beds. Length of stay has been ranked as the second important indicator of the evaluation. Considering the importance of this indicator from the experts' points of view, it should be noted that reducing unnecessary patient stay in hospitals could lead to better care for more patients, reduction of number of patients, and reduction of investments needed for and establishing new treatment centers. Also, the number of patients, bed turnover rate, and number of patient beds are the criteria that have been ranked third, fourth, and fifth, respectively. It should be noted, however, that even if the rank of a hospital evaluation indicator is low, it cannot be ignored because each index in turn can influence the optimal performance of hospitals. Hospitals rankings based on the weights obtained in Table 12 show an overview of hospitals performance. As it can be seen, Sina Hospital has been ranked first for both C_3 and C_1 indicators, which have been the most important indicators from the experts' point of view. This hospital has been selected as a reference hospital. Other hospitals should look for new ways to improve their performance, given their scores of indicators.

Overall, hospital performance evaluation is important to maintain public welfare, improve the ability and quality of health care, and ensure the sustainable development of the hospitals. In addition, the results of the performance evaluation can be useful not only for the hospitals' managers but also for the community.

Announcing the results of performance evaluations is a useful manner to improve social supervision on the hospitals.

The hospitals can identify their strengths and weaknesses using these results. High weight of a criterion and the good performance of a hospital in satisfying that criterion can bring a higher rank. Hospitals that rank higher in terms of medical services can serve as reference models for other hospitals. HPE results can be useful for patients, government, and hospitals' staff. Using these results, patients can become aware of the quality of hospitals' medical services, the government can focus on the social benefits of hospitals, and staff can strive for more sustainable development of hospital.

5. Conclusion

The purpose of this paper was to present a hybrid MCGDM-FPP technique for HPE to identify hospitals that better meet patients' needs. To this end, by combining GBWM and FPP, we introduced a decision model that includes a decision group consisting of a group supervisor and DMs. These DMs may have different levels of knowledge about HPE, so the proposed method does not consider equal importance for DMs' opinions. The importance of DMs' opinions is determined by the group supervisor. Data related to the selected criteria were collected for five hospitals for the year 2018. A four-person decision-making team of professors and experts was asked to complete the questionnaires. Finally, we implemented the proposed model and evaluated its feasibility. Sina Hospital, Baharloo Hospital, and Tehran Heart Center ranked first to third, respectively, for various values of alpha. The advantage of the proposed method is that it covers uncertain condition and does not need to calculate separately the consistency of the decision-making team members.

This study provides physicians and managers of health centers with information on the quality of hospital services. Provision of a clear and rational framework for performance evaluation is one of its advantages that can improve service quality. Also, using the proposed method, we can compare hospital performance scores based on each criterion and improve hospitals with low performance scores by implementing the necessary programs. Finally, we recommend hospital managers and health care providers to use the HPE's proposed framework. The proposed approach can be used to address other MCDM issues such as selecting a green or sustainable supplier. Other MCDM techniques such as WASPAS and SWARA can also be used to rank the alternatives.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Maghsoud Amiri: Conceptualization, Supervision, Investigation. **Mohammad Hashemi-Tabatabaei:** Methodology, Resources, Writing - original draft. **Mohammad Ghahremanloo:** Methodology, Resources. **Mehdi Keshavarz-Ghorabaee:** Supervision, Formal analysis, Validation, Software. **Edmundas Kazimieras Zavadskas:** Conceptualization, Supervision, Writing - review & editing. **Jurgita Antucheviciene:** Conceptualization, Supervision, Writing - review & editing.

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