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Intuitionistic Fuzzy Best-Worst Method for Multi-Criteria Decision Making with Application in Health Care Resource Allocation

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Abstract. In the health care industry, decision-making is critical for determining the most efficient use of limited resources. Multi-criteria decision-making is a significant area that has been used to solve complex problems. To construct an accurate, adaptable, and sustainable framework for decision-making, an intuitionistic fuzzy best-worst method for multi-criteria decision-making in healthcare resource allocation is being developed. To understand the resource allocation mechanisms in different hospitals, the proposed methods employ a pairwise comparison of seven main criteria: infrastructure, consultancy time, paramedics, hospital stay, healthcare resource allocation, healthcare professionals' satisfaction, and improvements in resource allocation. The weights calculated from the intuitionistic fuzzy best-worst method indicate that health professional satisfaction is the best criterion, whereas the consultancy time is the worst. The goal of this approach is to effectively handle the inherent ambiguity, complexity, and uncertainty that define problems with healthcare resource allocation. This methodology has a wide range of applications, including: hospital resource management, prioritizing patient care during peak times or emergencies such as pandemics, budgeting and financial planning, evaluating the cost-effectiveness of new treatments or technologies, public health planning, planning and executing community health interventions, strategic planning, and policy making.

1. Introduction

In today's complex socioeconomic environment, it is increasingly challenging for individual decision makers (DMs) to consider all the aspects of a problem. In major industries such as recruitment, scheduling, promotion planning, and reorganization, technical committees make critical decisions. Additionally, important judgments are typically made with the involvement

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of dedicated staff and subject matter experts in fields such as healthcare, judicial frameworks, and welfare programs. Given the existence of uncertain data, decision analysis is both necessary and acceptable. In recent years, researchers have proposed numerous innovative hypotheses and strategies that are frequently applied to address a wide range of everyday problems in sectors such as banking, administration, economy, production, systematization, and transportation. For health care decision makers, their primary role is to determine the most efficient allocation of limited resources while utilizing technical knowledge based on the information available at the moment. Decision making which refers to the reliability and personal satisfaction from set of choices [1, 2], the term multi criteria decision making (MCDM) describes the process of making decisions using multiple criteria. One of the best MCDM was proposed by Rezaei *et al.* [3] and MCDM is a critical component in program implementation science, system integration, and operational research and have multiple uses in variety of fields, including administration, technology, and finance etc.

Uncertain decision-making appears in a wide variety of human behaviours, specifically when dealing with sophisticated modelling. In management sciences and decision sciences, fuzzy set theory has been extensively used [4]. The health care industry is prone to uncertainties in decision making due to the complexity of the field and the high stakes involved in health care decisions. There are several examples of uncertainties that can arise in healthcare decision making. For instance, diagnosis of rare or complex conditions is often uncertain, and health care professionals must evaluate the available evidence, the patient's medical history and symptoms, and their own clinical judgement to arrive at a diagnosis. There is also often uncertainty about the effectiveness of different treatments, particularly for new or experimental treatments, and health care providers must consider the potential benefits and risks of each option. In addition, health care decisions frequently require balancing the benefits of treatment against the costs, which can be difficult given the challenge of predicting long-term outcomes. Patient preferences can also introduce uncertainty into the decision-making process. Health care providers must rely on their clinical judgement, available evidence, and patient input to make the best possible decisions given the available information. Over the past years , many approaches that has been presented to handle uncertainties within decision-making challenges becomes a demanding research problem. Concerning to medical and administrative aspects of health care, decision making may have an indirect or direct influence on the patient's welfare. In health care service system , when patient's are entered in to the hospital they are not treated as they arrived and alternatively optimized based on the priority and intensity of their requirements to the hospital. To reflect a mechanism during which inpatient beds are granted to elective admittance demands that are placed on hold on a schedule. For all waiting patient's, with the goal of boosting the accuracy of diagnostic , monitoring , the optimal prioritized allocation strategy must be designed. Both qualitative and quantitative aspects in multi-criteria decision making (MCDM) are challenging tasks. Now, the assessment of every patient admittance urgency is predicted on the basis of uncertain facts or fuzzy but there might be a significant link in between monitoring and evaluating standards.

Fuzzy judgments are typically used in decision-making to deal with uncertainties that arise in real-world circumstances. It is up to decision makers to determine the most better and worst criteria among a set of criteria while making decisions. A fuzzy planning model in decision making provides more accurate and reliable solution as possible whereas to handle uncertainties or unclear facts decision making is carried out. For the real based data where we have valid knowledge. It is appropriate for the situation where there are no surety related to problem outcomes so in this case decision making becomes too hard and consider to be sophisticated process. Over the past years, the BWM method has been extended to various fuzzy environments, including fuzzy sets [5], triangular fuzzy numbers (TFNs) [6,7], probabilistic hesitant fuzzy sets [8], Z-numbers [9], interval-valued fuzzy-rough numbers [10], interval rough numbers [11], intuitionistic fuzzy multiplicative preference relations (IFMPRs) [12], and IFPRs [13], among others. Later, Aboutorab *et al*. [9] transformed Z-numbers into TFNs and proposed the integration of the BWM and Z-numbers called the ZBWM method to solve the decision making problems with intuitionistic fuzzy multi preference relation (IFMPRs) under uncertain circumstances, Xia et al. [15] proposed the generalized intuitionistic fuzzy multiplicative weighted averaging (GIFMWA) operator.
In this paper, a fuzzy multi-criteria decision-making model is developed on the basis of the intuitionistic fuzzy best-worst technique [16] and through out in this paper BWM and intuitionistic fuzzy BWM are extended to solve multi-criteria decision making ($MCDM$) problems for 16 criteria pairwise comparison is held between BWM and intuitionistic fuzzy BWM with the help of consistency ratio and threshold which clearly depicts that intuitionistic fuzzy BWM will provide more consistent and reliable solution than BWM. In the past years, many approaches were used to solve multi-criteria decision making (MCDM) problems [12,17–19,27] and in the mobile phone selection problem, Rezaei [3] used the BWM method. Rezaei *et al*. [29] utilized the same method to assess suppliers' capabilities and willingness. The BWM approach was also employed by Sadaghiani *et al*. [30] to determine the importance of external forces in the oil and gas industry. Rezaei *et al*. [31] applied the BWM to rank suppliers of edible oils, considering both traditional and environmental factors. Furthermore, Rezaei [32] employed interval analysis and the BWM concept in a minmax model to generate multiple optimal intervals for criteria weights. In this paper , to study best worst and intuitionistic fuzzy best worst method in health care have several purposes. The following steps constitute the procurement strategy, which we put out to achieve the objective:

- In contrasting various treatments, surgeries, or intervention programmes in health care, decision-makers need to consider multiple criteria into consideration. The Best Worst and IFBW approaches can help with recognizing and emphasizing the most significant factors impacting the performance.
- To check reliability and consistency of pairwise comparisons consistency indexes ,consistency ratio, threshold are used for both Best Worst and IFBWM. The utilization of Best Worst and IFBW methods can enable health care providers to make better-informed decisions that result in improved patient outcomes. For instance, prioritizing the most essential

factors using these methods can assist providers in choosing the most efficient treatments or interventions for a specific patient.

- Weights evaluated for the given criteria by the Best worst and intuitionistic fuzzy best worst methods are extended to 16 criteria in this proposed study and in future with the help of this study the proposed BWM solver sheet could be easily proposed to tackle more than 16 criteria.
- Due to the limited nature of health care resources, it's important for decision-makers to allocate them efficiently. The utilization of Best Worst and IFBW methods can aid decision-makers in identifying the most crucial criteria and effectively allocating resources, resulting in optimal resource utilization.
- When making decisions in healthcare, it's crucial to consider patient preferences and values. The IFBW method is especially helpful in enabling decision-makers to integrate patient preferences and opinions in a more adaptable and nuanced manner, resulting in care that is more centered around the patient.

  Consequently, analyzing best worst and intuitionistic fuzzy best worst can give healthcare decision-makers essential tools for enhancing patient outcomes, optimising resource allocation, and embedding patient preferences into the decision-making process.

This article is a comparison of the Best-Worst Method (BWM) and Intuitionistic Fuzzy Best-Worst Method (IFBWM) of health care decision making. These approaches enable the decision-makers to benchmark different criteria when deciding between treatments, interventions, or resource allocation options. The results obtained by using the consistency indices and ratios are satisfactory and the methods take into account the preferences of the patients and as such it is possible to propose a care with a more human orientation. Weights of up to 16 criteria are considered in this work, and the framework can be extended to higher numbers in the future.

The rationale for using IFBWM is that it enables one to respond to the uncertainty, reluctance, and dynamism of a health care setting and particularly respond to such events as pandemics or changing patient demand. Unlike the more traditional approach, IFBWM is adaptive to new conditions and is based on the concept of fairness, resulting in a more equitable distribution of scarce health care resources. But it is more formal and therefore more effective and ethically acceptable in decision-making.

The way forward in future studies is to develop domain-specific emergency and chronic conditions models, integrating IFBWM with other multi-criteria decision-making techniques and implementing IFBWM to big data. Furthermore, IFBWM and machine learning, along with artificial intelligence, have the greatest potential to provide data-based real-time decision support. These opportunities can be understood as a mechanism for ensuring that IFBWM is a successful, adaptive and equitable model for healthcare decision making.

2. Intuitionistic fuzzy sets

The concept of intuitionistic fuzzy sets (IFS) was first explained by Atansassov [20] and it is a set of triplet represented as $\{\langle e, (\eta_{\tilde{L}}(e), \varphi_{\tilde{L}}(e))\rangle\}$ where $\eta_{\tilde{L}}(e), \varphi_{\tilde{L}}(e)$ denotes the degree of truth and untruth respectively and $\eta_{\tilde{L}}(e), \varphi_{\tilde{L}}(e) \in [0,1]$. Let $\tilde{S}$ be the non-empty set and mathematically a fuzzy subset $\tilde{L}$ of $\tilde{S}$ is represented as:

$$\tilde{L} = \{\langle e, \eta_{\tilde{L}}(e), \varphi_{\tilde{L}}(e)\rangle \mid e \in \tilde{S}\}. \tag{2.1}$$

Where $\eta_{\tilde{L}}$ and $\varphi_{\tilde{L}}$ are function from $\tilde{S}$ to the interval $[0,1]$ commonly called membership and non-membership function with

$$0 \leq \eta_{\tilde{L}}(e) + \varphi_{\tilde{L}}(e) \leq 1 \quad e \in \tilde{S}. \tag{2.2}$$

2.1. **Operations defined on intuitionistic fuzzy sets.** Let $\tilde{L_1}$ and $\tilde{L_2}$ denotes the two intuitionistic fuzzy sets, then the arithmetic operations and set theory on intuitionistic fuzzy sets are defined as:

$$\tilde{L_1} + \tilde{L_2} = \{\langle e, \eta_{\tilde{L_1}}(e) + \eta_{\tilde{L_2}}(e) - \eta_{\tilde{L_1}}(e) \cdot \eta_{\tilde{L_2}}, \varphi_{\tilde{L_1}}(e) \cdot \varphi_{\tilde{L_2}}(e)\rangle \mid e \in \tilde{S}\} \tag{2.3}$$

$$\tilde{L_1} \times \tilde{L_2} = \{\langle e, \eta_{\tilde{L_1}}(e)\eta_{\tilde{L_2}}(e), \varphi_{\tilde{L_1}}(e) + \varphi_{\tilde{L_2}}(e) - \varphi_{\tilde{L_1}}(e)\varphi_{\tilde{L_2}}(e)\rangle \mid e \in \tilde{S}\} \tag{2.4}$$

$$\tilde{L_1} \cup \tilde{L_2} = \{\langle e, \max(\eta_{\tilde{L_1}}(e), \eta_{\tilde{L_2}}(e)), \min(\varphi_{\tilde{L_1}}(e), \varphi_{\tilde{L_2}}(e))\rangle \mid e \in \tilde{S}\} \tag{2.5}$$

$$\tilde{L_1} \cap \tilde{L_2} = \{\langle e, \min(\eta_{\tilde{L_1}}(e), \eta_{\tilde{L_2}}(e)), \max(\varphi_{\tilde{L_1}}(e), \varphi_{\tilde{L_2}}(e))\rangle \mid e \in \tilde{S}\} \tag{2.6}$$

$$\tilde{L_1} : \tilde{L_2} = \{\langle e, \eta_{\tilde{L_1}:\tilde{L_2}}(e), \varphi_{\tilde{L_1}:\tilde{L_2}}(e)\rangle \mid e \in \tilde{S}\} \tag{2.7}$$

$$\tilde{L_1} - \tilde{L_2} = \{\langle e, \eta_{\tilde{L_1}-\tilde{L_2}}(e), \varphi_{\tilde{L_1}-\tilde{L_2}}(e)\rangle \mid e \in \tilde{S}\} \tag{2.8}$$

where

$$\eta_{\tilde{L_1}:\tilde{L_2}}(e) = \begin{cases} \frac{\eta_{\tilde{L_1}}(e)}{\eta_{\tilde{L_2}}(e)} & \text{if} \quad \eta_{\tilde{L_1}}(e) \leq \eta_{\tilde{L_2}}(e) \\ & \textit{and} \quad \eta_{\tilde{L_2}}(e) > 0 \\ & \textit{and} \quad \eta_{\tilde{L_1}}(e)\varpi_{\tilde{L_2}}(e) \leq \eta_{\tilde{L_2}}(e)\varpi_{\tilde{L_1}}(e) \\ 0 & \textit{otherwise} \end{cases} \tag{2.9}$$

$$\varphi_{\tilde{L_1}:\tilde{L_2}}(e) = \begin{cases} \frac{\varphi_{\tilde{L_1}}(e) - \varphi_{\tilde{L_2}}(e)}{1 - \varphi_{\tilde{L_2}}(e)} & \text{if} \quad \varphi_{\tilde{L_1}}(e) \leq \varphi_{\tilde{L_2}}(e) \\ & \textit{and} \quad \varphi_{\tilde{L_2}}(e) > 0 \\ & \textit{and} \quad \varphi_{\tilde{L_1}}(e)\varpi_{\tilde{L_2}}(e) \leq \varphi_{\tilde{L_2}}(e)\varpi_{\tilde{L_1}}(e) \\ 1 & \textit{otherwise} \end{cases} \tag{2.10}$$

and

$$\eta_{\tilde{L_1}-\tilde{L_2}}(e) = \begin{cases} \frac{\eta_{\tilde{L_1}}(e) - \eta_{\tilde{L_2}}(e)}{1 - \eta_{\tilde{L_2}}(e)} & \text{if} \quad \eta_{\tilde{L_1}}(e) \geq \eta_{\tilde{L_2}}(e) \\ 0 & \textit{otherwise} \end{cases} \tag{2.11}$$

$$\varphi_{\tilde{L_1}-\tilde{L_2}}(e) = \begin{cases} \frac{\varphi_{\tilde{L_1}}(e)}{\varphi_{\tilde{L_2}}(e)} & \text{if} \quad \varphi_{\tilde{L_1}}(e) \leq \varphi_{\tilde{L_2}}(e) \\ 1 & \textit{otherwise} \end{cases} \tag{2.12}$$

3. Best-worst multi-criteria decision making method

Every single day, to make judgements about certain aspects of our lives that are usually associated to our individual problems as well as in career. Decision-making tools assist us in the recognition, evaluation, and acceptance of alternatives on the basis of judgements, beliefs and preferences. Utilizing a variety of criteria, multi-criteria decision making are employed to control and coordinate decision and planning-related challenges. Over the past ten years several multi criteria decision making approaches have been implemented in a variety of supply chain management, health administration, resource management, etc. Pairwise comparisons among numerous criteria are essential for all of these techniques. One of the most significant area of decision making theory is multi-criteria-decision making (MCDM). Multi criteria problems are typically split into two categories: continuous and discrete with respect to the problem optimal solution. To cope with continuous problems, multi objective Decision-making (MODM) techniques are utilized. Multi-Attribute Decision-Making (MADM) techniques are proposed to deal with discrete problems. While performing pairwise comparisons, a vast strategies suffers from inconsistent results and was suggested by Rezaei [3]. Therefore, an innovative approach known as Best-Worst-Method (BWM) is used to solve MCDM problems and also resolve the inconsistency problem occurs in pairwise comparison , this technique demands for fewer comparisons as compared to previous MCDM strategies. In order to choose the best option in an MCDM problem , a wide range of possibilities are assessed in the context of variety of criteria. Both best (e.g. most appealing, most essential) and worst (e.g. least appealing, least significant) criteria are evaluated first by the decision maker in accordance with BWM. By employing pairwise comparison between the best and worst and then compared against the other criteria. By combining the weights from many evaluation criteria and possibilities, the best option is determined, and the outcomes of the acceptable option are computed. A consistency ratio is established for the BWM to examine the accuracy of comparisons. Following are the basic steps involved in developing BWM:

Step 1: To determine a set of criteria for making the decisions.
In the first step to assist in decision making relying on the study of research and individuals point of view, a set of k criteria $(s_1, s_2, s_3, \ldots, s_k)$ are determined.

Step 2: The best criteria (e.g. the most desirable, the most essential) and the worst criteria(least desirable, least significant) are chosen

Step 3: To express your priority for the best criteria over the other criteria, choose a number between 1 and 9 scale. The vector representation of best-to-other vector(BO) can be denoted as:

$$\bar{\alpha}_{\acute{B}} = (e_{\acute{B}1}, e_{\acute{B}2}, e_{\acute{B}3}, \ldots, e_{\acute{B}k})$$

where $e_{\acute{B}m}$ denotes the preference of best criteria B over criteria m. Also we have $e_{\acute{B}B}$=1. Every professionals who participated in decision making process may agreed on the obtained final value.

Step 4: To evaluate the preference of almost all of the criteria over the worst criteria using a scale from 1 to 9. The vector representation of others-to-worst(OW) are denoted as:

$$\bar{\alpha}_{\acute{w}} = (e_{\acute{1w}}, e_{\acute{2w}}, e_{\acute{3w}}, \ldots, e_{\acute{kw}})^T$$

where $e_{\acute{W}m}$ denotes the preference of all other criteria m over the worst criteria W. Also we have $e_{\acute{W}W}$=1. Every professionals who participated in decision making process may agreed on the obtained final value.

Step 5: To determine the optimal weights $(\acute{w}_1, \acute{w}_2, \acute{w}_3, \ldots, \acute{w}_k)$

To evaluate the optimal weight for the criteria in case of each pair $\frac{w_B}{w_m}$ and $\frac{w_m}{w_w}$ which then ultimately resulted in the form of weight as: $\frac{w_B}{w_m} = e_{\acute{B}m}$ and $\frac{w_m}{w_W} = e_{\acute{m}W}$ we must need to figure out the solution which satisfies the above condition for all m and also the greatest possible absolute differences $\mid \frac{w_B}{w_m} - e_{\acute{B}m} \mid$ and $\mid \frac{w_m}{w_W} - e_{\acute{m}W} \mid$ are minimized for all m.

Let us consider the sum and non-negativity condition for weights due to which the following problem occurs:

$$\tilde{\zeta} = \min / \max_m \left\{ \mid \frac{w_B}{w_m} - e_{\acute{B}m} \mid and \mid \frac{w_m}{w_W} - e_{\acute{m}W} \mid \right\} \tag{3.1}$$

such that $\sum_m w_m = 1$, $w_m \geq 0 \quad \forall m$

Now this programming model is remodeled into the following programming model which are defined as:

$$\min \delta$$

such that

$$|\frac{w_B}{w_m} - e_{\acute{B}m}| \leq \delta \quad \forall m$$

$$|\frac{w_m}{w_W} - e_{\acute{m}W}| \leq \delta \quad \forall m$$

$$\sum_m w_m = 1$$

$$w_m \geq 0 \quad \forall m$$

$$\min \delta$$

such that

$$|\frac{w_m}{w_B} - e_{\acute{m}B}| \leq \delta \quad \forall m$$

$$|\frac{w_W}{w_m} - e_{\acute{W}m}| \leq \delta \quad \forall m$$

$$\sum_m w_m = 1.$$

This model is in crisp environment so to convert this in to intuitionistic fuzzy model we need to replace the decision variables and parameters by intuitionistic fuzzy numbers so the model has the following form:

$$\min(\delta_\eta, \delta_\varphi)$$

such that;

$$|\frac{(w_\eta^m, w_\varphi{}^m)}{(w_\eta^B, w_\varphi{}^B)} - (\acute{e_\eta}^{mB}, \acute{e_\varphi}^{mB})| \leq (\delta_\eta, \delta_\varphi) \quad \forall m$$

$$\sum_{m=1} (w_\eta^m, w_\varphi^m) \leq 1$$

Using the arithmetic operation defined on intuitionistic fuzzy sets in Section **??** the above model is redesigned as:

$$\min(\delta_\eta, \delta_\varphi) \tag{3.2}$$

$$\frac{w_\eta^m}{w_\eta{}^B} \leq |\delta_\eta + \acute{e_\eta}^{mB} - \delta_\eta \acute{e_\eta}^{mB}| \quad \forall m \tag{3.3}$$

$$|\frac{w_\varphi^m - w_\varphi^B}{1 - w_\varphi^B}| \geq \delta_\varphi \acute{e_\varphi}^{mB} \quad \forall m \tag{3.4}$$

$$\frac{w_\eta^W}{w_\eta^m} \leq |\delta_\eta + \acute{e_\eta}^{Wm} - \delta_\eta \acute{e_\eta}^{Wm}| \quad \forall m \tag{3.5}$$

$$|\frac{w_\varphi^W - w_\varphi^j}{1 - w_\varphi^j}| \geq \delta_\varphi \acute{e_\varphi}^{Wj} \quad \forall m \tag{3.6}$$

$$w_\eta^m + w_\varphi^m \leq 1 \quad \forall m \tag{3.7}$$

$$\delta_\eta + \delta_\varphi \leq 1 \tag{3.8}$$

$$w_m = \frac{1 + w_\eta^m - w_\varphi^W}{2} \quad \forall m \tag{3.9}$$

$$\sum_{m=1}^{l} w_m = 1 \tag{3.10}$$

$$w_\eta^W, w_\eta^B, w_\varphi^B, w_\varphi^W, w_\varphi^m, w_\eta^B, \delta_\varphi, \delta_\eta, w_m \geq 0. \tag{3.11}$$

In the above model equation 3.2 denotes the objective function. Expressions 3.3 and 3.4 represents the preference of all other criteria over best criteria which will provide the membership and non-membership weight values while expressions 3.5 and 3.6 denotes the preference of worst criteria over the other criteria which will give the value of membership and non-membership weights. The expressions 3.7 and 3.8 ensures the condition for intuitionistic fuzzy sets. Equation 3.9 is used to defuzzify the weights. Equation 3.10 ensures that sum of weight must be equal to one and expression 3.11 describes the non-negativity of decision variables.

4. Case study

In the real world , hospital is one of the important area across all over the world. Hospital plays a vital role in providing the best services to their patient's in order to improve their repute and to make sure their patient's to better enjoy services. In this modern time period , patient's are demanding for quality which increases pressure on hospital administration. The case study that is under consideration are emergency department of hospital. Over the past years , across all over the world corona virus was the most prevailing disease and mostly people were affected by this disease. In case of COVID-19 pandemic , a fuzzy multi criteria decision analysis was conducted [21–24] and to evaluate the COVID-19 pandemic performance of insurance company in the health care treatment area an Intuitionistic MACROS fuzzy technique was adopted [25]. In Pakistan , today's most prevailing diseases are typhoid fever , dengue , diarrhea , etc. So in order to deal with these patient's the services provided by hospital includes patient appointments , availability of doctors , treatment time , in case of emergent condition patient's admittance , maintenance of patient's history , time required to shift patient's from OPD to ward, allocation of beds , nurse care, consultancy time needed to admitted patient's , role of lab technicians , quality of medicines provided to admitted patient's etc. Now the decision making process occurs at every stage for both emergent and non emergent cases. It involves evaluation , diagnostic, surgical decision making which occurs at every stage. In case of emergency department, as most of the time uncertain event occurs so in that time consultants need to take quick decision and select the best treatment area from all of the given opportunities in order to save their patient's life and by using fuzzy best-worst technique, group decision-making was employed in this domain [26]. A case study of maintenance assessment in hospitals using only a fuzzy best-worst multi-attribute decision-making approach utilizing triangular fuzzy numbers was carried in the past [27]. Best worst method was further extended to intuitionistic fuzzy best-worst technique by Mou *et al.* [12].

4.1. **Data collection.** The data is gathered from various hospitals in Islamabad and Rawalpindi by means of a questionnaire that inquiries about the allocation of health care resources across accident and emergency department. The overall theme will serve to identify the best criteria and least important, i.e., the worst criterion/theme, in order to devise the health care resource allocation criteria. This assessment helps to determine whether there exist sufficient and suitable medical facilities to treat emergency situations. The questionnaire has seven main criteria.

(1) Infrastructure
(2) Consultancy time
(3) Paramedics
(4) Hospital stay
(5) Impact of health care resource allocation

(6) Health professional's satisfaction
(7) Improvements in the allocation of health care resource allocation

In order to maximize resource utilization while preserving efficient patient care, this case study explores the use of the intuitionistic fuzzy best-worst method (IF-BWM) to reallocate beds within an emergency department. The following are the main objective of this case study:

- To list and rank the most important factors affecting the distribution of beds in the emergency department
- To utilize IF-BWM in order to ascertain the ideal resources distribution across various patient groups
- In order to demonstrate the benefits of using fuzziness in decision-making, the results of IFBWM and BWM are compared

Several factors have been considered to be crucial when it concerns emergency bed allocation. Based on medical professional's opinion, the weights for each criteria was determined first and then the best and worst weights for each criterion have been identified through employing the IF-BWM approach. In our case, professional's satisfaction is the best criteria whereas consultancy time is the least significant criteria. A pairwise comparisons are made between this best and worst criteria with the other criterias. To ensure that the allocation of the resources accessible is in compliance with the priorities, the weights that were computed were utilized to divide them among the various patient types. As according to professional's perspectives, health professional's satisfaction is the best criteria and consultancy time is the least significant criteria. Experts made pairwise comparison between the best, worst, and other criteria using intuitionistic fuzzy numbers. Using traditional BWM without the fuzziness to determine the comparative weights and resources allocation decisions, the same steps were carried out. Consistency index, consistency ratio are then evaluated using BWM and IFBWM. The table below summarizes the outcomes from both BWM and IFBWM assessments.

5. Results and discussion

The weights obtained through BWM and intuitionistic fuzzy BWM using BWM solver. In this paper, the two way comparison is presented and moreover BWM solver is upgraded to obtain the weight for 16 criteria. For BWM, the scale used to measure the preferences are varies from (1 , 2 , . . . , 9) and it is depending on decision makers while in intuitionistic fuzzy BWM the preferences lies between 0 to 1. The preference of best over best is always 1 and the prefrence of worst over worst is always one in both BWM and intuitionistic fuzzy BWM while other prefrences are indicated by decision maker. The comparative weights from the Best-Worst Method (BWM) and the Intuitionistic Fuzzy Best-Worst Method (IF-BWM) are highlighted in the following tables 1-8. These tables illustrate that each technique evaluates corresponding criteria, revealing beneficial knowledge about the decision-making process of allocating resources in healthcare.

Table 1: The best criteria is health professional's satisfaction whereas the worst criteria is consultancy time.

Table 2: Criteria 1.7 (If a person is in critical condition, then hospital administration assigns bed immediately) is best criteria whereas the criteria 1.8 (The emergency department have enough bed capacity to handle a rapid increase in the number of patients) is worst.

Table 3: Criteria 2.9 (To entertain the large group of people who are infected with typhoid, dengue, etc. have some special wards for their treatment designed administration.) is best criteria whereas the criteria 2.7 (People with infectious diseases but not in critical condition were treated the same as those who had in critical condition) is worst.

Table 4: Criteria 3.5 (Eight to twelve hours are sufficient for emergency staff in the emergency department at your hospital) is best criteria whereas the criteria 3.8 (Patients requiring care of a private nurse should contact the ward nurse and these services are available for admitted patients at an additional charge) is worst.

Table 5: Criteria 4.1 (Hospital registration form must be required to track patient personal, contact information, demographics treatment details and to collect patient consent for their planned treatment) is best criteria whereas the criteria 4.4 (Medicines provided by the hospital to admitted patients while providing them treatments are better in quality) is worst.

Table 6: Criteria 5.5 (In the last six months professional attended to patients with a case of medical complications) is best criteria whereas the criteria 5.7 (In the last six months professional was sometimes unable to obtain some services that were necessary for the patients (including unacceptable waiting time)) is worst.

Table 7: Criteria 6.10 (The general performance of the hospital is satisfactory) is best criteria whereas the criteria 6.1 (Health care service to all emergency cases is satisfactory) is worst.

Table 8: Criteria 7.13 (Employment of physicians and other health professionals should be increased) is best criteria whereas the criteria 7.2 (Allocation of resources should consider the number of patient visits (inpatient and outpatient) is worst.

Table 1. **Pairwise comparison of overall criteria using BWM and IFBWM**

Criteria	BO	OW	BWM Weight	$\eta(BO)$	$\eta(OW)$	$\varphi(BO)$	$\varphi(OW)$	IFBWM Weights
Infrastructure	8	2	0.007352941	0.125	0.9	0.532	0.19	0.518
Consultancy time	9	1	0.006535948	0.111	1	0.1013	1	0.5108
Paramedics	2	8	0.029411765	0.5000	0.2	0.177	0.57	0.488
Hospital stay	3	7	0.019607843	0.3333	0.3	0.01994	0.508	0.479
Impact of health care resource allocation	7	2	0.008403361	0.1428	0.8	0.3987	0.254	0.506
Health professional satisfaction	1	9	0.058823529	1	0.1	1	0.101	0.5216
Improvements in health resource allocation	7	2	0.016806723	0.285	0.4	0.44934	0.225	0.509

Table 2. **Pairwise comparison of infrastructure using BWM and IFBWM**

Criteria	BO	OW	BWM Weight	$\eta(BO)$	$\eta(OW)$	$\varphi(BO)$	$\varphi(OW)$	IFBWM Weights
1.1	2	7	0.1256	0.7	0.105	0.3	0.95	0.549
1.2	7	2	0.0359	0.20	0.4	0.6	0.42	0.4865
1.3	5	3	0.0502	0.29	0.26	0.4	0.63	0.50418
1.4	7	2	0.036	0.20	0.4	0.6	0.42	0.4865
1.5	8	2	0.0314	0.18	0.42	0.6	0.32	0.4739
1.6	6	8	0.0418	0.24	0.4	0.4	0.63	0.5
1.7	1	9	0.172	1	0.12	1	0.25	0.5362
1.8	9	1	0.01322	0.08	1	0.12	1	0.4934
1.9	2	7	0.1256	0.7	0.64	0.3	0.9	0.5525
1.10	7	2	0.035	0.20	0.3	0.6	0.57	0.4948
1.11	4	4	0.0628	0.36	0.105	0.59	0.99	0.5182
1.12	5	3	0.0502	0.3	0.43	0.48	0.09	0.5097
1.13	6	2	0.0418	0.24	0.36	0.4	0.07	0.5024
1.14	8	2	0.0314	0.18	0.21	0.6	0.45	0.485
1.15	4	4	0.0628	0.36	0.105	0.59	0.99	0.5182
1.16	3	5	0.0838	0.49	0.158	0.219	0.88	0.530289

Table 3. **Pairwise comparison of consultancy time using BWM and IFBWM**

Criteria	BO	OW	BWM Weight	$\eta(BO)$	$\eta(OW)$	$\varphi(BO)$	$\varphi(OW)$	IFBWM Weights
2.1	8	2	0.05122784	0.204	0.89	0.510	0.17	0.492
2.2	5	4	0.08196455	0.327	0.556	0.343	0.29	0.4755
2.3	7	3	0.05854611	0.2	0.7783	0.294	0.276	0.4711
2.4	6	4	0.06830379	0.27	0.67	0.343	0.29	0.4644
2.5	3	8	0.13660758	0.54	0.33	0.26	0.389	0.46044
2.6	8	2	0.05122784	0.204	0.89	0.69	0.15	0.4948
2.7	9	1	0.04553586	0.1817	1	0.100	1	0.46727
2.8	2	9	0.20491137	0.818	0.22	0.97	0.44	0.51707
2.9	1	9	0.25044723	1	0.182	1	0.100	0.46300
2.10	8	3	0.051228	0.204	0.89	0.600	0.17	0.5214

Table 4. **Pairwise comparison of paramedics using BWM and IFBWM**

Criteria	BO	OW	BWM Weight	$\eta(BO)$	$\eta(OW)$	$\varphi(BO)$	$\varphi(OW)$	IFBWM Weights
3.1	6	2	0.08352	0.34	0.67	0.36	0.29	0.50626
3.2	5	3	0.1002	0.40	0.56	0.298	0.35	0.49374
3.3	6	2	0.08352	0.33	0.67	0.358	0.29	0.50626
3.4	5	3	0.1002	0.20	0.55	0.13	0.8	0.5236
3.5	1	9	0.2506	1	0.2	1	0.10	0.5
3.6	4	4	0.12528	0.5	0.44	0.22	0.47	0.5418
3.7	6	2	0.084	0.33	0.67	0.316	0.33	0.4374
3.8	9	1	0.05568	0.22	1	0.105	1	0.49105

Table 5. **Pairwise comparison of hospital stay using BWM and IFBWM**

Criteria	BO	OW	BWM Weight	$\eta(BO)$	$\eta(OW)$	$\varphi(BO)$	$\varphi(OW)$	IFBWM Weights
4.1	1	5	0.10294	1	0.16	1	0.07	0.56405
4.2	2	5	0.1765	0.6	0.27	0.15	0.5	0.5429
4.3	2	4	0.1765	0.6	0.27	0.15	0.42	0.5429
4.4	5	1	0.04706	0.16	1	0.03	1	0.508
4.5	5	2	0.0706	0.24	0.7	0.04	0.33	0.5104
4.6	3	3	0.1176	0.4	0.404	0.07	0.44	0.5503
4.7	3	3	0.11764	0.4	0.404	0.07	0.37	0.55033

Table 6. **Pairwise comparison of impact of health care resource allocation using BWM and IFBWM**

Criteria	BO	OW	BWM Weight	$\eta(BO)$	$\eta(OW)$	$\varphi(BO)$	$\varphi(OW)$	IFBWM Weights
5.1	2	2	0.0797	0.39	0.64	0.22	0.500	0.50744
5.2	3	2	0.0531	0.26	0.67	0.33	0.317	0.4636
5.3	3	6	0.053	0.26	0.67	0.33	0.317	0.4636
5.4	3	6	0.0531	0.26	0.67	0.33	0.089	0.5148
5.5	1	4	0.2031	1	0.39	1	0.11	0.4184
5.6	3	2	0.1062	0.52	0.75	0.67	0.44	0.496
5.7	4	1	0.0797	0.39	1	0.410	1	0.5055
5.8	3	6	0.106	0.52	0.75	0.67	0.317	0.5206
5.9	3	2	0.1062	0.52	0.75	0.67	0.317	0.493
5.10	2	2	0.159	0.78	0.410	0.99	0.410	0.5022

Table 7. **Pairwise comparison of health professional satisfaction using BWM and IFBWM**

Criteria	BO	OW	BWM Weight	$\eta(BO)$	$\eta(OW)$	$\varphi(BO)$	$\varphi(OW)$	IFBWM Weights
6.1	4	1	0.053	0.40	1	0.28	1	0.4947
6.2	3	2	0.0708	0.53	0.75	0.24	0.08	0.4823
6.3	6	3	0.1062	0.800	0.50	0.21	0.75	0.477876
6.4	6	3	0.1062	0.800	0.50	0.21	0.7	0.477876
6.5	6	4	0.106	0.800	0.50	0.21	0.7	0.477876
6.6	6	3	0.1062	0.800	0.50	0.21	0.7	0.477876
6.7	6	3	0.1062	0.800	0.50	0.21	0.7	0.477876
6.8	6	4	0.1062	0.800	0.50	0.21	0.7	0.477876
6.9	3	2	0.0708	0.53	0.75	0.24	0.85	0.5044
6.10	1	4	0.133	1	0.39	1	0.36	0.5212
6.11	6	2	0.035	0.27	0.67	0.34	0.79	0.50530

Table 8. **Pairwise comparison of improvements in health resource allocation using BWM and IFBWM**

Criteria	BO	OW	BWM Weight	$\eta(BO)$	$\eta(OW)$	$\varphi(BO)$	$\varphi(OW)$	IFBWM Weights
7.1	3	2	0.0404	0.289	0.75	0.18	0.36	0.48447
7.2	4	1	0.0303	0.216	1	0.067	1	0.49575
7.3	3	2	0.0404	0.288	0.75	0.19	0.36	0.4894
7.4	2	3	0.0606	0.433	0.49	0.16	0.407	0.4839
7.5	3	2	0.0404	0.288	0.75	0.18	0.36	0.489
7.6	2	2	0.0606	0.433	0.49	0.16	0.407	0.484
7.7	3	2	0.0404	0.288	0.75	0.18	0.36	0.4894
7.8	3	2	0.0404	0.288	0.75	0.18	0.36	0.483919
7.9	2	2	0.0606	0.433	0.49	0.16	0.407	0.483919
7.10	2	3	0.0606	0.288	0.49	0.16	0.407	0.4894
7.11	2	3	0.0606	0.433	0.49	0.16	0.407	0.4983
7.12	2	2	0.0606	0.433	0.49	0.16	0.407	0.5096
7.13	1	4	0.1398	1	0.216	1	0.67	0.5076
7.14	2	2	0.1096	0.78	0.28	0.17	0.39	0.4867
7.15	2	3	0.071	0.509	0.43	0.17	0.39	0.49071
7.16	2	2	0.084	0.598	0.36	0.170	0.391	0.4967

It is impractical to expect the decision maker to achieve perfect consistency in the pairwise comparisons. Nevertheless, the study of BWM has yet to address the question of how much inconsistency is acceptable. To address this issue, a threshold must be established. A technique for determining consistency thresholds is presented motivated by Amenta *et al.* [37,38]. In this paper for the reliability of consistency level of pairwise comparison, it is only need to check that CR < Threshold, if this condition satisfies then consistency level of pairwise comparison is acceptable otherwise not acceptable. Table 9 indicates:

(1) The pairwise comparison of CR and Threshold of BWM and intuitionistic fuzzy BWM respectively.
(2) The twofold comparison, and it depicts that in case of paramedics, health professional's satisfaction, improvements in health care resource allocation the consistency ratio is less than threshold so the pairwise consistency level is acceptable and it concludes that pairwise comparisons are reliable for these cases and for others it is not acceptable.
(3) Using intuitionistic fuzzy BWM the pairwise comparison of CR and threshold holds for infrastructure, consultancy time, paramedics, impact of health care resource allocation, health professional's satisfaction, improvements in health care resource allocation, hospital stay in case of both membership and non-membership so the pairwise comparison consistency level is acceptable in each cases. Hence from above results, it can be seen that intuitionsitic fuzzy BWM ensures the reliability of pairwise comparison and give the best results than BWM.

Table 9. **Consistency index (CI), consistency ratio (CR) and threshold (TH) using BWM and IFBWM**

Criteria	CI	$\eta(CI)$	$\varphi(CI)$	CR	$\eta(CR)$	$\varphi(CR)$	TH	$\eta(TH)$	$\varphi(TH)$
Infrastructure	0.1454	0.0793	0.1454	0.8333	0.2683	0.35	0.3662	0.1	0.2
Consultancy time	0.1594	0.1594	0.2106	0.3662	0.05	0.296	0.2083	0.1667	0.3662
Paramedics	0.2506	0.2506	0.2506	0.0972	0.2844	1.25	0.3621	0.2844	0.75
Hospital stay	0.0941	1.2941	0.0588	0.5	0.3517	0.5	0.3517	0.3517	0.5
Impact of health care resource allocation	0.1594	0.1594	0.2872	0.3662	.3262	0.5714	0.208	0.3662	0.5
Health professional satisfaction	0.0903	0.0797	0.1024	0.2	0.3571	0.3657	0.2683	0.2683	2.333
Improvements in health care resource allocation	0.1059	0.0793	0.0793	0	0	0.2863	0.2863	0.3662	1
Overall criteria comparisons	0.0588	0.0588	0.0588	0.17	0.17	0.4	0.4	0.2	0.45

To reallocate resources in the Emergency Department (ED) based on multiple criteria, this study used the intuitionistic fuzzy best-worst method (IF-BWM). The outcomes are then compared with those attained by applying the conventional best-worst method (BWM). The key findings from the research we conducted are presented and discussed here: the best-worst method (BWM) and intuitionistic fuzzy sets are incorporated in the intuitionistic fuzzy best-worst method to cope with the instinctive uncertainty and ambiguity that emerge during decision-making. In order to prioritize criteria and allocate resources more effectively, decision-makers are permitted to offer more complicated judgments that capture both the membership and non-membership degrees of criteria. In contrast to conventional multi-criteria approaches, which requires accurate pairwise comparisons, the IFBWM optimizes the assessment process by concentrating on the best and worst criteria. By minimizing the cognitive strain on decision-makers while improving judgment consistency, this approach generates more reliable and consistent inferences. This study demonstrates the practical significance of the IFBWM in resource allocation by applying it specifically to the health care sector. Decisions pertaining to patient outcomes, cost, effectiveness, as well as accessibility, and additional influences are frequently complicated as well as critical for healthcare systems. Despite considering uncertainties in expert decisions, the IFBWM assists in properly evaluating these criteria and ensuring that resources are allocated in the manner that maximizes overall features.To compare the intuitionistic fuzzy best-worst method (IF-BWM) with the conventional best-worst method (BWM) to determine which technique is better for reallocating healthcare resources in the emergency department (ED). Below, we look at a few key areas:

- Weighting Criteria: Traditional BWM weighs the various criteria based on pairwise comparisons between the best and worst criteria as well as additional criteria, it performs with an expectation of exact conclusions, disregarding any ambiguity or uncertainty in professional assessments.By strongly preferring the most important criteria ranked by experts, this method typically produces a more precise weighting. Whereas, intuitionistic fuzzy sets which capture degrees of hesitation, non-membership, and membership, are integrated into

IF-BWM to produce a more balanced weight distribution. This approach incorporates the ambiguity and vagueness that characterize expert conclusions, enabling a more comprehensive evaluation of the relative weight of each criterion. Due to its fuzziness, all criteria can be assigned more weight without any one of them being given an overly significant weight. In contrast to BWM, IF-BWM enables a more sophisticated and evenly distributed set of weights, that better addresses expert inability and uncertainty. For circumstances in which there is a great deal of uncertainty, such as the emergency department, IF-BWM is more robust due to its capacity to handle imprecise decision-making processes.

- Equitable Allocation of Resources: IF-BWM optimizes the ability to respond to adapting patient demands by leading to more equitable and adaptable bed allocation. Through providing an extensive overview of resource distribution, the IF-BWM allocation is more compatible with a patient-centered criteria consisting of length of stay and satisfaction.
- Analyzing Sensitivity and Scenarios: In dynamic and uncertain situations, IF-BWM becomes more reliable whenever the allocations tend to be stable and more resistant to insignificant variations. This approach is ideal for the complicated and unpredictable circumstances of the emergency department as it can deal with wide range of scenarios with proficiency.
- Reliability in Decision Making: In healthcare, where preciseness is harder to accomplish the incorporation of the fuzziness in IF-BWM promotes a deeper and more comprehensive analysis of the circumstances related to decision-making processes. The emergency department and other contexts where decisions are frequently required in uncertain and unpredictable circumstances IF-BWM are more suitable due to its ability to deal with uncertainty and deviations, regardless of whether BWM is simpler to implement and assess.

6. Conclusion

The Best-Worst Method (BWM) and its modification, the Intuitionistic Fuzzy Best-Worst Method (IFBWM) are strong means to address the multi-criteria decision-making problem in healthcare. Such approaches are especially useful when there is uncertainty, ambiguity, and scarcity of resources. BWM can simplify the decision-making process and make it more uniform by prioritizing criteria by importance, and ranking them by the least importance, but IFBWM goes further, and enables the use of intuitionistic fuzzy sets to represent hesitation and missing information. Such integration helps decision-makers to think more realistically about alternatives and to make healthcare decisions far more consistent with patient values and priorities.

IFBWM is more accurate when dealing with inaccurate data, compared to traditional methods, and imposes less cognitive load on decision-makers, since fewer pairwise comparisons are needed. It is particularly helpful in the context of resource allocation since it enables the balancing of competing considerations, such as patient urgency, treatment effectiveness, and cost. Moreover, it is scalable and flexible, which also enables its application in a vast variety of healthcare contexts, such as

routine care decision-making and emergency response planning.
Another way in which BWM and IFBWM may be applied in the future is by extending it to other multi-criteria decision-making models such as Data Envelopment Analysis (DEA), Analytic Hierarchy Process (AHP), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). This type of hybrid models can utilize the benefits of multiple models to enhance reliability, scalability and applicability in real-time. IBFW can play a vital role in facilitating equitable, efficient and patient-centered decisions as healthcare systems move towards data-driven and technology-enabled decision support.

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