

Intuitionistic fuzzy MAUT-BW Delphi method for medication service robot selection during COVID-19

Daekook Kang^a, S. Aicevarya Devi^b, Augustin Felix^b, Samayan Narayanamoorthy^{c,*}, Samayan Kalaiselvan^d, Dumitru Balaenu^{e,f,g,*}, Ali Ahmadian^{h,i}

^a Department of Industrial and Management Engineering, Institute of Digital Anti-Aging Health Care, Inje University, 197 Inje-ro, Gimhae-si, Gyeongsangnam-do, 50834, Republic of Korea

^b Mathematics Division, School of Advanced Sciences, Vellore Institute of Technology, Chennai Campus, India

^c Department of Mathematics, Bharathiar University, Coimbatore 46, India

^d Department of Social Work, SRMV College of Arts and Science, Coimbatore 641020, India

^e Department of Mathematics, Cankaya University, 06530 Balgat, Ankara, Turkey

^f Lebanese American University, 11022801, Beirut, Lebanon

^g Department of Medical Research, China Medical University, Taichung 40402, Taiwan

^h Decision Lab, Mediterranean University of Reggio Calabria, Reggio Calabria, Italy

ⁱ Department of Mathematics, Near East University, Nicosia, TRNC, Mersin 10, Turkey

ARTICLE INFO

Keywords:

COVID-19, Service robots, Trapezoidal intuitionistic fuzzy number, FDM, SBWM, MAUT method, CTrIFCS algorithm

ABSTRACT

Coronavirus Disease 2019 (COVID-19), a new illness caused by a novel coronavirus, a member of the corona family of viruses, is currently posing a threat to all people, and it has become a significant challenge for healthcare organizations. Robotics are used among other strategies, to lower COVID's fatality and spread rates globally. The robot resembles the human body in shape and is a programmable mechanical device. As COVID is a highly contagious disease, the treatment for the critical stage COVID patients is decided to regulate through medication service robots (MSR). The use of service robots diminishes the spread of infection and human error and prevents frontline healthcare workers from exposing themselves to direct contact with the COVID illness. The selection of the most appropriate robot among different alternatives may be complex. So, there is a need for some mathematical tools for proper selection. Therefore, this study design the MAUT-BW Delphi method to analyze the selection of MSR for treating COVID patients using integrated fuzzy MCDM methods, and these alternatives are ranked by influencing criteria. The trapezoidal intuitionistic fuzzy numbers are beneficial and efficient for expressing vague information and are defuzzified using a novel algorithm called converting trapezoidal intuitionistic fuzzy numbers into crisp scores (CTrIFCS). The most suitable criteria are selected through the fuzzy Delphi method (FDM), and the selected criteria are weighted using the simplified best-worst method (SBWM). The performance between the alternatives and criteria is scrutinized under the multi-attribute utility theory (MAUT) method. Moreover, to assess the effectiveness of the proposed method, sensitivity and comparative analyses are conducted with the existing defuzzification techniques and distance measures. This study also adopt the idea of a correlation test to compare the performance of different defuzzification methods.

1. Introduction

Over the last 50 years, the robotic field reached an incredible height. A robot is typically a self-control, versatile and reprogrammable machine applied for precarious jobs. Robots are built with cameras, speech recognition, analytics, mobile and cloud technology, sensors and artificial intelligence. The usage of robots has been widely increased. Most robots are preferred in the industrial sector and are slowly being

introduced in the medical field. Robotics includes various areas of knowledge such as electrical, mechanical and industrial engineering and information technology. Robots can do a specific mission without human support, in minimum time and without flaws. Nowadays, n number of robots are available in the market that performs various tasks, and the initial investment is also very high. The selection of suitable robots for specific applications is a challenging task. It is more complex due to the addition of advanced features by the different

* Corresponding authors.

E-mail addresses: dkkang@inje.ac.kr (D. Kang), aicevaryadevi.s2019@vitstudent.ac.in (S.A. Devi), felix.a@vit.ac.in (A. Felix), snmphpd@buc.edu.in (S. Narayanamoorthy), kalaiselvansamayan@rmv.ac.in (S. Kalaiselvan), dumitru@cankaya.edu.tr (D. Balaenu), ahmadian.hosseini@unirc.it (A. Ahmadian).

<https://doi.org/10.1016/j.orp.2022.100258>

Received 25 July 2022; Received in revised form 22 October 2022; Accepted 26 October 2022

Available online 30 October 2022

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manufacturers. A variety of medication-service robots (MSRs) with varied features and specifications are available. So, the consumer must recognize suitable robots for the respective task. This issue can be sorted by analyzing the characteristics of different robots based on consumer requirements. The most desirable criteria for grading the robots are equipment cost, load capacity, speed, vendor service quality and programming flexibility [1]. The hospital sectors established the workload of serving robots, which aids robots user for better understanding and program developers of robots and robot sales companies to enrich the product.

1.1. Service robots

The Fraunhofer Institute for manufacturing engineering and automation released the first definition for service robots in 1993, “A service robot is a freely programmable kinematic device that performs semi or full automation services. Services are tasks that do not contribute only to the industrial sectors and the execution of useful work for humans and equipment”. According to the international federation of robotics (IFR), “A service robot is a robot that works partially or completely independent to perform services beneficial to the well-being of humans and equipment excluding manufacturing operations”. In contrast, the international standardization organization describes “a robot that performs useful tasks for humans or equipment, excluding industrial automation applications”. Service robots are machines that help humans and execute a succession of actions. In 2018, the use of service robots increased by 32% and was expected to be 45% by the end of 2022. The united national economic commission for Europe (UNECE) and IFR split the service robots into professional and personal/home service robots. Professional service robots are used in agriculture, logistics, mobile platform, rescue and safety, inspections, cleaning, underwater use, medicine and construction. Service robots play many roles in the medical sector like surgery, spot radiation, neurosurgery, colonoscopy, delicate surgical procedures and therapy to patients, teaching disabled children, serving patients, and performing several tasks associated with patient recovery [2]. Currently, service robots provide various benefits to the clinical sector, like precise tools for therapy and diagnosis, which act as an assistant during surgery and provide abundant care for patients. In contrast, all service robots enroll themselves in every role in the hospital sector. The main advantages of service robots are

1. Increased safety — The main goal of every organization is to offer protection for the life of employees. So, the high hazardous works are performed using robots.
2. Superior speed — Robots can perform their respective task non-stop, increasing productivity.
3. Huge saving — The service robots can reduce wastage, save cost and time and execute numerous tasks in the allotted period.
4. Full of perfection — Due to the installation of defined programs in serving robots, mistakes are avoided and are highly stable and precise.
5. Greater consistency — Robots are more consistent than humans while performing tasks, especially in cancer surgery which moves easily while the surgeon's hand does not fit.

Sterilization, cleaning, COVID-19 testing, logistics, social care and telehealth are the major healthcare sectors that use robots. Even challenges are faced by using service robots like unemployment, social acceptance, way of interaction with humans, functional requirements, performance doubts and lack of mobility. On one side, service robots help healthcare workers in all possible ways. On the other hand, increased use of service robots may reduce contact between people, leading to psychological problems. Another primary concern is reliability, safety processes while interacting with humans and doubt in cyber security. The robots used for disease diagnosis should not negatively impact the patients health, possibly leading to risk for patients' lives.

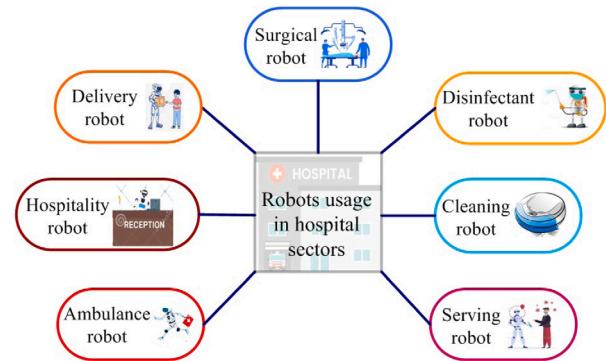


Fig. 1. Robots used in hospital sectors.

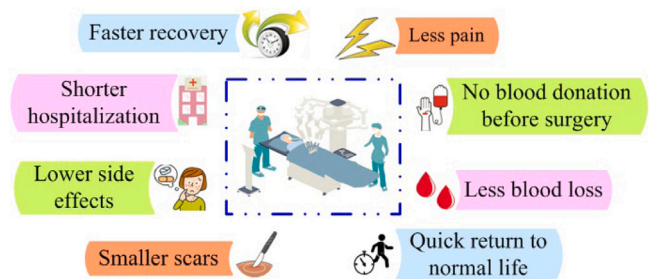


Fig. 2. Advantages of surgery robot.

1.2. Robots utilization in healthcare sectors

To combat the COVID pandemic, the various disciplines of healthcare sectors are employing robots along with frontline workers to decrease the COVID infection rates. For more than 30 years, robots have been applied in hospitals and were hugely increased in the pandemic, which also created a great revolution in healthcare sectors [3]. A few common departments in hospitals that used robots during a pandemic is represented in Fig. 1.

1.2.1. Surgical robot

The well-known robot in hospitals is surgical robots. Surgery using robots allows doctors to perform complex surgical procedures with greater precision. Surgery like autonomous cardiac ablation of the pulsating heart and minimal invasive surgery (MIS) needs the contribution of robots, which produce a high accuracy rate compared to human surgeons. The most popular and accessible surgical robot is Da Vinci robotic surgical system. It is a robotic-assisted surgeon where the human surgeon performs surgery with Da Vinci. The advantages that patients obtained from robot surgery are shown in Fig. 2.

1.2.2. Disinfectant robot

Contagious diseases like COVID can be controlled by keeping the indoor and outdoor environment clean and sanitized. The major sources for the transmission of the virus are door handles, elevators, lift buttons and direct contact with infected patients. Huge manpower is needed to create a sanitizing environment, which creates the fear of spreading the virus. So, the cleaning robots are perfect for sanitizing and disinfection. The robots clean large areas quickly and efficiently, protecting people from diseases, and are guided through remotes to spray the antiseptic mixtures. The remote facility aids humans in avoiding direct contact with disinfectant spray.

1.2.3. Cleaning robot

The COVID virus is highly contagious, so cleaning is essential in common public regions. The hospital buildings should maintain

cleanliness as it can spread the virus to non-infected patients. The COVID virus can spread through infected droplets, so the robots are utilized to clean floors and COVID patients isolated rooms to prevent the virus. Robovac or Roomba is an autonomous robotic vacuum cleaner with sensors and program controllers. UVD robots can disinfect patient rooms and hospital operation theaters without human interaction. It disinfects all environments that are potentially harboring dangerous microorganisms.

1.2.4. Serving robots

A serving robot performs semi-autonomous or fully-autonomous tasks, is capable of making decisions and work under unpredictable situation. In hospitals, serving robots execute various tasks like delivering fresh beds, clearing contaminated waste, supplying medicine and food to patients, and performing heavy-duty tasks.

1.2.5. Ambulance robot

According to statistics, the 8 lakh European countries people are affected by cardiac arrest annually, but out of this only 8% of people survive. The cardiac arrest patient can handle the situation in less than 6 mins. Though in such cases, the rescue robots perform as lifeguards. An ambulance or rescue robot fitted with an automated defibrillator is a lightweight medical device capable of providing first aid to victims suffering from sudden cardiac arrest. The use of rescue robots increases emergency response. During calamities, these robots play a vital role in affected regions.

1.2.6. Hospitality robot

Due to the pandemic and the consequent rise in healthcare worker fatality rates, the use of receptionists and nursing robots has increased rapidly. The death rate among healthcare workers can be decreased by utilizing the following robots: (i) nurse robot and (ii) receptionist robot. The nurse robot assists doctors and helps human nurses by decreasing their patient load during COVID. It serves medicine and food to patients. Due to the presence of a high percentage of older people, the hospitals in Japan use more nurse robots. A receptionist robot is supposed to help patients, collect information and guide patients to appropriate doctors. They can manage a lot of visitors and patients without getting exhausted and create an enjoyable environment in hospitals.

1.2.7. Delivery robot

The delivery robot in hospitals transfers the medical drugs and blood samples from one hospital to another. During the pandemic, the delivery robots aid in reducing the contact between humans. These fully autonomous robots can function in both ground and air. Fig. 3 represents the different kinds of robots used in healthcare industries.

1.3. Literature review

Since 2020, the robotics research related to COVID has increased. Relevant research on medical service robots was done. Yamaji K. et al. [4] studied the assistant robot used for percutaneous coronary intervention (PCI). Khan Z. et al. [5] described the different categories of robots like receptionists, nurses, ambulances, telemedicine, serving, cleaning, disinfection, surgical, and radiologist used in healthcare sectors. A fuzzy number is a quantity whose value is imprecise, rather than exact as is the case with "ordinary" (single-valued) numbers. Different types of fuzzy numbers are triangular, trapezoidal and Gaussian fuzzy number. The intuitionistic fuzzy number quantities also imprecise but contains belongingness and non-belongingness degrees, whereas fuzzy number contains only belongingness degree. The TrIFN contains the parameters ($a' < a < b < c < d < d'$) clearly reflects an element's variation. From 0 to 1, which represents its membership, the variable remains 1, and from 1 to 0, it decreases. From 1 to 0, which represents its non-membership, the variable remains 0, and from

0 to 1, it increases [6–8]. Ishikawa et al. [9] proposed the fuzzy-Delphi method (FDM) by combining the traditional Delphi technique and fuzzy set theory. The FDM is commonly applicable for selecting the most suitable features for alternatives in various applications. Hsu Y. et al. [10] utilized the FDM for recycling technology. Bui T. et al. [11] used for solid-waste management. Kareem A. et al. [12] applied for open-source software analysis. Amiri M. et al. [13] proposed the simplified best-worst method (SBWM) in 2021 to determine the weights of the criteria in decision-making problems. Nara E. et al. [14] analyzed the performance of occupational health and safety using the company competitiveness rate and ranked them with multi-attribute utility theory (MAUT). In 2010, Chatterjee P. et al. [1] utilized the compromise and outranking methods for industrial robot selection. Koulouriotis D.E. et al. [15] introduced the fuzzy digraph in the matrix approach in 2011. Rashid T. et al. [16] proposed the generalized interval-valued trapezoidal fuzzy number in TOPIS for robot selection in 2014. Sahu J. et al. [17] described mobile robot selection under different fuzzy membership functions. Parameshwaran R. et al. [18] applied the integrated decision-making approach by combining the FDM, fuzzy analytical hierarchical process and VIKOR for robot selection. For the industrial robot selection process, Ghorabae M. K. et al. [19] applied fuzzy VIKOR with interval type-2 fuzzy numbers. In 2019, Narayanamoorthy S. et al. [20] introduced fuzzy VIKOR with an interval-valued intuitionistic hesitant fuzzy set. Felix [21] designed the DEMATEL model for solid waste management. Deva and Felix [22] designed the bipolar model under DEMATEL method to represent in both positive and negative perspectives. Nasrollahi M. et al. [23] used the fuzzy best-worst method and PROMETHEE. Chodha V. et al. [24] selected the industrial arc welding robot using TOPIS methods, and the objective criteria are weighted using the entropy method. The fractional fuzzy models created to analyze the COVID problems through the fractional techniques [25–29]. The researchers works on COVID-19 in various categories like detection [30] and prediction [31] of COVID-19 using deep learning, IoT technology for medical advice [32] and the interrelation between the lockdown and the air and water quality during the pandemic [33]. Therefore, by collaborating the fuzzy MCDM methods, this work proposes an integrated MCDM method, which could perform different tasks in the proposed algorithm. This integrated MCDM method involves the FDM, SBWM and MAUT methods. The FDM aids in selecting the appropriate criteria that suit exactly for the problem. The SWBM and MAUT support in weighting the criteria and ranking the alternatives, respectively.

1.4. Benefits of integrated fuzzy methods

Based on the literature review, the medication robot selection was scrutinized using fuzzy integrated MCDM methods. This integrated fuzzy method is proposed by combining the FDM, SBWM and MAUT methods. In 1993, the FDM [9] was proposed by Ishikawa et al. in collaboration with the traditional Delphi method and fuzzy set theory. According to the problem, the FDM is a more efficient method for determining the suitability criteria from the grouping process. FDM chooses the best list of the problem usability evaluation criteria by gathering expert input to remove the unfit criteria. The SBWM [34] calculates the weights for criteria more straightforwardly than the best-worst method (BWM). It provides a quick and precise computational technique by calculating the relative significant value from best criteria to other criteria and worst criteria to other criteria. A few advantages of SBWM are simple to understand, lowering the calculation complexity, and high accuracy rate. Keeney and Raiffa developed the MAUT method in 1976. The most important qualities can be stated as criteria based on the evaluation of various alternatives. The MAUT is an efficient MCDM approach for these decision-making issues and comprises utility functions. The utility is a measure of desirability that provides a uniform scale for comparing and combining objective and subjective criteria. It also takes the decision-makers opinion over the set of alternatives and criteria.

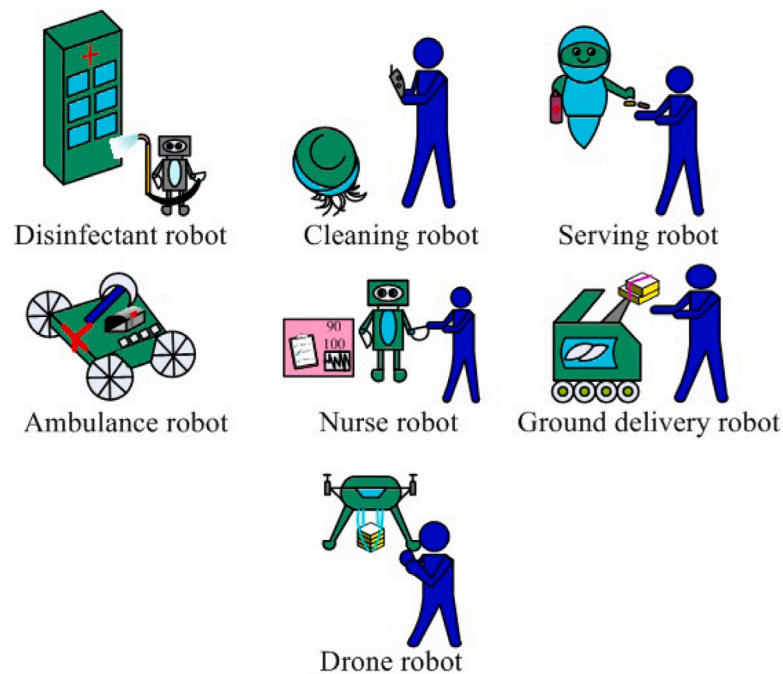


Fig. 3. Different types of robots used in healthcare sectors.

1.5. Motivation of the research

- The COVID-19 frontline hospital workers are affected and even die in enormous numbers. In India, over 87,000 healthcare workers [35] had affected by COVID-19 in six states –Maharashtra, Karnataka, Tamil Nadu, Delhi, West Bengal and Gujarat. More than 1 lakh cases were found among healthcare workers in Tamil Nadu. A possible way to reduce the infection and death cases the frontline healthcare workers can replace by robots. Because robots can work for extended periods without being fatigued and are not susceptible to COVID, never get sick, and do not require masks.
- Service robots can replace the hospital frontline workers like receptionists, nurses and caretakers because they contact COVID patients directly. Due to the availability of various medication service robots (MSR), selecting appropriate MSR was difficult. This motivates to propose the selection model using fuzzy set theory.
- The model uncertainties are handled by incorporating the intuitionistic fuzzy set (IFS) is the extension of the fuzzy set. The fuzzy set deals with the membership degree of the problem, whereas IFS deals with the membership and non-membership degrees of the problem. So, comparing with fuzzy set IFS produces a more accurate result.
- The literature review found that the MAUT approach was not used in selection of MSR. So, this work utilizes the fuzzy MAUT method as it allows the evaluation between more independent criteria and alternatives. It provides results based on the quantification of the data and decision-makers opinions.

1.6. Contribution of the research

- The medication service robots are selected based on fuzzy integrated MCDM methods, which can be utilized during the COVID period to prevent the spread rate. Recent studies on fuzzy MCDM robot selection and intuitionistic fuzzy sets are reviewed, and a integrated fuzzy MDCM approach is proposed.

- The vagueness or fuzziness in the selection process is tackled using trapezoidal intuitionistic fuzzy numbers (TriFN), which involves the belongingness and non-belongingness degrees of the problem.
- The new defuzzification technique is introduced for trapezoidal intuitionistic fuzzy context, which acts as a novelty of this study. The integrated fuzzy MCDM method encompasses three fuzzy MCDM methods. First, the FDM is applied to select the appropriate attributes. Second, the selected attributes are weighted based on their importance through the SBWM. Finally, the alternatives are selected based on the fuzzy MAUT method. The selected attributes are weighted based on their significance level. Both the subjective and objective criteria are taken into consideration.
- The proposed integrated fuzzy MCDM method is applied in selecting the MRS, and sensitivity analysis and comparative analysis were carried out to see the efficiency of the proposed method. The proposed hybrid fuzzy method showed a better result.

1.7. Novelty of the work

Defuzzification is the conversion of fuzzy to crisp data. It is difficult to generate the result in fuzzy quantities. So, defuzzification aids in transforming the fuzzy into crisp quantities. Therefore, the act of extracting a single number from the output of the aggregated fuzzy set is known as defuzzification. It is also known as the “rounding off” method. Various researchers introduce numerous defuzzification methods. Depending on Obricovic work in 2003 and Devi and Felix work in 2022, this study extends the defuzzification technique for the trapezoidal intuitionistic fuzzy context called converting trapezoidal intuitionistic fuzzy numbers into crisp scores (CTrIFCS), which is distinct from the existing defuzzification approaches. The main advantage of the proposed defuzzification method is it measures by splitting the trapezoidal membership and non-membership structures into three regions left, center and right scores, which generate a more accurate crisp values.

The main objective of the work is to analyze the ideal medication service robots based on the requirements of hospitals through fuzzy MCDM methods. Section 1 contains the introduction. Section 2 has

some definitions of fuzzy sets, intuitionistic fuzzy sets and trapezoidal intuitionistic fuzzy numbers. Section 3 holds the construction of the proposed methodology and its illustration is deliberated in Section 4. Section 5 establishes the results and discussion. Finally, Section 6 concludes the article and the references are given.

2. Preliminaries

Definition 2.1 (Fuzzy Set). A fuzzy set is an extension of the crisp set. It has a varying degree of membership function. Lofti A. Zadeh is the founder of the fuzzy set [36]. A fuzzy set \tilde{A} in the universe U can be defined as the set of ordered pairs, and it can be represented as

$$\tilde{A} = \{(x, \mu(x)) | x \in U\}$$

where x is a member of the fuzzy set \tilde{A} , $\mu(x)$ is a membership degree of x in \tilde{A} for all $\mu(x) \in [0, 1]$.

Definition 2.2 (Intuitionistic Fuzzy Set). In 1999, Atanasso introduced the concept of intuitionistic fuzzy set (IFS) as the extension of Zadeh's work [36]. Let \tilde{A}^i be the IFS in X , then

$$\tilde{A}^i = \{x, \mu_{\tilde{A}^i}(x), \nu_{\tilde{A}^i}(x) | x \in X\} \forall \mu_{\tilde{A}^i}(x) \rightarrow [0, 1], \nu_{\tilde{A}^i}(x) \rightarrow [0, 1]$$

where $\mu_{\tilde{A}^i}(x)$ is a membership degree and $\nu_{\tilde{A}^i}(x)$ is a non-membership degree in \tilde{A}^i which is the subset of X , for every element $x \in X$, $0 \leq \mu_{\tilde{A}^i}(x) + \nu_{\tilde{A}^i}(x) \leq 1$.

Additionally, $\pi_{\tilde{A}^i}(x) = 1 - \mu_{\tilde{A}^i}(x) - \nu_{\tilde{A}^i}(x)$ called the hesitation margin of x in X . $\pi_{\tilde{A}^i}(x) \in [0, 1]$ and $0 \leq \pi_{\tilde{A}^i}(x) \leq 1$ for every $x \in X$.

Definition 2.3. If \tilde{A} and \tilde{B} are two fuzzy IFS of the set X , then [34]

- (i) $\tilde{A} + \tilde{B} = \{x, \mu_{\tilde{A}^i}(x) + \mu_{\tilde{B}^i}(x) - \mu_{\tilde{A}^i}(x) \cdot \mu_{\tilde{B}^i}(x), \nu_{\tilde{A}^i}(x) \cdot \nu_{\tilde{B}^i}(x) | x \in X\}$
- (ii) $\tilde{A} \cdot \tilde{B} = \{x, \mu_{\tilde{A}^i}(x) \cdot \mu_{\tilde{B}^i}(x), \nu_{\tilde{A}^i}(x) + \nu_{\tilde{B}^i}(x) - \nu_{\tilde{A}^i}(x) \cdot \nu_{\tilde{B}^i}(x) | x \in X\}$
- (iii) $\tilde{A} \cup \tilde{B} = \{x, \min(\mu_{\tilde{A}^i}(x), \mu_{\tilde{B}^i}(x)), \max(\nu_{\tilde{A}^i}(x), \nu_{\tilde{B}^i}(x)) | x \in X\}$
- (iv) $\tilde{A} \cap \tilde{B} = \{x, \max(\mu_{\tilde{A}^i}(x), \mu_{\tilde{B}^i}(x)), \min(\nu_{\tilde{A}^i}(x), \nu_{\tilde{B}^i}(x)) | x \in X\}$
- (v) $\tilde{A}^c = \{x, \nu_{\tilde{A}^i}(x), \mu_{\tilde{A}^i}(x) | x \in X\}$

Definition 2.4 (Distance Measure on IFS). Let \tilde{A} and \tilde{B} are two fuzzy IFS [34], then some existing distance measures are

(i) Hamming distance

$$d_H(\tilde{A}, \tilde{B}) = \frac{1}{2} \sum_{j=1}^n |\mu_{\tilde{A}^i}(x_j) - \mu_{\tilde{B}^i}(x_j)| + |\nu_{\tilde{A}^i}(x_j) - \nu_{\tilde{B}^i}(x_j)| + |\pi_{\tilde{A}^i}(x_j) - \pi_{\tilde{B}^i}(x_j)|$$

(ii) Euclidean distance

$$d_e(\tilde{A}, \tilde{B}) = \sqrt{\frac{1}{2} \sum_{j=1}^n (\mu_{\tilde{A}^i}(x_j) - \mu_{\tilde{B}^i}(x_j))^2 + (\nu_{\tilde{A}^i}(x_j) - \nu_{\tilde{B}^i}(x_j))^2 + (\pi_{\tilde{A}^i}(x_j) - \pi_{\tilde{B}^i}(x_j))^2}$$

Definition 2.5. For IFS \tilde{A} , the scoring and accuracy functions are defined as

- (i) Scoring functions $SCO_{\tilde{A}} = (\mu_{\tilde{A}^i} - \pi_{\tilde{A}^i})^2 - (\nu_{\tilde{A}^i} - \pi_{\tilde{A}^i})^2$
- (ii) Accuracy function $Acc_{\tilde{A}} = (\mu_{\tilde{A}^i})^2 + (\nu_{\tilde{A}^i})^2 + (\pi_{\tilde{A}^i})^2$

Definition 2.6 (Intuitionistic Fuzzy Number). An IFN $\tilde{A}^i = \{x, \mu_{\tilde{A}^i}(x), \nu_{\tilde{A}^i}(x) | x \in R\}$ is called IFN [36] if it satisfies the following condition

- (i) An intuitionistic fuzzy subset of the real line
- (ii) Normal, i.e. for any $x \in R$ such that $\mu_{\tilde{A}^i}(x) = 1$ and $\nu_{\tilde{A}^i}(x) = 0$.
- (iii) A convex set for $\mu_{\tilde{A}^i}(x)$, i.e. $\mu_{\tilde{A}^i}(x) = (\lambda x_1 + (1 - \lambda)x_2) \geq \min(\mu_{\tilde{A}^i}(x_1), \mu_{\tilde{A}^i}(x_2)) \forall (x_1, x_2) \in R, \lambda \in [0, 1]$.
- (iv) A concave set for $\nu_{\tilde{A}^i}(x)$, i.e. $\nu_{\tilde{A}^i}(x) = (\lambda x_1 + (1 - \lambda)x_2) \leq \max(\nu_{\tilde{A}^i}(x_1), \nu_{\tilde{A}^i}(x_2)) \forall (x_1, x_2) \in R, \lambda \in [0, 1]$.

Definition 2.7 (Trapezoidal Fuzzy Number). The TrFN \tilde{A}_{Tr} with parameters $(a \leq b \leq c \leq d)$ is denoted as $\tilde{A}_{Tr} = (a, b, c, d)$ in a set of real

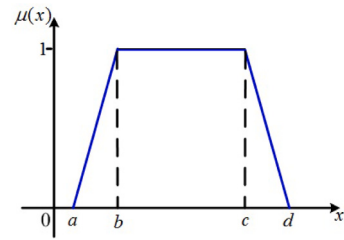


Fig. 4. Trapezoidal fuzzy number.

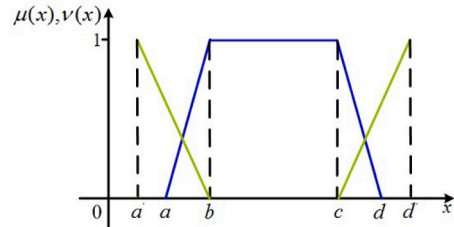


Fig. 5. Trapezoidal intuitionistic fuzzy number.

numbers R [37]. Fig. 4 depict the diagrammatic representation of TFN. The membership function is calculated as

$$\mu_{\tilde{A}_{Tr}}(x) = \begin{cases} 0, & x \leq a, x \geq d \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ 1, & b \leq x \leq c \\ \frac{d-x}{d-c}, & c \leq x \leq d \end{cases}$$

Definition 2.8 (Trapezoidal Intuitionistic Fuzzy number). The TrIFN \tilde{A}_{Tr}^i with parameters $(a' < a < b < c < d < d')$ is denoted as $\tilde{A}_{Tr}^i = \{(a, b, c, d), (a', b, c, d')\}$ in a set of real numbers R [37].

$$\mu_{\tilde{A}_{Tr}^i}(x) = \begin{cases} 0, & x \leq a, x \geq d \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ 1, & b \leq x \leq c \\ \frac{d-x}{d-c}, & c \leq x \leq d \end{cases} \quad \nu_{\tilde{A}_{Tr}^i}(x) = \begin{cases} 1, & x \leq a' \\ \frac{b-x}{b-a'}, & a' \leq x \leq b \\ 0, & b \leq x \leq c \\ \frac{x-c}{d'-c}, & c \leq x \leq d' \\ 1, & x > d' \end{cases}$$

where $\mu_{\tilde{A}_{Tr}^i}(x)$ represents a degree of membership and $\nu_{\tilde{A}_{Tr}^i}(x)$ represents a degree of non-membership for a trapezoidal intuitionistic fuzzy number. Fig. 5 depict the diagrammatic representation of TFN.

3. Methodology

3.1. Materials and methods

The integrated fuzzy methodological approach is designed as (1) Identifying the suitable criteria for the problem through the FDM. (2) Importance of criteria is calculated using the SBWM. (3) The ideal alternative is identified using the MAUT-MCDM method. (4) Simulation analysis is applied. (5) The outcomes are compared with existing models. Based on the experts' opinions, the decision matrices are framed. Section 3.2 proposes the new defuzzification method for the TrIFN.

3.2. Defuzzification tool

Defuzzification is a significant process in the fuzzy MCDM method and is also called an inverse fuzzification process. Generally, it transforms the fuzzy quantity into a single value called a crisp number.

Numerous defuzzification methods have been introduced in a fuzzy context, few are the center of gravity, weighted average method, and the center of sums. The CTrIFCS algorithm is proposed based on [38, 39]. These articles divulge the concept of the defuzzification procedure for the triangular fuzzy sets and triangular intuitionistic fuzzy sets through CFCS and CIFCS algorithms, respectively. The following steps are utilized in the CTrIFCS algorithm to defuzzy the TrIFN.

Step 1: Evaluate the normalized value for each TrIFN

$$\left(a_{ij}^t = \frac{a_{ij}^t - \min a_{ij}^t}{\Delta_{\min}^{\max}}, b_{ij}^t = \frac{b_{ij}^t - \min a_{ij}^t}{\Delta_{\min}^{\max}}, c_{ij}^t = \frac{c_{ij}^t - \min a_{ij}^t}{\Delta_{\min}^{\max}}, \right.$$

$$d_{ij}^t = \frac{d_{ij}^t - \min a_{ij}^t}{\Delta_{\min}^{\max}}, a_{ij}' = \frac{\max d_{ij}' - a_{ij}'}{\nabla_{\min}^{\max}}, b_{ij}' = \frac{\max d_{ij}' - b_{ij}'}{\nabla_{\min}^{\max}},$$

$$\left. c_{ij}' = \frac{\max d_{ij}' - c_{ij}'}{\nabla_{\min}^{\max}}, d_{ij}' = \frac{\max d_{ij}' - d_{ij}'}{\nabla_{\min}^{\max}} \right)$$

where $\Delta_{\min}^{\max} = \nabla_{\min}^{\max} = \max d_{ij}^t - \min a_{ij}^t$ and $\{a_{ij}^t, b_{ij}^t, c_{ij}^t, d_{ij}^t, a_{ij}', b_{ij}', c_{ij}', d_{ij}'\}$ are the parameters of the trapezoidal intuitionistic fuzzy number and t is the number of decision-matrix.

Step 2: Evaluate the left, center and right scores

$$\left(l_{ij}^t = \frac{b_{ij}^t}{1 + b_{ij}^t - a_{ij}^t}, c_{ij}^t = \frac{c_{ij}^t}{1 + c_{ij}^t - b_{ij}^t}, r_{ij}^t = \frac{d_{ij}^t}{1 + d_{ij}^t - c_{ij}^t}, \right.$$

$$\left. l_{ij}' = \frac{a_{ij}'}{1 + a_{ij}' - b_{ij}'}, c_{ij}' = \frac{b_{ij}'}{1 + b_{ij}' - c_{ij}'}, r_{ij}' = \frac{c_{ij}'}{1 + c_{ij}' - d_{ij}'} \right)$$

where $\{l_{ij}^t, c_{ij}^t, r_{ij}^t\}$ and $\{l_{ij}', c_{ij}', r_{ij}'\}$ are the left, center, right scores of membership and non-membership functions of the trapezoidal intuitionistic fuzzy number, respectively. The intersection of the increasing region determines the left score, the intersection of the stable region determines the center score, and the right score is determined by the intersection of decreasing region.

Step 3: Evaluate the left and right scores

$$\left(x_{lij}^t = \frac{c_{ij}^t(1 - c_{ij}^t) + (l_{ij}^t)^2}{1 + c_{ij}^t - l_{ij}^t}, x_{rij}^t = \frac{r_{ij}^t(1 - r_{ij}^t) + (c_{ij}^t)^2}{1 + c_{ij}^t - r_{ij}^t}, \right.$$

$$\left. x_{lij}' = \frac{l_{ij}'(1 - l_{ij}') + (c_{ij}')^2}{1 + c_{ij}' - l_{ij}'}, x_{rij}' = \frac{c_{ij}'(1 - c_{ij}') + (r_{ij}')^2}{1 + c_{ij}' - r_{ij}'} \right)$$

The conjoining score of left and center for membership and non-membership functions are obtained by combining the parameters l_{ij}^t, c_{ij}^t and l_{ij}', r_{ij}' , respectively. The conjoining score of center and right for membership and non-membership functions are acquired by merging the c_{ij}^t, r_{ij}^t and c_{ij}', r_{ij}' , respectively.

Step 4: Calculate the total normalized value

$$\left(x_{ij}^t = \frac{x_{rij}^t(1 - x_{rij}^t) + (x_{lij}^t)^2}{1 + x_{ij}^t - x_{rij}^t}, x_{ij}' = \frac{x_{lij}'(1 - x_{lij}') + (x_{rij}')^2}{1 + x_{ij}' - x_{lij}'} \right)$$

where x_{ij}^t and x_{ij}' are the normalized values of left and right scores.

Step 5: Determine the separated value

$$\left(Z_{ij}^t = \min a_{ij}^t + x_{ij}^t \times \Delta_{\min}^{\max}, Z_{ij}' = \frac{x_{ij}^t \times \Delta_{\min}^{\max}}{\max d_{ij}^t} \right)$$

where Z_{ij}^t and Z_{ij}' provides the crisp value of trapezoidal membership and non-membership functions, respectively.

The main features of the CTrIFCS algorithm are

- (1) Suitable for converting intuitionistic fuzzy numbers into intuitionistic crisp numbers.
- (2) The algorithm serves as a weighting function for the membership and non-membership functions.
- (3) It can be applied to MCDM models, which are under trapezoidal intuitionistic fuzzy context.

For instance: Let us consider the matrix

$$A = \begin{matrix} & C_1 \\ R_1 & [(0.80, 0.82, 0.84, 0.86, 0.75, 0.82, 0.84, 0.89)] \\ R_2 & [(0.85, 0.86, 0.87, 0.89, 0.83, 0.86, 0.87, 0.91)] \\ R_3 & [(0.82, 0.85, 0.88, 0.91, 0.80, 0.85, 0.88, 0.93)] \end{matrix}$$

The matrix A containing the trapezoidal intuitionistic fuzzy numbers, which includes the membership and non-membership degrees of the trapezoidal fuzzy context. Now, through the proposed CTrIFCS algorithm the matrix A is converted into intuitionistic fuzzy sets.

Initially, in step 1 normalizing the each value of matrix

$$A = \begin{matrix} & C_1 \\ R_1 & [(0.00, 0.18, 0.36, 0.55, 1.00, 0.61, 0.50, 0.22)] \\ R_2 & [(0.45, 0.55, 0.64, 0.82, 0.56, 0.39, 0.33, 0.11)] \\ R_3 & [(0.18, 0.45, 0.73, 1.00, 0.72, 0.440, 28, 0.00)] \end{matrix}$$

The values in R_1 and C_1 of matrix A are normalized $a_{11}^1 = \frac{0.80-0.8}{0.11} = 0.00, b_{11}^1 = \frac{0.82-0.8}{0.11} = 0.18, c_{11}^1 = \frac{0.84-0.8}{0.11} = 0.36, d_{11}^1 = \frac{0.86-0.8}{0.11} = 0.55, a_{11}' = \frac{0.93-0.75}{0.18} = 1.00, b_{11}' = \frac{0.93-0.82}{0.18} = 0.61, c_{11}' = \frac{0.93-0.84}{0.18} = 0.50, d_{11}' = \frac{0.93-0.89}{0.18} = 0.22.$

In step 2, the values of left, center and right scores are determined for normalized matrix

$$A = \begin{matrix} & C_1 \\ R_1 & [(0.15, 0.31, 0.46, 0.72, 0.55, 0.39)] \\ R_2 & [(0.50, 0.58, 0.69, 0.48, 0.37, 0.27)] \\ R_3 & [(0.36, 0.57, 0.79, 0.57, 0.38, 0.22)] \end{matrix}$$

The three different scores are evaluated for normalized matrix $l_{11}^1 = \frac{0.18}{1+0.18-0.00} = 0.15, c_{11}^1 = \frac{0.36}{1+0.36-0.18} = 0.31, r_{11}^1 = \frac{0.55}{1+0.55-0.36} = 0.46, l_{11}' = \frac{1.00}{1+1.00-0.61} = 0.72, c_{11}' = \frac{0.61}{1+0.61-0.50} = 0.55, r_{11}' = \frac{0.50}{1+0.50-0.22} = 0.39$

In step 3, the values obtained in step 2 are integrated to determine the left and right scores

$$A = \begin{matrix} & C_1 \\ R_1 & [(0.39, 0.19, 0.33, 0.56)] \\ R_2 & [(0.58, 0.44, 0.28, 0.40)] \\ R_3 & [(0.59, 0.28, 0.21, 0.45)] \end{matrix}$$

The left, center and right scores of membership and non-membership degrees are integrated to form complete left and right scores by conjoining the center score $x_{111}^1 = \frac{0.31(1-0.31)+(0.15)^2}{1+0.31-0.15} = 0.39, x_{111}^1 = \frac{0.46(1-0.46)+(0.31)^2}{1+0.31-0.46} = 0.19, x_{111}' = \frac{0.72(1-0.72)+(0.55)^2}{1+0.55-0.72} = 0.33, x_{111}' = \frac{0.55(1-0.55)+(0.39)^2}{1+0.55-0.39} = 0.56$

In step 4, the total normalized values are obtained

$$A = \begin{matrix} & C_1 \\ R_1 & [(0.25, 0.44)] \\ R_2 & [(0.51, 0.32)] \\ R_3 & [(0.42, 0.29)] \end{matrix}$$

The overall normalized score are determined by combining the left and right scores $x_{11}^1 = \frac{0.19(1-0.19)+(0.39)^2}{1+0.39-0.19} = 0.25, x_{11}' = \frac{0.33(1-0.33)+(0.56)^2}{1+0.56-0.33} = 0.44.$

In step 5, the final intuitionistic fuzzy matrix is obtained $A =$

$$\begin{matrix} & C_1 \\ R_1 & [(0.12, 0.44)] \\ R_2 & [(0.14, 0.32)] \\ R_3 & [(0.13, 0.29)] \end{matrix}$$

Finally, the trapezoidal intuitionistic fuzzy sets are converted into intuitionistic fuzzy sets $Z_{11}^1 = 0.8 + 0.25 \times 0.11 = 0.12, Z_{11}' = \frac{0.44 \times 0.18}{0.18} = 0.44$

3.3. The proposed MAUT-BW Delphi method

The proposed method encompasses the three stages. The first stage is selecting the problem's appropriate criteria from the available criteria. In the second stage, detecting the importance of selected criteria.

The final or third stage is to rank the alternatives. This method aids in understanding to work on both subjective and objective criteria of the problem.

Step 1: Design the possible alternatives and criteria

Let $A = \{A_1, A_2, \dots, A_m\}$ be the set of alternatives and $O = \{O_1, O_2, \dots, O_n\}$ be the set of objective criteria and $S = \{S_1, S_2, \dots, S_n\}$ be the set of subjective criteria and $C = \{C_1, C_2, \dots, C_n\}$ be the overall notation of criteria.

Step 2: Select the appropriate criteria based on the fuzzy Delphi method

The most compelling objective and subjective criteria are selected from the n number of criteria.

(i) Frame the linguistic decision matrix based on decision-makers for both subjective and objective criteria, and the criteria linguistic decision matrix is denoted as $CDM = \{CD_1, CD_2, \dots, CD_t\}$. The subjective and objective criteria are analyzed using the performance and specifications of criteria, respectively.

(ii) Using the linguistic terms, convert the criteria linguistic decision matrix into trapezoidal intuitionistic fuzzy matrices.

$$CDM = \begin{matrix} & C_1 & C_2 & \dots & C_n \\ D_1 & \begin{bmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \dots & \tilde{a}_{1n} \end{bmatrix} \\ D_2 & \begin{bmatrix} \tilde{a}_{21} & \tilde{a}_{22} & \dots & \tilde{a}_{2n} \end{bmatrix} \\ \vdots & \begin{bmatrix} \vdots & \vdots & \ddots & \vdots \end{bmatrix} \\ D_t & \begin{bmatrix} \tilde{a}_{t1} & \tilde{a}_{t2} & \dots & \tilde{a}_{tn} \end{bmatrix} \end{matrix} \quad (1)$$

where $\tilde{a}_{pj} = (a_{pj}, b_{pj}, c_{pj}, d_{pj}, a'_{pj}, b'_{pj}, c'_{pj}, d'_{pj})$. Let \tilde{a}_{pj} be the opinion of the decision-makers between D_p and C_j where $p = 1, 2, \dots, t; j = 1, 2, \dots, n$.

(iii) Aggregate the trapezoidal intuitionistic fuzzy decision matrices

The differing viewpoints are combined to produce a sensible outcome using the following formula

$$a_{pj} = a'_{pj} = \min\{a_{pj}\}, b_{pj} = \frac{1}{p} \sum b_{pj}, c_{pj} = \frac{1}{p} \sum c_{pj}, d_{pj} = d'_{pj} = \max\{d_{pj}\} \quad (2)$$

where $p = 1, 2, \dots, t; j = 1, 2, \dots, n$.

(iv) Defuzzify the aggregated matrix using the CTRIFCS algorithm, where the TrIFN is converted into IFS.

$$CDM = \begin{matrix} & C_1 & C_2 & \dots & C_n \\ D_1 & \begin{bmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \dots & \tilde{a}_{1n} \end{bmatrix} \\ D_2 & \begin{bmatrix} \tilde{a}_{21} & \tilde{a}_{22} & \dots & \tilde{a}_{2n} \end{bmatrix} \\ \vdots & \begin{bmatrix} \vdots & \vdots & \ddots & \vdots \end{bmatrix} \\ D_t & \begin{bmatrix} \tilde{a}_{t1} & \tilde{a}_{t2} & \dots & \tilde{a}_{tn} \end{bmatrix} \end{matrix}$$

where $\tilde{a}_{pj} = (\mu(x), \nu(x))$ where $p = 1, 2, \dots, t; j = 1, 2, \dots, n$.

(v) Convert the obtained IFS into crisp values using the scoring function.

$$SF = \frac{1}{2}(1 + \mu(x) - \nu(x)) \quad (3)$$

(vi) Find the threshold value T .

The suitable criteria are selected based on the threshold value.

$$T = \frac{\sum SF}{j} \quad (4)$$

where $j = 1, 2, \dots, n$.

Step 3: Construct the linguistic decision matrices

The linguistic decision matrices are framed based on decision-makers opinions exhibits the performance of alternatives and criteria. These matrices will furnish the problem to understand in the usual language. Let $D = \{D_1, D_2, \dots, D_t\}$ be linguistic decision matrices.

Step 4: Convert the linguistic decision matrices into trapezoidal intuitionistic fuzzy matrices (TrIFM)

The linguistic decision matrices $D_p, p = 1, 2, \dots, t$ are converted into trapezoidal intuitionistic fuzzy matrices $T_p, p = 1, 2, \dots, t$. Therefore, the

qualitative criteria are also converted into quantitative criteria.

$$T = \begin{matrix} & C_1 & C_2 & \dots & C_n \\ A_1 & \begin{bmatrix} \tilde{x}'_{11} & \tilde{x}'_{12} & \dots & \tilde{x}'_{1n} \end{bmatrix} \\ A_2 & \begin{bmatrix} \tilde{x}'_{21} & \tilde{x}'_{22} & \dots & \tilde{x}'_{2n} \end{bmatrix} \\ \vdots & \begin{bmatrix} \vdots & \vdots & \ddots & \vdots \end{bmatrix} \\ A_m & \begin{bmatrix} \tilde{x}'_{m1} & \tilde{x}'_{m2} & \dots & \tilde{x}'_{mn} \end{bmatrix} \end{matrix}$$

where $\tilde{x}'_{ij} = (a_{ij}, b_{ij}, c_{ij}, d_{ij}, a'_{ij}, b'_{ij}, c'_{ij}, d'_{ij})$. Let \tilde{x}'_{ij} be the opinion of the decision-makers between i th alternative and j th criteria where $p = 1, 2, \dots, t, i = 1, 2, \dots, m, j = 1, 2, \dots, n$.

Step 5: Aggregate the TrIFM

The different opinions of decision-makers about the relationship between the alternatives and criteria are aggregated through Eq. (2).

Step 6: Defuzzify the aggregated matrix

The aggregated matrix is defuzzified using the CTRIFCS algorithm and scoring function in Eq. (3).

Step 7: Evaluate the criteria weight using the simplified best–worst method.

The SBWM method evaluates the dual weights for criteria. One is best to others preference vector, and another is others to worst preference vector. The final weight vector for criteria are obtained by combining these two weights.

(i) Choose the best and worst criteria from the selected $\{C_1, C_2, \dots, C_n\}$ criteria.

(ii) The decision-makers determine the relative importance of the best criterion to the other criteria (best-to-others), where the vector is denoted as $C_{bj} = [C_{b1}, C_{b2}, \dots, C_{bn}]$. Through the following equation, the best criterion weights are calculated.

$$\sum_j \frac{1}{C_{bj}} W'_b = 1 \Rightarrow W'_b = \frac{1}{(\sum_j \frac{1}{C_{bj}})} \quad (5)$$

$$W'_b - C_{bj} W'_j = 0$$

where W'_b represents the weight of the best criteria.

$$C_{bj} W'_j = W'_b \Rightarrow W'_j = \frac{(W'_b)}{C_{bj}} \quad (6)$$

where $j = 1, 2, \dots, n$.

(iii) The decision-makers determine the relative importance of the worst criterion to the other criteria (best-to-others), where the vector is denoted as $C_{jw} = [C_{1w}, C_{2w}, \dots, C_{jw}]$ where $j = 1, 2, \dots, n$. Through the following equation, the worst criterion weight are calculated.

$$\sum_j C_{jw} W''_w = 1 \Rightarrow W''_w = \frac{1}{(\sum_j \frac{1}{C_{jw}})} \quad (7)$$

$$W''_j - C_{jw} W''_w = 0$$

where W''_j denotes the weight of the worst criteria.

$$W''_j = C_{jw} W''_w \quad (8)$$

(iv) The final weights of criteria are calculated using the linear combination of both best and worst.

$$W_j = \alpha W'_j + (1 - \alpha) W''_w \quad \text{where } \alpha \in [0, 1] \quad (9)$$

The α value in Eq. (7) signifies the importance of both preference vectors, i.e., BtoO and OtoW are determined by the decision-makers. The weight vector of criteria is represented as

$$W = [W_1, W_2, \dots, W_n] \quad (10)$$

Step 8: Evaluate the normalized matrix

The decision matrix is normalized depending on the beneficiary and non-beneficiary categories.

For beneficiary criteria,

$$r_{ij} = \frac{r_{ij} - \min(r_{ij})}{\max(r_{ij}) - \min(r_{ij})} \quad (11)$$

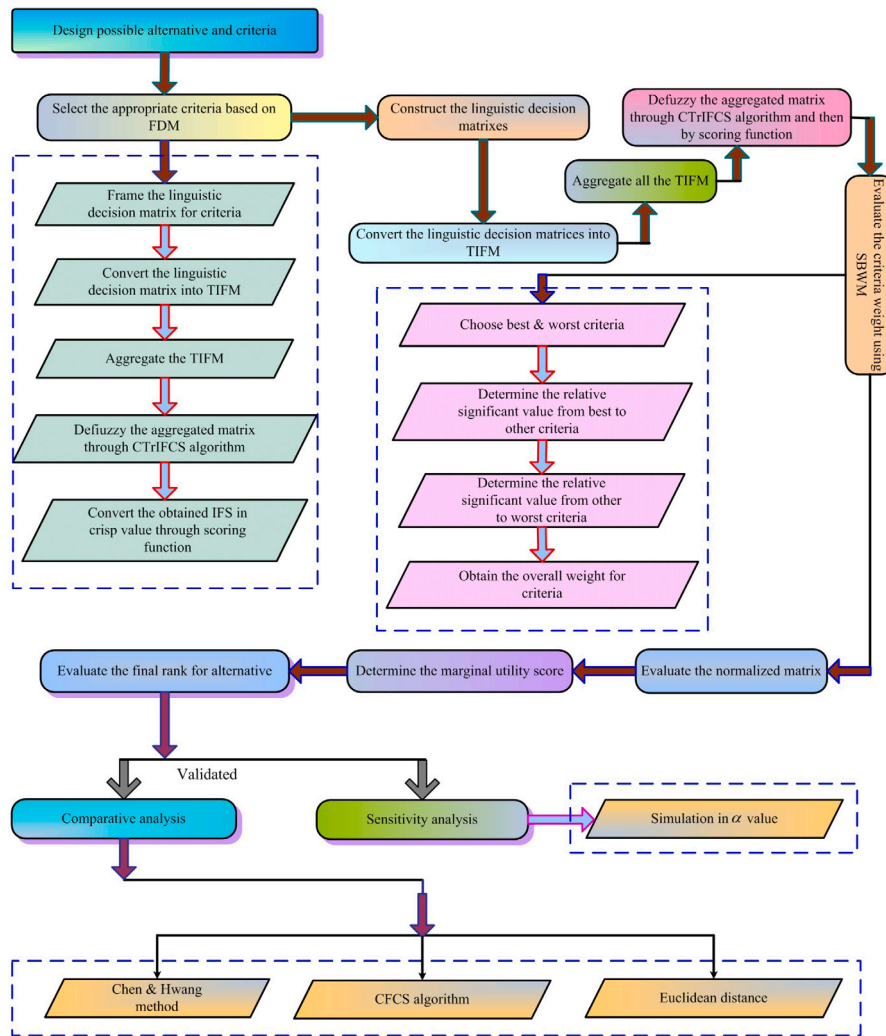


Fig. 6. Flow of the proposed method.

For non-beneficiary criteria,

$$r_{ij} = 1 + \left(\frac{\min(r_{ij}) - r_{ij}}{\max(r_{ij}) - \min(r_{ij})} \right) \quad (12)$$

where $i = 1, 2, 3, \dots, m$ and $j = 1, 2, 3, \dots, n$.

Step 9: Determine the marginal utility score

$$U_{ij} = \frac{e^{(r_{ij})^2} - 1}{1.71} \quad (13)$$

where $i = 1, 2, 3, \dots, m$ and $j = 1, 2, 3, \dots, n$.

Step 10: Evaluate the final ranking for the alternatives

$$U_{ij} = \sum_{j=1}^n U_{ij} \times W_j \quad (14)$$

where $i = 1, 2, 3, \dots, m$ and $j = 1, 2, 3, \dots, n$.

Therefore, the U_{ij} value provides the better performing alternative. The obtained result is validated through sensitivity and comparative studies. The flow of the proposed method are portrayed in Fig. 6.

4. Adaption of the proposed method for selecting the medication service robot

Hospitals place a high priority on patient safety, particularly during COVID. As a result, many hospitals climbed the robots for serving

COVID patients. One of the serving robots is a medication serving robot, which distributes medicine to COVID patients. It reduces direct contact between COVID patients and nurses, which aids in preventing the spread of infection. The main objective is to determine the ideal MSR based on the requirements of the hospital using fuzzy MCDM methods. The service robots are essential to manipulating virus proliferation. This work analyzes a MSR that gives medicine to COVID patients and reduces the infection rate among humans. Different medication service robots are analyzed with the appropriate criteria based on the need of hospitals [17].

Step 1: Let the set of alternatives be $A = \{A_1, A_2, A_3\}$ and the set of objective and subjective criteria are $O = \{O_1, O_2, \dots, O_8\}$ and $S = \{S_1, S_2, \dots, S_5\}$ are framed, respectively. Different types of medication serving robots are represented as alternatives. They are A_1 - Hospi robot [40], A_2 - Tug robot [41] and A_3 - Relay robot [42]. Singapore, USA and Switzerland are the origin of hospi, tug and relay robots, respectively. The alternatives are chosen based on the literature and are most commonly used serving robots in hospitals. The most common criteria for robot selection are equipment cost, load capacity, speed, vendor service quality, programming flexibility and man-machine interface. Table 1 depicts the objective and subjective criteria.

Step 2: Among 13 criteria, the FDM selects the most suitable criteria for the selection of MSR.

(i) The respective linguistic terms for criteria are allocated based on the opinion of decision-makers $D = \{D_1, D_2, D_3\}$. The decision-maker

Table 1
Possible criteria for selection of robots.

Notation	Criteria
O_1	Equipment cost
O_2	Load capacity
O_3	Charging time
O_4	Warranty
O_5	Run time
O_6	Speed
O_7	Ambient temperature
O_8	Manipulator reach
S_1	Vendor's service quality
S_2	Programming flexibility
S_3	Compliance (command)
S_4	Man-machine interface
S_5	Stability

Table 2
Linguistic terms.

Linguistic variables	Trapezoidal intuitionistic fuzzy number
Supreme low (SL)	(0.00,0.00,0.07,0.15;0.00,0.00,0.07,0.18)
Very low (VL)	(0.07,0.15,0.22,0.30;0.10,0.15,0.22,0.373)
Low (L)	(0.22,0.30,0.38,0.45;0.25,0.30,0.38,0.46)
Moderate (M)	(0.38,0.45,0.52,0.60;0.40,0.45,0.52,0.65)
High (H)	(0.52,0.60,0.68,0.75;0.55,0.60,0.68,0.70)
Very high (VH)	(0.68,0.75,0.83,0.90;0.68,0.75,0.83,0.92)
Supreme high (SH)	(0.83,0.90,0.95,1.00;0.85,0.90,0.95,1.00)

Table 3
Decision-makers opinions about the criteria.

	O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8	S_1	S_2	S_3	S_4	S_5
D_1	VH	VH	VH	M	SH	H	SL	L	H	VH	M	SH	H
D_2	VH	H	H	L	SH	VH	VL	M	H	SH	M	H	VH
D_3	VH	VH	VH	L	SH	H	SL	L	H	VH	M	H	VH

Table 4
Criteria defuzzified matrix.

O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8	S_1	S_2	S_3	S_4	S_5
0.76	0.73	0.73	0.46	0.88	0.68	0.31	0.46	0.58	0.83	0.63	0.81	0.77

1 (D_1) is an academic researcher from a private institute who has nine years of teaching and research experience in the robot field and conducted many workshops and conferences regarding robotics. The decision-maker 2 (D_2) is a mechatronics engineer who has five years of experience in the robotics field and the decision-maker 3 (D_3) is a nurse who has two years of experience in a private hospital and operated the robot during the COVID pandemic in the hospital and also from the literature review. Tables 2 and 3 contains the linguistic terms and the experts' opinion through linguistic variables about the criteria.

- (ii) The linguistic decision matrices are aggregated using Eq. (2).
- (iii) The aggregated matrix is converted into the trapezoidal intuitionistic fuzzy matrix.
- (iv) The TrIFM is converted into the intuitionistic fuzzy set through the proposed CTrIFCS algorithm.
- (v) The intuitionistic fuzzy matrix of the decision-makers are aggregated using Eq. (3). Table 4 expresses the defuzzified values for each criterion.

(vi) The most appropriate objective and subjective criteria are selected based on the obtained threshold value, where $T = 0.62$ for objective criteria and $T = 0.72$ for subjective criteria. The selected objective criteria are equipment cost O_1 , load capacity O_2 , charging time O_3 , run time O_5 and speed O_6 . The selected subjective criteria are programming flexibility S_2 , man-machine interface S_4 and stability S_5 .

Step 3: The linguistic decision matrices are framed between alternatives and selected criteria based on decision-makers. The objective and subjective criteria are analyzed using the specification and performance of robots. The specifications of robots are collected from literature

Table 5
Linguistic decision matrix of expert D_1 .

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	SH	VH	H	M	SL	M	M	M
A_2	M	M	VH	L	L	H	H	M
A_3	VH	H	M	L	SH	M	L	H

Table 6
Linguistic decision matrix of expert D_2 .

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	SH	SH	VH	M	VL	M	M	M
A_2	M	M	VH	L	M	H	H	M
A_3	VH	H	M	L	VH	M	L	H

Table 7
Linguistic decision matrix of expert D_3 .

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	SH	SH	H	M	SL	M	M	M
A_2	M	M	VH	L	M	H	H	M
A_3	VH	H	M	L	SH	M	L	H

Table 8
Defuzzified matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.77	0.70	0.61	0.52	0.33	0.53	0.54	0.46
A_2	0.53	0.53	0.67	0.45	0.47	0.60	0.64	0.46
A_3	0.68	0.59	0.52	0.45	0.70	0.53	0.46	0.53

Table 9
Relative significant value from BtoO and OtoW.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
Best to others [BtoO] (C_2)	0.67	0.79	0.78	0.76	0.80	0.67	0.67	0.76
Others to worst [OtoW] (C_1)	0.79	0.67	0.76	0.67	0.67	0.67	0.76	0.67

and data, and the performance level is collected from the experts'. Tables 5 6 and 7 express the opinion of the decision-makers about the relationship between alternatives and criteria.

Step 4: The linguistic decision matrices are converted into TrIFM using the proposed CTrIFCS algorithm, which analyzes the obtained information under belongingness and non-belongingness context.

Step 5: The trapezoidal intuitionistic fuzzy matrices are aggregated using Eq. (2).

Step 6: The aggregated matrix is defuzzified by CTrIFCS algorithm and Eq. (3). Table 8 expresses the defuzzified values of the performance level between alternatives and criteria.

Step 7: The criteria weights are calculated using SBWM. It provides the influencing level of criteria. Now, the objective and subjective criteria are considered together and denoted as $C = \{C_1, C_2, \dots, C_n\}$.

(i) Initially, the best and worst criteria are chosen by decision-makers. As the problem is based on finding the medication service robot, the load capacity (C_2) is chosen as the best criteria and equipment cost (C_1) is chosen as the worst criteria.

(ii) The priority level of the best criterion over the other criteria is determined.

(iii) The priority level of the other criteria over the worst criterion is determined. Table 9 represents the relative significant value of all criteria from best and worst criteria.

The priority level for best to other criteria are evaluated using Eq. (6)

$$W'_2 = \frac{1}{0.67 + 0.79 + 0.78 + 0.76 + 0.80 + 0.67 + 0.67 + 0.76} = 0.169$$

The rest of the criteria are calculated using Eq. (7)

$$0.169 - 0.67W'_1 = 0 \Rightarrow W'_1 = \frac{0.169}{0.67} = 0.25$$

Table 10
Normalized matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.00	1.00	0.63	1.00	0.00	0.00	0.47	0.00
A_2	1.00	0.00	1.00	0.00	0.37	1.00	1.00	0.00
A_3	0.38	0.38	0.00	0.00	1.00	0.00	0.00	1.00

Table 11
Marginal value matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.00	1.00	0.29	1.00	0.00	0.00	0.15	0.00
A_2	1.00	0.00	1.00	0.00	0.09	1.00	1.00	0.00
A_3	0.09	0.09	0.00	0.00	1.00	0.00	0.00	1.00

Table 12
Final rank for the alternatives.

Alternatives	Final score	Rank
A_1	0.26	2
A_2	0.61	1
A_3	0.23	3

Similarly, $W'_3 = 0.21, W'_4 = 0.22, W'_5 = 0.21, W'_6 = 0.25, W'_7 = 0.25, W'_8 = 0.22$.

The priority level for other criteria to worst are determined using Eq. (8)

$$W''_1 = \frac{1}{0.79 + 0.67 + 0.76 + 0.67 + 0.67 + 0.67 + 0.76 + 0.67} = 0.17$$

The remaining criteria are calculated using Eq. (9)

$$W''_2 - 0.67 \times 0.17 = 0 \Rightarrow W''_2 = 0.67 \times 0.17 \Rightarrow W''_2 = 0.11$$

Similarly, $W''_3 = 0.13, W''_4 = 0.11, W''_5 = 0.11, W''_6 = 0.11, W''_7 = 0.13, W''_8 = 0.11$.

(iv) After evaluating both the weights using a preference vector, the final criteria weights are calculated by combining the BtoO and OtoW using Eq. (10). The α value is assigned 0.5 so that BtoO and OtoW are preferred equally.

Therefore, each criterion $\{C_1, C_2, \dots, C_8\}$ are assigned the weight vector based on their performance.

$$C_1 \ C_2 \ C_3 \ C_4 \ C_5 \ C_6 \ C_7 \ C_8$$

$$W = [0.2 \ 0.1 \ 0.1 \ 0.1 \ 0.1 \ 0.1 \ 0.2 \ 0.1]$$

Step 8: The normalized matrix is evaluated by categorizing the criteria into beneficiary and non-beneficiary. The three different types of medication serving robots are analyzed with these criteria. The criterion C_1 is only under the non-beneficiary category and the rest of the criteria are under the beneficiary category. The normalized matrix is defined for the beneficiary and non-beneficiary criteria using Eqs. (11) and (12), respectively. Table 10 represents the normalized value calculated from the aggregated matrix.

Step 9: The marginal utility scores are calculated between each alternative and criteria using Eq. (13). Therefore, each alternative attains the maximum accuracy through marginal value with respect to all the criteria. Table 11 exhibits the marginal utility value.

The U_{ij} value of the alternative A_1 and the criteria C_3 are calculated as $U_{ij} = \frac{e^{(0.63)^2} - 1}{1.71} = 0.29$.

Step 10: The final ranking for the alternatives is determined by Eq. (14), the sum of all multiplication of marginal utility scores with the respective criteria weight vector. According to their final utility scores, the alternatives are ranked in descending order, so the best alternative contains the highest final utility score. Table 12 provides the rank for alternatives.

Table 13
Sensitivity Analysis.

α value	Outcomes	α value	Outcomes
0.0	$A_2 < A_1 < A_3$	0.6	$A_2 < A_1 < A_3$
0.1	$A_2 < A_1 < A_3$	0.7	$A_2 < A_1 < A_3$
0.2	$A_2 < A_1 < A_3$	0.8	$A_2 < A_1 < A_3$
0.3	$A_2 < A_1 < A_3$	0.9	$A_2 < A_1 < A_3$
0.4	$A_2 < A_1 < A_3$	1.0	$A_2 < A_1 < A_3$

Table 14
Comparative Analysis of defuzzification methods.

α value	Chen and Hwang method	CFCS algorithm	CTrIFCS Algorithm
0.1	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$
0.2	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$
0.3	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$
0.4	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$
0.5	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$
0.6	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$
0.7	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$
0.8	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$
0.9	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$
1.0	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$	$A_2 < A_1 < A_3$

Table 15
Aggregated decision matrix under IFS.

	C_1	C_2	C_3	C_4
A_1	(0.76,0.13,0.11)	(0.73,0.17,0.10)	(0.60,0.33,0.07)	(0.47,0.47,0.06)
A_2	(0.47,0.47,0.06)	(0.47,0.47,0.06)	(0.67,0.26,0.07)	(0.36,0.58,0.06)
A_3	(0.67,0.26,0.07)	(0.56,0.37,0.07)	(0.47,0.47,0.06)	(0.36,0.58,0.06)
	C_5	C_6	C_7	C_8
A_1	(0.17,0.69,0.14)	(0.47,0.47,0.06)	(0.47,0.47,0.06)	(0.47,0.47,0.06)
A_2	(0.43,0.51,0.06)	(0.56,0.37,0.07)	(0.56,0.37,0.07)	(0.47,0.47,0.06)
A_3	(0.73,0.17,0.10)	(0.47,0.47,0.06)	(0.36,0.58,0.06)	(0.56,0.37,0.07)

4.1. Sensitivity analysis

The sensitivity analysis aid in proving the reliability of the outcomes. This analysis can find the impact that occurs in output variables due to changes in the input variables. It is also called simulation analysis. The parameter α aids in finding the final weight vector for criteria, has been simulated by assigning the different values between the intervals [0,1]. The proposed method provided equal importance to both BtoO and OtoW. By changing the values of α from 0 to 1, the preference of the alternatives remains the same. If $\alpha = 0.0$ to 0.4, the importance of BtoO is less than OtoW. If $\alpha = 0.6$ to 1.0, the importance of the BtoO is higher than OtoW. Table 13 provides the rank for the alternatives based on the sensitivity study. The simulation values are depicted in Fig. 7.

4.2. Comparative analysis

The Chen and Hwang method [43] and the CFCS algorithm [38] are considered for the comparative analysis. The proposed CTrIFCS algorithm is designed to operate in a trapezoidal intuitionistic fuzzy context, whereas comparative methods function in a triangular fuzzy context. The ranking of the alternatives using the comparative methods is shown in Table 14. The Chen and Hwang method, the CFCS algorithm and the CTrIFCS algorithm are each visually represented in Figs. 8, 9 & 10, respectively. The Euclidean distance measure is also utilized in the comparative study. The aggregated decision matrix under the intuitionistic fuzzy set and weighted score function values between alternatives and criteria are presented in Tables 15 and 16.

The Euclidean distance is employed, and the PIS and NIS for the criterion C_3 is A_1 and A_3 with the aggregated decision rating of (0.60,0.33,0.07) and (0.47,0.47,0.06). The Euclidean distance between the PIS and NIS is $d_e(A_1, A_3) = 0.1352$. Simultaneously, the distance between the PIS A_1 and A_2 is $d_e(A_1, A_2) = 0.0703$. So, $d_e(A_1, A_3) >$

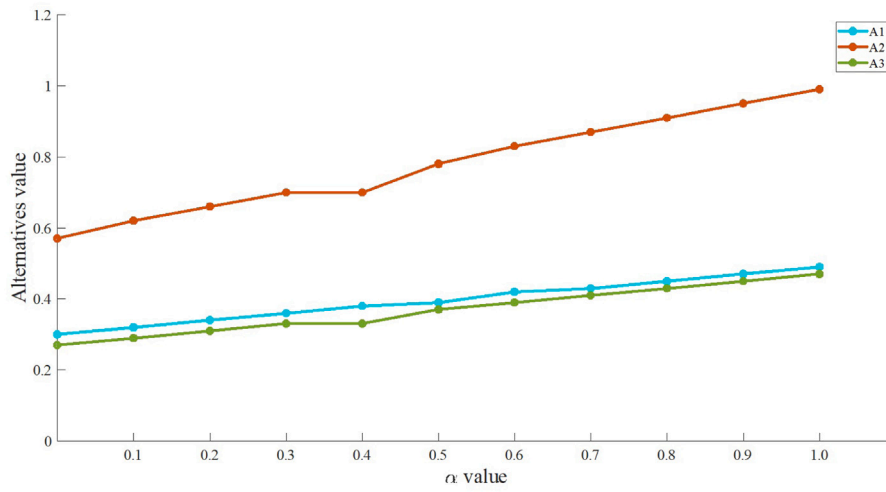


Fig. 7. Sensitivity analysis.

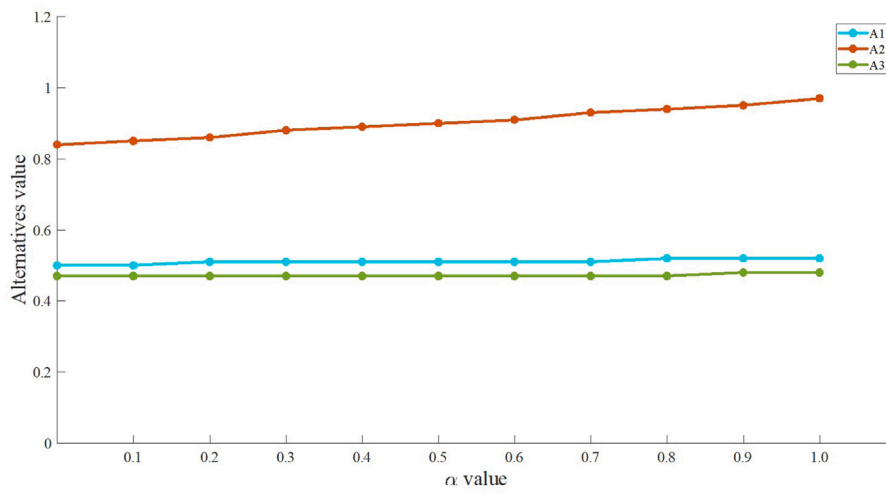


Fig. 8. Comparative analysis (Chen and Hwang method).

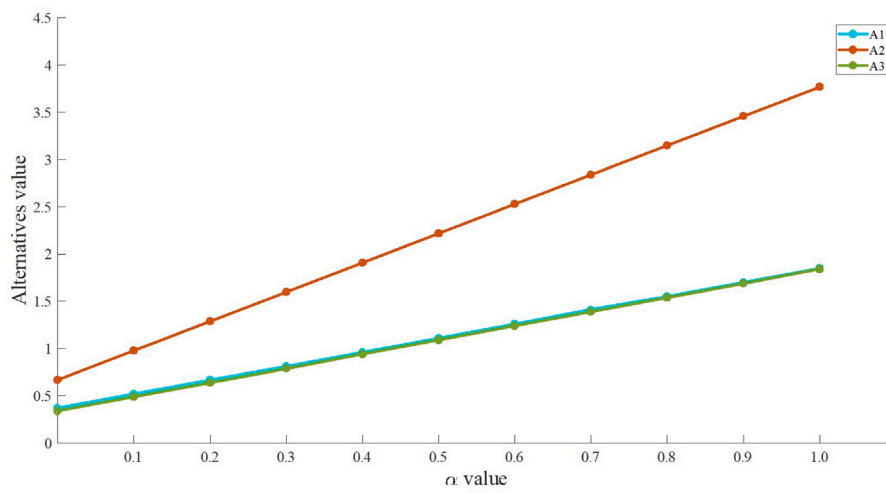


Fig. 9. Comparative analysis (CFCS algorithm).

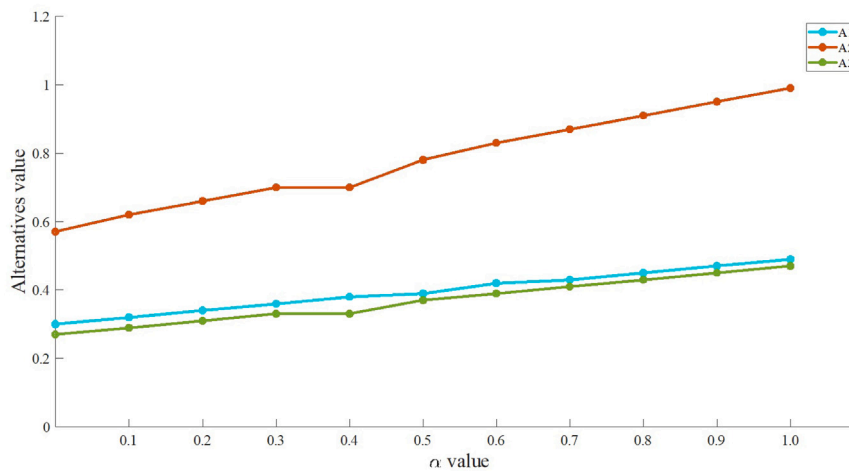


Fig. 10. Comparative analysis (CTrIFCS algorithm).

Table 16 Weighted score function values of aggregated decision matrix under IFS.

	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇	C ₈
A ₁	0.9396	0.9168	0.7483	0.5000	0.1088	0.5000	0.5000	0.5000
A ₂	0.5000	0.5000	0.8466	0.2923	0.4214	0.6808	0.6808	0.5000
A ₃	0.8466	0.6808	0.5000	0.2923	0.9168	0.5000	0.2923	0.6808
PIS (A ⁺)	A ₁	A ₁	A ₁	A ₁	A ₃	A ₂	A ₂	A ₃
NIS (A ⁻)	A ₂	A ₂	A ₃	A _{2, A₃}	A ₁	A _{1, A₃}	A ₃	A _{1, A₂}

Table 17 Ranking for selection of medication-service robots using different methods.

Method	Ranking
Proposed CTrIFCS Algorithm	A ₂ < A ₁ < A ₃
Chen and Hwang method	A ₂ < A ₁ < A ₃
CFCS algorithm	A ₂ < A ₁ < A ₃

Table 18 Spearman's rank correlation coefficient.

Method	CTrIFCS Algorithm	Chen and Hwang method	CFCS algorithm	Euclidean distance
CTrIFCS Algorithm	1	1	1	1
Chen and Hwang method	1	1	1	1
CFCS algorithm	1	1	1	1
Average	1	1	1	1

$d_e(A_1, A_2)$. Therefore, the distance between the PIS and NIS is the largest for the whole criteria and assured that the proposed method provides the trustable result. Table 17 presents the rank of the alternatives obtained from different methods.

Spearman's rank correlation coefficient

It measures the strength and direction of the association between two different sets of ranks. Here, it determines the ranking correlation between the three techniques represented in Table 18. The method with the greatest average correlation compared to the others is considered the best method for making decisions. The Spearman coefficient can range from +1 to -1, where a perfect association between ranks is represented by a value 1, no association between ranks is represented by a value 0, a perfect negative association between ranks is represented by a value -1.

The Spearman's rank coefficient reveals the more consistent method that suits decision-making. Since, all the methods has the Spearman's average score of 1, the involvement of the problems are differs in each method. The proposed CTrIFCS algorithm is more efficient as it evaluates the problem by including the membership and non-membership functions, whereas the comparative methods evaluates only by membership function.

Table 19 Alternatives rank obtained using ARAS method.

Alternatives	Final score	Rank
A ₁	0.56	2
A ₂	1.00	1
A ₃	0.49	3

Additionally, the results are compared with extant ARAS fuzzy method under the proposed CTrIFCS algorithm. The ARAS method demonstrates the performance of alternatives and also ratio of each alternative to the ideal alternative. Table 19 depicts the obtained rank of the alternatives through ARAS method and the rank remains the same. Therefore, the proposed CTrIFCS algorithm is very flexible to use under the extant fuzzy MCDM approaches.

5. Results and discussion

This work analyzes the efficient medication service robot using the integrated fuzzy MCDM methods. The coronavirus is highly contagious. The healthcare workers are infected in large numbers. Compared with other professionals, the ground zone healthcare workers were at risk of reporting a positive COVID-19. This can be resolved by replacing the frontline workers with robots. This COVID pandemic can be overcome by using robots to disinfect and avoid spreading the virus easily. Handling uncertainties in robot selection problems is one of the major concerns for decision-makers. The fuzzy logic aids in tackling the vagueness of the problem through linguistic terms. The major purpose of linguistic terms is to assess the decision-makers views on the quantitative and qualitative attributes without any constraints.

Based on the decision-makers opinion and the literature review, different types of robots are chosen as alternatives, and objective and subjective criteria are framed. Though numerous criteria are available for robot selection, the most important objective and subjective criteria for MSR are selected through the FDM. Therefore, FDM is utilized to select the appropriate criteria for MSR selection. After the criteria selection, the weights for the criteria are calculated using SBWM. The SBWM calculates the distance from the best and worst criteria to other criteria. The decision-makers frame the decision matrix by measuring the alternatives and criteria through linguistic variables, which also consider consumer expectations. These linguistic variables are fuzzified using the trapezoidal intuitionistic fuzzy set (TrIFS). The trapezoidal intuitionistic fuzzy sets are defuzzified by the averaging operator. The selection of a MSR is accomplished through the fuzzy MAUT method. Through this integrated fuzzy method, the alternative A₂ - Tug robot is ranked one, which also satisfies the need of the medical sector. The

alternatives A_1 - Hospi robot and A_3 - Relay robot are ranked second and third, respectively. The results are validated through sensitivity and comparative analysis. In sensitivity, the importance of BtoO and OtoW categories have fluctuated in SBWM. The α value is ranges from 0.0 to 1.0, where 0.0 to 0.4 provide more prominence to OtoW and less to BtoO. The values from 0.6 to 1.0 provide more prominence to BtoO and less to OtoW and the value 0.5 provide equal importance to BtoO and OtoW. Even after this simulation, the output remains the same. The tenacity of the proposed CTrIFCS algorithm is checked with comparative analysis. The comparative analysis used Chen and Hwang method and the CFCS algorithm. Chen and Hwang method worked under the belongingness of the set, determining the output through the mean value of the left and right scores $x^{crisp} = \frac{x_{ij1}^n + x_{ij2}^n}{2}$. In 2003, Obricovic introduced the CFCS algorithm. The output is determined by the weighted average, which includes the belongingness of the set. The proposed CTrIFCS algorithm presents the weighted average by including belongingness and non-belongingness of the set. Therefore, the proposed method resulted in A_2 - Tug robot as rank one and proved the proposed method's efficiency using the Euclidean distance, which measures the positive ideal solution (PIS) and negative ideal solution (NIS). The obtained PIS and NIS exist as the largest distance of criteria. The proposed methods evaluates membership and non-membership degrees in a trapezoidal intuitionistic fuzzy context are entirely different from the residual methods involving only the belongingness degree in the triangular fuzzy context. Moreover, the result remains the same when compared with fuzzy ARAS method. Therefore, the proposed method is also proved to be very efficient.

As the proposed method is an integrated technique, it encompasses a few advantages. This technique can be adopted for the analysis of all real-world problems. According to the problem, the most relevant criteria are selected. The criteria are weighted based on the relative significant value of the best and worst criteria. Therefore, the relation between the criteria is provided from the best and worst criteria. Finally, the grades are furnished for alternatives. This study also has some limitations. The result is obtained only for medication service robot and varies for other service robots like cleaning and ambulances. The considering criteria also differ according to the different characteristics robot and based on the requirements of consumers.

6. Conclusions

The COVID pandemic caused the most effect on people's lives. It impacted daily chores, the education system and working habits. The medical community faced many difficulties due to the coronavirus. The treatment of COVID patients also affects the medical personnel. Robots are a highly effective replacement for these healthcare frontline workers to control the spread of the virus. The selection of error-free medicine distribution robots for COVID patients is a challenging task. Therefore, this selection is managed through fuzzy decision-making by scrutinizing the different MSR specifications and performance. Initially, the suitable criteria are selected using the FDM and weighted through the SBWM. The robots are ranked using the fuzzy MAUT method. The trapezoidal intuitionistic fuzzy sets handled the vagueness of the problem. The proposed CTrIFCS algorithm differs from the earlier technique and is performed as a defuzzification tool for TrIFSS. The proposed integrated method aids in attaining the desired medication robots with minimum cost and maximum features. Additionally, the robustness of the proposed algorithm and method are validated through sensitivity and comparative studies. Further, this work can be extended to the various fuzzy numbers such as hexagonal, pentagonal and type-2 fuzzy set, q -rung orthopair fuzzy set to examine the suitable ventilators for COVID patients, where this world faced a shortage of ventilators during the COVID pandemic and also in various disciplines that are impacted by the COVID pandemic. Moreover, the bio-inspired algorithms [44,45] and clustering [46–49] concepts will be incorporated in the fuzzy MCDM methods.

Abbreviations

COVID-19	CoronaVirus Diseases-2019
IFS	Intuitionistic Fuzzy Set
TrFN	Trapezoidal Fuzzy Number
TrIFN	Trapezoidal Intuitionistic Fuzzy Number
CFCS	Converting Fuzzy into Crisp Score
CIFCS	Converting Intuitionistic Fuzzy into Crisp Score
CTrIFCS	Converting Trapezoidal Intuitionistic Fuzzy into Crisp Score
FDM	Fuzzy-Delphi Method
BWM	Best–Worst Method
SBWM	Simplified Best–Worst Method
MAUT	Multi-Attribute Utility Theory
MSR	Medication Service Robot
MIS	Minimal Invasive Surgery

CRedit authorship contribution statement

Daekook Kang: Investigation, Validation, Visualization, Funding acquisition, Writing – review & editing. **S. Aicevarya Devi:** Conceptualization, Data curation, Formal analysis, Writing – original draft. **Augustin Felix:** Resources, Supervision, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Samayan Narayanamoorthy:** Conceptualization, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – review & editing. **Samayan Kalaiselvan:** Writing – original draft, Data curation, Visualization, Writing – review & editing. **Dumitru Balaenu:** Resources, Visualization, Writing – review & editing. **Ali Ahmadian:** Resources, Validation, Visualization, Writing – review & editing.

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.

Data availability

No data was used for the research described in the article.

Acknowledgment

This work was supported by a National Research Foundation (NRF) of Korea grant funded by the Korean Government (MSIT) Grant NRF-2022R1C1C1006671.

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