



OPEN AI-assisted technology optimization in disability support systems using fuzzy rough MABAC decision-making

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The selection of AI-assistive technologies for disability support systems involves a complex decision-making problem due to the presence of uncertain evaluation criteria. The traditional methods of decision-making often do not succeed in addressing the challenges leading to potential inefficiencies in resource allocation. Aggregation operators are the fundamental tool to manage overall information into a single value. This characteristic of aggregation operators helps in ranking processes and decision-making scenarios. To overcome the issues of uncertainty and keep in mind the advantages of AOs, in this article, we have proposed the notion of fuzzy rough Maclaurin symmetric mean (FRMSM) aggregation theory. The MSM AOs reduce the sensitivity in huge amounts of data due to symmetric formulation. As a result, more accurate and authentic results can be obtained. As the MABAC approach uses border approximation area, so this characteristic reduces the bias and improves the accuracy. Therefore, we have proposed the MABAC approach based on FRMSM AOs. For the application of the proposed work, we have delivered an algorithm and initiated an illustrative example. We have utilized the proposed work for the optimization of AI-assisted technologies in disability support systems. Thus, it shows its potential for dealing with the problems arising from the selection process of inherent challenges and will offer a reliable tool to the stakeholders in the health and assistive technology design sectors. Additionally, we have proposed a comparative analysis of the initiated approach and discussed that the introduced approach is more reliable and trustable as compared to existing notions.

Keywords AI-assistive technologies, Maclaurin symmetric means aggregation operators, Fuzzy rough MABAC approach

AI assistive technologies are tools and systems that run on artificial intelligence. They can help improve life quality for a person who has disability or impairments. They could enable persons with physical, cognitive, or sensory disabilities to carry out tasks that may be perceived as cumbersome for them. Integration of AI can help tailor them to the needs of individual users. These can be speech recognition systems allowing persons with mobility impairment to talk to devices or AI-powered applications that aid persons who have visual impairments in perceiving their surroundings. Such intelligent artificial prosthetics and exoskeletons could aid those whose movements and hence their functions are lost because of an injury or a disease. In addition, there becoming increasingly frequent applications in assistance to hearing defects, like real-time captioning and sign language interpretation. AI supports cognition as well by technologies meant to support people suffering from learning disabilities, dementia, or brain injuries in terms of improving their memory and attention in terms of making a good decision. Virtual assistants, together with chatbots, facilitate a personalized manner of engaging daily, say, with schedules and reminders. With continuous learning, such an AI system improves. Consequently, functionality becomes enhanced as such systems give users a great deal of independence. These innovations transform the way disabled people engage and interact with the world, giving them greater access and facilitating inclusion.

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Q. What is the role of AI assistive technologies?

AI assistive technologies are crucial for a support system for people with disabilities as they encourage independence and enhance the quality of life. Such technologies provide personalized solutions in the areas of mobility, communication, and cognitive challenges. The AI systems, such as smart prosthetics and voice recognition, also manage daily tasks better. They monitor health, predict risks, and ensure proactive care. The AI system learns user behaviors improves with time, and ensures access is better. They enhance inclusion in school, in the workplace, and community. AI assistive technologies allow people with disabilities to live more independently and accomplish their daily tasks. Voice-controlled systems enable users to interact with devices with less need for physical input. AI-powered mobility aids, such as autonomous wheelchairs, enable individuals to move around in different environments easily. AI can monitor health conditions and alert or advise people on the necessary treatment in real time. Personalized content and interfaces make the digital space more accessible for people with visual or cognitive disabilities. Moreover, virtual assistants and chatbots offer emotional support and help in matters of mental health, leading to well-being. It fosters greater social inclusion and independence of users with disabilities through breaking barriers as AI technologies work.

Literature is rich in solving the problems in disability support systems and researchers tried their best to provide an accurate and valid method to choose the best AI assistive technology to help the disabled and make their individual lives easy. De Freitas et al.¹ AI of things applied to assistive technologies and produced a systematic review of assistive technologies. Ran et al.² studied the basic principle for the development of AI-based tools for assistive technology decision-making. Yanagawa et al.³ explored some new trends in AI-based assistive technologies for thoracic imaging. Zdravkova et al.⁴ discussed an AI perspective of cutting-edge communication and learning assistive technologies for disabled children. Brotosaputro et al.⁵ discussed their theory about AI-powered assistive technologies for improved accessibility. Lavric et al.⁶ proposed a comprehensive survey on emerging assistive technologies for visually impaired persons.

Motivation and contribution

This section of the article is about to discuss the motivation of the proposed work. We have also explored the contribution of the delivered approach.

Motivation

FRS are generally considered to provide a very flexible framework for managing vagueness and uncertainty and are often very relevant in AI assistive technologies. In sharp contrast to the crisp boundaries between classical sets, graded membership within FRSs and approximate reasoning permit the description of real-world complexities in human-centered applications of disability assistance, healthcare, and others. Thanks to this hybrid concept of FS and RS, AI systems can process fuzzy data but interpret it in a meaningful way. This is an absolute prerequisite in dealing with adaptive learning systems, rehabilitation tools, and assistive devices needing subtle decision-making. According to the theory of classical sets, elements are assigned to be absolute members of a set or not-at-all members of a given set. Thus, the crisp set theory is not so suitable for real-world problems of overlapping or uncertain boundaries. It actually cannot model imprecise data and relationships, rendering it inapplicable to dynamic, human-centered AI systems. Hence this utilization of FRS in AI assistive techniques is very handy. Moreover, the motivation behind proposing the idea of FRMSM AOS is the characteristics of these aggregation operators. (1) The defined AOS can aggregate the uncertain information as well as they can classify the data into upper and lower approximations. (2) These FRMSM AOs can capture the symmetric relationship among the input parameters while the traditional AOS can deal with input parameters independently. (3) The notion of FRMSM AOs provides a robust framework for complex decision-making models while the other AOs are limited in cases where interdependency among the criteria is required. (4) The MSM AOs reduce the sensitivity in huge amounts of data due to symmetric formulation while the other traditional AOs are sensitive in this characteristic. (5) MSM AOS are easy to use and maintain an efficient computational structure while some fuzzy AOs involve higher complexity in the case of big data. Hence these characteristics of MSM AOs motivate us to define these notions for FR structure and make use of these notions in MCDM approaches.

Contribution

In this article we have explored the notion of fuzzy rough Maclaurin symmetric means aggregation operators (FRMSM), fuzzy rough weighted Maclaurin symmetric means (FRWMSM) aggregation operators, fuzzy rough dual Maclaurin symmetric (FRDMSM) means aggregation operators and fuzzy rough dual weighted Maclaurin symmetric means (FRDWMSM) aggregation operators. We have explored the multi-attributive border approximation area comparison technique for these developed aggregation operators. For the utilization of the delivered approach, we have discussed an illustrative example of the classification of AI assistive technologies for disability support systems. We have compared our work with existing notions to explore the advantages of the initiated theory. The conclusion section discusses the overall developed theory and future direction of the delivered approach.

Literature review

A rough set (RS) delivered by Pawlak⁷ is a very powerful development for dealing with uncertainty and impreciseness in data analysis, mainly when information is partial or ambiguous. The basic idea behind the theory is to allow classification and approximation of data in such a way that data can be represented with lower and upper bounds describing, respectively, equivalence classes and relationships between them. This kind of approach is used in many diverse problem domains, such as decision-making, pattern recognition, and machine learning, in which exact knowledge is often missing. Indeed, from data with essential structure inherent to RSs,

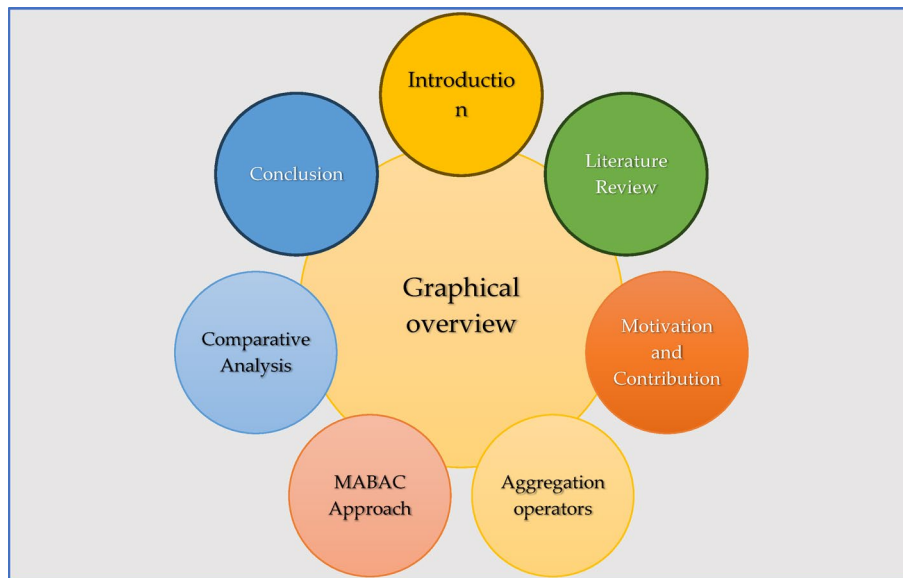


Fig. 1. Graphical overview of the whole manuscript.

it is possible to extract needed information, and prior knowledge about the mechanisms behind the system is not necessary. For managing vagueness and incompleteness, RSs can play a very pivotal role, making RS theory very important in analyzing complex, real-world data. RS takes the attention of the researchers and they have utilized this notion in different directions. Talasila et al.⁸ used the RS theory with recurrent neural networks in big data analysis for the prediction of diseases. Chen et al.⁹ proposed the application of RS for pressure injury risk in the elderly male population. Jiang et al.¹⁰ explored an aided diagnosis model of sub-health based on RS and fuzzy mathematics. Shende et al.¹¹ proposed uncertainty optimization-based RS and discussed its application. Zhou et al.¹² used neighbor RS to address smart elderly care in multi-level attributes. Li et al.¹³ also disclosed the RS optimization method for elderly evaluation. Trabelsi et al.¹⁴ discussed the handling of data with evidential attributes based on the RS model.

The notion of the fuzzy set (FS) has been delivered by Zadeh¹⁵ a remarkable achievement in handling imprecise and ambiguous data. FS usually generalizes the crisp set theory and assists in the conditions where the information is ambiguous and decision-making in these situations is very difficult through classical set theory. For example, to form the mathematical modeling of the data that Ali is young or Ali is healthy is imprecise and it is very difficult to make the mathematical model of the terms like healthy or young through classical set theory. In this case, only FS helps to discuss the situation and provide the mathematical modeling of these terms by the use of membership grade. In this case, through the notion of membership grade, the decision-making becomes very easy and the FS model becomes a handy tool to discuss such kinds of problems. FS has a remarkable utilization of different fields. Sanchez-Alvarez et al.¹⁶ proposed an adaptive approach with fuzzy logic and machine learning in adaptive and alternative communication systems. Castro et al.¹⁷ explored the prioritization of educational technologies for children with intellectual disabilities based on the fuzzy MCDM approach. Hezam et al.¹⁸ discussed assessing the barriers to digitally sustainable transportation systems for persons with disabilities using the idea of the Fermatean fuzzy double normalization-based multiple aggregation method. Albahri et al.¹⁹ explored the explainable AI model of autism triage levels using the notion of fuzzy MCDM approach. Chen et al.²⁰ explored that robotic exoskeletons can compensate for a decline in physical performance due to aging and loss of muscle strength. The symmetrical-based approaches applied in the majority of previous studies on exoskeleton acceptance fail to account for the asymmetry of the link between the antecedents. Their study is based on the configuration theory and the senior technology acceptance model. They have produced an FS qualitative comparative approach. Costa et al.²¹ proposed a model based on fuzzy logic to discuss the perception of disability from a public health perspective. RS theory can be merged with additional techniques, for example, fuzzy logic, to increase its applicability to a wide range of problems. The emphasis on approximation and granularity contained in RS theory, therefore, finds most practical use in cases where data is inconsistent and noisy.

RSs, through their foundational principles, offer a good solid footing in the development of models that support decision-making under uncertainty, hence their value both for theoretical research and practical applications. Many merged approaches have been developed based on the idea of RS and FS and the idea of fuzzy rough set (FRS)²² has been developed. The notion of FRS is the hybrid idea of RS and FS that can handle more advanced information. Due to its ability to discuss fuzzy information and handle the upper and lower approximation, FRS is a very handy approach for handling ambiguous and imprecise data effectively. Vluymans et al.²³ explored the application of FRS in machine learning. Kuncheva²⁴ discussed the application of FRS in feature selection. Wang et al.²⁵ utilized the idea of a directed FRS model in feature selection and classification. Ji et al.²⁶ explored FRS and FR neural networks for feature selection. Zhang et al.²⁷ proposed a novel FRS model

and discussed its application to MCDM approaches. Atef et al.²⁸ utilized the idea of multigranulation FRS and proposed new covering techniques and applications.

There exists a research gap in the literature in terms of structure. We can notice that the notion of the FS can only discuss the membership grade and it is free to classify the information in the form of upper and lower approximations which is the characteristic of rough structure. Moreover, the notion of RS can also discuss the upper and lower approximation of information but this structure can never discuss the vague and uncertain information. Furthermore, all the existing AOs that are based on fuzzy ideas are free to classify the data into upper and lower approximations. Now if decision makers want to discuss more advanced information in the form of fuzzy rough structure, then in this case the existing ideas are free to discuss such kind of data. Additionally, there exists a chance of data loss in the case of FS as well as RS. On the other hand, the developed ideas can discuss both limitations of existing theories in one structure making decision-making more reliable and trustworthy.

The rest of the article is organized as follows: In “[Introduction](#)” section we have discussed the introduction of AI assistive technologies and their role. In “[Literature review](#)” section is about the literature review of the study. In “[Fundamental concepts](#)” section we have explored some fundamental notions that can help us to define the proposed theory. In “[Fuzzy rough Maclaurin symmetric mean aggregation operators](#)” section is about the aggregation theory based on FRS. In “[MABAC methodology](#)” section we have proposed the MABAC approach and discussed the illustrative example. In “[Comparative analysis](#)” section is about the comparative analysis of the delivered approach. In “[Conclusion](#)” section we have discussed the conclusion remarks.

The graphical overview of the developed approach is given in Fig. 1.

Figure 1 describes the graphical abstract of the delivered approach. In this figure, we have given a precise picture of the study that we have carried out in this article.

Fundamental concepts

In this section, we have discussed the basic notion of FS and FRS. Moreover, we have discussed the idea of MSM operators and DMSM operators for non-negative numbers. We have explored the notion of score function and accuracy function that can help to classify the FRNs.

Definition 1 (Maclaurin²⁹). For the family of non-negative numbers $x_i, i = 1, 2, 3, \dots, n$, the notion of the Maclaurin symmetric means (MSM) operator is given by

$$MSM^{(a)}(x_1, x_2, x_3, \dots, x_n) = \left(\frac{\bigoplus_{1 \leq i_1 < i_2 < \dots < i_a \leq n} \left(\bigotimes_{i=1}^a x_{i_i} \right)}{\binom{n}{a}} \right)^{\frac{1}{a}}$$

where $\binom{n}{a} = \frac{n!}{a!(n-a)!}$ represents a binomial coefficient. MSM satisfies the following properties.

- $MSM^{(a)}(0, 0, 0, \dots, 0) = 0$
- $MSM^{(a)}(x, x, x, \dots, x) = x$
- $MSM^{(a)}(x_1, x_2, x_3, \dots, x_n) \leq MSM^{(a)}(x_1, x_2, x_3, \dots, x_n)$ if $x_i \leq x_j$ for all i .

Definition 2 (Maclaurin²⁹). For the family of non-negative numbers $x_i, i = 1, 2, 3, \dots, n$, the notion of dual Maclaurin symmetric means (DMSM) operator is given by

$$DMSM^{(a)}(x_1, x_2, x_3, \dots, x_n) = \frac{1}{a} \left(\bigotimes_{1 \leq i_1 < i_2 < \dots < i_a \leq n} \left(\bigoplus_{i=1}^a x_{i_i} \right) \right)^{\frac{1}{a}}$$

where $\binom{n}{a} = \frac{n!}{a!(n-a)!}$ represents a binomial coefficient.

Definition 3 (Zadeh¹⁵). Let \mathcal{U} be the universal set. The notion of FS is characterized by the membership function and defined by

$$\mathbb{F} = \{u, \mu(u) | u \in \mathcal{U}\}$$

where $\mu(u)$ denote the membership grade and its value belong to $[0, 1]$.

Definition 4 (Dubois and Prade²²). Assume that R is a fuzzy relation and \mathcal{U} is a universal set. Then (\mathcal{U}, R) is called fuzzy approximation space. Now for any FS $\mathbb{F} = \{(\mu(u)) : u \in \mathcal{U}\}$, the upper and lower approximation of \mathbb{F} concerning approximation space (\mathcal{U}, R) is given by

$$\begin{aligned} \overline{R}(u) &= \bigvee_{v \in \mathcal{U}} \{ \mu_R(u, v) \wedge \mu(v) \} \\ \underline{R}(u) &= \bigwedge_{v \in \mathcal{U}} \{ 1 - \mu_R(u, v) \vee \mu(v) \} \end{aligned}$$

Then the pair $(\overline{R}(u), \underline{R}(u))$ is called the fuzzy rough set (FRS). For the sake of simplicity, the notion $\mathbb{F} = (\underline{z}, \overline{z})$ is called FRN.

Definition 5 Let $\mathbb{F}_1 = (\underline{z}_1, \bar{z}_1)$ be a FRN, then the score function and accuracy function are defined as

$$Scr.(\mathbb{F}_1) = \frac{1}{2}(\underline{z}_1 + \bar{z}_1); \quad Scr. \in [0, 1]$$

and

$$Ac.(\mathbb{F}_1) = \frac{1}{2}(\underline{z}_1 - \bar{z}_1); \quad Ac. \in [0, 1]$$

Fuzzy rough Maclaurin symmetric mean aggregation operators

This section of the article is motivated to deliver the notion of fuzzy rough Maclaurin symmetric mean aggregation theory. We have delivered the notion of

- (a) Fuzzy rough Maclaurin symmetric means aggregation operators.
- (b) Fuzzy rough weighted Maclaurin symmetric means aggregation operators.
- (c) Fuzzy rough dual Maclaurin symmetric means aggregation operators.
- (d) Fuzzy rough dual-weighted Maclaurin symmetric means aggregation operators.

The overall discussion is given by

Definition 6 Let $\mathbb{F}_i = (\underline{z}_i, \bar{z}_i)$ ($i = 1, 2, 3, \dots, n$), and $\alpha = 1, 2, 3, \dots, n$, $l = 1, 2, 3, \dots, n$. The idea of FRMSM AOs is given as the mapping defined by

$$FRMSM : \mathbb{F}^n \rightarrow \mathbb{F}$$

$$FRMSM^{(\alpha)}(\mathbb{F}_1, \mathbb{F}_2, \mathbb{F}_3, \dots, \mathbb{F}_n) = \left(\frac{\bigoplus_{1 \leq l_1 < l_2 < \dots < l_\alpha \leq n} \left(\bigotimes_{i=1}^{\alpha} \mathbb{F}_{l_i} \right)}{\binom{n}{\alpha}} \right)^{\frac{1}{\alpha}} \quad (1)$$

where $\binom{n}{\alpha} = \frac{n!}{\alpha!(n-\alpha)!}$ represents a binomial coefficient.

Theorem 1 Let $\mathbb{F}_i = (\underline{z}_i, \bar{z}_i)$ ($i = 1, 2, 3, \dots, n$) be the family of FRNs, then the aggregated result by using Eq. (1) is again a FRN given by

$$FRMSM^{(\alpha)}(\mathbb{F}_1, \mathbb{F}_2, \mathbb{F}_3, \dots, \mathbb{F}_n) = \left(\left(\left(1 - \left(\prod_{1 \leq l_1 < l_2 < \dots < l_\alpha \leq n} \left(1 - \prod_{i=1}^{\alpha} \underline{z}_{l_i} \right) \right)^{\frac{1}{\alpha}} \right)^{\frac{1}{\alpha}} \right), \left(\left(1 - \left(\prod_{1 \leq l_1 < l_2 < \dots < l_\alpha \leq n} \left(1 - \prod_{i=1}^{\alpha} \bar{z}_{l_i} \right) \right)^{\frac{1}{\alpha}} \right)^{\frac{1}{\alpha}} \right) \right) \quad (2)$$

Definition 7 Let $\mathbb{F}_i = (\underline{z}_i, \bar{z}_i)$ ($i = 1, 2, 3, \dots, n$) and $\alpha = 1, 2, 3, \dots, n$, $l = 1, 2, 3, \dots, n$ be the family of FRNs. Then the notion of FRWMSM AOs is presented by

$$FRWMSM : \mathbb{F}^n \rightarrow \mathbb{F}$$

$$FRWMSM^{(\alpha)}(\mathbb{F}_1, \mathbb{F}_2, \mathbb{F}_3, \dots, \mathbb{F}_n) = \left(\frac{\bigoplus_{1 \leq l_1 < l_2 < \dots < l_\alpha \leq n} \left(\bigotimes_{i=1}^{\alpha} (\mathbb{F}_{l_i})^{\mathbb{W}^T} \right)}{\binom{n}{\alpha}} \right)^{\frac{1}{\alpha}} \quad (3)$$

where $\mathbb{W}^T = (\mathbb{W}_1^T, \mathbb{W}_2^T, \dots, \mathbb{W}_n^T)^T$ is the weight vectors (WVs) for \mathbb{F}_i ($i = 1, 2, 3, \dots, n$) with condition that $\mathbb{W}_i^T \in [0, 1]$ and $\sum_{i=1}^n \mathbb{W}_i^T = 1$.

Theorem 2 Let $\mathbb{F}_i = (\underline{z}_i, \bar{z}_i)$ ($i = 1, 2, 3, \dots, n$) be the family of FRNs, then the aggregated result by using Eq. (3) is again a FRN given by

$$FRWMSM^{(a)}(\mathbb{F}_1, \mathbb{F}_2, \mathbb{F}_3, \dots, \mathbb{F}_n) = \left(\left(\left(1 - \left(\prod_{1 \leq l_1 < l_2 < \dots < l_a \leq n} \left(1 - \prod_{i=1}^a (z_{l_i})^{\mathbb{W}_{l_i}^T} \right) \right)^{\frac{1}{a}} \right)^{\frac{1}{a}} \right), \right. \\ \left. \left(\left(1 - \left(\prod_{1 \leq l_1 < l_2 < \dots < l_a \leq n} \left(1 - \prod_{i=1}^a (\bar{z}_{l_i})^{\mathbb{W}_{l_i}^T} \right) \right)^{\frac{1}{a}} \right)^{\frac{1}{a}} \right) \right) \quad (4)$$

Definition 8 Let $\mathbb{F}_i = (z_i, \bar{z}_i)$ ($i = 1, 2, 3, \dots, n$) and $a = 1, 2, 3, \dots, n$, $l = 1, 2, 3, \dots, n$ be the family of FRNs. The idea of FRDMSM AOs is given by the mapping $FRDMSM: \mathbb{F}^n \rightarrow \mathbb{F}$ defined by

$$FRDMSM^{(a)}(\mathbb{F}_1, \mathbb{F}_2, \mathbb{F}_3, \dots, \mathbb{F}_n) = \frac{1}{a} \left(\bigotimes_{1 \leq l_1 < l_2 < \dots < l_a \leq n} \left(\bigoplus_{i=1}^a \mathbb{F}_{l_i} \right)^{\frac{1}{a}} \right) \quad (5)$$

Theorem 3 Let $\mathbb{F}_i = (z_i, \bar{z}_i)$ ($i = 1, 2, 3, \dots, n$) be the family of FRNs, then the aggregated result by using Eq. (5) is again a FRN given by

$$FRDMSM^{(a)}(\mathbb{F}_1, \mathbb{F}_2, \mathbb{F}_3, \dots, \mathbb{F}_n) = \left(1 - \left(\left(1 - \left(\prod_{1 \leq l_1 < l_2 < \dots < l_a \leq n} \left(1 - \prod_{i=1}^a (1 - z_{l_i}) \right) \right)^{\frac{1}{a}} \right)^{\frac{1}{a}} \right), \right. \\ \left. 1 - \left(\left(1 - \left(\prod_{1 \leq l_1 < l_2 < \dots < l_a \leq n} \left(1 - \prod_{i=1}^a (1 - \bar{z}_{l_i}) \right) \right)^{\frac{1}{a}} \right)^{\frac{1}{a}} \right) \right) \quad (6)$$

Definition 9 Let $\mathbb{F}_i = (z_i, \bar{z}_i)$ ($i = 1, 2, 3, \dots, n$) and $a = 1, 2, 3, \dots, n$, $l = 1, 2, 3, \dots, n$ be the family of FRNs. Then the notion of FRWDMSM AOs is mapping $FRWDMSM: \mathbb{F}^n \rightarrow \mathbb{F}$ defined by

$$FRWDMSM^{(a)}(\mathbb{F}_1, \mathbb{F}_2, \mathbb{F}_3, \dots, \mathbb{F}_n) = \frac{1}{a} \left(\bigotimes_{1 \leq l_1 < l_2 < \dots < l_a \leq n} \left(\bigoplus_{i=1}^a (\mathbb{W}_{l_i}^T \otimes \mathbb{F}_{l_i}) \right)^{\frac{1}{a}} \right) \quad (7)$$

where $\mathbb{W}^T = (\mathbb{W}_1^T, \mathbb{W}_2^T, \dots, \mathbb{W}_n^T)^T$ is the WVs for \mathbb{F}_i ($i = 1, 2, 3, \dots, n$) and $\mathbb{W}_i^T \in [0, 1]$ and $\sum_{i=1}^n \mathbb{W}_i^T = 1$.

Theorem 4 Let $\mathbb{F}_i = (z_i + \iota_{z_i}, \bar{z}_i + \iota_{\bar{z}_i})$ ($i = 1, 2, 3, \dots, n$) be the family of FRNs, then the aggregated result by using Eq. (7) is again FRN and it is given by

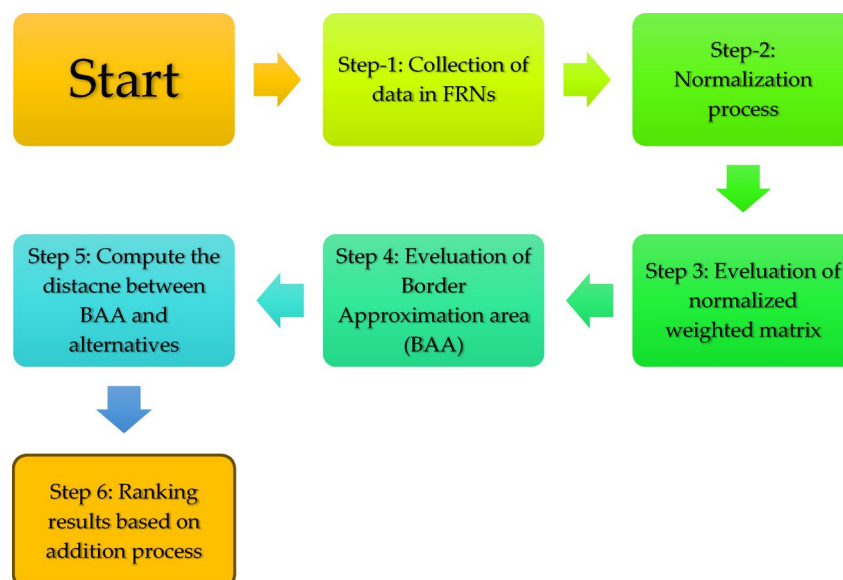


Fig. 2. Flow chart of the MABAC approach.

$$FRWDMSM^{(a)}(\mathbb{F}_1, \mathbb{F}_2, \mathbb{F}_3, \dots, \mathbb{F}_n) = \left(\begin{array}{c} 1 - \left(1 - \left(\prod_{1 \leq l_1 < l_2 < \dots < l_a \leq n} \left(1 - \prod_{i=1}^a (1 - z_{l_i})^{w_{l_i}} \right) \right)^{\frac{1}{a}} \right)^{\frac{1}{a}}, \\ 1 - \left(1 - \left(\prod_{1 \leq l_1 < l_2 < \dots < l_a \leq n} \left(1 - \prod_{i=1}^a (1 - \bar{z}_{l_i})^{w_{l_i}} \right) \right)^{\frac{1}{a}} \right)^{\frac{1}{a}} \end{array} \right) \quad (8)$$

MABAC methodology

Assume that the set $\mathcal{Q}_{altr.} = \{\mathcal{Q}_{altr.-1}, \mathcal{Q}_{altr.-2}, \dots, \mathcal{Q}_{altr.-n}\}$ denote the family of alternatives and the set $\mathcal{E}_{atr.} = \{\mathcal{E}_{atr.-1}, \mathcal{E}_{atr.-2}, \dots, \mathcal{E}_{atr.-m}\}$ represent the family of attributes. Assume that WVs for the attributes are represented as $\mathbb{W}^T = (\mathbb{W}_1^T, \mathbb{W}_2^T, \dots, \mathbb{W}_m^T)$ with condition that $\sum_{i=1}^m \mathbb{W}_i^T = 1$. Suppose experts provide their assessment in the form of FRNs. The overall description of the step-wise algorithm is proposed as:

Step 1 The assessment of experts based on FRNs for each alternative by keeping in mind each attribute is given in the form of a matrix

$$\begin{aligned} M = [\mathbb{F}_{ij}]_{n \times m} &= \begin{bmatrix} \mathbb{F}_{11} & \mathbb{F}_{12} & \dots & \mathbb{F}_{1j} \\ \mathbb{F}_{21} & \mathbb{F}_{22} & \dots & \mathbb{F}_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbb{F}_{i1} & \mathbb{F}_{i2} & \dots & \mathbb{F}_{ij} \end{bmatrix} \\ &= \begin{bmatrix} (z_{11}, \bar{z}_{11}) & (z_{12}, \bar{z}_{12}) & \dots & (z_{1j}, \bar{z}_{1j}) \\ (z_{21}, \bar{z}_{21}) & (z_{22}, \bar{z}_{22}) & \dots & (z_{2j}, \bar{z}_{2j}) \\ \vdots & \vdots & \ddots & \vdots \\ (z_{i1}, \bar{z}_{i1}) & (z_{i2}, \bar{z}_{i2}) & \dots & (z_{ij}, \bar{z}_{ij}) \end{bmatrix} \end{aligned}$$

Step 2 The normalization process is given in two cases given below.

Case-1: For benefit type attributes, no changes in the data as given in Step-1, and the formula is given by

$$N_{ij} = (z_{ij}, \bar{z}_{ij})$$

Case-2: For cost type attribute the data is normalized by taking the complement of the data in Step-1.

$$N_{ij} = (z_{ij}, \bar{z}_{ij})^c$$

where $(z_{ij}, \bar{z}_{ij})^c = (1 - z_{ij}, 1 - \bar{z}_{ij})$.

Step 3 Find out the normalized weighted matrix according to the formula

$$\mathbb{W}^T N_{ij} = \mathbb{W}_j^T N_{ij} = \left(\begin{array}{c} 1 - (1 - z_{ij})^{w_j^T} \\ 1 - (1 - \bar{z}_{ij})^{w_j^T} \end{array} \right)$$

Step 4 The overall results of the border approximation area are given in the form of a matrix given by

$$\mathcal{R} = [\mathcal{R}_j]_{1 \times m}$$

Here we use FRWMSM AOs.

Step 5 The distances between BBA and alternatives are computed by

$$\mathcal{S}_{ij} = \left\{ \begin{array}{ll} \mathcal{S}(\mathbb{W}^T N_{ij}, \mathcal{R}_j) & \text{if } \mathbb{W}^T N_{ij} > \mathcal{R}_j \\ 0 & \text{if } \mathbb{W}^T N_{ij} = \mathcal{R}_j \\ -\mathcal{S}(\mathbb{W}^T N_{ij}, \mathcal{R}_j) & \text{if } \mathbb{W}^T N_{ij} < \mathcal{R}_j \end{array} \right\}$$

where $\mathcal{S}(\mathbb{W}^T N_{ij}, \mathcal{R}_j)$ is the mean distance between $\mathbb{W}^T N_{ij}$ and \mathcal{R}_j .

If $\mathbb{F}_1 = (z_1, \bar{z}_1)$ and $\mathbb{F}_2 = (z_2, \bar{z}_2)$ be two FRNs the normalized Hamming distance for these two FRNs is given by

$$\mathcal{S}(\mathbb{F}_1, \mathbb{F}_2) = \frac{1}{4} (|z_1 - z_2| + |\bar{z}_1 - \bar{z}_2|), \quad (9)$$

where $\mathcal{S}(\mathbb{F}_1, \mathbb{F}_2) \in [0, 1]$.

Step 6 Finally, we add the values of each alternative's \mathcal{S}_i by the formula

$$\mathcal{L}_i = \sum_{\tau=1}^m \mathcal{S}_i$$

The flow chart of the proposed MABAC approach is given in Fig. 2.

Application of proposed model

AI assistive technologies in support systems for people with disabilities increase accessibility by offering personalized solutions to individuals with disabilities. Speech recognition, computer vision, and predictive algorithms help them communicate, move, and perform daily activities. Real-time assistance leads to increased independence and a better quality of life. Additionally, AI-driven devices can adapt to the needs of the users, thus offering personalized support that maximizes functionality and autonomy.

Here are ten AI assistive technologies designed to enhance healthcare and support systems for individuals with disabilities. The description of these technologies is given by

(1) AI-powered predictive analytics for rehabilitation

The variation that AI-based predictive analytics brings to rehabilitation allows for its application in data-driven insights toward the personalization of treatment plans. Machine learning models are used in analyzing patient data concerning the recovery trajectory, optimal therapy regimens, and outcomes. Complex fuzzy and rough set methodologies handle the uncertainties in medical data to make robust predictions. Real-time monitoring and adaptive adjustments can be made with the support of these techniques, enabling healthcare providers to tailor interventions effectively. Predictive analytics also makes resource allocation in rehabilitation centers timely to provide support for patients. This innovative approach fills the gap between traditional approaches and state-of-the-art AI solutions, advancing rehabilitation science.

(2) Speech recognition and natural language processing (NLP)

It enables machines to read, interpret, process, and give responses to human language using speech recognition and natural language processing. The latter employs the most advanced algorithms coupled with neural networks to achieve utmost accuracy in spoken words; in contrast, NLP comprehends, analyzes, and even generates human language so that other tasks such as sentiment analysis or translation and building chatbots are feasible. All of these technologies allow voice assistants, automated transcription tools, and other language-related applications that can be applied in any type of industry. Further developments are based on deep learning, linguistic analysis, and large datasets to enhance further human interaction with machines. The combination of speech recognition and NLP will always be a revolutionary process while discussing communications and accessibility through technology.

(3) AI-assisted prosthetics and exoskeletons

AI-assisted prosthetics and exoskeletons mark a leap in rehabilitation technology, toward personal and adaptive solutions in mobility-impaired individuals. Such systems utilize artificial intelligence in the analysis of sensor-based real-time data; thus, it enables a very precise adaptation in movement according to what the user intends and which environment. These prosthetic devices may be feasible through machine learning so that algorithms learn and adapt specific patterns of walking to enhance comfort, efficiency, and functionality. AI-powered exoskeletons are very important to patients with injuries or neurological disorders. It will enable them to regain better motor control and to have their muscles strengthened more effectively. Further, AI remains to open the potential of prosthetics, which will mean a better quality of life and more independence for the users. Assistive devices are continuously revolutionized with new definitions created due to advanced technology being embedded into human needs.

(4) Vision enhancement and object detection

The base for modern applications of artificial intelligence and computer vision comes fundamentally from key constituents such as vision enhancement and object detection. Algorithms as complex as those required in CNNs and deep models are used to process the visual data, analyze them, and produce meaning out of them. It is image clarity improvement mainly in poor light or with noise, which helps objects be spotted in images and

	\mathcal{E}_{atr-1}	\mathcal{E}_{atr-2}	\mathcal{E}_{atr-3}	\mathcal{E}_{atr-4}
$\mathcal{Q}_{altr.-1}$	H	L	M	H
$\mathcal{Q}_{altr.-2}$	E	E	I	I
$\mathcal{Q}_{altr.-3}$	L	H	H	M
$\mathcal{Q}_{altr.-4}$	M	I	E	L
$\mathcal{Q}_{altr.-5}$	L	H	H	H
$\mathcal{Q}_{altr.-6}$	E	I	E	E
$\mathcal{Q}_{altr.-7}$	H	M	L	L
$\mathcal{Q}_{altr.-8}$	I	L	M	M
$\mathcal{Q}_{altr.-9}$	H	I	H	H
$\mathcal{Q}_{altr.-10}$	M	H	L	L

Table 1. Linguistic data by experts.

Linguistic terms	FRNs
H	(0.25, 0.26)
L	(0.51, 0.62)
M	(0.57, 0.36)
E	(0.65, 0.46)
I	(0.75, 0.61)

Table 2. Conversion of the linguistic term into the FRNs.

	\mathcal{E}_{atr-1}	\mathcal{E}_{atr-2}	\mathcal{E}_{atr-3}	\mathcal{E}_{atr-4}
$\mathcal{Q}_{altr.-1}$	(0.25, 0.26)	(0.51, 0.62)	(0.57, 0.36)	(0.25, 0.26)
$\mathcal{Q}_{altr.-2}$	(0.65, 0.46)	(0.65, 0.46)	(0.75, 0.61)	(0.75, 0.61)
$\mathcal{Q}_{altr.-3}$	(0.51, 0.62)	(0.25, 0.26)	(0.25, 0.26)	(0.57, 0.36)
$\mathcal{Q}_{altr.-4}$	(0.57, 0.36)	(0.75, 0.61)	(0.65, 0.46)	(0.51, 0.62)
$\mathcal{Q}_{altr.-5}$	(0.51, 0.62)	(0.25, 0.26)	(0.25, 0.26)	(0.25, 0.26)
$\mathcal{Q}_{altr.-6}$	(0.65, 0.46)	(0.75, 0.61)	(0.65, 0.46)	(0.65, 0.46)
$\mathcal{Q}_{altr.-7}$	(0.25, 0.26)	(0.57, 0.36)	(0.51, 0.62)	(0.51, 0.62)
$\mathcal{Q}_{altr.-8}$	(0.75, 0.61)	(0.51, 0.62)	(0.57, 0.36)	(0.57, 0.36)
$\mathcal{Q}_{altr.-9}$	(0.25, 0.26)	(0.75, 0.61)	(0.25, 0.26)	(0.25, 0.26)
$\mathcal{Q}_{altr.-10}$	(0.57, 0.36)	(0.25, 0.26)	(0.51, 0.62)	(0.51, 0.62)

Table 3. Transformed form of data given in Table 1.

	\mathcal{E}_{atr-1}	\mathcal{E}_{atr-2}	\mathcal{E}_{atr-3}	\mathcal{E}_{atr-4}
$\mathcal{Q}_{altr.-1}$	(0.0555, 0.0584)	(0.1983, 0.2591)	(0.1833, 0.1015)	(0.0693, 0.0725)
$\mathcal{Q}_{altr.-2}$	(0.1893, 0.1159)	(0.2777, 0.1738)	(0.2830, 0.2022)	(0.2928, 0.2097)
$\mathcal{Q}_{altr.-3}$	(0.1329, 0.1759)	(0.0853, 0.0891)	(0.0667, 0.0697)	(0.1902, 0.1055)
$\mathcal{Q}_{altr.-4}$	(0.1553, 0.0853)	(0.3493, 0.2531)	(0.2227, 0.1376)	(0.1633, 0.2148)
$\mathcal{Q}_{altr.-5}$	(0.1329, 0.1759)	(0.2302, 0.1292)	(0.1573, 0.2072)	(0.0693, 0.0725)
$\mathcal{Q}_{altr.-6}$	(0.1893, 0.1159)	(0.1983, 0.2591)	(0.1833, 0.1015)	(0.2308, 0.1427)
$\mathcal{Q}_{altr.-7}$	(0.0559, 0.0584)	(0.2302, 0.1292)	(0.0667, 0.0697)	(0.1633, 0.2148)
$\mathcal{Q}_{altr.-8}$	(0.2421, 0.1716)	(0.1983, 0.2591)	(0.1573, 0.2072)	(0.1902, 0.1055)
$\mathcal{Q}_{altr.-9}$	(0.0559, 0.0584)	(0.2421, 0.1716)	(0.0559, 0.0584)	(0.0559, 0.0584)
$\mathcal{Q}_{altr.-10}$	(0.1553, 0.0853)	(0.0559, 0.0584)	(0.1329, 0.1759)	(0.1329, 0.1759)

Table 4. Normalized weighted matrix.

videos or supports applications for driverless cars, surveillance systems, or medical imaging change industries because they improve precision efficiency and making a decision under very complex visual environments.

(5) Brain-computer interfaces (BCIs)

BCIs are high-tech, advanced systems that create a communication link directly from the human brain to other external devices; they translate neural activity into actionable commands. BCIs let users exercise control over machines, prosthetics, or software applications without movement, thus letting individuals who otherwise could not do so again be mobile, regain speech capabilities, etc. BCIs are revolutionizing the way humans interface with machines, especially in gaming, aerospace, and neuromarketing. BCIs may change the nature of human cognition and the limits of technology integration by revolutionizing fields further through advancement in AI and neuroscience.

(6) Autonomous mobility solutions

It would fully transform the transport sector with autonomous mobility solutions that rely on sophisticated AI, machine learning, and sensor technologies to allow the operation of automobiles without any human intervention. From an improvement in road safety brought about by self-driving cars to autonomous drones for the delivery and logistics sectors, it transformed industry and transport alike. Some of the efficiency, lower running costs, and access for people living with a disability or in the under-served area, among others. Such solutions support sustainability because they will make it possible to find optimized routes and reduce the energy

used in transporting cargo to the minimal extent possible. This, therefore, changes how traveling will occur in the future as cities and their structure change forever.

(7) Intelligent assistive robots

Intelligent assistive robots are the latest devices that can make the lives of people more comfortable in their routine duties, in healthcare, or specialty work. Coupling AI with machine learning technologies along with sensor equipment makes it much more effective to perform functions according to any particular requirement of each human using this appliance. It finds extensive usage by helping them perform rehabilitative therapies besides homestay with the elderly or disabled. They increase productivity, safety, and independence in many environments by combining robotics and human-centered design. As the world continues to address health care and caregiving needs, the importance of intelligent assistive robots continues to grow with further development.

(8) AI-powered hearing aids

AI-powered hearing aids bring a new milestone in assistive technology, offering personalization and adaptability to help individuals who have hearing loss. Through artificial intelligence, these hearing aids analyze the sound environments in real time, making speech clearer and lessening background noises. Some of its features include auto volume, noise cancellation, and translation; hence, listening is not distracted. Moreover, the algorithms in AI will enable hearing aids to learn the preferences of a user with time and thus can be given personalized experience. This has hugely improved life because users have been empowered to communicate much better and also to socialize.

(9) Virtual health assistants (VHAs)

VHAs, or virtual health assistants, are AI-based tools for personalized health. These systems apply machine learning and natural language processing to interact with patients, answer health-related questions, remind patients of their medication and appointments, track symptoms, provide health assessments, and suggest lifestyle changes according to the individual's data. They increasingly become part of telemedicine platforms, thus improving access to healthcare services. VHAs would promote efficiency and reduce the burdens of healthcare professionals since their role would be automated tasks.

(10) AI-driven personalized therapy

Personalized therapy utilizes advanced algorithms in machine learning to make therapy tailored to individual patient information. Given medical history, genetic composition, and other lifestyle habits, AI would pick a suitable therapeutic option for any individual. In return, this will heighten positive outcomes and diminish negative consequences. The use of real-time patient data tracking makes AI platforms dynamically correct therapies in achieving enhanced outcomes. This approach is innovative and potentially revolutionary in making healthcare much more precise, efficient, and patient-centered.

These technologies ensure not only the improvement of individuals' quality of life for people with disabilities but also improve accessibility, autonomy, and efficiency for healthcare delivery.

Based on this information about the alternatives, the attributes of these alternatives are

- (1) Automation of task.
- (2) Continuous learning and improvement.
- (3) Multimodal interaction.

Now we use the step-wise algorithm of the proposed study to show the utilization of the delivered work.

Step 1 Assume that the decision analyst uses the attributes provided in Table 1 to evaluate the different options and report the evaluation values using the language terms “H” for high, “E” for exponential, “L” for low, “M” for medium, and “I” for inadequate. Additionally, Table 1 provides the conversion of language terms in the FRNs to provide context for these ideas.

By simply converting the information supplied by the experts in Table 1 into the FRNs, we may proceed to the following stage. Therefore, Table 3 shows the updated form of the data provided in Table 1 based on observations of the data in Table 2.

Step 2 All attributes are benefit types. No need to normalize the data given in Table 3.

Step 3 Find out the normalized weighted matrix according to the formula

$$\mathbb{W}^T N_{ij} = \mathbb{W}_j^T N_{ij} = \begin{pmatrix} 1 - (1 - \frac{z_{ij}}{z_{ij}^T})^{\mathbb{W}_j^T} \\ 1 - (1 - \frac{z_{ij}}{z_{ij}^T})^{\mathbb{W}_j^T} \end{pmatrix}$$

Let (0.20, 0.31, 0.24, 0.25) are the WVs for attributes used in this formula.

So, the normalized weighted matrix is given in Table 4.

Step 4 The border approximation area (BAA) is defined and overall results are presented in the form of matrix $\mathcal{R} = [\mathcal{R}_{ij}]_{1 \times m}$. Here we use FRWMSM AOs.

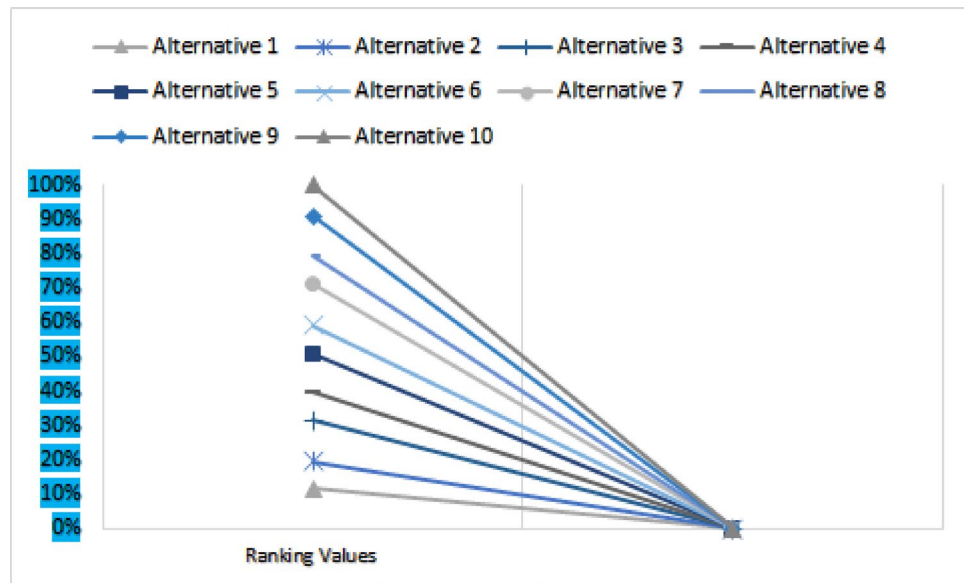


Fig. 3. Graphical ranking of water recycling technologies.

$$\begin{aligned}
 \mathcal{R}_1 &= (0.9382, 0.9336), \mathcal{R}_2 = (0.9855, 0.9725) \\
 \mathcal{R}_3 &= (0.9554, 0.9361), \mathcal{R}_4 = (0.9719, 0.9710) \\
 \mathcal{R}_5 &= (0.9390, 0.9403), \mathcal{R}_6 = (0.9752, 0.9569) \\
 \mathcal{R}_7 &= (0.9446, 0.9608), \mathcal{R}_8 = (0.9692, 0.9574) \\
 \mathcal{R}_9 &= (0.9150, 0.9146), \mathcal{R}_{10} = (0.9490, 0.9606)
 \end{aligned}$$

Step 5 The distances between BBA and alternatives are computed by

$$S_{ij} = \begin{cases} \mathcal{S}(\mathbb{W}^T N_{ij}, \mathcal{R}_j) & \text{if } \mathbb{W}^T N_{ij} > \mathcal{R}_j \\ 0 & \text{if } \mathbb{W}^T N_{ij} = \mathcal{R}_j \\ -\mathcal{S}(\mathbb{W}^T N_{ij}, \mathcal{R}_j) & \text{if } \mathbb{W}^T N_{ij} < \mathcal{R}_j \end{cases}$$

where $\mathcal{S}(\mathbb{W}^T N_{ij}, \mathcal{R}_j)$ is the mean distance between $\mathbb{W}^T N_{ij}$ and \mathcal{R}_j . Use Eq. (9) in this case to find out the distance.

$$S_{ij} = \begin{bmatrix} 0.4394 & 0.3536 & 0.3967 & 0.4325 \\ 0.0151 & 0.3766 & 0.3682 & 0.3638 \\ 0.3956 & 0.4292 & 0.4387 & 0.3989 \\ 0.0172 & 0.3351 & 0.3957 & 0.3912 \\ 0.3926 & 0.3800 & 0.3787 & 0.4343 \\ 0.0137 & 0.3686 & 0.4118 & 0.3896 \\ 0.4502 & 0.3890 & 0.4447 & 0.3843 \\ 0.0146 & 0.3673 & 0.3905 & 0.4077 \\ 0.4288 & 0.3539 & 0.4288 & 0.4288 \\ 0.0203 & 0.4488 & 0.4002 & 0.4002 \end{bmatrix}$$

Step 6 Finally, we add the values of each alternative's S_{ij} by the formula

$$\mathcal{L}_i = \sum_{\tau=1}^m S_{ij}$$

Notice that

$$\begin{aligned}
 \mathcal{L}_1 &= 1.6223, \mathcal{L}_2 = 1.1238 \\
 \mathcal{L}_3 &= 1.6629, \mathcal{L}_4 = 1.1393 \\
 \mathcal{L}_5 &= 1.5857, \mathcal{L}_6 = 1.1838 \\
 \mathcal{L}_7 &= 1.6684, \mathcal{L}_8 = 1.1802 \\
 \mathcal{L}_9 &= 1.6404, \mathcal{L}_{10} = 1.2696
 \end{aligned}$$

Methods	Score values	Ranking results
Hadi et al. ³⁰ approach	×	×
Merigo et al. ^{31,32} approach	×	×
Tesic et al. ³³ approach	×	×
Aydin ³⁴ approach	×	×
Zafar et al. ³⁵ approach	×	×
Lee et al. ³⁶ approach	×	×
Sarwar et al. ³⁷ approach	×	×
FRMSM (proposed)	$S_{cor.}(Q_{altr.-1}) = 0.7932,$ $S_{cor.}(Q_{altr.-2}) = 0.9680,$ $S_{cor.}(Q_{altr.-3}) = 0.8569,$ $S_{cor.}(Q_{altr.-4}) = 0.9425,$ $S_{cor.}(Q_{altr.-5}) = 0.7611,$ $S_{cor.}(Q_{altr.-6}) = 0.9313,$ $S_{cor.}(Q_{altr.-7}) = 0.9315,$ $S_{cor.}(Q_{altr.-8}) = 0.8941,$ $S_{cor.}(Q_{altr.-9}) = 0.7645,$ $S_{cor.}(Q_{altr.-10}) = 0.9294$	$Q_{altr.-2} > Q_{altr.-4} > Q_{altr.-7} > Q_{altr.-6}$ $> Q_{altr.-10} > Q_{altr.-8} > Q_{altr.-3}$ $> Q_{altr.-1} > Q_{altr.-9} > Q_{altr.-5}$
FRWMSM (proposed)	$S_{cor.}(Q_{altr.-1}) = 0.9904,$ $S_{cor.}(Q_{altr.-2}) = 0.9993,$ $S_{cor.}(Q_{altr.-3}) = 0.9923,$ $S_{cor.}(Q_{altr.-4}) = 0.9988,$ $S_{cor.}(Q_{altr.-5}) = 0.9861,$ $S_{cor.}(Q_{altr.-6}) = 0.9982,$ $S_{cor.}(Q_{altr.-7}) = 0.9981,$ $S_{cor.}(Q_{altr.-8}) = 0.9965,$ $S_{cor.}(Q_{altr.-9}) = 0.9871,$ $S_{cor.}(Q_{altr.-10}) = 0.9976$	$Q_{altr.-2} > Q_{altr.-4} > Q_{altr.-6} > Q_{altr.-7}$ $> Q_{altr.-10} > Q_{altr.-8} > Q_{altr.-2}$ $> Q_{altr.-1} > Q_{altr.-9} > Q_{altr.-4}$
FRDMSM (proposed)	$S_{cor.}(Q_{altr.-1}) = 0.0291,$ $S_{cor.}(Q_{altr.-2}) = 0.1948,$ $S_{cor.}(Q_{altr.-3}) = 0.0499,$ $S_{cor.}(Q_{altr.-4}) = 0.1249,$ $S_{cor.}(Q_{altr.-5}) = 0.0179,$ $S_{cor.}(Q_{altr.-6}) = 0.1230,$ $S_{cor.}(Q_{altr.-7}) = 0.1152,$ $S_{cor.}(Q_{altr.-8}) = 0.0848,$ $S_{cor.}(Q_{altr.-9}) = 0.0209,$ $S_{cor.}(Q_{altr.-10}) = 0.1092$	$Q_{altr.-2} > Q_{altr.-4} > Q_{altr.-6} > Q_{altr.-7}$ $> Q_{altr.-10} > Q_{altr.-8} > Q_{altr.-3}$ $> Q_{altr.-1} > Q_{altr.-9} > Q_{altr.-5}$
FRDWMSM (proposed)	$S_{cor.}(Q_{altr.-1}) = 0.0006,$ $S_{cor.}(Q_{altr.-2}) = 0.0107,$ $S_{cor.}(Q_{altr.-3}) = 0.0009,$ $S_{cor.}(Q_{altr.-4}) = 0.0049,$ $S_{cor.}(Q_{altr.-5}) = 0.0003,$ $S_{cor.}(Q_{altr.-6}) = 0.0048,$ $S_{cor.}(Q_{altr.-7}) = 0.0036,$ $S_{cor.}(Q_{altr.-8}) = 0.0028,$ $S_{cor.}(Q_{altr.-9}) = 0.0004,$ $S_{cor.}(Q_{altr.-10}) = 0.0031$	$Q_{altr.-2} > Q_{altr.-4} > Q_{altr.-6} > Q_{altr.-7}$ $> Q_{altr.-10} > Q_{altr.-8} > Q_{altr.-3}$ $> Q_{altr.-1} > Q_{altr.-9} > Q_{altr.-5}$

Table 5. Overall results.

Hence classification of the alternatives is given by

$$Q_{altr.-7} > Q_{altr.-3} > Q_{altr.-9} > Q_{altr.-1} > Q_{altr.-5} > Q_{altr.-10} > Q_{altr.-6} > Q_{altr.-8} > Q_{altr.-4} > Q_{altr.-2}$$

Hence $Q_{altr.-7}$ best alternative.

The graphical representation of the results is given in Fig. 3.

Figure 2 describes the geometrical representation of the MABAC approach produced in this approach. The score values for each alternative are discussed and we can see from the diagram that alternative 7 is the best.

Comparative analysis

In this section, we have studied the comparative analysis of the proposed work. We have discussed how the delivered approach is valuable in decision-making. Moreover, we have elaborated on that the initiated how the initiated work is valuable and superior to other decision-making approaches and it can handle the more advanced information. In this section we compare our work with Hadi et al.³⁰ approach, Merigo et al.^{31,32} approach, Tesic et al.³³ approach, and Aydin³⁴ approach. Moreover, we have compared our work with some classical approaches of PROMETHEE³⁵, AHP³⁶, and ELECTRIC II methods as well³⁷.

Here we have used the data of Table 1 and results for FRMSM AOs, FRWMSM AOs, FRDMSM AOs, and FRDWMSM AOs are given in Table 5.

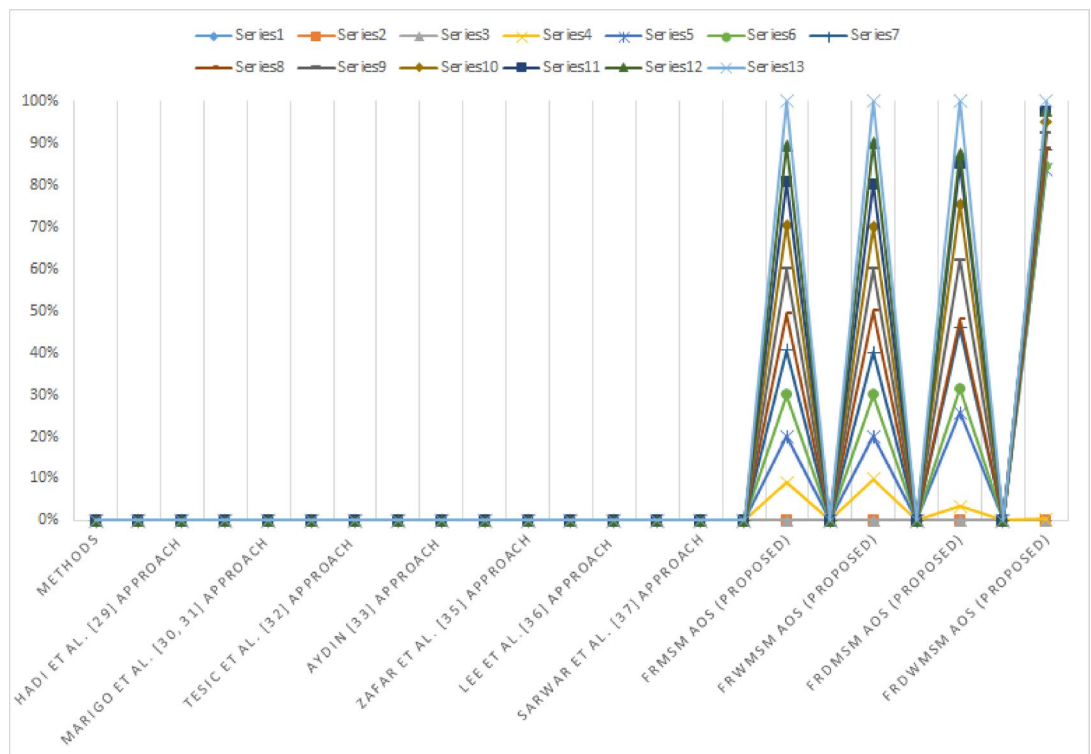


Fig. 4. Graphical representation of data given in Table 5.

Result and discussion

- Hadi et al.³⁰ approach is based on the MADM algorithm that relies on the notion of Fermatean fuzzy Hamacher AOs and this approach can never discuss the approximation given in Table 1 because fuzzy rough data can never be discussed/handled by these kinds of structures due to limitation in these ideas.
- Merigo et al.^{31,32} approach proposes fuzzy-induced generalized AOs and fuzzy generalized hybrid AOs based on fuzzy structure. Although the fuzzy idea generalizes the crisp set theory, however, it is limited in this case because the data that we have discussed for this case is fuzzy rough information consisting of upper and lower approximation. The delivered approach can handle the roughness of information but the existing approaches can never discuss it which shows the weakness of the existing theories.
- Tescic et al.³³ modified the MABAC approach by applying the rough numbers and delivered the application of this approach to decision-making. The existing theory can handle crisp information but here in this case we are handling fuzzy information and in this case, the existing notion is unable to handle it showing the limitation of the existing work. The developed approach not only handles the fuzzy rough information but also reduces the chance of data loss that is always needed for complex decision-making situations. Hence the delivered approach provides more space for decision makers to handle the more advanced information and make theory decisions through the delivered approach.
- Aydin³⁴ discussed the MABAC approach for the Fermatean fuzzy set and this approach never discusses the upper and lower approximation of the data making it a weak structure as compared to the delivered MABAC approach based on Maclaurin symmetric means AOs.
- If we compare our work with the classical approaches of the PROMETHEE approach developed by Zafar et al.³⁵, we can observe that these approaches can only discuss crisp information. While the MABAC approach developed here is based on a fuzzy rough structure, therefore the existing approach can never discuss the fuzzy information.
- Similarly, we can notice that Lee et al.³⁶ approach is also based on rough set theory. Although a rough set can classify the crisp information into upper and lower approximations, however, this structure lacks the characteristics to discuss the uncertain and ambiguous data. While the developed approach can cover this limitation. These advanced characteristics make the introduced notion dominant to existing notions.
- The idea of the ELECTRIC II approach developed by Sarwar et al.³⁷ was developed to discuss the risk evaluation and effects analysis in the manufacturing industry. This approach was developed under the notion of rough set theory. This approach fails to cover more advanced data in MCDM approaches as we have discussed in the introduced work. These limitations make existing ideas less applicable and in these cases the chance of data loss increases. The initiated work provides more space for decision-makers to choose more advanced data in MCDM to make this approach more reliable and beneficial for decision-making problems.

Moreover, the graphical representation of these results is given in the following Fig. 4.

Parameter values for FRMSM AOs	Score values	Ranking results
For $\alpha = 4$	$S_{cor.}(Q_{altr.-1}) = 0.7932,$ $S_{cor.}(Q_{altr.-2}) = 0.9680,$ $S_{cor.}(Q_{altr.-3}) = 0.8569,$ $S_{cor.}(Q_{altr.-4}) = 0.9425$ $S_{cor.}(Q_{altr.-5}) = 0.7611,$ $S_{cor.}(Q_{altr.-6}) = 0.9313,$ $S_{cor.}(Q_{altr.-7}) = 0.9315,$ $S_{cor.}(Q_{altr.-8}) = 0.8941$ $S_{cor.}(Q_{altr.-9}) = 0.7645,$ $S_{cor.}(Q_{altr.-10}) = 0.9294$	$Q_{altr.-2} > Q_{altr.-4} > Q_{altr.-7} > Q_{altr.-6}$ $> Q_{altr.-10} > Q_{altr.-8} > Q_{altr.-3}$ $> Q_{altr.-1} > Q_{altr.-9} > Q_{altr.-5}$
For $\alpha = 5$	$S_{cor.}(Q_{altr.-1}) = 0.8308,$ $S_{cor.}(Q_{altr.-2}) = 0.9743,$ $S_{cor.}(Q_{altr.-3}) = 0.8836,$ $S_{cor.}(Q_{altr.-4}) = 0.9537$ $S_{cor.}(Q_{altr.-5}) = 0.8038,$ $S_{cor.}(Q_{altr.-6}) = 0.9446,$ $S_{cor.}(Q_{altr.-7}) = 0.9448,$ $S_{cor.}(Q_{altr.-8}) = 0.9142$ $S_{cor.}(Q_{altr.-9}) = 0.8067,$ $S_{cor.}(Q_{altr.-10}) = 0.9398$	$Q_{altr.-2} > Q_{altr.-4} > Q_{altr.-7} > Q_{altr.-6}$ $> Q_{altr.-10} > Q_{altr.-8} > Q_{altr.-3}$ $> Q_{altr.-1} > Q_{altr.-9} > Q_{altr.-5}$
For $\alpha = 6$	$S_{cor.}(Q_{altr.-1}) = 0.8568,$ $S_{cor.}(Q_{altr.-2}) = 0.9785,$ $S_{cor.}(Q_{altr.-3}) = 0.9019,$ $S_{cor.}(Q_{altr.-4}) = 0.9613$ $S_{cor.}(Q_{altr.-5}) = 0.8336,$ $S_{cor.}(Q_{altr.-6}) = 0.9535,$ $S_{cor.}(Q_{altr.-7}) = 0.9538,$ $S_{cor.}(Q_{altr.-8}) = 0.9278$ $S_{cor.}(Q_{altr.-9}) = 0.8361,$ $S_{cor.}(Q_{altr.-10}) = 0.9495$	$Q_{altr.-2} > Q_{altr.-4} > Q_{altr.-7} > Q_{altr.-6}$ $> Q_{altr.-10} > Q_{altr.-8} > Q_{altr.-3}$ $> Q_{altr.-1} > Q_{altr.-9} > Q_{altr.-5}$
For $\alpha = 7$	$S_{cor.}(Q_{altr.-1}) = 0.8760,$ $S_{cor.}(Q_{altr.-2}) = 0.9815,$ $S_{cor.}(Q_{altr.-3}) = 0.9153,$ $S_{cor.}(Q_{altr.-4}) = 0.9667$ $S_{cor.}(Q_{altr.-5}) = 0.8556,$ $S_{cor.}(Q_{altr.-6}) = 0.9600,$ $S_{cor.}(Q_{altr.-7}) = 0.9602,$ $S_{cor.}(Q_{altr.-8}) = 0.9377$ $S_{cor.}(Q_{altr.-9}) = 0.8578,$ $S_{cor.}(Q_{altr.-10}) = 0.9566$	$Q_{altr.-2} > Q_{altr.-4} > Q_{altr.-7} > Q_{altr.-6}$ $> Q_{altr.-10} > Q_{altr.-8} > Q_{altr.-3}$ $> Q_{altr.-1} > Q_{altr.-9} > Q_{altr.-5}$
For $\alpha = 8$	$S_{cor.}(Q_{altr.-1}) = 0.8906,$ $S_{cor.}(Q_{altr.-2}) = 0.9838,$ $S_{cor.}(Q_{altr.-3}) = 0.9254,$ $S_{cor.}(Q_{altr.-4}) = 0.9708$ $S_{cor.}(Q_{altr.-5}) = 0.8724,$ $S_{cor.}(Q_{altr.-6}) = 0.9649,$ $S_{cor.}(Q_{altr.-7}) = 0.9651,$ $S_{cor.}(Q_{altr.-8}) = 0.9452$ $S_{cor.}(Q_{altr.-9}) = 0.8744,$ $S_{cor.}(Q_{altr.-10}) = 0.9619$	$Q_{altr.-2} > Q_{altr.-4} > Q_{altr.-7} > Q_{altr.-6}$ $> Q_{altr.-10} > Q_{altr.-8} > Q_{altr.-3}$ $> Q_{altr.-1} > Q_{altr.-9} > Q_{altr.-5}$
For $\alpha = 9$	$S_{cor.}(Q_{altr.-1}) = 0.9021,$ $S_{cor.}(Q_{altr.-2}) = 0.9856,$ $S_{cor.}(Q_{altr.-3}) = 0.9334,$ $S_{cor.}(Q_{altr.-4}) = 0.9740$ $S_{cor.}(Q_{altr.-5}) = 0.8858,$ $S_{cor.}(Q_{altr.-6}) = 0.9687,$ $S_{cor.}(Q_{altr.-7}) = 0.9689,$ $S_{cor.}(Q_{altr.-8}) = 0.9511$ $S_{cor.}(Q_{altr.-9}) = 0.8875,$ $S_{cor.}(Q_{altr.-10}) = 0.9660$	$Q_{altr.-2} > Q_{altr.-4} > Q_{altr.-7} > Q_{altr.-6}$ $> Q_{altr.-10} > Q_{altr.-8} > Q_{altr.-3}$ $> Q_{altr.-1} > Q_{altr.-9} > Q_{altr.-5}$
For $\alpha = 10$	$S_{cor.}(Q_{altr.-1}) = 0.9115,$ $S_{cor.}(Q_{altr.-2}) = 0.9870,$ $S_{cor.}(Q_{altr.-3}) = 0.9398,$ $S_{cor.}(Q_{altr.-4}) = 0.9766$ $S_{cor.}(Q_{altr.-5}) = 0.8966,$ $S_{cor.}(Q_{altr.-6}) = 0.9718,$ $S_{cor.}(Q_{altr.-7}) = 0.9720,$ $S_{cor.}(Q_{altr.-8}) = 0.9559$ $S_{cor.}(Q_{altr.-9}) = 0.8982,$ $S_{cor.}(Q_{altr.-10}) = 0.9694$	$Q_{altr.-2} > Q_{altr.-4} > Q_{altr.-7} > Q_{altr.-6}$ $> Q_{altr.-10} > Q_{altr.-8} > Q_{altr.-3}$ $> Q_{altr.-1} > Q_{altr.-9} > Q_{altr.-5}$

Table 6. Ranking results for sensitivity analysis.

In Fig. 4, we have delivered the geometrical representation of the proposed work. The diagram shows the aggregated results of the proposed aggregation operators. The results of the proposed FRMSM, FRWMSM, FRDMSM, and FRDWMSM AOs are summarized in this diagram. The existing notions have no results in this regard because these notions are limited and can never discuss fuzzy rough information.

Full form	Short form
Multi-attributive border approximation area comparison	MABAC
Fuzzy rough set	FRS
Fuzzy rough Maclaurin symmetric means	FRMSM
Fuzzy rough weighted Maclaurin symmetric means	FRWMSM
Fuzzy rough dual Maclaurin symmetric means	FRDMSM
Fuzzy rough dual weighted Maclaurin symmetric means	FRDWMSM
Rough set	RS
Fuzzy set	FS
Multi-criteria decision making	MCDM
Aggregation operators	AOs

Table 7. Some useful abbreviations.

Sensitivity analysis of the delivered approach

In this section, we have proposed the sensitivity analysis of the delivered approach based on different values of parameters. We have seen the effects for different values of parameter only for the case of FRMSM AOs and the results are combined in Table 6.

From the analysis of above Table 6, we can notice as we vary the value of the parameter from $\alpha = 4$ to $\alpha = 10$, the ranking result is the same. In this case, we can say that the parameter values have no effects on ranking results and this characteristic determines the stability of the proposed FRMSM AOs.

Conclusion

This approach combines fuzzy rough Maclaurin symmetric means aggregation theory with the MABAC approach, providing a very powerful framework for decision-making and classification tasks. It takes advantage of fuzzy logic strengths and rough set theory strengths in handling uncertainty and imprecision, which are very critical in complex decision environments. In terms of the classification of AI-assisted technologies in support systems for disability, this combination is very effective for the evaluation of technologies according to various criteria, including performance, accessibility, and adaptability. Fuzzy rough aggregation ensures that the final classification accounts for both inherent vagueness and relational dependencies between different attributes. This MABAC method would then be more approximate about the border areas while trying to improve the classification robustness. The current approach will combine fuzzy rough aggregation with MABAC to solve a problem in which the decision-making will have subjective information and uncertainty within them, like this kind of assistive technology evaluation. Ultimately, this approach is a systematic, transparent, and efficient method to find the best technologies for the user with a disability, thus being a promising solution in AI-powered support systems for disabilities.

The proposed work is limited because it uses only membership grades in the form of upper and lower approximation. If decision analyst uses the notion of the intuitionistic fuzzy set or intuitionistic fuzzy rough set model that uses the membership as well as non-membership grade then these developed notions fail to handle such kind of information. Similarly, as the Pythagorean fuzzy rough structure is a more advanced idea than fuzzy rough and intuitionistic fuzzy rough set then in this case, the developed idea of FRMSM fails to handle Pythagorean fuzzy rough information making the introduced approach limited.

In the future, we can extend these notions to integrated fuzzy models³⁸, and complex fuzzy rough approaches as given in^{39,40}. Moreover, some other aggregation operators like frank aggregation operators as discussed in⁴¹. The delivered theory can be extended to power aggregation operators as discussed in⁴².

Moreover, for a smooth understanding of acronyms used throughout the article, we have provided the short form and full form of useful acronyms in Table 7.

Data availability

The data analyzed or generated for this manuscript is contained in the manuscript and anyone can use it by just citing this article.

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Declarations

Competing interests

The authors declare no competing interests.

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