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Research Article

Three-Way Group Decisions with Incomplete Spherical Fuzzy Information for Treating Parkinson's Disease Using IoMT Devices

Chao Zhang [1,2] and Jingjing Zhang [1]

[1] *School of Computer and Information Technology, Shanxi University, Taiyuan 030006, China*
[2] *Key Laboratory of Computational Intelligence and Chinese Information Processing, Ministry of Education, Shanxi University, Taiyuan 030006, China*

Correspondence should be addressed to Chao Zhang; czhang@sxu.edu.cn

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As Internet of Things (IoT) is extensively employed in diverse realistic areas, it is vital to effectively and timely analyze the data collected by IoT devices. To cope with this problem, by integrating adjustable MG SF probabilistic rough sets (PRSs) with the TODIM (an acronym in Portuguese of interactive and multi-criteria decision-making) method, this paper explores a three-way multi-attribute group decision-making (MAGDM) approach in the context of multigranulation (MG) spherical fuzzy (SF) incomplete information systems (IISs) and further applies the presented method to the analysis of leg muscle data obtained from Internet of Medical Things (IoMT) devices for Parkinson's patients. First, the concept of MG SF IISs is established, and the completion method is provided. Then, adjustable MG SF PRSs are proposed for information fusion. Afterwards, considering the bounded rationality of decision-makers (DMs), a new three-way MAGDM method is designed by fusing adjustable MG SF PRSs with the TODIM method. Finally, in the context of IoMT-based detecting abnormal knee joints in Parkinson's patients, the applicability and validity of the presented method are eventually verified.

1. Introduction

IoT refers to the collection of diverse types of information in actual scenarios via various sensors, the intelligent analysis of the collected data, and the connection of objects from the network to achieve intelligent identification, positioning, supervision, and other tasks. Due to the advantages of high efficiency, accuracy, and security, IoT is now widely used in various areas, such as health management [1], smart home [2], intelligent logistics [3], smart parking [4], and water treatment [5]. Thus, the application of IoT is widespread and has great development prospects.

IoMT is the application of IoT in the medical area. The application of IoMT is usually divided into digital hospital construction and health management based on wearable sensors, of which digital hospital construction is only applicable to medical institutions, and the construction cost is high; hence, the scope of its application is relatively limited, whereas wearable sensors are widely used in individuals and families with their advantages of low power consumption, high reliability, and sensitivity. Wearable sensors can collect personal health data in real time and can achieve monitoring of physiological parameters such as blood sugar, blood oxygen, blood pressure, heart rate, and electromyography. Recently, many scholars have conducted meaningful researches on IoMT. For instance, Wei et al. [6] proposed an intelligent channel allocation algorithm in the context of IoMT. Jain et al. [7] explored the combination of IoMT with point-of-care testing devices to monitor infectious diseases. Wei et al. [8] put forward an intelligent nonstatic routing determination scheme to improve the stability of IoMT.

One of the challenges in the current application of IoMT devices is the effective analysis of the collected data. The three-way MAGDM approach is a valid one to handle the uncertain and multilevel complex data obtained from IoMT devices. Three-way decision (3WD) was initiated by Yao [9], and this theory originates from the research of decision-theoretic rough sets (DTRSs) [10, 11], which provides a sound semantic expression for three domains in DTRS models. Recently, Yao [12] investigated the "trisecting-acting-outcome" model (TAO model), where "trisecting" means to divide the domain into three parts, "acting" means to apply the corresponding strategy to the three-parted domains, and "outcome" means to evaluate and give feedback to the trisecting and acting. In view of the fact that 3WD is consistent with human thinking and cognitive characteristics and can efficiently deal with diverse uncertainties in practical decision-making, this paper selects the 3WD model as the basic modeling framework for solving MAGDM problems. In the past decade, 3WD has been widely and deeply studied in several fields. Zhang et al. [13] explored an MG 3WD rule in the hesitant fuzzy linguistic background. Ye et al. [14] established a three-way MAGDM method in an incomplete environment. In addition to the above works, there are many applications for 3WD [15–17].

In 2019, Gundogdu and Kahraman [18] proposed SFSs, which are developed from intuitionistic fuzzy sets (IFSs) [19], Pythagorean fuzzy sets (PFSs) [20], and neutrosophic sets (NSs) [21], with the aim of further characterizing diverse uncertainties of DMs in information depiction processes. IFSs are the first tool to include the notion of nonmembership degrees, and the membership degree $\mu(x)$ and nonmembership degree $\nu(x)$ satisfy the constraint $0 \leq \mu(x) + \nu(x) \leq 1$. Thus, IFSs are more accurate in terms of information depictions for uncertain information compared to classic FSs. PFSs are further extensions of IFSs, and $\mu(x)$ and $\nu(x)$ only need to satisfy $0 \leq \mu^2(x) + \nu^2(x) \leq 1$; thus, their membership functions own more flexibility. NSs add the uncertainty degree to the IFSs, so that a DM can use the membership degree, uncertainty degree, and nonmembership degree to characterize diverse decision information. SFSs are a further synthesis of the above three types of FSs, with the advantage that the membership degree, nonmembership degree, and hesitation degree can be, respectively, formulated, which allows DMs to provide a valid depiction of uncertain information. In summary, SFSs improve the accuracy of information depictions in decision-making problems and lay a solid foundation for subsequent information fusion and analysis. Based on the above advantages in information depictions, SFSs have been utilized to address a series of intelligent decision issues in recent years [22–26]. In addition, most of existing studies on SFSs are under complete ISs, whereas IISs are common in real life; thus, this paper is aimed at building MG SF IISs for handling missing information.

When dealing with behavioral decision-making issues, DMs are often bounded rationality rather than fully rationality, and they tend to pursue "satisfactory" solutions. Due to the limited information available to DMs, the final solution is often nonoptimal; hence, the psychological state of DMs has a great influence on final decision conclusions. The TODIM method [27] is a typical MAGDM method that includes the behavior of DMs in light of the prospect theory. For the sake of removing some subjective parameters owned by the prospect theory, the TODIM method concentrates on constructing a dominance function as a measure of the dominance of each alternative over the others, and the ranking results of all alternatives are finally acquired by the total dominance. Recently, the TODIM method owns a profound impact in the intelligent decision-making area and has made many important achievements. For instance, He et al. [28] investigated an effect analysis model and improved failure mode by referring to the TODIM method and probabilistic linguistic information for identifying the risks of wind turbine systems. Seker and Kahraman [29] put forward a brand-new MAGDM method by virtue of TOPSIS and TODIM methods. He et al. [30] explored a generalized TODIM method in the shadowed set background for addressing large-scale MAGDM. In addition to the above-stated methods, there exist many more meaningful applications of the TODIM method [31–33].

In light of the above analysis, the aim of this work is to explore an effective three-way MAGDM method in SF IISs. Since the traditional 3WD model does not consider the relative relationship of actions in different states, Jia and Liu [34] introduced relative loss functions into 3WD and explored a decision-making-driven 3WD model. Based on this advantage, the paper explores the decision-making-driven three-way MAGDM model in SF IISs by the TODIM method. The primary study motivations of this work are summed up below.

(1) Most of existing SF MAGDM methods are explored under complete ISs, and there is a lack of research in IISs. Therefore, in order to depict incomplete MAGDM information, this paper proposes the concept of MG SF IISs

(2) It is imperative to construct completion methods to patch the missing values for IISs and also to construct fusion strategies for MG information. Therefore, this paper proposes adjustable MG SF PRSs for information fusion

(3) The prevalence of finite rationality in MAGDM makes it necessary to use the TODIM method in MAGDM. In this paper, a combination of adjustable MG SF PRSs with the TODIM method is explored in the context of MG SF IISs for a three-way MAGDM method

Based on the above study motivations, the following innovation points of this paper are further summarized.

(1) The definition of MG SF IISs for a more comprehensive description of incomplete decision-making information is designed

(2) A completeness method is constructed for MG SF IISs to obtain MG SF ISs. On this basis, a definition of adjustable MG SF PRSs is given for multi-granularity information fusion

(3) A novel decision-making-driven three-way MAGDM method is established via adjustable MG SF PRSs and the TODIM method in the setting of MG SF ISs

The remainder of this work is listed below. Section 2 revisits fundamentals of SFSs, multigranulation probabilistic rough sets (MGPRSs), decision-making-driven 3WD, and the TODIM method. The notion of MG SF IISs is proposed, and the completeness method is constructed in Section 3, followed by the notion of adjustable MG SF PRSs for information fusion. The decision-making-driven three-way MAGDM method is established in Section 4 by using adjustable MG SF PRSs and the TODIM method. In Section 5, the applicability and effectiveness of the presented three-way MAGDM method are shown by a case study of IoMT-based detection of abnormal knee joints in Parkinson's patients. The last section summarizes the entire work related to this paper and provides a description of further study topics.

2. Preliminaries

The current section primarily revisits several basic notions, which include SFSs, MGPRSs, 3WD, and the TODIM methods.

2.1. SFSs. SFSs enhance the accuracy of decision-making issues in the stage of information depictions and make information depiction processes more comprehensive. The fundamental definitions of SFSs are introduced below.

Definition 1 (see [18]). Let U be a finite universe of discourse. An SFS $A_S{}^{\sim}$ on U is defined as follows:

$$\tilde{A_S} = \left\{ \left\langle x, \left(\mu_{\tilde{A_S}}(x), \nu_{\tilde{A_S}}(x), \pi_{\tilde{A_S}}(x) \right) | x \in U \right\rangle \right\}, \quad (1)$$

where $\mu_{A_S{}^{\sim}}(x)$: $U \longrightarrow [0, 1]$, $\nu_{A_S{}^{\sim}}(x)$: $U \longrightarrow [0, 1]$ and $\pi_{A_S{}^{\sim}}(x)$: $U \longrightarrow [0, 1]$ represent the membership degree, nonmembership degree, and hesitancy degree of $x \in U$ to $A_S{}^{\sim}$, respectively. For each $x \in U$, $0 \le \mu^2_{A_S{}^{\sim}}(x) + \nu^2_{A_S{}^{\sim}}(x) + \pi^2_{A_S{}^{\sim}}(x) \le 1$ is satisfied. Moreover, $r_{A_S{}^{\sim}}(x) = (1 - \mu^2_{A_S{}^{\sim}}(x) - \nu^2_{A_S{}^{\sim}}(x) - \pi^2_{A_S{}^{\sim}}(x))$ represents the refusal degree. In addition, $a_S{}^{\sim} = (\mu_{A_S{}^{\sim}}(x), \nu_{A_S{}^{\sim}}(x), \pi_{A_S{}^{\sim}}(x))$ is named a spherical fuzzy number (SFN). For the ease of descriptions, it is further simplified to $(\mu_{A_S{}^{\sim}}, \nu_{A_S{}^{\sim}}, \pi_{A_S{}^{\sim}})$.

In order to use SFNs in the latter decision-making algorithm, the basic operations for SFSs are described below.

Definition 2 (see [18]). Let U be a finite universe of discourse and $a_S{}^{\sim}$ and $b_S{}^{\sim}$ be two SFNs. Then:

(1) $\tilde{a}_S{}^c = \{\nu_{\tilde{A}_S}, \mu_{\tilde{A}_S}, \pi_{\tilde{A}_S}\}$

(2) $\tilde{a}_S \oplus \tilde{b}_S = \{(\mu^2_{\tilde{A}_S} + \mu^2_{\tilde{B}_S} - \mu^2_{\tilde{A}_S}\mu^2_{\tilde{B}_S})^{1/2}, \nu_{\tilde{A}_S}\nu_{\tilde{B}_S}, ((1 - \mu^2_{\tilde{B}_S})\pi^2_{\tilde{A}_S} + (1 - \mu^2_{\tilde{A}_S})\pi^2_{\tilde{B}_S} - \pi^2_{\tilde{A}_S}\pi^2_{\tilde{B}_S})^{1/2}\}$

(3) $\tilde{a}_S \otimes \tilde{b}_S = \{\mu_{\tilde{A}_S}\mu_{\tilde{B}_S}, (\nu^2_{\tilde{A}_S} + \nu^2_{\tilde{B}_S} - \nu^2_{\tilde{A}_S}\nu^2_{\tilde{B}_S})^{1/2}, ((1 - \nu^2_{\tilde{B}_S})\pi^2_{\tilde{A}_S} + (1 - \nu^2_{\tilde{A}_S})\pi^2_{\tilde{B}_S} - \pi^2_{\tilde{A}_S}\pi^2_{\tilde{B}_S})^{1/2}\}$

(4) $\lambda\tilde{a}_S = \{(1 - (1 - \mu^2_{\tilde{A}_S})^{\lambda})^{1/2}, \nu^{\lambda}_{\tilde{A}_S}, ((1 - \mu^2_{\tilde{A}_S})^{\lambda} - (1 - \mu^2_{\tilde{A}_S} - \pi^2_{\tilde{A}_S})^{\lambda})^{1/2}\}, \lambda > 0$

(5) $\tilde{a}_S{}^{\lambda} = \{\mu^{\lambda}_{\tilde{A}_S}, (1 - (1 - \nu^2_{\tilde{A}_S})^{\lambda})^{1/2}, ((1 - \nu^2_{\tilde{A}_S})^{\lambda} - (1 - \nu^2_{\tilde{A}_S} - \pi^2_{\tilde{A}_S})^{\lambda})^{1/2}\}, \lambda > 0$

(6) $\tilde{a}_S \ominus \tilde{b}_S = \{\max\{0, \sqrt{|\mu^2_{\tilde{A}_S} - \mu^2_{\tilde{B}_S}|/1 - \mu^2_{\tilde{B}_S}}\}, \min\{1, (\nu^2_{\tilde{A}_S}/\nu^2_{\tilde{B}_S})\}, \min\{1, (\pi^2_{\tilde{A}_S}/\pi^2_{\tilde{B}_S})\}\}$

(7) $\tilde{a}_S \oslash \tilde{b}_S = \{\min\{1, (\mu^2_{\tilde{A}_S}/\mu^2_{\tilde{B}_S})\}, \max\{0, \sqrt{|\nu^2_{\tilde{A}_S} - \nu^2_{\tilde{B}_S}|/1 - \nu^2_{\tilde{B}_S}}\}, \max\{0, \sqrt{|\pi^2_{\tilde{A}_S} - \pi^2_{\tilde{B}_S}|/1 - \pi^2_{\tilde{B}_S}}\}\}$

For the sake of conveniently obtaining the comparison results among SFNs, the score and accuracy functions of SFNs are introduced below.

Definition 3 (see [18]). Let $a_S{}^{\sim}$ be an SFN. The score function and accuracy function of $a_S{}^{\sim}$ are defined as follows:

$$\mathrm{Score}(\tilde{a}_S) = \left(\mu_{\tilde{A}_S} - \pi_{\tilde{A}_S}\right)^2 - \left(\nu_{\tilde{A}_S} - \pi_{\tilde{A}_S}\right)^2, \quad (2)$$

$$\mathrm{Accuracy}(\tilde{a}_S) = \mu^2_{\tilde{A}_S} + \nu^2_{\tilde{A}_S} + \pi^2_{\tilde{A}_S}. \quad (3)$$

For any two SFNs $a_S{}^{\sim}$ and $b_S{}^{\sim}$, if $\mathrm{Score}(\tilde{a}_S) < \mathrm{Score}(\tilde{b}_S)$, then $\tilde{a}_S < \tilde{b}_S$; if $\mathrm{Score}(\tilde{a}_S) > \mathrm{Score}(\tilde{b}_S)$, then $\tilde{a}_S > \tilde{b}_S$; if $\mathrm{Score}(\tilde{a}_S) = \mathrm{Score}(\tilde{b}_S)$ and $\mathrm{Accuracy}(\tilde{a}_S) < \mathrm{Accuracy}(\tilde{b}_S)$, then $\tilde{a}_S < \tilde{b}_S$; if $\mathrm{Score}(\tilde{a}_S) = \mathrm{Score}(\tilde{b}_S)$ and $\mathrm{Accuracy}(\tilde{a}_S) > \mathrm{Accuracy}(\tilde{b}_S)$, then $\tilde{a}_S > \tilde{b}_S$; if $\mathrm{Score}(\tilde{a}_S) = \mathrm{Score}(\tilde{b}_S)$ and $\mathrm{Accuracy}(\tilde{a}_S) = \mathrm{Accuracy}(\tilde{b}_S)$, then $\tilde{a}_S = \tilde{b}_S$.

The distance measure plays a significant role in actual decision-making processes. In order to efficiently describe and analyze the complicated relationship between two SFNs, the Euclidean distance between SFNs is presented below.

Definition 4 (see [18]). Let $a_S{}^{\sim}$ and $b_S{}^{\sim}$ be two SFNs. The Euclidean distance between $a_S{}^{\sim}$ and $b_S{}^{\sim}$ is defined as follows:

$$\mathrm{dis}\left(\tilde{a}_S, \tilde{b}_S\right) = \left(\frac{1}{2}\left(\left(\mu_{\tilde{A}_S} - \mu_{\tilde{B}_S}\right)^2 + \left(\nu_{\tilde{A}_S} - \nu_{\tilde{B}_S}\right)^2 + \left(\pi_{\tilde{A}_S} - \pi_{\tilde{B}_S}\right)^2\right)\right)^{1/2}. \quad (4)$$

2.2. MGPRSs. MGPRS is an integration of multigranulation rough sets (MGRSs) and probabilistic rough sets (PRSs); it not only owns the advantages of sound performances in the information fusion stage of MGRSs but also has the advantages of greater error tolerance of PRSs. Therefore, MGPRS is widely used to address various intelligent decision-making issues. The following part introduces the basic definition of MGPRSs.

Definition 5 (see [35]). Let U be a finite universe of discourse, $R_i (i = 1, 2, \cdots, l)$ be a binary relation on U, and Pr be a probability measure. For any $X \subseteq U$, $0 \leq \beta < \alpha \leq 1$, the lower approximation $\underline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{O}(X)$ and upper approximation $\overline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{O}(X)$ of optimistic MGPRSs are defined as follows:

$$\begin{aligned}
\underline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{O}(X) &= \left\{P\left(X\middle|[x]_{R_1}\right) \geq \alpha \vee P\left(X\middle|[x]_{R_2}\right) \geq \alpha \vee \cdots \vee P\left(X\middle|[x]_{R_l}\right) \geq \alpha \middle| x \in U\right\},\\
\overline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{O}(X) &= \left\{P\left(X\middle|[x]_{R_1}\right) > \beta \wedge P\left(X\middle|[x]_{R_2}\right) > \beta \wedge \cdots \wedge P\left(X\middle|[x]_{R_l}\right) > \beta \middle| x \in U\right\}.
\end{aligned} \tag{5}$$

In light of the above definition, $(\underline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{O}(X), \overline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{O}(X))$ is called an optimistic MGPRS.

According to the formulation of two approximations of optimistic MGPRSs, the following regions can be separated:

$$\begin{aligned}
\mathrm{POS}_{\alpha,\beta}^{O}(X) &= \underline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{O}(X),\\
\mathrm{NEG}_{\alpha,\beta}^{O}(X) &= U - \overline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{O}(X),\\
\mathrm{BND}_{\alpha,\beta}^{O}(X) &= \overline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{O}(X) - \underline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{O}(X).
\end{aligned} \tag{6}$$

Definition 6 (see [35]). Let U be a finite universe of discourse, $R_i (i = 1, 2, \cdots, l)$ be a binary relation on U, and Pr be a probability measure. For any $X \subseteq U$, $0 \leq \beta < \alpha \leq 1$, the lower approximation $\underline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{P}(X)$ and upper approximation $\overline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{P}(X)$ of pessimistic MGPRSs are defined as follows:

$$\begin{aligned}
\underline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{P}(X) &= \left\{P\left(X\middle|[x]_{R_1}\right) \geq \alpha \wedge P\left(X\middle|[x]_{R_2}\right) \geq \alpha \wedge \cdots \wedge P\left(X\middle|[x]_{R_l}\right) \geq \alpha \middle| x \in U\right\},\\
\overline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{P}(X) &= \left\{P\left(X\middle|[x]_{R_1}\right) > \beta \vee P\left(X\middle|[x]_{R_2}\right) > \beta \vee \cdots \vee P\left(X\middle|[x]_{R_l}\right) > \beta \middle| x \in U\right\}.
\end{aligned} \tag{7}$$

In light of the above definition, $(\underline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{P}(X), \overline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{P}(X))$ is called a pessimistic MGPRS.

Table 1: Loss functions.

	$X(P)$	$X^c(N)$
a_P	λ_{PP}	λ_{PN}
a_B	λ_{BP}	λ_{BN}
a_N	λ_{NP}	λ_{NN}

According to the formulation of two approximations of pessimistic MGPRSs, the following regions can be separated:

$$\begin{aligned}
\mathrm{POS}_{\alpha,\beta}^{P}(X) &= \underline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{P}(X),\\
\mathrm{NEG}_{\alpha,\beta}^{P}(X) &= U - \overline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{P}(X),\\
\mathrm{BND}_{\alpha,\beta}^{P}(X) &= \overline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{P}(X) - \underline{\sum_{i=1}^{l} R_{i(\alpha,\beta)}}^{P}(X).
\end{aligned} \tag{8}$$

2.3. Decision-Making-Driven 3WD Methods.

3WD provides a reasonable semantic interpretation for the positive, negative, and boundary domains in DTRSs, which is consistent with the style of human thinking and cognitive characteristics, and can efficiently handle various uncertainties in practical decision-making. The decision-making-driven 3WD method is listed as follows.

In classic MAGDM models, it is assumed that the alternative set is $U = \{x_1, x_2, \cdots, x_m\}$, where x_i represents the ith alternative. The attribute set is $V = \{y_1, y_2, \cdots, y_n\}$, where y_j represents the jth attribute. A DM evaluates all alternatives via attributes and obtains the assessment matrix $P = (q_{ij})_{m\times n} \bigcup_{i=1}^{n} X_i$, where q_{ij} denotes the assessment value of x_i on y_j. For any q_{ij}, $q_{ij} \in (q_{\min}^{j}, q_{\max}^{j})$ is true, where $q_{\min}^{j}, q_{\max}^{j}$ denote the minimum and maximum values of the assessment value on y_j, respectively. In general, if q_{ij} is a fuzzy number, then $q_{jk} \in [0, 1]$, $q_{\min}^{j} = 0$, and $q_{\max}^{j} = 1$. The weight set of attributes is $u = \{u_1, u_2, \cdots, u_n\}^T$, where u_j denotes the weight value of the jth attribute and u_j satisfies $0 \leq u_j \leq 1$ and $\sum_{j=1}^{n} u_j = 1$.

Yao [10] proposed the DTRS model with the help of the Bayesian theory with sound interpretations of thresholds. DTRS models usually contain three actions and two states, as presented in Table 1.

In DTRS models, for a state set $\Omega = \{X, X^c\}$, X and X^c, respectively, represent belonging to set X and not belonging to set X. For an action set $A = \{a_P, a_B, a_N\}$, a_P, a_B, and a_N, respectively, represent $x \in \mathrm{POS}(X)$, $x \in \mathrm{BND}(X)$, and $x \in \mathrm{NEG}(X)$. λ_{PP}, λ_{BP}, and λ_{NP} denote the loss of conducting actions a_P, a_B, and a_N when $x \in X$ is satisfied, whereas λ_{PN}, λ_{BN}, and λ_{NN} denote the loss of conducting actions a_P, a_B, and a_N when $x \in X^c$ is satisfied, respectively.

When the loss function satisfies $(\lambda_{PP} - \lambda_{BN})(\lambda_{NP} - \lambda_{BP}) < (\lambda_{BP} - \lambda_{PP})(\lambda_{BN} - \lambda_{NN})$ and the threshold satisfies $0 \le \beta < \gamma < \alpha \le 1$, then the following decision rules are true.

(*P*) if $\Pr(X|[x]) \ge \alpha$, then $x \in \mathrm{POS}(X)$

(*B*) if $\beta < \Pr(X|[x]) < \alpha$, then $x \in \mathrm{BND}(X)$

(*N*) if $\Pr(X|[x]) \le \beta$, then $x \in \mathrm{NEG}(X)$

where the threshold values α, β and γ refer to

$$\begin{aligned}\alpha &= \frac{\lambda_{PN} - \lambda_{BN}}{(\lambda_{PN} - \lambda_{BN}) + (\lambda_{BP} - \lambda_{PP})},\\ \beta &= \frac{\lambda_{BN} - \lambda_{NN}}{(\lambda_{BN} - \lambda_{NN}) + (\lambda_{NP} - \lambda_{BP})},\\ \gamma &= \frac{\lambda_{PN} - \lambda_{NN}}{(\lambda_{PN} - \lambda_{NN}) + (\lambda_{NP} - \lambda_{PP})}.\end{aligned} \tag{9}$$

In terms of the above 3WD models, let $\lambda'_{BP} = \lambda_{BP} - \lambda_{PP}$, $\lambda'_{NP} = \lambda_{NP} - \lambda_{PP}$, $\lambda'_{PN} = \lambda_{PN} - \lambda_{NN}$, and $\lambda'_{BN} = \lambda_{BN} - \lambda_{NN}$; then, the loss function of Table 1 is transformed into the relative loss function [34], as presented in Table 2.

Based on the relative loss function in Table 2, the relative loss function in terms of the evaluation value q_{ij} is obtained, as presented in Table 3.

In Table 3, the parameter $\sigma \in [0, 0.5]$, σ is the risk aversion coefficient, which indicates a DM's aversion to risk, and the larger σ indicates a DM's higher aversion to risk. The thresholds of the loss function in Table 3 refer to

$$\begin{aligned}\alpha &= \frac{(1-\sigma)\left(1-q_{ij}\right)}{(1-\sigma)\left(1-q_{ij}\right) + \sigma q_{ij}},\\ \beta &= \frac{\sigma\left(1-q_{ij}\right)}{\sigma\left(1-q_{ij}\right) + (1-\sigma) q_{ij}},\\ \gamma &= 1 - q_{ij}.\end{aligned} \tag{10}$$

2.4. The TODIM Method. The TODIM method [27] constructs the dominance degree function in light of the prospect theory, which can better reflect the bounded rationality and decision preferences of DMs. The concrete steps of the TODIM method are summed up below.

Suppose that the alternative set is $B = \{B_1, B_2, \cdots, B_m\}$, the attribute set is $C = \{C_1, C_2, \cdots, C_n\}$, the weight set of attributes is $w = \{w_1, w_2, \cdots, w_n\}^T$, and the evaluation value matrix is $T = (t_{ij})_{m\times n}$.

Step 1. The evaluation value matrix T is normalized via using the following formula to obtain $T' = (x_{ij})_{m\times n}$:

$$x_{ij} = \begin{cases} t_{ij} & \text{benefit attribute},\\ -t_{ij} & \text{cost attribute}.\end{cases} \tag{11}$$

Step 2. Based on the weight values of all attributes, the attribute with the largest weight value is determined to be the reference attribute C_r, and the relative weight of the attribute C_j with respect to C_r is calculated according to the following formula:

$$w_{jr} = \frac{w_j}{w_r}, \tag{12}$$

where $w_r = \max\{w_j, j = 1, 2, \cdots, n\}$.

Step 3. Calculate the degree of dominance of alternative B_i over the other alternatives B_k by using the following formula:

$$\begin{aligned}\vartheta(B_i, B_k) &= \sum_{j=1}^{n} \varsigma_j(B_i, B_k),\\ \varsigma_j(B_i, B_k) &= \begin{cases} \sqrt{\dfrac{(x_{ij} - x_{kj}) w_{jr}}{\sum_{j=1}^{n} w_{jr}}} & x_{ij} > x_{kj},\\ 0 & x_{ij} = x_{kj},\\ -\dfrac{1}{\theta}\sqrt{\dfrac{(x_{kj} - x_{ij})\sum_{j=1}^{n} w_{jr}}{w_{jr}}} & x_{ij} < x_{kj}.\end{cases}\end{aligned} \tag{13}$$

where the parameter θ is the attenuation coefficient and a smaller value of θ indicates a higher degree of risk aversion of a DM.

Table 2: Relative loss functions.

	$X(P)$	$X^c(N)$
a_P	0	λ'_{PN}
a_B	λ'_{BP}	λ'_{BN}
a_N	λ'_{NP}	0

Table 3: Relative loss functions in terms of q_{ij}.

	$X(P)$	$X^c(N)$
a_P	0	$1 - q_{ij}$
a_B	σq_{ij}	$\sigma\left(1 - q_{ij}\right)$
a_N	q_{ij}	0

Table 4: Relative loss functions in the SF environment.

	$R(P)$	$R^c(N)$
a_P	0	${\theta_{ij}}^c$
a_B	$\sigma\theta_{ij}$	$\sigma{\theta_{ij}}^c$
a_N	θ_{ij}	0

Input. An MG SF IISs (U, V, R_i^*, S).
Output. Sorting results of all alternatives.
Step 1. Transform MG SF IISs into MG SF complete ISs by using the presented completion method in Section 3.2.
Step 2. Calculate the attribute weights and the weight of DMs.
Step 3. Calculate the MG SF membership degree of x_j with respect to R_i.
Step 4. Determine the parameter η to obtain the adjustable MG SF membership degree $\theta_S^{R_{\tau(i)}}(x_j)$.
Step 5. Determine the parameter σ and calculate the relative loss function and the corresponding threshold for DMs.
Step 6. Calculate the weights of the threshold attributes.
Step 7. Integrate thresholds by using the TODIM method to obtain the optimal threshold.
Step 8. Separate the positive, negative, and boundary domains according to the optimal threshold, further classification of alternatives.
Step 9. According to the principle of positive ≻ boundary ≻ negative, we calculate the score function values of the three domains, respectively, and finally get the ranking results of all alternatives.

Algorithm 1

Step 4. Calculate the overall dominance $\phi(B_i)$ of each alternative $B_i (i = 1, 2, \cdots, m)$.

$$\phi(B_i) = \frac{\sum_{k=1}^{m} \vartheta(B_i, B_k) - \min_i \{\sum_{k=1}^{m} \vartheta(B_i, B_k)\}}{\max\{\sum_{k=1}^{m} \vartheta(B_i, B_k)\} - \min_i \{\sum_{k=1}^{m} \vartheta(B_i, B_k)\}}. \quad (14)$$

Step 5. Rank all alternatives by virtue of $\phi(B_i)$.

3. MG SF PRSs

In this section, the concept of MG SF IISs is firstly proposed, and the completion methods for IISs are given. Finally, the model of adjustable MG SF PRSs is established.

3.1. MG SF IISs. Given that most of the data have missing values, it is necessary to establish an IIS. The following part describes MG SF ISs and IISs.

Definition 7. An MG SF IS can be denoted as (U, V, R, S), where $U = \{x_1, x_2, \cdots, x_m\}$ is the set of alternatives, $V = \{y_1, y_2, \cdots, y_n\}$ is the set of attributes, $u = \{u_1, u_2, \cdots, u_n\}^T$ is the attribute weight set, $w = \{w_1, w_2, \cdots, w_l\}^T$ is a DM's weight set, $R = \{R_1, R_2, \cdots, R_l\}$ is the set of SF relations over $U \times V$, and S is the standard evaluation set.

Definition 8. An MG SF IIS can be denoted as (U, V, R_i^*, S), where U, V, and S have the same meaning as shown in Definition 7. R_i^* is the set of SF relations over $U \times V$, $T_i^* = (t_{jk})_{m\times n}$ is the matrix of evaluation values in R_i^*, t_{jk} is the evaluation value of x_j on y_k, and T_i^* contains missing values. We denote these missing values by $*$.

3.2. The Completion Method. For the IISs defined above, this section will propose a method based on average values for processing. The details of this method are presented as follows.

Definition 9. For an MG SF IISs (U, V, R_i^*, S), suppose t_{jk}' $(j = 1 \cdots m', t_{jk}' \neq *)$ is an evaluation values on y_k that is not a missing value, m' is the number of evaluation values. t_k^* is the missing value in the evaluation value on y_k, then for which t_k^* is filled with the following equation:

$$t_k^* = \frac{\sum_{j=1}^{m'} t_{jk}'}{m'}. \quad (15)$$

The above equation can transform an MG SF IIS (U, V, R_i^*, S) into a complete IS (U, V, R_i, S); thus, the subsequent algorithm is still established on the MG SF complete IS.

3.3. Adjustable MG SF PRSs. In this section, in light of the above presented IISs and the completion method, the concept of MG SF membership degrees and adjustable membership degrees will be established to replace the conditional probability in classic MGPRSs, and finally, the MG SF PRSs model will be established.

Definition 10. Let (U, V, R_i, S) be an MG SF complete IS. For any $x_j \in U$ and $y_k \in V$, $\theta_S^{R_i}(x_j)$ is the MG SF membership degree of x_j with respect to R_i, which is defined as follows:

$$\theta_S^{R_i}(x_j) = \left(\frac{\sum_{y_k \in V} u_k R_i(x_j, y_k) S(y_k)}{\sum_{y_k \in V} u_k R_i(x_j, y_k)}\right). \quad (16)$$

Definition 11. Let (U, V, R_i, S) be an MG SF complete IS. All the membership degrees $\theta_S^{R_i}(x_j)$ are arranged in ascending order to obtain that the ith ranked membership degree is $\theta_S^{R_{\tau(i)}}(x_j)$, and $\theta_S^{R_{\tau(i)}}(x_j)$ is called the adjustable MG SF membership degree of x_j with respect to R_i.

Table 5: Classification results of the presented method.

Domains	Alternatives
$POS_{\alpha,\eta}(S)$	$\varnothing$
$BND_{\alpha,\beta,\eta}(S)$	x_1, x_3, x_{17}
$NEG_{\beta,\eta}(S)$	$x_2, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{15}, x_{16}, x_{18}, x_{19}, x_{20}, x_{21}, x_{22}$

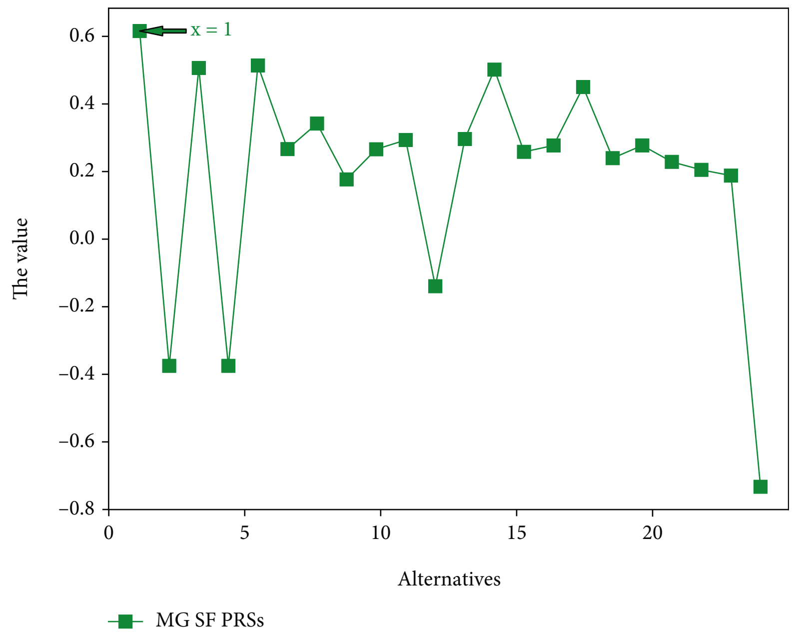

Figure 1: Ranking results of the presented method.

Table 6: Ranking results with different values of η.

η	Ranking results
$\eta = 1/3$	$x_3 \succ x_{16} \succ x_{12} \succ x_{17} \succ x_7 \succ x_{11} \succ x_{10} \succ x_4 \succ x_2 \succ x_{15} \succ x_9 \succ x_5 \succ x_6 \succ x_{19} \succ x_{21} \succ x_8 \succ x_{20} \succ x_{13} \succ x_{18} \succ x_{22} \succ x_{14} \succ x_1$
$\eta = 2/3$	$x_1 \succ x_3 \succ x_{17} \succ x_5 \succ x_{13} \succ x_{16} \succ x_7 \succ x_{12} \succ x_{15} \succ x_6 \succ x_9 \succ x_{14} \succ x_{19} \succ x_{20} \succ x_{21} \succ x_8 \succ x_{10} \succ x_{18} \succ x_{11} \succ x_4 \succ x_2 \succ x_{22}$
$\eta = 1$	$x_3 \succ x_1 \succ x_{22} \succ x_{17} \succ x_{13} \succ x_9 \succ x_{18} \succ x_{10} \succ x_{16} \succ x_{21} \succ x_5 \succ x_{12} \succ x_{14} \succ x_6 \succ x_7 \succ x_{19} \succ x_{15} \succ x_8 \succ x_4 \succ x_2 \succ x_{20} \succ x_{11}$

Based on the adjustable MG SF membership degree $\theta_S^{R_{\tau(i)}}(x_j)$, the following adjustable model MG SF PRSs can be established.

Definition 12. Let (U, V, R_i, S) be an MG SF complete IS with α and β as two thresholds and satisfying $0 \le \beta < \alpha \le 1$. For any $x_j \in U$, the adjustable MG SF probability lower and upper approximations of x_j with respect to (U, V, R_i, S) are defined as follows:

$$\underline{\sum_{i=1}^{l} R_i}^{\alpha,\eta}(S) = \left\{\theta_S^{R_{\tau(i)}}(x_j) \ge \alpha \,|\, x_j \in U\right\},$$
$$\overline{\sum_{i=1}^{l} R_i}^{\beta,\eta}(S) = \left\{\theta_S^{R_{\tau(i)}}(x_j) > \beta \,|\, x_j \in U\right\}. \tag{17}$$

where the parameter $\eta = i/l$ denotes the risk coefficient of a DM and satisfies $\eta \in [1/l, 1]$. If $\eta = 1/l$, then the risk attitude of a DM tends to be a fully risk-averse attitude; if $\eta = 1$, then the risk attitude of a DM tends to be a fully risk-seeking attitude. By referring to the above definitions, adjustable MG SF PRSs on (U, V, R_i, S) can be further shown as $(\underline{\sum_{i=1}^{l} R_i}^{\alpha,\eta}(S), \overline{\sum_{i=1}^{l} R_i}^{\beta,\eta}(S))$.

According to the region separation in the classic MGPRSs, three regions of MG SF PRSs can be further obtained below:

$$\mathrm{POS}_{\alpha,\eta}(S) = \underline{\sum_{i=1}^{l} R_i}^{\alpha,\eta}(S),$$
$$\mathrm{NEG}_{\beta,\eta}(S) = U - \overline{\sum_{i=1}^{l} R_i}^{\beta,\eta}(S), \tag{18}$$
$$\mathrm{BND}_{\alpha,\beta,\eta}(S) = \overline{\sum_{i=1}^{l} R_i}^{\beta,\eta}(S) - \underline{\sum_{i=1}^{l} R_i}^{\alpha,\eta}(S).$$

4. MAGDM Based on MG SF PRSs and TODIM

In this section, a novel MAGDM method by referring to adjustable MG SF PRSs and the TODIM method is constructed with MG SF IISs.

Suppose $U = \{x_1, x_2, \cdots, x_m\}$ is the set of alternatives, universe $V = \{y_1, y_2, \cdots y_n\}$ is set of attributes, $u = \{u_1, u_2, \cdots, u_n\}^T$ is the set of attribute weights, $w = \{w_1, w_2, \cdots, w_l\}^T$ is the set of DM weights, $R^* = \{R_1, \cdots R_i^* \cdots, R_l\}$ is the set of SF relationships established by each region on $U \times V$, and S is a standard evaluation set on V. Therefore, an MG SF IIS (U, V, R_i^*, S) can be established.

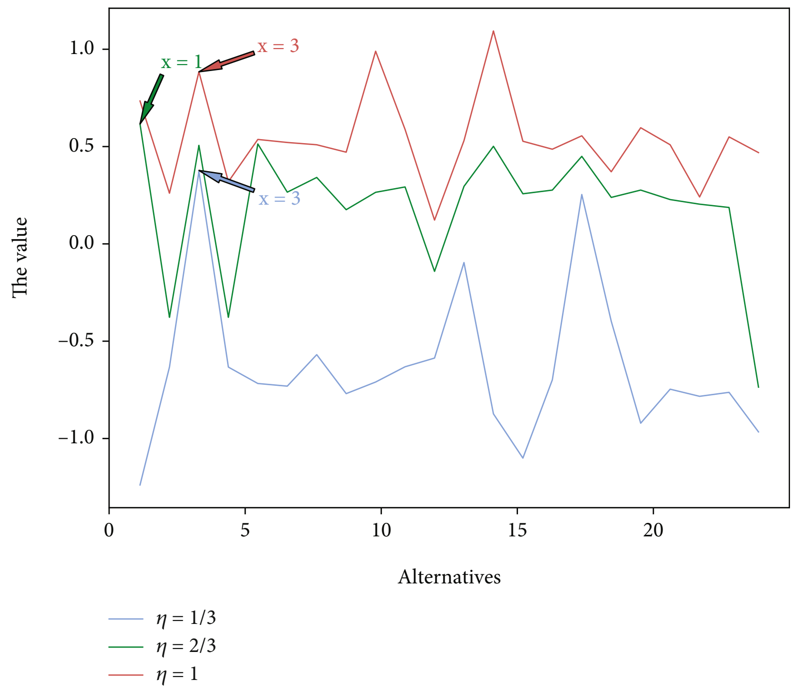

Figure 2: Ranking results with different values of η.

Table 7: Ranking results with different values of σ.

σ	Ranking results
$\sigma = 0$	$x_1 \succ x_3 \succ x_{17} \succ x_5 \succ x_{13} \succ x_{16} \succ x_7 \succ x_{12} \succ x_{10} \succ x_{18} \succ x_{15} \succ x_6 \succ x_9 \succ x_{14} \succ x_{19} \succ x_{20} \succ x_{21} \succ x_8 \succ x_{11} \succ x_4 \succ x_2 \succ x_{22}$
$\sigma = 0.25$	$x_1 \succ x_3 \succ x_{17} \succ x_5 \succ x_{13} \succ x_{16} \succ x_7 \succ x_{12} \succ x_{10} \succ x_{18} \succ x_{15} \succ x_6 \succ x_9 \succ x_{14} \succ x_{19} \succ x_{20} \succ x_{21} \succ x_8 \succ x_{11} \succ x_4 \succ x_2 \succ x_{22}$
$\sigma = 0.5$	$x_1 \succ x_5 \succ x_3 \succ x_{13} \succ x_{16} \succ x_7 \succ x_{12} \succ x_{10} \succ x_{18} \succ x_{15} \succ x_6 \succ x_9 \succ x_{14} \succ x_{17} \succ x_{19} \succ x_{20} \succ x_{21} \succ x_8 \succ x_{11} \succ x_4 \succ x_2 \succ x_{22}$

4.1. SF MAGDM. Given an MG SF IIS (U, V, R_i^*, S), the following attribute weights u_{ik} and DM weights w_i are first determined by using the deviation maximization method.

$$u_{ik} = \frac{\sum_{j=1}^{m}\sum_{l=1}^{m}\left(\mathrm{dis}\left(R_i\left(x_j, y_k\right), R_i\left(x_l, y_k\right)\right)\right)}{\sum_{k=1}^{n}\sum_{j=1}^{m}\sum_{l=1}^{m}\left(\mathrm{dis}\left(R_i\left(x_j, y_k\right), R_i\left(x_l, y_k\right)\right)\right)}, \tag{19}$$

$$w_i = \frac{\sum_{k=1}^{n}\sum_{o=1}^{n}\left(\mathrm{dis}\left(u_{ik}^{R_i}, u_{io}^{R_i}\right)\right)}{\sum_{i=1}^{l}\sum_{k=1}^{n}\sum_{o=1}^{n}\left(\mathrm{dis}\left(u_{ik}^{R_i}, u_{io}^{R_i}\right)\right)}. \tag{20}$$

In an MG SF IIS, the relative loss function in Table 3 can be transformed into the form of Table 4.

Accordingly, the threshold value can be further expressed as follows:

$$\begin{aligned} \alpha_{ij} &= \frac{(1-\sigma)\theta_{ij}{}^{c}}{(1-\sigma)\theta_{ij}{}^{c} + \sigma\theta_{ij}}, \\ \beta_{ij} &= \frac{\sigma\theta_{ij}{}^{c}}{\sigma\theta_{ij}{}^{c} + (1-\sigma)\theta_{ij}}. \end{aligned} \tag{21}$$

The thresholds for the l DMs can be obtained from the above equations, and these l DMs of thresholds are integrated by the TODIM method. The weights for threshold attributes need to be determined before using the TODIM method, and here, the entropy weight method is used to calculate them, with the following steps.

Let the threshold matrix be $\mathrm{TH} = (th_{ij}(\pi))_{q\times m}$, where $th_{ij}(\pi)$ is the hesitancy degree in th_{ij}.

Step 1. Calculate the information entropy of each index with the following formula.

$$H_j = -\frac{1}{\ln q}\sum_{i=1}^{q} p_{ij} \ln\left(p_{ij}\right), \tag{22}$$

where $p_{ij} = (th_{ij}(\pi))/(\sum_{i=1}^{q} th_{ij}(\pi))$, and when $p_{ij} = 0$, let $p_{ij} \ln(p_{ij}) = 0$.

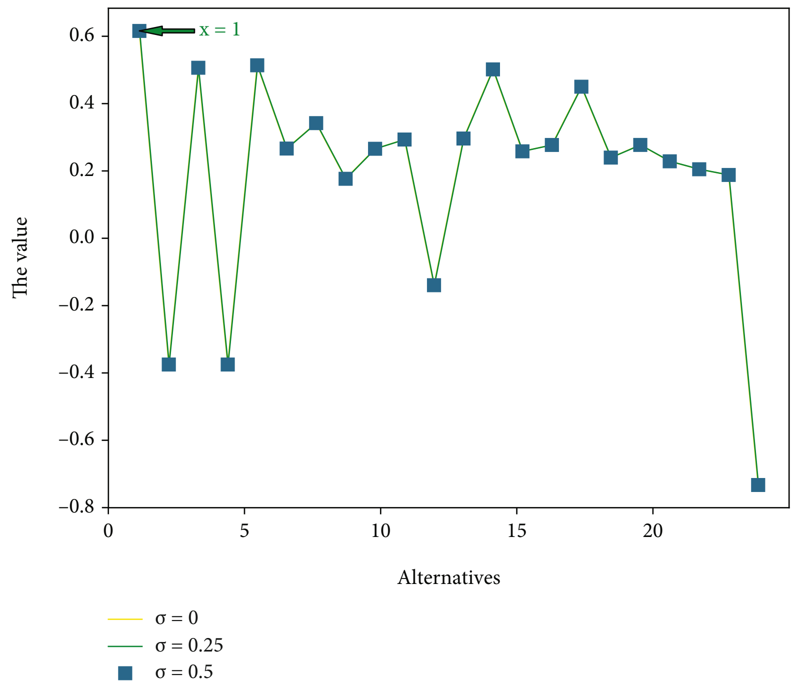

FIGURE 3: Ranking results with different values of σ.

Step 2. Calculate the entropy weight of each index, and the formula is as follows.

$$w_{th-j} = \frac{1 - H_j}{m - \sum_{j=1}^{m} (H_j)}. \tag{23}$$

Step 3. Obtain the weights of all evaluation indexes $w_{th} = (w_{th-1}, w_{th-2}, \cdots, w_{th-m})^T$.

After obtaining the index weights, the thresholds can be integrated by utilizing the TODIM method in Section 2.4. First, normalize the threshold matrix $\mathrm{TH} = (th_{ij})_{q\times m}$, then find the maximum weight and calculate the relative weight, then calculate the dominance and overall dominance, and finally rank the overall dominance to get the optimal threshold.

The previous steps obtained the conditional probabilities and optimal thresholds in 3WD. Next, we can separate the regions for all alternatives according to the rules in 3WD and separately calculate the score function values to obtain the final ranking results.

4.2. The Model Algorithm. In this section, the method of MAGDM in MG SF IISs is introduced, and its specific steps are shown below.

Remark 13. For the above model algorithm, the time complexity is shown below. In Step 1, the complexity is $O(qnm)$. In Step 2, the complexity is $O(qn^2m^2)$. In Step 3, the complexity is $O(qnm)$. In Step 4, the complexity is $O(m \log q)$. In Step 5, the complexity is $O(qm)$. In Step 6, the complexity is $O(qm)$. In Step 7, the complexity is $O(q^2m)$. In Step 8, the complexity is $O(m)$. In Step 9, the complexity is $O(m \log m)$. The overall time complexity of this algorithm is the largest of all steps; thus, the overall time complexity is $O(qn^2m^2)$.

5. Illustrative Cases in IoMT Systems

This section presents a case study in the context of a UCI data set (http://archive.ics.uci.edu/ml/datasets/Daphnet+Freezing+of+Gait) of freezing of gait recognition of Parkinson's disease patients by using IoMT devices and gives specific steps for SF MAGDM, and the results are presented and analyzed through graphs and charts. Then, this section concludes with a sensitivity analysis and a comparative analysis of the proposed method.

5.1. Case Descriptions. In the data set of freezing of gait recognition of Parkinson's disease patients, there are 22 subjects who performed three actions: walking, sitting, and standing, and during the actions, data related to the vastus medialis, semitendinosus, biceps femoris, and rectus femoris are recorded. Based on the presentation of the above data set, it is transformed into an MADGM problem; the aim of the problem is to find the subjects most likely to have abnormal knee joints.

Let $U = \{x_1, x_2, \cdots, x_{22}\}$ be a set of alternatives, denoting 22 subjects. $V = \{y_1, y_2, \cdots, y_4\}$ is four muscles, where y_1 is the rectus femoris, y_1 is the biceps femoris, y_1 is the vastus medialis, and y_1 is the semitendinosus. $R^* = \{R_1{}^*, R_2{}^*, R_3{}^*\}$ is an SF relation on three different actions. S is a standard evaluation set. According to the above statements, we can establish (U, V, R^*, S).

For (U, V, R^*, S), we employ the completion method in Section 3.2 to convert it into a complete IS (U, V, R, S).

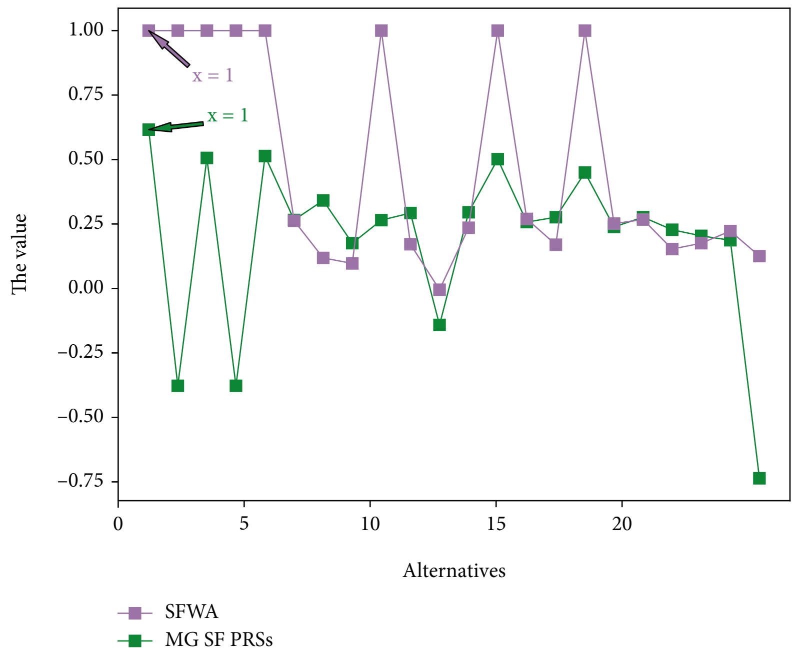

FIGURE 4: Comparative analysis results in terms of the SFWA method.

In order to facilitate the subsequent experiments, the data set needs to be preprocessed. First, the original data are processed by using the following normalization formula.

$$b_{ij} = \begin{cases} \dfrac{a_{ij} - \min\limits_i a_{ij}}{\max\limits_i a_{ij} - \min\limits_i a_{ij}}, & \text{benefit attribute,} \\ \dfrac{\max\limits_i a_{ij} - a_{ij}}{\max\limits_i a_{ij} - \min\limits_i a_{ij}}, & \text{cost attribute.} \end{cases} \tag{24}$$

The above formula is processed to obtain b_{ij}, and all attributes can be classified into benefit types. On this basis, the original data in the data set is transformed into an SFN $(b_{ij}, 1 - b_{ij}, \min(b_{ij}, 1 - b_{ij}))$. In addition, the standard evaluation set S can be determined via the formula below.

$$S = \left\{ \left\langle y_1, \left(\frac{\sum_{i=1}^{3}\sum_{j=1}^{22} b_{ij1}}{22 \times 3}, \frac{\sum_{i=1}^{3}\sum_{j=1}^{22} 1 - b_{ij1}}{22 \times 3}, \frac{\sum_{i=1}^{3}\sum_{j=1}^{22} \min\left(b_{j1}, 1 - b_{ij1}\right)}{22 \times 3} \right) \right\rangle, \cdots, \left\langle y_4, \left(\frac{\sum_{i=1}^{3}\sum_{j=1}^{22} b_{ij4}}{22 \times 3}, \frac{\sum_{i=1}^{3}\sum_{j=1}^{22} 1 - b_{ij4}}{22 \times 3}, \frac{\sum_{i=1}^{3}\sum_{j=1}^{22} \min\left(b_{ij6}, 1 - b_{ij4}\right)}{22 \times 3} \right) \right\rangle \right. . \tag{25}$$

Next, the decision is made according to the model algorithm proposed in Section 4, which proceeds as follows.

Step 1. The weights of four muscles and three actions are calculated according to formulas (19) and (20), respectively.

Step 2. The MG SF membership degree is calculated by using equation (15), based on which the MG SF membership degree is ranked according to formulas (2) and (3); we can obtain the adjustable MG SF membership degree.

Step 3. This paper takes a risk-neutral attitude; thus, the parameter $\eta = 2/3$ is taken to obtain the final membership degree in light of adjustable membership degree. The parameter $\sigma = 0.25$ is also taken and the relative loss function and threshold based on the membership degree and the formula that has been obtained.

Step 4. Use the entropy weight method to calculate the attribute weights of the thresholds, and next, the TODIM method is used to integrate the different thresholds of the three actions to obtain the best thresholds.

Step 5. Compare the threshold values with the final membership degrees obtained above and calculating the score function values of the threshold values and x_j in the final membership degrees, respectively. The 22 subjects x_j are classified via the score function values, and the classification results are shown in Table 5.

Step 6. Obtain the final ranking result of all alternatives: $x_1 \succ x_3 \succ x_{17} \succ x_5 \succ x_{13} \succ x_{16} \succ x_7 \succ x_{12} \succ x_{10} \succ x_{18} \succ x_{15} \succ x_6 \succ x_9 \succ x_{14} \succ x_{19} \succ x_{20} \succ x_{21} \succ x_8 \succ x_{11} \succ x_4 \succ x_2 \succ x_{22}$, as shown in Figure 1. Thus, the most likely of all subjects to have an abnormal knee joint is subject 1.

5.2. Sensitivity Analysis. In this section, for the sake of verifying the stability of the presented method, sensitivity analysis is performed for the parameters η and σ involved. The following Table 6 and Figure 2 and Table 7 and Figure 3 show the ranking results when the parameters η and σ are taken to different values, respectively.

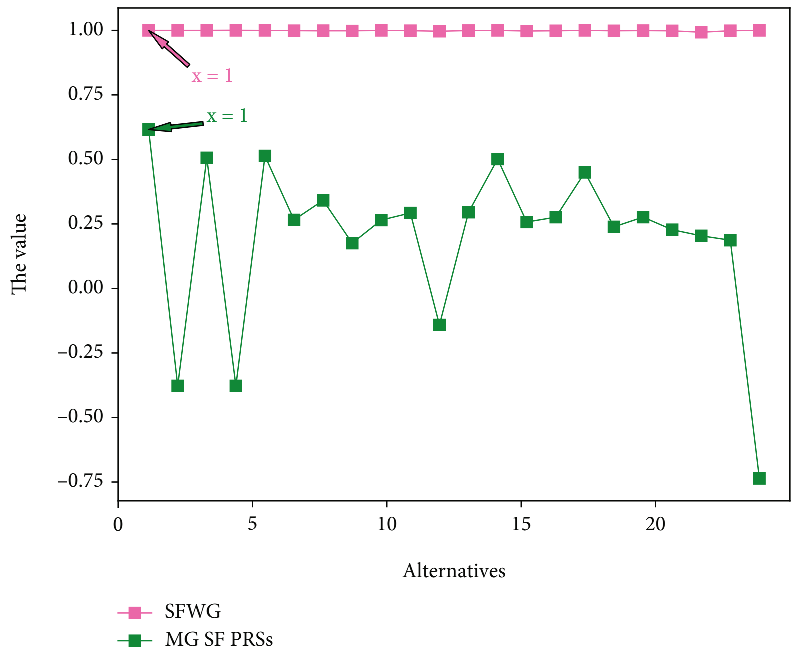

Figure 5: Comparative analysis results in terms of the SFWG method.

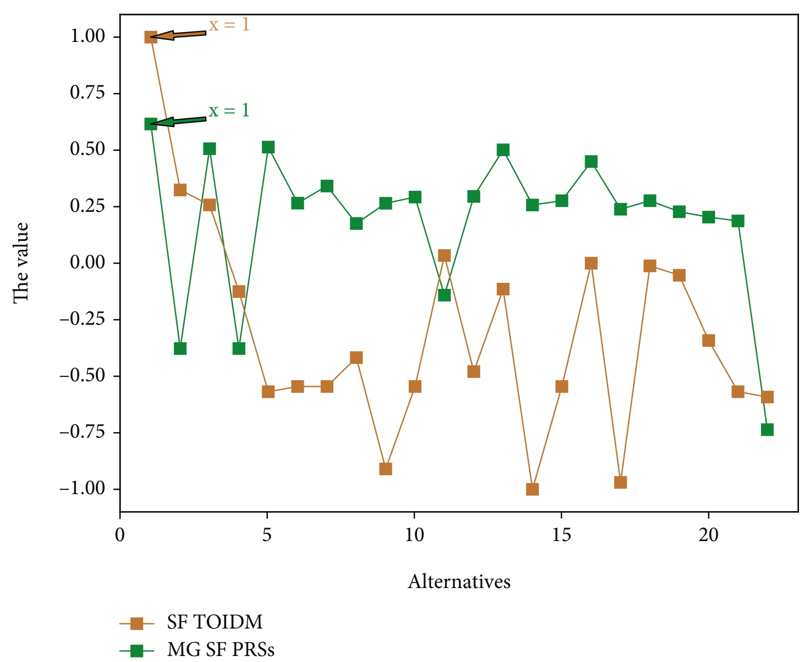

Figure 6: Comparative analysis results in terms of the SF TODIM method.

As can be seen in Table 6 and Figure 2, the final results obtained differ when diverse values of parameter n are taken, and the reason for this phenomenon is that parameter $n$represents different degrees of risk preferences in decision-making. When different risk preferences are chosen, the resulting final decision results may be different.

From Table 7 and Figure 3, it can be seen that when the parameters σ are taken as 0, 0.25, and 0.5, the final results obtained are all $x = 1$, whereas the overall ranking results do not change; thus, the presented decision-making method is stable for the parameter σ.

5.3. Comparative Analysis. This section provides a comparative analysis with two types of MAGDM methods, which are the SF aggregation operator method and the SF TODIM method.

5.3.1. The SF Aggregation Operator Method. In this section, SF arithmetic average aggregation operators (SFWA) and

SF geometric average aggregation operators (SFWG) in literature [18] are chosen to make comparative analysis in this paper. The comparison results are shown in Figures 4 and 5.

As can be seen in Figures 4 and 5, although the ranking results of SFWA, SFWG and this paper are not exactly the same, the final result obtained is $x = 1$. This paper uses the TODIM method to characterize the bounded rationality problem in the decision-making process, whereas SFWA and SFWG do not consider this scenario; hence, there is a situation that the ranking results of these methods are not exactly the same. It can be seen from Figure 6 that for 22 alternatives, the results of SFWG method are almost all the same and almost indistinguishable, whereas this paper has better differentiation for all alternatives.

5.3.2. The SF TODIM Method. In this section, the SF TODIM method and the presented method are selected for comparative analysis, and the final results are shown in Figure 6. From Figure 6, it can be seen that both the SF TODIM method and the method in this paper have obtained the final result of $x = 1$, although the ranking results are not exactly the same.

With the help of IoMT devices, this paper establishes an MAGDM method by combining adjustable MGPRSs with the TODIM method in the context of SFSs. In terms of information representation, the use of SFSs makes the information representation more accurate, which is conducive to recording numerous complicated realistic information. In terms of information fusion, this paper uses adjustable MGPRSs, which have better fault tolerance because they consider different risk preferences and set thresholds, which is conducive to reducing decision risks when fusing multisource information. For information analysis, the TODIM method is used to cope with the bounded rationality problem, which is conducive to modeling realistic decision scenarios owned by DMs. In sum, the presented MAGDM method has sound performances in information representation, information fusion, and information analysis.

6. Conclusions

In the current work, we utilize the auxiliary detection data of IoT in medicine for MAGDM problems, and we choose the case of gait freezing recognition of Parkinson's disease patients, for which an SF 3WD MAGDM method based on MGPRSs under bounded rationality is established. First, this paper constructs an MG SF IIS. Then, this paper proposes a completion method to obtain an MG SF complete IS. On this basis, this paper establishes adjustable MG SF PRSs by combining SFSs with MGPRSs. Afterwards, this paper constructs an MAGDM method in the context of SFSs by combining adjustable MG SF PRSs with the TODIM method. At last, the validity of the presented method is shown by a case of gait freezing recognition of Parkinson's disease patients in the UCI database.

Future research topics will be divided into three aspects as follows. First, further theoretical explorations in related fields of MG SF PRSs are necessary, such as attribute reductions, topological properties, rule acquisitions, and uncertainty measurements. Second, investigating new SF MAGDM methods in terms of various data types is necessary, such as multilabel data, shadowed sets, multiscale data, and other complicated fuzzy data. Third, applying the models and methods proposed in this paper to other broader scenarios is necessary, such as fault diagnosis, human-job matching, cloud models, mobile computing, mergers and acquisitions for enterprises [36].

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

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