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SUSTAINABLE MEDICAL SUPPLIER SELECTION BASED ON MULTI-GRANULARITY PROBABILISTIC LINGUISTIC TERM SETS

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Abstract. The sustainable medical supplier selection (SMSS) is an important issue facing the medical industry in the context of sustainable development, which can be regarded as a typical multi-attribute group decision making (MAGDM) problem. In the MAGDM process, linguistic term set (LTS) is particularly natural and convenient for decision makers (DMs) to express evaluation information. Especially, probabilistic linguistic term set (PLTS) is a very critical and effective tool, which can reflect the importance of different linguistic terms. Due to the different preferences and experience of different DMs, they may use multi-granularity probabilistic linguistic term sets (MGPLTSs) to represent different linguistic information. In this article, in order to study the comparison method of MGPLTSs, a new possibility degree formula is firstly proposed and its properties is proved. Then, in order to build a weight model, a possibility degree-based Best-Worst method (BWM) and a probability degree based-maximizing deviation method are established to calculate the subjective weights and objective weights of attributes, respectively. Where after, a MAGDM method is proposed by combining the ELimination Et Choix Traduisant la REalite (ELECTRE) method with Evaluation based on Distance from Average Solution (EDAS) method in the multi-granularity probabilistic linguistic information environment. Finally, the created MAGDM method is applied to the SMSS, and its effectiveness and advantages compared with other existing methods are verified.

Keywords: multi-attribute group decision making, sustainable medical supplier selection, multi-granularity probabilistic linguistic term sets, possibility degree, Best-Worst method, Maximizing deviation method, ELECTRE-EDAS method.

JEL Classification: C15, C44, C80, D70.

Introduction

In the modern business development model, supply chain management has become an important part of winning competition among enterprises, and it is an extremely intricate field. The goal of a complete supply chain is to determine the most reasonable and optimal choice

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from the perspective of different types of participants (Stević et al., 2017), which has attracted extensive attention (Cen et al., 2017; Ding et al., 2021; Gornall & Strebulaev, 2018). It involves many complex issues, and the procurement costs are inevitable. For the manufacturing industry, the cost of purchasing production materials usually accounts for 40% to 60% of the final sales (Gomes et al., 2015), but for the medical industry, the procurement cost accounts for a larger proportion. Therefore, a reasonable selection of suppliers helps the medical industry to reduce costs and optimize the use of resources (Rezaei et al., 2015). In addition, with the increase of natural disasters, various sudden diseases and health emergencies, it is more significant to choose high-quality and efficient medical suppliers. The medical industry and suppliers can become strategic partners and have a positive and far-reaching impact on each other's future business quality, thereby achieving a win-win situation. In recent years, many scholars have done a lot of researches on medical supplier selection. Liao et al. (2020) proposed a group decision-making method for medical suppliers. Jia et al. (2019) proposed an extended Multi-Attributive Border Approximation area Comparison (MABAC) method to solve a practical decision-making problem of selecting the best medical device supplier. Due to the implementation of environmental protection laws and the continuous increase in market demand for environmentally friendly products in recent years, the green supply chain and green supplier selection have received widespread attention (Green et al., 2012; Khaksar et al., 2016; Tian et al., 2021). But the choice of green suppliers ignores consideration of social factors. Then, the concept of sustainable supply chain management is proposed and it included three factors: economy, society and environment (Bai & Sarkis, 2018; Carter & Rogers, 2008; Peng et al., 2020). Therefore, the sustainable medical supplier selection (SMSS) includes several alternatives, several attributes (quantitative attributes and qualitative attributes) and many decision makers (DMs), it can be regarded as a typical multi-attribute group decision-making (MAGDM) problem.

Because the sustainability factors are very important for the medical supplier selection and have strategic significance, in recent years, many scholars have studied the MAGDM method to solve the problem of the SMSS. Pishvaee et al. (2014) proposed a multi-objective possibilistic programming model that considers economic, environmental and social factors to devise a sustainable medical supply chain network in a complex environment and made a further analysis based on a medical industry case. Stevic et al. (2020) developed a new method of sustainable supplier selection for the healthcare industry in a polyclinic. Ghadimi et al. (2018) proposed a multi-agent systems method as an effective way of automation and promoting the procedure of sustainable supplier selection. At present, the MAGDM method of sustainable supplier selection has become a hot spot.

MAGDM problem is a selection process, i.e., multiple DMs rank a group of feasible alternatives and determine the optimal alternative according to different attributes (Mao et al., 2019; Pang et al., 2016; Teng & Liu, 2019). In the SMSS, due to the fuzziness of human thinking, DMs may prefer to express attribute evaluation values through linguistic term set (LTS, also named linguistic evaluation scale) (Rodriguez et al., 2012) that is more convenient and natural than numbers. To address this issue, Rodríguez et al. (2011) proposed hesitant fuzzy linguistic term set (HFLTS), which allows DM to use several linguistic terms to express information. The decision makers (DM) involved in the sustainable medical supplier selection may come from different departments and have different knowledge backgrounds and linguistic preferences. Hesitant fuzzy linguistic term set (HFLTS) allows DMs to provide multiple linguistic terms to express information, but all linguistic terms have the same granularity levels and importance. For example, DM e_1 evaluates a supplier's product quality as $\{l_1^5, l_2^5\}$ based on LTS $S_1^5 = \{l^5_{-2} = \textit{very bad}, l^5_{-1} = \textit{bad}, l_0^5 = \textit{medium}, l_1^5 = \textit{good}, l_2^5 = \textit{very good}\}$. However, the S_1^5 may be not suitable for DM e_2 because his/her linguistic preference is LTS with 7-granularity level. Obviously, HFLTS cannot meet the needs of DMs. In contrast, multi-granularity probabilistic linguistic term set (MGPLTS) (Liu et al., 2021) provides linguistic terms with different granularity levels (similar to Likert scale of different levels) and corresponding probability values, which not only takes into account the advantages of probabilistic linguistic term set (Pang et al., 2016; Wang et al., 2021b), but also reflects the linguistic preference of DMs. For example, the evaluation information from DM e_1 is $\{l_1^5(0.7), l_2^5(0.3)\}$, and the evaluation information from DM e_2 is $\{l_2^7 = \textit{very good}\ (0.5), l_3^7 = \textit{extremely good}\ (0.5)\}$. If two DMs are equally important, the group evaluation information is an MGPLTS $\{l_1^5(0.35), l_2^5(0.15), l_2^7(0.25), l_3^7(0.25)\}$. As a powerful tool in SMSS, MGPLTS can capture fuzziness more accurately and further enhance the correctness of decision-making results. MGPLTS has strong applicability in individual and group decision-making, but there are few related studies. Since PLTS has similar properties to MGPLTS, the review on PLTS is helpful to the application and exploration of MGPLTS. The research of PLTSs can be divided into three categories:

(1) The basic theoretical research of PLTSs. The first is the normalization method of PLTSs, such as the average assignment method (Pang et al., 2016), full LTS assignment method (Liao et al., 2019), attitude-based assignment method (Song & Li, 2019), consistency-based assignment method (Liu et al., 2020; Wang et al., 2021a). The second is the operational laws of PLTSs (Gou & Xu, 2016; Liao et al., 2019; Pang et al., 2016), the comparison method developed to distinguish two PLTSs, such as score function and the variances function (Pang et al., 2016), expected value function (Wu et al., 2018), possibility degree (Bai et al., 2017; Chen et al., 2016; Feng et al., 2019; Liu & Li, 2018; Wu et al., 2019b), and the information measures of PLTSs, such as correlation measure (Wu et al., 2018), inclusion measures (Tang et al., 2019), entropy measure (Lin et al., 2019; Tang et al., 2019), similarity measures (Tang et al., 2019; Wu et al., 2018), and distance measures. Wu et al. (2018) proposed three distance measures of PLTSs including Hamming distance, Euclidean distance and generalized distance. Peng et al. (2018) put forward new distance measure of probabilistic linguistic integrated cloud. Lin et al. (2019) proposed a new distance measure based on transformation function of PLTSs.

(2) Aggregation operators of PLTSs. Wan et al. (2021a) proposed generalized probabilistic linguistic Choquet operator, which can effectively deal with the games between several subgroups. To deal with the interrelationship of input arguments, Peng et al. (2018) proposed probabilistic linguistic integrated cloud weighted Heronian mean (HM) operator. Although the Bonferroni mean (BM) operator and the HM operator can handle the relationship between the two arguments, the most common in real-life decision-making is the interrelationship between multiple arguments, and however,

the BM operator and HM operator are powerless. To solve this problem, Liu and Teng (2018) put forward probabilistic linguistic Archimedean Muirhead mean operator.

(3) Decision-making methods of PLTSs. Liu and Teng (2019) proposed an extended probabilistic linguistic TOmada de Decisão Interactiva Multicritérios (TODIM) method. Liao et al. (2019) introduced ELimination Et Choix Traduisant la REalite (ELECTRE) III method and apply it to nurse-patient relationship management. Wan et al. (2021c) combined prospect theory with the Gained and Lost Dominance Score (GLDS) method to take into account both individual semantics and psychological behavior.

Moreover, there are few studies on MGPLTS, Wang (2019) proposed several distance measures and entropy measures, and Liu et al. (2021) proposed the transformation function of MGPLTS and the multi-granularity probabilistic linguistic Choquet integral operator. The decision-making method of MGPLTS remains to be studied. Among the MAGDM method based on PLTSs, the ELECTRE method is one of the most widely used methods, which ranks alternatives by eliminating low-attractive alternatives and it does not require the independence of attributes (Botti et al., 2020; Haurant et al., 2011). Lin et al. (2019) proposed a new ELECTRE II method for PLTSs to deal with the edge node selection problem. Compared with TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) and VlseKriterijumska Opt imizacija Kompromisno Resenje (VIKOR), ELECTRE has more complex calculation process and heavy workload. Both TOPSIS and VIKOR rank the alternatives by calculating the distance of the extreme values (the maximal and minimal values) of the alternatives, but if the extreme value is not given properly or cannot be accurately calculated, the ranking result will be biased. To better overcome the defect, Keshavarz Ghorabaee et al. (2015) proposed the Evaluation based on Distance from Average Solution (EDAS) method, which ranks the alternatives according to the distance from the average. Therefore, EDAS method has higher efficiency and less workload.

The attribute weights are an important factor for ranking of alternatives, which include the subjective weights considering the knowledge and preference of DMs and the objective weights based on attribute evaluation information. The Best-Worst method (BWM) (Rezaei, 2015; Wan et al., 2021b; Wan & Dong, 2021) is improved on the basis of analytic hierarchy process (AHP) to obtain subjective weight, and its advantages are that it not only reduces the workload but also effectively improves consistency. Further, Ming et al. (2020) extended the BWM to PLTSs to obtain subjective weights. The deviation maximizing method (Xu & Zhang, 2013) is an important one to determine the objective weights, and it is based on the principle that the greater the difference between the evaluation information of the different alternatives, the easier it is to distinguish alternatives, and this attribute weight should be higher. In the information entropy combination weight (Zhou et al., 2017), the advantages of these two weight methods can be reflected together to overcome the shortcomings of using only subjective or objective weights. However, these traditional weight methods cannot directly process MGPLTS.

Although scholars have done a lot of works on PLTSs, there are still insufficient. First, due to the different knowledge and preference of each DM, DMs may easily use MGPLTSs to give evaluation information. But existing researches rarely involves comparison methods and decision-making methods of MGPLTSs. Second, the existing methods for comparing PLTSs have shortcomings. Among them, the existing possibility degree not only has the problem of information loss but also cannot handle MGPLTSs. Third, there is a lack of exploration in the application of possibility degree, such as the calculation of attribute weights. Based on the above motivation, to solve the problems in the existing PLTSs research and propose effective MAGDM methods for MGPLTSs, the main contributions of this article are as follows:

(1) A new possibility degree formula is proposed to deal with MGPLTSs, and proved the four properties of the new possibility degree formula.

(2) To effectively deal with the problem of MAGDM with unknown attribute weights, through the proposed possibility degree, a possibility degree-based BWM model and a probability degree based-maximizing deviation method are established to calculate the attributes subjective weights and attributes objective weights, and then the combination weights are obtained through the information entropy-based combination weights model.

(3) A new MAGDM method based on MGPLTSs is proposed. First, utilize the ELECTRE method to classify the results calculated by the new possibility degree. Then, according to the characteristics of the possibility degree, combined with the ELECTRE and EDAS method, the final score is calculated from the superior degree and inferior degree of the alternatives, and gives the ranking result of alternatives.

(4) The created MAGDM method is applied to the SMSS, and the effectiveness and superiority of this method are verified through two cases.

The rest of this article is organized as follows. Section 1 introduces the definition of multi-granularity linguistic term sets (MGLTSs), the definition of PLTSs and some operations of PLTSs. Section 2 reviews the existing possibility degree and proposes a new possibility degree formula of MGPLTSs. Section 3 proposes information entropy-based combination weights model to calculate the combination weight, including a possibility degree-based BWM model for subjective weights and a possibility degree-based maximizing deviation method for objective weights. Section 4 gives a new MAGDM method by integrating ELECTRE and EDAS methods. Section 5 first reviews the research on attribute selection in the SMSS. Then, the created MAGDM method is applied to the case of the SMSS and compared with the existing MAGDM method to verify its effectiveness and advantages. Last Section gives conclusions and future research directions.

1. Preliminaries

This section reviews the definitions of LTS, MGLTSs, PLTSs and MGPLTSs, the normalization methods of PLTSs.

Definition 1 (Teng & Liu, 2019). Assumed that $S=\left\{l_i \middle| i=-g,...,0,...,g,g\in N^+\right\}$ is a finite set containing an odd number of discrete linguistic terms, and $2g+1$ is the granularity of LTS.

In general, MGLTSs are called a set of LTSs with different granularity levels. Assumed that $S^{MG}=\left\{S^{t,n(t)} \mid t=1,2...,T\right\}$ are the MGLTSs, where $S^{t,n(t)}=\left\{l_{-g^{(t)}}^{n(t)},...,l_0^{n(t)},...,l_{g^{(t)}}^{n(t)}\right\}$ is tth LTS, and $n(t)=2g^{(t)}+1$ is the granularity of $S^{t,n(t)}$.

Definition 2 (Gou & Xu, 2016). Assumed that $S=\left\{l_i \middle| i=-g,...,0,...,g,g\in N^+\right\}$ is an LTS, the linguistic term l_i can express the equivalent information to a real number γ which is obtained by the transformation function φ:

$$\varphi:\left[l_{-g},l_g\right]\to\left[0,1\right],\varphi\left(l_i\right)=\frac{1}{2}\left(\frac{i}{g}+1\right)=\gamma. \quad (1)$$

Additionally, γ can express the equivalent information to the linguistic term l_i which is obtained by the transformation function φ^{-1}:

$$\varphi^{-1}:\left[0,1\right]\to\left[l_{-g},l_g\right],\varphi^{-1}\left(\gamma\right)=l_{(2\gamma-1)g}=l_i. \quad (2)$$

Definition 3 (Pang et al., 2016). Assumed that $S=\left\{l_i \middle| i=-g,...,0,...,g,g\in N^+\right\}$ is an LTS, a PLTS can be defined as:

$$L\left(p\right)=\left\{l_k\left(p_k\right)\middle| l_k\in S,p_k\geq 0,k=1,2,...,\#L\left(p\right),\sum_{k=1}^{\#L(p)}p_k\leq 1\right\}, \quad (3)$$

where $l_k\left(p_k\right)$ represents the linguistic term l_k and the corresponding probability value p_k, and $\#L\left(p\right)$ represents the number of different linguistic terms in PLTS.

If $\sum_{k=1}^{\#L(p)}p_k=1$, this means that the probability value of the PLTS is completely known;

If $0<\sum_{k=1}^{\#L(p)}p_k<1$, this means that the probability value of this PLTS is incomplete or partially unknown;

If $\sum_{k=1}^{\#L(p)}p_k=0$, this means that the probability value of the PLTS is completely unknown.

Definition 4 (Pang et al., 2016)**.** Assumed that $L\left(p\right)$ is a PLTS, and $0<\sum_{k=1}^{\#L(p)}p_k<1$, the normalizing method is proposed as follows:

$$\bar{L}\left(p\right)=\left\{l_k\left(\bar{p}_k\right)\middle| l_k\in S,\bar{p}_k\geq 0,k=1,2,...,\#L\left(\bar{p}\right),\sum_{k=1}^{\#L(p)}\bar{p}_k=1\right\}, \quad (4)$$

where $\bar{p}_k=p_k\Big/\sum_{k=1}^{\#L(p)}p_k, k=1,2,...,\#L\left(p\right)$.

Definition 5 (Pang et al., 2016). Assumed that $S^{1,n(1)}=\left\{l_i^{n(1)}\middle| i=-g^{(1)},...,0,...,g^{(1)},g^{(1)}\in N^+\right\}$ is 1th LTS with $2g^{(1)}+1$ granularity level, and $S^{2,n(2)}=\left\{l_i^{n(2)}\middle| i=-g^{(2)},...,0,...,g^{(2)},g^{(2)}\in N^+\right\}$ is 2th LTS with $2g^{(2)}+1$ granularity level. $L_1\left(p\right)$ and $L_2\left(p\right)$ are two PLTSs based on $S^{1,n(1)}$, and $L_3\left(p\right)$ is a PLTS based on $S^{2,n(2)}$. Then $L_1\left(p\right)$, $L_2\left(p\right)$ and $L_3\left(p\right)$ are MGPLTSs,

$$L_1\left(p\right)=\left\{l_{i_1}^{n(1)}\left(p_{i_1}\right)\middle| l_{i_1}^{n(1)}\in S^{1,n(1)},p_{i_1}\geq 0,i_1=0,1,...,\#L_1\left(p\right),\sum_{i_1=0}^{\#L_1(p)}p_{i_1}\leq 1\right\},$$

$$L_2(p)=\left\{ l_{i_2}^{n(1)}\left(p_{i_2}\right) \mid l_{i_2}^{n(1)} \in S^{1,n(1)}, p_{i_2} \geq 0, i_2=0,1,\ldots,\#L_2(p), \sum_{i_2=0}^{\#L_2(p)} p_{i_2} \leq 1 \right\},$$

$$L_3(p)=\left\{ l_{i_3}^{n(2)}\left(p_{i_3}\right) \mid l_{i_3}^{n(2)} \in S^{2,n(2)}, p_{i_3} \geq 0, i_3=0,1,\ldots,\#L_3(p), \sum_{i_3=0}^{\#L_3(p)} p_{i_3} \leq 1 \right\},$$

where $l_{i_1}^{n(1)}\left(p_{i_1}\right)$ represents the linguistic term $l_{i_1}^{n(1)}$ and the corresponding probability value p_{i_1}, $l_{i_2}^{n(1)}\left(p_{i_2}\right)$ and $l_{i_3}^{n(2)}\left(p_{i_3}\right)$ have the same meaning as $l_{i_1}^{n(1)}\left(p_{i_1}\right)$.

2. Possibility degree

2.1. Possibility degree of PLTSs

In the probabilistic linguistic MAGDM method, in order to distinguish different probabilistic linguistic evaluation information, an effective comparison method of PLTSs should be provided. Pang et al. (2016) introduced score function and the variance function. Then, Wu et al. (2018) proposed a more flexible expected value function. But, Bai et al. (2017) believed that the absolute superiority in the score function proposed by Pang et al. (2016) violated common sense. For this reason, Bai et al. (2017) proposed the possibility degree formula of PLTSs, which enriched the existing comparison methods of PLTSs.

Definition 6 (Bai et al., 2017)**.** Assumed that $\bar{L}(p)$ is a PLTS, and r_k is the subscript of the linguistic term. Let $L^{-}=\min\left(r_k\right)$ and $L^{+}=\max\left(r_k\right)$ be the lower bound and the upper bound of $L(p)$, respectively. The $b\left(L^{-}\right)=\min\left(r_k\right)\times \bar{p}_k$ is the lower area and the $b\left(L^{+}\right)=\max\left(r_k\right)\times \bar{p}_k$ is the upper area.

Definition 7 (Bai et al., 2017). Assumed that $\bar{L}_1(p)$ and $\bar{L}_2(p)$ are two arbitrary PLTSs on S, $S=\left\{ l_i \middle| i=-g,\ldots,0,\ldots,g, g\in N^{+}\right\}$. The possibility degree that $\bar{L}_1(p)$ is not less than $\bar{L}_2(p)$ can be defined as:

$$P\left(L_1(p)\geq L_2(p)\right)=0.5\times\left(1+\frac{\left(b\left(L_1^{-}\right)-b\left(L_2^{-}\right)\right)+\left(b\left(L_1^{+}\right)-b\left(L_2^{+}\right)\right)}{\left|b\left(L_1^{-}\right)-b\left(L_2^{-}\right)\right|+\left|b\left(L_1^{+}\right)-b\left(L_2^{+}\right)\right|+b\left(L_1\cap L_2\right)}\right),$$

where $b\left(L_1\cap L_2\right)$ represents the area of the intersection between $\bar{L}_1(p)$ and $\bar{L}_2(p)$.

But in some cases, the result of this possibility degree is counterintuitive. Subsequently, many studies put forward some different possibility degrees. Based on Bai et al. (2017), Liu and Li (2018) divided the two PLTSs into two situations according to whether the two PLTSs have the same linguistic terms, and further improved the possibility degree formula. Different from Bai's idea, Chen et al. (2016) also proposed the possibility degree formula in another way. However, according to the research of Feng et al. (2019), Chen's et al. (2016) possibility degree cannot satisfy transitivity. Therefore, Feng et al. (2019) proposed a new possibility degree formula. Subsequently, Wu et al. (2019b) discovered the deficiency of the possibility degree formula proposed by Feng et al. (2019) and further improved it.

Definition 8 (Wu et al., 2019b). Assumed that $\bar{L}_1(p)$ and $\bar{L}_2(p)$ are two arbitrary PLTSs on $S, S=\left\{l_i \middle| i=-g,...,0,...,g, g\in N^+\right\}$. The possibility degree that $\bar{L}_1(p)$ is not less than $\bar{L}_2(p)$ can be defined as:

$$P\left(\bar{L}_1(p)\geq \bar{L}_2(p)\right)=\begin{cases}\dfrac{D_1}{D_1-D_2}\times\left(1-\sum\limits_{\substack{l_k(\bar{p}_k)\in\bar{L}_1(p)\\ l_j(\bar{p}_j)\in\bar{L}_2(p)}} M\left(l_k,l_j\right)\right)+\sum\limits_{\substack{l_k(\bar{p}_k)\in\bar{L}_1(p)\\ l_j(\bar{p}_j)\in\bar{L}_2(p)}}\dfrac{\bar{p}_k}{\bar{p}_k+\bar{p}_j}M\left(l_k,l_j\right), & D_1\neq 0 \text{ or } D_2\neq 0\\ 0.5, & D_1=D_2=0\end{cases}, \quad (5)$$

$$D_o=\begin{cases}\dfrac{1}{\#L_1(\bar{p})\#L_2(\bar{p})}\sum\limits_{(r_k,r_j)\in F_o}\left(r_k-r_j\right)\bar{p}_k\bar{p}_j, & F_o\neq f\\ 0, & F_o=f\end{cases},$$

$$F_1=\left\{\left(l_k,l_j\right)\middle| r_k-r_j>0,\ l_k(\bar{p}_k)\in L_1(\bar{p}),\ l_j(\bar{p}_j)\in L_2(\bar{p})\right\},$$

$$F_2=\left\{\left(l_k,l_j\right)\middle| r_k-r_j<0,\ l_k(\bar{p}_k)\in L_1(\bar{p}),\ l_j(\bar{p}_j)\in L_2(\bar{p})\right\},$$

$$M\left(l_k,l_j\right)=\begin{cases}\bar{p}_k\bar{p}_j, & l_k=l_j\\ 0, & l_k\neq l_j\end{cases},$$

where $D_o\,(o=1,2)$ are the coefficients in Eq. (5), $F_o\,(o=1,2)$ are two sets divided according to the subscript size of the linguistic terms in two PLTSs $\bar{L}_1(p)$ and $\bar{L}_2(p)$.

2.2. Possibility degree of MGPLTSs

According to **Definition 2** and **Definition 8**, we propose a possibility degree of MGPLTSs.

Definition 9. Assumed that $\bar{L}_1(p)=\left\{l_k^{n(1)}(\bar{p}_k)\middle|k=1,2,...,\#L_1(\bar{p})\right\}$ is a PLTS on $S_1=\left\{l_i^{n(1)}\middle|i=-g^{(1)},...,0,...,g^{(1)},g^{(1)}\in N^+\right\}$ and $\bar{L}_2(p)=\left\{l_j^{n(2)}(\bar{p}_j)\middle|j=1,2,...,\#L_2(\bar{p})\right\}$ is a PLTS on $S_2=\left\{l_i^{n(2)}\middle|i=-g^{(2)},...,0,...,g^{(2)},g^{(2)}\in N^+\right\}$, this means that two PLTSs are with different granularity levels. The possibility degree of that $\bar{L}_1(p)$ is not less than $\bar{L}_2(p)$ can be defined as:

$$P\left(\bar{L}_1(p)\geq \bar{L}_2(p)\right)=\begin{cases}\dfrac{G_1}{G_1-G_2}\times\left(1-\sum\limits_{\substack{l_k^{n(1)}(\bar{p}_k)\in\bar{L}_1(p)\\ l_j^{n(2)}(\bar{p}_j)\in\bar{L}_2(p)}} M\left(l_k^{n(1)},l_j^{n(2)}\right)\right) \\ \quad +\sum\limits_{\substack{l_k^{n(1)}(\bar{p}_k)\in\bar{L}_1(p)\\ l_j^{n(2)}(\bar{p}_j)\in\bar{L}_2(p)}}\dfrac{\bar{p}_k}{\bar{p}_k+\bar{p}_j}M\left(l_k^{n(1)},l_j^{n(2)}\right), & G_1\neq 0 \text{ or } G_2\neq 0\\ 0.5, & G_1=G_2=0\end{cases}, \quad (6)$$

$$G_o = \begin{cases} \sum_{(r_k, r_j) \in F_o} \left(\left(\frac{1}{2}\left(\frac{r_k}{g^{(1)}} + 1 \right) - \frac{1}{2}\left(\frac{r_j}{g^{(2)}} + 1 \right) \right) \times \bar{p}_k \times \bar{p}_j \right), & F_o \neq f \\ 0, & F_o = f \end{cases},$$

$$F_1 = \left\{ \left(l_k^{n(1)}, l_j^{n(2)} \right) \middle| \frac{1}{2}\left(\frac{r_k}{g^{(1)}} + 1 \right) - \frac{1}{2}\left(\frac{r_j}{g^{(2)}} + 1 \right) > 0,\ l_k^{n(1)}\left(\bar{p}_k\right) \in \bar{L}_1(p),\ l_j^{n(2)}\left(\bar{p}_j\right) \in \bar{L}_2(p) \right\},$$

$$F_2 = \left\{ \left(l_k^{n(1)}, l_j^{n(2)} \right) \middle| \frac{1}{2}\left(\frac{r_k}{g^{(1)}} + 1 \right) - \frac{1}{2}\left(\frac{r_j}{g^{(2)}} + 1 \right) < 0,\ l_k^{n(1)}\left(\bar{p}_k\right) \in \bar{L}_1(p),\ l_j^{n(2)}\left(\bar{p}_j\right) \in \bar{L}_2(p) \right\},$$

$$M\left(l_k^{n(1)}, l_j^{n(2)} \right) = \begin{cases} \bar{p}_k \bar{p}_j, & \frac{1}{2}\left(\frac{r_k}{g^{(1)}} + 1 \right) = \frac{1}{2}\left(\frac{r_j}{g^{(2)}} + 1 \right) \\ 0, & \frac{1}{2}\left(\frac{r_k}{g^{(1)}} + 1 \right) \neq \frac{1}{2}\left(\frac{r_j}{g^{(2)}} + 1 \right) \end{cases}.$$

where $G_o\left(o = 1,2\right)$ are the coefficients in Eq. (6), $F_o\left(o = 1,2\right)$ are two sets divided according to the subscript size of the linguistic terms in two PLTSs $\bar{L}_1(p)$ and $\bar{L}_2(p)$.

Assumed that $\bar{L}_1(p)$, $\bar{L}_2(p)$ and $\bar{L}_3(p)$ are three PLTSs with different granularity levels, respectively. The MGPLTSs possibility degree has the following properties.

(1) (Normalization): $0 \le P\left(\bar{L}_1(p) \ge \bar{L}_2(p)\right) \le 1$.

(2) (Complementarity): $P\left(\bar{L}_1(p) \ge \bar{L}_2(p)\right) + P\left(\bar{L}_2(p) \ge \bar{L}_1(p)\right) = 1$.

(3) (Visualizability): For $L_1(p)$ and $L_2(p)$, if all $\frac{1}{2}\left(r_k / g^{(1)} + 1\right)$ in $L_1(p)$ are greater than the $\frac{1}{2}\left(r_j / g^{(2)} + 1\right)$ in $L_2(p)$, then $P\left(\bar{L}_1(p) \ge \bar{L}_2(p)\right) = 1$, and $P\left(\bar{L}_2(p) \ge \bar{L}_1(p)\right) = 0$.

(4) (Transitivity): If $P\left(\bar{L}_1(p) \ge \bar{L}_2(p)\right) \ge 0.5$, $P\left(\bar{L}_2(p) \ge \bar{L}_3(p)\right) \ge 0.5$, then $P\left(\bar{L}_1(p) \ge \bar{L}_3(p)\right) \ge 0.5$.

Obviously, these four properties hold.

From the above properties, the possibility degree of 0.5 is a special value.

If $P\left(\bar{L}_1(p) \ge \bar{L}_2(p)\right) < 0.5$, this means that $\bar{L}_1(p) \prec \bar{L}_2(p)$.

If $P\left(\bar{L}_1(p) \ge \bar{L}_2(p)\right) = 0.5$, this means that $\bar{L}_1(p) \sim \bar{L}_2(p)$.

If $P\left(\bar{L}_1(p) \ge \bar{L}_2(p)\right) > 0.5$, this means that $\bar{L}_1(p) \succ \bar{L}_2(p)$.

2.3. Comparison with existing possibility degree

2.3.1. Comparison with Bai's et al. (2017) possibility degree

The Bai's et al. (2017) possibility degree formula only involves part of the information in the two PLTSs, which may cause information distortion, and the comparison of the two PLTSs may have counter-intuitive results. For example, suppose $L_1(p) = \left\{ l_3^9(0.1), l_4^9(0.9) \right\}$, $L_2(p) = \left\{ l_1^9(0.5), l_2^9(0.5) \right\}$, $L_3(p) = \left\{ l_{-1}^9(0.4), l_2^9(0.2), l_3^9(0.4) \right\}$ and

$L_4(p)=\{l_{-1}^9(0.4),l_1^9(0.2),l_3^9(0.4)\}$ are four PLTSs in 9-granularity level. First, based on Bai et al.'s possibility degree formula $P(L_1(p)\geq L_2(p))=0.9286$. However, the subscripts of all linguistic terms in $L_1(p)$ are larger than the subscripts of all linguistic terms in $L_2(p)$. Thus, $L_1(p)$ should be absolutely better than $L_2(p)$, i.e., $P(L_1(p)\geq L_2(p))=1$. Second, $P(L_3(p)\geq L_4(p))=0.5$. However, from the comparison of the subscripts of the two PLTSs, it is intuitive that $L_3(p)$ should be better than $L_4(p)$. From these two examples, Bai's et al. possibility degree formula is not accurate. According to the created possibility degree formula Eq. (6), $P(L_1(p)\geq L_2(p))=1, P(L_3(p)\geq L_4(p))=0.5347$, this result is more credible. Therefore, the created possibility degree comprehensively considers all the information in the two PLTSs, avoids information loss, and provides a more accurate method for the calculation of possibility degree.

2.3.2. Comparison with Chen's et al. (2016) and Mao's et al. (2019) possibility degree

The Chen's et al. (2016) possibility degree and Mao's et al. (2019) possibility degree cannot satisfy transitivity, because they only involve the calculation of the probability value of linguistic terms and do not consider the subscript of linguistic terms. For example, $L_1(p)=\{l_2^9(0.5),l_3^9(0.5)\}, L_2(p)=\{l_1^9(0.5),l_4^9(0.5)\}$, and $L_3(p)=\{l_2^9(0.1),l_3^9(0.9)\}$ are three PLTSs in 9-granularity level. Based on the Chen's et al. and Mao's et al. possibility degree formulas, $P(L_1(p)\geq L_2(p))=0.5, P(L_2(p)\geq L_3(p))=0.5, P(L_1(p)\geq L_3(p))=0.3$. This Example shows that if $P(L_1(p)\geq L_2(p))\geq 0.5$, $P(L_2(p)\geq L_3(p))\geq 0.5$, we cannot get $P(L_1(p)\geq L_3(p))\geq 0.3$. According to the fourth property of the created possibility degree formula, the created possibility degree formula satisfies transitivity.

2.3.3. Comparison with Yu's et al. (2019b) possibility degree

Yu's et al. (2019b) possibility degree involves the comparison of the subscript of linguistic terms and the comparison of the probability value, but the subscript of linguistic terms and probability value do not participate in the calculation of the formula. Therefore, Yu's et al. possibility degree may cause the distortion of evaluation information.

2.3.4. Comparison with Wu's et al. (2019) possibility degree

Wu's et al. (2019) possibility degree is constructed on the basis of Feng's et al. possibility degree (Feng et al., 2019), but both of these two possibility degree formulas can only be used in the same granularity level and are not suitable for MGPLTSs. The created possibility degree formula takes into account MGPLTSs is given by different DMs, which is suitable for more complex linguistic environments.

3. Attribute weight model

In MAGDM, the attribute weights are an important factor affecting the final ranking of alternatives, which include the subjective weights considering the knowledge and preference of DMs, the objective weights based on attribute evaluation information and the combination weights combined with the advantages of subjective and objective weights. Therefore, selecting a reasonable calculation method of attribute weights is a key step in scientific decision-making.

3.1. Classic BWM

BWM was proposed by Rezaei (2015) on the basis of AHP. Compared with AHP, BWM has more obvious advantages: (1) If there are n attributes, and there are reference comparisons and secondary comparisons in AHP, which need $n(n\text{-}1)/2$ times, but BWM only needs $2n\text{-}3$ pairwise comparisons; (2) For AHP, a large number of pairwise comparison increases the workload and reduces the consistency, while BWM not only reduces the workload but also effectively improves the consistency. The detailed steps for obtaining attribute weights based on BWM are as follows:

Step 1. Determine the decision attribute set $A = \{a_1, a_2, ..., a_n\}$ involved in the current problem.

Step 2. Determine the best (e.g., most preferred, most important) and the worst (e.g., least preferred, least important) attribute by DMs' knowledge and experience.

Step 3. Perform pairwise comparisons to obtain the relative importance of the best attribute over all other attributes, using numbers between 1 and 9, and the result called as Best-to-Others is expressed by $C_B = (c_{B1}, c_{B2}, ..., c_{Bn})$, where c_{Bv} represents the preference of the best attribute a_B over attribute a_v. Note that $c_{BB} = 1$.

Step 4. Perform pairwise comparisons to obtain the relative importance of all the attributes over the worst attribute, using numbers between 1 and 9, and the result called as Others-to-Worst is expressed by $C_W = (c_{1W}, c_{2W}, ..., c_{nW})$, where c_{vW} represents the preference of the attribute a_v over worst attribute a_W. Note that $c_{WW} = 1$.

Step 5. Derive the optimal weights $w = (w_1^*, w_2^*, ..., w_n^*)$.

The optimal weight should conform to $w_B / w_v = c_{Bv}$ and $w_v / w_W = c_{vW}$, but the actual situation may not be true. Thus, make $\left| w_B / w_v - c_{Bv} \right|$ and $\left| w_v / w_W - c_{vW} \right|$ as small as possible. Considering the non-negative and summation conditions of weights, the final results are obtained from the following models:

$$\min \delta$$
$$s.t. \begin{cases} \left| w_B / w_v - c_{Bv} \right| \le \delta, \\ \left| w_v / w_W - c_{vW} \right| \le \delta, \\ \sum_{v=1}^{n} w_v = 1, \\ w_v \ge 0, (v = 1, 2, ..., n) \end{cases}.$$

Then, the optimal weights are $w = (w_1^*, w_2^*, ..., w_n^*)$.

3.2. Possibility degree-based BWM model for MGPLTSs

Traditional BWM uses numbers from 1–9 to indicate the importance of attributes after pairwise comparison. However, if MGPLTS is used to indicate the importance of attributes, the BWM model cannot be established directly. Based on the possibility degree, the combination of MGPLTS and BWM can be realized.

Definition 10 (Wu et al., 2019b). Assumed there are τDMs and n attributes, and $H = \left[P_{vt}\right]_{n\times n} \left(v = 1,2,...,n; t = 1,2,...,n\right)$ is called n-order PLTSs-based fuzzy complementary possibility degree matrix, where $P_{vt} = P\left(\bar{L}_v(p) \geq \bar{L}_t(p)\right)$, $\bar{L}_v(p)$ and $\bar{L}_t(p)$ are the PLTSs from DMs with respect to attribute a_v for attribute a_t, respectively. Based on the transitivity of Eq. (6), we know $P_{vt}^{\alpha} = 1 - P_{tv}^{\alpha}$, $P_{vt}^{u} \in [0,1]$.

Definition 11. Determine the best attribute a_B and worst a_W attribute. Assumed that $H = \left[P_{vt}\right]_{n\times n}$ is n-order PLTSs-based fuzzy complementary possibility degree matrix. If H satisfies

$$\begin{cases} P_{Bs} + P_{st} = P_{Bt} + 0.5 \\ P_{st} + P_{tW} = P_{sW} + 0.5 \end{cases} \quad \text{Best} \leq s \leq t \leq \text{Worst} \tag{7}$$

then H is called n-order PLTSs-based fuzzy complementary possibility degree matrix with additive consistency over the attribute set A.

Remark 1: The additive consistency is derived from the preference relations similar to the possibility degree, which is proposed by Tanino (1984).

Motivated by Li's et al. result (Li et al., 2019a), if possibility degree is an additive consistency, then the relationship between the possibility degree P_{Bv}, and the weights w_B and w_v can be given as:

$$P_{Bv} = \frac{n-1}{2}\left(w_B - w_v\right) + 0.5. \tag{8}$$

The relationship between the possibility degree P_{vW}, the weights w_v and w_W can be given as:

$$P_{vW} = \frac{n-1}{2}\left(w_v - w_W\right) + 0.5. \tag{9}$$

If Eqs (8) and (9) and do not hold, that is, the possibility degree does not have additive consistency, then the weight vector can be calculated by minimizing the maximum absolute difference $\left|\frac{n-1}{2}\left(w_B - w_v\right) + 0.5 - P_{Bv}\right|$ and $\left|\frac{n-1}{2}\left(w_v - w_W\right) + 0.5 - P_{vW}\right|$. Then, build the **Model 1**:

$$\min \max_{1\leq v\leq n} \left\{\left|\frac{n-1}{2}\left(w_B - w_v\right) + 0.5 - P_{Bv}\right|, \left|\frac{n-1}{2}\left(w_v - w_W\right) + 0.5 - P_{vW}\right|\right\}$$
$$s.t. \begin{cases} \sum_{v=1}^{n} w_v = 1, \\ w_v \geq 0, \ \left(v = 1,2,...,n\right). \end{cases} \tag{10}$$

Model 1 can be transformed into **Model 2**:

$$\min \delta$$
$$s.t. \begin{cases} \left|\frac{n-1}{2}\left(w_B - w_v\right) + 0.5 - P_{Bv}\right| \leq \delta, \\ \left|\frac{n-1}{2}\left(w_v - w_W\right) + 0.5 - P_{vW}\right| \leq \delta, \\ \sum_{v=1}^{n} w_v = 1, \\ \delta \geq 0, w_v \geq 0, \quad \left(v = 1,2,...,n\right). \end{cases} \tag{11}$$

By solving **Model 2**, if $\delta = 0$, it means that the possibility degree matrix is with full consistency. Then, we can get the final optimal subjective weights vector:

$$w = \left(w_1, w_2, ..., w_n\right). \quad (12)$$

Remark 2: If the calculated δ is small enough, then the consistency is acceptable. When $n = 2$ it always satisfies full consistency, and when $n = 3$, **Model 2** has a unique solution.

According to the above reasoning, the steps of attribute weights gotten by possibility degree-based BWM for MGPLTSs is given as

Step 1. Determine a set of decision attributes as $A = \{a_1, a_2, ..., a_n\}$.

Step 2. Select the best and the worst attributes by DMs.

Step 3. Obtains τ vectors $C_\alpha = (c_1, c_2, ..., c_n); (\alpha = 1, ..., \tau)$, which are given by each DM using MGPLTSs according to the importance of each attribute.

Step 4. Get the weighted evaluation vector based on the weight of DMs, and finally integrate the τ vectors into one vector.

Step 5. Obtain the matrix $H = \left[P_{vt}\right]_{n\times n}$ by pairwise comparison and the possibility degree according to Eq. (6).

Step 6. Calculate attribute weights $w = \left(w_1, w_2, ..., w_n\right)$ according to Eq. (11).

3.3. Possibility degree based-maximizing deviation method

For the MAGDM problem, under one attribute, the greater the difference between the evaluation information of the different alternatives, the easier it is to distinguish alternatives. Therefore, the weight of this attribute should be higher. Based on the maximizing deviation method (Xu & Zhang, 2013), we build a model to calculate the objective weights of attributes.

The weighted square possibility degree H_{uv} to which alternative x_u dominant other alternatives with respect to attribute a_v is defined:

$$H_{uv} = \sum_{d=1, d\neq u}^{m} \theta_v \left(P_{ud}^v\right)^2 \ \left(u = 1,2,...,m; v = 1,2,...,n\right), \quad (13)$$

where $P_{ud}^v = P^v\left(\bar{L}_u(p) \geq \bar{L}_d(p)\right)$ based on Eq. (6). $\bar{L}_u(p)$ and $\bar{L}_d(p)$ are the PLTSs of attribute a_v with respect to alternative x_u and alternative x_d, respectively. θ_v is the weight of attribute a_v.

The total weighted square possibility degree H_v to which all alternatives dominant the others with respect to attribute a_v is calculated as:

$$H_v = \sum_{u=1}^{m} H_{uv} = \sum_{u=1}^{m} \sum_{d=1, d\neq u}^{m} \theta_v \left(P_{ud}^v\right)^2 \left(v = 1,2,...,n\right). \quad (14)$$

Inspired by Xu and Zhang (2013), we establish a non-linear programming model (**Model 3**) to calculate the attributes objective weights which maximizes all deviation possibility degree for all the attributes.

$$\max H_v = \sum_{u=1}^{m} H_{uv} = \sum_{v=1}^{n}\sum_{u=1}^{m}\sum_{d=1,d\neq u}^{m} \theta_v \left(P_{ud}^{v}\right)^2$$
$$s.t.\begin{cases}\sum_{v=1}^{n}\left(\theta_v\right)^2 = 1, \\ \theta_v \geq 0,\ \left(v = 1,2,\ldots,n\right).\end{cases} \tag{15}$$

Lagrange multiplier function is constructed to solve **Model 3**:

$$L\left(\theta,\xi\right) = \sum_{v=1}^{n}\sum_{u=1}^{m}\sum_{d=1,d\neq u}^{m} \theta_v \left(P_{ud}^{v}\right)^2 + \frac{\xi}{2}\left(\sum_{v=1}^{n}\left(\theta_v\right)^2 - 1\right), \tag{16}$$

where ξ is a real number, representing the Lagrange multiplier variable.

Then, obtain the partial derivative and make it equal to 0:

$$\frac{\partial L}{\partial \theta} = \sum_{u=1}^{m}\sum_{d=1,d\neq u}^{m} \left(P_{ud}^{v}\right)^2 + \xi\theta_v = 0; \tag{17}$$

$$\frac{\partial L}{\partial \xi} = \frac{1}{2}\left(\sum_{v=1}^{n}\left(\theta_v\right)^2 - 1\right) = 0. \tag{18}$$

Solving Eqs (17) and (18), we get:

$$\theta_v = \frac{\sum_{u=1}^{m}\sum_{d=1,d\neq u}^{m} \left(P_{ud}^{v}\right)^2}{\sqrt{\sum_{v=1}^{n}\left(\sum_{u=1}^{m}\sum_{d=1,d\neq u}^{m} \left(P_{ud}^{v}\right)^2\right)^2}}; \tag{19}$$

$$\xi = \sqrt{\sum_{v=1}^{n}\left(\sum_{u=1}^{m}\sum_{d=1,d\neq u}^{m} \left(P_{ud}^{v}\right)^2\right)^2}. \tag{20}$$

By normalizing $\theta = \left(\theta_1,\theta_2,\ldots,\theta_n\right)$, the optimal objective weights $\theta^* = \left(\theta_1^*,\theta_2^*,\ldots,\theta_n^*\right)$ is obtained:

$$\theta_v^* = \frac{\sum_{u=1}^{m}\sum_{d=1,d\neq u}^{m} \left(P_{ud}^{v}\right)^2}{\sum_{v=1}^{n}\sum_{u=1}^{m}\sum_{d=1,d\neq u}^{m} \left(P_{ud}^{v}\right)^2}. \tag{21}$$

3.4. Information entropy-based combination weights' model

The subjective weights reflect the DMs' experience and knowledge, a subjective grasp of the current decision-making background, and reasonable consideration of the DMs' subjective preferences. However, the subjective weights are with subjective arbitrariness, which reduces the scientificness of decision-making. Although objective weights fully consider the evaluation information given by DMs, objective weights cannot reflect the subjective preference of DMs, and ignore the experience and knowledge accumulation of DMs. The objective weights are also affected by the weight calculation model and evaluation information, and the calculated attribute weights may be inconsistent with the actual importance of the attributes, which will further reduce the credibility of the decision-making results.

Therefore, the combination weights by information entropy are introduced to overcome the shortcomings of using only subjective or objective weights. Subjective weights $w=\left(w_1, w_2, \ldots, w_n\right)$, objective weights $\theta^*=\left(\theta_1^*, \theta_2^*, \ldots, \theta_n^*\right)$, and combination weights $\omega=\left(\omega_1, \omega_2, \ldots, \omega_n\right)$ should be as close as possible. According to the principle of minimum relative entropy, **Model 4** is established (Zhou et al., 2017):

$$\min F=\sum_{v=1}^{n}\left[\omega_v\left(\ln\omega_v-\ln w_v\right)\right]+\sum_{v=1}^{n}\left[\omega_v\left(\ln\omega_v-\ln\theta_v^*\right)\right]$$
$$s.t\begin{cases}\sum\limits_{v=1}^{n}\omega_v=1,\\ \omega_v\geq 0,\ \left(v=1,2,\ldots,n\right)\end{cases}. \quad (22)$$

Lagrange multiplier function is constructed to solve **Model 4**:

$$F\left(\omega_v,\beta\right)=\sum_{v=1}^{n}\left[\omega_v\left(\ln\omega_v-\ln w_v\right)\right]+\sum_{v=1}^{n}\left[\omega_v\left(\ln\omega_v-\ln\theta_v^*\right)\right]+\beta\sum_{v=1}^{n}\left(\omega_v-1\right), \quad (23)$$

where β is a real number, representing the Lagrange multiplier variable.

Then, obtain the partial derivative and make it equal to 0:

$$\frac{\partial F\left(\omega_v,\beta\right)}{\partial\omega_v}=2\ln\omega_v-\ln w_v-\ln\theta_v^*+2+\beta=0; \quad (24)$$

$$\frac{\partial F\left(\omega_v,\beta\right)}{\partial\beta}=\sum_{v=1}^{n}\left(\omega_v\right)-1=0. \quad (25)$$

Solving Eqs (24) and (25), we get:

$$\beta=2\ln\left(\sum_{v=1}^{n}\sqrt{w_v\theta_v^*}\right)-2; \quad (26)$$

$$\omega_v=\frac{\sqrt{w_v\theta_v^*}}{\sum\limits_{v=1}^{n}\sqrt{w_v\theta_v^*}}. \quad (27)$$

4. A new method for MAGDM with MGPLTSs

In what follows, we first describe the MAGDM problem in the multi-granularity probabilistic linguistic environment and propose an evaluation information classification method based on possibility degree and ELECTRE method. Based on the probability and the ELECTRE method. Then a new MAGDM method with MGPLTSs is proposed, which can be used to rank alternatives in practical decision-making applications.

4.1. Problem description

Suppose that there are m alternatives $X=\{x_1,x_2,...,x_m\}$, n attributes $A=\{a_1,a_2,...,a_n\}$, and τ DMs $E=\{e_1,e_2,...,e_\tau\}$. Suppose that the weights of DMs are $Y=(y_1,y_2,..,y_\tau)^T$ meeting $0\le y_\alpha \le 1(\alpha=1,2,...,\tau)$, $\sum_{\alpha=1}^{\tau} y_\alpha=1$. Suppose that $S^{MG}=\{S^{t,n(t)}\mid t=1,2...,T\}$ are MGLTSs, the DM $e_\alpha(\alpha=1,2,...,\tau)$ chooses an LTS $S^{t,n(t)}$ with $n(t)$ granularity level to give the decision matrix $J_\alpha=\left[L^{t,n(t)}_{\alpha,uv}(p)\right](\alpha=1,2,...,\tau)$, where $L^{t,n(t)}_{\alpha,uv}(p)$ is a PLTS, which represents the evaluation information of the alternative $x_u(u=1,2,...,m)$ about the attribute $a_v(v=1,2,...,n)$.

4.2. Ranking of alternatives based on ELECTRE- EDAS method

In ELECTRE method, the evaluation information is divided into dominating set and dominated set, and this feature is in line with the calculation result of the possibility degree. Based on Eq. (6), we calculate the possibility degree of evaluation information between different alternatives under each attribute. According to the numerical value of the possibility degree, we can define the four relationships between the two alternatives x_u and x_d $(u=1,2,...,m;d\ne u;d=1,2,...,m)$:

(1) Absolutely superior relationship: if $P^v\left(\bar{L}_u(p)\ge \bar{L}_d(p)\right)=1$, it means that under attribute v, the alternative x_u is absolutely superior to x_d, denoted by $x_u >^{AS}_v x_d$;

(2) Superior relationship: if $0.5\le P^v\left(\bar{L}_u(p)\ge \bar{L}_d(p)\right)<1$, it means that under attribute v, the alternative x_u is superior to x_d, denoted by $x_u >^{S}_v x_d$;

(3) Inferior relationship: if $0< P^v\left(\bar{L}_u(p)\ge \bar{L}_d(p)\right)<0.5$, it means that under attribute v, the alternative x_u is inferior to x_d, denoted by $x_u >^{I}_v x_d$;

(4) Absolutely inferior relationship: if $P^v\left(\bar{L}_u(p)\ge \bar{L}_d(p)\right)=0$, it means that under attribute v, the alternative x_u is absolutely inferior to x_d, denoted by $x_u >^{AI}_v x_d$.

The set of subscripts of all attributes is $V=\{v\,|\,v=1,2,...,n\}$, according to the four relations of x_u and x_d, they are divided into four category sets:

(1) Absolutely superior set. An attribute subscript set satisfying condition $x_u >^{v}_{AS} x_d$ is defined as an absolutely superior set:

$$V^{AS}_{ud}=\left\{v\,\middle|\,x_u >^{AS}_v x_d, v\in V\right\}. \tag{28}$$

(2) Superior set. An attribute subscript set satisfying condition $x_u >^{S}_v x_d$ is defined as a superior set:

$$V^{S}_{ud}=\left\{v\,\middle|\,x_u >^{S}_v x_d, v\in V\right\}. \tag{29}$$

(3) Inferior set. An attribute subscript set satisfying condition $x_u >^{I}_v x_d$ is defined as an inferior set:

$$V^{I}_{ud}=\left\{v\,\middle|\,x_u >^{I}_v x_d, v\in V\right\}. \tag{30}$$

(4) Absolutely inferior set. An attribute subscript set satisfying condition $x_u >^{AI}_v x_d$ is defined as an absolutely inferior set:

$$V^{AI}_{ud}=\left\{v\,\middle|\,x_u >^{AI}_v x_d, v\in V\right\}. \tag{31}$$

In the ELECTRE method, the concordance matrix is calculated by the dominant set, and the discordance matrix is calculated by the dominated set. This is consistent with the idea of calculating positive and negative distances from average in EDAS method. The ideas of these two methods are based on the superiority and inferiority of the alternatives. Combining the characteristics of the possibility degree, we firstly calculate the possibility degree superior score (PDSS) between x_u and $x_d \left(u=1,2,...,m; d \neq u; d=1,2,...,m\right)$ by:

$$PDSS_{ud} = \sum_{v \in V_{ud}^{AS}} \omega_v \left(P_{ud}^v - 0.5\right) + \sum_{v \in V_{ud}^{S}} \omega_v \left(P_{ud}^v - 0.5\right), \tag{32}$$

where $P_{ud}^v = P^v\left(\bar{L}_u(p) \geq \bar{L}_d(p)\right)$, ω_v is the weight of attribute a_v, and $0 \leq PDSS_{ud} \leq 0.5$, higher PDSS means alternative x_u is better than alternative x_d.

Then, calculate the possibility degree inferior score (PDIS) between x_u and x_d by

$$PDIS_{ud} = \sum_{v \in V_{ud}^{I}} \omega_v \left(P_{ud}^v - 0.5\right) + \sum_{v \in V_{ud}^{AI}} \omega_v \left(P_{ud}^v - 0.5\right), \tag{33}$$

where $-0.5 \leq PDIS_{ud} \leq 0$, lower PDIS means alternative x_u is worse than alternative x_d.

By calculating the PDSS and the PDIS between x_u and x_d, the PDSS matrix $R = \left(PDSS_{ud}\right)_{m \times m}$ and the PDIS matrix $Q = \left(PDIS_{ud}\right)_{m \times m}$ can be obtained, respectively.

Then calculate the total possibility degree superior score (TPDSS) and total possibility degree inferior score (TPDIS) of each alternative based on PDSS matrix and the PDIS matrix are shown as:

$$TPDSS_u = \sum_{d=1, d \neq u}^{n} PDSS_{ud}, \left(u=1,2,...,m\right); \tag{34}$$

$$TPDIS_u = \sum_{d=1, d \neq u}^{n} PDIS_{ud}, \left(u=1,2,...,m\right), \tag{35}$$

where $TPDSS_u \in \left[0, \frac{m-1}{2}\right]$, $TPDIS_u \in \left[-\frac{m-1}{2}, 0\right]$.

Then, normalize the values of the TPDSS and TPDIS are shown as:

$$NSS_u = \frac{TPDSS_u}{\max_u TPDSS_u}, \left(u=1,2,...,m\right); \tag{36}$$

$$NIS_u = \frac{TPDIS_u}{\min_u TPDIS_u}, \left(u=1,2,...,m\right). \tag{37}$$

The total score (TS) for each alternative is computed by:

$$TS_u = \frac{1}{2}\left(NSS_u + \left(1 - NIS_u\right)\right), \left(u=1,2,...,m\right), \tag{38}$$

where $0 \leq TS_u \leq 1$, and the higher the TS of the alternative x_u, the better the alternative.

4.3. ELECTRE-EDAS method based on MGPLTSs for MAGDM problem

Then, the ELECTRE-EDAS method based on MGPLTSs is proposed to deal with MAGDM problems. Figure 1 illustrates the structure and procedure of the method.

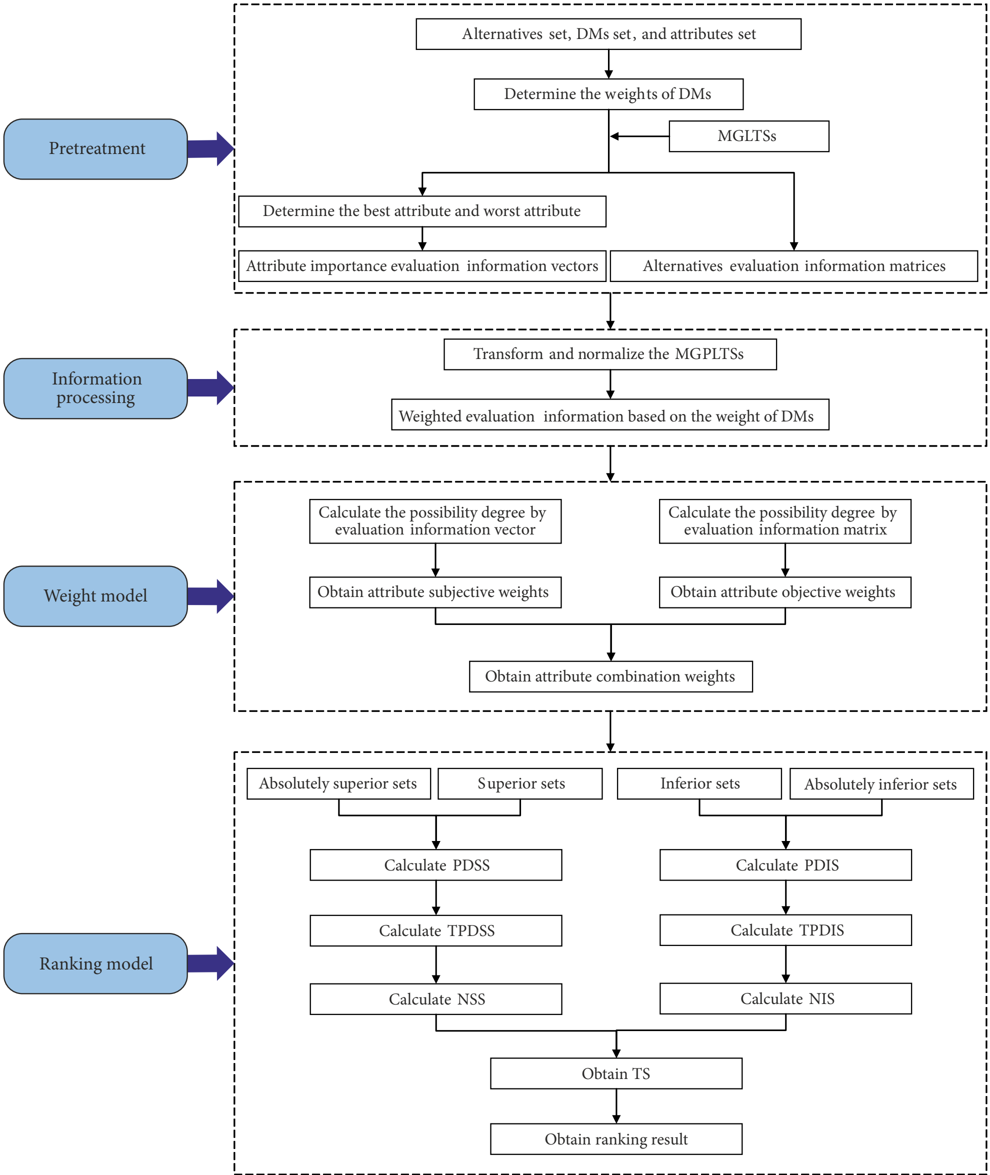

Figure 1. The flowchart of the created MAGDM method

The specific steps are as follows:

Step 1. Transform cost attributes into beneficial attributes. Assumed that the linguistic term under the cost attribute is l_g, after the transformation, it becomes l_{-g}.

Step 2. Normalize the MGPLTSs. According to the method introduced in **Definition 4**, all MGSPLTSs are standardized.

Step 3. Obtain weighted evaluation information matrices based on the weight of DM, and finally integrate the τ weighted matrices into one matrix.

Step 4. Calculate the combination weights of attributes.

(1) First, calculate the subjective weights by BWM model.
According to the BWM calculation steps in section 4.2, we can obtain the subjective weights $w=(w_1,w_2,...,w_n)$ by Eq. (11).

(2) Then, calculate the objective weights by maximizing deviation model.
According to the evaluation information under each attribute, the possibility degree matrix $H^v=\left[P_{ud}^v\right]\left(u=1,2,...,m;u\neq d;d=1,2,...,m;v=1,2,...,n\right)$ is calculated by pairwise comparison of alternatives.
The objective weights $\theta^*=\left(\theta_1^*,\theta_2^*,...,\theta_n^*\right)$ is calculated according to Eq. (21).

(3) Finally, obtain the combination weights $\omega=(\omega_1,\omega_2,...,\omega_n)$ according to Eq. (27).

Step 5. Classify the attributes based on the possibility degree $P_{ud}^v\left(u=1,2,...,m;u\neq d;d=1,2,...,m\right)$ by Eqs (28)–(31).

Step 6. Calculate the $PDSS_{ud}\left(u=1,2,...,m;u\neq d;d=1,2,...,m\right)$ by Eq. (32), and calculate the $PDIS_{ud}\left(u=1,2,...,m;u\neq d;d=1,2,...,m\right)$ by Eq. (33).

Step 7. Calculate the $TPDSS_u\left(u=1,2,...,m\right)$ and $TPDIS_u\left(u=1,2,...,m\right)$ by Eq. (34) and Eq. (35).

Step 8. Calculate the $NSS_u\left(u=1,2,...,m\right)$ and $NIS_u\left(u=1,2,...,m\right)$ by Eq. (36) and Eq. (37).

Step 9. Obtain the $TS_u\left(u=1,2,...,m\right)$ by Eq. (38). Then the final ranking of alternatives can be obtained.

5. Application examples

In what follows, the created MAGDM method was applied to solve the problem of the SMSS, and the validity and reliability of the method are verified. Finally, the created method was compared with the existing methods to illustrate the advantages.

5.1. The attributes of the SMSS

Supplier selection has been studied by scholars for decades (Rezaei et al., 2016), and the initial research on supplier selection can be traced back to 1966 (Dickson, 1966). Dickson investigated 273 purchasing managers from large and medium-sized enterprises by questionnaire to study the attributes of the supplier selection and obtained 23 possible important selection attributes (Dickson, 1966). Some of the selected attributes involved in the Dickson's study (Dickson, 1966) are still the basic attribute for selecting suppliers in the current business environment. The most important thing for the medical industry is to take care of patients, which means that medical products have higher requirements for hygiene and production levels than ordinary commodities. In addition, considering the particularity of the medical industry, the timeliness of the delivery of medical supplies is also a significant point. Comprehensively considering the above aspects and the perspective of sustainable suppliers, and referring to a large number of researches on sustainable supplier selection and medical supplier selection, Table 1 shows the attributes and their meanings.

Table 1. Attributes of sustainable and medical supplier selection

Attribute	Definition	References
Environmental attributes		
Environmental competencies	The company's measures and efforts for environmental protection	(Ghadimi et al., 2018; Stević et al., 2020; Wei et al., 2019; Zimmer et al., 2016)
Recycling	Reuse of raw materials	(Memari et al., 2019; Stević et al., 2020; Yu et al., 2019a)
Eco-design	Environmental impact of product lifecycle	(Memari et al., 2019; Yu et al., 2019a)
Green image	Establish the company's environmental image	(Ghadimi et al., 2018; Wei et al., 2019)
Pollution control	Establish guidelines to reduce the impact of polluting the environment	(Ghadimi et al., 2018; Stević et al., 2020)
Social attributes		
Health and safety	Employee health and life protection measures	(Memari et al., 2019; Stević et al., 2020; Yu et al., 2019a; Zimmer et al., 2016)
Disciplinary and practices	Develop safety measures and punishment system	(Ghadimi et al., 2018; Memari et al., 2019; Stević et al., 2020; Zimmer et al., 2016)
Staff training	Staff training and education	(Memari et al., 2019; Stević et al., 2020)
Information disclosure	Disclosure of information to stakeholders	(Stević et al., 2020; Yu et al., 2019a)
Employee rights and welfare	Respect the rights and interests of employees and protect their life needs	(Stević et al., 2020; Yu et al., 2019a)
Economic attributes		
Price	The value of products and services and the cost of transporting goods	(Ghadimi et al., 2018; Jia et al., 2019; Memari et al., 2019; (Stević et al., 2020; Wei et al., 2019; Yu et al., 2019a; Zimmer et al., 2016)
Delivery	Timeliness of delivery of products or services	(Ghadimi et al., 2018; Jia et al., 2019; Stević et al., 2020; Yu et al., 2019a; Zimmer et al., 2016)
Quality	The product quality meets the daily use, and the service quality is guaranteed	(Ghadimi et al., 2018; Jia et al., 2019; Memari et al., 2019; Stević et al., 2020; Yu et al., 2019a; Zimmer et al., 2016)
Reliability	The company's ability to accomplish the set goals	(Stević et al., 2020)
Technical capability	Ability to innovate products and services	(Ghadimi et al., 2018; Memari et al., 2019; Stević et al., 2020; Yu et al., 2019a; Zimmer et al., 2016)

Due to the particularity of the medical industry, product quality, price, and delivery time in economic attributes are more important than environmental attributes and social attributes. Therefore, we have summarized the environmental attributes and social attributes, and finally selected 5 attributes: (1) Environmental competencies, the ability to protect the environment and produce green products; (2) Social responsibility, respect and protect the rights and interests of employees, employee training, information publicity, and respect for the policies; (3) Price, the value of products and services and the cost of transporting goods; (4) Delivery, timeliness of delivery of products or services; (5) Quality, the product quality meets the daily use, and the service quality is guaranteed.

5.2. Application of the created MAGDM method

Case 1. Shandong Provincial Hospital is located in Jinan City, Shandong Province. It is a comprehensive hospital with medical treatment, scientific research and grassroots guidance. The equipment and products used for treatment in hospitals must strictly meet medical standards. Affected by COVID-19, the requirements for the supply of medical equipment have become stricter. Therefore, the sustainable medical supplier is particularly important. In 2021, Shandong Provincial Hospital needs to purchase a batch of medical equipment for the treatment of COVID-19. First, determine the three DMs $E=\{e_1,e_2,e_3\}$ for the supplier selection: The first DM e_1 has decades of leadership experience, doctor of economics, works in a hospital, and has experienced in sustainable supplier selection; The second DM e_2 is a doctor of medicine, working in a hospital; The third DM e_3 is a doctor of medicine, working in a hospital. Suppose the weights of DMs are $Y=(0.3,0.3,0.4)^T$. These three DMs have different habits and preferences for the granularity of LTSs with 3, 5 and 7 granularity levels.

$$S^{1,3}=\left\{l^3_{-1}=bad,\ l^3_0=medium,\ l^3_1=good\right\},$$

$$S^{2,5}=\left\{l^5_{-2}=very\ bad,\ l^5_{-1}=bad,\ l^5_0=medium,\ l^5_1=good,\ l^5_2=very\ good\right\},$$

$$S^{3,7}=\begin{Bmatrix} l^7_{-3}=extremely\ bad,\ l^7_{-2}=very\ bad,\ l^7_{-1}=bad, \\ l^7_0=medium,\ l^7_1=good,\ l^7_2=very\ bad,\ l^7_3=extremely\ good \end{Bmatrix}.$$

In this selection, a total of four medical equipment supplies are participated. Table 2 gives the basic information of these four potential suppliers.

According to the evaluation attributes A = {a_1 = Price, a_2 = Delivery, a_3 = Quality, a_4 = Environmental competencies, a_5 = Social responsibility} selected in Section 6.1, the DMs give evaluation information for four potential suppliers shown in Tables 3–5, respectively.

Table 2. Potential suppliers

Suppliers	Basic Information
Supplier x_1	Located in Jinan City, Shandong Province, founded in 2008, sells class II medical devices, machinery.
Supplier x_2	Located in Jinan City, Shandong Province, founded in 2010, sells class II medical devices.
Supplier x_3	Located in Jinan City, Shandong Province, founded in 2010, sells and R&D class II, III medical devices.
Supplier x_4	Located in Hefei, Anhui Province, established in 2016, sales R&D class II, III medical devices.

Table 3. The decision matrix U_1 provided by the DM e_1

	a_1	a_2	a_3	a_4	a_5
x_1	$\{l_0^7(1)\}$	$\{l_2^7(1)\}$	$\{l_1^7(1)\}$	$\{l_1^7(0.8), l_2^7(0.2)\}$	$\{l_0^7(0.8), l_1^7(0.2)\}$
x_2	$\{l_0^7(0.4), l_1^7(0.6)\}$	$\{l_1^7(0.3), l_2^7(0.7)\}$	$\{l_1^7(1)\}$	$\{l_2^7(1)\}$	$\{l_1^7(0.8), l_2^7(0.2)\}$
x_3	$\{l_{-1}^7(0.9), l_0^7(0.1)\}$	$\{l_2^7(1)\}$	$\{l_1^7(0.3), l_2^7(0.7)\}$	$\{l_1^7(1)\}$	$\{l_2^7(0.7), l_3^7(0.3)\}$
x_4	$\{l_{-2}^7(0.1), l_{-1}^7(0.9)\}$	$\{l_2^7(0.8), l_3^7(0.2)\}$	$\{l_1^7(1)\}$	$\{l_2^7(0.5), l_3^7(0.5)\}$	$\{l_2^7(1)\}$

Table 4. The decision matrix U_2 provided by the DM e_2

	a_1	a_2	a_3	a_4	a_5
x_1	$\{l_0^5(1)\}$	$\{l_0^5(0.4), l_1^5(0.6)\}$	$\{l_1^5(1)\}$	$\{l_1^5(1)\}$	$\{l_0^5(0.9), l_1^5(0.1)\}$
x_2	$\{l_0^5(1)\}$	$\{l_0^5(0.5), l_1^5(0.5)\}$	$\{l_0^5(0.5), l_1^5(0.5)\}$	$\{l_1^5(0.3), l_2^5(0.7)\}$	$\{l_1^5(1)\}$
x_3	$\{l_{-1}^5(0.8), l_0^5(0.2)\}$	$\{l_2^5(1)\}$	$\{l_1^5(0.6), l_2^5(0.4)\}$	$\{l_1^5(0.8), l_2^5(0.2)\}$	$\{l_1^5(0.9), l_2^5(0.1)\}$
x_4	$\{l_{-1}^5(1)\}$	$\{l_1^5(0.9), l_2^5(0.1)\}$	$\{l_1^5(1)\}$	$\{l_{-1}^5(0.7), l_0^5(0.3)\}$	$\{l_{-1}^5(0.5), l_0^5(0.5)\}$

Table 5. The decision matrix U_3 provided by the DM e_3

	a_1	a_2	a_3	a_4	a_5
x_1	$\{l_0^3(1)\}$	$\{l_0^3(1)\}$	$\{l_0^3(1)\}$	$\{l_0^3(0.9), l_1^3(0.1)\}$	$\{l_1^3(1)\}$
x_2	$\{l_0^3(0.5), l_1^3(0.5)\}$	$\{l_0^3(1)\}$	$\{l_0^3(0.2), l_1^3(0.8)\}$	$\{l_0^3(0.9), l_1^3(0.1)\}$	$\{l_{-1}^3(0.6), l_0^3(0.4)\}$
x_3	$\{l_0^3(1)\}$	$\{l_0^3(0.5), l_1^3(0.5)\}$	$\{l_1^3(1)\}$	$\{l_0^3(0.1), l_1^3(0.9)\}$	$\{l_1^3(1)\}$
x_4	$\{l_{-1}^3(0.2), l_0^3(0.8)\}$	$\{l_0^3(1)\}$	$\{l_0^3(1)\}$	$\{l_0^3(1)\}$	$\{l_{-1}^3(0.5), l_0^3(0.5)\}$

Step 1. Transform cost attributes into beneficial attributes.

Among the five attributes, only price is the cost attribute. After transformation, the evaluation information matrices $\tilde{U}_1, \tilde{U}_2, \tilde{U}_3$ are shown in Tables 6–8, respectively.

Table 6. The decision matrix $\tilde{U}_1$ provided by the DM e_1

	a_1	a_2	a_3	a_4	a_5
x_1	$\{l_0^7(1)\}$	$\{l_2^7(1)\}$	$\{l_1^7(1)\}$	$\{l_1^7(0.8), l_2^7(0.2)\}$	$\{l_0^7(0.8), l_1^7(0.2)\}$
x_2	$\{l_{-1}^7(0.6), l_0^7(0.4)\}$	$\{l_1^7(0.3), l_2^7(0.7)\}$	$\{l_1^7(1)\}$	$\{l_2^7(1)\}$	$\{l_1^7(0.8), l_2^7(0.2)\}$
x_3	$\{l_0^7(0.1), l_1^7(0.9)\}$	$\{l_2^7(1)\}$	$\{l_1^7(0.3), l_2^7(0.7)\}$	$\{l_1^7(1)\}$	$\{l_2^7(0.7), l_3^7(0.3)\}$
x_4	$\{l_1^7(0.9), l_2^7(0.1)\}$	$\{l_2^7(0.8), l_3^7(0.2)\}$	$\{l_1^7(1)\}$	$\{l_2^7(0.5), l_3^7(0.5)\}$	$\{l_2^7(1)\}$

Table 7. The decision matrix $\tilde{U}_2$ provided by the DM e_2

	a_1	a_2	a_3	a_4	a_5
x_1	$\{l_0^5(1)\}$	$\{l_0^5(0.4), l_1^5(0.6)\}$	$\{l_1^5(1)\}$	$\{l_1^5(1)\}$	$\{l_0^5(0.9), l_1^5(0.1)\}$
x_2	$\{l_0^5(1)\}$	$\{l_0^5(0.5), l_1^5(0.5)\}$	$\{l_0^5(0.5), l_1^5(0.5)\}$	$\{l_1^5(0.3), l_2^5(0.7)\}$	$\{l_1^5(1)\}$
x_3	$\{l_0^5(0.2), l_1^5(0.8)\}$	$\{l_2^5(1)\}$	$\{l_1^5(0.6), l_2^5(0.4)\}$	$\{l_1^5(0.8), l_2^5(0.2)\}$	$\{l_1^5(0.9), l_2^5(0.1)\}$
x_4	$\{l_1^5(1)\}$	$\{l_1^5(0.9), l_2^5(0.1)\}$	$\{l_1^5(1)\}$	$\{l_{-1}^5(0.7), l_0^5(0.3)\}$	$\{l_{-1}^5(0.5), l_0^5(0.5)\}$

Table 8. The decision matrix $\tilde{U}_3$ provided by the DM e_3

	a_1	a_2	a_3	a_4	a_5
x_1	$\{l_0^3(1)\}$	$\{l_0^3(1)\}$	$\{l_0^3(1)\}$	$\{l_0^3(0.9), l_1^3(0.1)\}$	$\{l_1^3(1)\}$
x_2	$\{l_{-1}^3(0.5), l_0^3(0.5)\}$	$\{l_0^3(1)\}$	$\{l_0^3(0.2), l_1^3(0.8)\}$	$\{l_0^3(0.9), l_1^3(0.1)\}$	$\{l_{-1}^3(0.6), l_0^3(0.4)\}$
x_3	$\{l_0^3(1)\}$	$\{l_0^3(0.5), l_1^3(0.5)\}$	$\{l_1^3(1)\}$	$\{l_0^3(0.1), l_1^3(0.9)\}$	$\{l_1^3(1)\}$
x_4	$\{l_0^3(0.8), l_1^3(0.2)\}$	$\{l_0^3(1)\}$	$\{l_0^3(1)\}$	$\{l_0^3(1)\}$	$\{l_{-1}^3(0.5), l_0^3(0.5)\}$

Step 2. Normalize the PLTSs. The sum of the probabilities of all PLTSs is 1, without normalization.

Step 3. Weighted evaluation matrices based on DM weight. The integrated matrix is shown in Table 9.

Table 9. The integrated matrix weighted by DMs

	a_1	a_2	a_3	a_4	a_5
x_1	$\{l_0^7(0.3), l_0^5(0.3), l_0^3(0.4)\}$	$\{l_2^7(0.3), l_0^5(0.12), l_1^5(0.18), l_0^3(0.4)\}$	$\{l_1^7(0.3), l_1^5(0.3), l_0^3(0.4)\}$	$\{l_1^7(0.24), l_2^7(0.06) l_1^5(0.3), l_0^3(0.36), l_1^3(0.04)\}$	$\{l_0^7(0.24), l_1^7(0.06), l_0^5(0.27), l_1^5(0.03), l_1^3(0.4)\}$
x_2	$\{l_{-1}^7(0.18), l_0^7(0.12), l_0^5(0.3), l_{-1}^3(0.2), l_0^3(0.2)\}$	$\{l_1^7(0.09), l_2^7(0.21), l_0^5(0.15), l_1^5(0.15), l_0^3(0.4)\}$	$\{l_1^7(0.3), l_0^5(0.15), l_1^5(0.15), l_0^3(0.08), l_1^3(0.32)\}$	$\{l_2^7(0.3), l_1^5(0.09), l_2^5(0.21), l_0^3(0.36), l_1^3(0.04)\}$	$\{l_1^7(0.24), l_2^7(0.06), l_1^5(0.3), l_{-1}^3(0.24), l_0^3(0.16)\}$

End of Table 9

	a_1	a_2	a_3	a_4	a_5
x_3	$\left\{l_0^7(0.03), l_1^7(0.27), l_0^5(0.06), l_1^5(0.24), l_0^3(0.4)\right\}$	$\left\{l_2^7(0.3), l_2^5(0.3), l_0^3(0.2), l_1^3(0.2)\right\}$	$\left\{l_1^7(0.09), l_2^7(0.21), l_1^5(0.18), l_2^5(0.12), l_1^3(0.4)\right\}$	$\left\{l_1^7(0.3), l_1^5(0.24), l_2^5(0.06), l_0^3(0.04), l_1^3(0.36)\right\}$	$\left\{l_2^7(0.21), l_3^7(0.09), l_1^5(0.27), l_2^5(0.03), l_1^3(0.4)\right\}$
x_4	$\left\{l_1^7(0.27), l_2^7(0.03), l_1^5(0.3), l_0^3(0.32), l_1^3(0.08)\right\}$	$\left\{l_2^7(0.24), l_3^7(0.06), l_1^5(0.27), l_2^5(0.03), l_0^3(0.4)\right\}$	$\left\{l_1^7(0.3), l_1^5(0.3), l_0^3(0.4)\right\}$	$\left\{l_2^7(0.15), l_3^7(0.15), l_{-1}^5(0.21), l_0^5(0.09), l_0^3(0.4)\right\}$	$\left\{l_2^7(0.3), l_{-1}^5(0.15), l_0^5(0.15), l_{-1}^3(0.2), l_0^3(0.2)\right\}$

Step 4. Calculate the combination weights of attributes.

(1) First, calculate the subjective weights based on BWM.
The best attribute is a_5, the worst attribute is a_2. The attribute importance evaluation vectors C given by the DM are shown in Tables 10–12.

Table 10. The vector C_1 given by the DM e_1

	a_1	a_2	a_3	a_4	a_5
e_1	$\left\{l_{-2}^7(0.2), l_{-1}^7(0.8)\right\}$	$\left\{l_{-2}^7(1)\right\}$	$\left\{l_1^7(0.8), l_2^7(0.2)\right\}$	$\left\{l_0^7(1)\right\}$	$\left\{l_2^7(1)\right\}$

Table 11. The vector C_2 given by the DM e_2

	a_1	a_2	a_3	a_4	a_5
e_2	$\left\{l_{-1}^5(0.1), l_0^5(0.9)\right\}$	$\left\{l_{-1}^5(0.7), l_0^5(0.3)\right\}$	$\left\{l_0^5(0.8), l_1^5(0.2)\right\}$	$\left\{l_0^5(1)\right\}$	$\left\{l_0^5(0.7), l_1^5(0.3)\right\}$

Table 12. The vector C_3 given by the DM e_3

	a_1	a_2	a_3	a_4	a_5
e_3	$\left\{l_{-1}^3(0.5), l_0^3(0.5)\right\}$	$\left\{l_{-1}^3(0.1), l_0^3(0.9)\right\}$	$\left\{l_0^3(1)\right\}$	$\left\{l_{-1}^3(0.2), l_0^3(0.8)\right\}$	$\left\{l_0^3(0.8), l_1^3(0.2)\right\}$

Then, get the weighted evaluation vector based on the weight of DMs shown in Table 13.

Table 13. The weighted vector

	a_1	a_2	a_3	a_4	a_5
	$\left\{ \begin{array}{l} l_{-2}^{7}(0.06), \\ l_{-1}^{7}(0.24), \\ l_{-1}^{5}(0.03), \\ l_{0}^{5}(0.27), \\ l_{-1}^{3}(0.2), \\ l_{0}^{3}(0.2) \end{array} \right\}$	$\left\{ \begin{array}{l} l_{-2}^{7}(0.3), \\ l_{-1}^{5}(0.21), \\ l_{0}^{5}(0.09), \\ l_{-1}^{3}(0.04), \\ l_{0}^{3}(0.36) \end{array} \right\}$	$\left\{ \begin{array}{l} l_{1}^{7}(0.24), \\ l_{2}^{7}(0.06), \\ l_{0}^{5}(0.24), \\ l_{1}^{5}(0.06), \\ l_{0}^{3}(0.36), \\ l_{1}^{3}(0.04) \end{array} \right\}$	$\left\{ \begin{array}{l} l_{0}^{7}(0.3), \\ l_{0}^{5}(0.3), \\ l_{-1}^{3}(0.08), \\ l_{0}^{3}(0.32) \end{array} \right\}$	$\left\{ \begin{array}{l} l_{2}^{7}(0.3), \\ l_{0}^{5}(0.18), \\ l_{1}^{5}(0.12), \\ l_{0}^{3}(0.32), \\ l_{1}^{3}(0.08) \end{array} \right\}$

The possibility degree matrix $H = \left[P_{vt}\right]_{n \times n}$ is calculated based on Eq. (6), and get.

$$H = \begin{bmatrix} 0.50 & 0.51 & 0.13 & 0.24 & 0.12 \\ 0.49 & 0.50 & 0.12 & 0.22 & 0.11 \\ 0.87 & 0.88 & 0.50 & 0.65 & 0.34 \\ 0.76 & 0.78 & 0.35 & 0.50 & 0.31 \\ 0.88 & 0.89 & 0.66 & 0.69 & 0.50 \end{bmatrix}.$$

According to Eq. (11), the **Model 5** is established according to matrix *H*:

$$\min \delta$$

$$s.t. \begin{cases} \left|2(w_5 - w_1) + 0.5 - 0.88\right| \le \delta, \\ \left|2(w_5 - w_2) + 0.5 - 0.89\right| \le \delta, \\ \left|2(w_5 - w_3) + 0.5 - 0.66\right| \le \delta, \\ \left|2(w_5 - w_4) + 0.5 - 0.69\right| \le \delta, \\ \left|2(w_1 - w_2) + 0.5 - 0.51\right| \le \delta, \\ \left|2(w_3 - w_2) + 0.5 - 0.88\right| \le \delta, \\ \left|2(w_4 - w_2) + 0.5 - 0.78\right| \le \delta, \\ w_1 + w_2 + w_3 + w_4 + w_5 = 1 \\ \delta \ge 0,\ w_v \ge 0,\ (v = 1,2,\ldots,5). \end{cases}$$

By solving **Model 5**, we get $w = (0.1040, 0.0990, 0.2640, 0.2140, 0.3190)$ and $\delta = 0.05$. δ is close to zero, therefore, it meets an acceptable level of consistency.

(2) Then, calculate the objective weights.

According to the evaluation information under each attribute, the possibility degree matrix $H^{v} = \left[P_{ud}^{v}\right](u = 1,2,3,4; u \ne d; d = 1,2,3,4; v = 1,2,3,4,5)$ is calculated by pairwise comparison of alternatives, and the results are shown in Table 14.

Table 14. Possibility degree matrix H^v

v	P_{12}^v	P_{13}^v	P_{14}^v	P_{21}^v	P_{23}^v	P_{24}^v	P_{31}^v	P_{32}^v	P_{34}^v	P_{41}^v	P_{42}^v	P_{43}^v
1	0.76	0.33	0.24	0.24	0.17	0.13	0.67	0.83	0.35	0.76	0.87	0.65
2	0.55	0.21	0.42	0.45	0.18	0.37	0.79	0.82	0.78	0.58	0.63	0.22
3	0.27	0.06	0.50	0.73	0.23	0.72	0.94	0.77	0.94	0.50	0.28	0.06
4	0.32	0.18	0.62	0.68	0.34	0.72	0.82	0.66	0.85	0.38	0.28	0.15
5	0.78	0.21	0.80	0.22	0.05	0.55	0.79	0.95	0.95	0.20	0.45	0.05

Build **Model 6** according to Eq. (15), and get

$$\max H_v = 3.86480_1 + 3.58140_2 + 4.12280_3 + 3.67790_4 + 4.320_5$$

$$s.t.\begin{cases}\theta_1 + \theta_2 + \theta_3 + \theta_4 + \theta_5 = 1 \\ \theta_v \geq 0,\ (v = 1,2,\ldots,5).\end{cases}$$

According to the Eq. (21), get $\theta^* = (0.1975, 0.1830, 0.2107, 0.1880, 0.2208)$.

(3) Finally, according to Eq. (22) and Eq. (27), obtain the combination weights:
$\omega = (0.1463, 0.1374, 0.2407, 0.2047, 0.2709)$.

Step 5. Based on the possibility degree $P_{ud}^v\left(u = 1,2,3,4; u \neq d; d = 1,2,3,4; v = 1,2,3,4,5\right)$, the attributes are classified according to Eqs (28)–(31), and the results are shown in Table 15.

Table 15. Absolutely superior, Superior, Inferior and absolutely inferior sets

Absolutely superior set	Superior set	Inferior set	Absolutely inferior set
$V_{12}^{AS} = f$	$V_{12}^{S} = \{1,2,5\}$	$V_{12}^{I} = \{3,4\}$	$V_{12}^{AI} = f$
$V_{13}^{AS} = f$	$V_{13}^{S} = f$	$V_{13}^{I} = \{1,2,3,4,5\}$	$V_{13}^{AI} = f$
$V_{14}^{AS} = f$	$V_{14}^{S} = \{3,4,5\}$	$V_{14}^{I} = \{1,2\}$	$V_{14}^{AI} = f$
$V_{21}^{AS} = f$	$V_{21}^{S} = \{3,4\}$	$V_{21}^{I} = \{1,2,5\}$	$V_{21}^{AI} = f$
$V_{23}^{AS} = f$	$V_{23}^{S} = f$	$V_{23}^{I} = \{1,2,3,4,5\}$	$V_{23}^{AI} = f$
$V_{24}^{AS} = f$	$V_{24}^{S} = \{3,4,5\}$	$V_{24}^{I} = \{1,2\}$	$V_{24}^{AI} = f$
$V_{31}^{AS} = f$	$V_{31}^{S} = \{1,2,3,4,5\}$	$V_{31}^{I} = f$	$V_{31}^{AI} = f$
$V_{32}^{AS} = f$	$V_{32}^{S} = \{1,2,3,4,5\}$	$V_{32}^{I} = f$	$V_{32}^{AI} = f$
$V_{34}^{AS} = f$	$V_{34}^{S} = \{2,3,4,5\}$	$V_{34}^{I} = \{1\}$	$V_{34}^{AI} = f$
$V_{41}^{AS} = f$	$V_{41}^{S} = \{1,2,3\}$	$V_{41}^{I} = \{4,5\}$	$V_{41}^{AI} = f$
$V_{42}^{AS} = f$	$V_{42}^{S} = \{1,2\}$	$V_{42}^{I} = \{3,4,5\}$	$V_{42}^{AI} = f$
$V_{43}^{AS} = f$	$V_{43}^{S} = \{1\}$	$V_{43}^{I} = \{2,3,4,5\}$	$V_{43}^{AI} = f$

Step 6. Calculate the $PDSS_{ud}\left(u=1,2,3,4;u\neq d;d=1,2,3,4\right)$ by Eq. (32), and calculate the $PDIS_{ud}\left(u=1,2,3,4;u\neq d;d=1,2,3,4\right)$ by Eq. (33), and get.

$$PDSS=\begin{bmatrix} - & 0.1208 & 0 & 0.1058 \\ 0.0922 & - & 0 & 0.1115 \\ 0.3147 & 0.3119 & - & 0.3379 \\ 0.0490 & 0.0720 & 0.0219 & - \end{bmatrix},$$

$$PDIS=\begin{bmatrix} - & -0.0937 & -0.3175 & -0.0512 \\ -0.0989 & - & -0.3010 & -0.0765 \\ 0 & 0 & - & -0.0192 \\ -0.0834 & -0.1094 & -0.3310 & - \end{bmatrix}.$$

Step 7. $TPDSS=\left(0.2266,0.2037,0.9645,0.1430\right)$ is obtained by Eq. (34) and $TPDIS=\left(-0.4559,-0.5046,-0.0219,-0.5553\right)$ is obtained by Eq. (35).

Step 8. $NSS=\left(0.2349,0.2112,1.0000,0.1482\right)$ is obtained by Eq. (36) and $NIS=\left(0.8211,0.9088,0.0395,1.0000\right)$ is obtained by Eq. (37).

Step 9. Obtain the $TS=\left(0.2069,0.1512,0.9802,0.0741\right)$ by Eq. (37). Then the final ranking of alternatives is $x_3\succ x_1\succ x_2\succ x_4$.

5.3. Analysis on weight method

In Section 4, we proposed the subjective weight determination method and the objective weight determination method based on the possibility degree of MGPLTSs, and in order to avoid the disadvantages of the single weight method, we also introduced the combination weight method. This section only uses subjective weights and objective weights calculated in Section 6.2 to recalculate **Case 1**, and the ranking results are shown in Table 16.

In Table 16, the ranking results based on the subjective weights and combination weights are the same, but in the ranking results based on objective weights, x_2 is the worst. This shows that different weights cause different ranking results, which means that a reasonable combination weight can obtain more accurate results while avoiding the disadvantages of subjective and objective weights.

Table 16. Ranking results of subjective, objective and combination weights

Methods	Score Values	Ranking Results
Subjective weights	$TS_1=0.2428, TS_2=0.2069, TS_3=0.9871, TS_4=0.0509$	$x_3\succ x_1\succ x_2\succ x_4$
Objective weights	$TS_1=0.1595, TS_2=0.0653, TS_3=0.9702, TS_4=0.1043$	$x_3\succ x_1\succ x_4\succ x_2$
Combination weights	$TS_1=0.2069, TS_2=0.1512, TS_3=0.9802, TS_4=0.0741$	$x_3\succ x_1\succ x_2\succ x_4$

5.4. Comparison of existing MAGDM methods based on Case 1

Compare the created MAGDM method with existing methods from (Wang, 2019) and (Lei et al., 2020) for **Case 1**. The ranking results of different methods are shown in Table 17.

As shown in Table 17, the ranking results obtained by Wang's (2019) MAGDM algorithm and the created MAGDM method are consistent, i.e., $x_3 \succ x_2 \succ x_1 \succ x_4$. The optimal alternative and the worst alternative obtained by Lei's et al. (2020) TOPSIS method are consistent with the Wang's MAGDM algorithm and the created MAGDM method. This shows that the created MAGDM method is reasonable and effective.

Table 17. Ranking results of different methods

Methods	Score Values	Ranking Results
Wang's (2019) MAGDM algorithm based on PT (λ = 1)	$C_1 = 0.4208, C_2 = 0.3975,$ $C_3 = 0.7356, C_4 = 0.3747$	$x_3 \succ x_1 \succ x_2 \succ x_4$
Lei's et al. (2020) TOPSIS method	$PLRCD_1 = 0.6402, PLRCD_2 = 0.6864,$ $PLRCD_3 = 0.1209, PLRCD_4 = 0.7648$	$x_3 \succ x_2 \succ x_1 \succ x_4$
The created MAGDM method	$TS_1 = 0.2069, TS_2 = 0.1512,$ $TS_3 = 0.9802, TS_4 = 0.0741$	$x_3 \succ x_1 \succ x_2 \succ x_4$

Compared with these two methods, the created MAGDM method does not need to normalize the number of linguistic terms in PLTS. For Lei's et al. (2020) TOPSIS method, $L_1(p) = \{l_{-2}(0.6), l_{-1}(0.4)\}$ and $L_2(p) = \{l_{-2}(0.8), l_0(0.2)\}$ are two PLTSs with 5-granularity level, the distance measure used to compare two PLTSs is $d(L_1(p), L_2(p)) = 0$. However, the linguistic terms in these two PLTSs are not the same, so the distance measure is not reasonable. In addition, in the created MAGDM method, the attribute weights are calculated by combination weights, which makes the decision result more reasonable.

5.5. Comparison of existing MAGDM methods based on Case 2

In order to better illustrate the feasibility and effectiveness of the created MAGDM method, we further compare the proposed method with Mao's et al. (2019) ELECTRE and TOPSIS method, Wei's et al. (2019) MABAC method, Yu's et al. (2019b) method based on the probabilistic linguistic weighted average (PLWA) operator, and Pang's et al. (2016) extended TOPSIS method by Case 2.

Case 2 (Mao et al., 2019). Suppose that there are four alternatives $X = \{x_1, x_2, x_3, x_4\}$, four attributes $A = \{a_1 =$Cloud computing, $a_2 =$ Big data, $a_3 =$Artificial intelligence, $a_4 =$Block chain$\}$, and the weights of four attributes are $w = (0.2418, 0.2638, 0.2496, 0.2448)^T$. Suppose that there are three DMs $E = \{e_1, e_2, e_3\}$, and the weights of DMs are $Y = (0.48, 0.20, 0.32)^T$. DMs give evaluation information through LTS with 9-granularity level.

$$S = \left\{ \begin{array}{l} l_{-4} = extremely\ bad,\ l_{-3} = very\ bad,\ l_{-2} = bad,\ l_{-1} = \ a\ little\ bad, \\ l_0 = medium,\ l_1 = a\ little\ good,\ l_2 = good,\ l_3 = very\ bad,\ l_4 = extremely\ good \end{array} \right\}.$$

The evaluation information matrix U_1, U_2, U_3 given by three DMs with MGPLTSs are shown in Tables 18–20, respectively. The ranking results of different methods are shown in Table 21.

Table 18. The decision matrix U_1 provided by the DM e_1

	a_1	a_2	a_3	a_4
x_1	$\{l_{-2}(0.4), l_1(0.5)\}$	$\{l_2(0.6), l_4(0.4)\}$	$\{l_0(1)\}$	$\{l_{-2}(0.4), l_{-1}(0.6)\}$
x_2	$\{l_4(1)\}$	$\{l_2(0.4), l_4(0.5)\}$	$\{l_0(0.3), l_1(0.3), l_2(0.4)\}$	$\{l_2(0.3), l_3(0.7)\}$
x_3	$\{l_1(0.3), l_2(0.7)\}$	$\{l_1(0.4), l_2(0.3), l_3(0.3)\}$	$\{l_2(1)\}$	$\{l_{-1}(0.8), l_1(0.2)\}$
x_4	$\{l_{-1}(1)\}$	$\{l_1(0.6), l_2(0.4)\}$	$\{l_0(0.5), l_2(0.5)\}$	$\{l_3(1)\}$

Table 19. The decision matrix U_2 provided by the DM e_2

	a_1	a_2	a_3	a_4
x_1	$\{l_{-1}(0.3), l_1(0.7)\}$	$\{l_2(0.4), l_3(0.2), l_4(0.4)\}$	$\{l_0(0.7), l_1(0.3)\}$	$\{l_{-1}(1)\}$
x_2	$\{l_3(0.4), l_4(0.5)\}$	$\{l_3(1)\}$	$\{l_3(0.5), l_4(0.5)\}$	$\{l_0(0.4), l_2(0.6)\}$
x_3	$\{l_0(0.7), l_1(0.3)\}$	$\{l_1(0.6), l_2(0.3)\}$	$\{l_1(0.3), l_2(0.7)\}$	$\{l_{-1}(1)\}$
x_4	$\{l_{-2}(1)\}$	$\{l_1(0.5), l_2(0.4)\}$	$\{l_{-1}(1)\}$	$\{l_1(0.1), l_2(0.2), l_3(0.7)\}$

Table 20. The decision matrix U_3 provided by the DM e_3

	a_1	a_2	a_3	a_4
x_1	$\{l_0(0.4), l_1(0.6)\}$	$\{l_3(0.6), l_4(0.4)\}$	$\{l_{-1}(0.2), l_0(0.8)\}$	$\{l_{-1}(1)\}$
x_2	$\{l_3(0.4), l_4(0.6)\}$	$\{l_1(0.3), l_2(0.7)\}$	$\{l_3(0.6), l_4(0.4)\}$	$\{l_2(1)\}$
x_3	$\{l_0(0.6), l_1(0.4)\}$	$\{l_1(1)\}$	$\{l_{-1}(0.2), l_2(0.8)\}$	$\{l_{-1}(0.7), l_1(0.3)\}$
x_4	$\{l_{-4}(0.4), l_{-2}(0.4)\}$	$\{l_1(0.5), l_2(0.5)\}$	$\{l_{-1}(0.8), l_1(0.2)\}$	$\{l_2(1)\}$

Table 21. Ranking results of different methods

Methods	Score Values	Ranking Results
Mao's et al. (2019) ELECTRE and TOPSIS method	$CD_1 = 0.32, CD_2 = 0.82,$ $CD_3 = 0, CD_4 = 0.13$	$x_2 \succ x_1 \succ x_4 \succ x_3$
Wei's et al. (2019) MABAC method	$PLSV_1 = -0.1343, PLSV_2 = 0.0098,$ $PLSV_3 = -0.1376, PLSV_4 = -0.0806$	$x_2 \succ x_4 \succ x_1 \succ x_3$
Yu's et al. (2019b) PLWA operator	$v_1 = 3, v_2 = 4, v_3 = 2, v_4 = 1$	$x_2 \succ x_1 \succ x_3 \succ x_4$
Pang's et al. (2016) extended TOPSIS method	$CI_1 = -1.0190, CI_2 = 0.0000,$ $CI_3 = -0.9641, CI_4 = -1.2524$	$x_2 \succ x_3 \succ x_1 \succ x_4$
The created MAGDM method	$TS_1 = 0.2183, TS_2 = 0.9477,$ $TS_3 = 0.2745, TS_4 = 0.1348$	$x_2 \succ x_3 \succ x_1 \succ x_4$

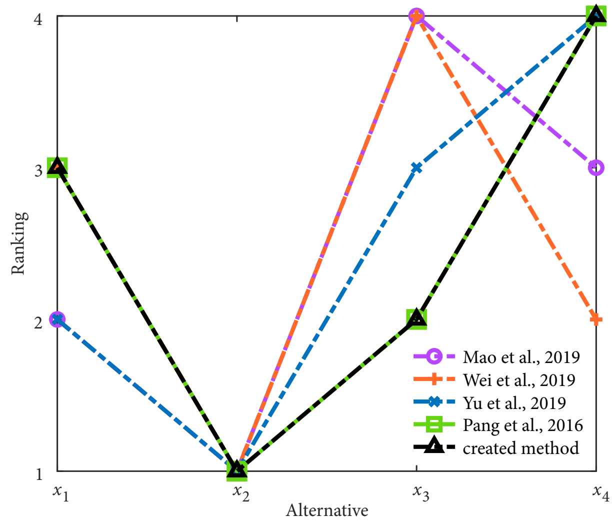

Figure 2. Ranking results of alternatives in different methods

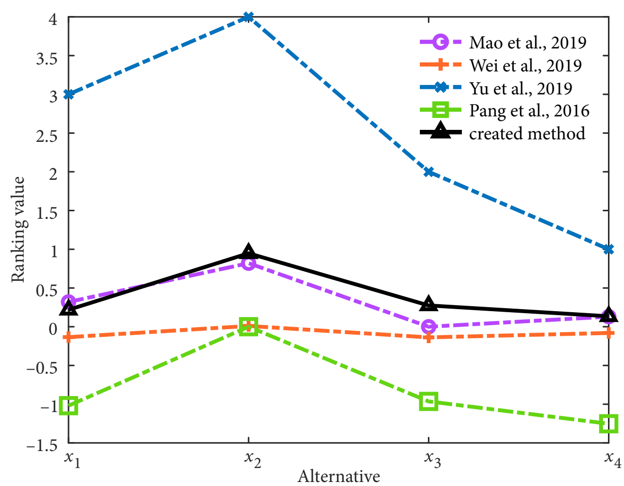

Figure 3. Ranking values of alternatives in different methods

As shown in Table 21 and Figure 2, for all methods mentioned above, the optimal alternative is always x_2. The ranking result of Pang's et al. (2016) extended TOPSIS method is consistent with the created MAGDM method, and other ranking results are slightly different. As shown in Figure 3, the ranking values of method (Yu et al., 2019b) are integers, while the degree of discrimination of the ranking values of method (2018) is relatively similar, and the distinction is not obvious. The reason why the ranking results of these methods are different is that the ranking mechanism of each method is different, which leads to different degrees of information distortion. The specific reasons and characteristics are explained in detail in sections 6.5.1–6.5.4.

5.5.1. Comparison with Mao's et al. (2019) ELECTRE and TOPSIS method

The information loss is considered as the fact that multiple results are inconsistent. In this method, the violation of possibility degree result and final ranking result are particularly prominent. For example, about the possibility degree result there is $x_3 \succ x_1$ (under the attributes a_1, a_3 and a_4, possibility degree ≥ 0.9), but for the final ranking result, we have $x_1 \succ x_3$ ($CD_1 = 0.32, CD_3 = 0$). Similarly, the violation occurs in the comparison between x_3 and x_4. The specific reasons for the different ranking results are shown as follows.

(1) The possibility degrees (Eqs (11) and (12) in Mao et al. (2019)), which are used to compare the two PLTS, only include the probability value, but don't include the corresponding linguistic terms.

(2) In ELECTRE method, the concordance index C (Eq. (59) in Mao et al. (2019)) and the discordance index D (Eq. (60) in Mao et al. (2019)), which are used to express the superiority degree and inferiority degree of alternatives, completely ignore the evaluation information with a probability degree less than 0.5, and the distance ratio used to indicate the inferiority degree in D expands the inferiority degree of the alternative.

Compared with Mao's et al. method, the proposed MGPLTS possibility degree has transitivity, because the calculation includes the probability value and the subscript of the linguistic terms. At the same time, the information aggregation tool of the alternatives in the created MAGDM method contains all the possibility degrees [0,1], and the superiority degree and inferiority degree of the alternatives are not exaggerated. Therefore, the ranking results of the created MAGDM method are more accurate and credible.

5.5.2. Comparison with Wei's et al. (2019) MABAC method

The specific reasons for the different ranking results are shown as follows.

(1) Normalization is the process of unifying the number of linguistic terms of different PLTS. In this method, the normalization method is to add some linguistic terms with a probability value of 0 (Definition 3 in Wei et al. (2019)). The probabilistic linguistic border approximation area (PLBAA) (Eqs (11)–(13) in Wei et al. (2019)) is obtained by multiplication, which means that the value of probability 0 is multiplied by a non-zero value, that is, the product result can only be 0.

(2) In MABAC method, PLBAA represents the average value of the evaluation information under the attribute. The superiority degree and inferiority degree of the alternatives are measured by calculating the distance between the evaluation information and the PLBAA. Under attributes a_2 and a_3, the corresponding distances are positive, which is inconsistent with the facts. This is because the probability information is lost when calculating PLBAA, making PLBAA smaller.

Compared with Wei's et al. method, the created MAGDM method does not involve the above two operations, which not only reduces the workload but also avoids information loss.

5.5.3. Comparison with Yu's et al. (2019b) PLWA operator

The specific reasons for the different ranking results are shown as follows.

(1) The probabilistic linguistic ordered weighted average (PLOWA) and PLWA operators are proposed by Yu et al. (2019b). Compared with PLWA, PLOWA has one descend-

ing process, but the calculation results are different, which means that PLWA operator does not have commutativity. In addition, after obtaining the PLWA or PLOWA result, the subscript of the linguistic terms is changed to an integer by rounding.

(2) The final ranking value of the alternatives is obtained by rounding the probability degree result to 0 or 1, which enlarges the degree of information loss.

Compared with Yu's et al. (2019b) method, the created MAGDM method has neither the rounding operation on the linguistic term subscript nor the operation to blur the possibility degree to 0 or 1, which avoids the loss of accuracy.

5.5.4. Comparison with Pang's et al. (2016) extended TOPSIS method

The specific reasons for the different ranking results are shown as follows.

(1) The distance measure has information loss because the probability value is directly multiplied by the subscript of the linguistic term, which means that as long as the subscript is 0, the result is 0. For example, $L_1(p)=\{l_0(0.4),l_2(0.6)\}$ and $L_2(p)=\{l_0(0.7),l_3(0.4)\}$ are two PLTSs, the $d\left(L_1(p),L_2(p)\right)=0$ (Eq. (19) in Pang et al. (2016)). However, the linguistic terms in the two PLTSs are not the same, obviously, this result is unreasonable. In addition, if the subscripts of linguistic terms in the two PLTSs are the same but belong to different granularity levels, this distance measure cannot be partitioned, which is obviously unreasonable.

(2) In TOPSIS method, the ranking value is determined by comparing the positive ideal solution (PIS) and the negative ideal solution (NIS). However, in this method, PIS and PIN are HFLTSs without probability information instead of PLTS. Obviously, this can produce a great of information loss.

Compared with the above four methods, the created MAGDM method is not necessary to normalize the PLTS and it can be used to deal with MGPLTSs, which is suitable for more complex decision-making environments. In addition, methods (Mao et al., 2019; Pang et al., 2016) only provide a method for determining attributes objective weights, while method (Yu et al., 2019b) does not consider the influence of attribute weights on decision-making results. On the contrary, the created MAGDM method includes the subjective and objective weights, which ensures decision-making result more reasonable.

5.6. Comparison with other supplier selection methods

As a MAGDM problem, SMSS is similar to sustainable supplier selection and medical supplier selection. To highlight the superiority of the created method in the SMSS method, compare it with the sustainable supplier selection method and the medical supplier selection method. The characteristics of different methods (information form, weight method, ranking method) are shown in Table 22.

(1) Information form. The information forms used in these six methods are different. Pythagorean 2-tuple linear numbers (He et al., 2019), triangular fuzzy number (Alamroshan et al., 2021), interval linear evaluations (Li et al., 2019b), fuzzy triangular number (Awasthi et al., 2018), triangular intrinsic fuzzy numbers (Wu et al., 2019a) are less applicable, and interval linguistic evaluations (Li et al., 2019b) need to convert the information form through a cloud model, which is cumbersome. The one that is

Table 22. Characteristics of other supplier selection methods

	Article	Information form	Weight method	Ranking methods
Medical supplier selection method	(Wei et al., 2019)	Probabilistic linguistic term sets	Combination weights: CRITIC method, Subjectively given	MABAC method
	(He et al., 2019)	Pythagorean 2-tuple linguistic numbers	Subjectively given	Taxonomy method and Operator
	(Alamroshan et al., 2021)	Triangular fuzzy number	BWM, ANP	VIKOR method
Sustainable supplier selection method	(Li et al., 2019b)	Interval linguistic evaluations	Combination weights	Cloud model and TOPSIS
	(Awasthi et al., 2018)	Fuzzy triangular number	AHP	VIKOR method
	(Wu et al., 2019a)	Triangular intuitionistic fuzzy numbers	Combination weights: AHP, Entropy method	Cumulative prospect theory
SMSS	This article	MGPLTS	Combination weights: BWM, Maximizing deviation method	ELECTRE-EDAS method

closest to the actual use environment is PLTS, but the MGPLTS used in this article is more suitable for complex environments than it.

(2) Weight method. The calculation of attribute weights in these methods includes subjective given and combination weights. The attribute weights are given subjectively ignore the influence of attribute weights on decision-making results, which makes the decision-making method lack rationality in dealing with specific problems. Combination weight is usually composed of a subjective weight method and an objective weight method. Subjective weight methods include AHP, ANP, BWM, etc., while AHP and ANP have a large amount of calculation and low consistency. BWM is an improved method based on AHP, which is more suitable for calculating the subjective weight. In addition, the combination method of combining the subjective and objective weights effectively is very important.

(3) Ranking methods. MABAC method (Wei et al., 2019) has been compared in section 6.5.2, and the results obtained by this method need to be improved. The calculation process of Taxonomy (He et al., 2019) is complicated and there are no outstanding highlights. Cloud model (Li et al., 2019b) is suitable for situations with a lot of data. When the data is less, the error is larger, and its conversion to the data leads to information loss. In addition, the EDAS method used in this article is an improvement based on the TOPSIS method (Li et al., 2019b) and the VIKOR method (Alamroshan et al., 2021), and the results are more reliable.

Compared with the existing supplier selection methods, the MGPLTS involved in this article is more suitable for the actual application environment, and the two methods that constitute the combination weight have higher consistency and rationality. In addition, the ELECTRE-EDAS method has fewer calculations and the results obtained are more reliable.

Conclusions

This article firstly proposes the possibility degree of MGPLTSs, and proves the four properties. At the same time, it is compared with the existing possibility degrees to show its rationality. Then, according to the characteristics of the new possibility degree, combined with BWM, a possibility degree-based BWM model is established to obtain the subjective weights, and the maximizing deviation method based on probability degree is proposed to calculate subjective weights of the attributes. Further, combination weights are obtained by information entropy. Moreover, a MAGDM method with MGPLTSs is proposed by integrating ELECTRE and EDAS method, and it is applied to the SMSS. In order to prove the reliability and effectiveness of the created MAGDM method, two cases were compared with the existing PLTSs decision-making methods. Of course, the limitation of the proposed method is not suitable for decision-making scenarios with too many attributes, which increases the workload of calculating the possibility degree.

In the future, we will use the created MAGDM method to project evaluation, emergency management, investment selection, etc. In addition, because different DMs may have conflicts when making decisions, it is necessary to adopt a consensus model in future decision-making methods.

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