Hindawi
Complexity
Volume 2021, Article ID 4839079, 20 pages
https://doi.org/10.1155/2021/4839079

Research Article

Probabilistic Linguistic-Based Group DEMATEL Method with Both Positive and Negative Influences

Yonghe Sun, Siyu Zhang, Zihang Huang, and Bin Miao

Faculty of Management and Economics, Kunming University of Science and Technology, Kunming, Yunnan 650093, China

Correspondence should be addressed to Zihang Huang; hzh1175593327@163.com

Received 5 June 2021; Accepted 23 August 2021; Published 14 September 2021

Academic Editor: Zeshui Xu

Decision-making trial and evaluation laboratory (DEMATEL) is a widely accepted factor analysis algorithm for complex systems. The rationality of the evaluation scale is the basis of sound DEMATEL decision-making. Unfortunately, the existing evaluation scales of DEMATEL failed to reasonably distinguish and describe the positive and negative influences between factors. Generally, the positive and negative influences between factors should be considered at the same time. In other words, negative influence between factors should not be directly ignored, which is improper and unrealistic. To better address this issue, we extend the evaluation scale of DEMATEL. We also integrate the scale-based group DEMATEL method with probabilistic linguistic term sets (PLTSs) to increase its effectiveness, which allows experts to express incomplete and uncertain linguistic preferences in DEMATEL decision-making. An experts' subjective weight adjustment method based on the similarity degree between PLTSs is introduced to determine experts' weights. Finally, an algorithm of probabilistic linguistic-based group DEMATEL method with both positive and negative influences is summarized, and an example is used to illustrate the proposed method and demonstrate its superiority. Our results demonstrate that the method proposed in this paper deals reasonably with realistic problems.

1. Introduction

As a factor analysis algorithm for complex socioeconomic system problems, by making full use of expertise and prior experience, decision-making trial and evaluation laboratory (DEMATEL) uses the form of an evaluation scale to judge the influence relationships between system factors and forms a direct influence matrix between factors. Then, the judgment of the relative importance and the direct and indirect causal relationships between the factors can be estimated through matrix operations.

The rationality of the evaluation scale of DEMATEL is the key to accurate decision-making. The evaluation scale of 0, 1, 2, and 3 was initially used to indicate the degree of direct influence between factors, representing "no influence," "low influence," "medium influence," and "high influence," respectively [1–3]. To effectively differentiate the intensity of influence between factors within a limited scale, Chiu et al. [4], Liou et al. [5], Tseng [6], Chen et al. [7], Lin et al. [8], and Uygun et al. [9] extended the DEMATEL scale to five levels, and the evaluation scale of 0, 1, 2, 3, and 4 was employed for complex problem analysis, where the scale value 0 still indicates "no influence," and 1, 2, 3, and 4, respectively, indicate "low influence," "medium influence," "high influence," and "very high influence." Huang et al. [10] and Tseng and Huang [11] proposed 11 evaluation levels, from 0 to 10, ranging from "no influence" to "very high influence," for influence relationship analysis. Dytczak and Ginda [12] further extended the DEMATEL evaluation scale to a more general form and reckoned that a scale reflecting the intensity of influences between factors could be expressed as 0 to N, where 0 means "no influence," and N is any assumed positive integer indicating the maximum degree of influence. Wu et al. [13] came up with a 1–5 scale, using 1 for "no influence," and 2, 3, 4, and 5 for "very low influence," "low influence," "high influence," and "very high influence," respectively. The 0–4 scale is the most widely used. Regrettably, although many scholars have studied and extended the DEMATEL scale, no existing scale can distinguish the positive and negative influences between factors, i.e., negative influences between factors are regarded and treated the same as positive influences resulting in those negative influences not being effectively reflected. The effects of positive and negative influences are obviously different, and it is unreasonable and inconsistent with practice to equate negative influences with positive ones. Therefore, in this paper, we define a new DEMATEL scale that considers and reflects both positive and negative influences between factors and propose operating rules and processing methods for matrices in the DEMATEL method using the new scale.

With regard to the judgment expression form, experts tend to make linguistic judgments when judging the influence relationships between factors due to the complex decision-making environment and the vagueness inherent in human thinking. Considering that experts may hesitate among several possible linguistic terms when expressing preferences by means of linguistic information, Rodríguez et al. [14] proposed hesitant fuzzy linguistic term sets (HFLTSs) on the basis of linguistic term sets [15] and hesitant fuzzy sets [16] to enable an expert to propose several possible values for a linguistic variable. In most studies on HFLTSs, all possible values given by experts have equal importance, which is unrealistic. To solve this problem, Pang et al. [17] developed the concept of probabilistic linguistic term sets (PLTSs) as an extension of HFLTSs. The linguistic term is associated with a probability that can be interpreted as a probabilistic distribution or degree of belief. Moreover, considering the limitations of experts' prior experience, such as knowledge width and professional background, partial ignorance is accepted.

Owing to its usefulness and efficiency, the PLTS has attracted a lot of researchers' attention, and fruitful research achievements regarding it has been published since it was introduced in 2016. Lin et al. [18] suggested a novel score-entropy-based ELECTRE II method to process the edge node selection problem with the evaluation information of PLTSs. Their main contributions in PLTSs are as follows: first, a novel distance measure for PLTSs was defined. Second, a novel comparison method based on the score function and information entropy of PLTSs was proposed. Then, the concordance and discordance values of alternatives were compared with the determined concordance and discordance levels according to the established rules. Lin et al. [19] evaluated ten regions' general higher education in China by probabilistic linguistic clustering algorithm based on the scale of higher education institutions, the number of higher education institutions, the number of students in higher education institutions, and the staff situation of the faculty. Jin et al. [20] proposed the concept of uncertain probabilistic linguistic term set (UPLTS) to serve as an extension of the existing tools, and we developed an aggregation-based method and presented the application of the UPLTSs in multiple attribute group decision-making. Liu et al. [21] developed the probabilistic linguistic Archimedean MM (PLAMM) operator, probabilistic linguistic Archimedean weighted MM (PLAWMM) operator, probabilistic linguistic Archimedean dual MM (PLADMM) operator, and probabilistic linguistic Archimedean dual weighted MM (PLADWMM) operator, and provided two multiple attribute decision-making (MADM) methods built on the proposed operators. Gu et al. [22] proposed a decision-making framework based on prospect theory. In this framework, the outcomes are characterized by probabilistic linguistic term sets (PLTSs), which furnishes a paradigm to extend prospect theory to accommodate other forms of fuzzy and linguistic input. Since then, PLTSs have been widely used in cloud decisions [23], investment decisions [24, 25], water security evaluation [26], and site selection of solar power plants [27]. Scholars have combined the WASPAS method, the Dempster–Shafer (D-S) evidence theory, the ELECTRE III method, the MULTIMOORA method, the ORESTE method, and the ANP method with PLTSs [28–33].

Much research has also been done on methodological improvements to PLTSs. Gou and Xu [34] pointed out that the operations of PLTSs proposed by Pang et al. [17] might cause the result to exceed the boundary of the linguistic term set and also to lose probabilistic information. Hence, they proposed new operation laws of PLTSs. Bai et al. [35] indicated that either comparison methods of fuzzy numbers did not fully consider fuzzy information, or the comparison process was too complicated. Hence, they proposed a possibility degree-based ranking method using the graphical method to analyze the structure of PLTSs. By analyzing some illustrative examples, Mao et al. [36] demonstrated two main drawbacks relating to PLTS ranking methods. On the one hand, their robustness was so poor that a small change in the probability might cause the reversal of a PLTS ranking. On the other hand, they might result in the unreasonable judgment that two different PLTSs were identical. To overcome these defects, they proposed a possibility algorithm for ranking PLTSs. In addition, they defined the Euclidean distance between PLTSs and presented a judgment similarity-based correction method for experts' subjective weights. However, they failed to fully consider the structure of PLTSs given by various experts, giving rise to poor reliability of similarity evaluations. So, this paper defines the similarity degree between PLTSs by combining the possibility algorithm of PLTS ranking and the Euclidean distance between PLTSs of Mao et al. [36], and devises a method to determine experts' weights.

Although the DEMATEL method has been widely applied in complicated socioeconomic system issues analysis, experts' judgments must be certain and precise, so the traditional method is infeasible when experts hesitate among several possible linguistic terms. As an uncertain linguistic preference expression method, PLTS has unique advantages in dealing with multi-attribute decision-making problems. Like HFLTS, it allows experts to express their views using several linguistic terms, and it extends HFLS by adding probability information to prevent the loss of original linguistic information provided by experts. In addition, it permits experts to give incomplete judgment information. The contributions of this paper are summarized as follows.

Therefore, based on the advantages of PLTSs in terms of information processing as well as accurate description of uncertainty, in this paper we combine the DEMATEL method with PLTSs and adopt PLTSs as the form of information collection to overcome the shortcomings of the traditional DEMATEL method. In addition, based on the unique data structure of PLTSs, our study redefines the similarity measure between PLTSs and designs a subjective expert weight method to facilitate a more scientific judgment of the importance of experts and achieve accurate aggregation of multigroup expert information. At the same time, in order to extend the traditional DEMATEL method to increasingly complex socioeconomic systems, we propose the concept of negative scaling. This will enable experts to express their multidimensional and multidirectional decision information more clearly, make comprehensive judgments on the causal relationships between influencing factors from multiple perspectives, and provide more accurate decision results. The motivation of this paper is to propose a probabilistic linguistic-based group DEMATEL method considering both the positive and negative influences between factors, where all information provided by experts is characterized by probabilistic linguistic terms, and the evaluation information can be partially ignored.

The remainder of this paper is organized as follows. Section 2 introduces the preliminary details of DEMATEL method and the PLTSs. In Section 3, we develop a new DEMATEL scale that considers both the positive and negative influences between factors, and we also give an improved method for adjustment of experts' subjective weights under probabilistic linguistic environment. Then, the procedures of the new group DEMATEL method are presented, and the algorithm corresponding to the new method is also summarized. In Section 4, an illustrative example is given, and our method is compared to other DEMATEL methods to illustrate its feasibility and effectiveness. Section 5 provides conclusions and suggests future work.

2. Preliminaries

In this section, we mainly recall the detailed procedures of traditional DEMATEL method and describe some concepts and operations related to PLTSs.

2.1. Decision-Making Trial and Evaluation Laboratory. DEMATEL is an effective method for system factors analysis, which can deal with complex socioeconomic problems by making full use of experts' knowledge and experience. In DEMATEL decision-making, experts are invited to judge the direct influence relationships between factors by using an evaluation scale of DEMATEL and form the direct influence matrices, and critical factors of the system will be identified by matrix operations. The procedures of traditional DEMATEL can be summarized as follows [37]:

Step 1: construct the direct influence matrix. let $E = \{e^1, e^2, \ldots, e^m\}$ be the set of experts, let $F = \{f_1, f_2, \ldots, f_n\}$ be a finite set of influencing factors. The experts are asked to judge the direct influence degree that factor f_i has on factor f_j by using the evaluation scale of DEMATEL, i.e. "no influence (0)," "low influence (1)," "medium influence (2)," "high influence (3)," and "very high influence (4)." Then, the direct influence matrix provided by expert $e^\lambda\,(\lambda = 1, \ldots, m)$ can be gotten as $A^\lambda = [a_{ij}^\lambda]_{n\times n}\,(i, j = 1, 2, \ldots, n)$, where a_{ij}^λ indicates the direct influence degree that factor f_i has on f_j given by the λth expert. By combining the judgments of all experts, the group direct influence matrix can be formed as $A = [a_{ij}]_{n\times n}$, where:

$$a_{ij} = \frac{\sum_{\lambda=1}^{m} a_{ij}^\lambda}{m}, i, j = 1, 2, \ldots, n. \tag{1}$$

Step 2: normalize the direct influence matrix. By using equation (2), the direct influence matrix $A = [a_{ij}]_{n\times n}$ can be normalized and the normalized direct influence matrix G will be obtained.

$$G = \frac{A}{\max\limits_{1\le i\le n} \sum_{j=1}^{n} a_{ij}}. \tag{2}$$

Step 3: calculate the total influence matrix. Let T be the total influence matrix, then its calculation formula is

$$T = \left[t_{ij}\right]_{n\times n} = G(I - G)^{-1}. \tag{3}$$

Step 4: determine the centrality of the factors and calculate the cause and effect groups. Let d_i and r_i, which can be calculated by equation (4) and (5), be the sums of the ith row and column of matrix T, respectively. Then, a causal diagram of system factors can be drawn, where d_i and r_i are located in the horizontal and vertical axes, respectively.

$$d_i = \sum_{j=1}^{n} t_{ij}, \quad i = 1, 2, \ldots, n, \tag{4}$$

$$r_i = \sum_{j=1}^{n} t_{ji}, \quad i = 1, 2, \ldots, n, \tag{5}$$

where d_i indicates the centrality of factor f_i in the entire system, and r_i indicates whether factor f_i belongs to the cause group or the effect group. Factors having positive values of r_i are in the cause group and dispatch influence to other factors, and factors having negative values of r_i are in the effect group and receive influence from other factors.

2.2. Probabilistic Linguistic Term Sets. As an extension of HFLTSs, PLTSs allow experts to hesitate among several possible linguistic terms when expressing their judgments under the linguistic environment. The probabilistic distribution of these linguistic terms is also collected in PLTSs, and partial ignorance is allowed. All these properties are desirable in expressing preferences in decision-making.

Definition 1 (see [17]). Let $S = \{s_0, s_1, \ldots, s_\tau\}$ be a linguistic term set (LTS). A PLTS can be defined as

$$L(p)=\left\{L^{(k)}\left(p^{(k)}\right)|L^{(k)}\in S, p^{(k)}\geq 0, k=1,2,\ldots,\#L(p), \sum_{k=1}^{\#L(p)} p^{(k)}\leq 1\right\}, \tag{6}$$

where $L^{(k)}(p^{(k)})$ is the linguistic term $L^{(k)}$ associated with its probability $p^{(k)}$, and $\#L(p)$ is the number of all different linguistic terms in $L(p)$.

Definition 2 (see [17]). The score $E(L(p))$ and the deviation degree $\sigma(L(p))$ of PLTS $L(p)=\{L^{(k)}(p^{(k)})| k=1,2,\ldots,\#L(p)\}$ are denoted by

$$\begin{aligned} E(L(p)) &= s_{\overline{\alpha}},\\ \sigma(L(p)) &= \frac{\left(\sum_{k=1}^{\#L(p)}\left(p^{(k)}\left(r^{(k)}-\overline{\alpha}\right)\right)^2\right)^{1/2}}{\sum_{k=1}^{\#L(p)} p^{(k)}}, \end{aligned} \tag{7}$$

where $\overline{\alpha}=\sum_{k=1}^{\#L(p)} r^{(k)}p^{(k)}/\sum_{k=1}^{\#L(p)} p^{(k)}$, and $r^{(k)}$ is the subscript of linguistic term $L^{(k)}$.

It can be noted from equation (6) that $\sum_{k=1}^{\#L(p)} p^{(k)}\leq 1$, that is to say, partial ignorance is acceptable. So, estimating the ignorance of probabilistic information is a crucial work for the use of PLTSs. To handle this issue, Pang et al. [17] assigned the ignorance $(1-\sum_{k=1}^{\#L(p)} p^{(k)})$ to the linguistic terms in $L(p)$ averagely as follows to get the associated complete PLTS $L(p)$ for $L(p)$.

Definition 3 (see [17]). Let $L(p)$ be a PLTS with $\sum_{k=1}^{\#L(p)} p^{(k)}\leq 1$. Then, the associated complete PLTS $L(p)$ can be defined by

$$\dot{L}(p)=\left\{L^{(k)}\left(\dot{p}^{(k)}\right)|k=1,2,\ldots,\#L(p)\right\}, \tag{8}$$

where $\dot{p}^{(k)}=p^{(k)}/\sum_{k=1}^{\#L(p)} p^{(k)}$, and $k=1,2,\ldots,\#L(p)$.

Definition 4 (see [17]). Let $L_1(p)=\left\{L_1^{(k)}(p_1^{(k)})|k=1,2,\ldots,\#L_1(p)\right\}$ and $L_2(p)=\left\{L_2^{(k)}(p_2^{(k)})|k=1,2,\ldots,\#L_2(p)\right\}$ be two complete PLTSs, where $\#L_1(p)$ and $\#L_2(p)$ are, respectively, the numbers of linguistic terms in $L_1(p)$ and $L_2(p)$. If $\#L_1(p)>\#L_2(p)$, then $(\#L_1(p)-\#L_2(p))$ linguistic terms will be added to $L_2(p)$. The added linguistic terms are the smallest ones in $L_2(p)$ and the probabilities related to the added linguistic terms are zero.

So far, the PLTSs $L_1(p)$ and $L_2(p)$ have been normalized. For convenience, we still denote the normalized PLTSs by $L_1(p)$ and $L_2(p)$.

Gou and Xu [34] extended LTS for PLTSs to $S=\{s_t|t=-\tau,\ldots,-1,0,1,\ldots,\tau\}$, and they defined some basic operational laws of PLTSs as

$$wL(p)=g^{-1}\left(\cup_{\eta^{(k)}\in g(L)}\left\{\left(1-\left(1-\eta^{(k)}\right)^{w}\right)\left(p^{(k)}\right)\right\}\right), \tag{9}$$

$$L_1(p)\oplus L_2(p)=g^{-1}\left(\cup_{\eta_1^{(i)}\in g(L_1),\eta_2^{(j)}\in g(L_2)}\left\{\left(\eta_1^{(i)}+\eta_2^{(j)}-\eta_1^{(i)}\eta_2^{(j)}\right)\left(p_1^{(i)}p_2^{(j)}\right)\right\}\right), \tag{10}$$

$$\begin{aligned} L^{w}(p) &= g^{-1}\left(\cup_{\eta^{(k)}\in g(L)}\left\{\left(\eta^{(k)}\right)^{w}\left(p^{(k)}\right)\right\}\right),\\ L_1(p)\otimes L_2(p) &= g^{-1}\left(\cup_{\eta_1^{(i)}\in g(L_1),\eta_2^{(j)}\in g(L_2)}\left\{\left(\eta_1^{(i)}\eta_2^{(j)}\right)\left(p_1^{(i)}p_2^{(j)}\right)\right\}\right), \end{aligned} \tag{11}$$

where $L(p)$, $L_1(p)$, and $L_2(p)$ are three PLTSs, and w is a positive real number; $\eta^{(k)}\in g(L)$, $\eta_1^{(i)}\in g(L_1)$, $\eta_2^{(j)}\in g(L_2)$, where $k=1,2,\ldots,\#L$, $i=1,2,\ldots,\#L_1$, $j=1,2,\ldots,\#L_2$; g and g^{-1} are the equivalent functions proposed by Gou et al. [38]:

$$g\colon [-\tau,\tau]\longrightarrow[0,1], g(L(p))=\left\{\left(\left(r^{(k)}/2\tau\right)+(1/2)\right)\left(p^{(k)}\right)\right\}=L_{\gamma}(p), \gamma\in[0,1], \tag{12}$$

$$g^{-1}\colon [0,1]\longrightarrow[-\tau,\tau], g^{-1}\left(L_{\gamma}(p)\right)=\left\{s_{(2\gamma-1)\tau}\left(p^{(\gamma)}\right)|\gamma\in[0,1]\right\}=L(p). \tag{13}$$

Definition 5 (see [31]). Let $S = \{s_\alpha | \alpha = -\tau, \ldots, -1, 0, 1, \ldots, \tau\}$ be an LTS. $L_1(p) = \{L_1^{(k_1)}(p_1^{(k_1)}) | k_1 = 1, 2, \ldots, \#L_1(p)\}$ and $L_2(p) = \{L_2^{(k_2)}(p_2^{(k_2)}) | k_2 = 1, 2, \ldots, \#L_2(p)\}$ are two complete PLTSs. Then, the possibility degree that $L_1(p)$ is not less than $L_2(p)$ can be defined by

$$P(L_1(p) \geq L_2(p)) = \sum_{k_1=1}^{\#L_1(p)} \sum_{k_2=1}^{\#L_2(p)} R\left(L_1^{(k_1)}, L_2^{(k_2)}\right), \quad (14)$$

where $R(L_1^{(k_1)}, L_2^{(k_2)}) = \begin{cases} p_1^{(k_1)} p_2^{(k_2)}, L_1^{(k_1)} > L_2^{(k_2)} \\ 1/2 p_1^{(k_1)} p_2^{(k_2)}, L_1^{(k_1)} = L_2^{(k_2)} \\ 0, L_1^{(k_1)} < L_2^{(k_2)} \end{cases}$, indicating the possibility degree that $L_1^{(k_1)}$ in $L_1(p)$ is not smaller than $L_2^{(k_2)}$ in $L_2(p)$.

The possibility degree has the following properties:

(1) $0 \leq P(L_1(p) \geq L_2(p)) \leq 1$

(2) $P(L_1(p) \geq L_1(p)) = 0.5$

(3) $P(L_1(p) \geq L_2(p)) + P(L_2(p) \geq L_1(p)) = 1$

(4) If $P(L_1(p) \geq L_2(p)) = P(L_2(p) \geq L_1(p))$, then $P(L_1(p) \geq L_2(p)) = P(L_2(p) \geq L_1(p)) = 0.5$

In addition, Mao et al. [36] also gave the equation for Euclidean distance calculation between two PLTSs.

Definition 6 (see [36]). Let $L_1(p)$ and $L_2(p)$ be two normalized PLTSs. The Euclidean distance between $L_1(p)$ and $L_2(p)$ is defined as

$$d(L_1(p), L_2(p)) = \sqrt{\sum_{k=1}^{\#L_1(p)} \left(p_1^{(k)} g\left(L_1^{(k)}\right) - p_2^{(k)} g\left(L_2^{(k)}\right)\right)^2 / \#L_1(p)}, \quad (15)$$

where $d(L_1(p), L_2(p)) \in [0, 1]$, and g is the equivalent function in equation (12).

3. New Group DEMATEL Method

3.1. Proposed New Scale for the DEMATEL Method. Four kinds of affecting decision-making factors, benefit, opportunity, cost, and risk could be fully taken into account to make optimal decisions. Similarly, positive and negative influences in DEMATEL are the two kinds of influence relationships between factors. When analyzing the factors in a system, they should be properly considered to reasonably determine the relationships between factors and their positions in the system. However, evaluation scales in exiting DEMATEL cannot distinguish these influences, and negative influences are treated as positive, which is not consistent with reality. To overcome the above drawbacks, we extend a DEMATEL scale to a more reasonable form by the following definition.

Definition 7. he evaluation scale for pairwise comparison in DEMATEL can be presented in nine levels, where −4, −3, −2, −1, 0, 1, 2, 3, and 4, respectively, represent "very high negative influence," "high negative influence," "medium negative influence," "low negative influence," "no influence," "low positive influence," "medium positive influence," "high positive influence," and "very high positive influence."

To facilitate the combination with PLTSs, the definition of LTS corresponding to the above scale is as follows.

Definition 8. Let s_α $(\alpha = -4, \ldots, 0, \ldots, 4)$ be possible values for the influence degree expressed by a linguistic form. Then, the LTS corresponding to the new scale of DEMATEL can be defined as: $S_D = \{s_{-4}$ = very high negative influence, s_{-3} = high negative influence, s_{-2} = medium negative influence, s_{-1} = low negative influence, s_0 = no influence, s_1 = low positive influence, s_2 = medium positive influence, s_3 = high positive influence, and s_4 = very high positive influence$\}$.

Based on the above scale, the direct influence matrix of influencing factors in DEMATEL can be expressed as follows.

Definition 9. For a group DEMATEL decision-making problem, let $E = \{e^1, e^2, \ldots, e^m\}$ be the set of experts, and let $F = \{f_1, f_2, \ldots, f_n\}$ be a finite set of influencing factors. The direct influence matrix provided by expert e^λ $(\lambda = 1, \ldots, m)$ using the new scale can be defined as\scale90%

$$A^\lambda = \left[a_{ij}^\lambda\right]_{n\times n} = A^{\lambda_+} + A^{\lambda_-} = \left[a_{ij}^{\lambda_+}\right]_{n\times n} + \left[a_{ij}^{\lambda_-}\right]_{n\times n}, \quad i, j = 1, 2, \ldots, n, \quad (16)$$

where $a_{ij}^\lambda \in \{-4, -3, -2, -1, 0, 1, 2, 3, 4\}$ indicates the direct influence direction and influence degree of factor f_i on factor f_j, $a_{ij}^{\lambda_+} \in \{0, 1, 2, 3, 4\}$ indicates the degree of positive direct influence of factor f_i on factor f_j, and $a_{ij}^{\lambda_-} \in \{-4, -3, -2, -1, 0\}$ indicates the degree of negative direct influence of factor f_i on factor f_j. A^{λ_+} and A^{λ_-} are the positive and negative direct influence matrices, respectively, which can be characterized as follows:

$$A^{\lambda_+} = \left[a_{ij}^{\lambda_+}\right]_{n\times n} = \left[\frac{\left(a_{ij}^\lambda + \left|a_{ij}^\lambda\right|\right)}{2}\right]_{n\times n}, \quad i, j = 1, 2, \ldots, n, \quad (17)$$

$$A^{\lambda_-} = \left[a_{ij}^{\lambda_-}\right]_{n\times n} = \left[\frac{\left(a_{ij}^\lambda - \left|a_{ij}^\lambda\right|\right)}{2}\right]_{n\times n}, \quad i, j = 1, 2, \ldots, n. \quad (18)$$

3.2. Determination of Experts' Weights. Determining experts' weights is an important part of integrating their judgment information. Subjective weights are often given in advance, which may be biased. Mao et al. [36] proposed a similarity-based adjustment coefficient to adjust them. However, this coefficient only considers the Euclidean distance between probabilistic linguistic matrices, and fails to fully consider the structural differences between PLTSs, resulting in poor reliability of similarity evaluation results. To overcome this, we define the similarity degree between two normalized PLTSs, which is based on the possibility degree in Definition 5 and the Euclidean distance in Definition 6.

Definition 10. Let $L_1(p) = \{L_1^{(k)}(p_1^{(k)}) | k = 1, 2, \ldots, \#L_1(p)\}$ and $L_2(p) = \{L_2^{(k)}(p_2^{(k)}) | k = 1, 2, \ldots, \#L_2(p)\}$ be two normalized PLTSs. $d(L_1(p), L_2(p)) \in [0, 1]$ is the Euclidean distance between $L_1(p)$ and $L_2(p)$, and $P(L_1(p) \geq L_2(p))$ is the possibility degree that $L_1(p)$ is not less than $L_2(p)$. Then, the similarity degree between $L_1(p)$ and $L_2(p)$ is defined as

$$\begin{aligned} C(L_1(p), L_2(p)) &= 2\left(0.5 - \left(0.5 - \left(\left(1 - \sqrt{d(L_1(p), L_2(p))}\right)/2\right) + \left|P(L_1(p) \geq L_2(p)) - 0.5\right|\right)/2\right), \\ &= \begin{cases} 2\left(0.5 - \dfrac{\left(0.5 - \left(1 - \sqrt{d(L_1(p), L_2(p))}\right)/2 + 0.5 - P(L_1(p) \geq L_2(p))\right)}{2}\right), P(L_1(p) \geq L_2(p) \in [0, 0.5], \\ 2\left(0.5 - \dfrac{\left(0.5 - \left(1 - \sqrt{d(L_1(p), L_2(p))}\right)/2 + P(L_1(p) \geq L_2(p)) - 0.5\right)}{2}\right), P(L_1(p) \geq L_2(p) \in (0.5, 1], \end{cases} \\ &= \begin{cases} 0.5 - 0.5\sqrt{d(L_1(p), L_2(p))} + P(L_1(p) \geq L_2(p)), P(L_1(p) \geq L_2(p) \in [0, 0.5], \\ 1.5 - 0.5\sqrt{d(L_1(p), L_2(p))} - P(L_1(p) \geq L_2(p)), P(L_1(p) \geq L_2(p) \in (0.5, 1]. \end{cases} \end{aligned} \tag{19}$$

Proposition 1. *For two normalized PLTSs $L_1(p)$ and $L_2(p)$, the similarity degree has the following desirable properties:*

(1) $C(L_1(p), L_2(p)) \in [0, 1]$

(2) $C(L_1(p), L_2(p)) = C(L_2(p), L_1(p))$

(3) $C(L_i(p), L_i(p)) = 1$

Proof

(1) Since $\sqrt{d(L_1(p), L_2(p))}, P(L_1(p) \geq L_2(p)) \in [0, 1]$, $0.5 - (1 - \sqrt{d(L_1(p), L_2(p))})/2$ and $|P(L_1(p) \geq L_2(p)) - 0.5| \in [0, 0.5]$, and we have $(0.5 - (1 - \sqrt{d(L_1(p), L_2(p))})/2 + |P(L_1(p) \geq L_2(p) - 0.5| /2) \in [0, 0.5]$. So, $C(L_1(p), L_2(p)) = 2(0.5 - 0.5 - (1 - \sqrt{d(L_1(p), L_2(p))})/2 + |P(L_1(p) \geq P(L_2(p))| - 0.5\ /2 \in [0, 1])$.

(2) $C(L_2(p), L_1(p)) = 2(0.5 - (0.5 - (1 - \sqrt{d(L_1(p), L_2(p))})/2 + |P(L_2(p) \geq L_1(p)) - 0.5|)/2)2\ (0.5 - (0.5 - (1 - \sqrt{d(L_1(p), L_2(p))}\ /2 + |1 - P(L_1(p) \geq L_2(p)) - 0.5\ \ /2|) = 2(0.5 - \ (0.5 - (1 - \sqrt{d}(L_1(p), L_2(p))\ /2) + |P(L_1(p) \geq L_2(p)) - 0.5|)/2) = C(L_1(p), L_2(p))$.

(3) Since $\sqrt{d(L_i(p), L_i(p))} = 0$, $P(L_i(p) \geq L_i(p)) = 0.5$, $0.5 - (1 - \sqrt{d(L_i(p), L_i(p))}/2) + |P(L_i(p) \geq L_i(p)) - 0.5| = 0$.
$C(L_i(p), L_i(p)) = 2(0.5 - (0.5 - (1 - \sqrt{d(L_i(p), L_i(p))})/2 + (|P(L_i(p)) \geq L_i(p) - 0.5|)\ /2) = 1$.

The similarity degree between two probabilistic linguistic decision matrices (PLDMs) is given as follows. □

Definition 11. Let $L^1 = [L_{ij}^1(p)]_{n\times n}$ and $L^2 = [L_{ij}^2(p)]_{n\times n}$ be two matrices with PLTSs. The similarity degree between them is

$$C\left(L^1, L^2\right) = \sum_{i=1}^{n}\sum_{j=1}^{n} \frac{C\left(L_{ij}^1(p), L_{ij}^2(p)\right)}{n^2}, \tag{20}$$

where $C(L_{ij}^1(p), L_{ij}^2(p))$ is the similarity degree between $L_{ij}^1(p)$ and $L_{ij}^2(p)$ by equation (19).

The relative consistent degree $\rho^{\lambda r}(\lambda, r = 1, \ldots, m, \lambda \neq r)$ between experts e^λ and e^r can be calculated as

$$\rho^{\lambda r} = \frac{C\left(L^\lambda, L^r\right)}{\sum_{k=1,k\neq r}^{m} C\left(L^k, L^r\right)}, \tag{21}$$

where $C(L^k, L^r)(k = 1, \ldots, m, k \neq r)$ is obtained by equation (20), and m is the number of experts.

Then, an adjustment coefficient ρ^λ of e^λ is defined as

$$\rho^\lambda = \frac{\sum_{r=1,r\neq\lambda}^{m} \rho^{\lambda r}}{(m-1)}. \tag{22}$$

According to the given experts' subjective weights η^λ and the adjustment coefficients ρ^λ, the final weights are

$$w^\lambda = \frac{\rho^\lambda \eta^\lambda}{\sum_{k=1}^{m} \rho^k \eta^k}, \quad \lambda = 1, \ldots, m. \tag{23}$$

3.3. Procedures for the New Group DEMATEL Method. Based on the above analysis, the probabilistic linguistic-based group DEMATEL method with both positive and negative influences is determined as follows, and its process can be illustrated in Figure 1.

Step 1: construct the original probabilistic linguistic decision matrix. The experts in the expert group E utilize the LTS S_D Definition deff8, to evaluate the direct influence relationships between factors in $F = \{f_1, f_2, \ldots, f_n\}$ by means of PLTSs to derive the original PLDMs. It should be noted that partial ignorance for the evaluation is acceptable. The PLDM L^λ provided by expert e^λ $(\lambda = 1, 2, \ldots, m)$ can be described as

$$L^\lambda = \left[L_{ij}^\lambda (p)\right]_{n\times n}, \quad i, j = 1, 2, \ldots, n, \tag{24}$$

where $L_{ij}^\lambda (p) = \{L_{ij}^{\lambda,k} (p^{\lambda,k}) | L_{ij}^{\lambda,k} \in S_D, p^{\lambda,k} \geq 0, k = 1, 2, \ldots, \#L_{ij}^\lambda (p), \sum_{k=1}^{\#L_{ij}^\lambda (p)} p^{\lambda,k} \leq 1\}$, $\lambda = 1, 2, \ldots, m$, indicating the evaluation result of the influence of factor f_i on factor f_j given by expert e^λ under the probabilistic linguistic environment.

Step 2: determine the experts' weights. First, we can get the complete and normalized form for each PLTS in $L^\lambda (\lambda = 1, 2, \ldots, m)$ according to Definitions deff3 and deff4. For convenience, the complete and normalized PLDMs are still denoted as $L^\lambda (\lambda = 1, 2, \ldots, m)$. Let $\eta = (\eta^1, \ldots, \eta^m)$ be the subjective weight vector of experts which is determined by a preliminary discussion of the expert group. Based on equations (19)–(23), the final weight vector $w = (w^1, \ldots, w^m)$ of experts can be obtained.

Step 3: determine the aggregated probabilistic linguistic decision matrix. Based on equations (9), (10), (12), and (13), the group's aggregated PLDM can be derived as

$$L = \left[L_{ij} (p)\right]_{n\times n}, \quad i, j = 1, 2, \ldots, n, \tag{25}$$

where $L_{ij} (p) = w^1 L_{ij}^1 (p) \oplus w^2 L_{ij}^2 (p) \oplus \cdots \oplus w^m L_{ij}^m (p)$.

Step 4: transform L to the direct influence matrix under the new scale. Based on Definition deff2, the score of each PLTS $L_{ij} (p)$ in L can be calculated as

$$E\left(L_{ij} (p)\right) = s_{\overline{\alpha}_{ij}}, \quad i, j = 1, 2, \ldots, n, \tag{26}$$

where $\overline{\alpha}_{ij} = \sum_{k=1}^{\#L_{ij} (p)} r_{ij}^k p_{ij}^k$, r_{ij}^k is the subscript of linguistic term L_{ij}^k, and $\sum_{k=1}^{\#L_{ij} (p)} p_{ij}^k = 1$.

Then, the aggregated direct influence matrix can be formed as $A = [a_{ij}]_{n\times n}$, where $a_{ij} = \text{round}(\overline{\alpha}_{ij})$, where $\text{round}(\cdot)$ is the usual rounding operation. The aggregated positive direct influence matrix and aggregated negative direct influence matrix, denoted as $A^+ = [a_{ij}^+]_{n\times n}$ and $A^- = [a_{ij}^-]_{n\times n}$, respectively, can be derived as per equation (17) and (18).

Step 5: calculate the normalized direct influence matrices. The normalized positive direct influence matrix G^+ and normalized negative direct influence matrix G^- can be calculated as

$$G^+ = \frac{A^+}{\max_{1\leq i\leq n} \sum_{j=1}^{n} a_{ij}^+}, \tag{27}$$

$$G^- = \frac{A^-}{\min_{1\leq i\leq n} \sum_{j=1}^{n} a_{ij}^-}. \tag{28}$$

Step 6: determine the total influence matrices. The total positive influence matrix T^+ and total negative influence matrix T^- can be determined as

$$T^+ = \left[t_{ij}^+\right]_{n\times n} = G^+ \left(I - G^+\right)^{-1}, \tag{29}$$

$$T^- = \left[t_{ij}^-\right]_{n\times n} = G^- \left(I - G^-\right)^{-1}, \tag{30}$$

where $i, j = 1, 2 \ldots, n$, and I is the unit matrix.

Step 7: determine the centrality of the factors and calculate the cause and effect groups. Let the vectors $D^+ = (d_1^+, \ldots, d_n^+)^T$ and $D^- = (d_1^-, \ldots, d_n^-)^T$ be the sums of rows of matrices T^+ and T^-, respectively, and let the vectors $R^+ = (r_1^+, \ldots, r_n^+)$ and $R^- = (r_1^-, \ldots, r_n^-)$ be the sums of columns of matrices T^+ and T^-, respectively. The ith elements in D^+, D^-, R^+, and R^- can be calculated as

$$d_i^+ = \sum_{j=1}^{n} t_{ij}^+, \quad i = 1, 2, \ldots, n, \tag{31}$$

$$d_i^- = \sum_{j=1}^{n} t_{ij}^-, \quad i = 1, 2, \ldots, n, \tag{32}$$

$$r_i^+ = \sum_{j=1}^{n} t_{ji}^+, \quad i = 1, 2, \ldots, n, \tag{33}$$

$$r_i^- = \sum_{j=1}^{n} t_{ji}^-, \quad i = 1, 2, \ldots, n. \tag{34}$$

Let $\vartheta_i = \vartheta_i^+ - \vartheta_i^- = (d_i^+ + r_i^+) - (d_i^- + r_i^-)$ and $\psi_i = \psi_i^+ - \psi_i^- = (d_i^+ - r_i^+) - (d_i^- - r_i^-)$.

Drawing on the thoughts of Saaty and Ozdemir [39], we propose that ϑ_i indicates the degree of importance that factor f_i plays in the entire system. The factor having greater absolute value of ϑ_i is more important. What is more, the factors that have positive values of ϑ_i have a positive influence on the whole system, and factors with negative values of ϑ_i have a negative influence on the whole system. We use ψ_i to calculate the cause and effect groups. Factors having positive values of ψ_i are in the cause group and dispatch

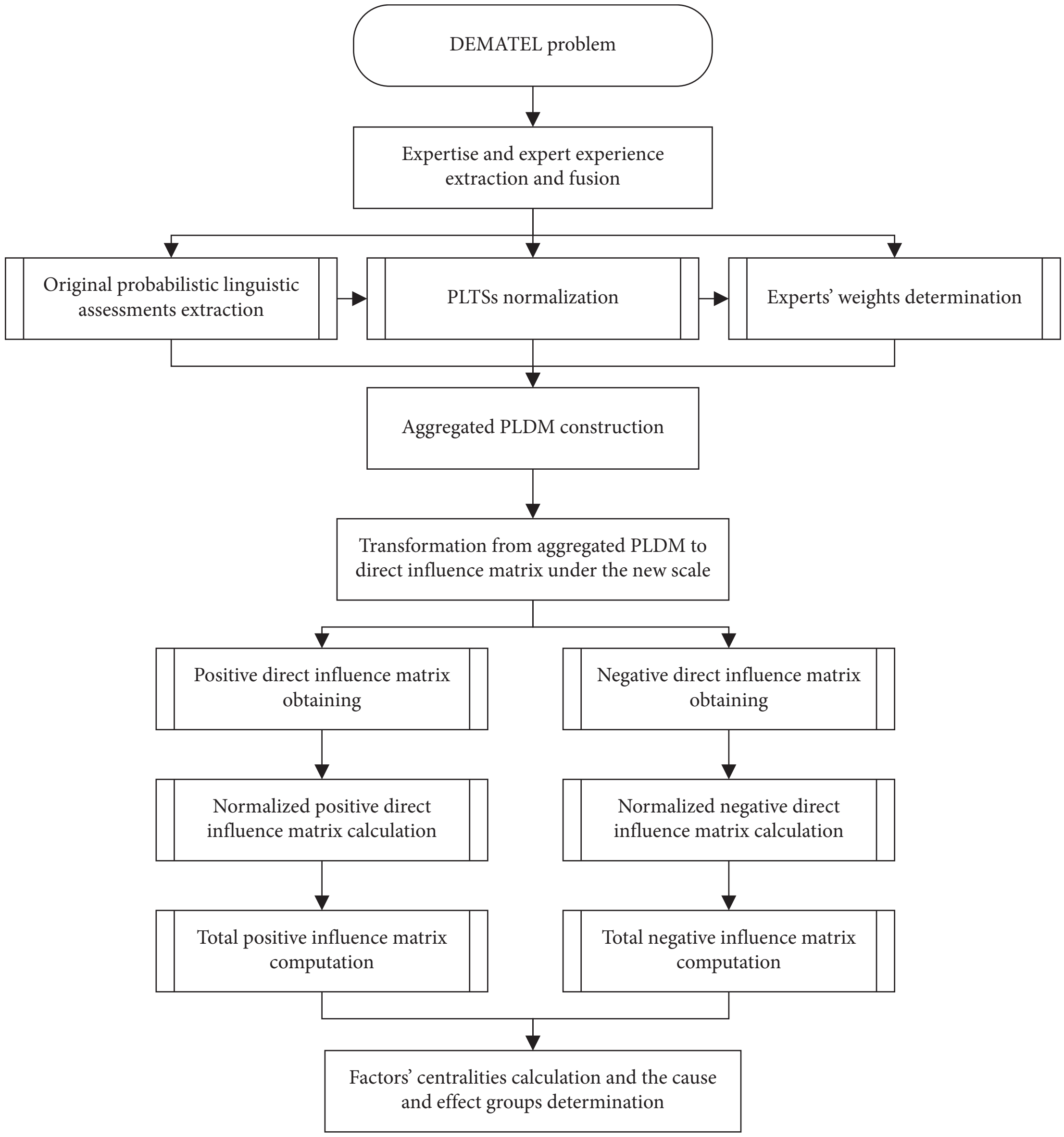


Figure 1: The process of the new group DEMATEL.

influence to other factors, and factors having negative values of ψ_i are in the effect group and receive influence from other factors.

The algorithm for the new group DEMATEL can be summarized in Algorithm 1.

As can be seen through the methodological process described above, the new group DEMATEL method improves several aspects of decision-making from a systems perspective. Firstly, this method changes the traditional form of information input by describing expert preferences through PLTSs, which not only retains more complete input information but also ameliorates the impact of incomplete information on the decision outcome. Secondly, this model revises the processing flow of input information and introduces the concept of negative scaling, allowing decision-makers to make two-way decisions. The addition of a negative influence matrix allows experts to more intuitively understand the degree and direction of influence of system factors in the decision-making process, making the results more interpretable. Finally, this study defines similarity measures based on the structure of PLTSs, designs an expert subjective weight method, outputs a more reliable aggregated initial influence matrix, and improves the accuracy of factor analysis. The new group DEMATEL method optimizes the decision-making process from a system perspective in terms of the input, processing, and output of information, respectively, making the efficient DEMATEL more applicable to complex decision-making systems based on the original one.

4. Illustrative Example

We provide an example of a pharmaceutical enterprise called M to illustrate the application of the proposed method. Wu

Inputs: the set of factors $F = \{f_1, \ldots, f_n\}$, linguistic term set $S_D = \{s_{-4}, \ldots, s_4\}$, set of evaluation grade levels $\Theta = \{\theta_{-4}, \ldots, \theta_4\}$, set of experts $E = \{e^1, \ldots, e^m\}$, subjective weight vector of experts $\eta = (\eta^1, \ldots, \eta^m)$.
Outputs: the ϑ_i and $\psi_i (i = 1, \ldots, n)$ values of factors.
Begin
% Original probabilistic linguistic decision matrices (PLDMs) construction
For $i = 1$ to n
  For $j = 1$ to n
    If $i \neq j$
      For $\lambda = 1$ to m
        Expert e^λ assesses the influence degree of factor f_i on f_j by $L_{ij}^\lambda (p) = \left\{L_{ij}^{\lambda,k} (p^{\lambda,k}) | L_{ij}^{\lambda,k} \in S_D, p^{\lambda,k} \geq 0, k = 1, 2, \ldots, \#L_{ij}^\lambda (p), \sum_{k=1}^{\#L_{ij}^\lambda (p)} p^{\lambda,k} \leq 1\right\}$
        EndFor
        Assign the assessment result to the element of PLDM L^λ by $L_{ij}^\lambda = L_{ij}^\lambda (p)$
      Else
        Assign linguistic term s_0 to the element of PLDM L^λ by $L_{ij}^\lambda = \{s_0 (1)\}$
      EndIf
    EndFor
EndFor
Get the PLDMs $L^\lambda (\lambda = 1, \ldots m)$
% Determine aggregated PLDM
Adjust subjective weight vector $\eta = (\eta^1, \ldots, \eta^m)$ of experts to the final weight vector $W = (w^1, \ldots, w^m)$
  For $i = 1$ to n
    For $j = 1$ to n
      Initialize the aggregation result by $L_{ij} (p) = \{s_{-4} (1)\}$
      If $i \neq j$
        For $\lambda = 1$ to m
          Make aggregation for the first λ experts by $L_{ij} (p) = L_{ij} (p) \oplus w^\lambda L_{ij}^\lambda (p)$
        EndFor
        Assign the aggregation result to the element of aggregated PLDM by $L_{ij} = L_{ij} (p)$
        Else
        Assign linguistic term s_0 to the element of aggregated PLDM by $L_{ij} = \{s_0 (1)\}$
      EndIf
    EndFor
EndFor
Get the aggregated PLDM $L = [L_{ij} (p)]_{n \times n}$
% Transform L to the direct influence matrix under the new scale
For $i = 1$ to n
    For $j = 1$ to n
      Obtain the direct influence degree of factor f_i on f_j by $a_{ij} = \text{round}(\sum_{k=1}^{\#L_{ij} (p)} r_{ij}^k p_{ij}^k)$
      Obtain the positive and negative direct influence degrees of factor f_i on f_j by $a_{ij}^+ = (a_{ij} + |a_{ij}|)/2$ and $a_{ij}^- = (a_{ij} - |a_{ij}|)/2$
      Construct direct influence matrix, positive and negative direct influence matrices by $A = [a_{ij}]_{n \times n}$, $A^+ = [a_{ij}^+]_{n \times n}$, and $A^- = [a_{ij}^-]_{n \times n}$
    EndFor
EndFor
Calculate the normalized positive and negative direct influence matrices by $G^+ = A^+ / \max_{1 \leq i \leq n} \sum_{j=1}^n a_{ij}^+$ and $G^- = A^- / \max_{1 \leq i \leq n} \sum_{j=1}^n a_{ij}^-$
Calculate the total positive and negative influence matrices by $T^+ = [t_{ij}^+]_{n \times n} = G^+ (I - G^+)^{-1}$ and $T^- = [t_{ij}^-]_{n \times n} = G^- (I - G^-)^{-1}$
Calculate the importance degree, cause and effect degree of factors by $\vartheta_i = (\sum_{j=1}^n t_{ij}^+ + \sum_{j=1}^n t_{ji}^+) - (\sum_{j=1}^n t_{ij}^- + \sum_{j=1}^n t_{ji}^-)$ and $\psi_i = (\sum_{j=1}^n t_{ij}^+ - \sum_{j=1}^n t_{ji}^+) - (\sum_{j=1}^n t_{ij}^- - \sum_{j=1}^n t_{ji}^-)$
End

Algorithm 1: The algorithm for the new group DEMATEL method.

and Shanley [40] pointed out that companies develop new knowledge based on their existing knowledge stock so as to keep pace with new developments and maintain innovation competence. Jiménez and Valle [41] recommended that innovation requires the transformation and development of existing knowledge by asking employees to share information and knowledge. As Nonaka [42] suggested, knowledge-sharing among employees plays a fundamental role in innovation.

Enterprise M has always taken pharmaceutical research and development (R&D) as the focus of innovation and the weapon to enhance the core competitiveness. So, it is important for enterprise M to analyze the relationships between influencing factors of knowledge-sharing among pharmaceutical R&D employees. In this example, five influencing factors of knowledge-sharing among pharmaceutical R&D employees in enterprise M are selected: the richness of knowledge transfer channels (f_1), knowledge-sharing ability of employees (f_2), implication and dispersion of knowledge (f_3), employees' hierarchy bias (f_4), and employees' willingness to share knowledge (f_5). Three experts, e^1, e^2, and e^3, are invited to analyze the direct influence relationships between influencing factors by using the new linguistic term set S_D, and the PLDMs L^λ $(\lambda = 1, 2, 3)$ provided by the experts are as follows:

$$L^1 = \begin{bmatrix} \{s_0(1)\} & \{s_2(0.6), s_3(0.4)\} & \underline{\{s_{-3}(0.5), s_{-2}(0.4)\}} & \{s_{-2}(0.3), s_{-1}(0.5), s_0(0.2)\} & \{s_0(0.6), s_1(0.4)\} \\ \{s_0(0.1), s_1(0.3), s_2(0.6)\} & \{s_0(1)\} & \{s_{-3}(0.6), s_{-1}(0.4)\} & \{s_0(1)\} & \{s_1(0.3), s_2(0.7)\} \\ \{s_0(0.2), s_1(0.8)\} & \{s_{-4}(0.2), s_{-3}(0.8)\} & \{s_0(1)\} & \{s_1(0.6), s_2(0.4)\} & \{s_{-2}(0.8), s_{-1}(0.2)\} \\ \{s_0(1)\} & \{s_{-1}(0.7), s_0(0.3)\} & \{s_0(0.1), s_1(0.9)\} & \{s_0(1)\} & \{s_{-4}(0.8), s_{-3}(0.2)\} \\ \{s_0(0.2), s_1(0.8)\} & \{s_1(0.3), s_2(0.7)\} & \{s_{-2}(0.2), s_{-1}(0.8)\} & \{s_{-2}(0.7), s_0(0.3)\} & \{s_0(1)\} \end{bmatrix},$$

$$L^2 = \begin{bmatrix} \{s_0(1)\} & \{s_3(0.7), s_4(0.3)\} & \{s_{-3}(0.1), s_{-2}(0.6), s_{-1}(0.3)\} & \underline{\{s_{-1}(0.7), s_0(0.2)\}} & \{s_1(0.7), s_2(0.3)\} \\ \{s_1(0.3), s_2(0.7)\} & \{s_0(1)\} & \{s_{-2}(0.7), s_{-1}(0.3)\} & \{s_0(1)\} & \{s_1(0.2), s_2(0.8)\} \\ \{s_1(0.7), s_2(0.3)\} & \{s_{-3}(0.7), s_{-2}(0.3)\} & \{s_0(1)\} & \{s_0(0.3), s_1(0.7)\} & \{s_{-2}(0.7), s_{-1}(0.3)\} \\ \{s_{-1}(0.2), s_0(0.8)\} & \{s_{-2}(0.5), s_{-1}(0.5)\} & \{s_1(0.2), s_2(0.8)\} & \{s_0(1)\} & \{s_{-4}(1)\} \\ \{s_1(0.7), s_2(0.3)\} & \{s_0(0.2), s_1(0.8)\} & \{s_{-3}(0.6), s_{-2}(0.4)\} & \{s_{-3}(0.2), s_{-2}(0.8)\} & \{s_0(1)\} \end{bmatrix},$$

$$L^3 = \begin{bmatrix} \{s_0(1)\} & \begin{matrix}\{s_2(0.7), s_3(0.2), \\ s_4(0.1)\}\end{matrix} & \{s_{-3}(0.5), s_{-2}(0.5)\} & \underline{\{s_{-1}(0.6), s_0(0.3)\}} & \begin{matrix}\{s_0(0.7), s_1(0.2), \\ s_2(0.1)\}\end{matrix} \\ \{s_2(0.4), s_3(0.6)\} & \{s_0(1)\} & \{s_{-2}(0.5), s_{-1}(0.5)\} & \{s_0(1)\} & \{s_2(0.6), s_3(0.4)\} \\ \{s_{-1}(0.2), s_0(0.8)\} & \begin{matrix}\{s_{-4}(0.2), s_{-3}(0.7), \\ s_{-1}(0.1)\}\end{matrix} & \{s_0(1)\} & \{s_0(0.8), s_1(0.2)\} & \{s_{-3}(0.4), s_{-2}(0.6)\} \\ \{s_0(1)\} & \{s_{-1}(0.9), s_0(0.1)\}, & \{s_2(0.3), s_3(0.7)\} & \{s_0(1)\} & \{s_{-4}(1)\} \\ \{s_0(0.1), s_1(0.9)\} & \{s_2(0.3), s_3(0.7)\}, & \{s_{-1}(0.6), s_0(0.4)\} & \{s_{-2}(0.8), s_{-1}(0.2)\} & \{s_0(1)\} \end{bmatrix}. \tag{35}$$

It can be noticed that L^1_{13}, L^2_{14}, and L^3_{14} are incomplete. Based on Definition deff3, the complete forms for these three PLTSs can be expressed as $\{s_{-3}(0.56), s_{-2}(0.44)\}$, $\{s_{-1}(0.78), s_0(0.22)\}$, and $\{s_{-1}(0.67), s_0(0.33)\}$, respectively. After preliminary discussion by the expert group, the subjective weight vector of experts is determined as $\eta = (0.32, 0.35, 0.33)$. According to the adjustment method of experts' weights proposed in Section 3.2, the final weight vector of experts is obtained as $w = (0.335, 0.337, 0.328)$.

4.1. Analysis of Influencing Factors by the Traditional DEMATEL Method. In the traditional DEMATEL method, experts usually use a scale of 0–4 to reflect the influence relationships between factors, which are expressed through a single linguistic term. That is to say, the corresponding linguistic value for the influence degree must be nonnegative, certain, and precise. Furthermore, partial ignorance is not allowed in the traditional DEMATEL method. So, the scores $E(L^\lambda_{ij}(p))$ of L^λ_{ij} $(i, j = 1, 2, \ldots, 5, \lambda = 1, 2, 3)$ are calculated, and only those $E(L^\lambda_{ij}(p))$ which corresponding PLTSs have complete probability information will be used. Then, the absolute values of $\mathrm{round}(E(L^\lambda_{ij}(p)))$ are used to characterize the experts' judgments, and the direct influence matrices A^λ_t $(\lambda = 1, 2, 3)$ can be expressed as follows, where "–" represents that an expert gave no exact judgment, so this judgment is not considered:

$$A^1_t = \begin{bmatrix} 0 & 2 & - & 1 & 0 \\ 2 & 0 & 2 & 0 & 2 \\ 1 & 3 & 0 & 1 & 2 \\ 0 & 1 & 1 & 0 & 4 \\ 1 & 2 & 1 & 1 & 0 \end{bmatrix},$$

$$A^2_t = \begin{bmatrix} 0 & 3 & 2 & - & 1 \\ 2 & 0 & 2 & 0 & 2 \\ 1 & 3 & 0 & 1 & 2 \\ 0 & 2 & 2 & 0 & 4 \\ 1 & 1 & 3 & 2 & 0 \end{bmatrix}, \tag{36}$$

$$A^3_t = \begin{bmatrix} 0 & 2 & 3 & - & 0 \\ 3 & 0 & 2 & 0 & 2 \\ 0 & 3 & 0 & 0 & 2 \\ 0 & 1 & 3 & 0 & 4 \\ 1 & 3 & 1 & 2 & 0 \end{bmatrix}.$$

Then, the aggregated direct influence matrix A_t can be obtained as follows, as per equation$A_t = \sum_{\lambda=1}^{m} \eta^{\lambda} A_t^{\lambda}$:

$$A_t = \begin{bmatrix} 0 & 2 & 2 & 1 & 0 \\ 2 & 0 & 2 & 0 & 2 \\ 1 & 3 & 0 & 1 & 2 \\ 0 & 1 & 2 & 0 & 4 \\ 1 & 2 & 2 & 2 & 0 \end{bmatrix}. \tag{37}$$

The total influence matrix T_t calculated per equations (27) and (29) is

$$T_t = \begin{bmatrix} 1.302 & 2.396 & 2.28 & 1.239 & 2.044 \\ 1.738 & 2.523 & 2.605 & 1.339 & 2.516 \\ 1.884 & 3.233 & 2.775 & 1.65 & 2.945 \\ 1.871 & 3.258 & 3.201 & 1.691 & 3.383 \\ 1.898 & 3.203 & 3.063 & 1.8 & 2.819 \end{bmatrix}. \tag{38}$$

Based on matrix T_t, equations (31) and (33) are used to calculate d_i^+ and r_i^+. The corresponding ϑ_i^+ and ψ_i^+ are shown in Table 1.

4.2. Analysis of Influencing Factors by the New Scale-Based DEMATEL Method. The new scale defined in this paper extends the scale to −4, −3, −2, −1, 0, 1, 2, 3, and 4, which can reflect both positive and negative influences between factors. Unlike the traditional DEMATEL method, the new scale-based DEMATEL method does not require the corresponding linguistic value for influence degree to be nonnegative. Therefore, the values of $\text{round}(E(L_{ij}^{\lambda}(p)))(i, j = 1, 2, \ldots, 5, \lambda = 1, 2, 3)$ are directly used to characterize the experts' judgments, and similarly, we use only those $\text{round}(E(L_{ij}^{\lambda}(p)))$ values which corresponding PLTSs have complete probability information. The direct influence matrices $A_s^{\lambda}(\lambda = 1, 2, 3)$ are

$$\begin{aligned} A_s^1 &= \begin{bmatrix} 0 & 2 & - & -1 & 0 \\ 2 & 0 & -2 & 0 & 2 \\ 1 & -3 & 0 & 1 & -2 \\ 0 & -1 & 1 & 0 & -4 \\ 1 & 2 & -1 & -1 & 0 \end{bmatrix}, \\ A_s^2 &= \begin{bmatrix} 0 & 3 & -2 & - & 1 \\ 2 & 0 & -2 & 0 & 2 \\ 1 & -3 & 0 & 1 & -2 \\ 0 & -2 & 2 & 0 & -4 \\ 1 & 1 & -3 & -2 & 0 \end{bmatrix}, \\ A_s^3 &= \begin{bmatrix} 0 & 2 & -3 & - & 0 \\ 3 & 0 & -2 & 0 & 2 \\ 0 & -3 & 0 & 0 & -2 \\ 0 & -1 & 3 & 0 & -4 \\ 1 & 3 & -1 & -2 & 0 \end{bmatrix}. \end{aligned} \tag{39}$$

Using the equation $A_s = \sum_{\lambda=1}^{m} \eta^{\lambda} A_s^{\lambda}$, the aggregated direct influence matrix is

$$A_s = \begin{bmatrix} 0 & 2 & -2 & -1 & 0 \\ 2 & 0 & -2 & 0 & 2 \\ 1 & -3 & 0 & 1 & -2 \\ 0 & -1 & 2 & 0 & -4 \\ 1 & 2 & -2 & -2 & 0 \end{bmatrix}. \tag{40}$$

The positive and negative direct influence matrices calculated by equations (17) and (18) are

$$\begin{aligned} A_s^+ &= \begin{bmatrix} 0 & 2 & 0 & 0 & 0 \\ 2 & 0 & 0 & 0 & 2 \\ 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 2 & 0 & 0 \\ 1 & 2 & 0 & 0 & 0 \end{bmatrix}, \\ A_s^- &= \begin{bmatrix} 0 & 0 & -2 & -1 & 0 \\ 0 & 0 & -2 & 0 & 0 \\ 0 & -3 & 0 & 0 & -2 \\ 0 & -1 & 0 & 0 & -4 \\ 0 & 0 & -2 & -2 & 0 \end{bmatrix}. \end{aligned} \tag{41}$$

The total positive and negative influence matrices calculated by equations (27)–(30) are

$$\begin{aligned} T_s^+ &= \begin{bmatrix} 0.714 & 1.143 & 0 & 0 & 0.571 \\ 1.429 & 1.286 & 0 & 0 & 1.143 \\ 0.49 & 0.327 & 0.143 & 0.286 & 0.163 \\ 0.245 & 0.163 & 0.571 & 0.143 & 0.082 \\ 1.143 & 1.429 & 0 & 0 & 0.714 \end{bmatrix}, \\ T_s^- &= \begin{bmatrix} 0 & 0.721 & 1.023 & 0.535 & 0.837 \\ 0 & 0.512 & 0.791 & 0.186 & 0.465 \\ 0 & 1.279 & 0.977 & 0.465 & 1.163 \\ 0 & 1.047 & 1.163 & 0.744 & 1.861 \\ 0 & 0.93 & 1.256 & 0.884 & 1.209 \end{bmatrix}. \end{aligned} \tag{42}$$

Based on matrices T_s^+ and T_s^-, d_i^+, r_i^+, d_i^-, and r_i^- are calculated by equations (31)–(34), and the values of ϑ_i and ψ_i are shown in Table 2.

4.3. Analysis of Influencing Factors by the DEMATEL Method Proposed in This Paper. According to Step 3 in Section 3.3, based on the PLDMs L^{λ} $(\lambda = 1, 2, 3)$, the elements in the aggregated PLDM L can be derived as shown in Table 3.

Then, following Step 4 in Section 3.3, the aggregated direct influence matrix, aggregated positive direct influence matrix, and aggregated negative direct influence matrix are given, respectively.

Table 1: ϑ_i^+ and ψ_i^+ values of factors by the traditional DEMATEL method.

	f_1	f_2	f_3	f_4	f_5	Sorting
ϑ_i	17.954	25.335	26.409	21.122	26.490	$f_5 \succ f_3 \succ f_2 \succ f_4 \succ f_1$
ψ_i	0.566	−3.890	−1.438	5.685	−0.923	$f_4 \succ f_1 \succ f_5 \succ f_3 \succ f_2$

Table 2: ϑ_i and ψ_i values by the new scale-based DEMATEL method.

	f_1	f_2	f_3	f_4	f_5	Sorting
ϑ_i	3.333	1.762	−6.971	−5.995	−3.855	$f_1 \succ f_2 \succ f_5 \succ f_4 \succ f_3$
ψ_i	−4.708	2.045	2.020	−1.225	1.868	$f_2 \succ f_3 \succ f_5 \succ f_4 \succ f_1$

$$A = \begin{bmatrix} 0 & 3 & -2 & -1 & 1 \\ 2 & 0 & -2 & 0 & 2 \\ 1 & -3 & 0 & 1 & -2 \\ 0 & -1 & 2 & 0 & -4 \\ 1 & 2 & -1 & -2 & 0 \end{bmatrix},$$

$$A^+ = \begin{bmatrix} 0 & 3 & 0 & 0 & 1 \\ 2 & 0 & 0 & 0 & 2 \\ 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 2 & 0 & 0 \\ 1 & 2 & 0 & 0 & 0 \end{bmatrix}, \quad (43)$$

$$A^- = \begin{bmatrix} 0 & 0 & -2 & -1 & 0 \\ 0 & 0 & -2 & 0 & 0 \\ 0 & -3 & 0 & 0 & -2 \\ 0 & -1 & 0 & 0 & -4 \\ 0 & 0 & -1 & -2 & 0 \end{bmatrix}.$$

The total positive influence matrix T^+ and total negative influence matrix T^- can be determined by equations (27)–(30) as

$$T^+ = \begin{bmatrix} 3.8 & 5.6 & 0 & 0 & 4 \\ 4 & 5 & 0 & 0 & 4 \\ 1.371 & 1.6 & 0.143 & 0.286 & 1.143 \\ 0.686 & 0.8 & 0.571 & 0.143 & 0.571 \\ 3.2 & 4.4 & 0 & 0 & 3 \end{bmatrix}, \quad (44)$$

$$T^- = \begin{bmatrix} 0 & 0.547 & 0.755 & 0.472 & 0.679 \\ 0 & 0.415 & 0.642 & 0.151 & 0.377 \\ 0 & 1.038 & 0.604 & 0.377 & 0.943 \\ 0 & 0.66 & 0.566 & 0.604 & 1.509 \\ 0 & 0.472 & 0.547 & 0.717 & 0.793 \end{bmatrix}.$$

Based on matrices T^+ and T^-, d_i^+, r_i^+, d_i^-, and r_i^- are calculated by equations (31)–(34), and the corresponding ϑ_i and ψ_i are shown in Table 4.

According to the results in Table 4, f_2 (knowledge-sharing ability of employees) and f_1 (richness of knowledge transfer channels) are the two most important influencing factors. Factors f_2, f_1, and f_5 (employees' willingness to share knowledge) have a positive impact on the whole knowledge-sharing system, while f_4 (employees' hierarchy bias) and f_3 (the implication and dispersion of knowledge) influence the whole system negatively. Factors f_3 and f_4 are on the cause group, and f_5, f_1, and f_2 are the factors to be influenced by other factors.

4.4. Comparisons and Discussion. To demonstrate that the proposed DEMATEL method is more reasonable and practical, an illustrative example was analyzed using traditional DEMATEL, the new scale-based DEMATEL, and the proposed DEMATEL method. The results of these methods and the rankings of the influencing factors are shown in Tables 1, 2, and 4. The main differences in some special attributes between these three methods are shown in Table 5. From the comparison, it can be seen that the proposed DEMATEL method has some merits.

(1) Positive and negative influence relationships between influencing factors are fully considered. In traditional DEMATEL, the evaluation scale values are all nonnegative integers. Thus, any negative influence will be analyzed and processed as a positive influence. In general, positive influences have positive effects and need to be strengthened, while negative influences have negative effects and need to be suppressed. It is unreasonable to process these two kinds of influences equally. On the contrary, the proposed new scale of DEMATEL extends the traditional one, and makes it possible to rationally distinguish and express positive and negative influences between factors. Therefore, by using the proposed new evaluation scale of DEMATEL, experts will no longer be confused when expressing the positive and negative influences between factors, and the actual influence relationships between factors will be better described and analyzed to make more scientific decisions.

(2) Partial ignorance is permitted. The corresponding linguistic values for influence relationships between factors must be complete in traditional DEMATEL and the new scale-based DEMATEL. In practical decision-making, however, experts may give incomplete judgment information because of the limitation of their professional background and previous experience. So, the experts are often forced to offer complete judgment information when a judgment oversteps an expert's expertise and experience, which may lead to judgmental distortion. When determining the influence relationship between two factors, once an expert gives an incomplete judgment, it must be deleted, and only complete judgments provided by other experts will be considered. On the contrary, the proposed

Table 3: Elements in group's aggregated PLDM L.

	Aggregated PLTSs
$L_{11}(p)$	$\{s_{0}(1)\}$
$L_{12}(p)$	$\{s_{2.416}(0.294), s_{2.736}(0.084), s_{2.744}(0.196), s_{3}(0.056), s_{4}(0.37)\}$
$L_{13}(p)$	$\{s_{-3}(0.028), s_{-2.656}(0.028), s_{-2.648}(0.19), s_{-2.32}(0.19), s_{-2.312}(0.132), s_{-2.248}(0.084), s_{-2}(0.132), s_{-1.944}(0.084), s_{-1.936}(0.066), s_{-1.64}(0.066)\}$
$L_{14}(p)$	$\{s_{-1.312}(0.15678), s_{-1}(0.2613), s_{-0.944}(0.07722), s_{-0.928}(0.04422), s_{-0.648}(0.1287), s_{-0.64}(0.10452), s_{-0.632}(0.0737), s_{-0.584}(0.02178), s_{-0.32}(0.05148), s_{-0.312}(0.0363), s_{-0.304}(0.02948), s_{-0.008}(0.01452)\}$
$L_{15}(p)$	$\{s_{0.368}(0.294), s_{0.696}(0.28), s_{0.832}(0.126), s_{0.992}(0.056), s_{1.104}(0.042), s_{1.12}(0.036), s_{1.128}(0.084), s_{1.368}(0.028), s_{1.384}(0.024), s_{1.472}(0.018), s_{1.712}(0.012)\}$
$L_{21}(p)$	$\{s_{1.104}(0.012), s_{1.368}(0.036), s_{1.472}(0.028), s_{1.696}(0.018), s_{1.704}(0.072), s_{1.712}0.084, s_{1.904}(0.054), s_{1.992}(0.042), s_{2}(0.168), s_{2.168}(0.108), s_{2.176}(0.126), s_{2.408}(0.252)\}$
$L_{22}(p)$	$\{s_{0}(1)\}$
$L_{23}(p)$	$\{s_{-2.32}(0.21), s_{-1.952}(0.21), s_{-1.944}(0.09), s_{-1.64}(0.14), s_{-1.592}(0.09), s_{-1.312}(0.14), s_{-1.304}(0.06), s_{-1}(0.06)\}$
$L_{24}(p)$	$\{s_{0}(1)\}$
$L_{25}(p)$	$\{s_{1.368}(0.036), s_{1.704}(0.084), s_{1.712}(0.144), s_{1.904}(0.024), s_{2}(0.336), s_{2.168}(0.056), s_{2.176}(0.096), s_{2.408}(0.224)\}$
$L_{31}(p)$	$\{s_{0.096}(0.028), s_{0.368}(0.112), s_{0.448}(0.112), s_{0.592}(0.012), s_{0.696}(0.448), s_{0.832}(0.048), s_{0.904}(0.048), s_{1.128}(0.192)\}$
$L_{32}(p)$	$\{s_{-3.648}(0.028), s_{-3.32}(0.098), s_{-3.312}(0.112), s_{-3.264}(0.012), s_{-3}(0.392), s_{-2.952}(0.042), s_{-2.944}(0.048), s_{-2.648}(0.168), s_{-2.552}(0.014), s_{-2.264}(0.056), s_{-2.224}(0.006), s_{-1.952}(0.024)\}.$
$L_{33}(p)$	$\{s_{0}(1)\}$
$L_{34}(p)$	$\{s_{0.368}(0.144), s_{0.696}(0.372), s_{0.824}(0.096), s_{0.992}(0.084), s_{1.112}(0.024), s_{1.12}(0.224), s_{1.376}(0.056)\}$
$L_{35}(p)$	$\{s_{-2.312}(0.224), s_{-2}(0.336), s_{-1.936}(0.152), s_{-1.64}(0.228), s_{-1.584}(0.024), s_{-1.304}(0.036)\}$
$L_{41}(p)$	$\{s_{-0.32}(0.2), s_{-0.008}(0.8)\}$
$L_{42}(p)$	$\{s_{-1.312}(0.315), s_{-1}(0.315), s_{-0.944}(0.035), s_{-0.936}(0.135), s_{-0.648}(0.035), s_{-0.64}(0.135), s_{-0.592}(0.015), s_{-0.32}(0.015)\}$
$L_{43}(p)$	$\{s_{1.104}(0.006), s_{1.368}(0.054), s_{1.472}(0.024), s_{1.696}(0.014), s_{1.712}(0.216), s_{1.904}(0.126), s_{1.992}(0.056), s_{2.176}(0.504)\}$
$L_{44}(p)$	$\{s_{0}(1)\}$
$L_{45}(p)$	$\{s_{-4}(0.8), s_{-3.648}(0.2)\}$
$L_{51}(p)$	$\{s_{0.368}(0.014), s_{0.696}(0.182), s_{0.832}(0.006), s_{0.992}(0.504), s_{1.12}(0.054), s_{1.128}(0.024), s_{1.384}(0.216)\}$
$L_{52}(p)$	$\{s_{1.104}(0.018), s_{1.368}(0.072), s_{1.472}(0.042), s_{1.696}(0.042), s_{1.704}(0.168), s_{1.904}(0.168), s_{1.984}(0.098), s_{2.168}(0.392)\}$
$L_{53}(p)$	$\{s_{-1.952}(0.072), s_{-1.648}(0.048), s_{-1.592}(0.288), s_{-1.536}(0.048), s_{-1.312}(0.192), s_{-1.256}(0.032), s_{-1.2}(0.192), s_{-0.944}(0.128)\}.$
$L_{54}(p)$	$\{s_{-2.32}(0.112), s_{-2}(0.448), s_{-1.952}(0.028), s_{-1.648}(0.112), s_{-1.52}(0.048), s_{-1.24}(0.192), s_{-1.2}(0.012), s_{-0.936}(0.048)\}$
$L_{55}(p)$	$\{s_{0}(1)\}$

Table 4: ϑ_i and ψ_i values of factors by the proposed DEMATEL method.

	f_1	f_2	f_3	f_4	f_5	Sorting
ϑ_i	24.004	25.683	−2.460	−0.818	16.484	$f_2 \succ f_1 \succ f_5 \succ f_4 \succ f_3$
ψ_i	−2.110	−2.853	3.980	1.324	−0.341	$f_3 \succ f_4 \succ f_5 \succ f_1 \succ f_2$

Table 5: Principal differences in some special attributes between three kinds of DEMATEL methods.

	Negative influences between factors	Incomplete information	Experts' hesitant information	Adjustment of experts' weights
Traditional DEMATEL method	×	×	×	×
New scale-based DEMATEL method	√	×	×	×
Proposed DEMATEL method	√	√	√	√

DEMATEL method allows experts to give incomplete judgment information, so that all judgment information will be adopted without losing valuable data. If the judgment information is incomplete, the probabilities in these incomplete PLTSs will be normalized to make them complete, as shown in Definition deff3.

(3) Hesitation among several possible values is allowed. In traditional DEMATEL and the new scale-based DEMATEL, the linguistic value of the influence degree must be certain and precise. However, due to the complexity of practical problems, experts may hesitate among several possible linguistic terms when judging the influence relationships between factors. In this case, if the experts are required to give precise judgment information, the judgment may be distorted. On the contrary, the proposed DEMATEL method allows experts to hesitate among several possible linguistic terms, and their preferences for these possible linguistic terms will be expressed in the form of a probability distribution. In this way, the expression of judgment information will be more flexible, and all valuable information will be collected and considered.

(4) An adjustment method of experts' subjective weights is introduced. In traditional DEMATEL and the new scale-based DEMATEL, it is often assumed that the experts are equally important, which is arbitrary, or the experts' weights are given directly by the expert group, which only considers the experts' confidence in their judgments and does not consider the reliability of experts' judgments. To overcome these defects, the proposed DEMATEL method introduces an experts' subjective weights adjustment method to determine the final experts' weights, which is based on the similarity degree between PLTSs defined in this paper. First, the subjective weights of experts are determined by the expert group through a preliminary discussion. Then, the final weights will be gotten by adjusting the subjective weights based on the similarity degree of experts' judgments which are expressed in PLTSs. On the one hand, the final weights can reflect experts' confidence in their judgments. On the other hand, the final weights which are determined by the similarity degree of judgments can reflect the reliability of experts' judgments to some extent. Therefore, the experts' weights determination method proposed in this paper is more reasonable.

Table 6: Initial subjective weights of three experts and adjusted weights.

Initial subjective weights	Adjusted weights
ω_1 $\omega_1^t = \{0.1, 0.3, 0.6\}$	$\omega_1^a = \{0.081, 0.224, 0.695\}$
ω_2 $\omega_2^t = \{0.2, 0.1, 0.7\}$	$\omega_2^a = \{0.155, 0.071, 0.774\}$
ω_3 $\omega_3^t = \{0.4, 0.3, 0.3\}$	$\omega_3^a = \{0.363, 0.250, 0.388\}$
ω_4 $\omega_4^t = \{0.5, 0.1, 0.4\}$	$\omega_4^a = \{0.430, 0.079, 0.491\}$
ω_5 $\omega_5^t = \{0.6, 0.2, 0.2\}$	$\omega_5^a = \{0.561, 0.172, 0.267\}$
ω_6 $\omega_6^t = \{0.8, 0.1, 0.1\}$	$\omega_6^a = \{0.773, 0.089, 0.138\}$

4.5. Sensitivity Analysis. In order to further validate the effectiveness and superiority of the new group method, the sensitivity of each of the three models will be tested and analyzed in this study using multiple sets of weights for three experts. The data for the six sets of weight changes required in the analysis are shown in Table 6, where the initial subjective weights of three experts given by the decision-maker is denoted as ω_t, according to the adjustment method of experts' weights proposed in Section 3.2, and the final weight vector of experts is denoted as ω_a.

Then, following steps in Sections 4.1–4.3, the results by the three algorithms with six sets of weight variations were obtained and are shown in Tables 7–9, respectively.

The results of the above calculations show that the line graphs of the DEMATEL method proposed in this paper change more significantly compared to the other two methods that have not been improved. The change in the new scale-based DEMATEL method is not obvious and the direction is basically flat, indicating that if the information is collected in a form other than PLTSs, the loss of information will affect the sensitivity of the ranking results and will also have a greater impact on the decision results. In contrast, the

Table 7: Results of the traditional DEMATEL method.

	f_1	f_2	f_3	f_4	f_5	Sorting	Line chart
ϑ^1	5.758	8.572	7.856	6.485	8.419	$f_2 \succ f_5 \succ f_3 \succ f_4 \succ f_1$	
ψ^1	0.077	−1.042	−1.723	2.874	−0.185	$f_4 \succ f_1 \succ f_5 \succ f_2 \succ f_3$	
ϑ^2	6.034	9.230	7.486	6.642	8.636	$f_2 \succ f_5 \succ f_3 \succ f_4 \succ f_1$	
ψ^2	−0.098	−1.548	−1.217	2.946	−0.083	$f_4 \succ f_5 \succ f_1 \succ f_3 \succ f_2$	
ϑ^3	17.954	25.335	26.409	21.122	26.490	$f_5 \succ f_3 \succ f_2 \succ f_4 \succ f_1$	
ψ^3	0.566	−3.890	−1.438	5.685	−0.923	$f_4 \succ f_1 \succ f_5 \succ f_3 \succ f_2$	
ϑ^4	12.397	17.142	16.834	14.095	16.957	$f_2 \succ f_5 \succ f_3 \succ f_4 \succ f_1$	
ψ^4	0.581	−2.522	0.151	3.537	−1.747	$f_4 \succ f_1 \succ f_3 \succ f_5 \succ f_2$	
ϑ^5	9.534	12.908	12.550	9.253	11.516	$f_2 \succ f_3 \succ f_5 \succ f_1 \succ f_4$	
ψ^5	0.433	−1.994	0.097	3.396	−1.932	$f_4 \succ f_1 \succ f_3 \succ f_5 \succ f_2$	
ϑ^6	8.450	11.494	10.751	7.387	10.197	$f_2 \succ f_3 \succ f_5 \succ f_1 \succ f_4$	
ψ^6	0.426	−1.570	0.580	2.235	−1.671	$f_4 \succ f_3 \succ f_1 \succ f_2 \succ f_5$	

Table 8: Results of the new scale-based DEMATEL method.

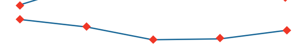
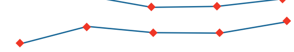
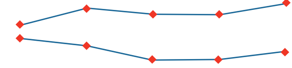
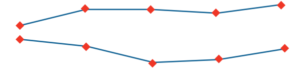
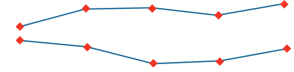
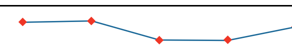
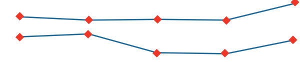
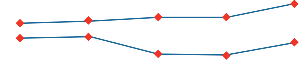
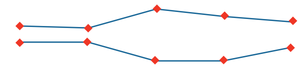
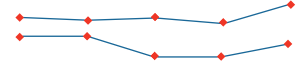
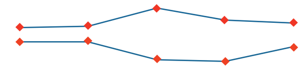
	f_1	f_2	f_3	f_4	f_5	Sorting	Line chart
ϑ^1	0.799	−4.551	−8.493	−7.028	−6.532	$f_1 \succ f_2 \succ f_5 \succ f_4 \succ f_3$	
ψ^1	−4.102	2.887	0.726	−0.727	−1.400	$f_2 \succ f_3 \succ f_4 \succ f_5 \succ f_1$	
ϑ^2	2.350	−0.599	−5.475	−5.060	−2.027	$f_1 \succ f_2 \succ f_5 \succ f_4 \succ f_3$	
ψ^2	−3.846	1.547	−0.449	−0.419	3.167	$f_5 \succ f_2 \succ f_4 \succ f_3 \succ f_1$	
ϑ^3	3.333	−0.599	−5.475	−5.060	−2.027	$f_1 \succ f_2 \succ f_5 \succ f_4 \succ f_3$	
ψ^3	−3.846	1.547	−0.449	−0.419	3.167	$f_5 \succ f_2 \succ f_4 \succ f_3 \succ f_1$	
ϑ^4	3.996	1.209	−3.953	−4.028	−0.871	$f_1 \succ f_2 \succ f_5 \succ f_4 \succ f_3$	
ψ^4	−4.045	1.057	0.845	−0.243	2.386	$f_5 \succ f_2 \succ f_3 \succ f_4 \succ f_1$	
ϑ^5	4.449	2.123	−2.863	−1.715	1.553	$f_1 \succ f_2 \succ f_5 \succ f_4 \succ f_3$	
ψ^5	−3.592	0.771	1.013	−0.543	2.351	$f_5 \succ f_3 \succ f_2 \succ f_4 \succ f_1$	
ϑ^6	4.286	2.014	−3.405	−2.453	1.499	$f_1 \succ f_2 \succ f_5 \succ f_4 \succ f_3$	
ψ^6	−3.429	0.880	1.233	−1.090	2.406	$f_5 \succ f_3 \succ f_2 \succ f_4 \succ f_1$	

Table 9: Results of the DEMATEL method proposed in this paper.

	f_1	f_2	f_3	f_4	f_5	Sorting	Line chart
ϑ^1	21.947	23.283	−5.576	−5.164	14.770	$f_2 \succ f_1 \succ f_5 \succ f_4 \succ f_3$	
ψ^1	−0.053	−0.453	−0.349	−0.519	1.374	$f_5 \succ f_1 \succ f_3 \succ f_2 \succ f_4$	
ϑ^2	18.747	24.083	−5.576	−5.160	14.770	$f_2 \succ f_1 \succ f_5 \succ f_4 \succ f_3$	
ψ^2	−3.353	−2.053	−0.349	−0.519	6.174	$f_5 \succ f_3 \succ f_4 \succ f_2 \succ f_1$	
ϑ^3	24.004	25.683	−0.818	−2.460	16.484	$f_2 \succ f_1 \succ f_5 \succ f_3 \succ f_4$	
ψ^3	−2.110	−2.853	3.980	1.324	−0.341	$f_3 \succ f_4 \succ f_5 \succ f_1 \succ f_2$	
ϑ^4	21.947	23.283	−4.933	−4.518	14.770	$f_2 \succ f_1 \succ f_5 \succ f_4 \succ f_3$	
ψ^4	−0.053	−0.453	−0.135	−0.733	1.374	$f_5 \succ f_1 \succ f_3 \succ f_2 \succ f_4$	
ϑ^5	23.341	23.958	−3.836	−4.428	13.500	$f_2 \succ f_1 \succ f_5 \succ f_3 \succ f_4$	
ψ^5	−2.773	−1.865	5.154	0.343	−0.586	$f_3 \succ f_4 \succ f_5 \succ f_2 \succ f_1$	
ϑ^6	23.547	25.150	−1.569	−4.034	16.103	$f_2 \succ f_1 \succ f_5 \succ f_3 \succ f_4$	
ψ^6	−1.653	−2.320	3.910	−0.059	0.040	$f_3 \succ f_5 \succ f_4 \succ f_1 \succ f_2$	

DEMATEL method proposed in this paper, which considers both negative scaling and PLTSs, is more superior.

Then, to intuitively observe the changes in the position of the factors in the system, this research analyses the sensitivity of the three models from the perspective of the factors, using the change in the position of the cause degree (ψ_i) of the factors as an example. The results of the change in the location of the factors are shown in Figures 2–6.

It is evident from Figures 2 to 6 that the DEMATEL method proposed in this paper is sensitive to the weight

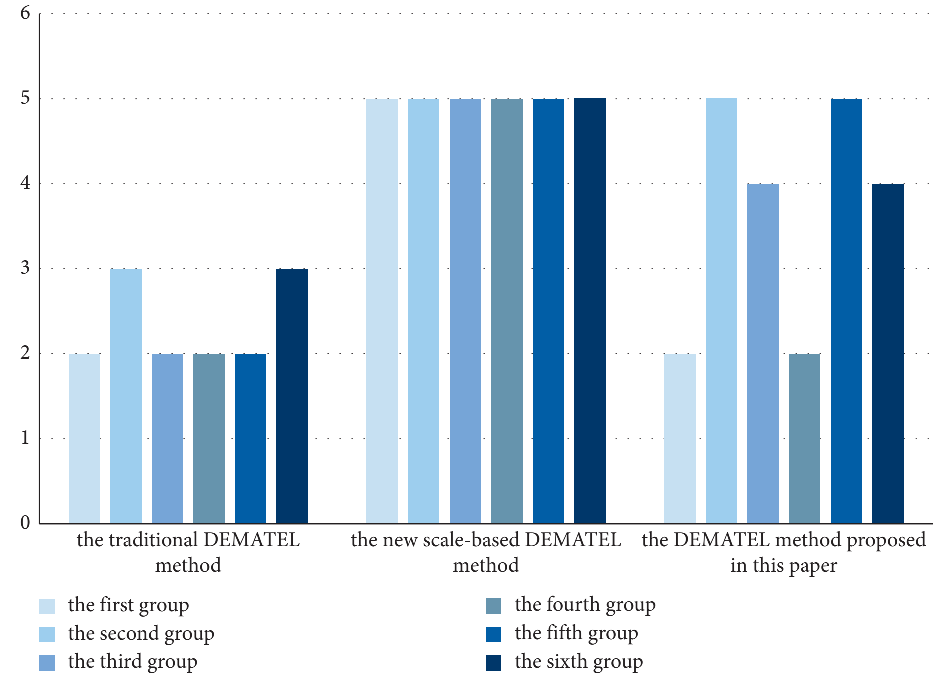


Figure 2: Location change of system element f_1.

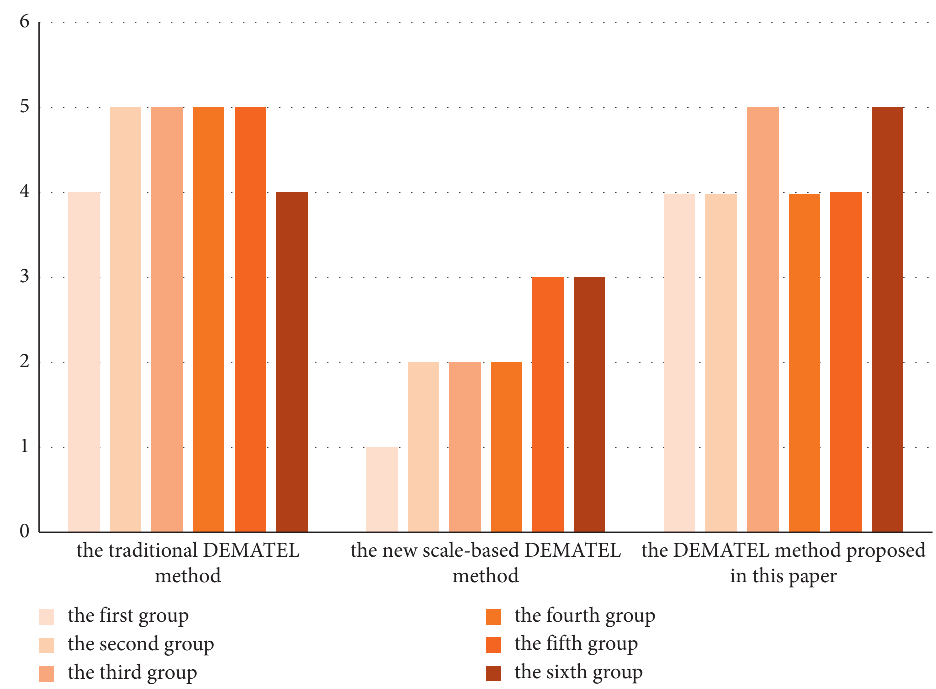


Figure 3: Location change of system element f_2.

change of experts, with more significant differences in the position of the factors in the system as the varying expert weights. By comparison, the new scale-based DEMATEL method is less sensitive and the weight change of experts has no greater impact on the decision outcome, which is judged to be inconsistent with the real world.

In addition, the traditional DEMATEL method has a relatively high sensitivity as does the DEMATEL method proposed in this paper, but the new group DEMATEL in this paper contains a more diverse amount of information and also adds a negative scale as a basis for evaluation. It can be seen that although the new group DEMATEL method is computationally complex, the sensitivity of this method does not decrease due to the increased amount of information and computational complexity; so, the new group DEMATEL model is more advantageous in solving more complex system issues.

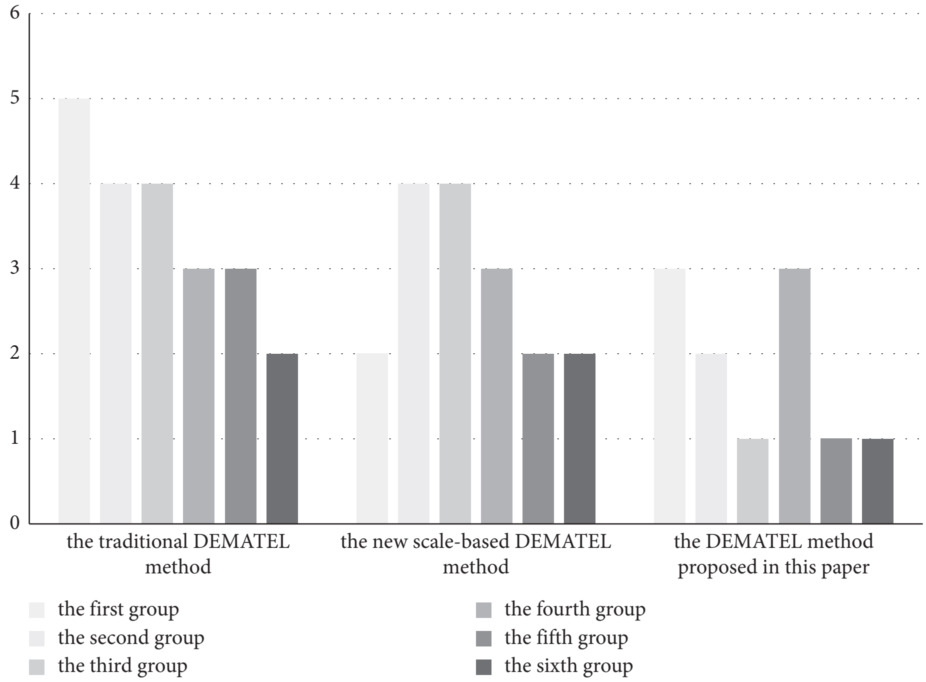


Figure 4: Location change of system element f_3.

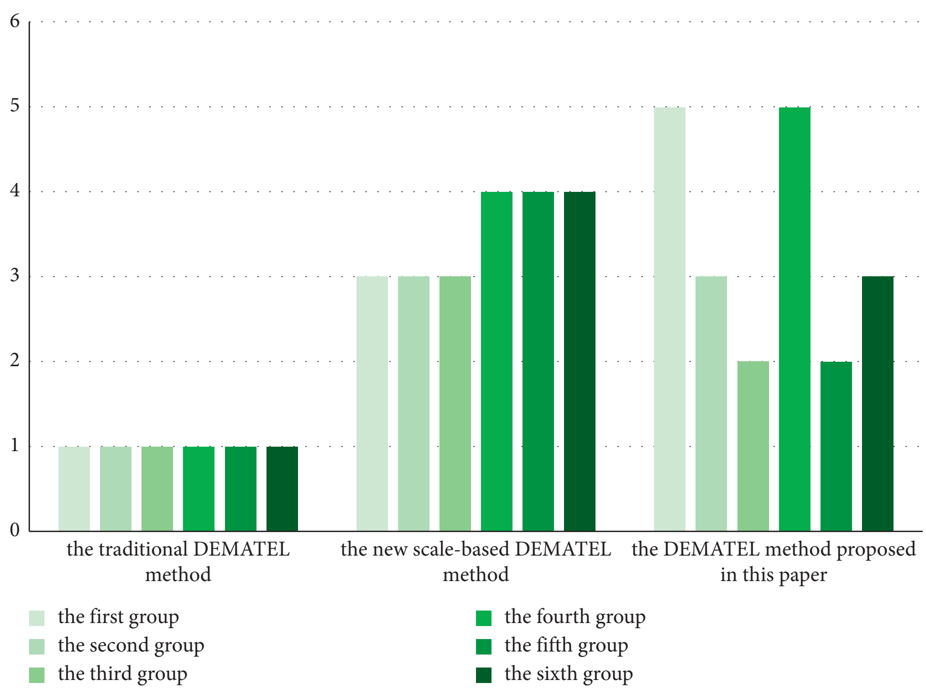


Figure 5: Location change of system element f_4.

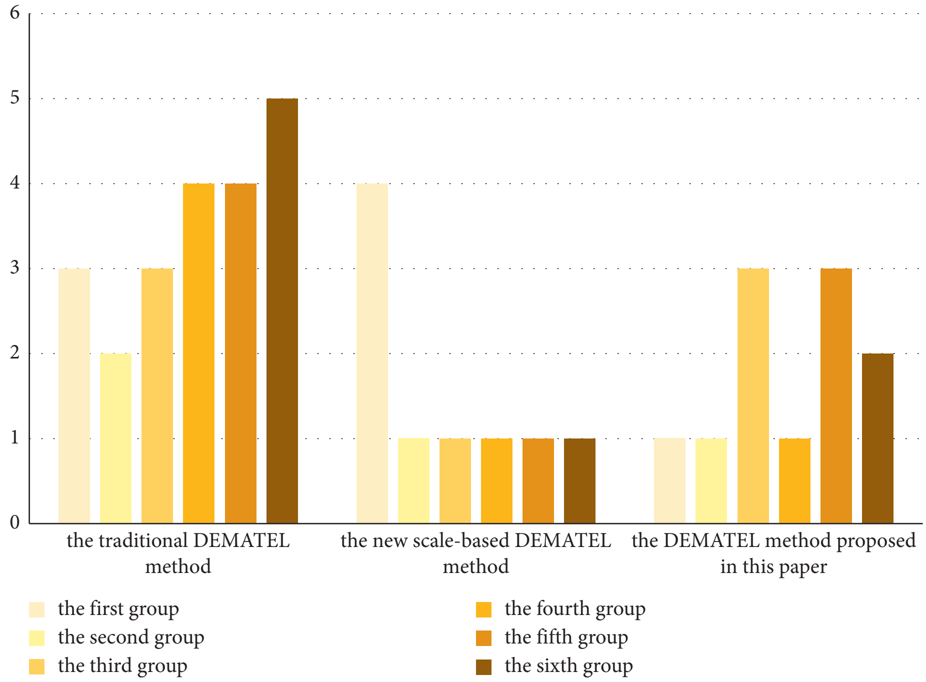


Figure 6: Location change of system element f_5.

5. Conclusions and Future Directions

The values of the existing evaluation scales of DEMATEL are all nonnegative integers without exception, and the negative influences between factors are expressed and treated as positive ones. However, positive and negative influences have different effects and need to be managed differently. In addition, the experts are assumed to be able to give precise and complete judgment information, which may lead to judgmental distortion when a judgment oversteps an expert's expertise and experience. In order to solve the mentioned problems, the new probabilistic linguistic-based group DEMATEL method is developed in this paper to analyze both positive and negative influence relationships between factors. To demonstrate the proposed DEMATEL method, an illustrative example of an innovative pharmaceutical enterprise is adopted. The proposed group DEMATEL method is compared to traditional DEMATEL and the new scale-based DEMATEL to prove the feasibility and advantages of the proposed new method. Our results show that the proposed DEMATEL method is more reasonable and practical.

The main contributions of this study can be summarized into four aspects. Firstly, by extending the traditional evaluation scale of DEMATEL, a new scale is defined to distinguish and describe both positive and negative influences between factors. The positive and negative direct influence matrices under the new scale are also defined, and the corresponding matrix operations of DEMATEL are introduced. This is the first time that negative influences between factors are considered in the method of DEMATEL; therefore, it is more in line with the practical situation of complex system factor analysis. Secondly, PLTS theory is introduced to integrate with the new scale-based group DEMATEL method, which allows experts to express incomplete and uncertain linguistic preference. Thirdly, to better determine the final experts' weights, an experts' subjective weights adjustment method based on the similarity degree of experts' judgments under the probabilistic linguistic environment is introduced. Fourthly, an algorithm of probabilistic linguistic-based group DEMATEL method with both positive and negative influences is summarized to make the idea and process of the proposed method clear.

In future research, we expect to employ the proposed DEMATEL method to solve practical system factor analysis problems, such as analysis of factors influencing the location selection of freight villages, factors influencing the implementation of innovation strategies, and analysis of influencing factors of green supplier selection.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research was funded by the National Natural Science Foundation of China (nos. 71561015 and 72061018).

References

[1] J. I. Shieh, H. H. Wu, and K. K. Huang, "A DEMATEL method in identifying key success factors of hospital service quality," *Knowledge Based Systems*, vol. 23, no. 3, pp. 277–282, 2010.

[2] H. H. Wu, H. K. Chen, and J. I. Shieh, "Evaluating performance criteria of employment service outreach program personnel by DEMATEL method," *Expert Systems with Applications*, vol. 37, no. 7, pp. 5219–5223, 2010.

[3] H. H. Wu and Y. N. Tsai, "A DEMATEL method to evaluate the causal relations among the criteria in auto spare parts industry," *Applied Mathematics and Computation*, vol. 218, no. 5, pp. 2334–2342, 2011.

[4] Y. J. Chiu, H. C. Chen, G. H. Tzeng, and J. Z. Shyu, "Marketing strategy based on customer behaviour for the LCD-TV," *International Journal of Management and Decision Making*, vol. 7, no. 7, pp. 143–165, 2006.

[5] J. J. H. Liou, G. H. Tzeng, and H. C. Chang, "Airline safety measurement using a hybrid model," *Journal of Air Transport Management*, vol. 13, no. 4, pp. 243–249, 2007.

[6] M. L. Tseng, "A causal and effect decision making model of service quality expectation using grey-fuzzy DEMATEL approach," *Expert Systems with Applications*, vol. 36, no. 4, pp. 7738–7748, 2009.

[7] F. H. Chen, T. S. Hsu, and G. H. Tzeng, "A balanced scorecard approach to establish a performance evaluation and relationship model for hot spring hotels based on a hybrid MCDM model combining DEMATEL and ANP," *International Journal of Hospitality Management*, vol. 30, no. 4, pp. 908–932, 2011.

[8] Z. C. Lin, G. E. Hong, and P. F. Cheng, "A study of patent analysis of LED bicycle light by using modified DEMATEL and life span," *Advanced Engineering Informatics*, vol. 34, pp. 136–151, 2017.

[9] O. Uygun, H. Kacamak, and U. A. Kahraman, "An integrated DEMATEL and Fuzzy ANP techniques for evaluation and selection of outsourcing provider for a telecommunication company," *Computers and Industrial Engineering*, vol. 86, pp. 137–146, 2015.

[10] C. Y. Huang, J. Z. Shyu, and G. H. Tzeng, "Reconfiguring the innovation policy portfolios for Taiwan's SIP Mall industry," *Technovation*, vol. 27, no. 12, pp. 744–765, 2007.

[11] G. H. Tzeng and C. Y. Huang, "Combined DEMATEL technique with hybrid MCDM methods for creating the aspired intelligent global manufacturing and logistics systems," *Annals of Operations Research*, vol. 197, no. 1, pp. 159–190, 2012.

[12] M. Dytczak and G. Ginda, "Is explicit processing of fuzzy direct influence evaluations in DEMATEL indispensable?" *Expert Systems with Applications*, vol. 40, no. 12, pp. 5027–5032, 2013.

[13] K. J. Wu, C. J. Liao, M. L. Tseng, and A. S. F. Chiu, "Exploring decisive factors in green supply chain practices under uncertainty," *International Journal of Production Economics*, vol. 159, pp. 147–157, 2015.

[14] R. M. Rodríguez, L. Martínez, and F. Herrera, "Hesitant fuzzy linguistic term sets for decision making," *IEEE Transactions on Fuzzy Systems*, vol. 20, no. 1, pp. 109–119, 2012.

[15] L. A. Zadeh, "The concept of a linguistic variable and its application to approximate reasoning—I," *Information Sciences*, vol. 8, no. 3, pp. 199–249, 1975.

[16] V. Torra, "Hesitant fuzzy sets," *International Journal of Intelligent Systems*, vol. 25, no. 6, pp. 529–539, 2010.

[17] Q. Pang, H. Wang, and Z. S. Xu, "Probabilistic linguistic term sets in multi-attribute group decision making," *Information Sciences*, vol. 369, pp. 128–143, 2016.

[18] M. W. Lin, Z. Y. Chen, H. C. Liao, and Z. S. Xu, "ELECTRE II method to deal with probabilistic linguistic term sets and its application to edge computing," *Nonlinear Dynamics*, vol. 96, no. 12, pp. 2125–2143, 2019.

[19] M. W. Lin, H. B. Wang, Z. S. Xu, Z. Q. Yao, and J. L. Huang, "Clustering algorithms based on correlation coefficients for probabilistic linguistic term sets," *International Journal of Intelligent Systems*, vol. 33, no. 12, pp. 2402–2424, 2018.

[20] C. Jin, H. Wang, and Z. S. Xu, "Uncertain probabilistic linguistic term sets in group decision making," *International Journal of Fuzzy Systems*, vol. 21, no. 4, pp. 1241–1258, 2019.

[21] P. D. Liu and F. Teng, "Some Muirhead mean operators for probabilistic linguistic term sets and their applications to multiple attribute decision-making," *Applied Soft Computing Journal*, vol. 68, pp. 396–431, 2018.

[22] J. Gu, Y. Zheng, X. L. Tian, and Z. S. Xu, "A decision-making framework based on prospect theory with probabilistic linguistic term sets," *Journal of the Operational Research Society*, vol. 72, no. 4, pp. 879–888, 2018.

[23] H. G. Peng, H. Y. Zhang, and J. Q. Wang, "Cloud decision support model for selecting hotels on TripAdvisor.com with probabilistic linguistic information," *International Journal of Hospitality Management*, vol. 68, pp. 124–138, 2018.

[24] X. Cheng, J. Gu, and Z. S. Xu, "Venture capital group decision-making with interaction under probabilistic linguistic environment," *Knowledge Based Systems*, vol. 140, pp. 82–91, 2018.

[25] Y. X. Zhang, Z. S. Xu, H. Wang, and H. C. Liao, "Consistency-based risk assessment with probabilistic linguistic preference relation," *Applied Soft Computing*, vol. 49, pp. 817–833, 2016.

[26] Y. X. Zhang, Z. S. Xu, and H. C. Liao, "Water security evaluation based on the TODIM method with probabilistic linguistic term sets," *Soft Computing*, vol. 23, no. 15, pp. 6215–6230, 2019.

[27] F. Xiao and J. Q. Wang, "Multistage decision support framework for sites selection of solar power plants with probabilistic linguistic information," *Journal of Cleaner Production*, vol. 230, pp. 1396–1409, 2019.

[28] R. Krishankumar, R. Saranya, R. P. Nethra, K. S. Ravichandran, and S. Kar, "A decision-making framework under probabilistic linguistic term set for multi-criteria group decision-making problem," *Journal of Intelligent and Fuzzy Systems*, vol. 36, no. 6, pp. 5783–5795, 2019.

[29] P. Li and C. P. Wei, "An emergency decision-making method based on D-S evidence theory for probabilistic linguistic term sets," *International Journal of Disaster Risk Reduction*, vol. 37, pp. 1–10, 2019.

[30] H. C. Liao, L. S. Jiang, B. Lev, and H. Fujita, "Novel operations of PLTSs based on the disparity degrees of linguistic terms and their use in designing the probabilistic linguistic ELECTRE III method," *Applied Soft Computing*, vol. 80, pp. 450–464, 2019.

[31] P. D. Liu and Y. Li, "An extended MULTIMOORA method for probabilistic linguistic multi-criteria group decision-making based on prospect theory," *Computers and Industrial Engineering*, vol. 136, pp. 528–545, 2019.

[32] X. L. Wu and H. C. Liao, "An approach to quality function deployment based on probabilistic linguistic term sets and ORESTE method for multi-expert multi-criteria decision making," *Information Fusion*, vol. 43, pp. 13–26, 2018.
[33] X. Y. Zhou, L. Q. Wang, J. D. Qin, J. Chai, and C. Q. G. Muñoz, "Emergency rescue planning under probabilistic linguistic information: an integrated FTA-ANP method," *International Journal of Disaster Risk Reduction*, vol. 37, pp. 1–14, 2019.
[34] X. J. Gou and Z. S. Xu, "Novel basic operational laws for linguistic terms, hesitant fuzzy linguistic term sets and probabilistic linguistic term sets," *Information Sciences*, vol. 372, pp. 407–427, 2016.
[35] C. Z. Bai, R. Zhang, L. X. Qian, and Y. N. Wu, "Comparisons of probabilistic linguistic term sets for multi-criteria decision making," *Knowledge Based Systems*, vol. 119, pp. 284–291, 2017.
[36] X. B. Mao, M. Wu, J. Y. Dong, S. P. Wan, and Z. Jin, "A new method for probabilistic linguistic multi-attribute group decision making: application to the selection of financial technologies," *Applied Soft Computing*, vol. 77, pp. 155–175, 2019.
[37] M. Yazdi, F. Khan, R. Abbassi, and R. Rusli, "Improved DEMATEL methodology for effective safety management decision-making," *Safety Science*, vol. 127, pp. 1–17, 2020.
[38] X. J. Gou, Z. S. Xu, and H. C. Liao, "Multiple criteria decision making based on Bonferroni means with hesitant fuzzy linguistic information," *Soft Computing*, vol. 21, no. 21, pp. 6515–6529, 2017.
[39] T. L. Saaty and M. Ozdemir, "Negative priorities in the analytic hierarchy process," *Mathematical and Computer Modelling*, vol. 37, no. 9-10, pp. 1063–1075, 2003.
[40] J. F. Wu and M. T. Shanley, "Knowledge stock, exploration, and innovation: research on the United States electromedical device industry," *Journal of Business Research*, vol. 62, no. 4, pp. 474–483, 2009.
[41] D. J. Jiménez and R. S. Valle, "Innovation, organizational learning, and performance," *Journal of Business Research*, vol. 64, no. 4, pp. 408–417, 2011.
[42] I. Nonaka, "A dynamic theory of organizational knowledge creation," *Organization Science*, vol. 5, no. 1, pp. 14–37, 1994.