Research Article

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

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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 “low influence,” “very 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, Rodriguez 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, PLTSs have 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 PLTs, our study redefines the similarity measure between PLTs 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 PLTs. 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 PLTs.

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 $A^\lambda = [a^\lambda_{ij}]_{n \times n} (i, j = 1, 2, \ldots, n)$, where $a^\lambda_{ij}$ indicates the direct influence degree that factor $f_i$ has on $f_j$ given by the $\lambda$th expert. By combining the judgments of all experts, the group direct influence matrix can be formed as $A = [a^g_{ij}]_{n \times n}$ where:

$$a^g_{ij} = \frac{\sum_{\lambda=1}^{m} a^\lambda_{ij}}{m}, \quad i, j = 1, 2, \ldots, n.$$  \hspace{1cm} (1)

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

$$G = \frac{A}{\max_{1 \leq i,j \leq n} \sum_{j=1}^{n} a^g_{ij}}.$$  \hspace{1cm} (2)

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

$$T = [t_{ij}]_{n \times n} = G(I - G)^{-1}.$$  \hspace{1cm} (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 $i$th 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.

$$d_i = \sum_{j=1}^{n} t_{ij}, \quad i = 1, 2, \ldots, n, \hspace{1cm} (4)$$

$$r_i = \sum_{j=1}^{n} t_{ji}, \quad i = 1, 2, \ldots, n, \hspace{1cm} (5)$$

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 HFLTs, PLTs 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 PLTs, and partial ignorance is allowed. All these properties are desirable in expressing preferences in decision-making.

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

$$E(L(p)) = s, \quad \sigma(L(p)) = \left(\frac{\sum_{k=1}^{\#L(p)} (p^{(k)}(r^{(k)} - \bar{r}))^2}{\sum_{k=1}^{\#L(p)} p^{(k)}}\right)^{1/2},$$

where $\bar{r} = \sum_{k=1}^{\#L(p)} r^{(k)} p^{(k)} / \sum_{k=1}^{\#L(p)} p^{(k)}$, 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 $\hat{L}(p)$ for $L(p)$.

$$\hat{L}(p) = \{L^{(k)}(p^{(k)})|k = 1, 2, \ldots, \#L(p), \sum_{k=1}^{\#L(p)} p^{(k)} \leq 1\},$$

**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 $\hat{L}(p)$ can be defined by

$$\hat{L}(p) = \{L^{(k)}(p^{(k)})|k = 1, 2, \ldots, \#L(p)\},$$

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

**Definition 4** (see [17]). Let $L_1(p) = \{L^{(k)}(p^{(k)})|k = 1, 2, \ldots, \#L_1(p)\}$ and $L_2(p) = \{L^{(k)}(p^{(k)})|k = 1, 2, \ldots, \#L_2(p)\}$ 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 $S = \{s_1, s_2, \ldots, -1, 0, 1, \ldots, \tau\}$, and they defined some basic operational laws of PLTSs as

$$gL(p) = g^{-1}\left(\bigcup_{u^{(k)} \in L_1(p)}\left\{1 - \left((1 - \eta^{(k)})^u\right)(p^{(k)})\right\}\right),$$

$$L_1(p) \oplus L_2(p) = g^{-1}\left(\bigcup_{u^{(k)} \in L_1(p)}\left\{(1 - \eta^{(k)})^u(p^{(k)})\right\}\right),$$

$$L_1(p) \otimes L_2(p) = g^{-1}\left(\bigcup_{u^{(k)} \in L_1(p)}\left\{(1 - \eta^{(k)})^u(p^{(k)})\right\}\right),$$

where $L(p)$, $L_1(p)$, and $L_2(p)$ are three PLTSs, and $u$ is a positive real number; $\eta^{(k)} \in g(L), \eta_1^{(j)} \in g(L_1), \eta_2^{(j)} \in g(L_2)$, where $k = 1, 2, \ldots, \#L_1, i = 1, 2, \ldots, \#L_1, j = 1, 2, \ldots, \#L_2$.

$g$ and $g^{-1}$ are the equivalent functions proposed by Gou et al. [38]:

$$g: [-\tau, \tau] \rightarrow [0, 1], g(L(p)) = \left(\left(\left(r^{(k)} / 2\tau\right) + (1/2)\right)(p^{(k)})\right) = L_1(p), \forall \in [0, 1],$$

$$g^{-1}: [0, 1] \rightarrow [-\tau, \tau], g^{-1}(L_1(p)) = \left\{s_{(2x-1)}(p^{(y)})|y \in [0, 1]\right\} = L(p).$$
Definition 5 (see [31]). Let \( S = \{ s_\alpha | \alpha = -r, \ldots, 0, 1, \ldots, r \} \) be an LTS. \( L_1(p) = \{ L_{1k}^{(k)}(p^{(k)}) \} \) \( k_1 = 1, 2, \ldots, \#L_1(p) \) and \( L_2(p) = \{ L_{2k}^{(k)}(p^{(k)}) \} \) \( k_2 = 1, 2, \ldots, \#L_2(p) \) are two complete PLTSs. Then, the possibility degree that \( L_1(p) \) is not less than \( L_2(p) \) can be defined by

\[
P(L_1(p) \succeq L_2(p)) = \sum_{k_1=1}^{\#L_1(p)} \sum_{k_2=1}^{\#L_2(p)} R(L_{1k}^{(k)}, L_{2k}^{(k)}).
\]

where \( R(L_{1k}^{(k)}, L_{2k}^{(k)}) = \left\{ \begin{array}{ll} P_1(L_{1k}^{(k)}) - L_{2k}^{(k)} > P_2(L_{2k}^{(k)}) & \text{if } 0, L_1^{(k)} < L_2^{(k)} \\ 1/2P_1(L_{1k}^{(k)})P_2(L_{2k}^{(k)}) & \text{if } L_1^{(k)} = L_2^{(k)} \end{array} \right. \)

calculating the possibility degree that \( L_1^{(k)} \) in \( L_1(p) \) is not smaller than \( L_2^{(k)} \) in \( L_2(p) \).

The possibility degree has the following properties:

1. \( 0 \leq P(L_1(p) \succeq L_2(p)) \leq 1 \)
2. \( P(L_1(p) \succeq L_2(p)) = 0.5 \)
3. \( P(L_1(p) \succeq L_2(p)) = 0.5 \)
4. \( P(L_1(p) \succeq L_2(p)) = 0.5 \)

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

\[
d(L_1(p), L_2(p)) = \left( \sum_{k=1}^{\#L_1(p)} \left( \frac{P_1(L_{1k}^{(k)}) - P_2(L_{2k}^{(k)})}{\#L_1(p)} \right)^2 \right)^{1/2},
\]

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 positive influence,” “high positive influence,” “medium positive influence,” “low positive influence,” “no influence,” “low negative influence,” “medium negative influence,” “high negative influence,” and “very high negative influence.”

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

Definition 8. Let \( s_\alpha \ (\alpha = -4, \ldots, 0, \ldots, 4) \) 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: \( S_0 = \{ s_\alpha \} = \{ \text{very high negative influence}, s_3 = \text{high negative influence}, s_2 = \text{medium negative influence}, s_1 = \text{low negative influence}, s_0 = \text{no influence}, s_1 = \text{low positive influence}, s_2 = \text{medium positive influence}, s_3 = \text{high positive influence}, s_4 = \text{very high positive influence} \} \).

The possible values \( \alpha \) can be possible values \( \{ -4, -3, -2, -1, 0, 1, 2, 3, 4 \} \) can be defined as:

\[
A^+ = \begin{bmatrix} a_{ij}^+ \end{bmatrix}, \quad a_{ij}^+ = \frac{a_{ij}^+ + a_{ij}^-}{2}, \quad i, j = 1, 2, \ldots, n, \tag{17}
\]

\[
A^- = \begin{bmatrix} a_{ij}^- \end{bmatrix}, \quad a_{ij}^- = \frac{a_{ij}^+ - a_{ij}^-}{2}, \quad i, j = 1, 2, \ldots, n. \tag{18}
\]

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 $L_1(p) = \{L_1^{(k)}(p_i^{(k)})| k = 1, 2, \ldots, \#L_1(p)\}$ and $L_2(p) = \{L_2^{(k)}(p_i^{(k)})| k = 1, 2, \ldots, \#L_2(p)\}$ 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

$$C(L_1(p), L_2(p)) = \begin{cases} 2(0.5 - (0.5 - \left(1 - \sqrt{d(L_1(p), L_2(p))}\right)/2) + |P(L_1(p) \geq L_2(p)) - 0.5|)/2, \\ 2(0.5 - (0.5 - \left(1 - \sqrt{d(L_1(p), L_2(p))}\right)/2 + 0.5 - P(L_1(p) \geq L_2(p)))/2, \\ 2(0.5 - (0.5 - \left(1 - \sqrt{d(L_1(p), L_2(p))}\right))/2 + P(L_1(p) \geq L_2(p)) - 0.5), \\ 0.5 - 0.5\sqrt{d(L_1(p), L_2(p))} + P(L_1(p) \geq L_2(p)), \\ 1.5 - 0.5\sqrt{d(L_1(p), L_2(p))} - P(L_1(p) \geq L_2(p)), \\ \end{cases}$$

where $P(L_1(p) \geq L_2(p)) \in [0,0.5]$, $P(L_1(p) \geq L_2(p)) \in (0.5,1]$, and $P(L_1(p) \geq L_2(p)) \in (0,0.5]$.

**(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. $C(L_1(p), L_1(p)) = 1$

**Proof**

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

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

3. Since $\sqrt{d(L_1(p), L_1(p))} = 0, P(L_1(p) \geq L_1(p)) = 0.5, 0.5 - (0.5 - (1 - \sqrt{d(L_1(p), L_1(p))})) / 2 + |P(L_1(p) \geq L_1(p)) - 0.5| = 0$, $C(L_1(p), L_1(p)) = 2(0.5 - (0.5 - (1 - \sqrt{d(L_1(p), L_1(p))})) / 2 + |P(L_1(p) \geq L_1(p)) - 0.5| / 2 = 1$.

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

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

$$C(L^1, L^2) = \sum_{i=1}^{n} \sum_{j=1}^{m} \frac{C(L^1_{ij}(p), L^2_{ij}(p))}{n^2},$$

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

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

$$\rho^{ij} = \frac{C(L^1, L^2)}{\sum_{k=1, k \neq r}^{m} C(L^k, L^r)},$$

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 $\rho^\lambda$ of $e^i$ is defined as

$$\rho^\lambda = \frac{\sum_{r=1, r \neq i}^{m} \rho^{ij}}{(m-1)}.$$
According to the given experts’ subjective weights \( \eta^i \) and the adjustment coefficients \( \rho^i \), the final weights are

\[
w^i = \frac{\rho^i \eta^i}{\sum_{k=1}^{m} \rho^k \eta^k}, \quad \lambda = 1, \ldots, m.
\]  

(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 \( S_D^{\lambda} \) Definition def8, 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 \( L^i \) provided by expert \( e^i (\lambda = 1, 2, \ldots, m) \) can be described as

\[
L^i = \left[ L^i_{ij} (p) \right]_{n \times n}, \quad i = 1, 2, \ldots, n,
\]  

(24)

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

Step 2: determine the experts’ weights. First, we can get the complete and normalized form for each PLTS in \( L^i (\lambda = 1, 2, \ldots, m) \) according to Definitions def3 and def4. For convenience, the complete and normalized PLDMs are still denoted as \( L^i (\lambda = 1, 2, \ldots, m) \). 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

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

(25)

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

Step 4: transform \( L \) to the direct influence matrix under the new scale. Based on Definition def2f, the score of each PLTS \( L_{ij} (p) \) in \( L \) can be calculated as

\[
E \left( L_{ij} (p) \right) = \bar{a}_{ij}, \quad i, j = 1, 2, \ldots, n,
\]  

(26)

where \( \bar{a}_{ij} = \sum_{k=1}^{\# L_{ij} (p)} \overline{L_{ij} (p)} \), \( \overline{L_{ij} (p)} \) is the subscript of linguistic term \( L^k_{ij} \), and \( \sum_{k=1}^{\# L_{ij} (p)} \overline{L_{ij} (p)} \) is 1.

Then, the aggregated direct influence matrix can be formed as \( A = [a_{ij}]_{m \times m} \), where \( a_{ij} = \text{round} (\bar{a}_{ij}) \), where round(\( \cdot \)) is the usual rounding operation. The aggregated positive direct influence matrix and aggregated negative direct influence matrix, denoted as \( A^+ = [a^+_{ij}]_{m \times m} \) and \( A^- = [a^-_{ij}]_{m \times m} \), 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

\[
G^+ = \frac{A^+}{\text{max}_{i, j = 1}^{\infty} a_{ij}},
\]  

(27)

\[
G^- = \frac{A^-}{\text{min}_{i, j = 1}^{\infty} a_{ij}}.
\]  

(28)

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

\[
T^+ = \left[ t^+_{ij} \right]_{m \times m} = G^+ (I - G^-)^{-1},
\]  

(29)

\[
T^- = \left[ t^-_{ij} \right]_{m \times m} = G^- (I - G^+)^{-1},
\]  

(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 \( D^+ = (d^+_{11}, \ldots, d^+_{nn})^T \) and \( D^- = (d^-_{11}, \ldots, d^-_{nn})^T \) be the sums of rows of matrices \( T^+ \) and \( T^- \), respectively, and let the vectors \( R^+ = (r^+_{11}, \ldots, r^+_{nn}) \) and \( R^- = (r^-_{11}, \ldots, r^-_{nn}) \) be the sums of columns of matrices \( T^+ \) and \( T^- \), respectively. The \( t \)th elements in \( D^+, D^-, R^+, \), and \( R^- \) can be calculated as

\[
d^+_i = \sum_{j=1}^{n} t^+_{ij}, \quad i = 1, 2, \ldots, n,
\]  

(31)

\[
d^-_i = \sum_{j=1}^{n} t^-_{ij}, \quad i = 1, 2, \ldots, n,
\]  

(32)

\[
r^+_i = \sum_{j=1}^{n} t^+_{ji}, \quad i = 1, 2, \ldots, n,
\]  

(33)

\[
r^-_i = \sum_{j=1}^{n} t^-_{ji}, \quad i = 1, 2, \ldots, n.
\]  

(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 \( \vartheta_i \) indicates the degree of importance that factor \( f_i \) plays in the entire system. The factor having greater absolute value of \( \vartheta_i \) is more important. What is more, the factors that have positive values of \( \vartheta_i \) have a positive influence on the whole system, and factors with negative values of \( \vartheta_i \) have a negative influence on the whole system. We use \( \psi_i \) to calculate the cause and effect groups. Factors having positive values of \( \psi_i \) are in the cause group and dispatch
influence to other factors, and factors having negative values of $\psi_i$ 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
Complexity

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 $\theta^i$ 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 $k = 1$ to $m$
        $L_{ij}^{(k)}(p) = [L_{ij}^{(k)}(p^{+}), L_{ij}^{(k)}(p^{-})]_{k}$
        $L_{ij}^{(k)}(p^{+})$, $L_{ij}^{(k)}(p^{-}) \in S_{D}, p^{+} \geq k, p^{-} \geq k, k = 1, 2, \ldots, m$
        EndFor
      Assign the assessment result to the element of PLDM $L_{ij}^{(k)} = L_{ij}^{(k)}(p)$
      Assign linguistic term $s_{ij}$ to the element of PLDM $L_{ij} = [s_{ij}(1)]$
    EndIf
EndFor
EndFor
Get the PLDMs $L^{(k)}(\lambda = 1, \ldots, m)$
\% 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 $a_{ij} = \text{round}(\sum_{k=1}^{m} L_{ij}^{(k)})$
    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 $A = [a_{ij}]_{n \times n}$, $A^+ = [a_{ij}^+]_{n \times n}$, $A^- = [a_{ij}^-]_{n \times n}$
  EndFor
EndFor
Get the aggregated PLDM $L = [L_{ij}(p)]_{n \times n}$
\% Compute the total positive and negative influence matrices by $G^+ = \sum_{j=1}^{n} a_{ij}^+ G^- = \sum_{j=1}^{n} a_{ij}^-$
Calculate the total positive and negative influence matrices by $T^+ = [t_{ij}]_{n \times n}$ and $T^- = [t_{ij}^-]_{n \times n}$
Calculate the importance degree, cause and effect degree of factors by $\theta^i = (\sum_{j=1}^{n} t_{ij}^+ + \sum_{j=1}^{n} t_{ij}^- - \sum_{j=1}^{n} t_{ij}^+ - \sum_{j=1}^{n} t_{ij})$ and $\psi^i = (\sum_{j=1}^{n} t_{ij}^+ - \sum_{j=1}^{n} t_{ij}^-) - (\sum_{j=1}^{n} t_{ij}^+ - \sum_{j=1}^{n} t_{ij})$
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-
sparking 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 \(S_\lambda\), and the PLDMs \(L^\lambda\) \((\lambda = 1, 2, 3)\) provided by the experts are as follows:

\[
L^1 = \begin{bmatrix}
    \{s_0(1)\} & \{s_2(0.6), s_3(0.4)\} & \{s_3(0.5), s_2(0.4)\} & \{s_2(0.3), s_1(0.5), s_0(0.2)\} & \{s_3(0.6), s_1(0.4)\} \\
    \{s_0(0.1), s_1(0.3), s_2(0.6)\} & \{s_0(1)\} & \{s_3(0.6), s_1(0.4)\} & \{s_0(1)\} & \{s_1(0.3), s_2(0.7)\} \\
    \{s_0(0.2), s_1(0.8)\} & \{s_4(0.2), s_3(0.8)\} & \{s_0(1)\} & \{s_1(0.6), s_2(0.4)\} & \{s_2(0.8), s_1(0.2)\} \\
    \{s_0(1)\} & \{s_3(0.7), s_0(0.3)\} & \{s_0(1)\} & \{s_1(0.9)\} & \{s_0(1)\} \\
    \{s_0(0.2), s_1(0.8)\} & \{s_1(0.3), s_2(0.7)\} & \{s_2(0.2), s_1(0.8)\} & \{s_2(0.7), s_0(0.3)\} & \{s_0(1)\}
\end{bmatrix}
\]

\[
L^2 = \begin{bmatrix}
    \{s_0(1)\} & \{s_3(0.7), s_4(0.3)\} & \{s_3(0.1), s_2(0.6), s_1(0.3)\} & \{s_3(0.7), s_0(0.2)\} & \{s_1(0.7), s_2(0.3)\} \\
    \{s_1(0.3), s_2(0.7)\} & \{s_1(1)\} & \{s_3(0.7), s_1(0.3)\} & \{s_0(1)\} & \{s_1(0.2), s_2(0.8)\} \\
    \{s_1(0.7), s_2(0.3)\} & \{s_3(0.7), s_2(0.3)\} & \{s_0(1)\} & \{s_0(0.3), s_1(0.7)\} & \{s_2(0.7), s_1(0.3)\} \\
    \{s_1(0.2), s_0(0.8)\} & \{s_2(0.5), s_1(0.5)\} & \{s_1(0.2), s_2(0.8)\} & \{s_0(1)\} & \{s_4(1)\} \\
    \{s_0(0.2), s_1(0.8)\} & \{s_0(0.2), s_1(0.8)\} & \{s_3(0.6), s_2(0.4)\} & \{s_3(0.2), s_2(0.8)\} & \{s_0(1)\}
\end{bmatrix}
\]

\[
L^3 = \begin{bmatrix}
    \{s_0(1)\} & \{s_3(0.7), s_2(0.2)\} & \{s_3(0.5), s_2(0.5)\} & \{s_2(0.6), s_0(0.3)\} & \{s_0(0.7), s_1(0.2), \} \\
    \{s_2(0.4), s_3(0.6)\} & \{s_0(1)\} & \{s_2(0.5), s_1(0.5)\} & \{s_0(1)\} & \{s_2(0.6), s_1(0.4)\} \\
    \{s_0(1)\} & \{s_3(0.1), s_0(0.1)\} & \{s_2(0.3), s_1(0.7)\} & \{s_0(1)\} & \{s_3(0.4), s_2(0.6)\} \\
    \{s_0(1)\} & \{s_3(0.9), s_0(0.1)\} & \{s_3(0.7), s_2(0.7)\} & \{s_0(1)\} & \{s_3(0.1)\} \\
    \{s_0(0.1), s_1(0.9)\} & \{s_2(0.3), s_1(0.7)\} & \{s_1(0.6), s_0(0.4)\} & \{s_3(0.8), s_1(0.2)\} & \{s_0(1)\}
\end{bmatrix}
\]

It can be noticed that \(L^1_{ij}, L^2_{ij}, \) and \(L^3_{ij}\) are incomplete. Based on Definition def3, 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 \([s_{-3}(0.67), s_0(0.33)], \) 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 \(E(L^\lambda_{ij})\) of \(L^\lambda_{ij} (i, j = 1, 2, \ldots, 5; \lambda = 1, 2, 3)\) 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 round \(E(L^\lambda_{ij}(p))\) are used to characterize the experts’ judgments, and the direct influence matrices \(A^\lambda_{ij} (\lambda = 1, 2, 3)\) can be expressed as follows, where “-” represents that an expert gave no exact judgment, so this judgment is not considered:

\[
A^1 = \begin{bmatrix}
    0 & 2 & -1 & 0 \\
    2 & 0 & 2 & 0 \\
    0 & 1 & 1 & 0 \\
    1 & 2 & 1 & 0
\end{bmatrix},
A^2 = \begin{bmatrix}
    0 & 3 & 2 & -1 \\
    2 & 0 & 2 & 0 \\
    0 & 2 & 2 & 0 \\
    1 & 1 & 3 & 2
\end{bmatrix},
A^3 = \begin{bmatrix}
    0 & 2 & 3 & 0 \\
    3 & 0 & 2 & 0 \\
    0 & 1 & 3 & 0 \\
    1 & 3 & 1 & 2
\end{bmatrix}.
\]
Then, the aggregated direct influence matrix \( A_t \) can be obtained as follows, as per equation \( A_t = \sum_{i=1}^{m} \eta^i A_i^L \):

\[
A_t = \begin{bmatrix}
0 & 2 & 2 & 1 & 0 \\
2 & 0 & 2 & 0 & 2 \\
1 & 3 & 0 & 1 & 2 \\
0 & 1 & 2 & 0 & 4 \\
1 & 2 & 2 & 0 & 0
\end{bmatrix}.
\] (37)

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

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

Based on matrix \( T_t \), equations (31) and (33) are used to calculate \( d_t^+ \) and \( r_t^- \). The corresponding \( \theta_t^+ \) and \( \psi_t^- \) 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 non-negative. Therefore, the values of round(\(E(L_t^L(p))\)) \((i, j = 1, 2, \ldots, 5; \lambda = 1, 2, 3)\) are directly used to characterize the experts’ judgments, and similarly, we use only those round(\(E(L_t^L(p))\)) values which corresponding PLTSs have complete probability information. The direct influence matrices \( A_i^L (\lambda = 1, 2, 3) \) are

\[
A_i^1 = \begin{bmatrix}
0 & 2 & -1 & 0 \\
2 & 0 & -2 & 0 \\
1 & -3 & 0 & 1 \\
0 & -1 & 1 & 0 \\
1 & 2 & -1 & -1
\end{bmatrix},
\] (39)

\[
A_i^2 = \begin{bmatrix}
0 & 3 & -2 & 1 \\
2 & 0 & -2 & 0 \\
1 & -3 & 0 & 1 \\
0 & -2 & 2 & 0 \\
1 & 1 & -3 & -2
\end{bmatrix},
\]

\[
A_i^3 = \begin{bmatrix}
0 & -3 & 0 & 0 \\
0 & -3 & 0 & 0 \\
0 & -1 & 3 & 0 \\
1 & 3 & -1 & -2
\end{bmatrix}.
\]

Using the equation \( A_t = \sum_{i=1}^{m} \eta^i A_i^L \), the aggregated direct influence matrix is

\[
A_t^L = \begin{bmatrix}
0 & 2 & -2 & -1 & 0 \\
2 & 0 & -2 & 0 & 2 \\
0 & -1 & 2 & 0 & -4 \\
1 & 2 & -2 & -2 & 0
\end{bmatrix}.
\] (40)

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

\[
A_+ = \begin{bmatrix}
0 & 2 & 0 & 0 & 0 \\
2 & 0 & 0 & 0 & 2 \\
0 & 2 & 0 & 0 & 0 \\
1 & 2 & 0 & 0 & 0
\end{bmatrix},
\]

\[
A_- = \begin{bmatrix}
0 & 0 & -2 & -1 & 0 \\
0 & 0 & 0 & -2 & 0 \\
0 & 0 & -2 & 0 & -2 \\
0 & 0 & -2 & 0 & -2
\end{bmatrix}.
\] (41)

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

\[
T_t^+ = \begin{bmatrix}
0.714 & 1.143 & 0 & 0 & 0.571 \\
1.429 & 1.286 & 0 & 0 & 1.143 \\
0.49 & 0.327 & 0.143 & 0.286 & 0.163 \\
0.245 & 0.163 & 0.571 & 0.143 & 0.082 \\
1.143 & 1.429 & 0 & 0.714 & 0
\end{bmatrix},
\]

\[
T_t^- = \begin{bmatrix}
0 & 0.721 & 1.023 & 0.535 & 0.837 \\
0 & 0.512 & 0.791 & 0.186 & 0.465 \\
0 & 1.279 & 0.977 & 0.465 & 1.163 \\
0 & 0.93 & 1.256 & 0.884 & 1.209
\end{bmatrix}.
\] (42)

Based on matrices \( T_t^+ \) and \( T_t^- \), \( d_t^+ \), \( r_t^- \), \( d_t^\prime \), and \( r_t^- \) are calculated by equations (31)–(34), and the values of \( \theta_t^+ \) and \( \psi_t^- \) 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 \( L_t^L (\lambda = 1, 2, 3) \), 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.
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 1: $\vartheta^*_i$ and $\psi^*_i$ values of factors by the traditional DEMATEL method.

|   | $f_1$ | $f_2$ | $f_3$ | $f_4$ | $f_5$ | Sorting |
|---|---|---|---|---|---|---|
| $\vartheta^*_i$ | 17.954 | 25.335 | 26.409 | 21.122 | 26.490 | $f_3 > f_5 > f_2 > f_4 > f_1$ |
| $\psi^*_i$ | 0.566 | -3.890 | -1.438 | 5.685 | -0.923 | $f_1 > f_3 > f_5 > f_2 > f_4$ |

### Table 2: $\vartheta_i$ and $\psi_i$ values by the new scale-based DEMATEL method.

|   | $f_1$ | $f_2$ | $f_3$ | $f_4$ | $f_5$ | Sorting |
|---|---|---|---|---|---|---|
| $\vartheta_i$ | 3.333 | 1.762 | -6.971 | -5.995 | -3.855 | $f_1 > f_2 > f_4 > f_5 > f_3$ |
| $\psi_i$ | -4.708 | 2.045 | 2.020 | -1.225 | 1.868 | $f_2 > f_3 > f_5 > f_4 > f_1$ |

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

\[
T^+ = \begin{bmatrix}
            3.8 & 5.6 & 0 & 0 & 4 \\
            4 & 5 & 0 & 0 & 4 \\
            0.547 & 0.755 & 0.472 & 0.679 \\
            0.415 & 0.642 & 0.151 & 0.377 \\
            1.371 & 1.6 & 0.143 & 0.286 & 1.143 \\
            0.686 & 0.8 & 0.571 & 0.143 & 0.571 \\
            0.547 & 0.755 & 0.472 & 0.679 \\
            0.415 & 0.642 & 0.151 & 0.377 \\
\end{bmatrix}
\]

\[
T^- = \begin{bmatrix}
            3.2 & 4.4 & 0 & 0 & 3 \\
            0 & 0 & -2 & -1 & 0 \\
            0 & 0 & -2 & 0 & 0 \\
            0 & -3 & 0 & 0 & -2 \\
            0 & -1 & 0 & 0 & -4 \\
            0 & 0 & -1 & -2 & 0 \\
\end{bmatrix}
\]

Based on matrices $T^+$ and $T^-$, $d_i^+$, $r_i^+$, $d_i^-$, and $r_i^-$ are calculated by equations (31)–(34), and the corresponding $\vartheta_i$ and $\psi_i$ are shown in Table 4.
| Table 3: Elements in group’s aggregated PLDM $L$. |
|---------------------------------------------------|
| **Aggregated PLTs** | |
| $L_1 (p)$ | $\{s_1 (1)\}$ |
| $L_1 (p)$ | $\{s_1 (0.028), s_{-1.52} (0.028), s_{-2.56} (0.028), s_{-3.22} (0.19), s_{-2.32} (0.19), s_{-2.12} (0.132), s_{-2.25} (0.084), s_{-2.132} (0.084), s_{-1.944} (0.084), s_{-1.956} (0.066), s_{-1.64} (0.066)\}$ |
| $L_1 (p)$ | $\{s_{-1.312} (0.15678), s_{-1.2613} (0.07722), s_{-0.444} (0.04422), s_{-0.444} (0.1287), s_{-0.444} (0.10452), s_{-0.357} (0.07737), s_{-0.357} (0.02718), s_{-0.315} (0.05148), s_{-0.315} (0.0363), s_{-0.315} (0.02948), s_{-0.315} (0.01452)\}$ |
| $L_1 (p)$ | $\{s_{0.94} (0.294), s_{0.94} (0.28), s_{0.83} (0.126), s_{0.94} (0.056), s_{1.104} (0.042), s_{1.12} (0.036), s_{1.12} (0.084), s_{1.12} (0.028), s_{1.12} (0.024), s_{1.472} (0.018), s_{1.712} (0.012)\}$ |
| $L_1 (p)$ | $\{s_{1.104} (0.012), s_{1.368} (0.036), s_{1.472} (0.028), s_{1.696} (0.018), s_{1.704} (0.072), s_{1.712} (0.084), s_{1.904} (0.054), s_{1.904} (0.042), s_{1.904} (0.168), s_{2.64} (0.108), s_{2.176} (0.126), s_{2.418} (0.252)\}$ |
| $L_1 (p)$ | $\{s_{1.104} (0.1)\}$ |
| $L_1 (p)$ | $\{s_{-2.12} (0.21), s_{-1.952} (0.21), s_{-1.94} (0.09), s_{-1.944} (0.09), s_{-1.932} (0.09), s_{-1.312} (0.14), s_{-1.304} (0.06), s_{-1.1} (0.06)\}$ |
| $L_1 (p)$ | $\{s_{1.104} (0.036), s_{1.104} (0.084), s_{1.12} (0.144), s_{1.904} (0.024), s_{1.904} (0.336), s_{1.904} (0.056), s_{1.904} (0.096), s_{2.84} (0.224)\}$ |
| $L_1 (p)$ | $\{s_{0.94} (0.028), s_{0.94} (0.112), s_{0.84} (0.112), s_{0.397} (0.012), s_{0.94} (0.448), s_{0.94} (0.048), s_{0.94} (0.048), s_{1.12} (0.192)\}$ |
| $L_1 (p)$ | $\{s_{-3.64} (0.028), s_{-3.312} (0.098), s_{-3.312} (0.112), s_{-3.312} (0.012), s_{-3.312} (0.392), s_{-3.251} (0.042), s_{-3.251} (0.048), s_{-2.68} (0.168), s_{-2.517} (0.014), s_{-2.26} (0.056), s_{-2.223} (0.006), s_{-1.992} (0.024)\}$ |
| $L_1 (p)$ | $\{s_{1.104} (0.1)\}$ |
| $L_1 (p)$ | $\{s_{0.94} (0.144), s_{0.94} (0.372), s_{0.84} (0.096), s_{0.94} (0.084), s_{1.12} (0.024), s_{1.12} (0.224), s_{1.904} (0.056)\}$ |
| $L_1 (p)$ | $\{s_{-2.312} (0.224), s_{-2.312} (0.336), s_{-1.956} (0.152), s_{-2.312} (0.228), s_{-1.944} (0.024), s_{-1.304} (0.036)\}$ |
| $L_1 (p)$ | $\{s_{-2.12} (0.2), s_{-0.08} (0.8)\}$ |
| $L_1 (p)$ | $\{s_{-1.312} (0.315), s_{-1.315} (0.15), s_{-0.444} (0.035), s_{-0.444} (0.139), s_{-0.444} (0.035), s_{-0.444} (0.135), s_{-0.444} (0.015), s_{-0.444} (0.015)\}$ |
| $L_1 (p)$ | $\{s_{1.104} (0.006), s_{1.368} (0.054), s_{1.472} (0.024), s_{1.696} (0.014), s_{1.712} (0.216), s_{1.904} (0.126), s_{1.94} (0.056), s_{2.176} (0.504)\}$ |
| $L_1 (p)$ | $\{s_{1.104} (0.1)\}$ |
| $L_1 (p)$ | $\{s_{0.94} (0.8), s_{3.048} (0.2)\}$ |
| $L_1 (p)$ | $\{s_{0.94} (0.014), s_{0.94} (0.182), s_{0.33} (0.006), s_{0.94} (0.054), s_{1.12} (0.024), s_{1.368} (0.216)\}$ |
| $L_1 (p)$ | $\{s_{1.104} (0.018), s_{1.368} (0.072), s_{1.472} (0.042), s_{1.696} (0.042), s_{1.704} (0.168), s_{1.904} (0.168), s_{1.94} (0.098), s_{2.176} (0.392)\}$ |
| $L_1 (p)$ | $\{s_{-2.12} (0.072), s_{-2.418} (0.048), s_{-1.944} (0.084), s_{-1.312} (0.192), s_{-2.312} (0.032), s_{-2.2} (0.192), s_{-2.418} (0.128)\}$ |
| $L_1 (p)$ | $\{s_{-2.31} (0.112), s_{-2.448} (0.028), s_{-1.448} (0.112), s_{-1.24} (0.048), s_{-1.24} (0.048), s_{-1.24} (0.048), s_{-1.24} (0.048)\}$ |
| $L_1 (p)$ | $\{s_{0.94} (0.1)\}$ |
Table 4: \( \theta_i \) and \( \psi_i \) values of factors by the proposed DEMATEL method.

|   | \( f_1 \) | \( f_2 \) | \( f_3 \) | \( f_4 \) | \( f_5 \) | Sorting |
|---|---|---|---|---|---|---|
| \( \theta_i \) | 24.004 | 25.683 | −2.460 | −0.818 | 16.484 | \( f_2 \succ f_1 \succ f_3 \succ f_4 \succ f_5 \) |
| \( \psi_i \) | −2.110 | −2.853 | 3.980 | 1.324 | −0.341 | \( f_3 \succ f_2 \succ f_1 \succ f_5 \succ f_4 \) |

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 | \( \times \)           | \( \times \)           | \( \times \)           | \( \times \)           |
| New scale-based DEMATEL method | \( \sqrt{\} \)     | \( \times \)           | \( \times \)           | \( \times \)           |
| Proposed DEMATEL method     | \( \sqrt{\} \)     | \( \sqrt{\} \)     | \( \sqrt{\} \)     | \( \sqrt{\} \)     |

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 def3. (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 |
|---------------------------|------------------|
| \( \omega^{i}_{1} \) \( \{0.1, 0.3, 0.6\} \) | \( \omega^{i}_{1} \) \( \{0.081, 0.224, 0.695\} \) |
| \( \omega^{i}_{2} \) \( \{0.2, 0.1, 0.7\} \) | \( \omega^{i}_{2} \) \( \{0.155, 0.071, 0.774\} \) |
| \( \omega^{i}_{3} \) \( \{0.4, 0.3, 0.3\} \) | \( \omega^{i}_{3} \) \( \{0.363, 0.250, 0.388\} \) |
| \( \omega^{i}_{4} \) \( \{0.5, 0.1, 0.4\} \) | \( \omega^{i}_{4} \) \( \{0.430, 0.079, 0.491\} \) |
| \( \omega^{i}_{5} \) \( \{0.6, 0.2, 0.2\} \) | \( \omega^{i}_{5} \) \( \{0.561, 0.172, 0.267\} \) |
| \( \omega^{i}_{6} \) \( \{0.8, 0.1, 0.1\} \) | \( \omega^{i}_{6} \) \( \{0.773, 0.089, 0.138\} \) |

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 \( \omega^{i} \), according to the adjustment method of experts’ weights proposed in Section 3.2, and the final weight vector of experts is denoted as \( \omega^{*} \).

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
DEMATEL method proposed in this paper, which considers both negative scaling and PLTs, 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 degree ($\psi_i$) 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...
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.
the traditional DEMATEL method
the new scale-based DEMATEL method
the DEMATEL method proposed in this paper

the first group
the second group
the third group

the fourth group
the fifth group
the sixth group

Figure 4: Location change of system element $f_3$.

Figure 5: Location change of system element $f_4$. 
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.
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