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Research Article

Probabilistic Linguistic PROMETHEE I and II Methods for Evaluation of the Reform Scheme of Postgraduate Innovation and Entrepreneurship Education Talent Training Mode under the Big Data Environment

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Talent training quality is an important field within higher education research. Innovating the talent training mode and deepening educational reform programs are both of great significance for enhancing the quality of postgraduate innovation and entrepreneurship education in universities. In this study, Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) I and II methods are extended with the probability linguistic term set (PLTS) to accurately express and quantitatively evaluate the reform scheme of postgraduate innovation and entrepreneurship education talent training mode under the big data environment. First, probabilistic linguistic PROMETHEE I and II methods are presented for quantitatively evaluating the reform scheme of postgraduate innovation and entrepreneurship education talent training, which have the advantages of good effectiveness and feasibility. Second, the PLTS is imported into the evaluation methods and applied to accurately depict qualitative information about the index data of the reform scheme effect by the degree of probability. Third, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) with PLTS is proposed to perform a comparative study and conduct visual analysis to verify the effectiveness of the extended probabilistic linguistic PROMETHEE I and II methods. Fourth, an empirical example illustrates the specific evaluation process, verifies the feasibility of the extended methods, and explains the effectiveness of the results. The research findings indicate that the proposed method to reform scheme evaluation can lead to better decision quality, especially in a complex fuzzy and uncertain decision-making environment.

1. Introduction

Higher education is key to the success of three world-renowned bay areas, the New York Bay area, the San Francisco Bay area, and the Tokyo Bay area [1]. The development of a higher education cluster is not only one of the core contents of the study of the Guangdong-Hong Kong-Macao Greater Bay Area [2], but it is also an important source of support for the construction of a first-class bay area, which will become a new growth pole for China's high-quality development. A survey from the innovation and entrepreneurship education alliance of China shows that Chinese graduate students are eager for innovation and entrepreneurship and hope that their universities will provide more opportunities to cultivate innovation and entrepreneurship.

In recent years, postgraduate innovation and entrepreneurship education have become a hot issue in the field of higher education. Many universities have put a lot of effort into improving their organizational systems, advancing their infrastructure, carrying out extracurricular activities, and increasing financial support for the talent training of postgraduate innovation and entrepreneurship education [3–6]. However, generally speaking, insufficient attention has been paid to the talent training mode of postgraduate innovation and entrepreneurship education, and the current understanding of the talent training effect is insufficient. Some studies think mechanical replication of the traditional market with low technology as the achievements of postgraduate innovation and entrepreneurship education. Some simply understand talent training innovation as "science and technology driven innovation," while ignoring ideology and consciousness innovation, which makes the talent training mode separate from professional education and knowledge education [7–9]. Therefore, research on the reform scheme of postgraduate innovation and entrepreneurship education talent-training mode is of great significance for universities to transform educational ideas, enhance educational modes, deepen educational reform, and improve the quality of talent training.

The evaluation of the reform scheme of the talent-training mode usually involves multiple criteria, such as innovative knowledge cultivation, innovative consciousness cultivation, and innovative ability cultivation, which can be modeled as a multiple criteria decision-making (MCDM) problem. MCDM, a very popular discipline of management science and operations research [10–13], can address the selection problem of optimal alternatives according to the priority of all feasible schemes when multiple or a finite number of decision criteria exist [14–16]. The Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) method, one of the most important MCDM methods, has a wide range of applications in many different areas [17–21]. Albadvi [22] proposed a preference ranking model based on the PROMETHEE method for developing national information strategies. Cavalcante et al. [23] proposed a multicriteria model integrating PROMETHEE and the Bayesian method to address the replacement problem in service production systems. Karande and Chakraborty [24] presented an integrated PROMETHEE and GAIA method to solve four nontraditional machining process selection problems. Pawe [25] presented a NEAT F-PROMETHEE to improve the process of mapping fuzzy numbers by the correction mechanism. Corrente et al. [26] developed and applied a hierarchical SMAA-PROMETHEE model to evaluate the sustainability of European cities. Bausys et al. [27] proposed an m-Generalized q-Neutrosophic PROMETHEE method to address path selection problems for an inspection robot. PROMETHEE includes some family methods, such as the PROMETHEE I and PROMETHEE II method. Although the PROMETHEE method can be used to process and evaluate numerical data, it is unable to address qualitative data or fuzzy data. Thus, Akram and Shumaiza [20] proposed a q-rung orthopair fuzzy PROMETHEE approach to address the problems of MCDM. Akram et al. [28] proposed a bipolar fuzzy PROMETHEE method for multicriteria group decision-making to select the green suppliers. In this paper, PROMETHEE I and PROMETHEE II are extended with the probability linguistic term set (PLTS) to accurately depict qualitative information or fuzzy information for evaluation of the reform scheme.

PLTS, provided by Pang et al. [29]; is a new type of linguistic variable used to accurately express qualitative data or fuzzy data. PLTS can express linguistic preference with multiple linguistic terms by making decision-makers (DMs) induce the weight of each language term in the form of a probability, which can reflect preference degrees of all possible linguistic information. For example, when DMs are evaluating the reform scheme of the talent training mode, based on the self-cognition and knowledge system of research problems, the DMs may consider that they are 70% sure the reform scheme effect is "very good," 20% sure it is "good," and 10% sure it is "bad." Because of the advantages of accurate expression of PTLS, some MCDMs are extended with probabilistic linguistic information to accurately express qualitative data or fuzzy data [30–36]. Liao et al. [37] proposed a linear programming method with probabilistic linguistic information for solving MCDM problems. Wang et al. [38] investigated multicriteria group decision problems with PLTSs. Chang et al. [39]; based on cumulative probability-based Hellinger distance, proposed a probabilistic linguistic TODIM method for waste mobile phone recycling. Darko and Liang [40] proposed a probabilistic linguistic WASPAS method by designing and reconciling prioritized Maclaurin symmetric mean aggregation operators for patients' prioritization. In this study, PROMETHEE I and II methods are extended with PLTS to accurately express and quantitatively evaluating the reform scheme of postgraduate innovation and entrepreneurship education talent training mode.

At present, research on the reform scheme of postgraduate innovation and entrepreneurship education talent training mode is still in the stage of theoretical discussion, meaning empirical research is lacking. Plus, there are few evaluation studies on the reform effect. Moreover, since the world has entered the era of big data, big data have become a major focus of academia, industry, and government agencies [41–43]. Big data technology is gradually promoting the reform and innovation of talent training mode in universities. This study is of great significance since it explores and evaluates the reform scheme of talent training mode of postgraduate innovation and entrepreneurship education in the big data environment.

The major of contributions in this paper are as follows: First, the principal contribution is that the PROMETHEE I and II methods are extended with the probabilistic linguistic environment for quantitatively evaluating the reform scheme of postgraduate innovation and entrepreneurship education talent training mode in the era of big data, since the research on the reform scheme is current in the stage of theoretical discussion, lacking empirical research. Second, the PLTS is shown to accurately depict qualitative information about the index data of the reform scheme evaluation by the degree of probability. Third, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) with PLTS is presented to conduct comparative analysis to verify the effectiveness of the extended probabilistic linguistic PROMETHEE I and II methods. The results demonstrate the advantages of good effectiveness and feasibility of the extended methods for evaluation of the reform scheme effect. Fourth, an empirical example demonstrates the specific evaluation process, proves the feasibility of the methods, and reveals the effectiveness of the results. The research findings on the reform scheme evaluation indicate that the extended methods can improve decision-making guidance and technical support for education departments, universities, and relevant teachers to guide the reform of postgraduate innovation and entrepreneurship education talent training mode.

The remaining parts of this paper are organized as follows: Section 2 describes some preliminaries, including PLTS, the PROMETHEE I and II methods. Section 3 extends the PROMETHEE I and II methods with the probabilistic linguistic environment. Section 4 provides details of the empirical analysis and discusses the results. Section 5 summarizes the paper.

2. Preliminaries

In this section, some basic concepts of the PLTS, normalization of PLTS, comparison between PLTSs, and PROMETHEE I and II methods are introduced.

2.1. Probabilistic Linguistic Term Set. Based on the additive linguistic term set $S = \{S_\alpha \mid \alpha = -\tau, \ldots, -1, 0, 1, \ldots, \tau\}$ [44, 45], the definition of the PLTS is given by Pang et al. [29] as follows:

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

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

Note that if $\sum_{k=1}^{\#L(p)} p^{(k)} = 1$, then the PLTS has the complete probabilistic information of all possible linguistic terms; if $\sum_{k=1}^{\#L(p)} p^{(k)} < 1$, then the PLTS has partial probabilistic information; if $\sum_{k=1}^{\#L(p)} p^{(k)} = 0$, then the PLTS has completely unknown probabilistic information.

In addition, the detailed process regarding the normalization of PLTS and the comparison between PLTSs can be obtained from the work of Pang et al. [29].

2.2. PROMETHEE I and II Methods. The PROMETHEE method, proposed by Brans [46], is a ranking decision analysis method that constructs "values outranking relations" to distinguish the best scheme. Based on pairwise comparisons of schemes, PROMETHEE uses the preference function, attribute value, and attribute weight given by the DMs to determine the rank of each scheme by the priority relationship. This method then uses the priority relationship to define the positive outranking flow and negative outranking flow of each scheme. The positive outranking flow shows that the chosen alternative outranks other alternatives, and the negative outranking flow shows that other alternatives outrank the chosen alternative [47]. According to the negative outranking flow and positive outranking flow, the best alternative can be determined [17]. The PROMETHEE I method can obtain a partial priority relationship, and the PROMETHEE II method can get the complete priority relationship. The specific steps are given as follows:

(1) Get the standardized decision matrix A, based on the original decision matrix $R = (r_{ij})_{m\times n}$.

$$\begin{cases} A_{ij} = \dfrac{r_{ij} - \min r_{ij}}{\max r_{ij} - \min r_{ij}} \text{ for benefit criteria}, \\ \\ A_{ij} = \dfrac{\max r_{ij} - r_{ij}}{\max r_{ij} - \min r_{ij}} \text{ for cost criteria}, \end{cases} \quad (2)$$

where $1 \leq i \leq m; 1 \leq j \leq n$.

(2) Compute the preference index:

$$\begin{cases} \pi(A_a, A_b) = \sum_{j=1}^{k} p_j(A_a, A_b) w_j, \\ \\ \pi(A_b, A_a) = \sum_{j=1}^{k} p_j(A_b, A_a) w_j. \end{cases} \quad (3)$$

Let $A_a, A_b \in A$, where A is a finite number of alternatives $A_1, A_2 \ldots A_m$. Furthermore, $k\,(1 \leq k \leq n)$ is the number of criteria; w_j is the weight of criterion j, and $\sum_{j=1}^{k} w_j = 1\,(1 \leq k \leq n)$. $p_j(A_a, A_b)$ and $p_j(A_b, A_a)$ are the preference functions of the alternatives A_a and A_b.

Generally speaking, in the PROMETHEE method, there are six kinds of preference functions, namely the usual criterion, quasicriterion, criterion with linear preference, level criterion, criterion with linear preference and indifference area, and Gaussian criterion. DMs usually select one type of preference function [46]. In addition, DMs can also construct new preference functions based on research problems.

(3) Obtain $\pi(A_a, A_b)$ and $\pi(A_b, A_a)$ for each pair of alternatives, where $\pi(A_a, A_b)$ represents how A_a is preferred to A_b over all the criteria, and $\pi(A_b, A_a)$ represents how A_b is preferred to A_a over all the criteria.

(4) Calculate the positive outranking flow:

$$\phi^{+}(A_a) = \frac{1}{n-1} \sum_{A_b \in A, a \neq b} \pi(A_a, A_b). \quad (4)$$

(5) Calculate the negative outranking flow:

$$\phi^{-}(A_a) = \frac{1}{n-1} \sum_{A_b \in A, a \neq b} \pi(A_b, A_a). \quad (5)$$

(6) Determine the net outranking flow:

$$\phi(A_a) = \phi^{+}(A_a) - \phi^{-}(A_a). \quad (6)$$

The PROMETHEE I method can obtain a partial priority relationship according to the negative outranking flow and positive outranking flow. The larger the positive outranking flow and the smaller the negative outranking flow of a scheme, the better the scheme. Three conditions for judging the priority of the scheme are as follows:

(1) A_a outranks A_b, denoted as $A_a P A_b$, if

$$\begin{cases} \phi^+(A_a) > \phi^+(A_b), \\ \phi^-(A_a) < \phi^-(A_b); \text{or}, \\ \phi^+(A_a) > \phi^+(A_b), \\ \phi^-(A_a) = \phi^-(A_b); \text{or}, \\ \phi^+(A_a) = \phi^+(A_b), \\ \phi^-(A_a) < \phi^-(A_b). \end{cases} \tag{7}$$

(2) A_a is indifferent to A_b, denoted as $A_a I A_b$, if

$$\begin{aligned} \phi^+(A_a) &= \phi^+(A_b), \\ \phi^-(A_a) &= \phi^-(A_b). \end{aligned} \tag{8}$$

(3) A_a and A_b cannot be compared, which is called the incomparable situation and is denoted as $A_a R A_b$, if

$$\begin{cases} \phi^+(A_a) > \phi^+(A_b), \\ \phi^-(A_a) > \phi^-(A_b); \text{or}, \\ \phi^+(A_a) < \phi^+(A_b), \\ \phi^-(A_a) < \phi^-(A_b). \end{cases} \tag{9}$$

The PROMETHEE II method can get the complete priority relationship according to the net outranking flow. The higher the net outranking flow $\phi(a)$, the better the alternative. Two conditions for judging the priority of the scheme are as follows:

$$\begin{aligned} &(1)\ A_a \text{ outranks } A_b, \text{ if and only if } \phi(A_a) > \phi(A_b), \\ &(2)\ A_a \text{ is indifferent to } A_b, \text{ if and only if } \phi(A_a) = \phi(A_b). \end{aligned} \tag{10}$$

3. Probabilistic Linguistic PROMETHEE I and II Methods

In this section, the probabilistic linguistic PROMETHEE I and II methods are extended and presented to quantitatively evaluate the reform scheme of postgraduate innovation and entrepreneurship education talent training mode in the era of big data.

For the problem of talent training mode reform scheme evaluation with PLTS, suppose there are $A_i\,(i = 1, 2, \ldots m)$ alternatives and $C_j\,(j = 1, 2, \ldots n)$ criteria. Based on the additive linguistic term set $S = \{S_\alpha \mid \alpha = -\tau, \ldots, -1, 0, 1, \ldots, \tau\}$ [44, 45], the DMs can evaluate the alternatives A_i for criterion C_j by PLTSs to construct decision matrix $R = (r_{ij})_{m\times n}$. The specific steps are detailed below:

Step 1: construct the original decision matrix $R = (r_{ij})_{m\times n}$.

The original decision matrix can be constructed according to $r_{ij} = L_{ij}(p) = \{L_{ij}^{(k)}(p_{ij}^{(k)}) \mid i \in [1, m], j = [1, n], k \in [1, \#L(p)], \sum_{k=1}^{\#L(p)} p_{ij}^{(k)} \leq 1\}$, where r_{ij} is the jth criteria value with respect to the ith alternative by DMs. $L^{(k)}(p^{(k)})$ represents the linguistic term $L^{(k)}$ associated with probability $p^{(k)}$, and $\#L^{(p)}$ is the number of all of the different linguistic terms in $L^{(p)}$. Then, the original decision matrix $R = (r_{ij})_{m\times n}$ can be constructed:

$$R = \begin{bmatrix} L_{11}(p) & L_{12}(p) & \cdots & L_{1n}(p) \\ L_{21}(p) & L_{22}(p) & \cdots & L_{2n}(p) \\ \cdots & \cdots & \cdots & \cdots \\ L_{m1}(p) & L_{m2}(p) & \cdots & L_{mn}(p) \end{bmatrix}. \tag{11}$$

Step 2: transform the original decision matrix R into decision matrix X.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}, \tag{12}$$

where $x_{ij} = \sum_{k=1}^{\#L_{ij}(p)} r^{(k)} p^{(k)} / \sum_{k=1}^{\#L_{ij}(p)} p^{(k)}$ according to Pang et al. [29]; $r^{(k)}$ is the subscript of linguistic term $L^{(k)}$, and $1 \leq i \leq m, 1 \leq j \leq n$.

Step 3: get the standardized decision matrix A, based on the decision matrix X:

$$\begin{cases} A_{ij} = \dfrac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} & \text{for benefit criteria}, \\ \\ A_{ij} = \dfrac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}} & \text{for cost criteria}, \end{cases} \tag{13}$$

where $1 \leq i \leq m; 1 \leq j \leq n$.

Step 4: compute the preference index:

$$\begin{cases} \pi(A_a, A_b) = \sum_{j=1}^{k} p_j(A_a, A_b) w_j, \\ \\ \pi(A_b, A_a) = \sum_{j=1}^{k} p_j(A_b, A_a) w_j, \end{cases} \tag{14}$$

where A is a finite number of alternatives $A_1, A_2 \ldots A_m$, $j, k\,(1 \leq j, k \leq n)$ is the number of the criteria, w_j is the weight of criterion j, and $\sum_{j=1}^{k} w_j = 1\,(1 \leq j \leq n)$. $p_j(A_a, A_b)$ and $p_j(A_b, A_a)$ are the preference functions of the alternative A_a and A_b. In this paper, the weight of each criterion can be obtained by analytic hierarchy process [48], proposed by Saaty [49, 50]. Furthermore, this study employs the linear priority relation function, presented by Hu and Jiang [51], as the preference function to induce the preference index.

Step 5: calculate the positive outranking flow $\phi^+(A_a)$ and the negative outranking flow $\phi^-(A_a)$:

$$\phi^+(A_a) = \frac{1}{n-1} \sum_{A_b \in A, a \neq b} \pi(A_a, A_b), \tag{15}$$

$$\phi^-(A_a) = \frac{1}{n-1} \sum_{A_b \in A, a \neq b} \pi(A_b, A_a). \tag{16}$$

Step 6: determine the net outranking flow $\phi(A_a)$:

$$\phi(A_a) = \phi^+(A_a) - \phi^-(A_a). \tag{17}$$

The probabilistic linguistic PROMETHEE I method can obtain a partial priority relationship according to the negative outranking flow and positive outranking flow. Three conditions for judging the priority of the scheme in the probabilistic linguistic environment are as follows:

(1) A_a outranks A_b, denoted as A_aPA_b, if

$$\begin{cases} \phi^+(A_a) > \phi^+(A_b), \\ \phi^-(A_a) < \phi^-(A_b); \text{or}, \\ \phi^+(A_a) > \phi^+(A_b), \\ \phi^-(A_a) = \phi^-(A_b); \text{or}, \\ \phi^+(A_a) = \phi^+(A_b), \\ \phi^-(A_a) < \phi^-(A_b). \end{cases} \tag{18}$$

(2) A_a is indifferent to A_b, denoted as A_aIA_b, if

$$\begin{aligned} \phi^+(A_a) &= \phi^+(A_b), \\ \phi^-(A_a) &= \phi^-(A_b). \end{aligned} \tag{19}$$

(3) A_a and A_b cannot be compared, which is called the incomparable situation and is denoted as A_aRA_b, if

$$\begin{cases} \phi^+(A_a) > \phi^+(A_b), \\ \phi^-(A_a) > \phi^-(A_b); \text{or}, \\ \phi^+(A_a) < \phi^+(A_b), \\ \phi^-(A_a) < \phi^-(A_b). \end{cases} \tag{20}$$

The probabilistic linguistic PROMETHEE II method can get the complete priority relationship according to the net outranking flII $\phi(A_a)$, the better the alternative. Two conditions for judging the priority of the scheme in the probabilistic linguistic environment are as follows:

(1) A_a outranks A_b, if and only if $\phi(A_a) > \phi(A_b)$, (21)

(2) A_a is indifferent to A_b, if and only if $\phi(A_a) = \phi(A_b)$. (22)

4. Empirical Analysis

4.1. Datasets. Mass entrepreneurship and innovation have become a national development strategy for China's economy. Simultaneously, China's higher education has gradually entered the stage of "popular education" from "elite education." In the big data environment, big data gives graduate students new opportunities and challenges for innovation and entrepreneurship. Moreover, big data have become increasingly used in the field of education, which not only brings greater development space but also poses unprecedented challenges to educational researchers. Talent training quality is a key index of education quality in universities, and it is an important field of higher education research. Transforming the educational concept, innovating the talent-training mode, and deepening the educational reform are of great significance for improving the talent training quality of postgraduate innovation and entrepreneurship education in universities. Furthermore, due to the uncertainty and fuzziness of the information environment, the decision-making process becomes more and more complex, which brings great difficulties and challenges to scientific decision-making. In this study, based on PLTS, the probabilistic linguistic PROMETHEE I and II methods are extended to accurately depict the uncertainty and fuzziness of the information involved in the reform scheme evaluation under the big data environment.

An example is given to verify the effectiveness of the extended probabilistic linguistic PROMETHEE I and II methods for reform scheme evaluation. Eight reform schemes $A_i\,(i = 1, 2, 3, 4, 5, 6, 7, 8)$ are selected and combined with literature research and questionnaire survey in the era of big data, the evaluation problems of the reform scheme of postgraduate innovation and entrepreneurship education talent training mode are assessed based on PLTS according to the following five criteria: (1) C_1: innovative knowledge cultivation; (2) C_2: innovative consciousness cultivation; (3) C_3: innovative ability cultivation; (4) C_4: innovative quality cultivation; and (5) C_5: innovative talent cultivation. Obviously, C_1, C_2, C_3, C_4, and C_5 are all benefit criteria for the reform scheme evaluation. The detailed processes are given.

4.2. Empirical Evaluation

Step 1. Construct the original decision matrix R with PLTSs.

In this subsection, the first step is to obtain evaluation information for the eight selected reform schemes $A_i\,(i = 1, 2, 3, 4, 5, 6, 7, 8)$ from the DMs, which can be expressed by the following additive linguistic term set: $S = (S_{-3} =$ extremely bad, $S_{-2} =$ very bad, $S_{-1} =$ bad, $S_0 =$ general, $S_1 =$ good, $S_2 =$ very good, $S_3 =$ extremely good). Then, the original decision matrix can be constructed, as given in Table 1, provided by the DMs.

Step 2. Transform the original decision matrix R into decision matrix X. The transformed decision matrix X can be obtained according to (12):

Table 1: The original decision matrix.

	C_1	C_2	C_3	C_4	C_5
A_1	S_1 (0.67)S_2 (0.33)	S_0 (0.33)S_1 (0.33)S_2 (0.33)	S_2 (0.67)S_3 (0.33)	S_{-1} (0.67)S_0 (0.33)	S_2 (1)
A_2	S_2 (0.67)S_3 (0.33)	S_1 (0.67)S_2 (0.33)	S_1 (0.33)S_2 (0.67)	S_1 (0.33)S_2 (0.67)	S_2 (0.33)S_3 (0.67)
A_3	S_0 (0.33)S_1 (0.33)S_2 (0.33)	S_1 (0.33)S_2 (0.67)	S_1 (0.67)S_2 (0.33)	S_{-1} (0.33)S_0 (0.33)S_1 (0.33)	S_1 (0.33)S_2 (0.67)
A_4	S_2 (0.67)S_3 (0.33)	S_{-2} (0.67)S_{-1} (0.33)	S_{-1} (0.33)S_0 (0.67)	S_{-2} (0.33)S_0 (0.33)S_1 (0.33)	S_{-2} (0.67)S_{-1} (0.33)
A_5	S_2 (0.33)S_3 (0.67)	S_2 (0.67)S_3 (0.33)	S_{-2} (0.67)S_{-1} (0.33)	S_{-1} (0.33) S_0 (0.33)S_1 (0.33)	S_0 (0.33)S_1 (0.33)S_2 (0.33)
A_6	S_{-3} (0.33)S_{-2} (0.67)	S_{-2} (1)	S_1 (0.33)S_2 (0.67)	S_1 (0.33)S_2 (0.67)	S_1 (0.67)S_2 (0.33)
A_7	S_{-2} (0.33)S_{-1} (0.67)	S_0 (0.67)S_1 (0.33)	S_{-2} (0.33)S_{-1} (0.33)S_0 (0.33)	S_1 (0.67)S_2 (0.33)	S_0 (0.33)S_2 (0.67)
A_8	S_1 (0.33)S_2 (0.67)	S_{-1} (0.33)S_0 (0.33)S_1 (0.33)	S_1 (0.33)S_2 (0.67)	S_1 (0.33)S_2 (0.67)	S_0 (0.33)S_1 (0.33)S_2 (0.33)

$$X = \begin{bmatrix} 1.33 & 0.99 & 2.33 & -0.67 & 2.00 \\ 2.33 & 1.33 & 1.67 & 1.67 & 2.67 \\ 0.99 & 1.67 & 1.33 & 0.00 & 1.67 \\ 2.33 & -1.67 & -0.33 & -0.33 & -1.67 \\ 2.67 & 2.33 & -1.67 & 0.00 & 0.99 \\ -2.33 & -2.00 & 1.67 & 1.67 & 1.33 \\ -1.33 & 0.33 & -0.99 & 1.33 & 1.34 \\ 1.67 & 0.00 & 1.67 & 1.67 & 0.99 \end{bmatrix}. \tag{23}$$

Step 3. Get the standardized decision matrix A, based on the decision matrix X. Because C_1, C_2, C_3, C_4, and C_5 are all benefit criteria for the reform scheme evaluation, the standardized decision matrix A can be easily obtained according to (13):

$$A = \begin{bmatrix} 0.7320 & 0.6905 & 1.0000 & 0.0000 & 0.8456 \\ 0.9320 & 0.7691 & 0.8350 & 1.0000 & 1.0000 \\ 0.6640 & 0.8476 & 0.7500 & 0.2863 & 0.7696 \\ 0.9320 & 0.0762 & 0.3350 & 0.1453 & 0.0000 \\ 1.0000 & 1.0000 & 0.0000 & 0.2863 & 0.6129 \\ 0.0000 & 0.0000 & 0.8350 & 1.0000 & 0.6912 \\ 0.2000 & 0.5381 & 0.1700 & 0.8547 & 0.6935 \\ 0.8000 & 0.4619 & 0.8350 & 1.0000 & 0.6129 \end{bmatrix}. \tag{24}$$

Step 4. Compute the weight of each criterion, which can be obtained by the analytic hierarchy process [48].

$$\begin{aligned} W &= (w_1, w_2, w_3, w_4, w_5) \\ &= (0.1251, 0.1092, 0.2293, 0.2625, 0.2739). \end{aligned} \tag{25}$$

Step 5. Compute the preference index. The preference index can be computed according to (14), given in Table 2.

Step 6. Calculate the positive outranking flow $\phi^+(A_a)$ and the negative outranking flow $\phi^-(A_a)$. The positive outranking flow $\phi^+(A_a)$ and the negative outranking flow $\phi^-(A_a)$ can be obtained according to (15) and (16). The results are given in Table 3.

4.3. Empirical Results

4.3.1. Probabilistic Linguistic PROMETHEE I Method. According to the three conditions for judging the priority of the scheme in the probabilistic linguistic environment, given in (18)–(20), the probabilistic linguistic PROMETHEE I method can obtain a partial priority relationship according to the negative outranking flow and positive outranking flow. The priority rank of all the schemes, produced by the probabilistic linguistic PROMETHEE I method, is given in Table 4.

In order to facilitate intuitive analysis, the results for visual analysis, produced by the probabilistic linguistic PROMETHEE I method, are shown in Figure 1.

From Figure 1, it is obvious that the ranking results of the eight schemes are $A_2 \succ A_8 \succ A_6 \succ A_1 \succ A_7 \succ A_5 \succ A_4$ and $A_2 \succ A_8 \succ A_3 \succ A_7 \succ A_5 \succ A_4$. However, A_6 and A_1 cannot be compared with A_3. These are incomparable situations, denoted as A_6RA_3 and A_1RA_3, respectively, which further illustrates that the probabilistic linguistic PROMETHEE I method can obtain a partial priority relationship.

4.3.2. Probabilistic Linguistic PROMETHEE II Method. According to the two conditions for judging the priority of the scheme in the probabilistic linguistic environment, given in (21) and (22), the probabilistic linguistic PROMETHEE II method can get the complete priority relationship according to the net outranking flow. The results of $\phi(A_a)$, computed by (17), are given in Table 3. The higher the net outranking flow $\phi(A_a)$, the better the alternative. Finally, the priority rank of all the schemes, produced by the probabilistic linguistic PROMETHEE II method, is given in Table 5.

In order to facilitate intuitive analysis, the results for visual analysis, produced by the probabilistic linguistic PROMETHEE II method, are shown in Figure 2.

From Figure 2, it is obvious that the ranking results of the eight schemes are $A_2 \succ A_8 \succ A_6 \succ A_3 \succ A_1 \succ A_7 \succ A_5 \succ A_4$, which further illustrates that the probabilistic linguistic PROMETHEE II method can get the complete priority relationship according to the net outranking flow.

Table 2: The preference index.

A_a	A_b							
	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
A_1	—	0.0378	0.0867	0.4512	0.2930	0.2471	0.3152	0.1265
A_2	0.3384	—	0.3035	0.6886	0.4848	0.2851	0.3914	0.1561
A_3	0.0923	0.0086	—	0.4272	0.2149	0.1971	0.2457	0.0850
A_4	0.0632	0.0000	0.0335	—	0.0768	0.1249	0.1294	0.0165
A_5	0.1425	0.0337	0.0587	0.3143	—	0.2343	0.1505	0.0838
A_6	0.2625	0.0000	0.2068	0.5283	0.4003	—	0.1906	0.0215
A_7	0.2244	0.0000	0.1492	0.4266	0.2103	0.0844	—	0.0304
A_8	0.2710	0.0000	0.2238	0.5490	0.3788	0.1505	0.2657	—

Table 3: The positive outranking flow, the negative outranking flow, and the net outranking flow.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
$\phi^+(A_a)$	1.5575	2.6478	1.2707	0.4443	1.0178	1.6100	1.1253	1.8389
$\phi^-(A_a)$	1.3942	0.0801	1.0622	3.3852	2.0589	1.3235	1.6884	0.5198
$\phi(A_a)$	0.1633	2.5677	0.2085	−2.9409	−1.0412	0.2866	−0.5632	1.3190

Table 4: The priority rank produced by probabilistic linguistic PROMETHEE I.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
Priority rank	A_1PA_4 A_1PA_5 A_1PA_7	A_2PA_1 A_2PA_3 A_2PA_4 A_2PA_5 A_2PA_6 A_2PA_7 A_2PA_8	A_3PA_4 A_3PA_5 A_3PA_7	—	A_5PA_4	A_6PA_1 A_6PA_4 A_6PA_5 A_6PA_7	A_7PA_4 A_7PA_5	A_8PA_1 A_8PA_3 A_8PA_4 A_8PA_5 A_8PA_6 A_8PA_7

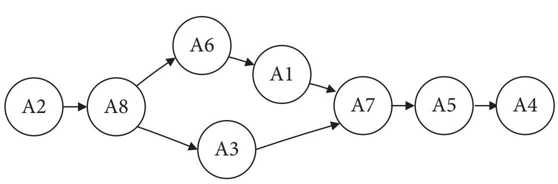

Figure 1: The ranking results produced by the probabilistic linguistic PROMETHEE I method.

Table 5: The priority rank produced by probabilistic linguistic PROMETHEE II.

Scheme	$\phi(A_a)$	Rank
A_1	0.1633	5
A_2	2.5677	1
A_3	0.2085	4
A_4	−2.9409	8
A_5	−1.0412	7
A_6	0.2866	3
A_7	−0.5632	6
A_8	1.3190	2

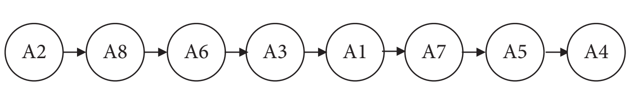

Figure 2: The ranking results produced by the probabilistic linguistic PROMETHEE II method.

From Figures 1 and 2, we can see that the best ranking scheme is A_2, the worst ranking scheme is A_4, and the overall ranking trend is not much different, between the PROMETHEE I and II methods, which verifies the effectiveness and feasibility of probabilistic linguistic PROMETHEE I and II methods for the reform scheme evaluation of postgraduate innovation and entrepreneurship education talent training mode under the big data environment.

4.4. Further Discussion and Comparative Analysis. For the purpose of comparative analysis to further illustrate the effectiveness of the extended methods, the TOPSIS method [52], one of the classic MCDM methods, with the PLTSs is utilized for a comparative study. The specific processes are as follows:

Step 1: construct the original decision matrix R with PLTSs

Step 2: transform the original decision matrix R into decision matrix X

Step 3: get the standardized decision matrix A, based on the decision matrix X

Step 4: compute the weight of each criterion by AHP

Step 5: calculate the weighted standardized decision matrix

Step 6: calculate the distance from each scheme to the positive ideal solution and the negative ideal solution

Table 6: The relative closeness of each scheme by TOPSIS with PLTSs.

Scheme	Relative closeness	Rank
A_1	0.5622	5
A_2	0.9065	1
A_3	0.5941	4
A_4	0.2667	8
A_5	0.4407	7
A_6	0.6642	3
A_7	0.5590	6
A_8	0.7472	2

Step 7: obtain the relative closeness of each scheme

Step 8: sort the schemes

According to the above steps, through simple calculation, the relative closeness of each scheme can be obtained easily. The results are given in Table 6.

From Table 6, it is obvious that the ranking results of all the schemes are 5, 1, 4, 8, 7, 3, 6, 2. That is to say, the priority rank of the eight schemes is $A_2 \succ A_8 \succ A_6 \succ A_3 \succ A_1 \succ A_7 \succ A_5 \succ A_4$, which is the same as the results by the probabilistic linguistic PROMETHEE II method. These research results further reveal and verify the good effectiveness and feasibility of the probabilistic linguistic PROMETHEE II method for reform scheme evaluation. The research results also indicate that the PLTS has good effectiveness and feasibility, as it can accurately depict qualitative information about the index data of the reform scheme effect. In addition, the results of the probabilistic linguistic PROMETHEE II method are not much different from the results of the probabilistic linguistic PROMETHEE I method. The best ranking scheme is A_2, and the worst ranking scheme is A_4. The research results further indicate the good effectiveness of the extended probabilistic linguistic PROMETHEE I method for reform scheme evaluation.

Besides, the research on the reform scheme of the talent-training mode of postgraduate innovation and entrepreneurship education is still in the stage of theoretical discussion, lacking empirical research, and evaluation research on the reform effect is relatively limited. Therefore, this study is of great significance for exploring and evaluating the reform scheme of talent training mode of postgraduate innovation and entrepreneurship education. Moreover, the research findings for reform scheme evaluation by comparative analysis obtained in this paper can improve decision quality, especially in a complex fuzzy and uncertain decision-making environment.

5. Conclusion

Strengthening postgraduate innovation and entrepreneurship education and talent cultivation are key practical requirements for universities to meet in order to serve the country by helping to change the mode of economic development and building an innovative country. Additionally, in the field of education, big data will inevitably become a cutting-edge research hotspot involving educational researchers all over the world.

Studies on the reform scheme of talent training mode of postgraduate innovation and entrepreneurship education are largely theoretical and lacking empirical research. Evaluation research on the effect of the talent training mode reform scheme is relatively limited. Therefore, this paper aims to propose effective methods for the reform scheme evaluation of postgraduate innovation and entrepreneurship education talent training mode under the big data environment. The main work of the paper is as follows:

(1) Two effective evaluation methods, the probabilistic linguistic PROMETHEE I and II methods, are presented to assess the reform scheme of postgraduate innovation and entrepreneurship education talent training mode under the big data environment.

(2) The PROMETHEE I and II methods are extended with PLTS for reform scheme evaluation and are shown to the advantages of good effectiveness and feasibility

(3) PLTS is imported into the evaluation methods, which can accurately express and quantitatively evaluating the reform scheme effect

(4) A case study is carried out and comparative analysis is conducted to verify the extended methods

(5) According to the comparative study and visual analysis, the extended methods to reform scheme evaluation can improve decision quality for education departments, universities, and relevant teachers to guide the reform of postgraduate innovation and entrepreneurship education talent training model, especially in the complex fuzzy and uncertain decision-making environment.

In future work, the reform strategy and countermeasure implementation of postgraduate innovation and entrepreneurship education talent training mode under the big data environment will be further developed by using technology of hesitant fuzzy sets [53], probabilistic hesitant fuzzy sets [54], MCDM, machine learning, data mining, artificial intelligence, and big data to reduce the constraints of small samples for large-scale real data analysis in the complex fuzzy and uncertain decision-making environment.

Data Availability

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

Conflicts of Interest

The author declares that there are no conflicts of interest.

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