

Research Article

Evaluation of Urban Industry-Education Integration Based on Improved Fuzzy Linguistic Approach

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Integration of industry and education is a strategic measure to address the structural imbalance issues in the scientific and technological development and industrial transformation, as well as educational system. Currently, joint efforts of governments, universities, and enterprises have achieved improvements in integrating education and various related industries. However, the evaluation of industry-education integration has not received sufficient attention it deserves. Based on the context-input-process-product (CIPP) evaluation model, this paper proposes an evaluation index system for urban industry-education integration. Considering the vagueness and uncertainty of the indexes, the evaluation model is established using intuitionistic fuzzy analytic hierarchy process (IFAHP) method and 2-tuple linguistic information representation approach. A case study indicates that industry-education integration environment is the most important division of evaluation, with local regulation being the most important evaluation index. The evaluation model is proven to be effective in improving the urban industry-education integration.

1. Introduction

Integration of industry and education is of great significance for facilitating the connections among education, talent, industry, and innovation and efficiently contributing to a healthy and sustainable economic growth [1]. As the central government serves as one agent of industry-education integration, local governments are also playing important roles in promoting industry-education integration through their engagement in various activities [2]. In China, 50 cities have implemented trials of integrating the industry and education since 2019 [3]. The evaluation is vital to the development of urban industry-education integration. A scientific evaluation framework can help assess the quality of integration and discover its merits and drawbacks.

For the evaluation of industry-education integration, most existing research focused on the performance and partnership sustainability in integration of industry and education. Liu et al. [4] built the performance evaluation model of university-industry cooperation based on

improved gray incidence. Su [5], by placing the environment, input, output, working, and effect as dimensionality in a structural equation model, conducted an empirical study of the performance evaluation model for industry-university-research cooperation through the overall model analysis, the overall disaggregation model analysis, and the partial disaggregation model analysis. Kaklauskas et al. [6] developed an evaluation system for university-industry partnership sustainability. Their system could perform a multiple criteria assessment of alternative university-industry partnership life cycles, calculate their market and fair values, and conduct online negotiations to select the most efficient alternatives. Suh et al. [7] analyzed the satisfaction of university-industry cooperation efforts based on the Kano model. Twenty major factors of university-industry cooperation were largely divided into four sectors. The satisfaction levels of each factor as well as the gap between the satisfaction levels were analyzed. Gibson et al. [8] adopted the hierarchical decision model to evaluate university-industry collaborative research centers. Three objectives, pursuit of research, producing

graduates, and accelerating knowledge and technology transfer (KTT), were included in the hierarchical structure. Moreover, the structure assigned six goals as new knowledge, stakeholder satisfaction, student involvement, student development, KTT mediums, and KTT objects. Xie et al. [9] proposed a systematic model, combining the analytic hierarchy process and Delphi method to evaluate the cooperation between higher vocational college and enterprise.

However, these studies just dealt with quantitative data or linguistic terms, neglecting the fuzzy preferences of decision makers. Urban industry-education integration is a complex system involving multisubject. The information for its evaluation is featured by multisource, randomness, and ambiguity. For such complex decision-making process, decision makers often use fuzzy sets or fuzzy linguistic variables to express fuzzy preferences [10]. Therefore, this paper proposes a synthetic model built with intuitionistic fuzzy analytic hierarchy process (IFAHP) and 2-tuple linguistic information representation. The IFAHP method is used to obtain weights of the indexes, and the 2-tuple linguistic approach is used to calculate the total evaluation score.

For calculating the weight, the analytic hierarchy process (AHP) [11] is one of the most recommended methods. In practice, however, decision makers might be reluctant or unable to assign the crisp evaluation values to the comparison. In order to describe the uncertain information, the fuzzy set theory characterized by membership function was proposed by Zadeh [12]. Nevertheless, the fuzzy set is only applicable for representing affirmative information, but not for negative and hesitant information. Antanassov extended Zadeh's fuzzy set to the intuitionistic fuzzy set [13], which consisted of a membership function, a nonmembership function, and a hesitancy function. The introduction of the intuitionistic fuzzy set into the traditional AHP method yielded an improved method as IFAHP [14]. The IFAHP method can allow each pairwise comparison to be represented by an intuitionistic fuzzy number that is described by a membership function and a nonmembership function. Since the intuitionistic fuzzy set is effective in describing vagueness and uncertainty, the IFAHP method provides a more accurate description of the decision-making process [15]. As for decision makers' weights, Wan et al. [16] proposed an intuitionistic fuzzy programming method with interval-valued intuitionistic fuzzy preference relations. Wang et al. [17] constructed an intuitionistic fuzzy linear programming model to derive decision makers' weights.

For the uncertainty of indexes, Zadeh proposed the linguistic variables to express evaluation information [18]. To computing the linguistic variables, Herrera and Martínez proposed the 2-tuple fuzzy linguistic representation model [19]. Using the 2-tuple linguistic model, the decision makers' preferences are transformed into 2-tuple linguistic information, which can effectively avoid information distortion or loss, thus make more accurate calculation results [20]. Since it was proposed, the theory of 2-tuple linguistic has been developed rapidly, especially in the 2-tuple linguistic information aggregation operators. Generalized ordered weighted average operator [21], harmonic operator [22],

hybrid geometric aggregation operator [23], hybrid arithmetic aggregation operator [24], and density aggregation operator [25] have accordingly been proposed and applied to the multicriteria decision-making (MCDM) problems. Wan et al. [26] presented a hybrid method integrating 2-tuple linguistic analytic network process and interval 2-tuple ELECTRE II for MCDM. Shi et al. [27] used interval 2-tuple linguistic variables to deal with uncertain linguistic assessment of alternatives.

Hence, a synthetic evaluation model for urban industry-education integration was proposed in this paper. The contributions of this paper are highlighted as three aspects. (1) The evaluation index system is constructed based on the context-input-process-product model. (2) The evaluation index weights are determined by the IFAHP method, considering decision makers' fuzzy preferences. (3) The evaluation results are calculated by the 2-tuple linguistic model, which can avoid information distortion or loss.

Apart from the introduction, the rest of this paper is organized as follows. Section 2 builds an evaluation index system for urban industry-education integration, based on the CIPP evaluation model. Section 3 uses the IFAHP method, in conjunction with the 2-tuple linguistic approach, to establish the evaluation model. Section 4 verifies the feasibility and practicality of the proposed model through a case study. Section 5 provides some concluding remarks.

2. Evaluation Index

2.1. CIPP Evaluation Model. The CIPP model was proposed by Stufflebeam in the 1960s [28]. Mainly used for evaluation in the field of education in its early stage, the model was soon extended to social management, business, and military fields. The CIPP model includes four phases: context evaluation, input evaluation, process evaluation, and product evaluation [29]. The purpose of the CIPP model is not to prove, but to improve. To be more specific, the use of the CIPP model is not simply to obtain an evaluation result, but rather to improve and optimize the evaluation object [30].

In the context evaluation phase, the expert needs to evaluate needs, problems, favorable conditions and opportunities, and related background conditions and developments. In the input evaluation phase, the expert assists to formulate the project plan by determining and evaluating alternative methods. Subsequently, the program plan, staffing, and budget are assessed to determine if it is feasible to meet the established needs and expected goals. In the process evaluation phase, the expert monitors, records, and evaluates the implementation of the project plan. In the product evaluation phase, the expert determines and evaluates the costs and products, including both expected and unexpected products and short-term and long-term products. The core components of the CIPP model are shown in Figure 1.

The evaluation of urban industry-education integration aims to promote the city to deepen the integration of industry and education and to facilitate the connections among the education chain, the talent chain, the industry chain, and the innovation chain. Therefore, this evaluation

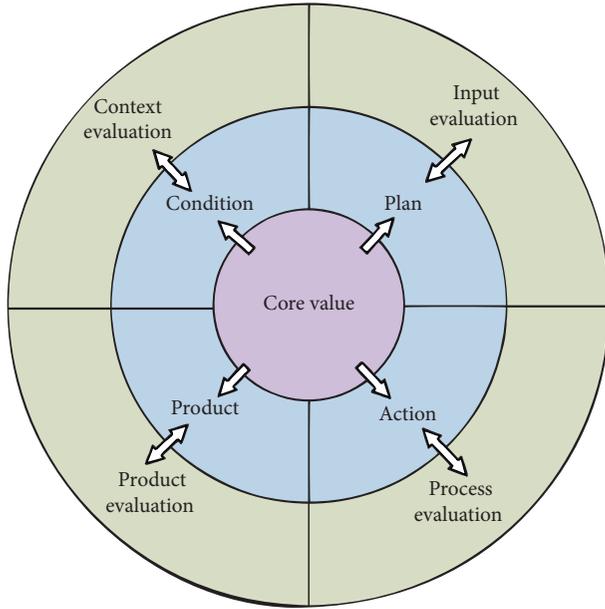


FIGURE 1: The core components of the CIPP model [31].

system is improvement-oriented, with the core idea of the CIPP modeling. The CIPP model provides a theoretical framework for constructing of the evaluation index system for urban industry-education integration.

2.2. Evaluation Index Structure. According to the CIPP evaluation model, this study constructs urban industry-education integration evaluation index system from four dimensions: the industry-education integration environment (context evaluation), the industry-education integration resources (input evaluation), the industry-education integration process (process evaluation), and the industry-education integration effect (product evaluation). Among them, the industry-education integration environment includes local regulation [6, 32], public service [33], and social culture [34]. The industry-education integration resource includes fund investment [35, 36], teaching staff [37], and platform construction [38, 39]. The industry-education integration process includes talent training [37, 40], cooperative innovation [41, 42], and technology transfer [42–44]. The industry-education integration effect includes student development [37, 45], enterprise development [7, 42], and city development [46]. The descriptions and definitions of the evaluation indexes are listed in Table 1.

3. Evaluation Method

Fuzzy linguistic approach [18] uses linguistic variables valued as words to express qualitative decision information, which enhances the feasibility and reliability of qualitative decision-making. In quantitative decision-making problems, fuzzy sets contain membership functions only, making it hard to describe the degree of uncertainty. To overcome the limitation, Antanassov extended fuzzy set to intuitionistic fuzzy set [13]. In the decision-making method, Xu

extended the classical AHP to the context of intuitionistic fuzzy set, constructing an improved method, i.e., IFAHP (intuitionistic fuzzy analytic hierarchy process) [14]. Meanwhile, Herrera et al. proposed 2-tuple fuzzy linguistic representation model to avoid the linguistic information loss and distortion when computing with words [19]. This study uses IFAHP to calculate weights of the indexes and employs the 2-tuple linguistic approach to evaluate urban industry-education integration. The workflow of the integrated evaluation method is shown in Figure 2.

3.1. Intuitionistic Fuzzy Analytic Hierarchy Process. Intuitionistic fuzzy analytic hierarchy process (IFAHP) is a fuzzy decision-making method based on Zadeh’s fuzzy set theory. This method takes into account the hesitation displayed by the experts during the evaluation. Thus, the assembly methods of qualitative and quantitative factors can achieve an agreement. Meanwhile, this method can automatically correct the inconsistent intuitionistic fuzzy preference relations that emerge in the evaluation without returning to the expert for re-evaluation, thus improving the accuracy and operability of the evaluation [14].

Intuitionistic fuzzy set is a basic concept in IFAHP. Let X be a fixed nonempty universe set, and an intuitionistic fuzzy set A in X is defined as $A = \{ \langle x, \mu_A(x), \nu_A(x) \rangle | x \in X \}$, where $\mu_A(x) \in [0, 1]$ and $\nu_A(x) \in [0, 1]$ represent, respectively, the degree of membership and nonmembership of element x to set A , satisfying $0 \leq \mu_A(x) + \nu_A(x) \leq 1$ for all $x \in X$. $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$ is called the intuitionistic fuzzy index of $x \in X$. It represents the hesitancy degree of $x \in X$. The pair $\langle \mu_A(x), \nu_A(x) \rangle$ is called an intuitionistic fuzzy value.

The process of calculating the evaluation index weights of urban industry-education integration using the IFAHP method is elaborated as follows.

3.1.1. Constructing the Intuitionistic Fuzzy Comparison Matrix. According to the established evaluation index system for urban industry-education integration, experts are invited to assess the importance of each index relative to the corresponding division. According to their judgments, an intuitionistic fuzzy comparison matrix, i.e., $R = (r_{ik})_{m \times m}$, which describes the intuitionistic fuzzy preference relationship, is then established. The element of the intuitionistic fuzzy comparison matrix can be written as $r_{ik} = (\mu_{ik}, \nu_{ik})$, where μ_{ik} denotes the degree to which the i th index is preferred to the k th index, ν_{ik} indicates the degree to which the i th index is not preferred to the k th index, and π_{ik} is interpreted as a hesitancy degree, $\pi_{ik} = 1 - \mu_{ik} - \nu_{ik}$.

3.1.2. Checking the Consistency. The consistency of the intuitionistic fuzzy comparison matrix can be judged by the distance of the intuitionistic fuzzy sets [47]. The checking formula is as follows:

$$d(\bar{R}, R) = \frac{1}{2(m-1)(m-2)} \sum_{i=1}^m \sum_{k=1}^m (|\bar{\mu}_{ik} - \mu_{ik}| + |\bar{\nu}_{ik} - \nu_{ik}| + |\bar{\pi}_{ik} - \pi_{ik}|), \quad (1)$$

TABLE 1: Evaluation index system for urban industry-education integration.

Division	Index	Interpretation of index
Industry-education integration environment (A_1)	Local regulation (B_{11})	(i) Fiscal, tax, financial, land, and other incentive policies (ii) Education and industry guidance policies (iii) Laws and regulations on the protection of rights and interests of participants in industry-education integration
	Public service (B_{12})	(i) Talent agency service (ii) Technology intermediary service
	Social culture (B_{13})	(i) Public cooperation development awareness (ii) Enthusiasm of enterprises to participate in school
Industry-education integration resource (A_2)	Fund investment (B_{21})	(i) Government education and technology funding (ii) Enterprise R&D and education expenditure
	Teaching staff (B_{22})	(i) Proportion of teachers with double qualifications in schools (ii) Proportion of part-time teachers in enterprises (iii) Number of part-time professional leaders (industry professors)
	Platform construction (B_{23})	(i) Students internship training base (ii) Students innovation and entrepreneurship base (iii) Industry-education integration innovation platform
Industry-education integration process (A_3)	Talent training (B_{31})	(i) School and enterprise cooperate to set majors, develop programs, and build courses (ii) Enterprise staff training coverage (iii) Dynamic adjustment of demand-oriented talent training structure
	Cooperation innovation (B_{32})	(i) Teachers' participation in enterprise technology development (ii) School undertaking enterprise scientific research projects (iii) Regional innovation network synergy
	Technology transfer (B_{33})	(i) Innovation needs release and innovation achievements' identification in enterprises (ii) Innovation needs identification and innovation achievements' transfer in schools (iii) Introduction, absorption, and productization of innovation achievement in enterprises
Industry-education integration effect (A_4)	Student development (B_{41})	(i) Student-employment satisfaction and employer satisfaction (ii) Social and economic benefits of student entrepreneurship
	Enterprise development (B_{42})	(i) Authorized patents obtained by the enterprise (ii) Product sales revenue per capita
	City development (B_{43})	(i) Regional technical personnel (ii) Regional high-tech industry output

where $R = (r_{ik})_{m \times m}$ is the intuitionistic fuzzy comparison matrix and $\bar{R} = (\bar{r}_{ik})_{m \times m}$ is the corresponding perfect consistent intuitionistic fuzzy comparison matrix of R . The construction process of \bar{R} is as follows:

(i) When $k > i + 1$, let $\bar{r}_{ik} = (\bar{\mu}_{ik}, \bar{\nu}_{ik})$, in which

$$\bar{\mu}_{ik} = \frac{\sqrt[k-i-1]{\prod_{t=i+1}^{k-1} \mu_{it} \mu_{tk}}}{\sqrt[k-i-1]{\prod_{t=i+1}^{k-1} \mu_{it} \mu_{tk}} + \sqrt[k-i-1]{\prod_{t=i+1}^{k-1} (1 - \mu_{it})(1 - \mu_{tk})}}, \quad k > i + 1, \quad (2)$$

$$\bar{\nu}_{ik} = \frac{\sqrt[k-i-1]{\prod_{t=i+1}^{k-1} \nu_{it} \nu_{tk}}}{\sqrt[k-i-1]{\prod_{t=i+1}^{k-1} \nu_{it} \nu_{tk}} + \sqrt[k-i-1]{\prod_{t=i+1}^{k-1} (1 - \nu_{it})(1 - \nu_{tk})}}, \quad k > i + 1. \quad (3)$$

(ii) When $k = i + 1$, let $\bar{r}_{ik} = r_{ik}$.

(iii) When $k < i$, let $\bar{r}_{ik} = (\bar{\nu}_{ki}, \bar{\mu}_{ki})$.

If $d(\bar{R}, R) < 0.1$, the intuitionistic fuzzy comparison matrix R is of acceptable consistency. Otherwise, if

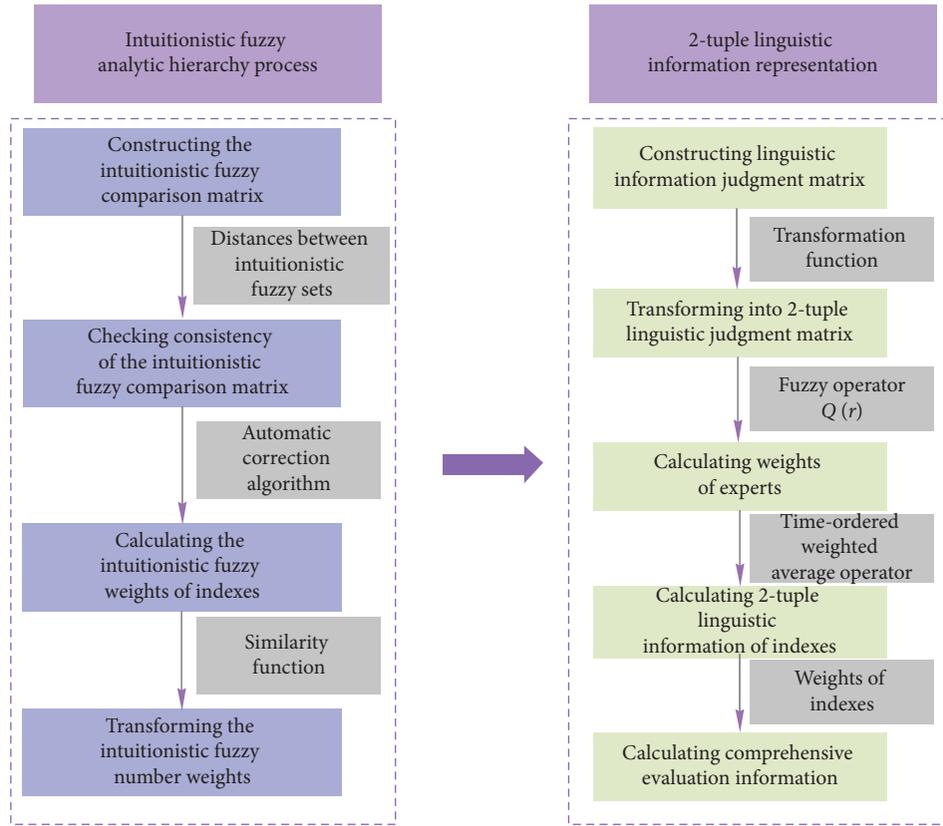


FIGURE 2: Workflow of the integrated evaluation method.

$d(\bar{R}, R) \geq 0.1$, the intuitionistic fuzzy comparison matrix R is of unacceptable consistency. In the meantime, we can obtain a new intuitionistic fuzzy comparison matrix $\bar{R} = (\bar{r}_{ik})_{m \times m}$ by combining the intuitionistic fuzzy comparison matrix R and the corresponding perfect consistent intuitionistic fuzzy comparison matrix \bar{R} . In the new intuitionistic fuzzy comparison matrix, each element is defined as follows:

$$\bar{\mu}_{ik} = \frac{(\mu_{ik})^{1-\sigma} (\bar{\mu}_{ik})^\sigma}{(\mu_{ik})^{1-\sigma} (\bar{\mu}_{ik})^\sigma + (1 - \mu_{ik})^{1-\sigma} (1 - \bar{\mu}_{ik})^\sigma}, \quad (4)$$

$$i, k = 1, 2, \dots, m,$$

$$\bar{\nu}_{ik} = \frac{(\nu_{ik})^{1-\sigma} (\bar{\nu}_{ik})^\sigma}{(\nu_{ik})^{1-\sigma} (\bar{\nu}_{ik})^\sigma + (1 - \nu_{ik})^{1-\sigma} (1 - \bar{\nu}_{ik})^\sigma}, \quad (5)$$

$$i, k = 1, 2, \dots, m,$$

where $\sigma \in [0, 1]$ is a controlling parameter. The smaller the value of σ is, the closer \bar{R} is to R .

For the new intuitionistic fuzzy comparison matrix \bar{R} , the following formula is used to check the consistency:

$$d(\bar{R}, \bar{R}) = \frac{1}{2(m-1)(m-2)} \sum_{i=1}^m \sum_{k=1}^m (|\bar{\mu}_{ik} - \bar{\mu}_{ki}| + |\bar{\nu}_{ik} - \bar{\nu}_{ki}| + |\bar{\pi}_{ik} - \bar{\pi}_{ki}|). \quad (6)$$

If $d(\bar{R}, \bar{R}) < 0.1$, the intuitionistic fuzzy comparison matrix \bar{R} is of acceptable consistency. Otherwise, the controlling parameter σ is adjusted to obtain a new intuitionistic fuzzy comparison matrix \bar{R} until $d(\bar{R}, \bar{R}) < 0.1$.

3.1.3. Calculating the Intuitionistic Fuzzy Weight of Index.

For the intuitionistic fuzzy comparison matrix $\bar{R} = (\bar{r}_{ik})_{m \times m}$ with acceptable consistency, the normalizing rank summation method [14] is used to calculate the weight of each index:

$$\omega_i = \left(\frac{\sum_{k=1}^m \bar{\mu}_{ik}}{\sum_{i=1}^m \sum_{k=1}^m (1 - \bar{\nu}_{ik})}, 1 - \frac{\sum_{k=1}^m (1 - \bar{\nu}_{ik})}{\sum_{i=1}^m \sum_{k=1}^m \bar{\mu}_{ik}} \right), \quad i = 1, 2, \dots, m. \quad (7)$$

3.1.4. Transforming the Intuitionistic Fuzzy Number Weight.

According to the similarity function [48] of the intuitionistic fuzzy number, the intuitionistic fuzzy number weight of the evaluation index can be transformed into a real number weight:

$$L(\omega_i) = \frac{1 - \nu_{\omega_i}}{1 + \pi_{\omega_i}}, \quad (8)$$

where ω_i is the intuitionistic fuzzy number weight of the index i relative to the previous layer, $\omega_i = (\mu_i, \nu_i)$, $\pi_i = 1 - \mu_i - \nu_i$, and $L(\omega_i)$ is the real number weight of the index i relative to the previous layer.

3.2. 2-Tuple Linguistic Approach. 2-tuple linguistic approach was developed by Herrera et al. to describe and process linguistic information [19]. This approach can effectively avoid the linguistic information loss and distortion during processing, thus making the evaluation more accurate. 2-tuple linguistic information is a concept based on symbolic translation.

Let $S = \{s_0, s_1, s_2, \dots, s_t\}$ be a finite and totally ordered discrete linguistic term set with odd cardinality, where s_i represents a possible value for a linguistic variable. $\beta = [0, t]$ is a number value representing the aggregation result of linguistic symbolic. Then, the function Δ used to obtain the 2-tuple linguistic information equivalent to β is defined as

$$\begin{aligned} \Delta: [0, t] &\longrightarrow S \times [-0.5, 0.5], \\ \beta &\longrightarrow \Delta(\beta) = (s_i, \alpha), \end{aligned} \quad (9)$$

where $i = \text{round}(\beta)$, $\alpha = \beta - i$, $\alpha \in [-0.5, 0.5)$, $\text{round}(\cdot)$ is the usual round operation, s_i has the closest index label to β , and α is the value of the symbolic translation.

Let $S = \{s_0, s_1, s_2, \dots, s_t\}$ be a linguistic term set and (s_i, α) be a linguistic 2-tuple. There is always a function Δ^{-1} , such that, from a 2-tuple it returns, its equivalent numerical value $\beta \in [0, t] \subset R$, which is

$$\begin{aligned} \Delta^{-1}: S \times [-0.5, 0.5] &\longrightarrow [0, t], \\ \Delta^{-1}(s_i, \alpha) &= i + \alpha = \beta. \end{aligned} \quad (10)$$

From equations (9) and (10), we can conclude that the conversion of a linguistic term into a linguistic 2-tuple consist of adding a value 0 as symbolic translation [24]: $\Delta(s_i) = (s_i, 0)$.

The steps to evaluate urban industry-education integration using the 2-tuple linguistic approach are as follows.

3.2.1. Constructing the Linguistic Term Judgment Matrix. Experts are invited to select elements from the linguistic term set S to evaluate the evaluation object, thereby a

linguistic term judgment matrix is formed. Generally speaking, $S = \{s_0 = \text{VB}(\text{very bad}), s_1 = \text{W}(\text{weak}), s_2 = \text{B}(\text{bad}), s_3 = \text{N}(\text{normal}), s_4 = \text{G}(\text{good}), s_5 = \text{E}(\text{excellent}), \text{ and } s_6 = \text{VG}(\text{very good})\}$.

3.2.2. Transforming into 2-Tuple Linguistic Judgment Matrix. A single linguistic term is generally transformed into a 2-tuple linguistic expression through equation (9) so that the entire linguistic term judgment matrix is transformed into a 2-tuple linguistic judgment matrix.

3.2.3. Calculating the Weights of Different Experts by the Fuzzy Operator $Q(r)$. For the weights of experts v_i , fuzzy operator $Q(r)$ can be used to calculate

$$v_i = Q\left(\frac{i}{m}\right) - Q\left(\frac{i-1}{m}\right), \quad (11)$$

where $v_i \in [0, 1]$, $\sum_{i=1}^m v_i = 1$,

$$Q(r) = \begin{cases} 0, & r < a, \\ \frac{(r-a)}{(b-a)}, & a \leq r \leq b, \\ 1, & r > b, \end{cases} \quad (12)$$

where $a, b \in [0, 1]$, under the principle of at least half, most, and as many as possible, the parameter (a, b) are $(0, 0.5)$, $(0.3, 0.8)$, and $(0.5, 1)$ separately.

3.2.4. Calculating 2-Tuple Linguistic Information of Indexes. The time-ordered weighted averaging operator (T-OWA) [49] is adopted to gather the linguistic evaluation information of each expert to obtain the 2-tuple linguistic information of urban industry-education integration evaluation indexes.

Assuming $\{(s_1, \alpha_1), (s_2, \alpha_2), \dots, (s_m, \alpha_m)\}$ is a set of linguistic evaluation information of a group of experts, the T-OWA operator is defined as follows:

$$(\bar{s}, \bar{\alpha}) = \Phi((s_1, \alpha_1), (s_2, \alpha_2), \dots, (s_m, \alpha_m)) = \Delta\left(\sum_{i=1}^m c_i v_i\right), \quad \bar{s} \in S, \bar{\alpha} \in [-0.5, 0.5], \quad (13)$$

where c_i represents the i th element in the set $\{\Delta^{-1}(s_i, \alpha_i), i = 1, 2, \dots, m\}$ arranged in the descending order, v_i is the weight of the i th expert, and $(\bar{s}, \bar{\alpha})$ represents the 2-tuple linguistics after the experts' linguistic evaluation information being assembled.

3.2.5. Calculating 2-Tuple Linguistic Information of Divisions. The 2-tuple linguistic information of indexes are synthesized to obtain the 2-tuple linguistics information of the j th division, where ω_{jk} is the weight of the k th index under the j th division (according to the aforementioned IFAHP method):

$$(s_j, \alpha_j) = \Delta \left(\sum_{k=1}^l \omega_{jk} \Delta^{-1}(s_k, \alpha_k) \right), \quad j = 1, 2, \dots, q, k = 1, 2, \dots, l. \quad (14)$$

3.2.6. *Calculating the Comprehensive Evaluation Result.* The final evaluation result is obtained by synthesizing the 2-tuple linguistic information of each division:

$$(s, \alpha) = \Delta \left(\sum_{j=1}^q \omega_j \Delta^{-1}(s_j, \alpha_j) \right), \quad s \in S, \alpha \in [-0.5, 0.5]. \quad (15)$$

4. Case Study

4.1. *Background of Study Area.* Xuzhou, a city in east China, is taken as a case study to demonstrate the application of the evaluation index system and evaluation model of urban industry-education integration. Xuzhou is the geographic and economic center of over 20 cities that spread over four provinces in east and middle China as Jiangsu province, Shandong province, Henan province, and Anhui province. In China's regional economic layout, Xuzhou serves as the juncture of east coastal opening-up area and middle-west developing area, bridging the Yangtze River Delta and the Bohai Rim Economic Circle. Xuzhou is also known as "a city of science and education" with a galaxy of talents. In 2019, Xuzhou has 230 technological innovation platforms above the provincial level, 54 incubators above the provincial level, and 738 high-tech enterprises. 12,603 patents have been granted in the city, 2,448 of which are invention patents, averagely 13.58 invention patents per 10,000 people. There are 10 general colleges and universities in Xuzhou, holding of 206,600 students and 56,100 graduates. Besides, the city has 85,300 students and 23,000 graduates under secondary vocational education. Therefore, Xuzhou, with its solid foundation for integration of industry and education, is taken as the case study of the present paper.

4.2. *Evaluation Index Weights Calculated by IFAHP Method.* To calculate the evaluation index weights of urban industry-education integration, the study follows the procedure of intuitionistic fuzzy analytic hierarchy process, which is as follows.

4.2.1. *Constructing the Intuitionistic Fuzzy Pairwise Comparison Matrix.* According to the structure of the evaluation index of urban industry-education integration and the requirements of the comparison matrix in IFAHP, we construct the relation table of intuitionistic fuzzy preference. Six experts are invited to evaluate the importance of the evaluation index to form an intuitionistic fuzzy comparison matrix.

Table 2 is an intuitionistic fuzzy comparison matrix $R^{(1)}$ for the relative importance of each division, by taking the expert (F₁) as an example.

TABLE 2: Intuitionistic fuzzy comparison matrix $R^{(1)}$ from expert (F₁).

$R^{(1)}$	A_1	A_2	A_3	A_4
A_1	(0.5, 0.5)	(0.5, 0.5)	(0.6, 0.3)	(0.5, 0.5)
A_2	(0.5, 0.5)	(0.5, 0.5)	(0.7, 0.2)	(0.2, 0.7)
A_3	(0.3, 0.6)	(0.2, 0.7)	(0.5, 0.5)	(0.1, 0.8)
A_4	(0.5, 0.5)	(0.7, 0.2)	(0.8, 0.1)	(0.5, 0.5)

4.2.2. *Checking the Consistency of Intuitionistic Fuzzy Preference Relations.* According to equations (2) and (3), the perfect consistent intuitionistic fuzzy comparison matrix $\bar{R}^{(1)}$ corresponding to $R^{(1)}$ can be calculated with Matlab, and the results are presented in Table 3.

Using equation (1), we calculate $d(\bar{R}^{(1)}, R^{(1)}) = 0.2362 > 0.1$, indicating that the intuitionistic fuzzy comparison matrix $R^{(1)}$ is of unacceptable consistency. Take $\sigma = 0.3$ and use equations (4) and (5) to synthesize $R^{(1)}$ and $\bar{R}^{(1)}$, we obtain a new intuitionistic fuzzy comparison matrix $\tilde{R}^{(1)}$, as listed in Table 4.

From equation (1), we can get $d(\bar{R}^{(1)}, \tilde{R}^{(1)}) = 0.0686 < 0.1$, which indicates that the intuitionistic fuzzy comparison matrix $\tilde{R}^{(1)}$ is of acceptable consistency.

We repeat the process to perform consistency checking on the intuitionistic fuzzy comparison matrices of the other experts (F₂–F₆) and then obtain the intuitionistic fuzzy comparison matrices $\tilde{R}^{(2)}$ to $\tilde{R}^{(6)}$ with acceptable consistency, as shown in Tables 5 to 9.

4.2.3. *Aggregating the Intuitionistic Fuzzy Preferences of Different Experts.* For the group decision-making problem of intuitionistic fuzzy information, Liao and Xu [50] argued that if the intuitionistic fuzzy preferences given by all experts meet acceptable consistency, the intuitionistic fuzzy preferences synthesized by the SIFWG operator should also meet acceptable consistency. The definition of SIFWG operator is as follows.

Let $\alpha_j = (\mu_{\alpha_j}, \nu_{\alpha_j}), j = 1, 2, \dots, n$, be a list of intuitionistic fuzzy numbers and $\gamma_j (j = 1, 2, \dots, n)$ be the corresponding weights with $\gamma_j \in [0, 1]$ and $\sum_{j=1}^n \gamma_j = 1$; then, the SIFWG operator is a mapping $\Theta^n \rightarrow \Theta$, such as

$$\text{SIFWG}_\gamma(\alpha_1, \alpha_2, \dots, \alpha_n) = \bigotimes_{j=1}^n \alpha_j^{\lambda_j} = \left(\prod_{j=1}^n \mu_{\alpha_j}^{\lambda_j}, \prod_{j=1}^n \nu_{\alpha_j}^{\lambda_j} \right). \quad (16)$$

In group decision-making, $\gamma_j (j = 1, 2, \dots, n)$ is the weight of experts. Meng et al. [51] proposed a method using projection to calculate the weights of experts in intuitionistic fuzzy group decision-making. Taking this method, the weights of the six experts (F₁–F₆) in the division evaluation, respectively, are 0.1688, 0.1619, 0.1625, 0.1560, 0.1693, and 0.1815.

According to equation (16), intuitionistic fuzzy comparison matrices $\tilde{R}^{(1)}, \tilde{R}^{(2)}, \dots, \tilde{R}^{(6)}$ with acceptable consistency can be used to synthesize a new intuitionistic fuzzy comparison matrix \tilde{R} (as listed in Table 10) with acceptable consistency.

TABLE 3: Perfect consistent intuitionistic fuzzy comparison matrix $\bar{R}^{(1)}$.

$\bar{R}^{(1)}$	A_1	A_2	A_3	A_4
A_1	(0.5, 0.5)	(0.5, 0.5)	(0.7, 0.2)	(0.1695, 0.6667)
A_2	(0.5, 0.5)	(0.5, 0.5)	(0.7, 0.2)	(0.2059, 0.5)
A_3	(0.2, 0.7)	(0.2, 0.7)	(0.5, 0.5)	(0.1, 0.8)
A_4	(0.6667, 0.1695)	(0.5, 0.2059)	(0.8, 0.1)	(0.5, 0.5)

TABLE 4: Intuitionistic fuzzy comparison matrix $\bar{R}^{(1)}$ synthesized by $R^{(1)}$ and $\bar{R}^{(1)}$.

$\bar{R}^{(1)}$	A_1	A_2	A_3	A_4
A_1	(0.5, 0.5)	(0.5, 0.5)	(0.6314, 0.2672)	(0.383, 0.5518)
A_2	(0.5, 0.5)	(0.5, 0.5)	(0.7, 0.2)	(0.2018, 0.6441)
A_3	(0.2672, 0.6314)	(0.2, 0.7)	(0.5, 0.5)	(0.1, 0.8)
A_4	(0.5518, 0.383)	(0.6441, 0.2018)	(0.8, 0.1)	(0.5, 0.5)

TABLE 5: Intuitionistic fuzzy comparison matrix $\bar{R}^{(2)}$ from expert (F_2).

$\bar{R}^{(2)}$	A_1	A_2	A_3	A_4
A_1	(0.5, 0.5)	(0.6, 0.3)	(0.6288, 0.2495)	(0.2344, 0.6287)
A_2	(0.3, 0.6)	(0.5, 0.5)	(0.6, 0.3)	(0.2492, 0.6131)
A_3	(0.2495, 0.6288)	(0.3, 0.6)	(0.5, 0.5)	(0.3, 0.6)
A_4	(0.6287, 0.2344)	(0.6131, 0.2492)	(0.6, 0.3)	(0.5, 0.5)

TABLE 6: Intuitionistic fuzzy comparison matrix $\bar{R}^{(3)}$ from expert (F_3).

$\bar{R}^{(3)}$	A_1	A_2	A_3	A_4
A_1	(0.5, 0.5)	(0.5, 0.5)	(0.3756, 0.5118)	(0.708, 0.1635)
A_2	(0.5, 0.5)	(0.5, 0.5)	(0.7, 0.2)	(0.281, 0.5988)
A_3	(0.5118, 0.3756)	(0.2, 0.7)	(0.5, 0.5)	(0.5, 0.5)
A_4	(0.1635, 0.708)	(0.5988, 0.281)	(0.5, 0.5)	(0.5, 0.5)

TABLE 7: Intuitionistic fuzzy comparison matrix $\bar{R}^{(4)}$ from expert (F_4).

$\bar{R}^{(4)}$	A_1	A_2	A_3	A_4
A_1	(0.5, 0.5)	(0.6, 0.3)	(0.2862, 0.5505)	(0.4201, 0.4977)
A_2	(0.3, 0.6)	(0.5, 0.5)	(0.2, 0.7)	(0.2466, 0.6517)
A_3	(0.5505, 0.2862)	(0.7, 0.2)	(0.5, 0.5)	(0.5, 0.5)
A_4	(0.4977, 0.4201)	(0.6517, 0.2466)	(0.5, 0.5)	(0.5, 0.5)

TABLE 8: Intuitionistic fuzzy comparison matrix $\bar{R}^{(5)}$ from expert (F_5).

$\bar{R}^{(5)}$	A_1	A_2	A_3	A_4
A_1	(0.5, 0.5)	(0.5, 0.5)	(0.8304, 0.1575)	(0.5878, 0.4016)
A_2	(0.5, 0.5)	(0.5, 0.5)	(0.3, 0.6)	(0.8052, 0.1686)
A_3	(0.1575, 0.8304)	(0.6, 0.3)	(0.5, 0.5)	(0.3, 0.6)
A_4	(0.4016, 0.5878)	(0.1686, 0.8052)	(0.6, 0.3)	(0.5, 0.5)

TABLE 9: Intuitionistic fuzzy comparison matrix $\bar{R}^{(6)}$ from expert (F_6).

$\bar{R}^{(6)}$	A_1	A_2	A_3	A_4
A_1	(0.5, 0.5)	(0.9, 0.1)	(0.868, 0.0683)	(0.7867, 0.1115)
A_2	(0.1, 0.9)	(0.5, 0.5)	(0.7, 0.2)	(0.5469, 0.3258)
A_3	(0.0683, 0.868)	(0.2, 0.7)	(0.5, 0.5)	(0.1, 0.9)
A_4	(0.1115, 0.7867)	(0.3258, 0.5469)	(0.9, 0.1)	(0.5, 0.5)

TABLE 10: Synthesized intuitionistic fuzzy comparison matrix \tilde{R} .

\tilde{R}	A_1	A_2	A_3	A_4
A_1	(0.5, 0.5)	(0.5895, 0.3174)	(0.5688, 0.2347)	(0.4859, 0.3226)
A_2	(0.3174, 0.5895)	(0.5, 0.5)	(0.4865, 0.3127)	(0.3444, 0.4455)
A_3	(0.2347, 0.5688)	(0.3127, 0.4865)	(0.5, 0.5)	(0.2402, 0.6397)
A_4	(0.3226, 0.4859)	(0.4455, 0.3444)	(0.6397, 0.2402)	(0.5, 0.5)

4.2.4. *Calculating the Weights of the Indexes.* For the intuitionistic fuzzy comparison matrix \tilde{R} , the intuitionistic fuzzy number weights of the divisions $A_1, A_2, A_3,$ and A_4 are calculated by equation (7), and they are $\omega_1 = (0.2379, 0.6243), \omega_2 = (0.1829, 0.692), \omega_3 = (0.1429, 0.7417),$ and $\omega_4 = (0.2117, 0.6523).$

Use equation (8) to transform the intuitionistic fuzzy number weights of the divisions $A_1, A_2, A_3,$ and A_4 into the corresponding real number weights, respectively: $L(\omega_1) = 0.2893, L(\omega_2) = 0.2398, L(\omega_3) = 0.2029,$ and $L(\omega_4) = 0.2681.$

By repeating the process of calculating the division weights, we calculate the weights of the indexes under each division. The results are shown in Figure 3.

4.3. *Evaluation Results Obtained by 2-Tuple Linguistic Approach.* In order to apply the 2-tuple linguistic model to evaluation of urban industry-education integration, we calculate the scores in the context of linguistic information representation one by one next.

4.3.1. *Constructing the Linguistic Term Judgment Matrix.* According to the interpretation to indexes in Table 1, we compile the table of index scoring (school edition/enterprise edition) and invite six experts to evaluate the industry-education integration in Xuzhou by choosing one comment from the linguistic term set S . Their evaluation results are shown in Table 11.

4.3.2. *Transforming into 2-Tuple Linguistic Judgment Matrix.* According to the definition of 2-tuple linguistic information, the linguistic term judgment matrix is then transformed into 2-tuple linguistic judgment matrix by equation (9), as shown in Table 12.

4.3.3. *Calculating the Weights of Different Experts.* The fuzzy operator $Q(r)$ can be used to calculate the weights of experts. Under most principles, equation (12) can be written as

$$Q(r) = \begin{cases} 0, & r < 0.3, \\ \frac{r - 0.3}{0.8 - 0.3}, & 0.3 \leq r \leq 0.8, \\ 1, & r > 0.8. \end{cases} \quad (17)$$

Therefore, we can get $Q(0) = 0, Q(1/6) = 0, Q(2/6) = 0.066, Q(3/6) = 0.4, Q(4/6) = 0.733, Q(5/6) = 1,$ and $Q(6/6) = 1.$

From equation (12), the weights of experts can be calculated as follows:

$$\begin{aligned} \nu_1 &= Q\left(\frac{1}{6}\right) - Q(0) = 0, \\ \nu_2 &= Q\left(\frac{2}{6}\right) - Q\left(\frac{1}{6}\right) = 0.066, \\ \nu_3 &= Q\left(\frac{3}{6}\right) - Q\left(\frac{2}{6}\right) = 0.334, \\ \nu_4 &= Q\left(\frac{4}{6}\right) - Q\left(\frac{3}{6}\right) = 0.333, \\ \nu_5 &= Q\left(\frac{5}{6}\right) - Q\left(\frac{4}{6}\right) = 0.267, \\ \nu_6 &= Q\left(\frac{6}{6}\right) - Q\left(\frac{5}{6}\right) = 0. \end{aligned} \quad (18)$$

4.3.4. *Calculating the Evaluation Result by Synthesizing the 2-Tuple Linguistic Information.* This section illustrates the process of aggregating 2-tuple linguistic information using the T-OWA operator, by taking the index “local regulation” as an example. Based on the definition of real numbers and 2-tuple linguistic transformation functions, it can be known that

- For the evaluation of $E_1, \Delta^{-1}(s_4, 0) = 4$
- For the evaluation of $E_2, \Delta^{-1}(s_3, 0) = 3$
- For the evaluation of $E_3, \Delta^{-1}(s_3, 0) = 3$
- For the evaluation of $E_4, \Delta^{-1}(s_4, 0) = 4$
- For the evaluation of $E_5, \Delta^{-1}(s_3, 0) = 3$
- For the evaluation of $E_6, \Delta^{-1}(s_2, 0) = 2$

Thereby, we sort the elements in the set $\{\Delta^{-1}(s_4, 0), \Delta^{-1}(s_3, 0), \Delta^{-1}(s_3, 0), \Delta^{-1}(s_4, 0), \Delta^{-1}(s_3, 0), \Delta^{-1}(s_2, 0)\}$ from large to small to get $\{c_1, c_2, c_3, c_4, c_5, c_6\} = \{4, 4, 3, 3, 3, 2\}.$ According to (13), we can get $(\bar{s}, \bar{\alpha}) = \Delta(\sum_{i=1}^6 c_i \nu_i) = \Delta(3.066).$ According to the definition of real number and 2-tuple linguistic transformation function, $k = \text{Round}(3.066) = 3, \alpha_k = 3.066 - 3 = 0.066,$ and $\Delta(3.066) = (s_3, 0.066).$ Therefore, the 2-tuple linguistic information of the index “local regulation” after aggregation is $(s_3, 0.066).$

Similarly, the 2-tuple linguistic information of other indexes after aggregation is obtained, as shown in Table 13.

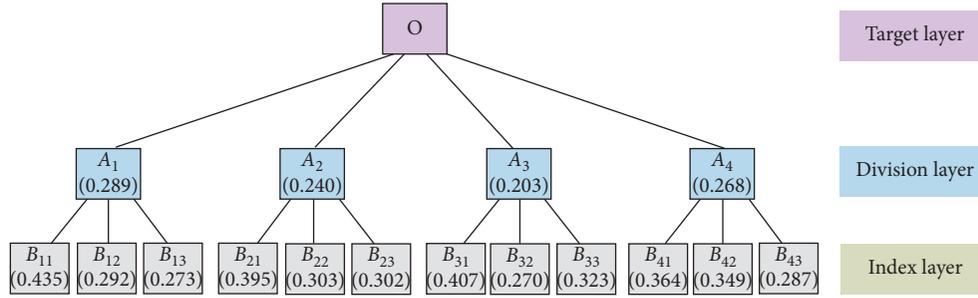


FIGURE 3: Evaluation index weights of urban industry-education integration.

TABLE 11: Linguistic term judgment matrix.

Index	E_1	E_2	E_3	E_4	E_5	E_6
Local regulation	G	N	N	G	N	B
Public service	N	N	N	N	B	B
Social culture	N	G	G	N	B	W
Fund investment	N	N	G	G	N	B
Teaching staff	E	N	G	VB	B	W
Platform construction	G	N	G	G	N	B
Talent training	G	N	N	E	G	B
Cooperation innovation	G	W	N	N	G	N
Technology transfer	G	W	B	N	N	W
Student development	N	G	G	N	G	N
Enterprise development	G	G	N	B	N	N
City development	G	N	G	N	N	N

TABLE 12: 2-tuple linguistic judgment matrix.

Index	E_1	E_2	E_3	E_4	E_5	E_6
Local regulation	$(S_4, 0)$	$(S_3, 0)$	$(S_3, 0)$	$(S_4, 0)$	$(S_3, 0)$	$(S_2, 0)$
Public service	$(S_3, 0)$	$(S_3, 0)$	$(S_3, 0)$	$(S_3, 0)$	$(S_2, 0)$	$(S_2, 0)$
Social culture	$(S_3, 0)$	$(S_4, 0)$	$(S_4, 0)$	$(S_3, 0)$	$(S_2, 0)$	$(S_1, 0)$
Fund investment	$(S_3, 0)$	$(S_3, 0)$	$(S_4, 0)$	$(S_4, 0)$	$(S_3, 0)$	$(S_2, 0)$
Teaching staff	$(S_5, 0)$	$(S_3, 0)$	$(S_4, 0)$	$(S_0, 0)$	$(S_2, 0)$	$(S_1, 0)$
Platform construction	$(S_4, 0)$	$(S_3, 0)$	$(S_4, 0)$	$(S_4, 0)$	$(S_3, 0)$	$(S_2, 0)$
Talent training	$(S_4, 0)$	$(S_3, 0)$	$(S_3, 0)$	$(S_5, 0)$	$(S_4, 0)$	$(S_2, 0)$
Cooperation innovation	$(S_4, 0)$	$(S_1, 0)$	$(S_3, 0)$	$(S_3, 0)$	$(S_4, 0)$	$(S_3, 0)$
Technology transfer	$(S_4, 0)$	$(S_1, 0)$	$(S_2, 0)$	$(S_3, 0)$	$(S_3, 0)$	$(S_1, 0)$
Student development	$(S_3, 0)$	$(S_4, 0)$	$(S_4, 0)$	$(S_3, 0)$	$(S_4, 0)$	$(S_3, 0)$
Enterprise development	$(S_4, 0)$	$(S_4, 0)$	$(S_3, 0)$	$(S_2, 0)$	$(S_3, 0)$	$(S_3, 0)$
City development	$(S_4, 0)$	$(S_3, 0)$	$(S_4, 0)$	$(S_3, 0)$	$(S_3, 0)$	$(S_3, 0)$

Then, according to the index weights and 2-tuple linguistic information in Table 13, the 2-tuple linguistic information of division is calculated by equation (14). Take the division “industry-education integration environment” as an example:

$$\begin{aligned}
 (s_1, \alpha_1) &= \Delta \left(\sum_{k=1}^3 \omega_{1k} \Delta^{-1}(s_k, \alpha_k) \right) \\
 &= \Delta (0.435 \times 3.066 + 0.292 \times 2.733 + 0.273 \\
 &\quad \times 2.799) = (s_3, -0.104).
 \end{aligned}
 \tag{19}$$

Similarly, the 2-tuple linguistic information of other divisions is obtained, as shown in Table 14.

Finally, based on the division weights and 2-tuple linguistic information in Table 14, equation (15) is used to calculate the 2-tuple linguistic information of industry-education integration in Xuzhou:

$$\begin{aligned}
 (s, \alpha) &= \Delta \left(\sum_{j=1}^4 \omega_j \Delta^{-1}(s_j, \alpha_j) \right) \\
 &= \Delta (0.289 \times 2.896 + 0.240 \times 2.904 + 0.203 \times 2.9 \\
 &\quad + 0.268 \times 3.188) \\
 &= (s_3, -0.023).
 \end{aligned}
 \tag{20}$$

TABLE 13: 2-tuple linguistic information of index.

Index	Weight	2-Tuple linguistic information
Local regulation	0.435	$(s_3, 0.066)$
Public service	0.292	$(s_3, -0.267)$
Social culture	0.273	$(s_3, -0.201)$
Fund investment	0.395	$(s_3, 0.066)$
Teaching staff	0.303	$(s_2, 0.199)$
Platform construction	0.302	$(s_3, 0.4)$
Talent training	0.407	$(s_3, 0.4)$
Cooperation innovation	0.270	$(s_3, 0.066)$
Technology transfer	0.323	$(s_2, 0.133)$
Student development	0.364	$(s_3, 0.4)$
Enterprise development	0.349	$(s_3, 0.066)$
City development	0.287	$(s_3, 0.066)$

TABLE 14: 2-tuple linguistic information of division.

Division	Weight	2-Tuple linguistic information
Industry-education integration environment	0.289	$(s_3, -0.104)$
Industry-education integration resource	0.240	$(s_3, -0.096)$
Industry-education integration process	0.203	$(s_3, -0.1)$
Industry-education integration effect	0.268	$(s_3, 0.188)$

The result shows that the integration of industry and education in Xuzhou falls into “normal” level.

4.4. Comparative Analysis with Existing Method. To demonstrate the advantages of the proposed method, this section conducts comparative analysis with the integrated method based on AHP and fuzzy comprehensive evaluation (FCE) [52]. According to the index weights in Figure 3 and the index information in Table 11, the index layer FCE is calculated as follows:

$$\begin{aligned}
 SA_1 &= (0.435, 0.292, 0.273) \begin{pmatrix} 0 & 0 & 0.167 & 0.500 & 0.333 & 0 & 0 \\ 0 & 0 & 0.333 & 0.667 & 0 & 0 & 0 \\ 0 & 0.167 & 0.167 & 0.333 & 0.333 & 0 & 0 \end{pmatrix} \\
 &= (0, 0.046, 0.215, 0.503, 0.236, 0, 0).
 \end{aligned}
 \tag{21}$$

Similarly,

$$\begin{aligned}
 SA_2 &= (0.051, 0.051, 0.167, 0.349, 0.333, 0.051, 0), \\
 SA_3 &= (0, 0.153, 0.122, 0.378, 0.280, 0.068, 0), \\
 SA_4 &= (0, 0, 0.058, 0.548, 0.394, 0, 0),
 \end{aligned}
 \tag{22}$$

where SA_{1-4} represents the results of index layer fuzzy comprehensive evaluations, respectively.

The division layer FCE is calculated according to each division weight and corresponding single-factor matrix of the division layer:

$$\begin{aligned}
 S &= (0.289, 0.240, 0.203, 0.268) \begin{pmatrix} 0 & 0.046 & 0.215 & 0.503 & 0.236 & 0 & 0 \\ 0.051 & 0.051 & 0.167 & 0.349 & 0.333 & 0.051 & 0 \\ 0 & 0.153 & 0.122 & 0.378 & 0.280 & 0.068 & 0 \\ 0 & 0 & 0.058 & 0.548 & 0.394 & 0 & 0 \end{pmatrix} \\
 &= (0.012, 0.056, 0.143, 0.453, 0.310, 0.026, 0),
 \end{aligned}
 \tag{23}$$

where S represents the result of division layer fuzzy comprehensive evaluation.

In line with the maximum membership degree principle, the comprehensive evaluation result for the integration of industry and education in Xuzhou is “normal” (s_3).

Compared with the existing method, the proposed method of this paper has some advantages:

- (1) Although the evaluation results are the same, the evaluation information provided by the proposed method is more abundant. In addition to judging the

level of urban industry-education integration, the 2-tuple linguistic information can also clarify the distance between the actual situation and the evaluation level.

- (2) Consistency check is a critical procedure in AHP. If the preference relation matrix [52] is of unacceptable consistency, it needs to be re-scored by experts for a new round of consistency check. However, in the proposed method, an automatic correction algorithm is used to improve the consistency of intuitionistic fuzzy preference relations without the need for re-participation of experts.
- (3) When aggregating the preference relations of different experts, the existing method suppose that the experts' weights are equal. However, the proposed method, using projection to calculate the experts' weights, is more in line with group decision-making in intuitionistic fuzzy environment.

5. Conclusions

This paper has established a theoretical framework for evaluating urban industry-education integration using the IFAHP method and the 2-tuple linguistic approach. The proposed evaluation system can analyze the level of urban industry-education integration, identify the problems in urban industry-education integration, and propose the strategies to promote the integration of industry and education. The following conclusions are derived from the study:

- (1) The new evaluation index system for urban industry-education integration based on the CIPP model consists of 4 divisions and 12 indexes. Among the 4 divisions, the industry-education integration environment is the most important (weight 0.289). Among the 12 indexes, local regulation is the most important (comprehensive weight 0.126). From the improvement-oriented evaluation index system, it is concluded that the policy environment provides guarantee for the interests of participants in industry-education integration. The government is expected to provide continuous public services and formulate preferential policies for education, taxation, land, and finance.
- (2) Integrated by IFAHP and 2-tuple linguistic approach, the proposed evaluation method can describe vagueness and uncertainty of the complex linguistic information. An automatic correction algorithm is used while calculating weights to improve the consistency of intuitionistic fuzzy preference relations. The time-ordered weighted averaging operator (T-OWA) is used in linguistic information integration to mitigate the loss of original information. The new method can help the participants in industry-education integration (governments, universities, enterprises, and other parties) recognize factors under improvement to guarantee their cooperation.

- (3) The case study shows that the integration of industry and education in Xuzhou falls into "normal" (s_3) level. Despite sufficient educational resources and quality industrial conditions, the integration of industry and education in Xuzhou is not satisfactory as expected. The main cause for underdevelopment of its industry-education integration is manifested by two indexes of "technology transfer" and "teaching staff," which are evaluated as "bad" (s_2). This is attributed to the fact that scientific research of universities in Xuzhou cannot meet the needs of local enterprises, and the market for technical services is underdeveloped. In terms of teaching staff, teachers in vocational colleges generally do not have work history in enterprises, and technical experts in enterprises rarely have access to teaching in schools.

Despite that the proposed evaluation system displays improved performance in industry-education integration, there are several limitations in this study. When using 2-tuple linguistic information representation, the study does not consider the uncertainty of linguistic information. It would be valuable to introduce another dimensional linguistic information that represents the uncertainty of experts' judgment. Moreover, we do not take into account the agreement degree among individual intuitionistic fuzzy preference relations of the decision makers. The evaluating process would be improved by developing a consensus-based algorithm to group decision-making with individual intuitionistic fuzzy preference relations. Finally, the number of experts in the case study for evaluating urban industry-education integration is limited to six, leaving another direction for improvement in future research.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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