# Classifying Evaluation Method of Innovative Teachers' Teaching Ability Based on Multi Source Data Fusion

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**Abstract.** Massive teaching ability data leads to a large difference between the evaluation index and the actual index. Therefore, a classification evaluation method for innovative teachers' teaching ability based on multi-source data fusion is proposed. Integrate innovative teachers' teaching data feature level multi-source data to generate scene data that can accurately describe learners' learning characteristics. The model of teachers' practical teaching ability is constructed, the information flow expressing the constraint parameters is obtained, and the convergent solution of teaching ability evaluation is calculated. Use the analytic hierarchy process to calculate the data similarity, and use the quantitative recursive analysis method to describe the form of evaluation data. Integrate the five dimensional characteristic data of learner situation, time situation, location situation, equipment situation, event situation and learning scene, build an evaluation model based on multi-source data fusion, and achieve the classified evaluation of innovative teachers' teaching ability. The experimental results that the maximum values of the teaching skill index, learning input index and learning harvest index of this method are 9.8, 9.6 and 9.2 respectively, which shows that the classification evaluation results are accurate.

**Keywords:** Multi-Source Data Fusion · Innovative Teachers · Teaching Ability · Classification Evaluation

## 1 Introduction

In the construction of college faculty, the construction of the teaching staff is an indispensable part. In these aspects, the most fundamental indicator for creative teaching ability is the storage capacity of creating words and the ability to apply vocabulary. This data can also serve as an important indicator to evaluate the quality of innovative teaching, which means that the language learning ability is the application ability of vocabulary. However, in the traditional evaluation method for innovative teaching ability, it adopts a subjective scoring method. The advantage of manual evaluation lies in its flexibility, but it also has a great deal of subjectivity. If there are some complex


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factors added, it will lead to significant evaluation deviations. At the same time, there is no clear evaluation standard in the evaluation process, which results in differences in evaluation criteria for the same person. This greatly affects the accuracy of evaluation. When evaluating innovative teaching ability, it should not be judged from a single perspective, but should be comprehensively judged from multiple dimensions and levels. Moreover, a certain evaluation standard should be established to facilitate unified measurement under different variable conditions. In the current research methods, a manually constructed evaluation method has been proposed. This method uses subject syllabus, textbooks, teaching aids, and other materials as carriers, with subject knowledge as the foundation. It adopts methods such as "ontology analysis", "data collection", "entity extraction", "relationship extraction", and "homogeneous data fusion" to conduct hierarchical evaluation of the teaching ability of creative teachers. [2]. Although this method can ensure the professionalism of the knowledge map in the education field, it is time-consuming and laborious. Different experts may have different understandings of the same knowledge point. For basic mathematics, preciseness and consistency are difficult to be guaranteed; Later, a semi-structured data classification evaluation method was proposed, which directly extracts entities from semi-structured texts on the network to evaluate the classification results of innovative teachers' teaching abilities. Although such methods can save a lot of construction costs and quickly build an assessment map, which is not an appropriate choice for mathematical disciplines with strict logic. Aiming at the above problems, a classification evaluation method of innovative teachers' teaching ability based on multi-source data fusion is designed. In order to ensure the rationality and effectiveness of the method design, a comparative experiment is conducted by simulating the innovative teaching environment. The effectiveness and accuracy of the proposed method are verified through the effective proof of experimental data.

## 2 Innovative Teachers' Teaching Data Feature Level Multi-source Data Fusion

This project plans to use multi-source information fusion technology to mine the information attributes of different types of information, and achieve the fusion of different types of information to enhance the reusability of information resources. The process of extracting features essentially involves extracting learning behaviors from learners from different sources and extracting characteristic features from them. Looking back at the past descriptions of information attributes in learning scenarios, different scholars have categorized the information attributes of scenarios into various types from different perspectives [3]. The first is learner situation, including name, age, class, learning period, school and other information; The second is time situation, including classroom learning time, recess time, entertainment and leisure time, physical exercise time, evening self-study time, etc.; The third is location situation, including inside and outside school; The fourth is the event situation, including various courses; The fifth is the device scenario, including hardware and software.

The learning context information characteristics of the above five dimensions well represent the data characteristics of various heterogeneous data sources. Through these five characteristics, it is possible to accurately describe the real learning and living scenarios of learners in each heterogeneous data source, and thus bridge the gap between different heterogeneous data sources [4]. These five shared data attributes form five data dimensions, which together constitute the learner's authentic learning context: learner context, temporal context, spatial context, device context, and event context. On these five data dimensions, feature-level data fusion methods are used to integrate teaching data. The feature-level data fusion mainly goes through several stages: hierarchical extraction of semantic features of each data dimension, feature-level fusion of hierarchical semantics, and feature-level fusion of cross-dimensional and cross-layer associated semantics fusion processes. The specific content is shown in Fig. 1.

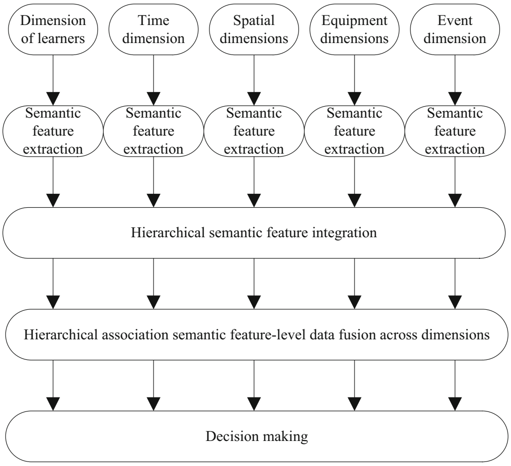



**Fig. 1.** Innovative teacher teaching data feature level multi-source data fusion process

It can be seen from Fig. 1 that the hierarchical extraction of the semantic features of each data dimension mainly refers to the hierarchical extraction of the semantic features, the determination of the semantic attributes, and the determination of the multi-level semantic logical relationship between the semantic same level, superior and subordinate of each data dimension. For example, the semantic attributes of the temporal dimension can be divided into two categories: weekdays and holidays. Weekdays can further be divided into different granularity semantic information such as classroom learning time and self-study time. [5]. The feature level data fusion of hierarchical semantics is mainly to classify the education data of various heterogeneous data sources according to these hierarchical semantics, adopt the corresponding fine-grained fusion strategy for feature level data fusion, generate scene data that can accurately describe the learning characteristics of learners, and eliminate the inconsistent and redundant relationship between the data structure and the same semantics gathered at the same granularity [6]. The feature level data fusion of cross hierarchical association semantics is mainly to describe learners' learning characteristics more objectively and accurately. According to the similar semantics of different dimensions and levels, these data with association semantics are further feature level fusion to generate scene data with deep semantic knowledge.

# 3 Classifying Evaluation of Innovative Teachers' Teaching Ability

## 3.1 Analysis Model of Innovative Teachers' Teaching Ability

According to the structure of in-service teachers' practical teaching ability, the relationship between the ability to adjust teaching, practical teaching implementation ability, practical teaching evaluation ability, practical teaching research ability, and the ability to cooperate with enterprise teachers is analyzed and combed to form the relationship connotation of teachers' practical teaching ability [7, 8]. Based on the analysis of whether the category of teachers' practical teaching ability can cover the practical teaching, a model of teachers' practical teaching ability is constructed, as shown in Fig. 2.

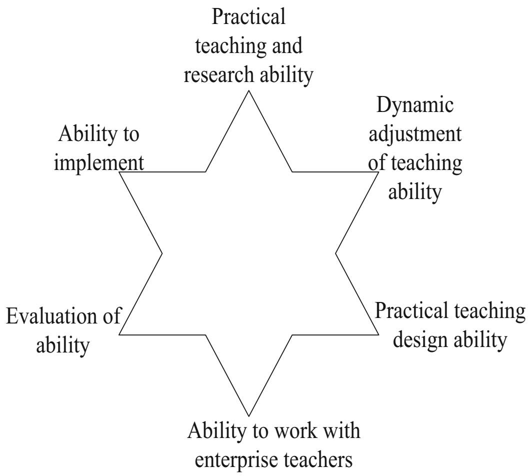



**Fig. 2.** Model of teachers' practical teaching ability

In order to accurately evaluate teacher quality, it is necessary to establish a sample-based model for teacher quality constrained parameters. Based on this, a new evaluation indicator system called the Teacher Quality Evaluation Indicator System is proposed. On this basis, this project aims to characterize the parameterized index of teaching ability evaluation by establishing a parameterized distribution model based on high-dimensional specificity of teaching ability. According to (1), an information flow model representing the constraint parameters of educational ability, which represents the differential equation, is constructed.

$$a_n = f(t_0 + n\Delta t) + \omega \quad (1)$$

In formula (1), $f(\cdot)$ is the multiple value function; $\omega$ is the measurement function; $n$ is the number of teaching ability evaluation indicators; $\Delta t$ is the evaluation cycle. This project plans to adopt a correlation fusion method to calculate the solution vector for teacher ability evaluation within the high-dimensional feature distribution space and obtain the feature training subset for teacher ability evaluation. Based on the statistical data obtained in the previous stage, a data flow model for teaching ability evaluation is constructed, focusing on the statistical features distribution sequence of a set of multivariate variables. That is, the teaching ability evaluation has a convergent solution, and the constraint condition is Formula (2):

$$\phi_a(\omega) = -\frac{1}{2}\omega^2\sigma^2 \tag{2}$$

In Formula (2), $\sigma$ represents the evaluation solution vector. Based on this, a data information flow model for teaching ability assessment is constructed, and a set of scalar sampling sequences is generated to generate a big data distribution model, providing accurate data input basis for teaching ability assessment.

### 3.2 Similarity Calculation of Teaching Ability Data Based on Analytic Hierarchy Process

Because there is no connection between the unstructured data of textbooks using traditional methods and semi-structured data such as Baidu Encyclopedia and Interactive Encyclopedia, the data sources are scattered, not authoritative and not systematic [10]. Based on this, considering the existing tags, textbooks and other unstructured texts, this paper proposes a method to calculate the similarity of teaching ability data based on AHP.

Step 1: Pretreatment layer.

The encyclopedia data obtained by the crawler generally contains a large amount of redundant information, which cannot be directly used for entity alignment, and the subsequent work depends on the description information of each entity. Therefore, this layer mainly preprocesses the data. For encyclopedic data, it specifically includes: using the redirection mechanism and synonym tags in the encyclopedia to remove irrelevant entities, expanding synonymous entities, and obtaining a complete set of encyclopedic entities [11]; Then, the description information in the entity set is preprocessed by word segmentation; Finally, align entities among encyclopedias according to the processed entities in the encyclopedia (for text data, preprocessing includes regular text preprocessing operations such as word segmentation, etc.).

Step 2: String matching layer.

It is mainly used to match entities with exactly the same name and description information in the encyclopedia space. For example, the "unary linear equation" in Baidu Encyclopedia and the "unary linear equation" in Interactive Encyclopedia are two entities that match exactly [12]. At this time, only one of them is retained.

Step 3: semantic matching layer.

Entity alignment can generally be converted into judging the semantic similarity of entities. In most cases, the Chinese semantic knowledge base will be used to calculate the semantic similarity between entity pairs. Based on the semantic similarity calculation, the semantic similarity of two entities in HowNet is considered, as shown in the formula (3):

$$\mathrm{Sim}_i(\mathrm{A}_i, \mathrm{B}_i) = \frac{\lambda}{l + \lambda} \tag{3}$$

In formula (3), $\mathrm{A}_i$, $\mathrm{B}_i$ represents the name of an entity in Interactive Encyclopedia and Baidu Encyclopedia respectively; $i$ represents the number of adjustments; $\lambda$ represents an adjustable parameter; $l$ represents the distance between two semaphores in the semaphore hierarchy [13].

Step 4: Morphological matching layer.

Morphological matching layer mainly calculates the similarity between attribute tags and abstract text on the basis of semantic correlation. The attribute tag refers to the description content of an entity information on Baidu Encyclopedia and Interactive Encyclopedia, and the abstract text refers to the content of a concept introduced in relatively refined words on Baidu Encyclopedia and Interactive Encyclopedia. The similarity of attribute tags is calculated by editing distance algorithm. Considering the influence of the number of attribute matches on the similarity, the formula is normalized, such as Formula (4):

$$g\left(h^{\mathrm{A}_i}, h^{\mathrm{B}_i}\right) = \frac{\sum_{i \in n} \mathrm{s_e}\left(h^{\mathrm{A}_i}, h^{\mathrm{B}_i}\right)}{l} \tag{4}$$

In formula (4), $\mathrm{s_e}\left(h^{\mathrm{A}_i}, h^{\mathrm{B}_i}\right)$ represents the edit distance between two attribute values; $h^{\mathrm{A}_i}$, $h^{\mathrm{B}_i}$ represents the entity attribute set in Baidu Encyclopedia and Interactive Encyclopedia respectively.

Text similarity is calculated by cosine similarity algorithm based on TF-IDF [14, 15]. First, convert the keywords extracted from Interactive Encyclopedia and Baidu Encyclopedia into vector form, and then calculate the cosine similarity between the two vectors, as shown in Formula (5):

$$\mathrm{Sim}_i\left(\overline{\mathrm{A}_i}, \overline{\mathrm{B}_i}\right) = \frac{\sum_{i=1}^{l} (a_i \times b_i)}{\sqrt{\sum_{i=1}^{l} (a_i)^2 \times \sum_{i=1}^{l} (b_i)^2}} \tag{5}$$

In formula (5), $\overline{\mathrm{A}_i}$, $\overline{\mathrm{B}_i}$ represents the vector form converted from interactive encyclopedia and Baidu encyclopedia data respectively; $a_i$, $b_i$ represents vector data of Interactive Encyclopedia and Baidu Encyclopedia respectively.

### 3.3 Classification of Evaluation Data Based on Quantitative Analysis

The method of quantitative recursive analysis was applied to analyze the big data information model of teacher quality evaluation, with the control objective function for predicting and estimating teacher quality set as formula (6):

$$Q = \max \sum_{j=1}^{5} u_j a_n \tag{6}$$

In formula (6), $u_j = u_1, u_2, u_3, u_4, u_5$ represents five data dimensions, namely learner situation, time situation, location situation, equipment situation and event situation.

Using the grey model, a quantitative recursive evaluation of teacher's educational ability level is conducted, assuming historical data of the distribution of teacher's educational ability. When the initial value of the disturbance feature is fixed, the probability density functional for predicting and estimating teacher's educational ability can be obtained as formula (7):

$$\rho(t) = ka_n(\mathrm{t}) \tag{7}$$

In formula (7), $k$ represents the number of iterations. Based on this, the evaluation results of teacher quality are obtained through the prediction and estimation of teacher quality, as well as the quantification and regression analysis of teacher quality.

In order to build an educational data model with strong flexibility and high reusability [16], to reduce the amount of data exchange between different data, and to meet the needs of different data sources for different data views, it is also necessary to formalize the data. This link is based on the calculation results of the model data attribute and semantic uniqueness operation link. It formally describes the learner situation data in the model, and further combines these independent data dimensions in multiple dimensions to build a multi-dimensional education data model. For the five independent data dimensions that make up the data model, since the learner dimension is static information data, its formal description is not marked in the model, thus, the learning situation data description of the model can be represented by five tuples, each of which is independent and interconnected to form a multi-dimensional education data model with different combinations, which is represented by characters in turn as $\mathrm{P}_1, \mathrm{P}_2, \mathrm{P}_3, \mathrm{P}_4, \mathrm{P}_5$, and each tuple is composed of an even pair $\langle P, C\rangle$, where, $C$ represents the classification semantics of each attribute. The formal description of the shared education data model formed by F is Formula (8):

$$\langle P, C\rangle = \begin{bmatrix} \langle P_1^1, C_1^1\rangle & \langle P_2^1, C_2^1\rangle & \langle P_3^1, C_3^1\rangle & \langle P_4^1, C_4^1\rangle & \langle P_5^1, C_5^1\rangle \\ \langle P_1^2, C_1^2\rangle & \langle P_2^2, C_2^2\rangle & \langle P_3^2, C_3^2\rangle & \langle P_4^2, C_4^2\rangle & \langle P_5^2, C_5^2\rangle \\ \langle P_1^3, C_1^3\rangle & \langle P_2^3, C_2^3\rangle & \langle P_3^3, C_3^3\rangle & \langle P_4^3, C_4^3\rangle & \langle P_5^3, C_5^3\rangle \\ \langle P_1^4, C_1^4\rangle & \langle P_2^4, C_2^4\rangle & \langle P_3^4, C_3^4\rangle & \langle P_4^4, C_4^4\rangle & \langle P_5^4, C_5^4\rangle \\ \langle P_1^5, C_1^5\rangle & \langle P_2^5, C_2^5\rangle & \langle P_3^5, C_3^5\rangle & \langle P_4^5, C_4^5\rangle & \langle P_5^5, C_5^5\rangle \end{bmatrix} \tag{8}$$

Formula (8) takes the time context dimension as an example, $\langle P, C\rangle$ can be a set consisting of $<$ 18:30, dinner time $\geq$ 20:30, evening self-study time $\geq$ 22:30, and night sleep time $>$ 22:30. The model can not only form a single dimension data model view such as location situation and event situation, but also form a multi-dimensional data view, as shown in Fig. 3.

Through Fig. 3, it is convenient for each data system to dynamically obtain personalized data model views according to its own data analysis needs. The shared education data model constructed in this way can not only reduce the amount of data exchanged and transmitted between heterogeneous data systems, but also reduce the complexity of data analysis, effectively reduce the lack of data information, and help to deeply mine the real learning needs of learners.

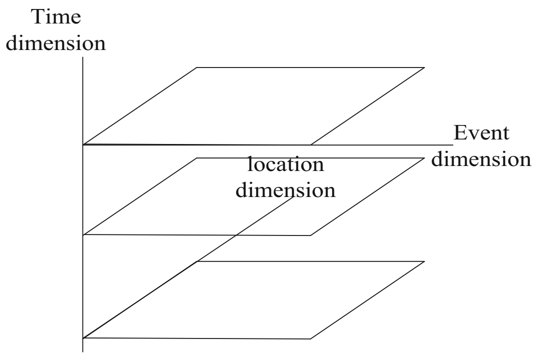



**Fig. 3.** Data Model View of Different Dimension Combinations

### 3.4 Classification Evaluation Based on Multi-source Data Fusion

Based on the formal description results of the evaluation data, the operation mechanism of standardizing the 5-dimensional feature fusion data. In order to build a highly shared educational data model, it is also necessary to analyze the data standard format of the 5-dimensional feature fusion data, and generate a general and standard data exchange format. According to the data structure of the 5-dimensional feature fusion data obtained from the previous analysis: learner situation, time situation, location situation, equipment situation, and event situation, combined with the standardized description of the specification statement structure, the general data specification format of the 5-dimensional feature fusion data is obtained. This universal data format maps out the learner's status as: {learner} attached with learner's personal semantic tag | {a certain time point} attached with time classification semantic tag | {a certain place} attached with place classification semantic tag | {what device is used} attached with device classification semantic tag | {something has been done, what results are achieved, and how long it takes} attached with topic event classification semantic tag. Based on this, an evaluation model is constructed. As shown in Fig. 4.

The evaluation model constructed by multi-source data fusion method, as shown in Formula (9):

$$J_{\mathrm{a}}^{0} = \left(T_{\mathrm{a}}^{0} - T_{0}\right)\eta_{0} \tag{9}$$

In formula (9), $J_{\mathrm{a}}^{0}$ represents the effective value; $T_{\mathrm{a}}^{0}$, $T_0$ represents the value of the evaluation criteria without and after participation; $\eta_0$ is the variable weighting coefficient. After the evaluation, it needs to be identified. After the evaluation, certification needs to be conducted, and the evaluation data obtained through certification is regarded as valid values, following the process as described in formula (10).

$$J' = \frac{\eta_A f_A + \eta_B f_B}{\eta_A + \eta_B} \tag{10}$$

In formula (10), $\eta_A$, $\eta_B$ represents high-order parameter and low order parameter respectively; $f_A$, $f_B$ represents high-quality data of continuous variables respectively.

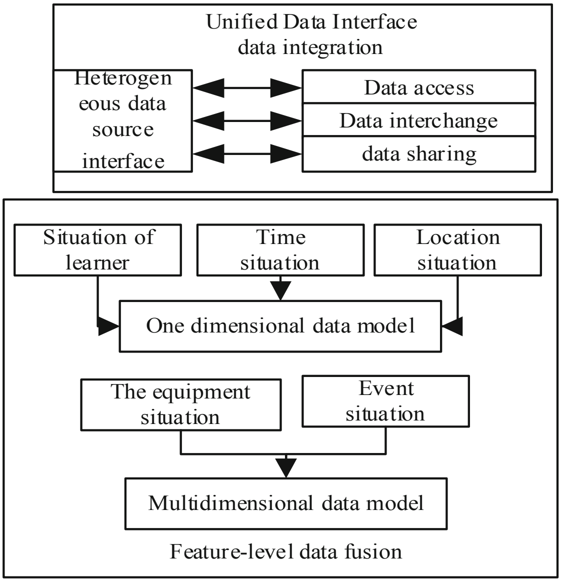



**Fig. 4.** Evaluation model

Through the introduced feedback calculation, the data features in the educational process can be comprehensively represented, and by inputting them into the feedback model, a comprehensive evaluation of students can be achieved.

# 4 Simulation Experiment

Based on this, a hierarchical evaluation model for the teaching ability of innovative teachers is constructed through the fusion of multiple sources of information to verify the correctness of the model. Different innovative classrooms are selected for simulated experiments, and conventional evaluation methods are used for comparative evaluation to ensure the effectiveness of the experiments.

## 4.1 Parameter Setting

In order to ensure the effectiveness of the evaluated method, the parameters are set, the reference data used for network feedback is set outside the range [10001250], and the innovative teaching content is set as follows: English grammar, vocabulary explanation, sentence pattern analysis, oral practice, writing practice, and English dialogue. The teaching duration is 15 min, 30 min, 35 min, 40 min, 45 min, and 50 min respectively.

## 4.2 Experimental Indicators

SPSS was calculated to ensure the effectiveness of the experiment. The computation of SPSS is performed to ensure the effectiveness of the experiment. The calculated values obtained from SPSS are greater than or equal to 0.95, so the values obtained from SPSS are effectively fitted to obtain Formula (11):

$$Z(k) = \frac{z[u(g-1)]}{1 + z^2(g-1)} \geq 0.95 \tag{11}$$

In Formula (11), $z$ represents reference data; $g$ represents a high-order parameter; $u$ represents the matching data. Due to the comparison between modes and methods, a significant error may occur. To ensure the accuracy of the experimental results, the measured results were permutation with the actual results, and a measuring proportion method was adopted to eliminate random bias. The proportion factor changes with the number of experiments, but the range of the proportion factor value chosen is between 2.45 and 6.55. A method that can exclude non-zero errors was used to prevent the occurrence of non-zero errors by calculating zero-point values.

### 4.3 Analysis of Experimental Data

Choose English grammar, vocabulary explanation and English dialogue as standard data, which can be directly downloaded from the school homepage. The experimental data set is shown in Fig. 5.

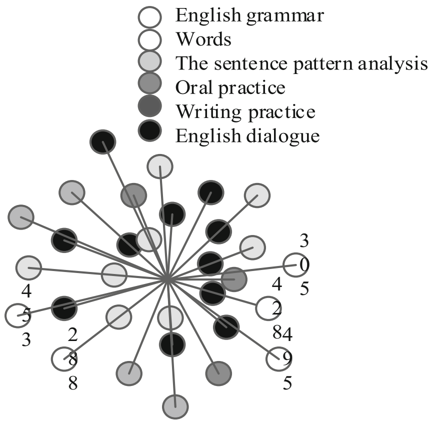



**Fig. 5.** Experimental data set

It can be seen from Fig. 5 that the data type is characterized by permutation and dispersion. After factor analysis of the selected data, it is found that the variance contribution rate of each factor after rotation is balanced, and the load of each index on each factor is greater than 0.5, which indicates that the correlation between each index and the corresponding factor is relatively close, so the three main factors are extracted. For the convenience of discussion, the extracted main factors are named F1, F2, and F3. The indicators with high load on F1 factor are teaching attitude, classroom mental state, teaching ideas, language explanation, after-school guidance, and interaction between students and teachers, which represent teachers' personal teaching skills. Therefore, F1 is named as teaching skills, corresponding to the basic teaching ability level of ideological and political teachers. The indicators with higher load on factor F2 are classroom participation, learning interest, after-school input and learning enthusiasm, which to some extent reflects the students' learning input, and also reflects the ideological and political teachers' classroom teaching guidance ability. Therefore, factor F2 is named as learning input, which corresponds to the higher teaching ability level of ideological and political teachers. The indicators with high load on F3 factor are overall learning gains, classroom evaluation and far-reaching influence, which reflect students' classroom gains. Therefore, F3 factor is named learning gains, reflecting teachers' high-level teaching ability.

### 4.4 Experimental Results and Analysis

The evaluation method based on manual construction, the classification evaluation method based on semi-structured data and the classification evaluation method are respectively used to compare and analyze the teaching skill index F1, the learning input index F2 and the learning harvest index F3. The values of the indices range from 1 to 10, and the higher the value, the more accurate the evaluation results.

#### 4.4.1 Teaching Skill Index

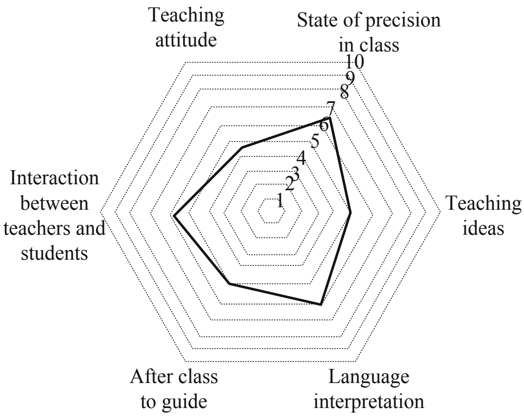
The comparative analysis results of the three teaching skill indexes are shown in Fig. 6.

From Fig. 6 that the teaching skill index of the classification evaluation method can reach 9.8 at most, while the teaching skill index of the evaluation method based on manual construction and the classification evaluation method based on semi-structured data can reach 6.5 and 7 at most, which is quite different from the ideal index. This shows that the assessment result of teaching skill index using the classification assessment method is accurate. The main reason is that the proposed method integrates the characteristic level multi-source data of innovative teachers' teaching data, and generates the scene data that can accurately describe learners' learning characteristics, which can better optimize the evaluation effect of teaching skill index.

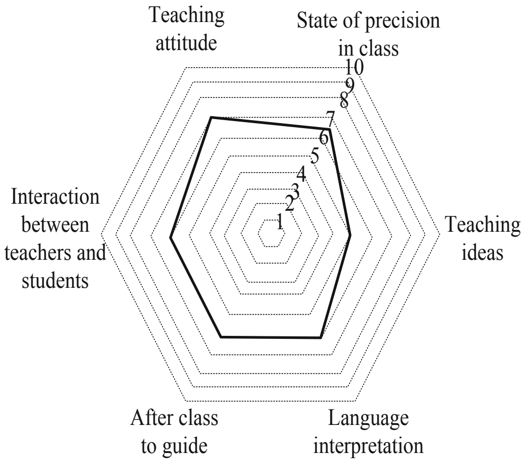
#### 4.4.2 Learning Input Index

The comparative analysis results of learning input indexes of the three methods are shown in Fig. 7.

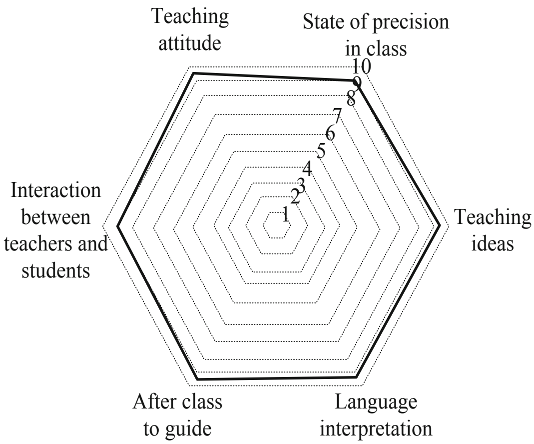
From Fig. 7 that the learning input index of the evaluation method based on manual construction and the classification evaluation method based on semi-structured data can reach 5 and 7 respectively, while the learning input index of the classification evaluation method can reach 9.6. This shows that the evaluation result of learning input index using the classification evaluation method is accurate. The main reason is that the proposed method uses analytic hierarchy process to calculate the similarity of teaching ability data, and describes the form of evaluation data through quantitative recursive analysis, which improves the evaluation performance.




(a) Evaluation method based on manual construction

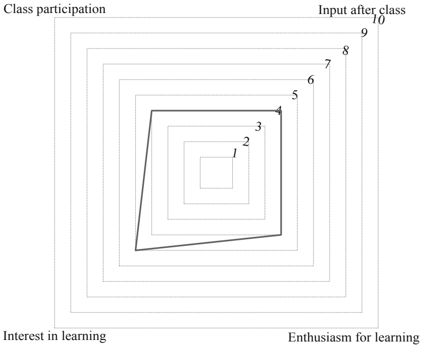



(b) Classification and evaluation method based on semi-structured data

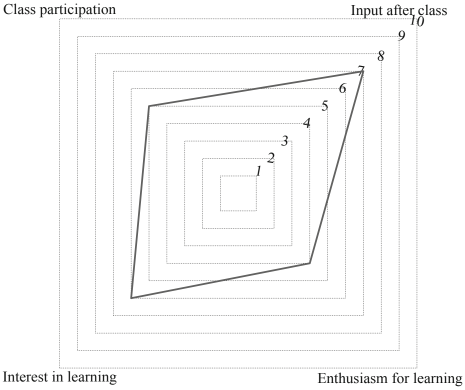



(c) Classification and evaluation method

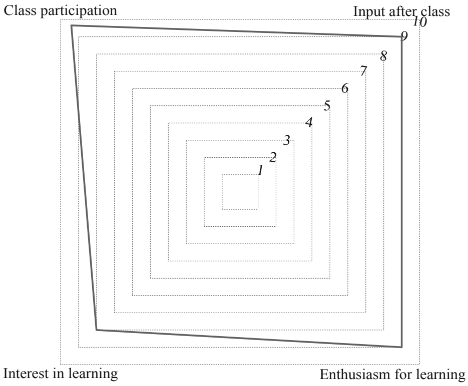
**Fig. 6.** Comparison results of teaching skill indexes of three methods




(a) Evaluation method based on manual construction




(b) Classification and evaluation method based on semi-structured data

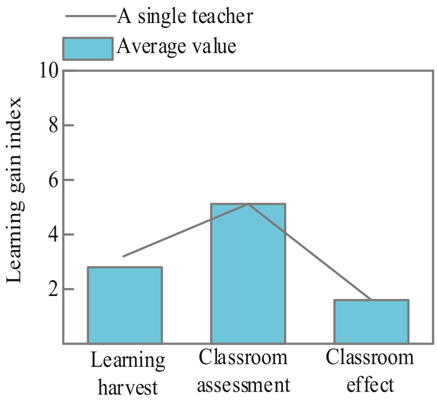



(c) Classification and evaluation method

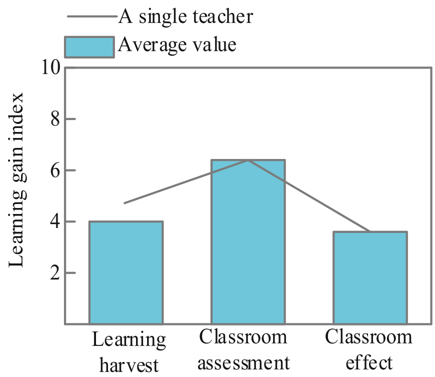
**Fig. 7.** Comparison Results of Learning Input Index of Three Methods

### 4.4.3 Learning Harvest Index

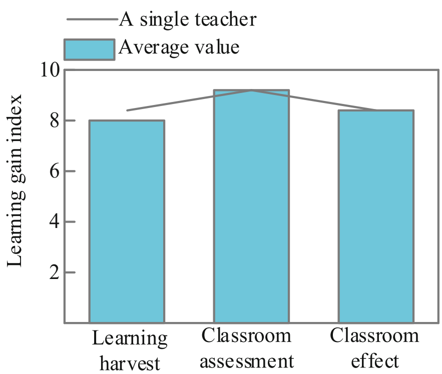
The three methods learn the harvest index, and the comparative analysis results are shown in Fig. 8.




(a) Evaluation method based on manual construction




(b) Classification and evaluation method based on semi-structured data




(c) Classification and evaluation method

**Fig. 8.** Comparison Results of Learning Harvest Index of Three Methods

From Fig. 8 that the learning harvest index of the evaluation method based on manual construction and the classification evaluation method based on semi-structured data can reach 5 and 6.8 respectively, while the learning harvest index of the classification evaluation method can reach 9.2. This shows that the evaluation result of learning harvest index using the classification evaluation method is accurate. The proposed method integrates the five-dimensional characteristic data of learner situation, time situation, location situation, equipment situation, event situation and learning situation, and constructs an evaluation model, which improves the accuracy of learning harvest index evaluation.

## 5 Conclusion

In view of the poor evaluation effect, this paper proposes a research on the classification evaluation method of innovative teachers' teaching ability. Based on the characteristic level multi-source data fusion of innovative teachers' teaching data, this paper implements the classification evaluation of innovative teachers' teaching ability from four aspects: the construction of innovative teachers' teaching ability analysis model, the calculation of teaching ability data similarity based on hierarchical analysis, the classification of evaluation data based on quantitative analysis, and the classification evaluation based on multi-source data fusion. The experimental results show that the proposed method has a good classification effect.

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2. The first batch of collaborative education projects of the Ministry of Education in 2022: "Training of young teachers' teaching innovation ability based on the" rain classroom "intelligent teaching platform" research results

3. The construction achievements of "History of Chinese and Foreign Educational Thoughts", a high-quality online open course of Xi'an Siyuan University in 2021;

4. The construction results of the school-level teaching team of Xi'an Siyuan University "Teaching team of core pedagogy curriculum group";

5. Construction achievements of the scientific research innovation team of Xi'an Siyuan University "Shaanxi regional basic education scientific research innovation team".

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