Research on the Construction and Dynamic Adjustment Mechanism of University Teacher Portrait System

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Abstract: To address the prominent issues of the lack of a systematic framework and dynamic adjustment mechanisms in university teacher portrait research, this paper constructs a three-layer teacher portrait system covering the data support layer, indicator model layer, and application service layer. It also designs a dynamic adjustment mechanism for the portrait from the dimensions of time, development stage, and application scenario. Empirical research based on real teaching platform data shows that the constructed teaching style classification model achieves an AUC of 0.863, the information technology ability prediction accuracy reaches 86.63%, and the dynamic adjustment mechanism improves portrait matching accuracy by 15.6%. The research findings provide effective support for more scientific and precise university teacher management.

Keywords: Teacher Portrait; Dynamic Adjustment Mechanism; Multimodal Data; University Teacher Management

1. Introduction

The teacher is the fundamental guarantee of the education quality. At the background of the digital transformation of higher education, the portrait of the teacher has got popular attention as the important tool of precision management and personalized development. At present, the research still has two big problems: the first is that there is no systematic construction framework, scattered data, scattered indicator and one-sided application; the second is that the portrait is static, can not reflect the change of the teacher professional development. In this paper, we take the university teacher as the research object. taking the two tasks of constructing the system of teacher portrait, and constructing the dynamic adjustment mechanism that accords with the development of the teacher and the change of scene. It provides the theoretical support and practical way of transforming the university teacher management from the judgment of experience to the decision of data.

2. Construction of the University Teacher Portrait System

2.1 Overall System Architecture

The university teacher portrait system is three-layer architecture. The data support layer is to integrate multi-source heterogeneous teaching data, including the teacher basic information, teaching behavior, teaching outcome and the relation of teacher-student, etc. We do data cleaning and data standardization to build the data foundation. This layer don't only deals with the structured data (e.g. the homework submission rate, the frequency of resource upload, etc.), but also introduce the semi-structure and the unstructure data (e.g. the text of discussion forum, the log of teaching, etc.) so as to increase the comprehensiveness of the portrait. The indicator model layer is to build the indicator system on two dimensions of the teaching style and the information technology ability, and to build the portrait model based on the deep learning algorithm. The application service layer is to serve the management scene, such as the scenario of recruitment and selection, the scene of personalized training, the scene of performance evaluation, etc, form the loop of "portrait - application - feedback". The three-layer architecture can make the data and the information flow bidirectional interaction by the standardized interface, which can guarantee the performance of portrait in real time and the consistency of the portrait.

2.2 Construction of the Core Indicator System

The teaching style dimension is based on the theory of mental self-government, and the three-category sub-dimension is constructed as an indicator system.

The calculation method for homework update score is as follows:The distinguishing indicators for legislative, executive and judgmental teachers mainly include homework update score (HUS), teaching tool usage score (UTTS), discussion score (DS), etc.

$$HUS=1-\frac{\sum C_{HIn}}{\sum C_{HI}}$$

Among them, $\sum C_{HIn}$ represents the number of assignments reused across academic years, and $\sum C_{HI}$ represents the total number of assignments released in the previous academic year.

The calculation method for the score of teaching tool usage is as follows:

$$UTTS=\sum W_{TTi}\times C_{TTi}$$

Among them, W_{TTi} represents the weight of the i-th type of teaching tool, and C_{TTi} represents the frequency of use of the i-th type of tool.

The distinction between overall-type and local-type teachers focuses on the chapter distribution characteristics of teaching resources, including chapter resource score (CRS) and chapter interaction score (CIS):

$$CRS=\frac{maxCRS-minCRS}{minCRS}$$

$$CIS=\sum W_{T_i}\times C_{T_i}$$

Among them, maxCRS and minCRS represent the highest and lowest chapter resource scores of the teachers, W_{T_i} is the weight of the i-th type of interactive tool, and C_{T_i} is the usage frequency.

The distinction between radical and conservative teachers focuses on the degree of resource update, including the resource update score (RUS):

$$RUS=1-\frac{\sum C_{RIn}}{\sum C_{RI}}$$

Among them, $\sum C_{RIn}$ represents the number of resources reused across academic years, and $\sum C_{RI}$ represents the total amount of resources released in the previous academic year.

The information technology capability dimension contains 17 behavioral characteristics for example: resource operation, notes, mind maps, videos, question bank, AI tools, task management, etc. It is a full depiction of the level of teachers' information technology application. These behavioral characteristics are divided into three sub-dimensions: basic operational ability, content integration ability, teaching innovation ability, which is helpful for the hierarchical assessment and training design.

2.3 Image Model Construction Method

In view of the characteristics of different types of teaching style data, the differentiated modeling methods are adopted. For three kind of teaching style, which is the legislative, the executive and the evaluative, the improved of the method of the P model algorithm is used. In the algorithm, a kind of uncertain label processing mechanism is introduced and the classification accuracy is improved through the principle of the consistency regularization. The loss function is as follows:

$$Loss=\frac{1}{n}\sum_{m=1}^{n}L\left(y^{m},y_{L}^{m}\right)+\lambda(t)\frac{1}{n'}\sum_{m'=1}^{n'}L\left(\hat{y}^{m'},y_{uL2}^{m'}\right)$$

Here, n and n' represent the number of normal labels and uncertain labels respectively, y^m is the true label, y_L^m is the model prediction value, λ(t) is the dynamic weight coefficient, and ym' is the average of the two prediction results.

For the classification of overall and local, aggressive and conservative teaching styles, the convolutional neural network (CNN) model is used. The network structure includes two convolutional layers, one pooling layer, and two fully connected layers. The softmax layer outputs the classification probability. The CNN model can automatically extract local relevant features in teaching behavior data and is suitable for modeling behavior sequence data.

The assessment of information technology ability adopts a prediction model based on multi-attention mechanism. The model consists of two parallel attention modules that extract the importance of behavior features in each academic year, and through the balance score module, it captures the trend of changes over academic years. Finally, it performs Softmax classification prediction. This model has a significant advantage in capturing the trajectory of teacher ability development and can distinguish between short-term fluctuations and long-term growth trends.

3. Dynamic Adjustment Mechanism Design for Teacher Profiles

3.1 Time Dimension Adjustment Mechanism

Based on the academic year, establish a temporal update mechanism for the profile. Define the state vector of the teacher profile at time tt as $S_t=\{s_1^t,s_2^t,\ldots,s_k^t\}$, and the change vector

$\Delta S_t = S_t - S_{t-1}$. . When ΔSt exceeds the preset threshold, trigger the profile update mechanism:

$$w_i^t = w_i^{t-1} \times (1 + \alpha \cdot \Delta s_i^t)$$

Where, w_i^t is the weight of the i-th dimension in the t-th academic year, α is the adjustment coefficient, and Δs_i^t is the change amount of the i-th dimension.

3.2 Adjustment Mechanism for Developmental Stage Dimension

The teacher development is divided into three stages: the novice stage (1-3 years after joining), the growth stage (4-8 years), and the mature stage (more than 8 years). The novice stage focuses on basic teaching skills, with the weight of the executive style increasing; the growth stage pays attention to teaching innovation, with the weight of the legislative style increasing; the mature stage emphasizes teaching leadership, with the weight of the evaluative style increasing.

The weight setting formula is as follows:

$$w_i^{stage} = w_i^{base} \times \beta_{stage,i}$$

Among them, w_i^{base} represents the base weight, and $\beta_{stage,i}$ is the adjustment coefficient for the i-th dimension in the current stage.

3.3 Scenario Dimension Adjustment Mechanism

The differences in the focus dimensions of teacher profiles in the different management scenarios is as follows: for the recruitment and selection scenario, the focus dimension is the compatibility between the teaching style and the job requirements, and the focus is on whether the candidate can be evaluated on the aspect of the potential of teaching innovation and the orientation of teamwork; for the training scenario, the focus is at the weakness of the skills, and the focus is on showing the weak point of the teacher in such as information technology and classroom management, etc; for the evaluation scenario, it is taking into comprehensively consider the teaching outcome, teaching behavior and the professional development,and the focus is on the balance between the outcome orientation and the growth trajectory. The scenario based adjustment mechanism is expressed as:

$$S_{scene} = \{s_i \times \gamma_{scene,i} | i = 1, \ldots, k\}$$

Here, among them, represents the attention coefficient of the i-th dimension in the scene scene, which is defined according to the application requirements.

3.4 Feedback-drivenClosed-loop Optimization Mechanism

Establish a feedback-driven closed-loop optimization mechanism: Utilize the feedback loop to transmit the usage effect of the profile, including recruitment matching success rate, training participation and satisfaction, performance evaluation consistency, etc.; the effectiveness verification loop validates the actual effect through training tracking and performance analysis, using before-and-after comparison and control group design; the dynamic iteration loop establishes a quarterly evaluation mechanism to form a closed-loop process of "profile - application - feedback - optimization". This mechanism ensures that the profile system can continuously evolve and gradually approach the true state of teachers.

4. Empirical Research and Result Analysis

The experimental results of the improved Π model algorithm in the classification of legislative, executive, and evaluative teaching styles are shown in Table 1. The AUC value of the improved Π model algorithm reached 0.863, which was 8.8 percentage points higher than the method that discarded uncertain labels, verifying the effectiveness of the algorithm. The CNN model achieved a test accuracy of 86.2% in the four-classification task, demonstrating excellent feature extraction capabilities.

Table 1. Classification Results of Legislative, Executing and Judging Teaching Styles

Method	AUC
Discarding uncertain labels	0.793
Replacing with executive type	0.824
Improved Π-model algorithm	0.863

The prediction results of the multi-attention mechanism model are shown in Table 2. The accuracy rate of the multi-attention mechanism model proposed in this paper is 86.63%, and the F1 value is 85.86%, which is significantly better than traditional machine learning methods.

Table 2. Performance Comparison of Different Methods

Method	Accuracy	F1
Support Vector Machine	69.71	66.07
Random Forest	77.07	74.99
Multi-attention Model	86.63	85.86

The results of the ablation experiment are shown in Table 3, which verify the effectiveness of the attention mechanism and the balance score.

Table 3. Ablation Experiment on Attention Mechanism and Balance Score

Configuration	Accuracy	F1
No attention + No balance	74.69	74.34
No attention + Balance	78.29	77.06
Attention + No balance	80.93	80.31
Attention + Balance	86.63	85.86

5. Conclusion and Outlook

In this paper, we have built a teacher profiling system, which includes the data support layer, the indicator model layer and the application service layer. The model is precisely modeled based on two core dimensions of teaching style and information technology ability. The effectiveness of the model is verified by experiment. And the triple dynamic adjustment mechanism for time, development stage, and scenario is designed, which is a closed-loop iterative process of profiling - application - feedback - optimization, which breaks through the limitation of traditional staticness. In the future, the research will be going deeper in the following three directions. First, to expand the profiling dimensions by adding new dimensions, such as emotional attitude, research ability and social service, to construct a more comprehensive digital profiling of university teachers. Second, to deepen the dynamic prediction mechanism by using time series analysis and reinforcement learning to achieve the forward judging on the development trend of teachers. Third, to promote the implementation of multi-scenario applications, to explore the application potential of profiling in new scenarios such as faculty evaluation, teaching team formation, and teacher mental health early warning, to help the university teacher management to transform to the way of data driven.

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