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Research on dynamic evaluation model of "double qualification" ability of hotel management teachers driven by algorithm optimization

Manli Qian[1] *and Yonghui Qian*[1,*]

[1] School of Economics and Management, Fuyang Institute of Technology, Fuyang City, Anhui Province, 236031, China

SUMMARY: *Facing the static and unitary problem of teacher ability evaluation under the background of digital transformation of the hotel industry and the integration of industry and education of vocational education, this paper constructs a dynamic evaluation model of "double qualification" ability of hotel management teachers driven by algorithm optimization. Focusing on teaching transformation ability, industry practice ability, digital technology application ability, collaborative development ability and teaching-practice coupling relationship, this paper established a hierarchical evaluation index system, and designed multi-source heterogeneous data preprocessing, feature extraction, index relationship modeling, adaptive weight update and time series feature fusion methods to form a dynamic evaluation framework for teachers 'ability. Experimental results show that the overall performance of the proposed model is better than that of the static weighted model, random forest model, LSTM model and TCN model. The Accuracy, F1-score and Stability reach 94.3%, 93.5% and 95.2% respectively, and the MAE and RMSE are reduced to 0.031 and 0.049 respectively. The dynamic evolution analysis showed that the comprehensive score of teachers' "double qualification" increased from 0.667 to 0.806, and the teaching-practice coupling strength increased from 0.68 to 0.82. The research shows that the model can effectively identify the stage differences and evolution trajectories of the "double-qualification" ability of hotel management teachers, and provide technical support for teacher development diagnosis, school-enterprise collaborative training and digital evaluation of vocational education.*

KEYWORDS: *Algorithm optimization; Hotel management teacher; Double-teacher ability; Dynamic evaluation model*

1 Introduction

Under the background of the digital transformation of the hotel industry, the upgrading of smart services and the continuous deepening of the integration of production and education, hotel management teachers have changed from a single classroom teacher to a "double teacher" subject with the ability of teaching organization, post practice, technology application and collaborative education. Busulwa et al. (2024) pointed out that the hotel and tourism curriculum system is being reconstructed around digital transformation, and teachers need to translate the technological changes in the industry into the curriculum competence structure [1]. Choe and Kim (2024) proposed that tourism and hotel education is moving from traditional classroom to real task and Living Lab scene, and teachers' ability evaluation should

*lansemengxiang1985@126.com
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also shift from static qualification judgment to continuous recognition oriented to practical performance [2]. Therefore, the "double-teacher" ability of hotel management teachers has shown the characteristics of multi-dimensional coupling, scene dependence and dynamic evolution, and the traditional one-time assessment method is difficult to accurately reflect its true level.

The existing teacher ability evaluation methods mostly rely on questionnaire surveys, expert ratings and fixed-weight statistics. Although they are easy to implement, they face obvious shortcomings in the integration scenario of vocational education and digital education. Firstly, the source of evaluation data is relatively single, and it is difficult to integrate multi-source heterogeneous information such as classroom teaching, enterprise practice, student feedback, training experience and achievement output at the same time. Secondly, the index weight is usually preset and unchanged for a long time, which is difficult to depict the fluctuation of teachers 'ability in different stages and different task situations. Third, the evaluation results are mostly post-hoc descriptions, and lack of continuous tracking of the change trend of ability status. Estaji et al. (2024) pointed out in their study on teachers' evaluation literacy in the digital environment that teachers' evaluation competence has involved composite components such as knowledge, technology, context and implementation strategy [12]. Chiu et al. (2024) also showed that the formation of teachers' technology competence was a dynamic process jointly influenced by context support and practice participation when studying teachers' digital competence development [13]. This indicates that the ability evaluation of hotel management teachers' "double qualification" needs to shift from static weighting to dynamic modeling.

It is of great significance to introduce algorithm optimization and computer technology into this field. On the one hand, multi-source data acquisition, feature coding, time series modeling and machine learning recognition can improve the fineness and continuity of capability representation. On the other hand, the intelligent optimization algorithm can adaptively optimize the evaluation index weights, model parameters and state update rules, so as to improve the evaluation accuracy, stability and robustness. Sabharwal and Miah (2024) proposed a teacher effectiveness evaluation framework based on machine learning, and proved that ML methods can identify teacher performance differences from complex educational data [20]. Chiu et al. (2025) developed the scale of teachers' AI ability and constructed quantifiable ability dimensions, which provided a method reference for the computational expression of teachers' ability [16].

Based on this, this paper constructs a dynamic evaluation model driven by algorithm optimization for the "double teacher" ability evaluation scenario of hotel management teachers. The research contents include: constructing an evaluation index system integrating teaching ability, industry practice ability and digital technology application ability, designing multi-source heterogeneous data preprocessing and feature extraction methods, establishing an adaptive update mechanism of index weights, forming a dynamic evaluation model integrating time series features, and verifying the effectiveness of the model through comparative experiments and ablation experiments. The innovation of this paper is that the "double-teacher" evaluation is transformed from static assessment into a data-driven dynamic modeling problem, the algorithm optimization is introduced to enhance the weight and parameter adjustment ability, and the time series evolution analysis is combined to improve the accuracy and interpretability of the change trend identification of teachers 'ability. To further illustrate the differences between this paper and existing studies, Table 1 compares some representative literatures with this study.

Table 1: Comparison between this study and some representative literature

Literature	Research Object	Methodological Features	Difference from This Study
Busulwa et al. (2024) [1]	Hotel and tourism education curricula	Digital transformation readiness analysis	Focuses on curriculum systems and does not involve dynamic evaluation of the “dual-qualified” competencies of hotel management teachers
Choe and Kim (2024) [2]	Higher education in tourism and hospitality	Living Lab practice analysis	Emphasizes cultivation pathways but lacks a quantitative model
Estaji et al. (2024) [12]	Teacher assessment literacy in digital environments	Review and factor integration	Can support indicator design, but does not construct a computational model
Chiu et al. (2025) [16]	Teachers’ AI competence	Scale development and validation	Provides quantifiable dimensions, but does not conduct temporal evaluation
Sabharwal and Miah (2024) [20]	General teacher evaluation	Machine learning-based identification	Introduces machine learning, but is not tailored to the “dual-qualified” context of hotel management teachers
This study	“Dual-qualified” competencies of hotel management teachers	Multi-source data fusion, feature extraction, adaptive weight updating, and temporal modeling	Simultaneously addresses domain specificity, dynamic evolution, and model interpretability

2 Evaluation index system and data representation of "double-qualified" ability of hotel management teachers

2.1 Analysis on the connotation of "double-qualified" ability of hotel management teachers

The "double-qualified" ability of hotel management teachers is not a simple superposition of teaching qualifications and professional experience, but a composite ability set that realizes knowledge mapping, task transfer and ability reconstruction between the teaching system and the hotel business system. Its core is not that teachers have two attributes of "teaching" and "doing" at the same time, but that they can transform hotel operation processes, service standards, post specifications and industry experience into curriculum resources, practical tasks and evaluation rules, and continuously revise the practical guidance plan according to teaching feedback, forming a closed-loop mechanism of "industry task input-teaching process transformation - ability result output". Therefore, the "double-qualified" ability is essentially a dynamic ability state oriented to real career scenarios, rather than a static identity label.

From the perspective of ability structure, the "double qualification" ability of hotel management teachers can be abstracted into four interrelated subspaces: teaching transformation ability, industry practice ability, digital technology application ability and collaborative development ability. Teaching transformation ability emphasized curriculum design, case reconstruction, practice teaching organization and learning effectiveness feedback. Industry practice ability emphasizes the understanding, analysis and guidance of business processes such as front office, guest room, catering, revenue management and service quality control; The application ability of digital technology emphasizes the collection, processing and application of teaching platform, process data and intelligent tools. Collaborative development ability emphasizes school-enterprise collaboration, resource integration, reflective improvement and continuous iteration. The four kinds of abilities are not linear parallel, but form the main structure around the dual coupling of "teaching and practice", and are supported by "technology and collaboration".

In order to facilitate the subsequent dynamic evaluation modeling, the teacher's "double-teacher" ability at time t is expressed as a multi-dimensional state vector:

$$\mathbf{A}_t = [T_t, P_t, D_t, C_t]^{\mathrm{T}} \tag{1}$$

Among them, T_t represents the teaching transformation ability, P_t represents the industry practice ability, D_t represents the digital technology application ability, and C_t represents the collaborative development ability. After normalization, each component takes the value of [0,1], so as to ensure that the data from different sources can be compared and fused in a unified space.

Considering that the key to the ability of "double teacher" is not only the level of single ability, but the degree of synergy between teaching ability and industry practice ability, the dual coupling strength is further defined as follows:

$$\mathrm{H_t} = \frac{2\mathrm{T_t}\mathrm{P_t}}{\mathrm{T_t} + \mathrm{P_t} + \varepsilon} \tag{2}$$

Here, ε is the minimal constant used to avoid the denominator being zero. This equation reflects the essential characteristics of "double-teacher" ability: when teachers only perform outstanding in one side of classroom teaching or industry practice, the overall coupling value will not be improved synchronously. Ht will only increase if the teaching transformation ability maintains a high consistency with the industry practice ability. It can be seen that the "double qualification" ability of hotel management teachers should be regarded as the result of the joint effect of multi-dimensional ability state and dual coupling relationship.

Furthermore, in order to describe the comprehensive level of teachers' ability in different stages, the overall ability score can be written as follows.

$$\mathrm{S_t} = \alpha\mathrm{T_t} + \beta\mathrm{P_t} + \gamma\mathrm{D_t} + \delta\mathrm{C_t} + \lambda\mathrm{H_t} \tag{3}$$

where $\alpha,\beta,\gamma,\delta,\lambda$ are the weight parameters to be optimized, which satisfies:

$$\alpha + \beta + \gamma + \delta + \lambda = 1, \quad \alpha, \beta, \gamma, \delta, \lambda \geq 0 \tag{4}$$

Equation (3) shows that the "double-qualification" ability of hotel management teachers is not determined by a single dimension, but is jointly determined by teaching, practice, technology, collaboration and their coupling relationship. Such an expression can not only retain the connotation characteristics of "double-teacher" ability in the context of vocational education, but also provide a computable basis for the subsequent index system design, weight adaptive update and dynamic evaluation model construction.

2.2 The construction of evaluation index system for the integration of teaching ability and industry practice ability

In order to make the evaluation of hotel management teachers' "double-qualification" ability shift from conceptual description to computational analysis, this paper constructs a hierarchical evaluation index system around the coupling relationship between teaching ability and industry practice ability on the basis of the aforementioned ability connotation analysis. The system no longer deals with classroom teaching ability and enterprise practice ability separately, but takes "whether teaching transformation can effectively undertake industry tasks, and whether industry practice can feed back teaching design" as the main line, and describes teachers 'ability structurally. Specifically, the index system adopts a three-level structure of "target layer, dimension layer and index layer", in which the target layer corresponds to the comprehensive ability of hotel management teachers to "double teacher", the dimension layer includes the teaching ability subsystem T and the industry practice ability subsystem P, and the index layer is composed of quantifiable, collected and updatable subdivision indicators. The evaluation index system is shown in Table 2.

Table 2: Evaluation index system for the integration of teaching ability and industry practice ability

Dimension Level	Indicator Level	Indicator Description	Data Type
Teaching Competence (T)	Course Content Restructuring Ability	The ability to transform hotel business processes into course modules, cases, and task-based learning units	Text data, course archives
Teaching Competence (T)	Practical Teaching Organization Ability	The ability to conduct situational simulations, practical training guidance, project-based teaching, and task-driven instruction	Process records, observational data
Teaching Competence (T)	Teaching Evaluation and Feedback Ability	The ability to diagnose and provide feedback on students' learning outcomes, skill performance, and problem areas	Evaluation records, outcome data
Teaching Competence (T)	Digital Teaching Resource Development Ability	The ability to use platforms, systems, and digital tools to develop teaching resources	Platform logs, resource data
Industry Practice Competence (P)	Job Process Understanding Ability	The level of mastery of job processes in front office, housekeeping, food and beverage, revenue management, and related positions	Practice records, assessment data
Industry Practice Competence (P)	Operational Problem Analysis Ability	The ability to analyze service anomalies, complaint handling, cost control, and quality improvement issues	Case data, task outcomes
Industry Practice Competence (P)	Enterprise Project Participation Ability	The ability to participate in enterprise projects, practical guidance, and collaboration on real-world tasks	Project archives, enterprise evaluations
Industry Practice Competence (P)	Industry Standard Updating Ability	The ability to track and absorb changes in industry standards, service specifications, and technologies	Training data, update records

In the teaching ability subsystem, the index setting focuses on the ability of teachers to reconstruct the curriculum of hotel business knowledge, organize practical teaching and evaluate and feedback. The ability of curriculum reconstruction reflects the ability of teachers to transform business knowledge such as front office reception, room management, catering service, and revenue management into teaching modules and case tasks. The organization ability of practical teaching reflects the implementation ability of teachers in practical training, situational simulation, project teaching and task driving. The evaluation feedback ability is used to describe the teacher's ability to diagnose and revise the students' learning process, operation results and job adaptability. The industry practice ability subsystem focuses on the teachers' understanding of the real job process of the hotel, their ability to analyze and deal with operational problems, and their ability to participate in school-enterprise projects and job guidance. The relationship between the two kinds of abilities is not parallel accumulation, but bidirectional mapping is formed through curriculum design, task embedding and practice feedback.

To enhance the computability of the index system, suppose that the teaching ability subsystem contains m indicators and the industry practice ability subsystem contains n indicators, then the indicator observation vector of the teacher at time t can be expressed as follows.

$$X_t=\left[x_{1,t},x_{2,t},\dots,x_{m,t},y_{1,t},y_{2,t},\dots,y_{n,t}\right]^T \tag{5}$$

Here, $x_{i,t}$ represent indicators related to teaching ability, and $y_{j,t}$ represent indicators related to industry practice ability. After standardization, the scores of teaching ability and industry practice ability are calculated as follows.

$$T_t=\sum_{i=1}^{m} w_i\, x_{i,t},\quad P_t=\sum_{j=1}^{n} v_j\, y_{j,t} \tag{6}$$

Among them, w_i and v_j are the weights of teaching ability and industry practice ability indicators, respectively. Further considering the fusion degree of the two, the fusion evaluation item can be defined as follows.

$$F_t=\eta_1 T_t+\eta_2 P_t+\eta_3 \frac{2T_tP_t}{T_t+P_t+\varepsilon} \tag{7}$$

Here,η_1,η_2, and η_3 are the fusion coefficients, which satisfy $\eta_1+\eta_2+\eta_3=1$. Equation (7) not only retains the independent contributions of the two types of abilities, but also introduces a coupling term to depict the integration strength of the "double-teacher" ability, so that the evaluation results can more truly reflect the teacher's penetration level between teaching and practice.

2.3 Multi-source heterogeneous Data Collection and teacher ability feature representation method

In order to realize the dynamic identification of the "double-qualification" ability of hotel management teachers, the evaluation model should not only rely on a single questionnaire or outcome score, but should synchronously collect heterogeneous data from multiple scenarios such as teaching implementation, industry practice, digital application and collaborative development, and map them into a unified ability feature space. Considering that teachers 'behavior not only has structural index characteristics, but also contains log sequence, text record and stage change information, this paper constructs a processing flow of "multi-source collection, data cleaning, feature coding, time series fusion and ability representation". Figure 1 shows the process of multi-source heterogeneous data collection and teacher ability feature representation.

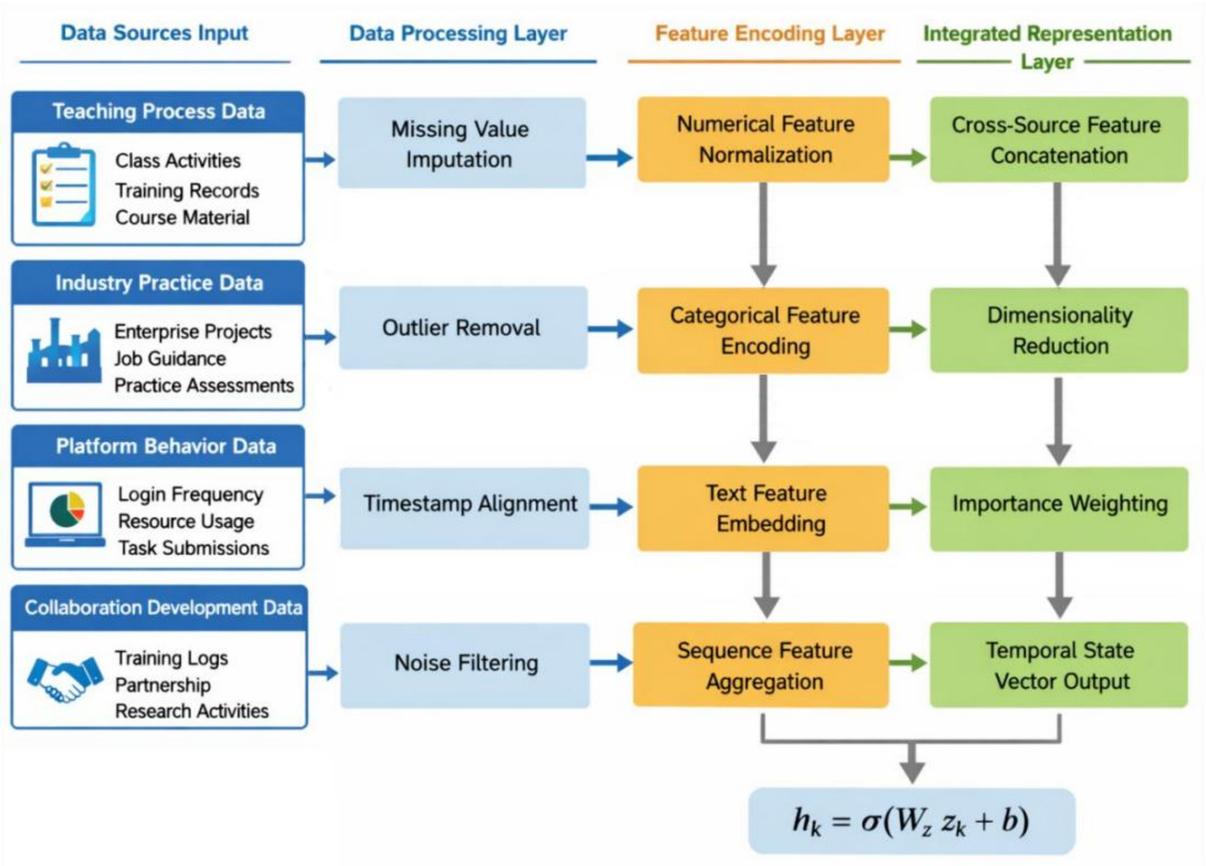

Figure 1: Multi-source heterogeneous data collection and characterization process of teacher ability characteristics

In the data collection stage, this paper divides the original data into four categories: one is structured numerical data, such as course completion rate, the number of training guidance, the frequency of enterprise project participation and training hours. The second type is categorical data, such as course type, post type, cooperative enterprise type and task level. Three types are textual data, such as teaching reflection, enterprise evaluation, case description and student feedback. The four categories are sequential data, such as platform access trajectory, task submission interval and phasic assessment changes. Due to the obvious differences in sampling frequency, dimension scale and semantic expression between different source data, alignment must be completed through a unified time window. Let the time window length be $\Delta\tau$, then the original observation of the teacher in the KTH window can be expressed as follows.

$$\mathcal{D}_k = \{x_k^{(n)}, x_k^{(c)}, x_k^{(t)}, x_k^{(s)}\} \tag{8}$$

Here, $x_k^{(n)}$ represents the set of numerical features, , $x_k^{(c)}$ represents the set of categorical features, $x_k^{(t)}$ represents the set of textual features, and $x_k^{(s)}$ represents the set of sequence features.

In the feature encoding stage, numeric data is normalized to eliminate the effects of different dimensions:

$$\tilde{x}_{i,k} = \frac{x_{i,k} - x_i^{min}}{x_i^{max} - x_i^{min} + \varepsilon} \tag{9}$$

Categorical data are represented by one-hot encoding or low-dimensional embedding to preserve class discrimination. For textual data, the semantic vectorization method was used to map teaching reflection, enterprise evaluation and student feedback into dense representation $e_k^{(t)}$. For sequential data, the statistical features such as frequency, duration, volatility and trend slope are extracted in the time window to form a sequence representation vector $e_k^{(s)}$. On this basis, the unified feature vector of the teacher within window k can be expressed as follows.

$$z_k = [\,\tilde{x}_k^{(n)} \parallel e_k^{(c)} \parallel e_k^{(t)} \parallel e_k^{(s)}\,] \tag{10}$$

Here, the symbol "‖" denotes vector concatenation. Due to the high dimension of the features after direct concatenation and the difference in the contribution of different source features to the ability evaluation, this paper further introduces the weighted fusion mechanism to obtain the final representation vector:

$$h_k = \sigma(W_z z_k + b) \tag{11}$$

Here, W_z is the feature mapping matrix, b is the bias term, and $\sigma(\cdot)$ is the nonlinear activation function. Equation (11) can compress redundant dimensions and enhance key feature responses while preserving the complementarity of multi-source information, so that the teacher ability representation is transformed from discrete data sets into a unified low-dimensional state representation.

The key of the above method is to transform the relevant evidence of hotel management teachers' "double-teacher" ability from scattered, heterogeneous and asynchronous data sources into a unified feature vector that can be input into the model. On the one hand, this method can preserve the differences of teaching activities, industry practice and technology application. On the other hand, it also provides a continuous data basis for subsequent weight adaptive update, dynamic evaluation and ability evolution analysis. Through multi-source heterogeneous data collection and feature representation, teachers 'ability is no longer simplified as a single static score, but expressed as a dynamic state that can be calculated, tracked and updated.

2.4 Index association analysis under dynamic evaluation requirements

The "double-teacher" ability evaluation of hotel management teachers is not a simple weighted sum of multiple independent indicators, but a dynamic system including multi-dimensional index interaction, stage change transfer and state continuous update. There is an obvious coupling relationship between teaching ability, industry practice ability, digital technology application ability and collaborative development ability: the improvement of curriculum reconstruction ability usually depends on the input of practical experience, the depth of enterprise project participation will reverse affect the quality of case development and teaching organization, and the intensity of platform use and the efficiency of data feedback will further change the level of teaching evaluation and collaborative improvement.

Therefore, in the dynamic evaluation scenario, there is not only horizontal correlation between each index, but also vertical temporal dependence and cross-stage conduction characteristics.

Let the indicator observation vector of the teacher at time t be as follows.

$$\mathbf{q}_t = [q_{1,t}, q_{2,t}, \dots, q_{p,t}]^{\mathrm{T}} \tag{12}$$

Here, p denotes the total number of indicators and qi,t denotes the normalized observation of the ith indicator at time t. In order to describe the correlation degree between different indicators at the same time, a static correlation matrix is constructed:

$$R_t = \left[r_{ij,t}\right]_{p\times p}, \quad r_{ij,t} = \frac{\mathrm{cov}(q_{i,t}, q_{j,t})}{\sigma(q_{i,t})\sigma(q_{j,t}) + \varepsilon} \tag{13}$$

Here, $r_{ij,t}$ denotes the correlation strength between index i and index j, and ε is a minimal constant. Equation (13) can be used to identify the synchronous change relationship between teaching indicators and practice indicators, and provide a basis for subsequent fusion modeling.

However, only analyzing the static correlation at the same moment is still not enough to support the dynamic evaluation, because the change of teacher ability often has lag and accumulation. To this end, a delay correlation term is further introduced to define the dynamic correlation strength between index i and index j under time delay τ:

$$\phi_{ij}(\tau) = \frac{1}{T-\tau}\sum_{t=\tau+1}^{T} q_{i,t-\tau}\, q_{j,t} \tag{14}$$

Equation (14) reflects the degree of influence of early index changes on subsequent index states. For example, an increase in the frequency of enterprise project participation is often not immediately reflected in the quality of course implementation, but will be reflected in the reconstruction of teaching resources and case updates after several stages. By introducing the time delay term, the conduction chain in the formation process of "double teacher" ability can be more accurately described.

Considering that the contribution of data in different time periods to the current capability state is not the same, this paper uses the time decay mechanism to construct the dynamic association weight. Let the current time be t, then the time-weighted association value of index i and index j is as follows.

$$\tilde{r}_{ij,t} = \sum_{k=1}^{t} \omega_{t-k}\, r_{ij,k}, \quad \omega_{t-k} = \frac{e^{-\mu(t-k)}}{\sum_{s=1}^{t} e^{-\mu(t-s)}} \tag{15}$$

Here, μ is the time decay coefficient. The formula can highlight the influence of recent data on the current evaluation results, while retaining historical trajectory information, which is suitable for the dynamic identification of teachers 'ability state evolution with stages.

On this basis, all index relationships can be represented as dynamic association graph Gt=(V,Et). The node set V represents each evaluation index, and the edge set Et is determined by the dynamic incidence matrix $\tilde{R}_{\mathrm{t}} = \left[\tilde{r}_{ij,t}\right]$. When $\tilde{r}_{ij,t}$ is higher than the threshold θ, it is considered that there is a significant association between index i and index j at the current stage, i.e.

$$a_{ij,t} = \begin{cases} 1, & \tilde{r}_{ij,t} \geq \theta \\ 0, & \tilde{r}_{ij,t} < \theta \end{cases} \tag{16}$$

Here, At=[$a_{ij,t}$] is the dynamic adjacency matrix. Through Equation (16), the originally discrete multi-index set can be transformed into a relationship network that changes with time, so that the capability evaluation changes from "index stacking" to "relationship driving".

Furthermore, in order to measure the structural impact of an indicator on the overall capability assessment at the current stage, the importance coefficient of the indicator node can be defined as follows.

$$c_{i,t} = \sum_{j=1}^{p} a_{ij,t}\ \tilde{r}_{ij,t} \tag{17}$$

If an index maintains strong correlation with multiple key indicators at the same time, its $c_{i,t}$ value is higher, indicating that the index has a stronger hub role in dynamic assessment. For the "double-teacher" ability of hotel management teachers, the curriculum reconstruction ability, enterprise practice participation and the depth of digital resource use usually show high centrality in the dynamic correlation network, which also shows that the subsequent model design cannot simply adopt fixed weights, but should be adaptively updated according to the relationship strength.

In summary, the index association relationship under dynamic evaluation requirements has three obvious characteristics. First, there is a significant interaction coupling between multi-dimensional indicators. Second, the ability change has cross-stage conduction and lag influence; The third is that the index action strength of different stages will drift with time. Therefore, the "double qualification" ability evaluation of hotel management teachers should be established on the unified framework of "multi-index correlation-time delay conduction - time decay - relationship update". The above analysis not only provides a basis for the dynamic adjustment of index weights, but also lays a foundation for the subsequent construction of a dynamic evaluation model driven by algorithm optimization.

3 Design of "double teacher" ability dynamic evaluation model driven by algorithm optimization

3.1 Overall framework design of dynamic evaluation model

In order to realize the continuous identification and dynamic update of the "double qualification" ability of hotel management teachers, this paper constructs a dynamic evaluation model driven by algorithm optimization. The model no longer treats teacher ability as a one-time calculation result, but defines it as a state system that evolves under continuous input of multi-source data. On the whole, the model is composed of multi-source data input layer, feature representation layer, dynamic relationship modeling layer, adaptive weight optimization layer and state output layer. At the same time, time coding, coupling strength calculation and evaluation score update mechanism are introduced to form a closed-loop process of "data acquisition, feature fusion, relationship modeling, weight optimization and dynamic output". The overall framework of the model is shown in Figure 2.

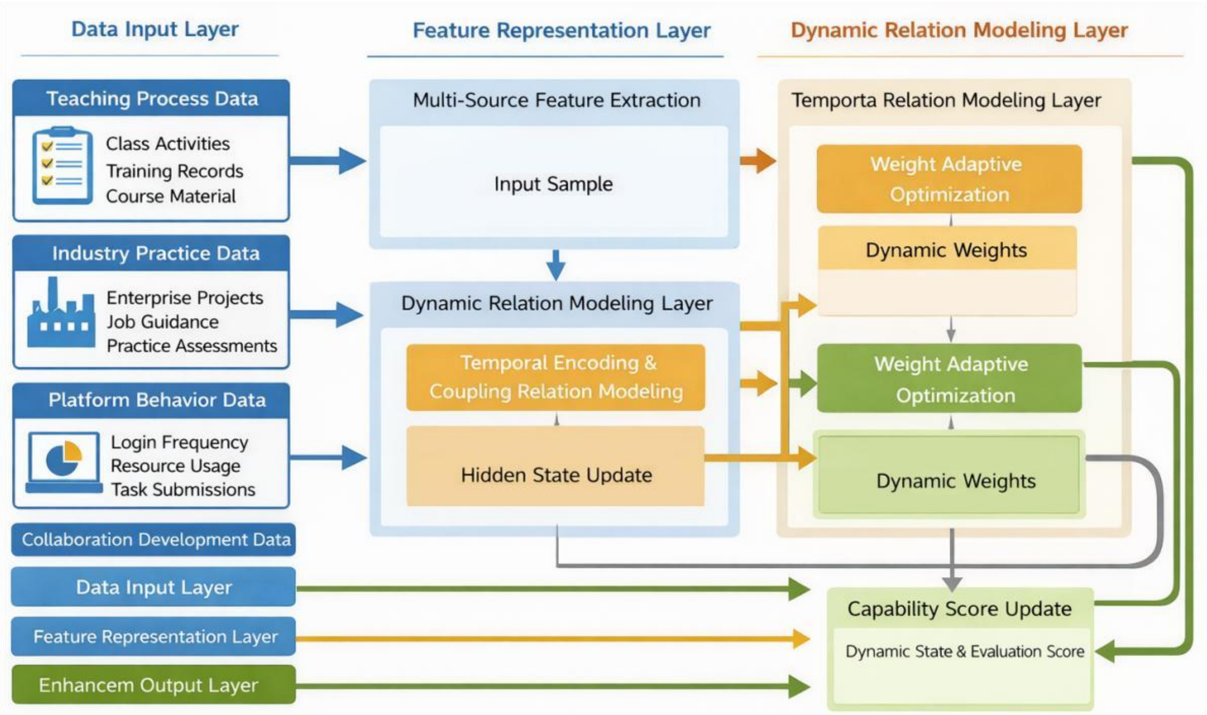

Figure 2: Overall framework diagram of dynamic evaluation model

In the data input layer, the model receives the teaching process data, industry practice data, digital platform behavior data and collaborative development data, and maps them into a unified observation sequence. Let the input sample of the teacher at time t be as follows.

$$X_t=[x_t^{(T)},x_t^{(P)},x_t^{(D)},x_t^{(C)}] \tag{18}$$

Among them, $x_t^{(T)}$ represents the observation of teaching dimension, $x_t^{(P)}$ represents the observation of industry practice dimension, $x_t^{(D)}$ represents the observation of digital technology application dimension, and $x_t^{(C)}$ represents the observation of collaborative development dimension. After preprocessing and feature encoding, the model obtains a unified state representation vector ht, which is used to describe the comprehensive ability characteristics of teachers at the current stage.

In the dynamic relationship modeling layer, the model focuses on the interaction dependence and time conduction relationship between indicators. Because the improvement of teaching ability often depends on the input of industry practical experience, and the application ability of digital technology will affect the efficiency of teaching feedback and the quality of collaborative improvement, the model adopts the relationship modeling mechanism to describe the coupling structure between multi-dimensional features, and preserves the evolution trajectory of ability through time coding. Let the hidden state at the current time be st, then its update process can be expressed as follows.

$$s_t=f(h_t,s_{t-1},A_t) \tag{19}$$

Here, A_t is the dynamic incidence matrix of the current stage, and $f(\cdot)$represents the state transition function. Equation (19) shows that the teacher's current ability status not only depends on the current observation characteristics, but also is jointly affected by the ability status of the previous stage and the index relationship structure.

In order to enhance the model's ability to depict the differences in data contributions at different stages, this paper introduces a dynamic weight parameter into the adaptive weight optimization layer, and jointly optimizes the teaching ability, industry practice ability, digital technology application ability, collaborative development ability and dual coupling term. The teacher's comprehensive assessment score at time t is defined as follows.

$$S_t=\alpha_t T_t+\beta_t P_t+\gamma_t D_t+\delta_t C_t+\lambda_t H_t \tag{20}$$

Among them, T_t,P_t,D_t and C_t respectively represent the scores of four types of core competence, H_t represents the coupling strength between teaching ability and industry practice ability, $\alpha_t,\beta_t,\gamma_t,\delta_t$ and λ_t are time-varying weight parameters, which are satisfied:

$$\alpha_t+\beta_t+\gamma_t+\delta_t+\lambda_t=1, \quad \alpha_t,\beta_t,\gamma_t,\delta_t,\lambda_t\geq 0 \tag{21}$$

Different from the static weighted model, the weight in Equation (20) will be dynamically adjusted with the change of data distribution, stage characteristics and ability correlation strength, so that the model can more accurately reflect the focus transfer in the evolution process of teachers 'ability. For example, the model can automatically improve the contribution ratio of practical ability and coupling items in the centralized development stage of industry projects. In the stage of curriculum reconstruction and teaching feedback strengthening, the weight of teaching ability and digital technology application ability can be improved.

In the state output layer, the model finally outputs the teacher's dynamic ability state vector and comprehensive evaluation score, and supports trend analysis, stage comparison and ability early warning. In order to ensure the iterative optimization ability of the model, the evaluation score update results are fed back to the weight optimization module, forming a circular correction mechanism. In this way, the dynamic evaluation model can not only give the ability level at a certain point, but also identify the change direction, fluctuation range and structural shortcomings of the ability.

In summary, the overall framework constructed in this paper has three technical features. First, multi-source heterogeneous data is used as a unified input to improve the evidence integrity of capability identification. Secondly, dynamic relationship modeling and time encoding mechanism are used to describe the interactive evolution between indicators. Thirdly, the weight is adaptively updated by algorithm optimization, and the accuracy, stability and scene adaptability of the evaluation results are improved. Based on this overall framework, the data preprocessing and feature extraction method of teachers 'ability, the adaptive update mechanism of index weights, and the construction of a dynamic evaluation model integrating time series features will be further expanded in the future.

3.2 Teacher ability data preprocessing and feature extraction method

In order to ensure the input quality of the dynamic assessment model of the "double qualification" ability of hotel management teachers, it is necessary to perform unified preprocessing and feature extraction on teaching process data, industry practice data, platform behavior data and collaborative development data. Due to the obvious differences in sampling period, data type, scale range and noise level between different sources, it is easy to cause problems such as time misalignment, dimension imbalance and local abnormal amplification if the data are directly input into the model. Therefore, this paper constructs a preprocessing process of "multi-source data access, data quality processing, classification coding, time window statistics, and fusion compression output", whose core goal is to transform discrete, heterogeneous, and asynchronous original records into continuous, compact, and computable feature vectors of teachers 'ability. Figure 3 shows the process of teacher ability data preprocessing and feature extraction.

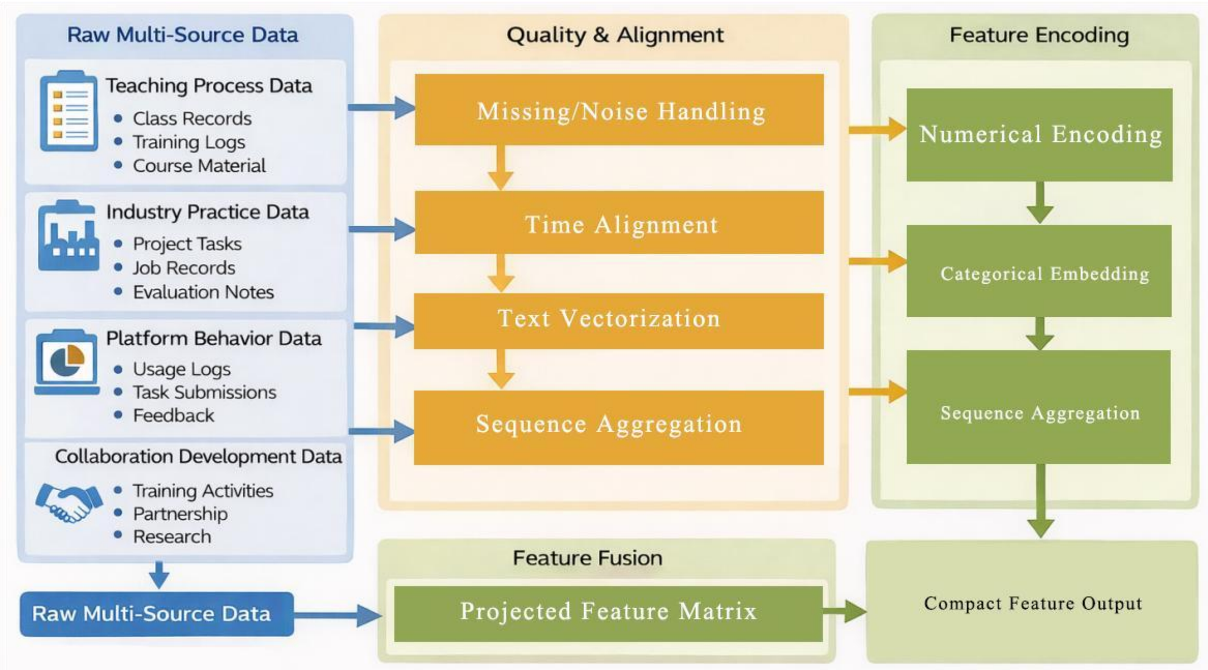

Figure 3: Data preprocessing and feature extraction process of teacher competence

In the raw data access phase, let the input set of the teacher at time t be as follows.

$$\mathcal{R}_t = \left\{\mathbf{r}_t^{(1)}, \mathbf{r}_t^{(2)}, \mathbf{r}_t^{(3)}, \mathbf{r}_t^{(4)}\right\} \tag{22}$$

Among them, $\mathbf{r}_t^{(1)}$ represents teaching process data, $\mathbf{r}_t^{(2)}$ represents industry practice data, $\mathbf{r}_t^{(3)}$ represents platform behavior data, and $\mathbf{r}_t^{(4)}$ represents collaborative development data. For the problem of missing values and outliers, this paper adopts neighborhood imputation and robust pruning strategies, respectively. For continuous features $r_{i,t}$, the robust transformation result is defined as follows.

$$\tilde{r}_{i,t} = \frac{r_{i,t} - Q_2(r_i)}{Q_3(r_i) - Q_1(r_i) + \epsilon} \tag{23}$$

Here, $Q_1(r_i)$, $Q_2(r_i)$, and $Q_3(r_i)$ denote the first, median, and third quartile, respectively, and ϵ is a minimal constant. This formula can effectively weaken the abnormal disturbance in the number of enterprise practices, platform access frequency and feedback duration.

Due to the obvious stage change of teachers' ability, this paper further aligns the multi-source data in time according to a fixed time window Δ, and extracts local statistics for the behavior sequence. For the sequence variables zk in window $[\mathrm{t} - \Delta + 1, \mathrm{t}]$, construct the aggregate representation as follows.

$$\mathrm{u_t} = \left[\frac{1}{\Delta}\sum_{\mathrm{k=t-\Delta+1}}^{\mathrm{t}} \mathrm{z_k}, \max_{\mathrm{k\in[t-\Delta+1,t]}} \mathrm{z_k}, \min_{\mathrm{k\in[t-\Delta+1,t]}} \mathrm{z_k}, \frac{1}{\Delta - 1}\sum_{\mathrm{k=t-\Delta+2}}^{\mathrm{t}} (\mathrm{z_k} - \mathrm{z_{k-1}})\right] \tag{24}$$

Equation (24) describes the mean, upper bound, lower bound and average increment of the window, which can be used to describe the active degree, fluctuation range and change direction of the teacher in the stage.

In the feature encoding stage, the numerical data were directly entered into the standardized map. Categorical data is transformed into low-dimensional representation by embedding matrix. The text data were cleaned by word segmentation, keyword screening and semantic coding to obtain text vectors. For sequential data, the time window aggregation method is used to form phase behavior characteristics. Then, the four intermediate representations are concatenated into a unified input matrix:

$$\mathrm{Y_t} = \mathrm{y_t^{(n)}} \oplus \mathrm{y_t^{(c)}} \oplus \mathrm{y_t^{(w)}} \oplus \mathrm{y_t^{(s)}} \tag{25}$$

Here, $\oplus$ denotes the cross-source feature concatenation, and $\mathrm{y_t^{(n)}}$, $\mathrm{y_t^{(c)}}$, $\mathrm{y_t^{(w)}}$, and $\mathrm{y_t^{(s)}}$ represent the intermediate representations of numerical, categorical, textual, and sequence features, respectively.

Considering the high dimension of features after direct concatenation and the uneven contribution of information from different sources, a gated compression mechanism is used to obtain compact representations:

$$\mathrm{f_t} = \mathrm{ReLU}(\mathrm{W_f Y_t} + \mathrm{b_f}) \odot \sigma(\mathrm{W_g Y_t} + \mathrm{b_g}) \tag{26}$$

Here, $\mathrm{W_f}$ and $\mathrm{W_g}$ are mapping matrices, $\mathrm{b_f}$ and $\mathrm{b_g}$ are bias terms, and $\odot$ represents element-wise product. Equation (26) enhances key ability information and suppresses redundant noise by means of "main feature mapping + gated screening", and finally obtains the teacher's fusion feature vector at time t:

$$\mathrm{c_t} = \mathrm{W_c f_t} + \mathrm{b_c} \tag{27}$$

Here, $\mathrm{c_t}$ is the input representation of the subsequent dynamic evaluation model. Different from the general framework of 3.1, this section only deals with the conversion problem from raw data to feature vectors, and does not involve dynamic relationship modeling, weight adaptive optimization, and final ability score calculation. Through the above processing, the data related to the teacher's "double-teacher" ability are uniformly mapped into a stable, continuous, and low-redundant feature space, which provides high-quality input for the subsequent evaluation model.

3.3 Adaptive update mechanism of index weight based on algorithm optimization

Although the fixed weight can complete the linear evaluation of the "double qualification" ability of hotel management teachers, it is difficult to reflect the differences in the influence of teaching tasks, enterprise practice tasks and platform behavior tasks in different stages on the ability structure. In order to improve the responsiveness of the model to stage changes and index association changes, this paper constructs an adaptive update mechanism of index weights based on algorithm optimization, and its update process is shown in Figure 4.

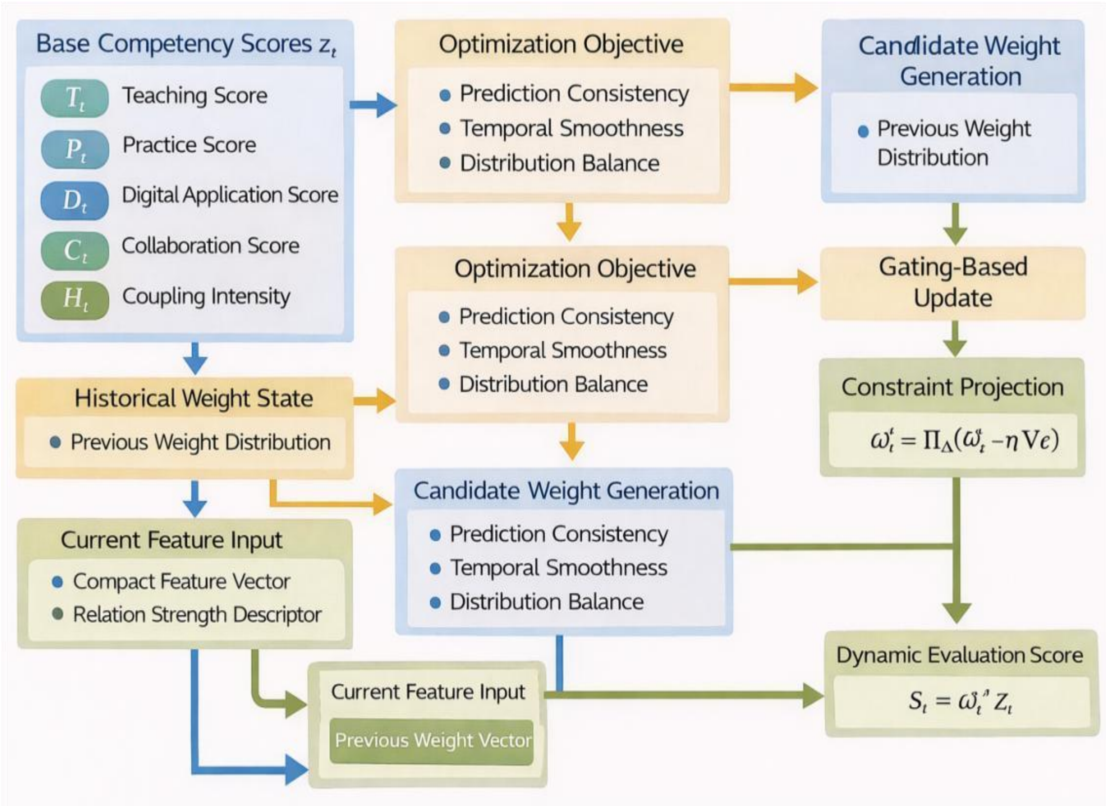

Figure 4: Adaptive updating mechanism of indicator weights based on algorithm optimization

The mechanism takes teaching ability, industry practice ability, digital technology application ability, collaborative development ability and dual coupling strength as the basic input, and combines the feature representation of the current stage and the weight state of the previous stage to dynamically adjust the contribution degree of each index. Let the vector of basic capability components be:

$$\mathbf{z}_t = [T_t, P_t, D_t, C_t, H_t]^{\mathrm{T}} \tag{28}$$

In order to ensure the accuracy, smoothness and stability of weight update, the optimization objective function is constructed as follows.

$$\mathcal{J}_t = (y_t - \omega_t^{\mathrm{T}} \mathbf{z}_t)^2 + \rho \|\omega_t - \omega_{t-1}\|_2^2 + \nu \|R_t \omega_t\|_2^2 \tag{29}$$

Among them, the first term is used to constrain the deviation between the evaluation output and the target signal, the second term is used to suppress the drastic fluctuations in the weights of adjacent stages, and the third term is used to enforce the consistency between the weight allocation and the current index correlation structure. In this way, the weights are no longer dependent on preset constants, but are driven by both stage data and relationship strength.

In the process of candidate weight generation, this paper introduces a gated fusion strategy to map the current feature information and historical weight status into the intermediate update result:

$$\widehat{\omega}_t = g_t \square \phi(e_t, c_t) + (1-g_t) \square \omega_{t-1} \tag{30}$$

where c_t is the compact feature representation, ct is the relationship strength description vector, and gt is the gating coefficient. The formula can adaptively adjust the proportion of new information introduction and historical information retention according to the change of stage.

Since the optimization results need to meet the constraints of non-negative and sum to 1, the final weight vector is further obtained by using simplex projection:

$$\omega_t=\Pi_{\Delta}(\widehat{\omega}_t-\eta\nabla J_t) \tag{31}$$

Here, ΠΔ denotes the projection operator. The updated weight vector can be used to calculate the comprehensive evaluation score at the current stage, so that the model can automatically adjust the evaluation center with the change of teaching focus, practice focus and platform interaction characteristics, and improve the adaptability and accuracy of the dynamic evaluation of "double-teacher" ability.

3.4 Construction of "double-teacher" ability dynamic evaluation model based on timing features

The "double qualification" ability of hotel management teachers is not a static result at a single time point, but a sequential state that continuously changes with teaching tasks, enterprise practice tasks and platform behaviors. It is easy to ignore historical accumulation, phase inertia and mutation response when evaluating only according to the characteristics of the current stage. To this end, on the basis of compact feature representation and adaptive weight update, this paper constructs a dynamic evaluation model fusing time series features. The model structure is shown in Figure 5, and its core process includes six links: sequence input, temporal encoding, state memory update, dynamic weight injection, capability trajectory inference and result output.

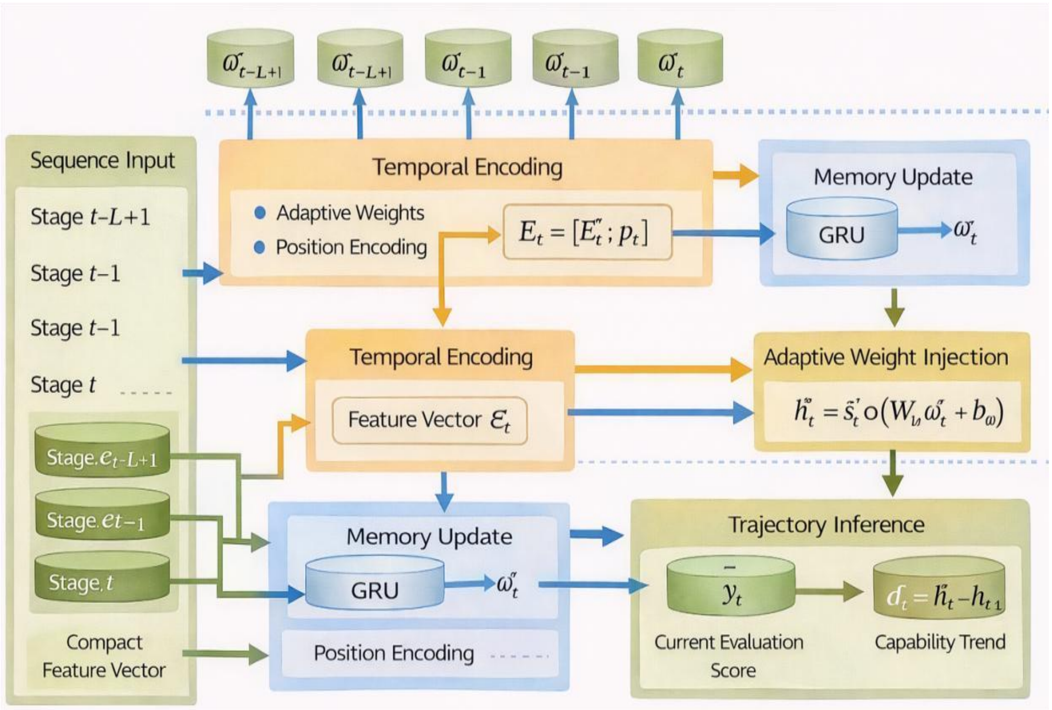

Figure 5: Dynamic Evaluation Model with Temporal Feature Fusion

Let the fused feature sequence of the teacher in L consecutive stages be {et−L+1,... ,et}, and the corresponding adaptive weight sequence is {ωt−L+1,... ,ωt}. In order to enhance the model's ability to perceive the sequence of stages and the rhythm of changes, the position encoding is first introduced into the feature representation to obtain the timing input:

$$\mathbf{E}_t = [\mathbf{e}_t; \mathbf{p}_t] \tag{32}$$

Here, $\mathbf{p}_t$ is the time-location encoding vector. Then, the gated recurrent unit is used to update the state memory, so that the historical dependence of the teacher's ability can be continuously retained. The hidden state transition can be expressed as follows.

$$\mathbf{s}_t = \mathrm{GRU}(\mathbf{E}_t, \mathbf{s}_{t-1}) \tag{33}$$

St in Equation (33) represents the temporal ability state of the current stage, which contains not only the current feature information but also the cumulative influence of the previous stage, so it is more suitable to describe the gradual evolution process of the "double-teacher" ability.

Considering that the evaluation center of gravity will migrate in different periods, the adaptive weight vector obtained in Section 3.3 is further injected into the state space to realize the dynamic modulation of stage focus. The weighted capability representation is written as follows.

$$\mathrm{h_t} = \mathrm{s_t} \odot (\mathrm{W}_\omega \omega_\mathrm{t} + \mathrm{b}_\omega) \tag{34}$$

Here, W_ω is the weight mapping matrix and b_ω is the bias term. The function of this formula is to adjust the activation intensity of each ability component in the time series state according to the current weight distribution, so that the teaching ability dominant stage, practical ability dominant stage and collaborative development strengthening stage can reflect different state response characteristics.

In the dynamic evaluation output layer, the model simultaneously generates the current stage ability score and the development trend vector. The current comprehensive assessment results are defined as follows.

$$\hat{\mathrm{y}}_\mathrm{t} = \mathrm{W_y h_t} + \mathrm{b_y} \tag{35}$$

In order to describe the change direction of capability, the state difference is further introduced to construct the trend term:

$$\mathrm{d_t} = \mathrm{h_t} - \mathrm{h_{t-1}} \tag{36}$$

Among them, $\mathrm{d_t}$ can be used to identify stage features such as capability improvement, stabilization, and fluctuation retreat. When $\|d_t\|^2$ continues to increase, it indicates that teachers' ability structure is undergoing obvious adjustment. When it fluctuates in a small range, it indicates that the capacity state tends to be stable.

In order to ensure that the model can not only fit the current rating, but also maintain time continuity, this paper constructs a joint training objective:

$$\mathcal{L} = \sum_{\mathrm{t=1}}^{\mathrm{T}} (\mathrm{y_t} - \hat{\mathrm{y}}_\mathrm{t})^2 + \kappa \sum_{\mathrm{t=2}}^{\mathrm{T}} \| \mathrm{h_t} - \mathrm{h_{t-1}} \|_2^2 \tag{37}$$

Among them, the first term is used to bound the error between the predicted score and the target score, and the second term is used to suppress the abnormal oscillation of the state trajectory. Through this objective function, the model can effectively respond to the changes of key stages while maintaining the smoothness of time series.

In summary, the dynamic evaluation model fused with time series features extends the teacher's "double-teacher" ability from the discrete stage score to the continuous ability trajectory, and realizes the unified identification of the current level, evolution trend and abnormal fluctuations. The model can not only depict the accumulation and stage of teachers 'ability, but also form linkage with the weight adaptive mechanism mentioned above, which provides a core model basis for dynamic performance analysis and ablation experimental verification in subsequent experiments.

4 Experiment design and result analysis

4.1 Data source and experimental environment configuration

In order to verify the effectiveness of the dynamic evaluation model constructed in this paper, the experimental data are selected from the development files of teachers, teaching platform logs, enterprise practice records and collaborative training records of hotel management major in a higher vocational college, and the continuous observation sequence is constructed by month. The sample contains a total of 96 teachers, 12-month time-series segments, and 18432 original records. Among them, 6240 pieces of teaching process data, 3584 pieces of enterprise practice data, 6912 pieces of platform behavior data, and 1696 pieces of collaborative development data. Before the experiment, the missing values were interpolated, the outliers were truncated by quantile, and the training set, validation set and test set were divided according to 7:1.5: 5:1.5. The experimental environment uses Python 3.10, PyTorch 2.1 and CUDA 12.1, and the server is configured with Intel Xeon Gold 6330 CPU, NVIDIA RTX 4090 GPU and 64 GB memory. To ensure a fair comparison, all models used the same data partition, batch size and training round, the time window length was set to 6, the initial learning rate was set to 0.001, the batch size was set to 32, and the maximum training round was set to 120. The experimental environment and data configuration are shown in Table 3.

Table 3: Data sources and experimental environment configuration

Item	Configuration	Data/Parameters
Teacher Sample Size	Full-time and practice-guidance teachers in the hotel management program	96
Time Span	Continuous monthly observations	12 months
Total Number of Raw Records	Aggregated multi-source heterogeneous data	18,432
Teaching Process Data	Classroom, practical training, and course resource records	6,240
Enterprise Practice Data	Project participation, job guidance, and enterprise evaluations	3,584
Platform Behavior Data	Logins, resource access, and task submissions	6,912
Collaborative Development Data	Training, teaching research, and school-enterprise collaboration records	1,696
Dataset Split	Training / Validation / Test	70% / 15% / 15%
Software Environment	Python / PyTorch / CUDA	3.10 / 2.1 / 12.1
Hardware Environment	CPU / GPU / Memory	6330 / RTX 4090 / 64 GB
Training Parameters	Time window / Batch size / Epoch / Learning rate	6 / 32 / 120 / 0.001

It can be seen from Table 3 that the experimental data covers four core scenarios of teaching, practice, platform and collaboration at the same time, which can completely support the dynamic evaluation of "double-teacher" ability.

4.2 Comparing the model with the evaluation index setting

In order to verify the effectiveness of the proposed model in the dynamic evaluation of "double-teacher" ability, four kinds of comparison methods are set up in the experiment: static weighted scoring model (SWS), Random Forest evaluation model (RF), Long Short-Term memory network model (LSTM), and Temporal Feature enhancement model (TCN). Among them, SWS is used to test the baseline level of fixed-weight methods, RF is used to reflect the nonlinear fitting ability of traditional machine learning methods, LSTM is used to characterize the performance of common time series modeling, and TCN is used to compare the effect of convolutional time series feature extraction. The model in this paper is denoted as AOTM-DDE. The evaluation indicators are Accuracy, F1, MAE, RMSE and Stability. The first two measures the classification and recognition ability, MAE and RMSE measure the continuous scoring error, and Stability is used to describe the degree of output fluctuation in adjacent stages. All models used the same training set, validation set and test set, and unified training rounds and learning rate. The comparison model and evaluation index Settings are shown in Table 4.

Table 4: Comparison of models and evaluation index Settings

Model / Metric	Core Mechanism	Input Dimension	Key Parameters	Parameters (M)	Evaluation Metrics
SWS	Fixed-weight linear aggregation	32	Manual weighting	0.01	Accuracy, MAE
RF	Multi-tree ensemble regression/classification	32	Trees = 200, Depth = 12	0.43	Accuracy, F1, MAE, RMSE
LSTM	Temporal state memory	32	Hidden = 64, Layers = 2	0.58	Accuracy, F1, MAE, RMSE, Stability
TCN	Dilated convolution-based temporal modeling	32	Channels = 64, Kernel = 3	0.62	Accuracy, F1, MAE, RMSE, Stability
AOTM-DDE	Adaptive weighting + temporal fusion	32	Hidden = 64, Window = 6	0.71	Accuracy, F1, MAE, RMSE, Stability

It can be seen from Table 4 that the comparison model covers three types of methods: static evaluation, traditional machine learning and deep time series modeling at the same time, which can comprehensively test the improvement effect of the proposed model in terms of dynamic evaluation accuracy and stability.

4.3 Dynamic evaluation model overall performance analysis

In order to systematically verify the effectiveness of the dynamic evaluation model constructed in this paper, this paper compares and analyzes the five methods of SWS, RF, LSTM, TCN and AOTM-DDE from three levels of overall recognition ability, error control ability and multi-index change trend.

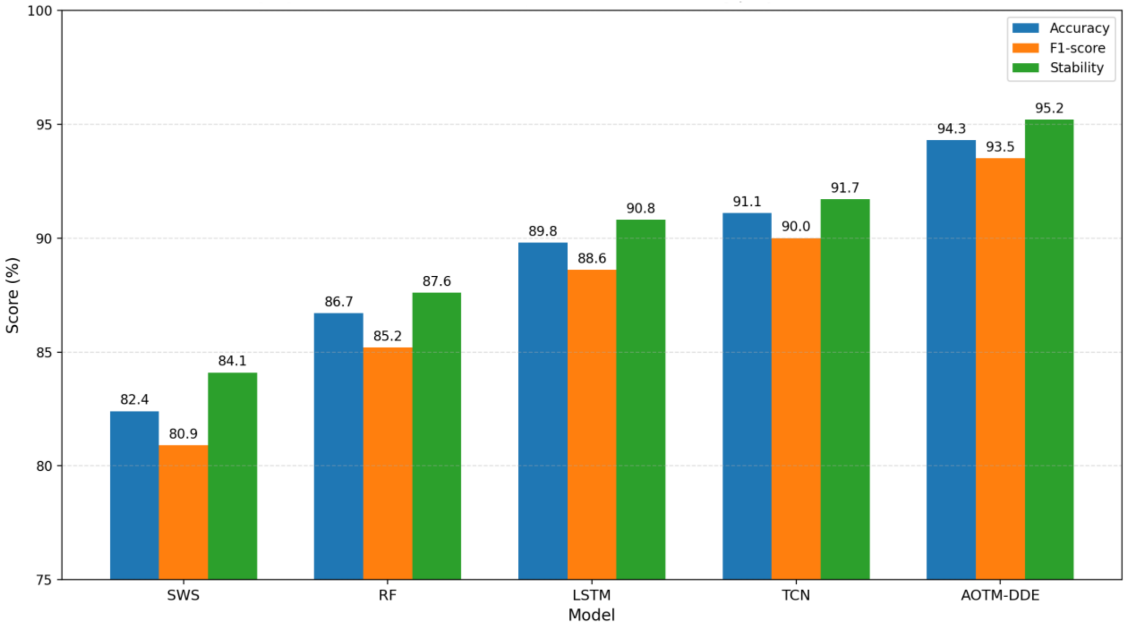

Figure 6: Comparison plot of the overall performance of the dynamic evaluation model

As can be seen from Figure 6, AOTM-DDE achieves the best results in the three core indicators of Accuracy, F1-score and Stability, reaching 94.3%, 93.5% and 95.2% respectively. This compares to 82.4%, 80.9% and 84.1% for SWS, 86.7%, 85.2% and 87.6% for RF, 89.8%, 88.6% and 90.8% for LSTM, and 91.1%, 90.0% and 91.7% for TCN. This indicates that the proposed model is superior to the comparison models in terms of overall recognition accuracy, category discrimination ability, and stage output stability. Especially in the Stability index, AOTM-DDE is 3.5 percentage points higher than TCN, indicating that the model can better adapt to the stage evolution process of teachers "' double-teacher "ability after the introduction of adaptive weight update and temporal state modeling.

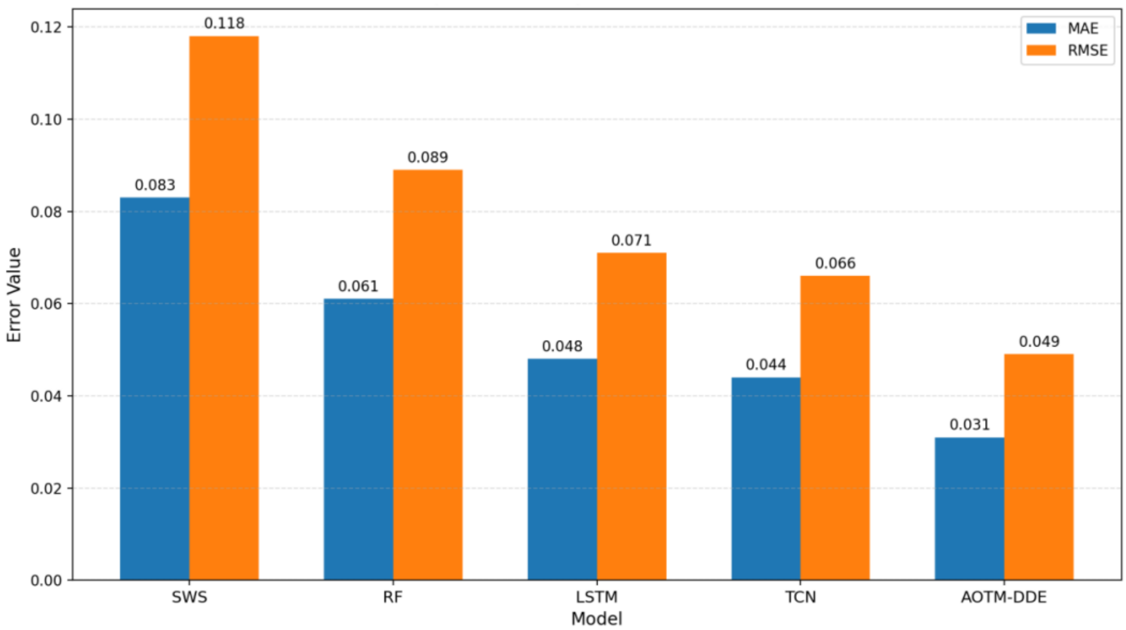

Figure 7: Comparison plot of dynamic evaluation model error

Figure 7 further shows that AOTM-DDE also performs best in terms of error control, and its MAE and RMSE are reduced to 0.031 and 0.049, respectively, which are significantly lower than 0.083 and 0.118 of SWS. It is also better than RF's 0.061 and 0.089, LSTM's 0.048 and 0.071, and TCN's 0.044 and 0.066. Among them, compared with the current better-performing TCN, the MAE and RMSE of the proposed model are decreased by 0.013 and 0.017, respectively. This result shows that the static weighted model is difficult to accurately describe the center of gravity transfer of the "double-teacher" ability in different stages. Although the traditional machine learning method has certain nonlinear fitting ability, it lacks continuous temporal state constraints. However, the proposed model effectively reduces the prediction bias of the comprehensive rating through the joint effect of multi-source feature fusion, weight adaptive update and temporal memory mechanism.

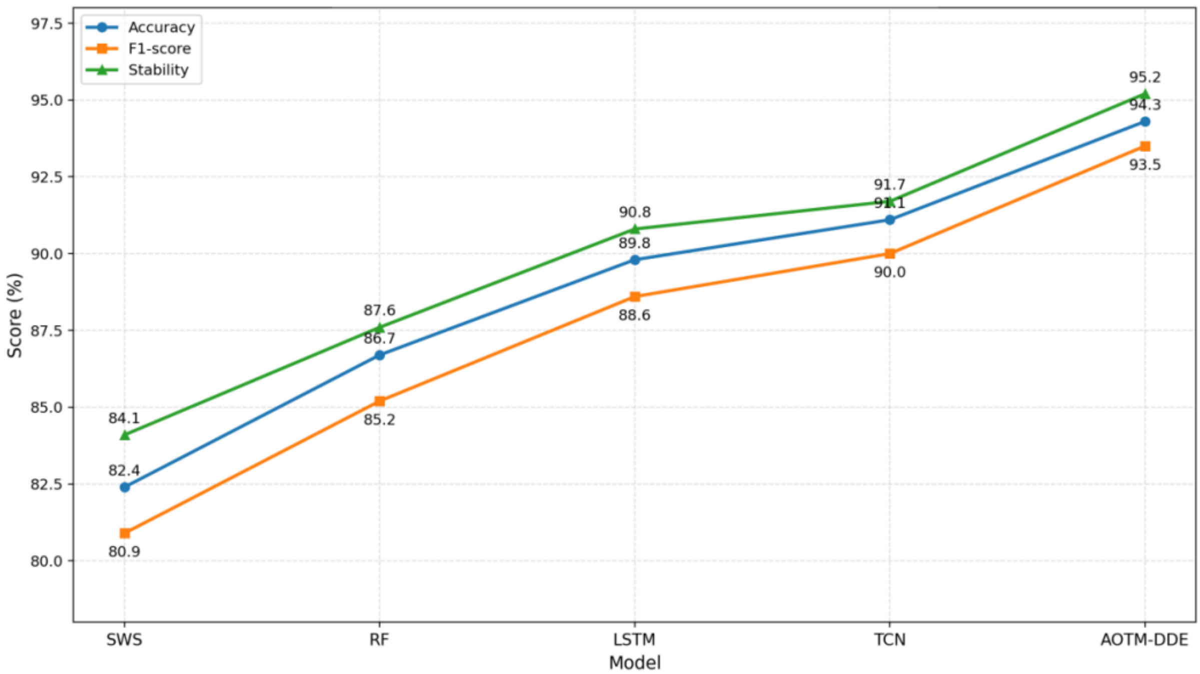

Figure 8: Dynamic evaluation model performance change trend graph

Figure 8 further shows the change trend of different models in the three indicators of Accuracy, F1-score and Stability. It can be seen that AOTM-DDE is at the highest position on the three performance curves, indicating that the proposed model has better comprehensive performance in recognition accuracy, category discrimination ability and stage stability. Compared with SWS and RF, AOTM-DDE significantly improved the three indicators. Compared with LSTM and TCN, the curve of the proposed model still keeps the overall lead, indicating that it can not only use the timing features, but also strengthen the expression ability of key indicators in different stages through the dynamic weight mechanism. The simultaneous rise of the three indicators also indicates that the proposed method does not only achieve local improvement in a single evaluation dimension, but achieves a more balanced optimization in the overall performance.

4.4 Analysis of ablation experiments on key modules of the model

In order to verify the contribution of each key module to the dynamic evaluation performance of the "double-teacher" ability of hotel management teachers, this paper sets up four groups of ablation experiments based on the complete model AOTM-DDE, removing the adaptive weight update module, the timing feature fusion module, the index relationship constraint module and the dual coupling term respectively, and tests them under the same data division and training parameters. The results of ablation experiments are shown in Table 5.

Table 5: Results of ablation experiments on key modules of the model

Model Configuration	Accuracy (%)	F1-score (%)	Stability (%)	MAE	RMSE
Without adaptive weight updating module	91.8	90.7	91.9	0.041	0.061
Without temporal feature fusion module	90.9	89.6	90.2	0.045	0.067
Without indicator relationship constraint module	92.6	91.4	92.8	0.038	0.057
Without dual-coupling term	92.1	90.9	92.0	0.040	0.060
Full model AOTM-DDE	94.3	93.5	95.2	0.031	0.049

From Table 5, we can see that the full model achieves the optimal results in all indicators. After removing the time series feature fusion module, the Accuracy, F1-score and Stability decreased to 90.9%, 89.6% and 90.2%, respectively, while the MAE and RMSE increased to 0.045 and 0.067. It shows that the teacher's "double-teacher" ability has obvious stage continuity, and the lack of time series modeling will significantly weaken the evaluation accuracy. After removing the adaptive weight update module, the model Accuracy and F1-score decrease by 2.5 % and 2.8 %, respectively, indicating that the fixed weight is difficult to adapt to the change of evaluation center at different stages. After removing the index relationship constraint module and the dual coupling term, the performance of the model also decreased, indicating that the dynamic association between indicators and the teaching-practice coupling relationship played an important role in improving the consistency and professional pertinence of the evaluation results. On the whole, time series feature fusion and adaptive weight update contribute the most.

4.5 Analysis of the dynamic evolution results of "double qualification" ability of hotel management teachers

After completing the overall performance verification, this paper further uses AOTM-DDE to analyze the stage evolution results of the "double qualification" ability of hotel management teachers. In order to improve the interpretability of the results, the 12-month observation period was divided into the initial stage, the middle stage and the later stage, and the stage mean values of teaching ability, industry practice ability, digital technology application ability, collaborative development ability, dual coupling strength and comprehensive score were calculated respectively. The results are shown in Table 6.

Table 6: Dynamic evolution results of "double qualification" ability of hotel management teachers

Stage	Teaching Competence (T)	Practical Competence (P)	Digital Application (D)	Collaborative Development (C)	Coupling Strength (H)	Comprehensive Score (S)
Initial Stage (Months 1–4)	0.71	0.66	0.62	0.64	0.68	0.667
Middle Stage (Months 5–8)	0.78	0.74	0.71	0.72	0.76	0.742
Late Stage (Months 9–12)	0.84	0.81	0.79	0.77	0.82	0.806

As can be seen from Table 6, the overall ability of teachers to "double teacher" showed a continuous upward trend, and the comprehensive score increased from 0.667 in the early stage to 0.806 in the late stage, with an increase of 20.8%. Among them, the teaching ability increased from 0.71 to 0.84, indicating that teachers showed a strong accumulation effect in curriculum reconstruction, practical teaching organization and feedback correction. Industry practice ability increased from 0.66 to 0.81, indicating that enterprise project participation and job guidance experience had a significant role in promoting ability improvement. The increase of digital technology application ability was the most obvious, from 0.62 to 0.79, indicating that the use of platform tools and data-driven teaching methods were gradually mature in the later stage.

It is worth noting that the dual coupling strength increased from 0.68 to 0.82, which is higher than the single teaching ability and collaborative development ability, indicating that the connection between teaching ability and industry practice ability is continuously enhanced. This shows that the improvement of "double-teacher" ability is not the independent growth of a single ability, but the synchronous and coordinated evolution between teaching and practice. On the whole, the model in this paper can clearly describe the dynamic development process of the "double qualification" ability of hotel management teachers from basic adaptation, collaborative promotion to stable reinforcement, and provide a quantitative basis for the diagnosis of teachers' ability and the formulation of phased training strategies.

5 Conclusion

5.1 Research Conclusions

Focusing on the static, unitary and empirical problems existing in the ability evaluation of hotel management teachers' "double qualification", this paper constructs a dynamic evaluation model driven by algorithm optimization, and carries out systematic research from four levels: index system design, multi-source data representation, weight adaptive update and time series feature fusion. The results show that the "double-qualification" ability of hotel management teachers is not a simple superposition of teaching ability and industry practice ability, but a dynamic ability structure of teaching transformation, industry practice, digital technology application, collaborative development and teaching-practice coupling. Based on this, this paper represents the teacher's ability status as a computable multi-dimensional feature vector, and enhances the model's ability to identify stage differences and ability evolution through dynamic relationship modeling and weight update mechanism. The experimental results show that the overall performance of the proposed model AOTM-DDE is better than that of the comparison methods. The Accuracy, F1-score and Stability of AOTM-DDE reach 94.3%, 93.5% and 95.2%, respectively, which are significantly higher than those of SWS (82.4%, 80.9% and 84.1%). It is also better than TCN 91.1%, 90.0% and 91.7%; MAE and RMSE decreased to 0.031 and 0.049, respectively, which were further decreased compared with 0.044 and 0.066 of TCN. Ablation experiments show that after removing the temporal feature fusion module, the Accuracy is reduced to 90.9%, and the F1-score is reduced to 89.6%, indicating that temporal modeling plays a key role in the identification of capability evolution. After removing the adaptive weight update module, the Accuracy drops to 91.8%, indicating that the dynamic weight mechanism can effectively improve the adaptation ability of the model to stage differences. The dynamic evolution analysis also showed that the comprehensive score of teachers '" double teacher "increased from 0.667 in the initial stage to 0.806 in the later stage, with an increase of 20.8%, in which the application ability of digital technology increased from 0.62 to 0.79, and the coupling strength of teaching-practice increased from 0.68 to 0.82. These results show that the method in this paper can not only realize the ability level identification, but also better describe the development trajectory and structural change characteristics of the "double qualification" ability of hotel management teachers.

5.2 Application value and future research direction of the model

The dynamic evaluation model constructed in this paper has strong application expansion value. At the practical level, the model can be used for the diagnosis of hotel management teacher development, the quality monitoring of school-enterprise collaborative training, the tracking of teacher training effectiveness and the evaluation of "double-qualified" construction level, which provides data support and quantitative basis for vocational colleges to carry out the construction of teachers. Compared with the traditional evaluation methods based on annual assessment or expert experience judgment, the model in this paper can continuously identify teachers 'ability based on multi-source heterogeneous data, which can not only reflect the current ability status, but also reveal the phased change trend, so as to improve the objectivity, dynamics and interpretability of the evaluation results. At the management level, the model can also support the identification of teachers 'ability shortboards, the adjustment of training paths and the optimization of resource allocation, and provide technical support for schools to formulate differentiated teacher development programs. The follow-up research can still be deepened from three directions. First, the sample scope is further expanded, and data from different regions and different levels of vocational colleges are introduced to improve the generalization ability of the model. The second is to enhance the ability to process unstructured data, and incorporate classroom videos, voice interaction and richer text evaluation information into the ability modeling process. Thirdly, combining causal analysis, explainable artificial intelligence and early warning mechanism design, the application depth of the model in capacity improvement intervention, development prediction and education management decision-making was improved. In the future, with the continuous advancement of the digital construction of vocational education, the dynamic assessment model is expected to play a stronger supporting role in the governance of teacher development.

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