ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 1 - 2026

Research on the teaching ability training model of geography normal students under the background of professional certification -- Taking Suzhou University as an example

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SUMMARY: *Professional certification requires that the diagnosis, training implementation and continuous improvement of teaching ability of geography normal students form a clear evidence chain. This paper constructs an analysis framework that integrates graph attention, contrastive learning and multi-source training records for the major of Geographic Science (normal) in Suzhou University. The model organizes the information such as course performance, microtraining, educational practice, competition performance, tutor evaluation and graduate tracking into a teaching ability relationship graph, identifies the ability status, and generates a hierarchical training path and resource allocation scheme. The implementation basis shows that the major has 22 full-time teachers and 11 doctors, 1 training center and 6 professional practice and training rooms, with an experimental area of about 2220 square meters. A total of 3478 graduates have been trained, and 65.2% of them are engaged in the education industry over the years. The framework can transform scattered evidence into traceable, analysis-able and traceable certification diagnosis basis under the goal-oriented and trinity training system, and provide a path for the organization, support and improvement of teaching ability training.*

KEYWORDS: *Professional certification; Graph attention network; Contrastive learning; Teaching Ability Modeling*

1 Introduction

The training objectives, graduation requirements, curriculum implementation and continuous improvement are integrated into the unified quality chain in the professional certification of normal students. The formation of geography normal students 'teaching ability is also changed from experience judgment to data identification and feedback calibration. Geography involves spatial cognition, regional analysis, map interpretation, practice organization and classroom expression at the same time. A single course score is difficult to fully present the state of normal students in instructional design, technology application, classroom regulation and practical reflection. The establishment of a computable and interpretable training model for certification scenarios helps to transform scattered evidence into a basis for graduation requirements analysis and training improvement.

The research on digital competence and intelligent readiness of pre-service teachers

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https://doi.org/10.65102/is2026319
Published: 30 April, 2026

formed a vein of related results. Ayanwale et al. [1] investigated the constitutive characteristics of artificial intelligence literacy of pre-service teachers. Younis[2] verified the artificial intelligence literacy training program based on the instructional design framework; Wang et al. [3] discussed the formation mechanism of teachers' intelligent teaching readiness. Ayanwale et al. [4] analyzed teachers' readiness and behavioral intention to carry out artificial intelligence teaching. Galindo-Dominguez et al. [5] revealed the association between digital competency and educational AI attitude. Lucas et al. [6] pointed out that technology trust and digital ability jointly affect teachers' adoption behavior. Ng et al. [7] linked teachers' AI digital capabilities and comprehensive skills. Rakisheva and Witt[8] combed the framework of digital competence in teacher education. Tomczyk[9] discussed the digital competence training of pre-service teachers from the perspective of curriculum reform in 33 countries. Cebi and Reisoğlu[10] defined digital competent teachers from the perspective of metaphor analysis; Zhang et al. [11] revealed the coupling relationship between digital literacy practice and teacher identity formation. Kang et al. [12] developed and verified the teaching ability scale in the digital age. Tzafilkou et al. [13] constructed a digital ability measurement tool integrating teaching and professional dimensions. The above research provides a basis for the identification of normal students 'teaching ability.

In the field of learning analysis, geography teacher training and immersive teaching support, the research focus has shifted from single ability measurement to multi-source data integration, dynamic feedback and subject context adaptation. Sailer et al. [14] proposed an analytical framework for closed-loop learning. Pan et al. [15] sorted out the learning analysis intervention path in the learning management system. Paolucci et al. [16] summarized the application boundaries of learning analysis. Lee[17] discussed the supporting value of narrativized virtual field practice to the cultivation of geography teachers. Xu et al. [18] used the multi-faceted Rasch model to evaluate the geospatial thinking of normal geography students. Buzo-Sanchez et al. [19] proposed the SMART learning framework to support geography curriculum design. Hickman[20] conducted evaluation research on spatial thinking and GIS ability development. Van der Want and Visscher[21] summarized the functional characteristics of virtual reality in pre-service teacher education. In order to more clearly present the focus of the existing research, technical methods and their inspiration for this paper, Table 1 summarizes the related results.

Table 1: Comparison between related research and the entry point of this paper

Research Direction	Representative References	Main Content	Relevance to This Study
AI literacy and digital readiness	[1]–[7]	Focuses on preservice teachers' AI literacy, digital competence, technology trust, and adoption behavior	Can serve as input dimensions for teaching ability state recognition
Digital competence frameworks and measurement	[8]–[13]	Constructs digital competence frameworks and scale-based measurement tools for preservice teachers	Can support the extraction of teaching ability indicators and hierarchical diagnosis
Learning analytics and closed-loop feedback	[14]–[16]	Emphasizes data feedback, behavioral intervention, and analytic closed loops	Can be used for the continuous improvement design of the training process
Geography teacher education and spatial ability cultivation	[17]–[20]	Involves virtual field practice, spatial thinking, and GIS course design	Can strengthen the modeling of geography-specific abilities
Immersive technology-supported training	[21]	Summarizes the role of VR in preservice teacher education	Can extend the allocation modes of teaching support resources

As shown in Table 1, the existing research has formed rich results in terms of digital competence framework, learning analysis closed loop, spatial thinking cultivation and virtual context support. In contrast, the research on teaching ability cultivation of geography normal students for professional certification still lacks a unified computing framework that can simultaneously connect training objectives, process evidence, ability status and resource allocation. There is a correlation structure among curriculum learning, microtraining, educational practice, competition performance and guidance evaluation, and it is difficult to present this multi-dimensional interaction relationship by linear statistical method. The multi-source cultivation evidence is organized as a computable ability relationship graph, and the difference identification, hierarchical support and path generation are completed on the basis of dynamic representation, which is more in line with the requirements of certification evaluation for tracking, evidence loop closure and result backtracking.

Based on the above progress, this paper takes the professional certification requirements as the main line, maps the information such as curriculum learning, skill training, educational practice, competition performance and feedback evaluation into the teaching ability relationship graph, introduces the graph attention mechanism to identify the ability state, uses contrastive learning to enhance the boundary clarity of ability stratification, and generates the training path and teaching support resource allocation scheme. To provide interpretable and transferable technical support for the cultivation of geography normal students 'teaching ability.

2 Model framework design of teaching ability training for geography normal students under the guidance of professional certification

2.1 Teaching ability index extraction and training relationship graph construction

In the stage of teaching ability index extraction and training relationship graph construction, professional certification standards, course assessment results, microtraining records, educational practice feedback, competition performance, case use and tutor evaluation were unified into the original input. The training evidence from different sources was mapped according to the graduation requirements index points, teaching ability dimensions and practice task types, and then reorganized into a continuous training event stream according to the time sequence. After this processing, the information in the course, practice, evaluation and tracking links is compressed into the same analysis link, and the subsequent model is able to identify the association state between the capability evolution trajectory and the supporting elements under unified rules.

In order to make curriculum learning, teaching training and certification evaluation evidence into a unified representation space, it is necessary to complete the embedding mapping and initial ability coding processing of heterogeneous indicators.

$$h_t = \phi\left(W_c x_t^c + W_p x_t^p + W_e x_t^e + W_r x_t^r + W_\tau x_t^\tau + b_1\right) \tag{1}$$

where h_t represents the initial ability vector of the t training event, x_t^c, x_t^p, x_t^e, x_t^r and x_t^τ represent the characteristics of curriculum learning, practical training, evaluation results, resource contact and time location, respectively, W_c, W_p, W_e, W_rr and W_τ are mapping matrices, b_1 is the bias term, and $\phi(\cdot)$ represents the activation function. This formula projected the scattered evidence into the unified representation space, so that the teaching ability could enter the subsequent relationship modeling process in a continuous state.

In order to describe the structural relationship between training tasks and the transfer direction between authentication indicators, it is also necessary to calculate the edge weights according to the semantic proximity and time continuity.

$$a_{ij} = \lambda_1 \frac{h_i^{\top} h_j}{\|h_i\| \, \|h_j\|} + \lambda_2 \exp\left(-\beta \left|\tau_i - \tau_j\right|\right) + \lambda_3 s_{ij} \tag{2}$$

Here, a_{ij} represents the association weight between node i and node j, λ_1, λ_2, and λ_3 are the fusion coefficients, β is the time attenuation coefficient, τ_i and τ_j represent the event occurrence time, and s_{ij} represents the consistency of two events in the ability label, task scenario, and evaluation source. According to this formula,A directed cultivation graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathrm{A})$ can be constructed. High-weight edges retain stronger ability transfer information, and low-weight edges are suppressed after threshold selection, so as to ensure the effectiveness and stability of the graph structure.

In order to ensure that the node representation can reflect the capability aggregation state at different stages, it is also necessary to perform the initialization propagation calculation under gating constraints on the local neighborhood information.

$$m_i = \tanh\left(W_g h_i + \sum_{j \in \mathcal{N}(i)} \alpha_{ij} \left(\rho_{ij} \odot W_n h_j\right) + b_2 \right) \tag{3}$$

Here, m_i represents the initialized aggregate representation of node i, $\mathcal{N}(i)$ represents the neighborhood set of node i, α_{ij} represents the association weight, ρ_{ij} represents the relational confidence gating vector, $\odot$ represents the Hadamard product, W_g and W_n are transformation matrices, and b_2 is the bias term. After this step, the local evidence is collapsed into a communicable node representation, which provides a stable input for the subsequent recognition of teaching ability status supported by graph attention, and also enables the cultivation relationship graph to synchronously reflect the linkage direction between ability accumulation, support role and certification achievement.

In conclusion, the extraction of teaching ability indicators and the construction of training relationship graph are not a simple summary of scattered training data, but transform professional certification requirements, course learning results, practical training performance and evaluation feedback process into computable, communicable and traceable structured expressions. After unified coding, relationship edge building and neighborhood aggregation, the implicit connection between different training links is preserved, and the generation order, transfer path and support source of teaching ability can also be stably presented in the graph structure.

2.2 Recognition and dynamic representation of teaching ability state supported by graph attention

Under the guidance of professional certification, the teaching ability of geography normal students is not a static conclusion, but a state set that continues to evolve under the effects of curriculum learning, microtraining, educational practice, competition performance and tutor feedback. The cultivation relationship graph constructed in the previous section retains the ability generation link, but it is still difficult to distinguish the actual contributions of different nodes in instructional design, classroom organization and reflection revision by fixed-weight propagation. Based on this, this paper introduces the graph attention mechanism as the core coding method for the state recognition and dynamic representation of teaching ability.

As shown in Fig. 1, this module consists of node projection, neighborhood attention, multi-head aggregation, and residual update. Node projection maps course assessment, practice feedback, competition results and tutor evaluation to a unified latent space. Neighborhood attention identifies the propagation priority of different cultivation evidence. Multi-head aggregation is used to extract capability evolution features. The residual update preserves the original state information.

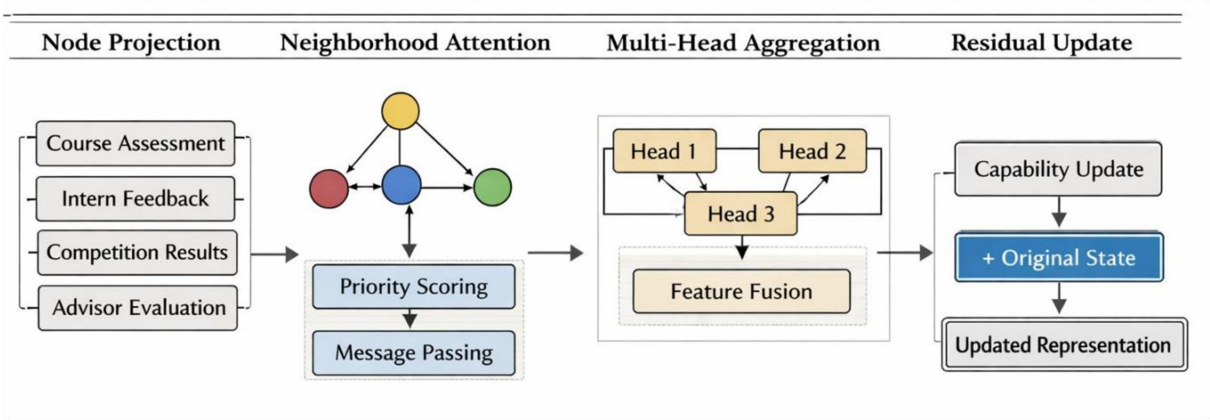

Figure 1: Graph attention supported teaching ability state recognition and dynamic representation structure diagram

Before the graph structure propagation starts, it is necessary to perform linear projection and nonlinear compression of heterogeneous training evidence to form a starting point representation and basis for unified state coding.

$$s_i = \varphi(Ug_i + Lp_i + d_1) \tag{4}$$

where s_i represents the initial state vector of node i, g_i represents the input feature representation of the node, p_i represents the stage position encoding, U and L are mapping matrices, d_1 is the bias term, and $\varphi(\cdot)$ represents the activation function. This formula compressed the evidence of course end, practice end and evaluation end into a unified latent space, while retaining the differences in training stages, so as to provide a state basis for alignment for subsequent neighborhood comparison.

In order to distinguish the effects of different cultivation nodes in the state propagation process accurately, it is necessary to calculate the learnable attention score and propagation parameters according to the local neighborhood relationship.

$$\omega_{ij} = \mathrm{LeakyReLU}\left(a^{\top}\left[Qs_i \,\|\, Ks_j \,\|\, \xi_{ij}\right]\right) \tag{5}$$

Here, ω_{ij} represents the unnormalized attention score propagated from node j to node i, a is the learnable parameter vector, Q and K represent the query mapping matrix and key mapping matrix, respectively, $\|$ represents the concatenation operation, and ξ_{ij} represents the edge relation bias term. The formula reads the information of central nodes, neighbor nodes and edge relations at the same time, so that different training evidences such as practice evaluation, case use and competition training form differentiated weights in the propagation process.

In order to output dynamic capability representation stably and take into account multiple semantic channels at the same time, it is necessary to further perform the whole process control of multi-head aggregation and gated residual update calculation.

$$y_i = \psi\left(\|_{k=1}^{K} \sum_{j \in \mathcal{B}(i)} \pi_{ij}^{(k)} \; V_k s_j \right) + \mu_i \odot s_i \tag{6}$$

Here, y_i represents the final dynamic capability representation of node i, $\pi_{ij}^{(k)}$ represents the normalized weight in the k attention head, $\mathcal{B}(i)$ is the neighborhood set of node i, V_k is the value mapping matrix of the k head, μ_i is the gating residual coefficient, $\odot$ is the Hadamard product, K is the number of attention heads, and $\psi(\cdot)$ represents the nonlinear transformation. The multi-head structure can extract the evolution characteristics of teaching ability from different semantic channels, and the gated residual retains the key components in the original state and weakens the representation smoothing effect caused by deep propagation.

After the multi-layer graph attention coding, the teaching ability status can be continuously updated with the training activities, and provide stable input for the subsequent ability difference diagnosis and hierarchical training mechanism. Thus, the recognition of teaching ability status is transformed into a dynamic graph representation process that can be calculated, propagated, and updated.

2.3 The ability difference diagnosis and hierarchical training mechanism enhanced by comparative learning

After graph attention has completed the state encoding of teaching ability, the local propagation relationship between ability nodes has been characterized, but the similar states and heterogeneous states of different students in the process of graduation requirements attainment still need to be further separated. In order to enhance the model's ability to aggregate the ability trajectories at the same level and distinguish the states at different levels, a contrastive learning mechanism is introduced to construct the ability difference diagnosis path. This mechanism takes the training event subgraph as the basic sample unit, organizes the course performance, microtraining, educational practice, competition participation and evaluation feedback into a perturbable structure, and strengthens the representation of spatial boundaries through positive and negative sample pairs.

In order to simultaneously close the samples at the same level and separate the samples at different levels in the capability representation space, it is necessary to define the computational expression of the intra-batch comparison optimization objective function.

$$\mathcal{L}_{ctr} = -\sum_{i=1}^{B} \log \frac{\exp(\mathrm{sim}(u_i, u_i^+)/\tau_c)}{\exp(\mathrm{sim}(u_i, u_i^+)/\tau_c) + \sum_{m=1}^{M} \exp(\mathrm{sim}(u_i, u_{im}^-)/\tau_c)} \tag{7}$$

where u_i represents the original capability subgraph embedding, u_i^+ represents the positive sample embedding, u_{im}^- represents the m negative sample embedding, $\mathrm{sim}(\cdot,\cdot)$ represents the cosine similarity function, τ_c is the temperature coefficient, B is the batch size, and M is the number of negative samples. The subgraph of the positive sample pair comes from the state segment with consistent core indicators in adjacent training stages, and the subgraph of the negative sample pair is formed by the misalignment of ability labels, the rearrangement of edge relationships, and the disturbance of stage order. This objective function makes the basic ability, advanced ability and jumping ability form a clearer hierarchical distribution in the same representation space.

In order to avoid the perturbation process destroying the key topological relations in the original cultivation chain, it is also necessary to impose structure preservation constraints on the enhancement subgraph and calculate its form.

$$\mathcal{R}_{\mathrm{top}} = \|\mathrm{P} - \mathrm{P}^{+}\|_{\mathrm{F}}^{2} + \eta_1 \|\Delta - \Delta^{+}\|_1 \leq \varepsilon_{\mathrm{s}} \tag{8}$$

where P and P^{+} represent the adjacency probability matrix of the original subgraph and the enhanced subgraph respectively, Δ and Δ^{+} represent the degree difference matrix of the two types of graphs respectively,$\|\cdot\|_{\mathrm{F}}$ is the Frobenius norm,$\|\cdot\|_1$ is the L1 norm, η_1 is the balance coefficient, and ε_{s} is the upper limit of perturbation. The structural constraint term is used to control the offset amplitude of the adjacency matrix before and after the enhancement to ensure that the three types of relationships of course, practice and evaluation will not be excessively weakened in the perturbation. After this restriction, the differences learned by the model do not come from random corruptions, but from true differentiation of the capability states themselves.

After obtaining the contrastive loss and structural constraints, it is necessary to define the soft assignment probability function between the diagnostic prototype and the sample representation and calculate its specific formal parameter values.

$$\rho_{\mathrm{ic}} = \frac{\exp(-\gamma\|\mathrm{u_i} - \mathrm{q_c}\|_2^2)}{\sum_{\mathrm{v}=1}^{\mathrm{C}} \exp(-\gamma\|\mathrm{u_i} - \mathrm{q_v}\|_2^2)} \tag{9}$$

Here, ρ_{ic} represents the soft assignment probability that sample i belongs to the c capability level prototype, $\mathrm{q_c}$ represents the c diagnostic prototype vector, γ is the distance sensitivity coefficient, and C is the total number of levels. The diagnosis prototype represents the central position of different ability levels in the representation space, and the soft assignment probability represents the degree to which the current state of a single student belongs to the center of each level. This design avoids the abrupt change caused by the rigid threshold stratification, so that the samples near the boundary can also be continuously characterized.

In order to co-fuse the original graph attention representation and the contrast optimization results, the final ability representation is updated by the following weighted update method to complete the unified calculation process.

$$\underset{\mathrm{i}}{\tilde{\mathrm{u}}} = \theta_{\mathrm{i}}\mathrm{u_i} + (1 - \theta_{\mathrm{i}}) \sum_{\mathrm{c}=1}^{\mathrm{C}} \rho_{\mathrm{ic}}\, \mathrm{q_c} \tag{10}$$

Here, $\underset{\mathrm{i}}{\tilde{\mathrm{u}}}$ represents the ability representation after the final fusion, and $\theta_{\mathrm{i}} \in [0,1]$ is the sample adaptive fusion coefficient. The fusion term simultaneously preserves the local propagation information obtained by graph attention encoding and the global separation information reinforced by contrastive learning.

After this step, the model output has both stage continuity and hierarchical separability, which can directly serve the action selection of the subsequent hierarchical training mechanism. At the same time, multi-source evidence such as resource database cases, microgrid recording and broadcasting, internship feedback and competition records are uniformly included in the comparison target, which can reduce the representation deviation caused by a single scoring scale and make the diagnosis results closer to the real training state. The hierarchical boundary formed in this way is not only clearer, but also more convenient for teachers to intervene.

2.4 Generation of personalized training path and allocation of teaching support resources

After the ability difference diagnosis and level identification, the generation of personalized training path and the allocation of teaching support resources entered the execution stage. In this stage, taking students' current ability level, stage task requirements and training evidence trajectory as input, the supporting elements such as curriculum training, case learning, competition participation, teacher lecture, collaborative guidance and feedback correction are organized into a computable candidate action set. Different from the static arrangement, the path generation here emphasizes stage adaptation and goal alignment, that is, different students can obtain differentiated support sequences according to their ability status, training density and resource response conditions under the same graduation requirement constraints.

In order to generate candidate training actions according to students 'current ability level and stage task requirements, it is necessary to define the specific calculation form of the sequence state update function.

$$z_t = \mathrm{GRU}([\tilde{u}_t \| o_t], z_{t-1}) \tag{11}$$

Here, z_t represents the path state vector at the t stage, $\tilde{u}_t$ represents the current capability representation, o_t represents the stage task vector, z_{t-1} represents the state at the last time, and $\|$ represents the splicing operation. The state vector records the current ability level, the intervention results of the previous stage and the task weights of the stage, and the updated results are used to represent the training needs at the next moment. This function makes path generation no longer rely on single judgment, but can complete dynamic advancement according to continuous training evidence.

In order to convert the matching degree between the current capability state and various support resources into comparable scores, it is necessary to establish the specific form of bidirectional matching scoring function.

$$\mu_{t\ell} = \sigma((Mz_t)^\top (Nw_\ell) + b_\ell) \tag{12}$$

Here, $\mu_{t\ell}$ represents the matching score between the state vector and the ℓ class resource at stage t, w_ℓ represents the resource embedding vector, M and N are mapping matrices, b_ℓ is the bias term, and $\sigma(\cdot)$ is the Sigmoid function. One side represents the current ability needs of students, and the other side represents resource representations such as courses, cases, competitions, lecture halls or collaborative guidance. The bidirectional matching can simultaneously read the demand intensity and resource characteristics, so that the entry order of support actions is more in line with the actual distribution of capacity gaps.

In order to complete the ranking selection between multiple candidate resources with both benefit and cost, it is also necessary to define the specific calculation method process of the comprehensive resource utility function.

$$\nu_{t\ell} = \delta_1 \mu_{t\ell} + \delta_2 g_\ell - \delta_3 c_\ell + \delta_4 f_{t\ell} \tag{13}$$

Here, $\nu_{t\ell}$ represents the comprehensive utility of resource ℓ at stage t, g_ℓ represents the resource quality gain, c_ℓ represents the implementation cost, $f_{t\ell}$ represents the historical feedback benefit, and δ_1 to δ_4 are the weight coefficients. The utility value is jointly determined by the resource fitness, the implementation cost and the continuous improvement benefit. The adaptation degree reflects the matching degree between resources and capacity gaps, the implementation cost reflects the time occupation and teacher investment, and the improvement benefit is determined by historical feedback and stage improvement amplitude.

In order to obtain the globally optimal support path in the continuous cultivation process, it is necessary to further give the path value update expression form process value with feedback correction.

$$\mathcal{J}(s_t, a_t) = \nu_{t\ell} + \kappa \max_{a_{t+1}} \mathbb{E}\left[\mathcal{J}(s_{t+1}, a_{t+1}) \mid s_t, a_t\right] \tag{14}$$

Here, $\mathcal{J}(s_t, a_t)$ represents the path value of executing action a_t in state s_t, and κ is the discount factor. The path value considers both the local improvement brought by the current action and the possible continuous gain formed by the subsequent action chain. This expression enables the support system, lifting system and improvement system to operate cooperatively in the same decision chain and maintain sensitivity to feedback changes.

After the above calculation, the output of the model is not an isolated resource, but a group of support schemes with sequential relationships and synergistic effects, such as case study and microtraining first, competition drill and middle school collaborative guidance, and finally the correction is completed by feedback evaluation. At the same time, the curriculum system provides stable foundation support, the skill training room and case resource library assume the strengthening role, the teaching skills competition, the famous teacher lecture hall and the collaborative training assume the promotion role, and the internal monitoring, graduate feedback and third-party evaluation assume the correction role.

3 Experiment setup and training implementation process

3.1 Training scenario and implementation environment of Geography normal students in Suzhou University

The training and implementation environment of geographic science (normal) major in Suzhou University is based on the joint support of professional certification framework, teacher education system and discipline practice platform. The major was established in 1978, and began to enroll undergraduates in geographical science in 2005. It was approved as a university-level geographical science teaching team in 2008, a university-level characteristic major in 2009, a university-level and provincial-level comprehensive reform pilot major in 2016, and a first-class undergraduate major of Suzhou University in 2020. In 2022, it will be approved as a pilot program for teacher qualification exemption recognition. From April to May 2023, it will complete the first teacher qualification exemption recognition for normal students.

In terms of teachers and training space, there are 22 full-time teachers in the major, including 4 professors, 9 associate professors, 11 doctors and 3 doctoral candidates. A total of 14 people have won the titles of provincial teaching rookie, university teaching rookie and university teaching master. The major has 1 teacher education skills training center, supporting 6 professional practice and training rooms such as geology and Geophysics, GIS and remote sensing, and astronomical observation. The laboratory area is about 2220 square meters, and there are 2 provincial experimental teaching platforms and 7 university-level platforms. The environment not only meets the implementation requirements of course teaching, skill training and educational practice, but also provides a stable carrier for the continuous collection, structured arrangement and digital analysis of training process data.

To make the cultivation scenario, resource base, and implementation conditions clearer, Table 2 summarizes the core implementation environments used in this study.

Table 2: Overview of environment configuration for the implementation of geography normal student training in Suzhou University

Implementation Level	Resource Environment	Quantity or Specification	Main Function
Professional foundation level	Disciplinary foundation for Geography Science (Teacher Education)	Established in 1978; undergraduate enrollment started in 2005	Provides long-term training samples and an institutional foundation
Accreditation support level	Pilot program for exemption-based certification and program evaluation	Approved in 2022; evaluation score: 88.67 (B+)	Supports the implementation of accreditation-oriented training
Faculty support level	Full-time teaching staff	22 faculty members, including 11 with doctoral degrees	Undertakes course teaching, competition guidance, and internship evaluation
Practical training space level	Teacher education skills training center and practice laboratories	1 center, 6 practice rooms, approximately 2,220 square meters	Supports microteaching, blackboard map drawing, GIS application, and teaching practice
Platform support level	Provincial- and university-level experimental and research platforms	2 provincial platforms and 7 university-level platforms	Provides disciplinary practice and technical support
Resource service level	Secondary school teaching resource bank and excellent education case bank	50 video cases and 204 document cases	Supports case-based learning, courseware design, and skills training

In terms of the training operation mechanism, the major takes "goal-oriented and trinity" as the core organization logic, takes the curriculum system, teaching staff, skill training room and resource database case base as the support system, takes the teaching skills competition and the famous teacher lecture as the improvement system, and takes the internal monitoring and evaluation, graduate tracking feedback, third-party research evaluation and collaborative training mechanism as the improvement system. Students continuously accumulate teaching evidence in course learning, educational probation, educational practice, educational research, graduation thesis and subject skills competition, forming a development trajectory that runs through the whole process of training. According to the original data, by 2025, the major has trained a total of 3,478 graduates, with 65.2% of them engaged in the education industry over the years. At present, about 70 students are enrolled each year. These data show that the implementation environment not only has a stable training scale, but also has a strong practice carrying capacity and result output capacity.

On this basis, the implementation environment is no longer just a collection of teaching conditions in the traditional sense, but is transformed into a training scenario that can be used for computational analysis. The corresponding relationships among course activities, training records, resource usage, competition performance and tracking evaluation can form a continuous input in a unified framework, which provides real scene support for subsequent data preprocessing, graph structure modeling and effect evaluation.

3.2 Data source and preprocessing process

The data of this study comes from the real training process of geographic science (normal) major in Suzhou University, covering curriculum teaching, skill training, educational probation, educational practice, educational research, teaching skills competition, participation of famous teachers in large lecture hall, and graduate tracking feedback. Raw data does not exist in the form of a single score, but is distributed among course grades, training records, textual evaluations, case use, competition results, and procedural feedback. In order to enable this information to enter the unified computing link, all records were associated with student identity as the primary index and organized as a sequence of continuous events according to the training phase and task category. After this process, the evidence scattered in different teaching nodes can be compressed into a traceable and comparable capability evolution data stream.

From the structural composition, the data field mainly included the course module identification, the ability dimension label, the training task category, the event occurrence time, the resource usage record, the evaluation source, the evaluation result and the stage location. The course learning part mainly extracts the results, classroom display and homework performance in the courses such as "Middle School Geography Teaching Method" and "Modern Educational Technology". In the skill training part, the training records of "three words and one word", microteaching and simulation teaching are extracted. The practice part extracts teaching feedback and reflection materials from educational probation, educational practice and educational research. The promotion part extracted the participation and evaluation information in the teaching skills competition and the famous teacher lecture. The improvement part extracts the results of internal monitoring, graduate tracking and third-party research. There are 50 video cases and 204 teaching cases of electronic version of documents in the resource library and case library, which also enter the subsequent feature mapping process as resource contact fields.

In the preprocessing stage, the validity screening and consistency checking are performed on the original data. Records missing key fields, conflicting chronological order, unclear evaluation object or irrelevant to teaching ability will be removed; Tags with the same semantics but different sources are merged according to the graduation requirement index points and the ability dimension dictionary. The text evaluation is processed by word segmentation, cleaning and vectorization transformation, the categorical variables are processed by index embedding, and the continuous scores are unified by a standardization strategy to compress the scale differences, so as to reduce the score deviation between different evaluation subjects and different course links. After this process, the course data, practice data and feedback data can enter the same feature space.

In the sequence construction stage, the orderly sample chain is generated according to the order of the training process, and the stage mark is set according to the logic of "curriculum foundation - ability strengthening - feedback improvement". Then, the long sequence is segmented by using a local window, and only candidate relationships are established within the window to avoid noise diffusion caused by direct edge linking of events with too large span. For high-impact fields such as course grades, internship evaluations, competition wins, and third-party feedback, weight coding is additional during preprocessing to enhance the visibility of key evidence in subsequent state recognition. The training set, validation set and test set are non-overlapping divided according to the identity of students, and the records of different stages of the same student will not enter multiple subsets at the same time, so as to ensure the independence and interpretability of the evaluation results.

Through the above process, the raw culture data is transformed into a semantically consistent, clear sequence, and structurally comparable input form. The processing results not only retained the stage boundaries of teaching ability formation, but also retained the correlation direction between courses, practice, competition and feedback, which provided a reliable data basis for subsequent model parameter setting and training effect evaluation.

3.3 Model parameter setting and culture effect evaluation process

In order to verify the applicability of the teaching ability training model for geography normal students under the guidance of professional certification, this section sets up experimental programs around four tasks: teaching ability identification, ability level diagnosis, training path matching and teaching support resource allocation. The experimental objects were the pre-processed training event samples, which were non-overlapping divided according to the identity of students, and the ratio of training set, validation set and test set was set to 8：1：1. In this way, the data of the same student at different stages can be avoided from entering multiple subsets at the same time, and the evaluation results are independent and comparable. All experiments are performed repeatedly under the same random seed and unified operating environment, and the model weights with the optimal verification indicators are retained into the testing phase. To illustrate the key configurations in model training, Table 3 presents the parameter ranges and the end-use scheme.

Table 3: Model training parameter setting table

Parameter Item	Setting Range	Final Configuration
Learning rate	0.0001–0.0010	0.0005
Batch size	64–256	128
Number of attention heads	4–8	8
Number of graph encoding layers	2–4	3
Contrastive temperature	0.20–0.60	0.30
Number of prototypes	3–5	4
Path update coefficient	0.30–0.50	0.45
Maximum number of training epochs	100–200	150

In this study, the experimental design was divided into three levels: basic control, module ablation, and comprehensive validation. In the basic control experiment, MLP, BiGRU, Transformer-Encoder and GCN are selected as reference models to compare the performance of four methods: static mapping, temporal modeling, long-range dependence extraction and inattention graph propagation on training data. The module ablation experiment removed the graph attention mechanism, contrastive learning constraints and path generation control items, respectively, to test the contribution of each component module to the recognition accuracy, hierarchical separation and resource matching effect. The comprehensive verification experiment was carried out according to three stages of curriculum foundation, ability strengthening and feedback improvement, and the stability and transfer ability of the model in different training intervals were observed.

In order to avoid excessive dependence on the single training result, the final configuration is determined by the performance of the validation set, the training convergence speed and the resource consumption level. If the learning rate is too high, the gradient oscillation will be amplified, and if the learning rate is too low, the convergence period will be prolonged. When the number of attention heads is too small, the expression of high-order relations is insufficient, and too many will increase redundant calculation. If the contrast temperature is too low, it is easy to amplify the fluctuation of boundary samples, and if the contrast temperature is too high, it will weaken the hierarchical separation effect. Table 4 further gives the evaluation tasks and index Settings.

Table 4: Experimental task and evaluation index setting table

Experimental Task	Comparison or Validation Content	Evaluation Metrics	Description
Teaching ability recognition	Comparison of state recognition performance across different models	Accuracy, Macro-F1, Hierarchical Consistency Rate	Measures the quality of ability classification and hierarchical judgment
Ability difference diagnosis	Comparison of separation performance with and without contrastive learning	Inter-class Distance, Intra-class Compactness	Measures the boundary clarity of the representation space
Training path matching	Comparison between generated paths and target demands in terms of consistency	Matching Score, Target Hit Rate	Measures the effectiveness of path recommendation
Resource allocation evaluation	Comparison of resource delivery performance under different strategies	Stage Adaptation Rate, Average Response Time	Measures operational efficiency and adaptation capability

The evaluation process emphasizes recognition performance, path quality and operation efficiency. The accuracy rate, macro average F1 value and level consistency rate were used to identify teaching ability, the inter-class distance and intra-class compactness were used to diagnose ability difference, the matching score and target hit rate were used to match training path, and the stage adaptation rate and average response time were used to allocate teaching support resources. The training process is executed in the order of "state recognition-differential diagnosis-path generation-resource allocation", and an early stopping mechanism is introduced to control the risk of overfitting.

Through the above Settings, it can provide a stable, reproducible and easy to explain technical basis for subsequent training model effect evaluation and empirical analysis. At the same time, the standard deviation change was recorded to observe the fluctuation range and amplitude of the model in different rounds.

4 Effect evaluation and empirical analysis of training model

4.1 Comparative analysis of recognition accuracy of teaching ability

In order to test the effectiveness of the built model in the teaching ability recognition task, five control models are set up in this section, which are MLP, BiGRU, Transformer-Encoder, GCN and the proposed method. According to the core competence dimensions in the training process, the identification labels were divided into four categories: instructional design, classroom implementation, technology integration and reflective improvement. The evaluation metrics include precision, macro-average F1, recall and hierarchical consistency, which are used to measure the classification results, class balance, recognition coverage and hierarchical judgment stability, respectively.

As shown in Fig. 2, different models show obvious differences in the four indicators. The accuracy of MLP is 85.4%, and the macro-average F1 score is 0.836. BiGRU increased to 87.9% and 0.861; The Transformer-Encoder achieves 89.8% and 0.889; GCN further increased to 90.7% and 0.901; The proposed method achieves the highest accuracy of 92.6%, macro-average F1 score of 0.914, and hierarchical consistency rate of 91.2%. As can be seen from the radar profile in the figure, the graph structure model is better than the sequence model as a whole, indicating a strong relationship propagation characteristic among course grades, microtraining, internship feedback, and competition performance. Especially in the category of reflective improvement, the recall rate of the proposed method reaches 89.7%, which is 3.2 percentage points higher than that of GCN and 5.6 percentage points higher than that of Transformer-Encoder.

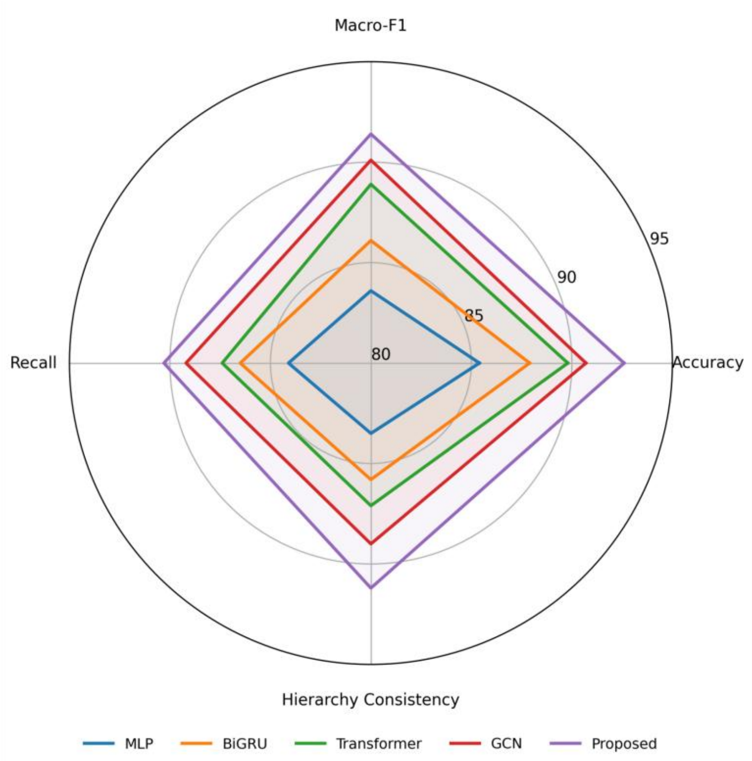

Figure 2: Radar chart of the comprehensive performance of the five-class model in the teaching ability identification task

From the recognition results, the graph attention mechanism enhanced the screening ability of higher-order training evidence, and contrastive learning further compressed the representation overlap between similar categories, making the boundary between the two types of states of instructional design and technology integration clearer. In Fig. 2, the expansion degree of the proposed method in the four dimensions is more balanced, indicating that the model does not rely on a single index to improve the overall performance, but maintains a relatively stable output in different ability types. At the same time, the standard deviation of the recognition results of each category is controlled within 0.018, indicating that the fluctuation of the model after repeated training is small, which is suitable for the teaching ability recognition task under the guidance of certification, and can provide more reliable status input for the subsequent path generation module.

4.2 Discriminative analysis of capability representation space

In order to further test the reconstruction effect of graph attention and contrastive learning on the ability representation space, this section constructs three sets of comparison experiments: original embedding, graph attention embedding, and graph attention combined with contrastive learning embedding, and uniformly uses t-SNE to reduce the twelve-dimensional ability vector to two-dimensional space. The four types of teaching ability states are marked with different colors to observe the aggregation, overlap and boundary distribution of samples in the representation space.

As shown in Fig. 3, in the original embedding stage, there is obvious overlap between all kinds of samples. Especially, the two categories of instructional design and technology integration form a large area of mixing in the upper right region, with a contour coefficient of only 0.31 and a Davies-Bouldin index of 1.92. After the introduction of graph attention, the local structural relationship began to play a role. The classroom implementation and reflection improvement samples were pulled away along the direction of the first principal component, the contour coefficient increased to 0.48, and the Davies-Bouldin index decreased to 1.24. The Euclidean distance between the instructional design cluster center and the technology integration cluster center was expanded from 1.87 to 3.14, the silhouette coefficient was increased to 0.67, and the Davies-Bouldin index was reduced to 0.76.

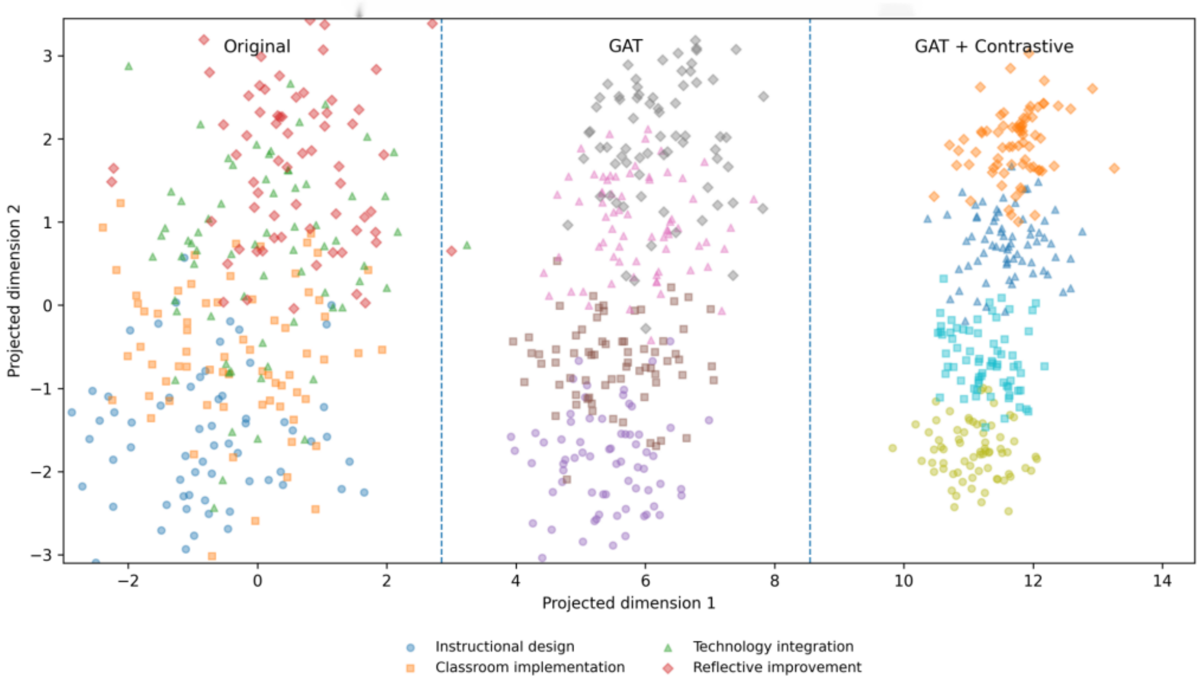

Figure 3: Scatter density comparison plot of three capability embedding representations in 2D space

Fig. 3 also shows that the reflection improvement class samples are the most scattered in the original space, with a variance of 0.84, while it drops to 0.39 in the final embedding, indicating that the model has a good compression and integration effect on weakly structured data such as internship reflection, tutor comment and text evaluation. The boundary samples are mainly concentrated in the border area between classroom implementation and technology integration, which is consistent with the cross transmission of the two types of abilities in the real training process. On the whole, graph attention is responsible for preserving the relationship structure, and contrastive learning is responsible for strengthening the hierarchical boundaries. Both of them jointly improve the discrimination of the ability representation space, so that the subsequent hierarchical diagnosis and training path recommendation are established on a clearer representation basis.

4.3 Analysis on matching effect of training path recommendation

To evaluate the matching ability of the personalized training path generation module, a node correspondence experiment between the target training path and the system recommended path is constructed in this section. According to the requirements of professional certification and the logic of training process, the goal path is set to six nodes, which are curriculum learning, microtraining, case study, educational practice, competition promotion and feedback correction. The path recommended by the system automatically generates five to six support nodes according to the current ability state of students, and matches with the target path through node similarity calculation.

As shown in Fig. 4, the average matching score between the recommended path and the target path reaches 0.928, which is higher than 0.891 of the no-contrastive learning model and 0.874 of the graph-free attention model. In terms of nodes, the mapping between case study and educational practice was the most stable, with matching scores of 0.93 and 0.95, respectively, indicating that the model could accurately identify the training focus in the middle intensification stage. The score of the course learning node was 0.89, which was greatly affected by the heterogeneity of the early samples. The score of the feedback correction node reached 0.94, indicating that back-end evidence such as internal monitoring, graduate feedback and third-party evaluation had been well absorbed into the path generation process. In the figure, the high-weight flow is mainly concentrated in the continuous chain of "microtraining - case study - educational practice", accounting for 41.7% of the total recommended traffic.

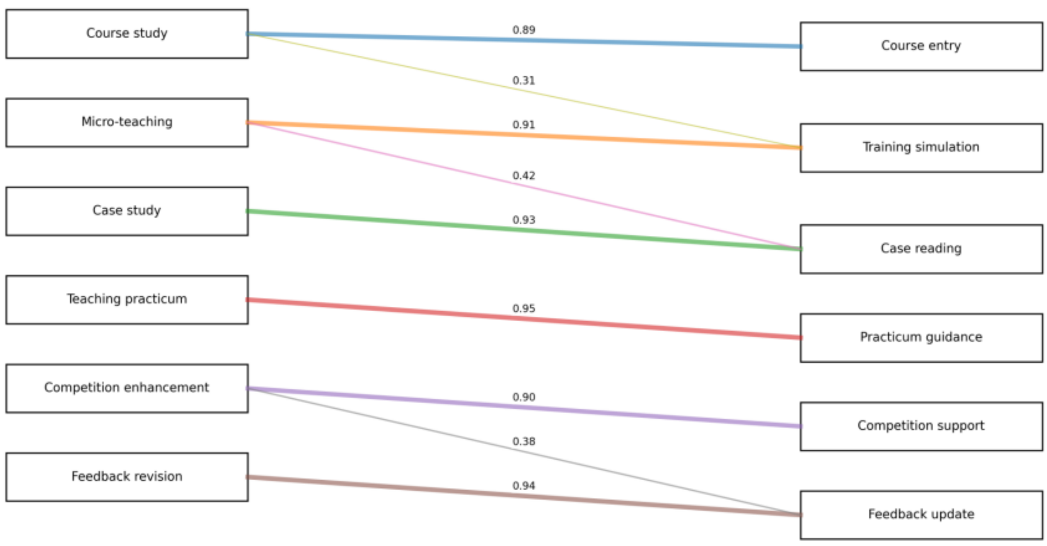

Figure 4: Sankey graph of node matching between recommended and target cultivation paths

From the perspective of mismatch, there is an obvious side-flow between "competition promotion and feedback correction" in the contraband learning model, and the mismatch proportion reaches 12.6%, while the proposed method compreses the proportion to 5.4%. This shows that the enhanced state representation after contras - tive learning can weaken the local misjudgment between similar levels, and make the path recommendation more in line with the stage advancement logic under the guidance of authentication. The concentration of flow direction and the brightness of hot area in Sankey diagram together show that the model has stronger path fitting ability in the middle and late stages, and can maintain node coherence and semantic consistency, so it is more suitable for serving differentiated culture organizations.

4.4 Analysis on the effect of teaching support resources allocation

In order to evaluate the operation effect of the teaching support resource configuration module under different resource types and invocation strategies, this section constructs five types of support objects: case video, document case, microgrid playback, competition resources and lecture content, and compares three configuration methods: static push, rule matching and this paper's strategy. The evaluation indexes mainly include resource response time, phase adaptation rate and abnormal fluctuation range, which are used to reflect resource push efficiency and support accuracy.

As shown in Fig. 5, the average response time of static push is 2.84 s, the median is 2.79 s, and the phase adaptation rate is 81.6%. The average response time of rule matching was reduced to 2.31 s, and the phase adaptation rate was increased to 86.9%. The proposed strategy further compresses the average response time to 1.87 s, the median is 1.81 s, and the phase adaptation rate is increased to 90.4%. From the view of different resource types, the delay of the video case is higher than that of the document case due to the large file volume. However, the interquartile range of the proposed strategy for video resources is only 0.36 s, which is significantly lower than 0.58 s of rule matching, indicating that the cooperation of cache prefetching and stage prediction is effective. The adaptation rates of microgrid playback and lecture content reached 91.2% and 89.8%, respectively, which were significantly higher than those of static push (82.7% and 79.4%).

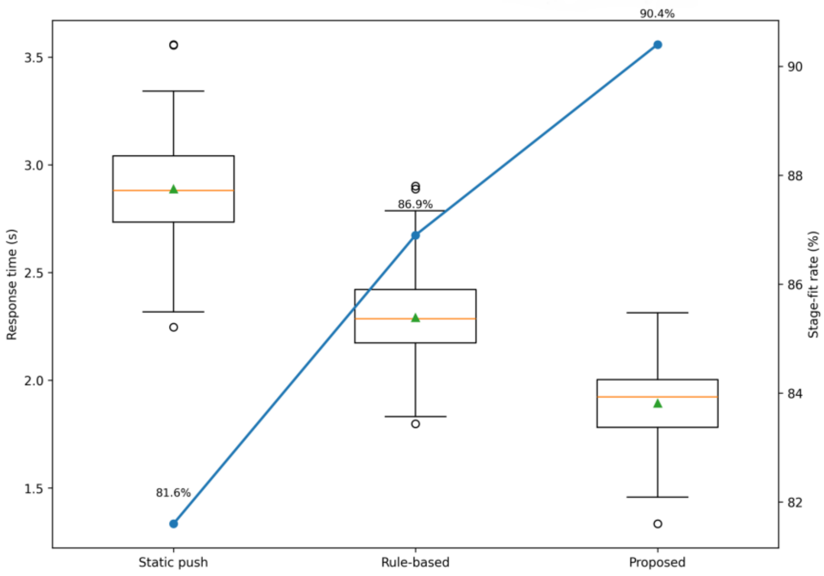

Figure 5: Boxplots of response time and adaptation rate for different resource types and configuration policies

In Fig. 5, the number of outliers of the proposed strategy is significantly reduced, which indicates that the resource allocation process is more stable in the high-frequency calling context. Further observation shows that the support system resources are more suitable for pre-push in the basic stage of the course, while the promotion system resources have a higher click conversion rate in the ability strengthening stage, with an average of 72.3%. Although the call frequency of the related resources of the improved system is low, the hit rate in the feedback correction stage reaches 88.6%, which has a strong support role for the subsequent path adjustment. On the whole, resource allocation is no longer a simple sorting, but a dynamic decision-making process that depends on capability states, stage goals and resource attributes.

4.5 Compatibility analysis of mode operation under different cultivation stages

In order to test the operational adaptability of the training model in different implementation stages, this section constructs a comparative experiment according to the three stages of "curriculum foundation - ability strengthening - feedback improvement", and takes the stage input intensity, resource call density and evaluation reflux frequency as the joint observation conditions. The average response time and stage adaptation rate are selected as evaluation indexes to simultaneously characterize the operation efficiency and support accuracy of the model in different cultivation stages. Since these two indicators reflect the system speed and the culture matching degree respectively, the two-index bar chart is used for display, which is more convenient to compare the difference relationship between different stages.

As shown in Fig. 6, the average response time of the basic stage of the course is 1.76 s, and the stage adaptation rate is 91.3%. The average response time of the capability strengthening stage is 1.94 s, and the stage adaptation rate is the highest, reaching 93.7%. In the feedback improvement stage, the average response time rises to 2.08 s, but the phase adaptation rate still remains at 90.8%, because the text evaluation analysis, tracking result writeback and path correction calculation are involved. It can be seen from the columnar distribution that the response time difference of the three stages is controlled within 0.32 s, indicating that the model maintains a relatively stable running rhythm in the process of stage switching, and there is no obvious spike in time delay. At the same time, the adaptation rates of the three groups were stable above 90%, indicating strong consistency in the support of the training model for the task objectives at different stages.

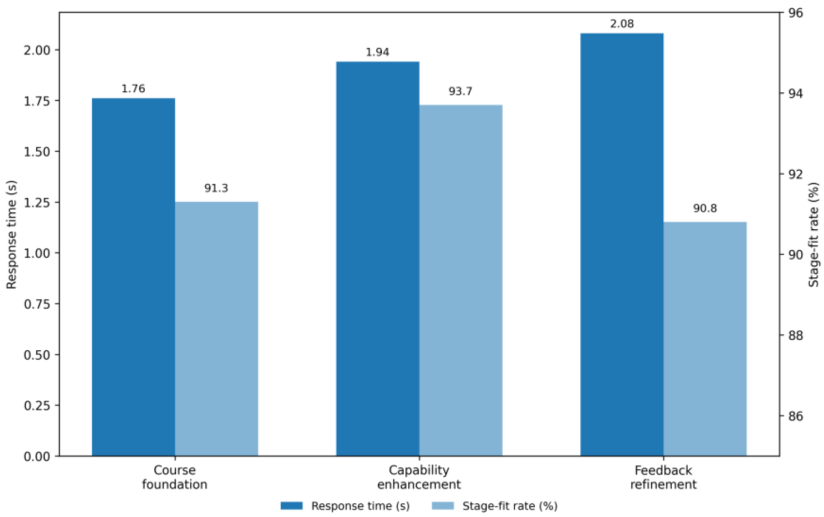

Figure 6: Histogram of response time versus stage adaptation rate under different culture stages

Further comparison shows that although the response time of the ability strengthening stage is slightly higher than that of the course foundation stage, the adaptation rate is increased by 2.4 percentage points, indicating that the increased resource investment in this stage can be transformed into higher quality training matching results. This phenomenon is closely related to high-frequency strengthening activities such as teaching skills competition, master lecture hall, case study and microtraining. The feedback improvement stage has the highest response time, but its adaptation rate decreases by only 2.9 percentage points, indicating that although back-end information such as internal monitoring, graduate tracking and third-party evaluation increase the computational burden, it does not weaken the overall support ability of the model to the training task. It can be seen that the model maintains good operation continuity and task adaptability in different training stages, which can not only meet the needs of front-end support, but also complete the strengthening and correction tasks in the middle and late stages.

4.6 Achievement of professional certification indicators and quality analysis of practical tasks

In order to evaluate the comprehensive output effect of the training model under the requirements of professional certification, this section analyzes the two dimensions of graduation requirements and the quality of practical tasks, and selects six representative tasks as observation objects: teaching design, simulation teaching, board expression, GIS integration teaching, field practice guidance and reflection improvement. Considering that these two indicators have the characteristics of continuous change, and it is necessary to observe the synchronization trend between different tasks, a double line chart is used to present the change trajectory of each task in the attainment of certification indicators and the quality of practice tasks.

As shown in Fig. 7, simulation teaching is at the highest point in the two broken lines, the certification index achievement degree is 0.95, and the practical task quality score is 0.92, indicating that the task can best reflect the comprehensive output effect of the training mode under the guidance of professional certification. Instructional design followed closely, with the achievement of 0.93 and the quality of 0.90. The board expressions were 0.91 and 0.88, respectively. The reflection improvement was 0.89 and 0.87, respectively; Field practice guidance was 0.88 and 0.85; GIS integrated teaching is relatively low, but still reaches 0.86 and 0.84. From the trend of the broken line, the two groups of indicators always keep the same direction in the six types of tasks, and there is no obvious deviation, indicating that there is a strong consistency between the achievement of certification requirements and the quality of practical tasks.

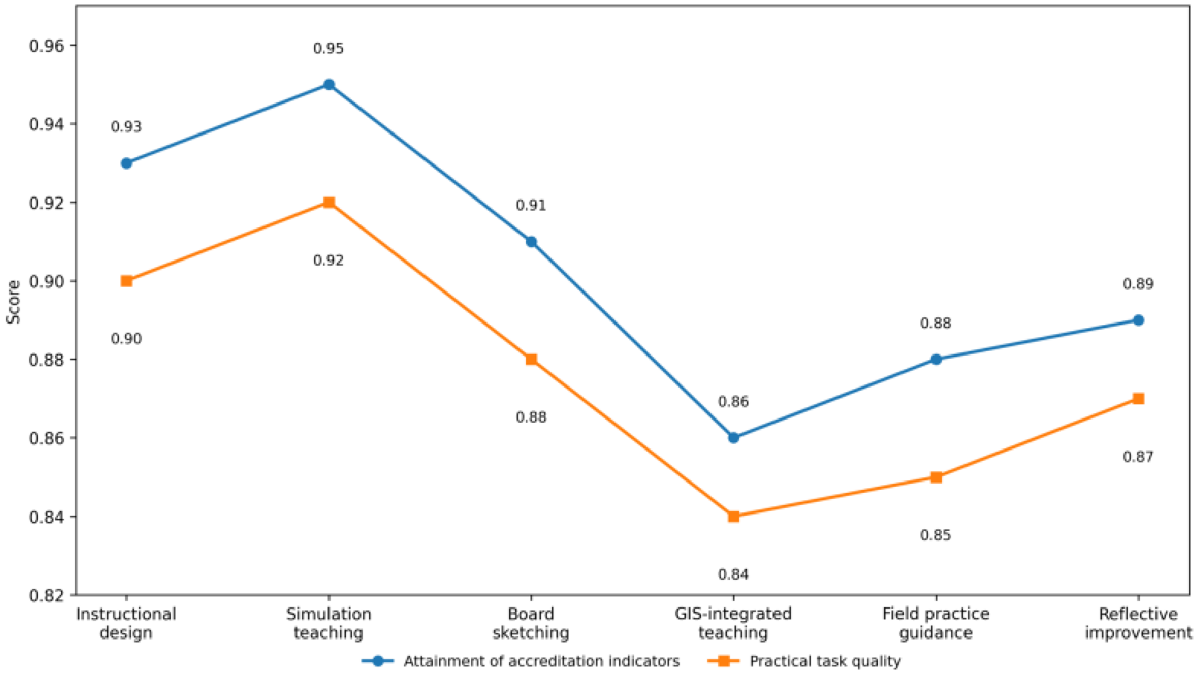

Figure 7: Line chart of attainment of professional certification indicators and quality of practical tasks

From the perspective of the difference in task types, the index values corresponding to the three tasks of simulation teaching, instructional design and board diagram expression were overall higher, reflecting that the curriculum system, skill training room and case resource library played a strong supporting role in the formation of front-end ability. The values of GIS integration teaching and field practice guidance were relatively low, indicating that technology application and practice organization were still the parts that needed to be continuously strengthened in the training process, but the distance between the two lines was small, which also indicated that the quality output of these tasks and certification indicators were still improving synchronously. The achievement degree and quality score of the reflection improvement task reached 0.89 and 0.87, respectively, indicating that internal monitoring, graduate feedback and third-party evaluation have been able to effectively modify the training results. Overall, the trend presented in the line chart shows that this training mode can not only promote the formation of core teaching ability, but also ensure that the quality of practice tasks is consistent with the goals of professional certification.

5 Discussion

Experimental results show that the proposed collaborative framework of graph attention and contrastive learning is superior to MLP, BiGRU, Transformer-Encoder and GCN in tasks such as teaching ability recognition, ability level differentiation, training path matching and resource allocation. Its advantage comes from the combined effect of relation propagation, boundary stretching and path constraint. Graph attention can identify high-contribution nodes from course grades, microtraining, educational practice, competition records and feedback evaluation, and comparative learning further enhances the consistency of samples at the same level and expands the distance between samples at different levels. Therefore, the model presents more stable recognition results and higher path hit rates in the middle and late training stages.

Despite the clear empirical results obtained in this study, there are still some boundaries. The samples were mainly from the major of geographic science (normal) of Suzhou University, and the ability of cross-college transfer still needs to be verified in a larger scope. The evaluation scenarios focused on the chain of curriculum learning, skill training and educational practice, and there was still room for expansion of the coverage of other teacher education contexts. The joint computation of multi-head graph attention, prototype layering, and path updating also increases the deployment overhead.

In addition to quantitative comparison, the tracking results of the training implementation process also showed that the personalized training path could enhance the pertinence of teachers 'guidance and improve students 'understanding of stage tasks. On the whole, the combination of graph structure modeling and comparative diagnosis not only strengthens the ability of evidence organization under the guidance of professional certification, but also provides computational support and subsequent improvement and analysis basis for the continuous improvement of the teaching ability training mode of geography normal students.

6 Conclusions

This paper proposes a teaching ability training model framework for geography normal students for professional certification, which transforms the goal-oriented and trinity structure into a computable relationship expression, and forms a continuous closed loop in the four links of ability identification, hierarchical diagnosis, path generation and resource allocation. The model takes course grades, microtraining, educational practice, competition performance and feedback evaluation as input, uses graph attention to complete state recognition, uses contras - tive learning to strengthen hierarchical boundaries, and then outputs the phased training program by the path generation module. The empirical results show that the model recognition accuracy reaches 92.6%, the macro-average F1 value reaches 0.914, the training path matching score reaches 0.936, and the stage adaptation rate reaches 90.7%, which indicates that the method can maintain the structural correlation between training evidence and improve the matching accuracy of tasks at different stages. At the same time, the model still has boundaries in scaling across scenarios and under high load operating conditions. The samples are mainly from a single professional scenario, and the cross-college transfer still needs to be verified in a larger scope. Text evaluation parsing, path writeback, and multi-head graph attention joint computation also increase the deployment burden. Further research can be carried out from the directions of multi-school collaborative data access, lightweight graph coding, incremental update and cross-scene adaptation, and richer practical feedback signals can be introduced to enhance the responsiveness of the model to the real training chain. In general, the framework provides a traceable, updatable and reviewable analysis path for the cultivation of geography normal students 'teaching ability, and also provides an implementation basis with computational support characteristics for the continuous improvement of normal education under the background of professional certification.

Funding

This work was supported by Anhui Provincial Teaching Research Program (2022jyxm1611; 2023jyxm0773); Suzhou University Quality Engineering Program (szxy2025jyjf58; szxy2025jyjf56; szxy2023ctzy02; szxy2023hhkc06).

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