ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

Research on the Embedded Intelligent Optimization Model of University Specialty Layout and Network Ideological and Political Education for Digital Economy Transformation

Ruiqian Su[1] *and Yan Zhuang*[2,*]

[1] School of Foreign Languages, Xiamen Institute of Technology, Xiamen, 361021, Fujian, China

[2] School of Liberal Arts Education and Art Media,Xiamen Institute of Technology, Xiamen, 361021, *Fujian, China*

SUMMARY: *For the needs of professional layout adjustment and network ideological and political coordination optimization in universities under the background of digital economy transformation, this paper constructs an embedded intelligent optimization model of professional layout and network ideological and political, and completes the design of optimization method and system implementation. Aiming at the problems of demand response lag, separation of education orientation and insufficient decision support in the process of traditional major adjustment, this paper studies the integration of industrial demand, professional construction foundation, employment feedback, course operation status and network ideological and political resources into the unified computing framework, and forms a continuous mechanism of professional feature representation, ideological and political embedding recognition, optimization solution and feedback update. The experiment was based on the data of 12 universities in Fujian Province from 2020 to 2024, involving 72 undergraduate majors. After expanding by "Institution-Profession-year", 864 samples were formed. The results show that the Accuracy of the proposed model on the test set is 89.3%, Macro-F1 is 87.6%, and AUC is 0.928, which is better than the comparison methods. The average response time of the system is 1.89 s under the condition of 250 concurrency, and the request success rate remains above 99.1%, which shows good stability and availability. The results show that this method can provide strong computing support and practical reference for the optimization of professional structure and network ideological and political construction in universities in the transformation of digital economy.*

KEYWORDS: *Digital economy transformation; College specialty layout; Network ideological and political; Intelligent optimization model*

1 Introduction

The continuous evolution of the digital economy is profoundly changing the way of industrial organization, the ability structure of positions and the logic of talent training. For colleges and universities, the professional layout is no longer a problem of the increase or decrease of disciplines and the allocation of scale in the traditional sense, but an important issue related to the talent supply structure, the efficiency of educational resources allocation, and whether the education orientation can adapt to the new development pattern. If the professional setting

*daisychng324@163.com
https://doi.org/10.65102/is20261018
Published: 30 April, 2026

still stays in static experience judgment, and the network ideological and political education is still limited to course addition or module splicing, it is difficult to respond to the rapid update of the digital industry, the strong transfer of job ability, and the networked learning scene of students. Facing the transformation of digital economy, colleges and universities need to establish a closer collaborative relationship between professional adjustment, curriculum organization, ability training and value guidance, so that the optimization of professional layout and network ideological and political embedding can form an overall mechanism that works together.

Existing research has discussed the digital transformation of higher education, the improvement of teachers 'digital ability, the construction of ideological and political courses and the adjustment of professional structure, but most of the related results are scattered in the level of education governance, teaching reform or platform application. For the analysis of how to realize the linkage between "professional layout optimization" and "network ideological and political embedding" under the unified computing framework. There is still a lack of more complete theoretical modeling and technical path. Some studies emphasize the response of professional Settings to the needs of regional industries, but less depict the value shaping dimension in the process of talent training. Another part of the research focuses on the content dissemination and teaching integration of network ideological and political science, but fails to incorporate it into the optimization of professional structure, resource allocation adjustment and decision-making feedback. As a result, when promoting the construction of majors related to digital economy transformation, colleges and universities often attach more importance to skill matching than to education integration, attach more importance to local reform than to system coordination, and it is difficult to form an optimization mechanism that takes into account both development efficiency and education quality.

With the continuous improvement of education data platforms, learning behavior recording systems, employment feedback databases and regional industrial information networks, a large number of heterogeneous data are stored in different business systems, which contain multi-dimensional information such as changes in professional needs, the growth of students 'ability, the effect of curriculum operation and the level of ideological and political penetration. The development of computer technologies such as data mining, machine learning, knowledge graph and intelligent optimization provides new method support for dynamic identification and fine decision-making of specialty layout in colleges and universities. Transforming multi-source education data into a feature set that can be calculated, correlated and iteratively updated, and constructing an embedded intelligent optimization model on this basis can help break through the limitations of relying on artificial experience, feedback lag and extensive adjustment in traditional management methods, so as to improve the response ability of university specialty layout to the needs of digital economy transformation.

Based on this, this paper focuses on the problem of specialty layout in colleges and universities for digital economy transformation, tries to introduce the network ideological and political embedding mechanism into the intelligent optimization process, and constructs an optimization model that takes into account industrial demand adaptation, educational resource collaboration and value guidance integration. On this basis, the major layout optimization method and system implementation path are further designed, and the feasibility of the model and system is verified through experimental testing, in order to provide research ideas with computational support for the professional structure adjustment and network ideological and political digital construction in colleges and universities.

2 Related Research

Around the relationship between digital economy and higher education transformation, the academic community has formed a rich research accumulation. Kholiavko et al. pointed out that higher education bears the dual functions of digital talent supply and innovation ability cultivation in the development of digital economy, and the talent training system within colleges needs to be adjusted synchronously with the process of industrial digitalization, which provides a macro basis for the study of professional layout [1]. Nunez-Canal et al. focused on the digital ability of university teachers, and believed that educational reform under the digital environment was not only reflected in the introduction of technical tools, but also reflected in the remodeling of teaching organization mode and ability structure [2]. de Obesso et al. further discussed the digital competency of university teachers from the perspective of student perception, indicating that the effect of digital transformation would directly affect the learning experience and training quality [3]. Through bibliometric analysis, Zhao et al. found that the research on higher education digitalization is gradually shifting from platform application to the direction of governance mechanism, ability evaluation and system optimization [4].

In terms of the research on talent cultivation and professional structure adaptation, de Villiers Scheepers et al. put forward the concept of "digital vocational competence", emphasizing that graduates' employability has changed from traditional knowledge mastery to the comprehensive unification of compound digital literacy, collaboration ability and technical adaptability [5]. Tee et al., based on the analysis of employers' needs, found that there was still a significant gap between the supply of digital skills and the job demand of college graduates, which meant that the professional layout could not only expand or contract according to the discipline inertia, but should establish a dynamic adjustment mechanism oriented to industrial demand [6]. Hakansson Lindqvist et al. pointed out from the perspective of lifelong learning that the transformation of higher education in the digital era requires the professional system to have stronger openness, renewal and cross-border integration capabilities [7]. This kind of research provides a practical basis for the optimization of specialty layout in colleges and universities, but most of them still stay at the level of policy analysis or ability framework, and lack of discussion on the linkage relationship between majors, resource allocation constraints and intelligent solution paths.

In terms of the integration of online ideological and political education and curriculum education, Yang et al believe that under the environment of "Internet +", the mode of curriculum education is shifting from offline embedding to online and offline collaborative embedding, and the teaching platform has become an important carrier of value guidance [8]. Wei discussed the curriculum ideological and political design around the blended teaching mode, and pointed out that the implementation of ideological and political education in the network environment needs to rely on the collaborative organization of teaching activity chain, task chain and evaluation chain [9]. Zhang took College English courses under the background of new liberal arts as an example to show that ideological and political integration should not be understood as a simple superposition, but should form an internal coupling with curriculum objectives, knowledge structure and ability training process [10]. Mei further pointed out in the case study of ideological and political courses in higher education that the effective implementation of ideological and political courses depends on the joint support of course content, teaching media and evaluation mechanism [11]. Cao, starting from the integration path of traditional culture, emphasized that the communication mode of ideological and political content in digital platforms would affect students' acceptance and educational effect [12]. Existing research focuses on a single course or specific teaching scene, and there is still a lack of unified modeling of how network ideological and political education enters the decision-making process of professional layout optimization in colleges and universities.

The development of artificial intelligence and educational decision-making technology provides methodological support for the systematic solution of the above problems. Chan proposed the policy framework of artificial intelligence education in colleges and universities, emphasizing that AI technology not only serves as teaching assistance, but also can enter the links of governance decision-making, resource allocation and training mode optimization [13]. Marengo et al. showed through systematic review that the application of artificial intelligence in higher education has expanded from learning analysis to multiple levels such as recommendation, prediction and decision support [14]. Castilla-martinez et al. also pointed out that the value of AI in colleges and universities is increasingly reflected in the ability to integrate and interpret complex educational data [15]. Wagner et al. built a course recommendation system to support risk students to select courses, indicating that data-driven methods can improve the matching accuracy of training paths [16]. Khan and Polyzou revealed the importance of learning trajectory data for course configuration and decision feedback from the perspective of conversational recommendation [17]. Xue et al. further applied the demand-driven planning method to curriculum arrangement and teacher allocation, which indicated that the educational planning problem had a strong intelligent optimization research foundation [18]. This paper summarized the representative results, as shown in Table 1.

Table 1: Main contents and implications of related studies

Scholar	Research Topic	Main Content	Implications for This Study
Kholiavko et al. [1]	Higher education and the digital economy	Emphasized the key role of higher education in supplying digital talent	Specialty layout should be linked to digital economy demands
Núñez-Canal et al. [2]	Teachers' digital competence	Pointed out that educational transformation depends on the improvement of digital competence	Specialty optimization should take teaching implementation conditions into account
de Obesso et al. [3]	Student perception and digital competence	Evaluated the quality of digital teaching from the learner's perspective	Model evaluation should incorporate a student feedback dimension
de Villiers Scheepers et al. [5]	Digital employability	Constructed a framework for digital employability	Specialty layout indicators should reflect job adaptability
Tee et al. [6]	Skills gap and employment demand	Revealed the mismatch between graduates' digital skills and market demand	Specialty adjustment should introduce a demand forecasting mechanism
Wei [9]	Curriculum ideological and political education in blended teaching	Discussed implementation paths of ideological and political education in online environments	Online ideological and political education can be transformed into quantifiable embedded indicators
Zhang [10]	Curriculum ideological and political education in the context of New Liberal Arts	Emphasized the intrinsic coupling between ideological-political elements and course objectives	Ideological-political embedding should not remain an external add-on
Wagner et al. [16]	Course recommendation systems	Used data-driven methods to improve training–matching effectiveness	Recommendation ideas can be borrowed to construct a specialty optimization model
Xue et al. [18]	Demand-driven educational planning	Applied optimization methods to curriculum and faculty allocation	Provides a methodological reference for system-level intelligent solving

In general, the existing results have laid a research foundation from the aspects of digital transformation, ability training, curriculum ideological and political education and intelligent decision-making, but there are still two shortcomings. First, most of the professional layout research and network ideological and political research are carried out separately, and lack a unified feature expression framework. Second, the existing educational intelligence models more serve course recommendation, teaching evaluation or course arrangement decision-making, and less integrate industrial needs, professional structure, education objectives and network ideological and political embedding requirements into the same optimization model. Based on this, this paper intends to construct an embedded intelligent optimization model of specialty layout and network ideological and political education for the transformation of digital economy on the basis of multi-source education data, so as to realize the collaborative optimization of specialty structure adjustment and value guidance.

3 The construction of embedded intelligent optimization model of college specialty layout and network ideological and political education for digital economy transformation

3.1 Characteristic representation and demand analysis of specialty layout in universities

The professional layout of colleges and universities is not a simple arrangement of enrollment scale, professional number and course categories, but a dynamic system affected by the changes in industrial structure, regional development orientation, school foundation and talent training objectives. After entering the transformation stage of digital economy, the external environment faced by professional setting shows obvious complexity. On the one hand, the expansion of digital industry brings rapid change of job types, and the traditional professional boundaries are constantly broken. On the other hand, the internal curriculum resources, teachers reserve, platform conditions and education requirements can not be synchronized to complete the linear adjustment. If we still use static statistics to judge whether a major will go or stay, it is easy to cause a disconnect between professional supply and industrial demand, and it is difficult to embed the requirements of network ideological and political education into the decision-making process of professional layout. Therefore, in the model construction stage, this study first characterizes the professional layout of colleges and universities, and then performs a structural analysis of the talent demand under the guidance of digital economy, so as to provide computable input for subsequent intelligent optimization.

Considering that the dimension, frequency and semantic level of data from different sources are not consistent, it is necessary to standardize the original indicators first. If the original value of an index is x and its standardized result is denoted as $\hat{x}$, then:

$$\hat{x} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

After standardization, the core representation of college major i can be written as a five-dimensional feature vector:

$$f_i = [r_i,\ c_i,\ e_i,\ u_i,\ m_i] \tag{2}$$

Among them, r_i represents the support degree of professional resources, reflecting the completeness of teachers, experimental platform, curriculum library and practice base. c_i

indicates the degree of correlation between major and regional digital industry chain; e_i indicates the matching degree of graduate employment and job competency; u_i represents the flexibility of professional update, which is used to describe the adjustment space of course content, training direction and ability module. m_i stands for ideological and political embedding foundation degree, which mainly corresponds to network course resources, value guidance nodes, and education bearing conditions in digital teaching scenarios. The purpose of this process is not to compress complex professional development issues into a single score, but to preserve the structural differences between the internal elements of the professional layout through the vectorization expression.

At the level of demand analysis, the requirements of digital economy for talent training in colleges and universities cannot be expressed only by the number of employees. If we only judge the importance of majors based on the scale of recruitment, we often ignore variables such as job ability transfer, technology update frequency and regional policy orientation. Based on this, the external demand vector is expressed as follows in this paper.

$$d = [p,\ t,\ g,\ s] \tag{3}$$

where p is the intensity of regional industrial job demand, t is the activity of technology iteration, g is the weight of policy support, and s is the level of composite digital skills gap. The vector is generated by annual industry reports, job data, regional development planning and graduate tracking feedback, and is used to describe the comprehensive traction of digital economy transformation on the professional structure of colleges and universities in a certain period. Because the ideological and political embedding foundation degree m_i enters the decision item separately in the subsequent priority index, the matching degree calculation is only carried out for the four dimensional features of resource support degree, industry correlation degree, employment matching degree and update elasticity. In order to measure the degree of adaption between professional representation and external demand, this paper defines the function of professional adaption as follows.

$$M_i = \sum_{k=1}^{4} w_k\ \hat{f}_{ik}\hat{d}_k \tag{4}$$

In the equation, w_k is the weight of each rights protection, and $\sum_{k=1}^{4} w_k$ is satisfied. The larger M_i is, the closer the major is to the state required by the development of digital economy in terms of resource base, industrial connection, employment feedback and renewal potential.

Only the matching degree is not enough to support the professional layout decision, because colleges and universities will also be constrained by factors such as enrollment scale, school cost and structural balance in the actual adjustment. In order to identify the priority direction of major expansion, retention or adjustment, this paper further constructs a major layout priority index:

$$P_i = \alpha M_i - \beta \Delta_i + \gamma m_i \tag{5}$$

Among them, Δ_i represents the deviation of professional supply and demand, reflecting the distance between the current training scale and the target demand. As a basic degree of ideological and political embedding, m_i enters the decision-making item, which aims to avoid the simple pursuit of market signals by professional layout optimization, while ignoring the fundamental task of moral education in colleges and universities. α, β and γ are the adjustment parameters. The formula shows that professional optimization is not a one-way concentration to high-demand majors, but a relative balance between demand adaptation, structural deviation correction and education orientation maintenance. As shown in Figure 1, this section forms the analysis chain of "multi-source data access - feature standardization - professional vector construction - demand vector generation - matching degree calculation - priority output".

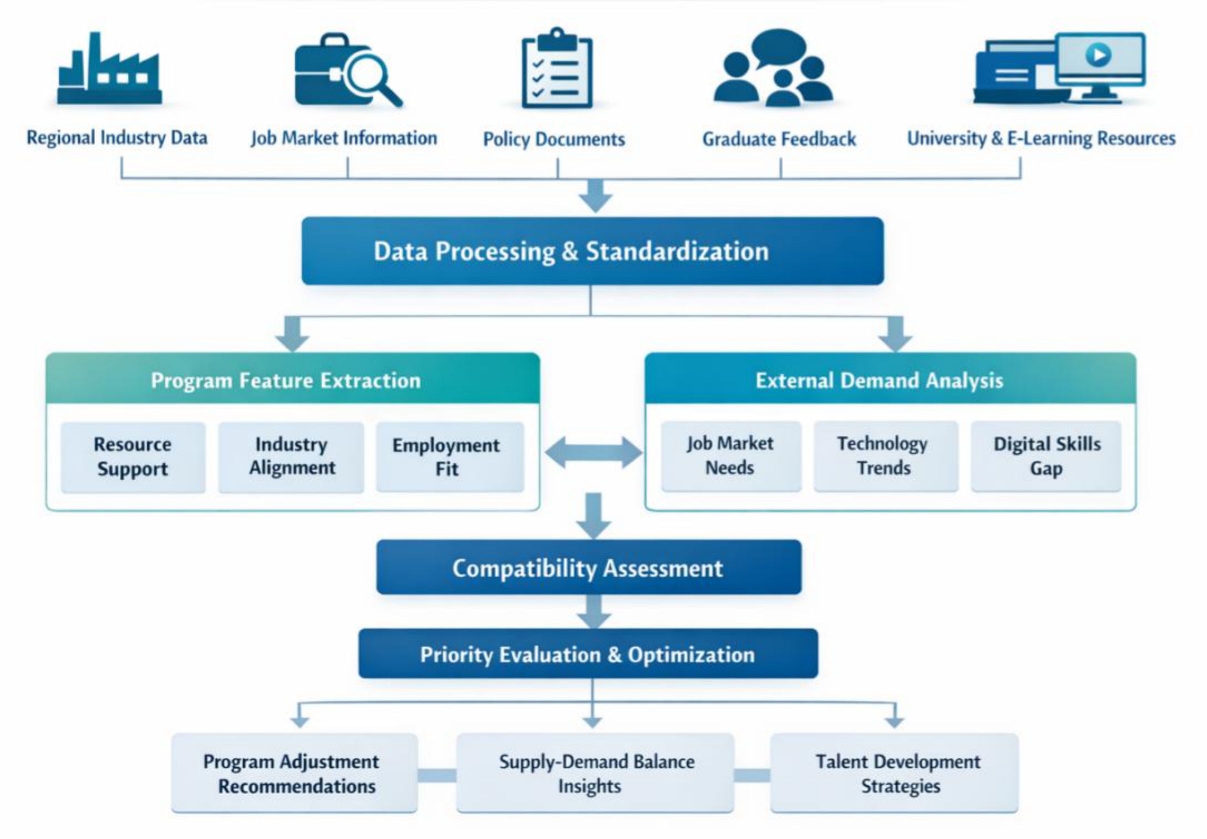

Figure 1: Characteristic representation and demand analysis framework of specialty layout in colleges and universities

3.2 Network ideological and political embedding mechanism and intelligent optimization model design

After completing the feature representation and demand analysis of specialty layout in colleges and universities, there is a key problem to be further solved: how to enter the process of specialty layout optimization and form stable computational constraints without destroying the logic of specialty development. Professional adjustment under the background of digital economy is not just a passive response to industrial needs. If the model only seeks to match jobs, expand enrollment or improve resource utilization, it is easy to marginalize the education goal in the optimization process. Based on this, this paper regards network ideological and political affairs as structural variables that can be embedded, transmitted and evaluated, and introduces them into the professional optimization model to realize embedded intelligent optimization through the way of "content mappingweight distribution-target constraint-iterative correction".

Assuming that the course units, practical links, platform resources and online teaching activities of major i together constitute the ideological and political bearing set S_i, its network ideological and political embedding strength is defined as follows.

$$E_i = \frac{1}{|S_i|}\sum_{j=1}^{|S_i|} \rho_{ij}\ q_{ij} \tag{6}$$

Here, ρ_{ij} represents the association weight between the JTH teaching unit and the ideological and political goals, and q_{ij} represents the implementable quality of the unit in the network environment. A larger E_i indicates that the major has a strong ideological and political embedding foundation in digital platforms, curriculum resources and teaching organizations.

To avoid network ideology and politics being treated as simple plus points in the model, this paper further introduces a gated fusion mechanism to jointly encode the professional layout vector f_i and the ideological and political embedding strength E_i obtained in Section 3.1. Its fusion is expressed as follows.

$$z_i = \delta_i f_i + (1 - \delta_i) g_i \tag{7}$$

Here, g_i is the ideological and political embedding extension vector, and δ_i is the adaptive gating coefficient. The coefficient is determined by the degree of professional response to the industry and the carrying capacity of education, which can be written as follows.

$$\delta_i = \frac{1}{1 + \exp[-(w^\top f_i + \mu E_i + b)]} \tag{8}$$

where, w, μ and b are the parameters to be learned. The effect of this design is that when a certain professional industry has high suitability but the ideological and political embedding foundation is weak, the model will automatically enhance the influence of education constraints. On the contrary, if a major has strong network ideological and political support, it retains the leading role of its original layout characteristics.

As shown in Figure 2, the model constructed in this paper consists of a data input layer, an ideological and political embedding layer, a feature fusion layer, a multi-objective optimization layer, and a decision output layer. The data input layer receives industry demand, professional operation, student development and network teaching data. The ideological and political embedding layer completes the identification and strength calculation of ideological and political nodes. Feature fusion layer generates unified professional representation. The multi-objective optimization layer jointly solved the problem among demand adaptation, structure balance and education orientation. The output layer gives suggestions for professional expansion, adjustment, integration and key construction.

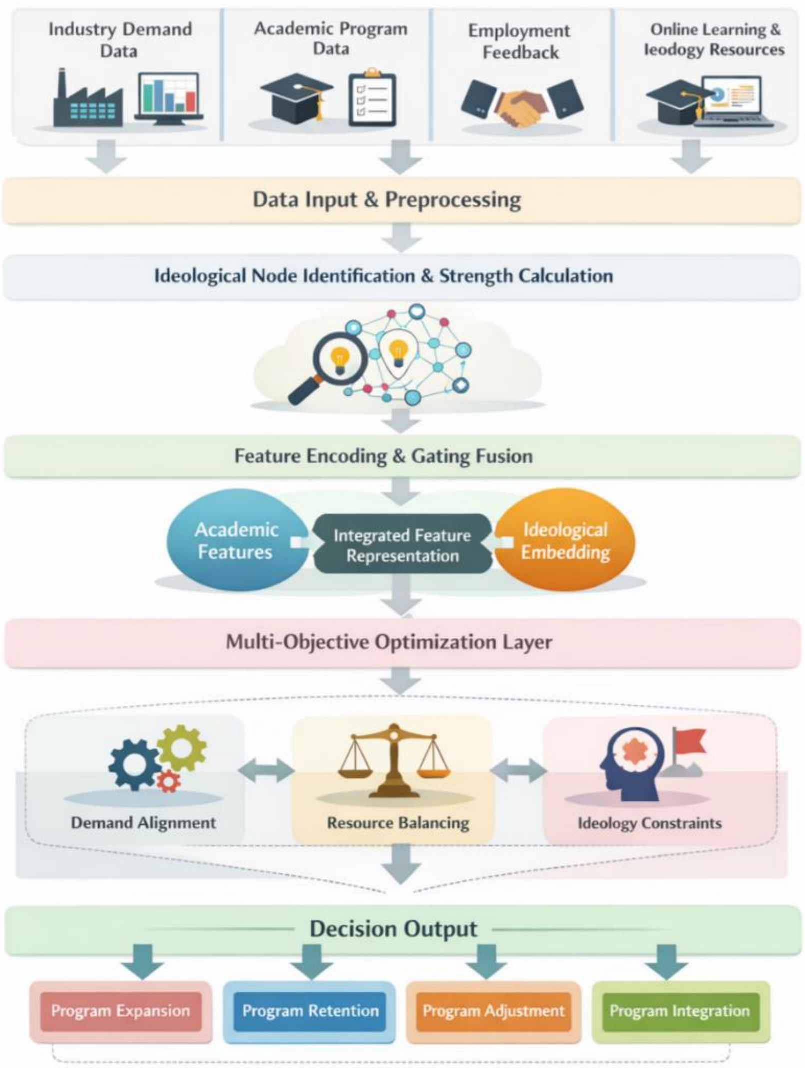

Figure 2: Structure of network ideological and political embedded intelligent optimization model

In terms of optimization objective design, this paper does not adopt a single benefit maximization method, but constructs a multi-objective joint function:

$$\mathcal{L} = \lambda_1 \mathcal{L}_d + \lambda_2 \mathcal{L}_b + \lambda_3 \mathcal{L}_e \tag{9}$$

Among them, $\mathcal{L}_d$ represents the deviation loss between professional layout and digital economy demand, $\mathcal{L}_b$ represents the loss of resource allocation and structural balance, $\mathcal{L}_e$ represents the deviation loss of education caused by insufficient ideological and political embedding in the network, and $\lambda_1, \lambda_2, \lambda_3$ are weight coefficients. In order to improve the stability of the solution, this paper adopts an iterative strategy based on the combination of gradient update and constraint correction, and the parameter update rule is as follows.

$$\Theta^{(t+1)} = \Theta^{(t)} - \eta \nabla \mathcal{L}(\Theta^{(t)}) + \xi \Omega^{(t)} \tag{10}$$

Here, $\Theta^{(t)}$ is the model parameter at the TTH iteration, η is the learning rate, $\Omega^{(t)}$ is the constraint correction term, and ξ is its adjustment coefficient. This item is used to suppress the excessive expansion of some majors due to the fluctuation of external demand in the optimization process, and to ensure the necessary stability and continuity of the professional layout adjustment.Therefore, network ideology and politics are no longer outside the professional layout model, but enter the decision-making process at the same time in three ways: pre-embedding variables, fusion features and optimization constraints.

4 Optimization method design of specialty layout in colleges and universities for digital economy transformation

The adjustment of major layout is not an isolated judgment of a single major, but a linkage configuration between enrollment scale, curriculum resources, teacher ability, industrial suitability and education orientation. Therefore, this paper designs the optimization method as a continuous solution process of "candidate generation, multi-objective evaluation, constraint correction, iterative update, and result output", and makes the network ideological and political embedding requirements run through the whole process of professional adjustment. Its overall process is shown in Figure 3. The goal of this method is not only to identify which majors need to be expanded or compressed, but more importantly to form a set of optimization mechanisms for the layout of majors that can be continuously updated under the changing needs of the digital economy.

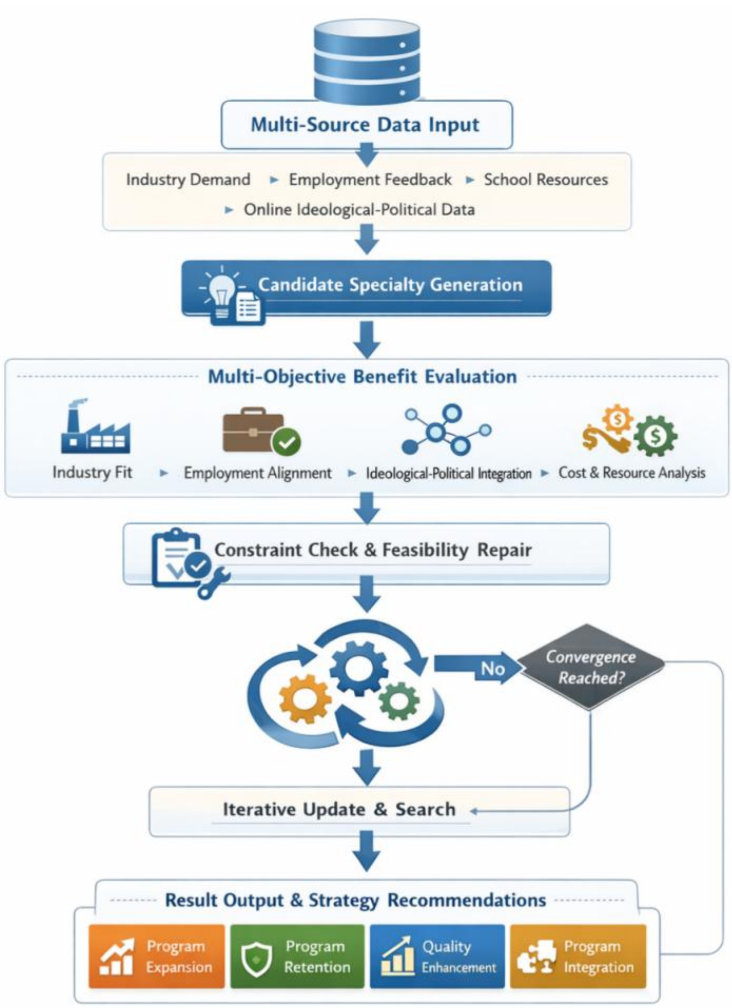

Figure 3: Process of professional layout optimization method

Let the set of existing majors in universities be $\mathcal{A} = \{a_1, a_2, \ldots, a_n\}$, and the corresponding layout decision vector is denoted as:

$$x = [x_1, x_2, \ldots, x_n]^T \tag{11}$$

where $x_i \in [-1,1]$ represents the adjustment direction and intensity of professional a_i, $x_i > 0$ represents expansion or key construction, $x_i < 0$ represents compression or integration, and $x_i = 0$ represents maintaining the status quo. In order to comprehensively measure the allocation value of different majors in the transformation of digital economy, this paper defines the comprehensive income function of a single major as follows.

$$R_i = \phi_1 c_i + \phi_2 e_i + \phi_3 u_i + \phi_4 E_i - \phi_5 k_i \tag{12}$$

where c_i is the degree of industrial correlation, e_i is the degree of employment suitability, u_i is the update elasticity, E_i is the strength of network ideological and political embedding, k_i is the cost required for the adjustment of the major, $\phi_1 \sim \phi_5$ are weight parameters. This formula integrates the originally scattered school-running benefits, social needs and education requirements into a unified evaluation framework to avoid professional optimization being simplified into a single employment orientation or a single scale orientation. At the overall solution level, this paper constructs the objective function of professional layout optimization:

$$\max F(x) = \sum_{i=1}^{n} x_i R_i - \psi \sum_{i=1}^{n} |x_i - \bar{x}| \tag{13}$$

where, the former term represents the comprehensive benefits brought by professional adjustment, the latter term is used to suppress the structural imbalance caused by excessive layout fluctuations, ψ is the balance coefficient, and $\bar{x}$ is the average adjustment amplitude. The reason for this is that the adjustment of professional structure in colleges and universities usually has path dependence and organizational inertia. If a round of optimization is excessively concentrated in hot areas, it is easy to cause problems such as imbalance of course supply, resource crowding and talent training chain breakage.

As shown in Figure 3, when the algorithm runs, it first generates candidate adjustment sets according to industry demand prediction, graduate feedback data and school resources, and then calculates the comprehensive income and constraint state for each major, and then enters the iterative update stage. To ensure the feasibility of the solution, the joint projection rule of resource constraint and scale constraint is set as follows.

$$x^{(t+1)} = \Pi_{\mathcal{C}}\left(x^{(t)} + \eta \nabla F(x^{(t)})\right) \tag{14}$$

Here, $\Pi_{\mathcal{C}}(\cdot)$ denotes the projection operator on the constraint set C, and η is the iteration step. This formula means that after each round of update, the system will remap the decision results to the executable space to meet the realistic conditions such as the total number of students, the load of teachers, the capacity of the platform and the integrity of the curriculum system. If the difference between the results of two successive iterations is lower than the threshold ε, the algorithm is considered to converge, and the judgment condition is as follows.

$$\left\| x^{(t+1)} - x^{(t)} \right\|_2 < \varepsilon \tag{15}$$

After convergence is reached, the system outputs four kinds of suggestions: professional expansion, retention, optimization and promotion, and integration and adjustment, and synchronously generates a list of network ideological and political embedding and strengthening, which is used to support the implementation of subsequent systems. Compared with the traditional professional adjustment method relying on expert experience, this method can integrate demand identification, benefit evaluation, constraint control and education orientation into a continuous calculation process, and provide a clear method basis for subsequent system design and experimental verification.

5 Design and implementation of professional layout optimization system in Colleges and Universities under the network Ideological and political embedding

The embedded intelligent optimization model constructed in the previous section needs to be further transformed into a deployable, callable and traceable system form in order to truly serve the professional adjustment decision of colleges and universities. The optimization of major layout is not a one-time calculation task, but a dynamic process of continuous revision with the change of industrial structure, the fluctuation of enrollment feedback, the update of course operation status, and the evolution of network ideological and political implementation effects. If the system only undertakes the function of result display, it is difficult to support colleges and universities to carry out continuous decision-making in complex situations. Based on this consideration, this paper integrates data access, state representation, model solving, result pushing and manual feedback into a unified operation link, and constructs a college specialty layout optimization system under network ideological and political embedding. The overall structure is shown in Figure 4.

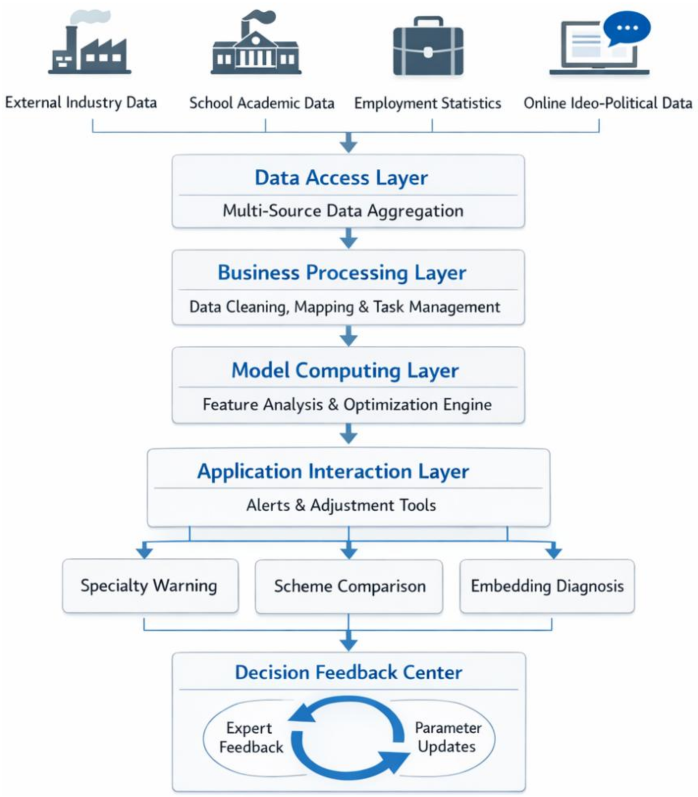

Figure 4: System structure of specialty layout optimization in colleges and universities under network ideological and political embedding

The system adopts "four layers and one center" architecture, including data access layer, business processing layer, model calculation layer, application interaction layer and decision feedback center. The data access layer is responsible for gathering professional construction data, employment destination data, regional industry demand data, online course operation data and network ideological and political resources data. The business processing layer undertakes tasks such as data cleaning, label mapping, permission verification and task scheduling. The model calculation layer calls the feature representation model and optimization method constructed in Chapter 3 and Chapter 4 to calculate the professional state in a unified way. The application interaction layer provides professional early warning, layout adjustment, ideological and political embedded diagnosis and scheme comparison functions for managers. The decision feedback center records the manual correction results and updates the model parameters reversely. Figure 4 illustrates the closed-loop relationship of the system from the multi-source data entry to the result feedback backflow. In order to ensure that the multi-source data has a unified expression form within the system, let the system input matrix at time t be:

$$X^{(t)} = [x_1^{(t)}, x_2^{(t)}, \dots, x_n^{(t)}] \tag{16}$$

where $x_i^{(t)}$ represents the state vector of major i at time t, which contains information such as resource input, industrial demand, employment feedback, course operation, and ideological and political embedding. The system compresses data from different sources into a unified state representation through the fusion operator:

$$h_i^{(t)} = \theta_1 r_i^{(t)} + \theta_2 d_i^{(t)} + \theta_3 y_i^{(t)} + \theta_4 s_i^{(t)} \tag{17}$$

where, $r_i^{(t)}$ is the resource state vector, $d_i^{(t)}$ is the industry demand state vector, $y_i^{(t)}$ is the employment feedback state vector, $s_i^{(t)}$ is the network ideological and political state vector, and $\theta_1 \sim \theta_4$ is the fusion weight. This representation can transform heterogeneous data originally distributed in different business platforms into professional runtime representations that can be uniformly invoked by models, thereby improving the consistency and scalability of system analysis.

In the actual implementation process, the system divided the professional adjustment suggestions into four categories: expansion, steady state, optimization and improvement, and integration and reconstruction. In order to reduce the strong dependence on experience in management judgment, this paper sets up a professional adjustment trigger score:

$$G_i^{(t)} = \kappa_1 P_i^{(t)} + \kappa_2 E_i^{(t)} - \kappa_3 B_i^{(t)} \tag{18}$$

where $P_i^{(t)}$ is the professional priority index, $E_i^{(t)}$ is the effectiveness of network ideological and political embedding, $B_i^{(t)}$ is the deviation of resource load, and $\kappa_1, \kappa_2, \kappa_3$ are the adjustment coefficients. When $G_i^{(t)}$ exceeds the preset threshold, the system triggers the key construction or expansion proposal. When it is in the middle range, the system outputs maintenance and local optimization suggestions. When it persistently falls below the lower bound of the threshold, it enters the integrated warning queue. In order to evaluate the degree of agreement between the system output results and the human decision, the scheme acceptance agreement rate is further defined as follows.

$$A = \frac{N_{acc}}{N_{all}} \tag{19}$$

where N_{acc} represents the number of suggestions adopted by management and N_{all} represents the total number of suggestions output by the system. This index can be used to measure the acceptability and application value of the system in real management scenarios.

Around the above operation logic, the system forms a number of interrelated business modules at the functional level. The inputs, outputs and functions of the relevant modules are shown in Table 2. Table 2 is not a simple list of function names, but corresponds to the complete implementation chain of the system from data aggregation, feature calculation, intelligent solution to feedback update. With this modular design, the system can not only support the structural optimization of the professional layout, but also identify the weak nodes in the network ideological and political embedding.

Table 2: System core functional modules and their roles

Module Name	Main Input	Main Output	Functional Role
Data access module	Industry, employment, teaching, and ideological-political data	Unified-format data stream	Completes multi-source data aggregation and standardization
Feature computation module	Specialty status data	Comprehensive specialty representation vector	Supports subsequent model computation
Optimization solving module	Representation vectors and constraint parameters	Specialty adjustment recommendations	Outputs results such as expansion, maintenance, and integration
Ideological-political diagnosis module	Course and platform operation records	Identification of embedding intensity and weak points	Identifies weaknesses in online ideological and political education
Visualization and interaction module	Model results and historical records	Charts, warnings, and comparison pages	Supports management decision-making and scheme interpretation
Feedback update module	Manual adoption results	Parameter revision information	Improves the system's continuous adaptability

In terms of deployment mode, the front-end of the system uses a visual dashboard to show the changes in professional popularity, the deviation trend of supply and demand, and the ideological and political embedding distribution. The back-end uses a service interface to encapsulate the core functions of feature extraction, optimization solution and result writeback, so that different colleges and management departments can call analysis results on a unified platform and retain operation traces. In this way, the system implementation is no longer just an external display of the model results, but an organization of the network ideological and political embedding requirements, professional layout optimization logic and management feedback mechanism into a circulable digital platform, which provides a clear system foundation for subsequent experimental testing.

6 Experimental results and analysis

6.1 Performance test of embedded intelligent optimization model

In order to test the effectiveness of the embedded intelligent optimization model constructed in this paper in the adjustment of university major layout, the experiment selects the major construction data, the destination data of graduates, the job demand data of regional digital industry, and the data of online courses and network ideological and political resources of 12 universities in Fujian province from 2020 to 2024, forming 864 "major-year" samples. According to the professional adjustment results, the samples were marked as four categories: expansion and construction, maintaining stability, optimization and promotion, and integration and adjustment, and the training set, validation set and test set were divided according to 7:1:2. The comparison models include optimization model without Ideological and political Constraints (No-Embed), XGBoost, MLP and expert scoring based on artificial rules. The evaluation indicators are Accuracy, Macro-F1, High-Priority Recall and AUC, which are used to investigate the performance of the model in overall recognition, class balance and key specialty discrimination at the same time.

The proposed model has strong adaptability in multi-source heterogeneous data processing. Compared with traditional methods that rely on a single statistical index, the model does not regard professional layout as a simple scale ranking problem, but integrates industrial demand, resource load, employment feedback and network ideological and political embedding status into a unified solution framework. The test results show that after adding the network ideological and political embedding, the model is more stable in high-priority professional identification, and the discrimination of the extended construction class and the optimization promotion class samples is closer to the actual decision-making scenario. The reason is that after the network ideological and political variables enter the model, it not only makes up for the problem of excessive emphasis on market signals in professional evaluation, but also improves the model's ability to identify long-term education orientation.

From the perspective of the iterative process, the proposed model is superior to other methods in terms of the convergence speed of the objective function and the later fluctuation control. Figure 5 shows the changes in the target scores of different models within 60 iterations. It can be seen that the model in this paper has reached 0.75 after the 20th round, increased to 0.86 in the 40th round, and stabilized near 0.89 after the 50th round. The No-Embed model finally converged to 0.81, XGBoost was stable at 0.76, MLP was stable at 0.74, and the expert scoring method stayed at about 0.60 for a long time. This result shows that the embedded design not only improves the optimization upper bound, but also improves the stability of the model under continuous update. Further statistics show that the standard deviation of the proposed model in the last 10 iterations is only 0.011, which is significantly lower than 0.024 of the No-Embed model and 0.029 of the MLP, indicating that the output results of the proposed model are more suitable for practical professional layout adjustment.

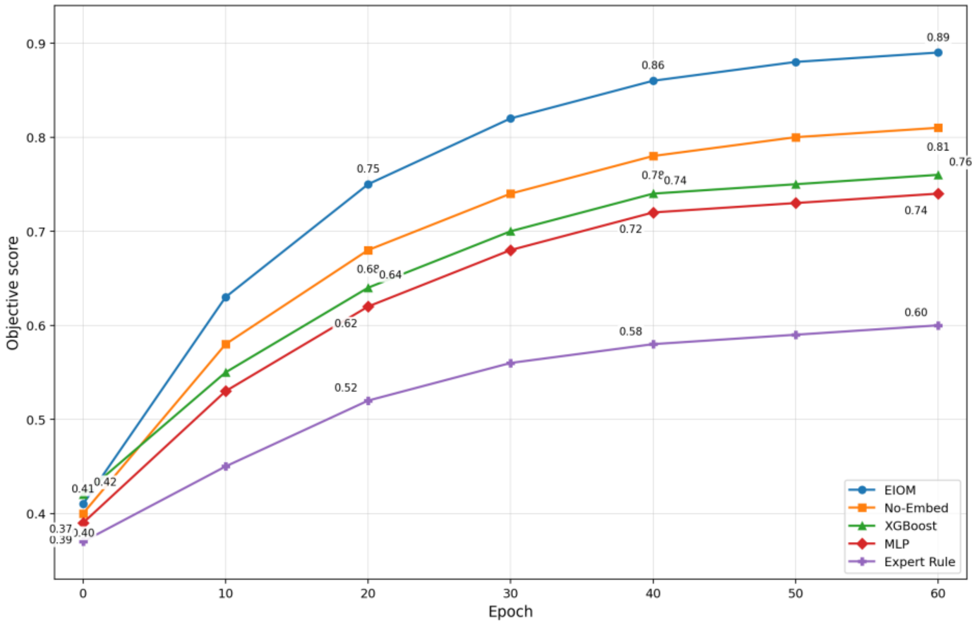

Figure 5: Convergence results of target scores for different models

In terms of classification performance, the proposed model also shows obvious advantages. Figure 6 illustrates the main metrics of different models on the test set. The Accuracy of the model in this paper reaches 89.3%, Macro-F1 is 87.6%, High-Priority Recall is 85.1%, and AUC is 0.928, which are the highest in each group. Compared with No-Embed model, it increases by 4.6 percentage points, 5.5 percentage points, 6.7 percentage points and 0.047 respectively. Compared with XGBoost, it is increased by 6.4 percentage points, 7.3 percentage points, 9.5 percentage points and 0.061 respectively. It is worth noting that the improvement of High-Priority Recall is of more practical significance, because the optimization of professional layout in colleges and universities pays more attention to the accurate identification of key construction directions and potential adjustment directions, rather than only pursuing the overall classification accuracy. The superiority of the proposed model in this indicator indicates that it is more sensitive to the identification of key specialties in the transformation of the digital economy.

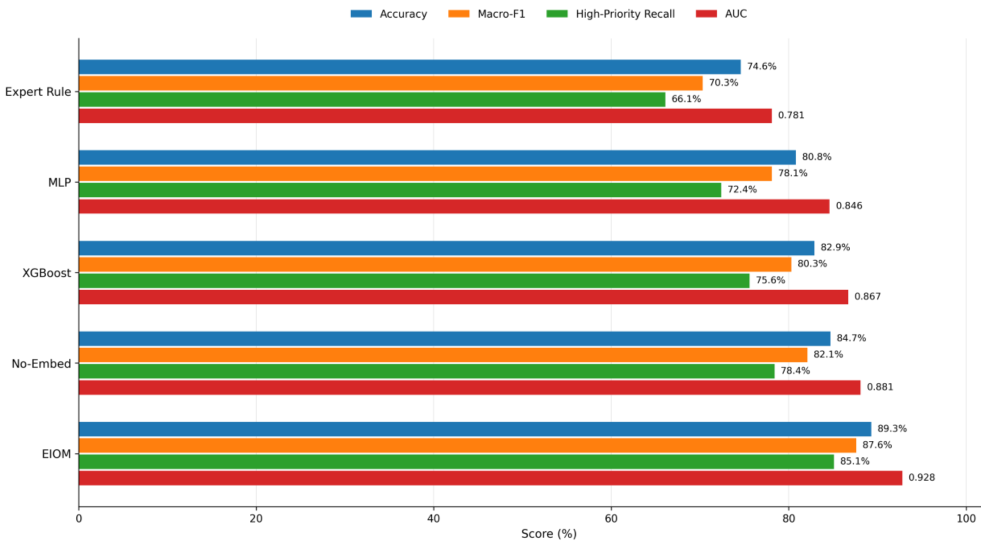

Figure 6: Comparison of test set performance of different models

From the results distribution, there is no significant difference between the proposed model and other methods in the recognition of the samples of "maintaining stability", but the judgment of the two samples of "expanding construction" and "optimization and promotion" is more accurate. The average recognition accuracy of the proposed model on these samples reaches 88.5%, which is higher than 82.9% of No-Embed model and 80.6% of XGBoost. This shows that the advantage of the model does not only come from the fitting of the majority class samples, but is reflected in the identification of the key objects of structural adjustment. At the same time, the average decision time of a single round of the model in this paper is 0.18 s, which is slightly higher than 0.11 s of XGBoost, but significantly lower than 1.34 s of multi-round artificial rule evaluation, which still has good real-time analysis ability.

6.2 Test of professional layout optimization system in Colleges and universities

System test is an important part to verify whether the platform can support the stable operation of the business. In this section, the functional test and typical business process verification are combined to comprehensively test the professional layout optimization system in colleges and universities constructed in this paper. The test focus is not on the interface display itself, but on the usability and stability of the system in the links of data access, professional diagnosis, scheme generation, ideological and political embedding recognition, and result writeback.

The test environment is deployed on an Ubuntu 22.04 server, the backend uses Python 3.11, FastAPI and Nginx, the data layer uses PostgreSQL 14 and Redis 7.0, and the pressure test tool is Apache JMeter 5.6.3. The test data comes from the professional construction, graduate flow, regional industry demand and online course operation records of 12 universities in the past five years, covering 72 undergraduate majors, 186,000 course behavior records and 34,000 employment feedback records. The system test is divided into two parts: one is functional test under black box condition, and the other is performance test under concurrent load. The functional test is based on the input, processing, and output as expected, and the performance test is based on the average response time, P95 response time, throughput, request success rate, and recommended refresh delay.

From the perspective of functional operation, each core module of the system can complete the preset task, and the output results are basically consistent with the manual verification results. The eight core functions of login authentication, professional data import, feature calculation, optimization solution, ideological and political diagnosis, early warning push, historical scheme comparison and feedback writing back all passed the test. The feature calculation module can automatically fill in the missing fields in the case of incomplete multi-source data, and the success rate of missing repair reaches 96.8%. The optimization solution module did not break in 20 consecutive rounds of scheme generation tests. The ideological and political diagnosis module can identify the problems of insufficient value guidance nodes, weak platform interaction chain, and low frequency of ideological and political material invocation in curriculum resources. Table 3 presents the main functional test results. It can be seen that except for the average response time of the "historical scheme comparison" module, which is slightly higher, the other functions remain within 2.5 s, and the overall operation is relatively stable.

Table 3: Main functional test results of the system

Functional Module	Number of Tests	Average Response Time / s	Success Rate / %	Result Description
User login and permission verification	100	0.34	100.0	Role identification was accurate, and all unauthorized access attempts were blocked
Specialty data import	80	1.27	98.8	Supports batch import, and abnormal fields can be automatically flagged
Feature computation and standardization	60	2.14	100.0	Multi-source indicator calculation results were consistent with manual verification
Optimization scheme generation	50	2.46	100.0	Can output recommendations for expansion, retention, optimization, and integration
Online ideological-political embedding diagnosis	50	2.21	98.0	Can identify weak resource nodes and disconnections between courses
Warning push and result display	60	0.59	100.0	Page refresh operated normally, and message delivery had no omissions
Historical scheme comparison	40	2.83	97.5	Cross-year comparison was correct, though response was slightly slower for some large files
Feedback write-back and parameter update	40	0.73	100.0	Manual revisions can be written back and used to update model parameters

In order to further observe the performance of the system in real business, this paper selects the 2024 digital economy related professional layout adjustment task of an application-oriented university as a typical test object. The majors in the test include data science and big data technology, e-commerce, information management and information system, digital media technology, financial engineering, and logistics management. After receiving the job demand of regional digital industry, the employment quality of graduates, the coverage rate of curriculum resources and the network ideological and political embedding indicators, the system generates comprehensive priority scores for each major, and gives corresponding adjustment suggestions. The results showed that the comprehensive priority scores of data science and big data technology, e-commerce and digital media technology reached 0.91, 0.86 and 0.79, respectively, and the system suggested that it should be included in the key construction and expansion sequence. The score of information management and information system was 0.71, and the optimization scheme of "maintaining the main direction and strengthening the curriculum update" was suggested. Financial engineering and logistics management scored 0.63 and 0.60, respectively, and the system suggested maintaining the scale but strengthening the restructuring of courses related to digital platform operation and data analysis capabilities. At the same time, in the diagnosis of network ideological and political embedding, the system finds that the industry ethical case resources of e-commerce majors are rich, and the embedding effectiveness reaches 0.82. Although the industry matching degree of data science and big data technology majors is high, the ideological and political embedding effectiveness is only 0.68, and the main shortcomings focus on the insufficient coverage of data ethics, algorithmic responsibility and platform governance issues. The relevant results are shown in Figure 7.

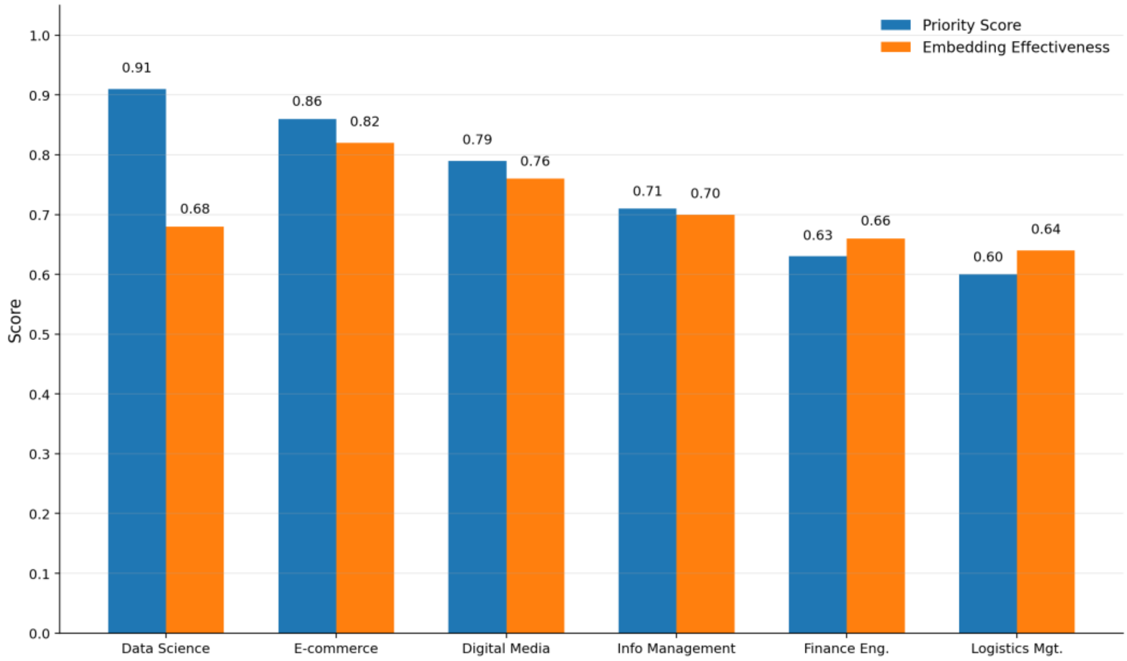

Figure 7: Test results of specialty layout optimization in typical colleges and universities

Figure 7 shows that the system does not simply give homogeneous enrollment expansion suggestions based on the industry popularity, but takes professional development potential and network ideological and political embedding conditions into consideration. Although the major of data science and big data technology had the highest total score, the system did not directly determine them as the object of "unconditional expansion", but gave the prompt of "strengthening the content of data ethics and technical responsibility" simultaneously. Due to the high industrial suitability and ideological and political embedding effectiveness of e-commerce major, its construction priority is more stable. The results show that the system can deal with the logic of professional development and education orientation in the same decision-making interface, which is significantly different from the traditional management method that only looks at the employment rate or enrollment scale.

In terms of concurrent performance, the system shows better carrying capacity. In this paper, the number of concurrent users is set to 50, 100, 150, 200 and 250, and continuous pressure measurement is carried out for 20 min to calculate various performance indicators. The results show that when the number of concurrency increases from 50 to 250, the average response time increases from 0.62 s to 1.89 s, the P95 response time increases from 1.08 s to 2.96 s, and the throughput increases from 82 req$\cdot$s^{-1} to 238 req$\cdot$s^{-1}. The request success rate always remains above 99.1%. The overall interaction response was kept within an acceptable range. Figure 8 illustrates how the main performance metrics of the system change under concurrent load. It can be seen that with the rise of access pressure, the response time increases, but the overall curve is relatively smooth, there is no sudden jitter and a wide range of timeouts. Especially within 200 concurrent, the average response time is always less than 1.5s, which can meet the daily use needs of the university management platform.

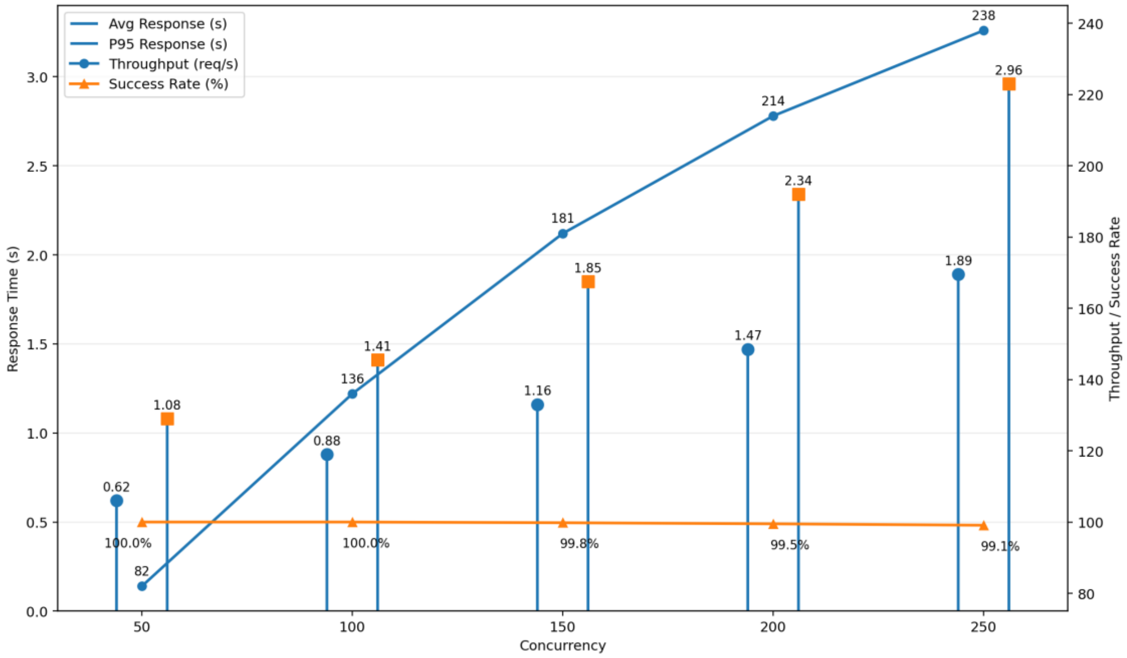

Figure 8: System performance variation under concurrent load

Combined with the results of functional test and stress test, the system has three characteristics. First, the core business chain is complete, and the connection between data import, feature calculation, scheme generation and feedback update is smooth, and there is no task interruption caused by improper module coupling. Second, the system output has good business interpretation, which can give structural adjustment suggestions and network ideological and political improvement directions for different majors at the same time, rather than only generating a single ranking result. Third, the platform still maintains a high success rate and low delay under medium and high concurrency conditions, indicating that it has the technical foundation for landing application in school-level management scenarios.

7 Conclusions

Focusing on the problem of professional layout adjustment and network ideological and political collaboration embedding under the condition of digital economy transformation, this paper constructs an embedded intelligent optimization model for multi-source education data. On this basis, the optimization method design, system implementation and experimental verification are completed. The research shows that after the industrial demand, professional construction foundation, employment feedback, course operation status and network ideological and political resources are integrated into the unified computing framework, the adaptation strengths and weaknesses in the professional structure of colleges and universities can be more accurately identified, and then the pertineness and interpretability of the professional layout adjustment can be improved. The experimental results show that the proposed model is superior to the comparison methods in terms of accuracy, macro average F1 value, high priority identification ability and system operation stability, which indicates that network ideological and political education is not an external additional variable in the process of professional optimization, but an important constraint and value dimension that can participate in decision making.

At the same time, the system constructed in this paper has the functions of data access, feature calculation, scheme generation, embedded diagnosis and feedback reflux, which can provide relatively complete auxiliary decision support for university management departments. However, it should also be noted that there are still some limitations in this study. Firstly, the sample sources mainly focus on the data of regional universities, and the heterogeneity between cross-regions and cross-types of universities still needs to be further verified. Secondly, although the quantitative expression of the network ideological and political embedding effect improves the computability of the model, the deep description of the education effect still needs to be improved by combining longer period tracking data. Third, the system is currently more suitable for structure diagnosis and scheme recommendation, and there is still room for expansion of policy interaction analysis in complex management situations.

The follow-up research can be further deepened in three directions. First, more abundant industrial real-time data and learning process data are introduced to enhance the responsiveness of the model to dynamic changes. The second is to further improve the accuracy of professional association identification and education factor modeling by combining knowledge graph, graph neural network and other methods. The third is to promote the continuous application of the system in more university scenarios, and constantly revise the parameters and rules through multiple rounds of feedback, so that the optimization of professional layout and network ideological and political construction in colleges and universities form a more stable coordination mechanism in the digital environment.

Acknowledgments

This research was supported by the 2025 University-level Scientific Research Fund Project (Special Fund for Online Ideological and Political Education) of Xiamen Institute of Technology (Grant No. KYZXSZ202503), titled Research on the Construction of the Basic Theoretical System of Online Ideological and Political Education.

This research is a phased achievement of the Higher Education Reform and Research Project of the Fujian Institute of Higher Education (Project No.: FGJY202513)

References

[1] Kholiavko N, Popelo O, Melnychenko A, et al. The role of higher education in the digital economy development[J]. Revista Tempos E Espaços Em Educação, 2022, 15(34): 3.

[2] Núñez-Canal M, de Obesso M M, Pérez-Rivero C A. New challenges in higher education: A study of the digital competence of educators in Covid times[J]. Technological Forecasting and Social Change, 2022, 174: 121270.

[3] de Obesso M M, Núñez-Canal M, Pérez-Rivero C A. How do students perceive educators' digital competence in higher education?[J]. Technological Forecasting and Social Change, 2023, 188: 122284.

[4] Zhao B, Zhou J. Research hotspots and trends in digitalization in higher education: A bibliometric analysis[J]. Heliyon, 2024, 10(21).

[5] de Villiers Scheepers M, Mulcahy R, Fleishman D, et al. Digital career competencies: A co-created scale for the digital employability competencies we’ve overlooked[J].

Industry and Higher Education, 2024, 38(5): 411-422.

[6] Tee P K, Wong L C, Dada M, et al. Demand for digital skills, skill gaps and graduate employability: Evidence from employers in Malaysia[J]. F1000Research, 2024, 13: 389.

[7] Håkansson Lindqvist M, Mozelius P, Jaldemark J, et al. Higher education transformation towards lifelong learning in a digital era–a scoping literature review[J]. International Journal of Lifelong Education, 2024, 43(1): 24-38.

[8] Yang C, Xu D, Yin S. Construction of moral education in college English with blended learning in the "internet+ era"[C]//SHS Web of Conferences. EDP Sciences, 2022, 140: 01036.

[9] Wei C. The Design and Exploration of Ideological and Political Teaching in College English under the Mixed Teaching Model[J]. Frontiers in Educational Research, 2023, 6(2).

[10] Zhang B. Practical Research of Ideological and Political Education in College English Course under the Background of New Liberal Arts[J]. OALib, 2023, 10(11): 1-18.

[11] Mei Z. Integration of curriculum ideology and politics in higher education: a case study of English linguistics in China[C]//Frontiers in Education. Frontiers Media SA, 2024, 9: 1389469.

[12] Cao W. Implementation of Ideological-political Education in College English Courses: A Perspective of Traditional Chinese Culture[J]. International Journal of New Developments in Education, 2024, 6(11).

[13] Chan C K Y. A comprehensive AI policy education framework for university teaching and learning[J]. International journal of educational technology in higher education, 2023, 20(1): 38.

[14] Marengo A, Pagano A, Pange J, et al. The educational value of artificial intelligence in higher education: A 10-year systematic literature review[J]. Interactive Technology and Smart Education, 2024, 21(4): 625-644.

[15] Castillo-Martínez I M, Flores-Bueno D, Gómez-Puente S M, et al. AI in higher education: A systematic literature review[C]//Frontiers in Education. Frontiers Media SA, 2024, 9: 1391485.

[16] Wagner K, Merceron A, Sauer P, et al. A Course Recommender System Built on Success to Support Students at Risk in Higher Education[J]. Journal of Educational Data Mining, 2024, 16(1): 330-364.

[17] Khan M A Z, Polyzou A. Session-based methods for course recommendation[J]. Journal of Educational Data Mining, 2024, 16(1): 164-196.

[18] Xue G, Offodile O F, Razavi R, et al. Addressing staffing challenges through improved planning: Demand-driven course schedule planning and instructor assignment in higher education[J]. Decision Support Systems, 2024, 187: 114345.

[19] Schuetze H G, de Vries W, Álvarez Mendiola G. Digitalization of Higher Education: An Introduction[J]. Journal of Comparative & International Higher Education, 2024, 16(2).

[20] Paños-Castro J, Korres O, Iriondo I, et al. Digital transformation and teaching innovation in higher education: A case study[J]. Education Sciences, 2024, 14(8): 820.

[21] Ličen S, Prosen M. Strengthening sustainable higher education with digital technologies: development and validation of a digital competence scale for university teachers (DCS-UT)[J]. Sustainability, 2024, 16(22): 9937.

[22] Dang T D, Phan T T, Vu T N Q, et al. Digital competence of lecturers and its impact on student learning value in higher education[J]. Heliyon, 2024, 10(17).