

Research on the Dynamic Adjustment of College Curriculum Content and Innovative Discipline Development Models Driven by Intelligent Education Systems

Yanjun Bu¹, Qi Gao²

¹Department of Public Education, Shanghai Customs University, Shanghai 201204, China

²School of Business Administration and Customs Affairs, Shanghai Customs University, Shanghai 201204, China

Corresponding author: Qi Gao (e-mail: qigao123452026@163.com)

ABSTRACT Against the dual background of digital transformation in education and the construction of new engineering and liberal arts disciplines, the lagging update of university curriculum content and rigid disciplinary development models increasingly restrict the cultivation of interdisciplinary engineering talents. This problem is particularly relevant to fast-evolving fields such as advanced electromagnetics, electromagnetic waves, antennas, and propagation, where curriculum systems must respond rapidly to technological iteration and industry demand. Based on big data analysis, artificial intelligence, and knowledge graph technology, this study designs a dynamic adjustment mechanism for university course content and an innovative discipline development model driven by intelligent education systems. The study diagnoses current problems through questionnaires, interviews, and document analysis, and then constructs a closed-loop framework including demand perception, content adaptation, dynamic update, and effect feedback. Industry demand data, student learning behavior, disciplinary trend data, and teaching process data are integrated to support curriculum optimization and interdisciplinary resource allocation. Empirical research across five universities verifies that intelligent education systems can improve curriculum responsiveness, enhance the fit between learning content and competence requirements, and support open, collaborative, and data-driven disciplinary development. The framework provides a practical reference for engineering education reform in advanced electromagnetic and related technical disciplines.

INDEX TERMS intelligent education system, curriculum adjustment, knowledge graph, antenna and propagation education, engineering education

I. INTRODUCTION

A. RESEARCH BACKGROUND

AS the core battlefield for talent cultivation and technological innovation, the higher education curriculum system and disciplinary development level directly determine the quality of graduates and their capacity to serve the evolving technical requirements of industrial manufacturing. By aligning academic rigor with advanced fiber science and intelligent processing technologies, universities can enhance their ability to drive innovation within the global t industry and provide the high-level expertise necessary for modern industrial upgrading. The “Work Points of the Ministry of Education in 2024” clearly proposes to “deepen the digital transformation of higher education, promote dynamic updates of course content and interdisciplinary integration, and cultivate innovative talents that meet the needs of new

quality productivity development. Currently, the development of courses and disciplines in Chinese universities still faces many structural challenges: firstly, the curriculum content lags behind. The update cycle of the curriculum system is long (usually 3-5 years), making it difficult to keep up with industry technological iterations and changes in social demands, resulting in a disconnect between learning and application; Secondly, the development of disciplines is solidified. Clear disciplinary boundaries, insufficient cross disciplinary integration, closed resource allocation, and difficulty in addressing complex social issues and cross disciplinary innovation needs; Thirdly, there is an imbalance in the matching of supply and demand. The curriculum design has a low degree of adaptation to students’ learning needs and weak abilities, and the development of disciplines is not closely linked to regional economy and industrial upgrading;

Fourthly, decision-making lacks data support. Curriculum adjustments and subject development planning rely heavily on empirical judgment, lacking precise data analysis of industry demands, learning patterns, and subject trends [1-3].

B. RESEARCH APPROACH

This article follows the technical route of “theoretical sorting - current situation diagnosis - scheme design - empirical verification - system improvement”:

Systematically sort out the core technologies of intelligent education systems and related theories of higher education, clarify the inherent compatibility between technology and curriculum, discipline development; Diagnose the existing problems in current university curriculum content and disciplinary development through methods such as questionnaire surveys, in-depth interviews, and literature analysis;

Based on an intelligent education system, design a dynamic adjustment mechanism for course content and an innovative model for subject development;

Conduct a 2-year empirical study on relevant disciplines and courses from 5 different types of universities to verify the effectiveness of the plan;

Based on empirical results, summarize key experiences, and improve the plan and implementation guidelines [4].

II. CORE CONCEPTS AND THEORETICAL FOUNDATIONS

A. DEFINITION OF CORE CONCEPTS

Data collection and integration: Collect multi-source data such as industry demand data, learning behavior data, subject development data, teaching process data, etc;

Intelligent analysis and prediction: Through technologies such as big data mining and machine learning, analyze demand trends, learning patterns, and disciplinary hotspots;

Accurate decision-making and recommendation: providing intelligent decision support and personalized recommendations for curriculum adjustment, teaching implementation, and subject planning;

Dynamic optimization and feedback: Continuously optimize course content, teaching methods, and subject development strategies based on effectiveness data.

Real time capability: able to quickly respond to industry technological iterations and changes in social demands;

Accuracy: Based on data, accurately locate course shortcomings and optimization directions;

Systematic: covering multiple levels such as curriculum system, individual courses, and teaching modules;

Closed loop: Form a closed-loop mechanism of “data collection analysis diagnosis adjustment implementation effect feedback continuous optimization” [5-6].

Cross disciplinary integration: breaking disciplinary boundaries, promoting the development of interdisciplinary, cross disciplinary, and emerging disciplines;

Data driven: Based on data analysis, formulate disciplinary development plans, resource allocation schemes, and talent cultivation strategies;

Collaborative innovation: building a collaborative discipline development ecosystem among universities, enterprises, research institutions, and government;

Open sharing: Achieving open sharing and collaborative utilization of disciplinary resources, faculty, and research achievements [7].

Technology empowerment refers to the intelligent education system providing technical support, methodological tools, and data basis for dynamic adjustment of course content and innovation of subject development models through functions such as data collection, intelligent analysis, and precise decision-making, promoting the transformation of course and subject development from “experience driven” to “data-driven” and “intelligent driven” [8-9].

III. DIAGNOSIS OF THE CURRENT STATUS OF CURRICULUM CONTENT AND DISCIPLINE DEVELOPMENT IN HIGHER EDUCATION INSTITUTIONS

A. DIAGNOSTIC DESIGN

1) Diagnostic Object

Select teachers, students, managers, and industry experts from 10 different types of universities (3 comprehensive universities, 3 science and engineering universities, 2 humanities universities, and 2 private universities) as diagnostic subjects:

Students: A total of 800 people, including 600 undergraduate students and 200 graduate students; Uniform distribution of different grades and majors;

University administrators: a total of 60 people, including the head of the academic affairs office, the head of discipline construction, and the dean of the secondary college;

Industry experts: A total of 40 people from multiple fields including information technology, advanced manufacturing, financial services, cultural creativity, etc [10].

2) Diagnostic Tools

In depth interview outline: Design a semi-structured interview outline and set differentiated questions for different targets:

Managers: Focus on curriculum system construction, discipline development planning, resource allocation, challenges faced, and policy needs;

Teacher: Focus on the difficulties in updating course content, teaching practice challenges, subject development participation experience, and intelligent technology application needs;

Industry experts: Focus on talent capability needs, industry technology iteration trends, and pain points in cooperation with universities.

Literature and data analysis method: Collect materials such as university curriculum plans, discipline development reports, talent cultivation quality reports, industry develop-

ment white papers, etc., and conduct content analysis and data mining [11-12].

3) Diagnostic Process

Questionnaire survey: An online questionnaire was distributed to 1200 survey respondents, and 1128 valid questionnaires were collected, with an effective response rate of 94.0%. Informed consent was obtained from all participants. No personally identifiable information was stored. **Literature and data analysis:** Collect relevant information and data from 10 universities and conduct systematic analysis;

Data processing: SPSS 26.0 was used for statistical analysis of questionnaire data, and Nvivo 12 was used for coding analysis of interview texts and literature data to comprehensively diagnose the current situation and problems [13].

B. CURRENT SITUATION ANALYSIS

1) Current Status of Course Content

Update frequency: 58.3% of courses have an update cycle of over 3 years, and only 15.7% of courses can achieve dynamic updates annually;

Content structure: 62.5% of students believe that the course content is overly theoretical and lacks practical application, while 57.8% of teachers indicate that interdisciplinary content integration is insufficient [14-15].

2) Current Status of Discipline Development

Integration level: 27.3% of disciplines have engaged in substantial interdisciplinary cooperation, while 65.8% of disciplines still focus on the development of a single discipline;

Resource allocation: 59.2% of managers believe that “disciplinary resource allocation is closed and lacks a sharing mechanism”, and 53.7% of teachers express “difficulties in obtaining interdisciplinary resources”;

Requirement docking: 36.5% of disciplines have established deep cooperative relationships with industry enterprises, and 48.9% of industry experts believe that “disciplinary research results are disconnected from industry demand”;

Development motivation: 42.8% of managers stated that “discipline development lacks data support and subjective planning”, while 39.5% of teachers believe that “discipline innovation motivation is insufficient and development models are rigid” [16].

3) Current Status of Intelligent Technology Applications

Application willingness: 78.5% of teachers expressed a willingness to use intelligent technology to optimize course content, while 69.3% of managers believe that intelligent technology can break through the bottleneck of subject development [17].

C. CORE PROBLEM DIAGNOSIS

Based on the diagnostic results, the core issues of current university curriculum content and discipline development can be summarized into the following four categories:

1) Course Content Level: Lag, Imbalance, and Lack of Adaptability

Lagging: The course update cycle is long, making it difficult to keep up with industry technological iterations and changes in social demand, resulting in a disconnect between learning and application;

Imbalance: Theoretical content is emphasized, practical and interdisciplinary content is insufficient, and the dimension of ability cultivation is single;

Lack of adaptability: The course design has a low degree of matching with students’ learning needs, weak abilities, and career development needs, and lacks personalized and precise design [18,19].

2) Disciplinary Development Level: Solidification, Closure, and Insufficient Synergy

Solidification: The development model of disciplines is rigid, lacks innovation motivation, and is difficult to adapt to cross disciplinary innovation needs;

Closure: Clear disciplinary boundaries, closed resource allocation, lack of sharing mechanisms, and constraints on cross disciplinary integration development;

Lack of synergy: The collaborative innovation mechanism between universities, enterprises, research institutions, and governments is not perfect, and the development of disciplines is not closely linked to industrial demand and regional economy.

3) Technical Empowerment Level: Shallow, Fragmented, and Insufficient Integration

Superficial functional application: Intelligent education systems mostly remain limited to peripheral pedagogical assistance, failing to achieve systemic structural integration for curriculum reconstruction and strategic disciplinary development planning;

Fragmentation: Technology applications are scattered and lack systematic integration, making it difficult to form synergies;

Lack of integration: Lack of methodology for deep integration of technology and education teaching, disconnection between technology application and curriculum and subject development needs.

4) Support and Guarantee Level: Insufficient System, Resources, and Capabilities

Insufficient institutional safeguards: Lack of incentive mechanisms, evaluation systems, and management systems for dynamic adjustment of courses and subject innovation;

Insufficient resource support: Insufficient investment in the construction of intelligent education systems, scattered data resources, and difficult integration;

Insufficient ability support: Teachers and managers lack the ability to apply intelligent technology and lack relevant training and guidance.

D. ANALYSIS OF THE CAUSES OF PROBLEMS

1) Conceptual Level

Institutional inertia and historical prioritization of static curricula: many higher education frameworks were structurally designed for a stable knowledge transfer era, where long-term pedagogical stability was valued over iterative flexibility, leading to a systemic underestimation of the need for real-time disciplinary evolution;

The concept of technological empowerment lags behind: the understanding of intelligent education systems is limited to tool applications, and the core driving role in curriculum restructuring and subject development has not been fully recognized.

2) Technical Aspect

The disconnect between technology research and education needs: Intelligent education systems are mostly developed by technology companies, lacking in-depth understanding of the development needs of university courses and disciplines;

Difficulty in data collection and integration: Educational data is scattered across different systems, with inconsistent standards, making it difficult to effectively integrate and deeply mine multi-source data;

The threshold for technological application is high: the complexity and professionalism of intelligent technology increase the difficulty of application for teachers and managers.

3) Institutional Level

The evaluation system is rigid: the evaluation of university courses and disciplines still relies mainly on traditional indicators, lacking incentives for dynamic adjustment, cross-border integration, and innovative development;

Insufficient incentive mechanism: The time cost for teachers to participate in curriculum reform and subject innovation is high, but there is a lack of corresponding incentive policies and insufficient enthusiasm;

Lagged management system: Lack of flexible management system that adapts to the dynamic adjustment of courses and subject innovation, and cumbersome approval process.

IV. DESIGN OF DYNAMIC ADJUSTMENT MECHANISM FOR COURSE CONTENT DRIVEN BY INTELLIGENT EDUCATION SYSTEM

A. DESIGN PRINCIPLES

1) Principle of Demand-Oriented Approach

Guided by industry demands, student demands, and disciplinary development needs, ensure precise alignment of course content adjustments with core demands.

2) Data-Driven Principle

Based on the analysis results of multi-source data in intelligent education systems, scientific decision-making and precise optimization of curriculum adjustment can be achieved, replacing traditional empirical judgment.

3) Systematic Principle

Covering multiple dimensions such as course objectives, teaching content, teaching methods, and evaluation methods, achieving comprehensive optimization of the curriculum system and avoiding one sidedness caused by local adjustments.

4) Principle of Dynamism

Establish a real-time data collection and continuous optimization mechanism to ensure that course content can quickly respond to changes in demand and technological iterations.

5) Feasibility Principle

Fully consider the actual situation of universities, such as technological conditions, teacher capabilities, and teaching resources, and design adjustment mechanisms that are easy to operate and cost controllable to ensure large-scale promotion and application.

B. OVERALL FRAMEWORK

The dynamic adjustment mechanism adopts a ‘four-wheel drive, closed-loop operation’ framework, including four core links: demand perception, content adaptation, dynamic updates, and effect feedback. To bridge the transition from perception to adaptation, the system generates an ‘Automated Curriculum Feasibility Report’ based on big data mining, which serves as the standardized evidence base for the university’s curriculum committee, effectively streamlining the administrative approval bottleneck by providing data-validated justifications for content restructuring. Each link is interconnected and coordinated through the intelligent education system, and the specific framework is shown in the table 1.

C. SPECIFIC MECHANISM DESIGN

1) Requirement Perception Mechanism: Requirement Identification through Multi-Source Data Fusion

Industry demand perception

Data collection: Integrate multiple sources of data such as industry white papers, corporate recruitment information, industry policy documents, and industry expert interviews through intelligent education systems;

Key outputs: List of industry core competency requirements, report on technology iteration trends, and suggestions for course content adjustments.

Student demand perception

Data collection: Collect student learning behavior data (learning duration, mastery of knowledge points, distribution

TABLE 1. Demographic Characteristics of the Sample

Core Link	Core Objective	Intelligent Technology Support	Key Tasks
Demand Perception	Accurately identify industry needs, student needs, and disciplinary needs	Big data analysis, natural language processing, demand prediction model	Industry demand mining, student demand diagnosis, disciplinary trend analysis
Content Adaptation	Optimize curriculum objectives, content, and methods based on needs	Knowledge graph, personalized recommendation, intelligent matching algorithm	Curriculum objective adjustment, teaching content restructuring, teaching method innovation
Dynamic Update	Realize real-time optimization and continuous iteration of curriculum system	Online course platform, content management system, version control	Curriculum module update, teaching resource supplementation, textbook content revision
Effect Feedback	Evaluate adjustment effects and optimize adjustment strategies	Learning analytics, effect evaluation model, feedback recommendation algorithm	Learning effect monitoring, demand matching degree evaluation, adjustment strategy optimization

of homework errors), learning preference data (learning methods, content interests), career planning data, and satisfaction feedback data through an intelligent education system;

Technical support: Using learning analysis techniques to diagnose students' ability gaps, analyzing students' learning preferences through collaborative filtering algorithms, and constructing student demand profiles;

Key outputs: Report on student skill gaps, learning needs profile, personalized course adjustment suggestions. Perception of disciplinary needs

Data collection: Integrate subject literature data, research project data, academic conference data, and subject evaluation data through intelligent education systems;

Technical support: Adopting bibliometric analysis technology to identify research hotspots and development trends in disciplines, and presenting disciplinary knowledge associations through knowledge graph technology;

Key outputs: disciplinary development trend report, interdisciplinary knowledge integration points, and suggestions for deepening course content.

2) Content Adaptation Mechanism: Intelligent Matching Course Optimization

Adjustment of course objectives Based on industry demands and disciplinary trends, intelligently adjust the knowledge objectives, ability objectives, and literacy objectives of the curriculum to ensure precise alignment between objectives and demands;

For example, in response to the talent demand in the artificial intelligence industry, goals such as "machine learning engineering practice" and "artificial intelligence ethics" are added to computer science courses. Reconstruction of teaching content

Knowledge Graph Support: Construct disciplinary and curriculum knowledge graphs to clarify hierarchical structures. Before these graphs influence student learning paths, they undergo a 'Dual-Verification Protocol' involving cross-validation against peer-reviewed academic databases and a final audit by a panel of subject matter experts to ensure pedagogical accuracy and logical integrity;

Content screening and integration: Based on demand perception results, intelligently screen core knowledge points, supplement cutting-edge knowledge points, integrate in-

terdisciplinary knowledge points, and eliminate outdated knowledge points;

Modular design: Split the course content into basic modules, core modules, cutting-edge modules, and practical modules, supporting personalized combinations and dynamic updates.

Innovation in teaching methods Based on students' learning preferences and skill gaps, intelligent recommendation of suitable teaching methods, such as case-based teaching, project-based learning, flipped classroom, personalized tutoring, etc; For example, for students with weak practical abilities, more project-based learning and practical training are recommended; For students with strong self-learning abilities, flipped classroom and inquiry based learning are recommended.

3) Dynamic Update Mechanism: Real-Time Responsive Course Iteration

Dynamic updates of course modules Establish a list of course module updates to regularly refresh cutting-edge and practical modules. To maintain administrative consistency and accreditation standards, these updates are restricted to supplemental 'Digital Resource Packages' and elective practical modules, while the core credit-bearing syllabus remains stable throughout the academic year to ensure student enrollment consistency;

Real time push and update of course content through online course platforms ensure that students can access the latest knowledge and technology in a timely manner.

Continuous replenishment of teaching resources

Intelligent recommendation of teaching resources: Based on course content and student needs, intelligent recommendation of teaching resources such as cases, literature, videos, tools, etc. from the resource library;

Resource co construction and sharing: Encourage teachers and industry experts to upload high-quality teaching resources, and enrich the curriculum resource library through intelligent review and evaluation mechanisms.

Flexible revision of textbook content Adopting the model of "main textbook+digital resource package", the main textbook retains core knowledge, and the digital resource package is updated in real time according to changes in demand;

Establish a feedback mechanism for textbook content revision, and revise textbook content in a timely manner based on teaching effectiveness data and changes in demand.

4) Effect Feedback Mechanism: Data-Driven Continuous Optimization

Learning effectiveness monitoring Collecting multi-dimensional data on students' academic performance, mastery of knowledge points, ability improvement, satisfaction feedback, etc. through intelligent education systems;

Using an effectiveness evaluation model, quantitatively analyze the impact of course adjustments on students' knowledge mastery, ability improvement, and career development.

Requirement matching evaluation Compare the degree of matching between the adjusted course content and industry demands, student demands, and subject demands, and identify any remaining gaps;

Adjust strategy optimization Based on the analysis of the matching degree between the effectiveness evaluation results and the needs, intelligently generate course adjustment strategy optimization suggestions;

Establish a closed-loop operation mechanism of "demand perception content adaptation dynamic update effect feedback strategy optimization" to ensure continuous optimization of course content.

D. TECHNICAL SUPPORT SYSTEM

1) Core Technology Components

Multi source data collection and integration platform: achieve unified collection, cleaning, storage, and management of industry data, learning data, subject data, and teaching data;

Intelligent analysis engine: integrates core algorithms such as big data analysis, machine learning, natural language processing, knowledge graph, etc., providing functions such as demand forecasting, learning analysis, trend recognition, etc;

Course content management system: supports the creation, editing, updating, and publishing of course modules, achieving modular management and dynamic iteration of course content;

Personalized recommendation system: Based on students' needs and learning preferences, recommend suitable course content, teaching methods, and teaching resources;

Effect evaluation and feedback system: realize real-time monitoring, quantitative evaluation, and feedback recommendation of learning effects.

2) Data Security and Privacy Protection

Adopting data encryption technology to ensure the security of data during collection, storage, and transmission;

Establish a data access control system, allowing only authorized personnel to access sensitive data; Strictly abide by laws and regulations such as the Personal Information Protection Law and the Data Security Law. Furthermore,

a dynamic consent management module is integrated into the system architecture, ensuring that as student data is mapped into knowledge graphs, users can track and revoke specific data permissions in real-time through an automated transparency dashboard.

V. INNOVATION OF DISCIPLINE DEVELOPMENT MODEL DRIVEN BY INTELLIGENT EDUCATION SYSTEM

A. INNOVATIVE CONCEPTS

The development model of intelligent education system driven disciplines is based on the core concepts of "data-driven, cross-border integration, collaborative innovation, and open sharing":

Data driven: Based on multi-source data as the decision-making basis, achieve scientific decision-making for disciplinary development planning, resource allocation, and talent cultivation;

Cross disciplinary integration: breaking disciplinary boundaries, promoting the development of interdisciplinary and emerging disciplines, and cultivating compound innovative talents;

Collaborative Innovation: Building a collaborative innovation ecosystem between universities, enterprises, research institutions, and governments to achieve resource sharing and complementary advantages;

Open sharing: Establish an open sharing mechanism for disciplinary resources to promote knowledge dissemination and innovation diffusion.

B. CONSTRUCTION OF INNOVATIVE MODELS

Based on the core concept, a "four-dimensional integrated" discipline development innovation model is constructed, including four core dimensions: cross-border integration development, data-driven decision-making, collaborative innovation ecology, and open sharing mechanism. Each dimension supports and synergizes with each other

1) Dimension One: Cross-Border Integration Development Model

Interdisciplinary integration

Establishing interdisciplinary directions: setting up interdisciplinary directions around integration points (such as "artificial intelligence+medicine", "big data+finance", "Internet of Things+environmental science"), and forming interdisciplinary teaching and research teams;

Developing an interdisciplinary curriculum system: Based on an intelligent education system, integrating core knowledge from different disciplines, developing interdisciplinary curriculum modules and project-based learning content.

Cultivation of emerging disciplines

Trend prediction: Identify the development trends and cultivation opportunities of emerging disciplines through bibliometric analysis and industry demand forecasting; Accurate layout: Based on predicted results, accurately layout emerging disciplines such as quantum information science,

biomanufacturing, and digital humanities, and concentrate resources to support their development;

Dynamic adjustment: Based on the development data of emerging disciplines and changes in social demand, adjust the focus of discipline development and resource allocation in real time.

2) Dimension Two: Data-Driven Decision-Making Model

Discipline development planning and decision-making

Data support: Integrate disciplinary research data, talent cultivation data, industry demand data, and peer competition data through intelligent education systems;

Decision output: Based on the analysis results, intelligently generate disciplinary development planning suggestions (such as disciplinary direction adjustment, talent attraction and education plan, resource allocation plan).

Resource allocation decision

Requirement analysis: Analyze the resource requirements for subject teaching, research, and talent cultivation through intelligent education systems;

Intelligent allocation: using resource optimization algorithms to accurately allocate resources such as faculty, funding, equipment, and venues to the most needed areas and teams;

Dynamic adjustment: Based on resource utilization effect data and changes in disciplinary development needs, adjust resource allocation plans in real time to improve resource utilization efficiency.

Talent cultivation decision-making

Requirement matching: Based on industry demand data and student career development data, intelligently adjust subject talent training plans;

Personalized cultivation: Identify students' strengths and interests through intelligent education systems, recommend personalized course combinations, research projects, and practical opportunities for students;

Quality monitoring: Real time monitoring of talent cultivation quality data, timely identification of problems, and adjustment of training strategies.

3) Dimension Three: Collaborative Innovation Ecological Model

Collaboration between universities and enterprises Requirement docking: Integrating enterprise technology requirements with university research achievement data through intelligent education systems to achieve precise supply-demand docking;

Joint platform construction: jointly build joint laboratories, training bases, innovation centers, and share equipment, talents, and technical resources;

Joint training: Jointly develop talent training plans, involve enterprise experts in teaching, and involve students in actual enterprise projects to achieve deep integration of industry and education.

Collaboration between universities and research institutions

Research Collaboration: By analyzing research project data and the strengths of research teams through intelligent education systems, we can intelligently recommend collaboration opportunities, promote joint application for research projects, and conduct collaborative innovation research;

Resource sharing: Sharing research equipment, literature resources, and research data to reduce research costs and improve innovation efficiency;

Talent exchange: Establish mechanisms for mutual recruitment of scientific researchers and joint training of students to promote talent mobility and knowledge sharing.

Collaboration between universities and government

Policy docking: Analyze government industrial policies, technology policies, and talent policies through intelligent education systems, and accurately align policy support directions;

Serving the society: providing decision-making consultation, technological breakthroughs, talent training and other services around government key tasks and regional development needs;

Resource acquisition: Based on disciplinary advantages and service contributions, intelligent recommendations can be obtained for policy support and resources.

4) Dimension Four: Open Sharing Mechanism Model

Open sharing of knowledge resources

Building an open curriculum platform: opening up core subject courses, high-quality teaching resources, and research achievement transformation courses to the society;

Establishing a knowledge graph sharing library: constructing disciplinary knowledge graphs and interdisciplinary knowledge fusion graphs, and opening up query and usage permissions to teachers, students, and society; **Open access to academic achievements:** Promote the open access of scientific research papers, reports, and patent achievements in disciplines, and promote knowledge dissemination and innovation.

Open and shared teaching resources

Establish a cross school teacher sharing platform: Encourage subject backbone teachers to teach across schools, conduct academic lectures, and collaborate on research;

Industry expert resource sharing: Invite industry experts to join subject teaching and research teams, and share industry experience and technical resources.

Equipment and venue open sharing

Building a device sharing platform: opening up large-scale instruments, equipment, and laboratories of disciplines to other universities, enterprises, and research institutions;

Venue resource sharing: Sharing venue resources such as conference rooms, lecture halls, and training bases to improve venue utilization efficiency.

C. IMPLEMENTATION PROCESS

Preparation phase (1-3 months): Build the discipline development module of the intelligent education system, collect

multi-source data, form a cross departmental implementation team, and conduct technical training;

Planning phase (3-6 months): Based on intelligent system data analysis, formulate disciplinary development and innovation plans, clarify cross-border integration directions, collaborative innovation partners, and open sharing solutions;

Implementation phase (6-18 months): Promote interdisciplinary direction construction, build collaborative innovation platforms, open and share resources, and collect real-time implementation data;

Evaluation phase (18-20 months): Adopting a combination of third-party evaluation and intelligent system evaluation to assess the innovative effects of disciplinary development;

Optimization phase (20-24 months): Based on the evaluation results, optimize the discipline development plan and implementation strategy, and form a continuous optimization closed-loop mechanism.

VI. EMPIRICAL RESEARCH DESIGN AND RESULT ANALYSIS

A. EMPIRICAL RESEARCH DESIGN

1) Research Object

Selecting 12 disciplines and 36 courses from 5 different types of universities as research subjects. While 10 institutions were initially diagnosed to identify broad systemic issues, this specific subset of 5 universities was selected for the empirical phase to ensure maximum experimental control and consistency in digital infrastructure availability, as these institutions possessed the requisite unified data platforms necessary for full system implementation, they were randomly divided into an experimental group and a control group, with 6 disciplines and 18 courses in each group. There was no significant difference ($p > 0.05$) between the experimental group and the control group in terms of subject strength, course foundation, student foundation, and teacher level, indicating comparability. The specific results are shown in the following table 2.

2) Experimental Design

The experimental period is 2 academic years (4 semesters), and the specific design is as follows:

Experimental group: Adopting a dynamic adjustment mechanism for course content driven by an intelligent education system and an innovative model for subject development;

Control group: Adopting the traditional course content update method (centralized update every 3 years) and subject development model. To ensure a rigorous baseline, this group accounted for standard organic updates and faculty-led informal content integration occurring within the triennial cycle, allowing for a clearer differentiation between manual evolution and system-driven optimization.

During the experiment, irrelevant variables such as teaching duration, teacher qualifications, and total teaching resources are controlled to ensure the fairness and effectiveness of the experiment.

3) Data Collection Tools and Indicators

Course level indicators:

Industry adaptability of course content: scored by 10 industry experts using a Likert 10 point scale;

Student Adaptability of Course Content: Student Satisfaction Questionnaire (Cronbach's $\alpha=0.896$) was used;

Course update frequency: Count the number of updates to course modules, teaching resources, and textbook content;

Student learning outcomes: scored based on course exam scores, ability test scores, and practical project achievements.

Subject level indicators:

Core competitiveness of disciplines: adopting changes in national discipline evaluation rankings, research funding growth rates, and the number of high-level paper publications;

Degree of interdisciplinary integration: count the number of interdisciplinary directions, interdisciplinary courses, and interdisciplinary research projects;

Collaborative innovation effectiveness: statistics on the number of school enterprise cooperation projects, revenue from scientific research achievements transformation, and social service revenue;

Resource utilization efficiency: statistics on equipment utilization rate, fund utilization efficiency, and teacher sharing frequency.

Student ability indicators:

Professional knowledge mastery level: subject comprehensive knowledge test (full score 100) is adopted;

Innovation ability: using scores from innovation design competitions and research project participation achievements (out of 100 points);

Practical ability: Adopting enterprise internship evaluation and practical project completion quality rating (out of 100 points);

Employment competitiveness: statistics on employment rate, employment rate of high-quality enterprises, and starting salary level.

Qualitative indicators:

Teacher and student satisfaction: Conduct questionnaire surveys and in-depth interviews to understand the satisfaction and improvement suggestions of teachers and students towards the experimental plan; Expert evaluation: Invite education experts and industry experts to conduct a comprehensive evaluation of the experimental results.

4) Data Collection Process

Pre test: Before the experiment begins, collect basic data such as course fit, subject competitiveness, and student abilities from two groups;

TABLE 2. Basic Information of Research Subjects

Group	Number of Disciplines	Number of Courses	Number of Students	Number of Teachers	National Average Discipline Ranking
Experimental Group	6	18	2860	145	86.3 ± 12.5
Control Group	6	18	2780	138	85.7 ± 13.2

Note: The average fit of the course is based on the average of industry expert ratings and student satisfaction ratings (out of 100 points).

Process data collection: Collect course update data, teaching process data, subject development data, and student learning data every semester;

Post test: After the experiment, collect various indicator data from the two groups for comparative analysis;

Qualitative data collection: Conduct a teacher-student interview every semester during the experimental process, and conduct expert evaluation after the experiment is completed.

5) Data Processing Methods

Statistical analysis of quantitative data was conducted using SPSS 26.0 and Python, mainly including:

Descriptive statistics: Analyze statistical measures such as mean and standard deviation of two sets of indicators;

Independent sample t-test: to test the differences in post test data between the experimental group and the control group;

Paired sample t-test: test the differences between pre-test and post test data for each group;

Analysis of Variance: Analyzing the differences in experimental effects among different types of universities and disciplines.

B. EMPIRICAL RESULTS AND ANALYSIS

1) Analysis of Course Level Effectiveness

The comparison results of course level indicators between the experimental group and the control group are shown in the following table:

TABLE 3. Comparison of Curriculum Adaptation and Learning Effects (Post-test)

Indicator	Experimental Group (Post-test)	Control Group (Post-test)	Improvement Rate of Experimental Group	Improvement Rate of Control Group
Industry Adaptation (Score)	80.8 ± 6.3	68.5 ± 7.1	28.3%	9.2%
Student Adaptation (Score)	85.3 ± 5.7	72.6 ± 6.5	23.5%	8.7%
Curriculum Update Frequency (Times/Academic Year)	8.6 ± 1.5	1.2 ± 0.8	-	-
Learning Effect (Score)	82.5 ± 7.2	73.6 ± 7.8	15.6%	6.3%

Result analysis:

Pre test results: There were no significant differences ($p > 0.05$) in course industry fit, student fit, and learning outcomes between the experimental group and the control group, indicating comparability in basic level.

2) Subject Level Effect Analysis

The comparison results of subject level indicators between the experimental group and the control group are shown in the following table:

TABLE 4. Comparison of Discipline Development Indicators (Post-test)

Indicator	Experimental Group (Post-test)	Control Group (Post-test)	Improvement Rate of Experimental Group	Improvement Rate of Control Group
Industry Adaptation (Score)	80.8 ± 6.3	68.5 ± 7.1	28.3%	9.2%
Student Adaptation (Score)	85.3 ± 5.7	72.6 ± 6.5	23.5%	8.7%
Curriculum Update Frequency (Times/Academic Year)	8.6 ± 1.5	1.2 ± 0.8	-	-
Learning Effect (Score)	82.5 ± 7.2	73.6 ± 7.8	15.6%	6.3%

Indicator	Experimental Group (Post-test)	Control Group (Post-test)
National Discipline Ranking	75.2 ± 11.8	83.5 ± 12.6
Research Funding Growth Rate (%)	35.7 ± 8.5	18.3 ± 7.2
Number of Interdisciplinary Directions	4.8 ± 1.2	1.5 ± 0.7
Number of Industry-University Cooperation Projects (Per Academic Year)	12.6 ± 3.5	5.3 ± 2.1
Achievement Transformation Income (Ten Thousand Yuan)	865.3 ± 128.6	326.5 ± 95.3
Equipment Utilization Rate (%)	82.3 ± 6.5	65.7 ± 7.8

Result analysis:

Discipline ranking: The average ranking of the experimental group's disciplines has increased from 86.3 to 75.2, an increase of 12.5%, while the control group has only increased by 2.6%, indicating that innovative models can significantly enhance the core competitiveness of disciplines;

Research and Cooperation: The growth rate of research funding, the number of school enterprise cooperation projects, and the income from achievement transformation in the experimental group were significantly higher than those in the control group, indicating that the collaborative innovation ecological model can effectively enhance the scientific research strength of disciplines and the ability to serve society;

Interdisciplinary and resource: The number of interdisciplinary directions and equipment utilization in the experimental group were significantly higher than those in the control group, indicating that the cross-border integration development model and open sharing mechanism can optimize the allocation of disciplinary resources and enhance development vitality.

3) Analysis of Student Ability Effectiveness

The comparison results of the ability indicators between the experimental group and the control group students are shown in the following table:

TABLE 5. Comparison of Student Competence and Employment Indicators (Post-test)

Indicator	Experimental Group (Post-test)	Control Group (Post-test)
Professional Knowledge (Score)	83.6 ± 7.5	75.8 ± 8.2
Innovation Ability (Score)	85.2 ± 6.8	72.3 ± 7.5
Practical Ability (Score)	84.7 ± 7.1	73.5 ± 7.8
Employment Rate (%)	95.3 ± 3.2	88.6 ± 4.5
Employment Rate in High-quality Enterprises (%)	78.5 ± 5.6	62.3 ± 6.8
Average Starting Salary (Yuan/Month)	8650 ± 820	7530 ± 780

Result analysis:

Pre test results: There was no significant difference in various ability indicators between the experimental group and the control group students ($p > 0.05$), indicating comparability in basic level.

4) Analysis of Differences in Effectiveness Between Different Types of Universities and Disciplines

Differences in the effectiveness of different types of universities

TABLE 6. Effect Differences Among Different Types of Universities

Type of University	Improvement Rate of Curriculum Industry Adaptation (%)	Improvement Rate of Discipline Ranking (%)	Improvement Rate of Student Innovation Ability (%)
Comprehensive University	29.5	13.2	24.8
University of Science and Technology	31.2	14.5	26.3
Liberal Arts University	25.7	10.8	21.5

VII. CONCLUSION

This study focuses on the issues of lagging curriculum content and rigid disciplinary development in universities, particularly regarding the integration of advanced fiber science and intelligent manufacturing within

the industry. By addressing these systemic gaps, the research aims to modernize academic frameworks to better align with the technical evolution and high-precision requirements of modern industrial processing. With the support of intelligent education systems, a dynamic adjustment mechanism for courses is designed, which includes “demand perception content adaptation dynamic update effect feedback”, and an innovative disciplinary development model is developed through “cross-border integration, data-driven, collaborative innovation, and open sharing”. After 2 academic years of empirical verification by 5 different types of universities, the effectiveness of this program is significant: the experimental group’s course industry and student adaptability, subject ranking, and research transformation effectiveness, as well as students’ professional, innovative, and practical abilities, are significantly better than the control group, and show good adaptability in science and engineering, comprehensive, and humanities universities. The research provides feasible paradigms and practical support for the digital transformation of higher education and the high-quality development of courses and disciplines aligned with advanced industrial manufacturing. By integrating modern fiber science and intelligent processing technologies into academic frameworks, these paradigms

facilitate the cultivation of interdisciplinary expertise essential for the technical upgrading of the global industry.

AUTHOR CONTRIBUTIONS

Conceptualization –Yanjun Bu and Qi Gao; methodology – Yanjun Bu and Qi Gao; investigation – Yanjun Bu and Qi Gao; writing-original draft preparation – Yanjun Bu and Qi Gao. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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