



Digital Twin System Construction and Simulation Optimization for Collaborative Effectiveness of Industry-Education Integration

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SUMMARY: *The current level of cooperation between industries and education in the sphere of college and university integration can no longer meet modern social needs due to the continued growth of social economy and artificial intelligence. As a response to this issue, this paper explores a digital twin system designed to enhance the collaborative performance of industry-education integration. Utilizing the theory behind digital twin systems, the research defines the main functional modules necessary to implement this application, obtains research data using web crawling, and creates a resource recommendation module of industry-education integration using the combination of LDA model with a content-based recommendation algorithm. Through the support of development software and image processing methods, the practical training module is developed and implemented. Based on this, an enhanced LSTM network is proposed and a back propagation Rprop algorithm is used to develop a student management early-warning module, thus finalizing the whole system module design. Then, the experimental simulation is made taking into consideration the system functional modules. The simulation outcomes show that the prediction errors of red, orange, yellow, and green warnings are 0.0315, 0.0233, 0.0309 and 0.0045 respectively, which are all less than 0.05. These results confirm the usefulness of the student management early-warning module of the digital twin system, as well as offer the foundation of similar optimization measures. The study helps in the enhancement of practical competence of students and problem-solving abilities, and its ultimate aim is to contribute to the improvement of the collaborative performance of industry-education integration.*

KEYWORDS: *LDA model; content recommendation algorithm; LSTM network; synergistic effectiveness of industry-education integration; digital twin system*

1 Introduction

The talent cultivation model based on industry-education integration has become a major concern for both the educational field and the industrial sector [1]. As a key approach to developing application-oriented and practice-oriented professionals, industry-education integration plays an essential role in talent training. However, in actual implementation, some vocational skills training remains detached from real workplace tasks, relevant data are insufficiently authentic, and existing platforms often offer limited functions, making them unable to fully satisfy enterprise demand for accounting professionals [2, 3]. At present, the

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fast advancement of 5G, the Internet of Things, big data, and related technologies has made the development of industry-education integration increasingly dependent on digital twin support [4, 5]. By combining physical models, sensor-updated information, and operational history records, digital twin technology integrates simulation processes involving multiple disciplines, physical variables, scales, and probabilities, while establishing a virtual-space mapping that can represent the full life-cycle status of the corresponding physical equipment [6-8]. Owing to its strengths in precise simulation and real-time monitoring, digital twin technology offers a new technical path for the construction and operation of campus-based industry-education integration. Through the fusion of real-world data and virtual models, it enables multidimensional intelligent applications in teaching, management, and service, while also driving enterprise working modes toward greater intelligence and digitalization [9, 10]. More specifically, by reproducing authentic enterprise work scenarios, a digital twin system can create a highly realistic learning environment for students, making the in-depth connection between industry and education easier to achieve and helping cultivate professionals who better match market needs, thereby supporting the coordinated progress of education and industry [11, 12]. Under such circumstances, research on digital twin systems carries clear practical value and importance.

Numerous academic studies have examined industry-education integration. For example, Yanan et al. [13] incorporated courses such as Industrial Internet Technology and Industrial APP Development into the curriculum and introduced enterprise cases into classroom teaching, which enabled students to gain a clearer understanding of the skills and knowledge required to become application-oriented professionals in the industrial Internet sector. Using linear regression together with a moderating-effect model, the researchers in [14] explored the impact of industry-education integration on employment quality in higher vocational institutions. Their results showed an inverted U-shaped relationship between the level of integration and employment quality, while teachers' practical teaching competence was identified as the strongest predictor of employment outcomes. Zhang H et al. [15] assessed the sustainable development of agricultural machinery education in Chinese agricultural colleges during 2021-2023 and found that the scores of several indicators remained relatively low, particularly in craftsmanship cultivation, the level of industry-education integration, and the consistency between training programs and social needs. On that basis, they proposed a new framework for industry-education integration built on collaboration among government, universities, and enterprises. Through a multi-case study design, the authors of [16] investigated university-industry innovation partnerships and concluded that successful cooperation depends primarily on individuals rather than institutions, with personal motivation and absorptive capacity constituting the main factors that determine whether such partnerships succeed or fail.

With continuing advances in science and technology, the industry-education integration model must also undergo constant renewal in order to remain aligned with the needs of the current era. Wang et al. [17] examined the difficulties encountered in the development of industry-education integration and pointed out that the barrier between enterprise technological confidentiality and educational dissemination weakens knowledge exchange, while the indifferent attitude of enterprises toward student internships restricts the improvement of practical ability. On this basis, they emphasized the need to build an active digital ecosystem to support reform in industry-education integration. Zhang H [18] reviewed the major themes of the 2024 World Congress on the Development of Vocational and Technical Education in relation to industry-education integration, covering the internal driving mechanism through which such integration advances vocational and higher education, recent progress in international cooperation in vocational education research, and the future direction of industry-education integration in this field. He et al. [19] developed and implemented a cross-technology

information management system grounded in digital technology, which effectively addressed the mismatch between talent demand in industry and talent cultivation in education. By incorporating fuzzy algorithms, the system realized educational quality evaluation and produced positive effects on teaching outcomes, instructional quality, and the development of professional competence. Lu et al. [20] investigated the transformation path of industry-education integration in the age of artificial intelligence. They established a three-dimensional framework composed of “technical skill mapping - collaboration mechanism innovation - real-scene reconstruction” to clarify the practical value of artificial intelligence technology, then used in-depth interviews to examine the educational mechanism of school-enterprise cooperation, and ultimately implemented a talent cultivation ecosystem that achieved better results in industry-education integration. Tang et al [21] the changes in industry requirements were dynamically updated, and the knowledge map created was incorporated into the industry-teaching integration course system, which addressed the issue of students not being able to comprehend the industry requirements based on the industry viewpoint.

Wu et al [22] investigated the optimization of faculty development in vocational colleges in Shandong Province from the perspective of industry-education integration. Grounded in human capital theory, the TPACK framework, and an AI-supported learning model, their study revealed imbalances in both the structural composition and capability profile of the existing teaching staff. In response, they proposed an optimization path centered on stronger policy incentives for industry-education integration and enhanced AI-related competence training, thereby markedly increasing the proportion of dual-qualified teachers, the level of enterprise involvement, and the coverage of digital teaching. Zhang H [23] reformed the conventional “manual drawing-software operation” teaching approach by introducing case-based instruction, project-driven learning, three-dimensional modeling, and virtual reality technology. Together with measures such as teacher training and school-enterprise collaboration, these changes significantly strengthened students’ drawing skills and innovative thinking, while further improving the teaching system for industry-education integration. Miao et al [24], on the other hand, used the intelligent technology based on back-propagation neural network to construct a multimodal teaching quality assessment system to deal with problems such as mismatch of industry demand and outdated teaching content in talent cultivation, and the model has a better performance on teaching quality prediction, which promotes a deeper integration between industry and education.

Meanwhile, digital twin technology has opened up a new avenue for research on innovation in the industry-education integration model. In response to the national initiative for reform in this field, Na [25] applied digital twin technology to the dynamic simulation of industry-education integration and proposed a digital twin-based safety training framework for the architecture and construction sector. By combining this framework with a virtual reality training environment, they created a professional practice scenario for students. The results showed that the framework demonstrated clear value in safety training effectiveness, cost-benefit performance, employee behavior monitoring, and safety education. [26] applied digital twin technology to the dynamic simulation of industry-education integration and proposed a digital twin-based safety training framework for the architecture and construction sector. By combining this framework with a virtual reality training environment, they created a professional practice scenario for students. The results showed that the framework demonstrated clear value in safety training effectiveness, cost-benefit performance, employee behavior monitoring, and safety education. Acker et al [27] prescribed digital twins using technologies such as Unity and the Robotics Operating System in order to improve students’ understanding of K-12 industrial robotics in order to assist students in gaining a deeper understanding of industrialization and expertise in conjunction with higher education.

Sepasgozar et al [28] pioneered a variety of case study projects for innovative education and practical training, such as virtual tours, digital twin-based architectural education systems, and data visualization of immersive practical training environments, and the research is of practical relevance in the fields of architecture, mining, and urban planning. Filipescu et al [29] developed a remote monitoring and control system for a multifunctional robotic cell based on the Internet of Things and digital twin technology. By integrating the concepts of Industry/Education 4.0 and Industry/Education 5.0, the system creates an intelligent, flexible, and scalable environment that is more suitable for applications involving the integration of industry and education. Meng et al. [30] addressed the issue of how to carry out rail transit practical training in a safe and efficient manner by proposing a virtual training platform supported by digital twin technology. Through teaching practice, they confirmed that the platform was feasible for enhancing teaching quality and strengthening students' practical competence as well as innovative ability. Even so, current studies on digital twin systems related to industry-education integration remain relatively limited, with insufficient theoretical support and a lack of practical application experience.

Based on the theory of digital twins, the digital twin system that is developed in this research to enhance collaborative performance in industry-education integration can be subdivided into three main functional modules which include a resource recommendation module, a practical training module, and a student management early-warning module. When the data collection and preprocessing are done, the resource recommendation module is established through the combination of the LDA model and a content-based recommendation algorithm. The development software, image-processing methods, LSTM network, and the back-propagation Prop algorithm then create the practical training module and the student management early-warning module. Lastly, the system functional modules are subjected to simulation analysis to confirm the applicability of the suggested scheme and suggest additional optimization schemes that will enhance the effectiveness of collaboration of industry-education integration.

2 Construction of Digital Twin System under the Perspective of Industry-Education Integration

The creation of a digital twin system to boost the coordinated action of industry-education integration is not only a basic necessity in the advancement of industrial colleges in the digital economy, but also a significant signal of a more advanced stage of integration between the industry and education. At the same time, digital twin technology has become one of the critical pillars upon which such coordination can be achieved. The system sorts and presents information in digital form by collecting, packaging, and processing real-time and authentic data on enterprise data, so that all the participants may share resources with each other. The digital twin system application in the coordinated development of industry-education integration also helps to implement enterprise projects and facilitate innovative approaches to the training of talents in colleges and universities.

2.1 Digital Twin Concept and Reference Architecture

2.1.1 Concept of digital twin systems

Digital twin system is the process of digital modeling of a particular target object using the data interconnection. In this case, the target object, i.e. the physical entity, stands as the real world object, which was selected to be digitally mapped. The digital version of it, commonly known as the virtual entity, is the digital mapping or mirror image of that physical entity. Data

connectivity is used to ensure that the physical entity and the virtual entity are kept in step both in terms of accuracy and time and the idea of the digital twin system is shown in Figure 1. Physical entity, virtual entity, and service application can be made to have interactive connection and coordinated operation with support of data-driven operation, dynamic iteration, and virtual-real interaction. Data-driven includes both activities such as data collection and data analysis, as well as activities such as data-based decision-making and execution, which ultimately form knowledge in iterative optimization. Dynamic iteration means that virtual entities receive data generated by physical entities in real time to complete iterative optimization, while physical entities receive feedback data from virtual entities in real time to complete assisted decision-making. Virtual interaction refers to the two-way mapping, real-time connection and dynamic interaction between physical entities and virtual entities to provide users with application services such as visualization, simulation, prediction and projection.

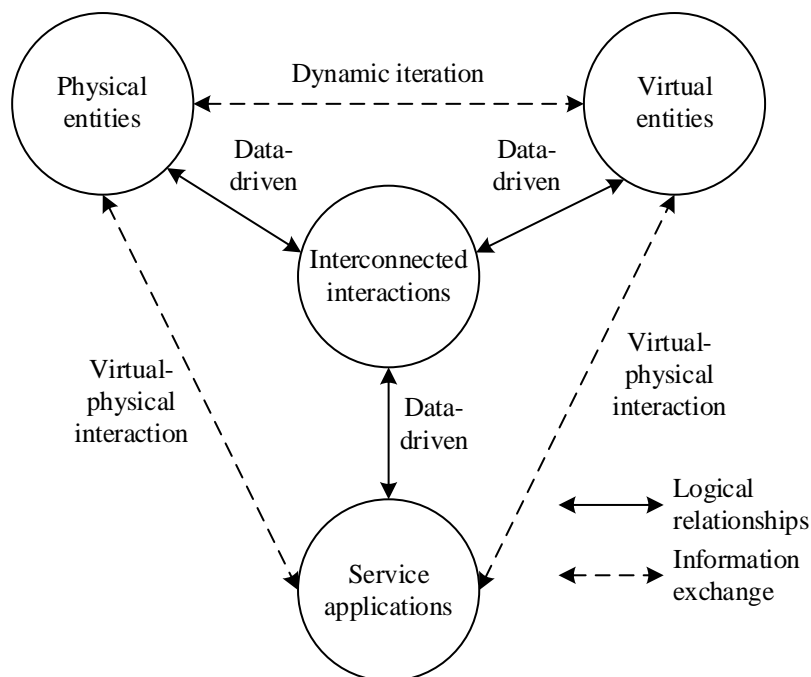


Figure 1: The concept of digital twin system

2.1.2 Reference Architecture for Digital Twin Systems

Digital twin system is a data-driven system that facilitates dynamic interaction between the entities connecting a target object to its digital representation. Its structure consists of such components as the target entity, the digital entity, interactive data connections as well as the models, data, interfaces, and other similar parts that are used in the connection process. The reference architecture of this system consists of three main modules: an industry-education integration resource recommending module, a practical training module, and a student management early-warning module. Digital twins offer smart assistance with improving the collaborative efficiency of industry-education integrations by creating an exact real-time digital mapping of physical objects in digital space and performing simulation, verification, prediction, and regulation of the whole lifespan of physical objects via real-time simulation and data analysis.

2.2 Module for recommending resources for integration of education and industry

2.2.1 Data preparation

By analyzing the list of projects approved for the integration of industry and education released by the Higher Education Department, approximately 70,000 data items were crawled from 2014 to 2023, including "Company Name", "Project Type", "Project Name", "Undertaking school", and "Time". Then, based on each enterprise's name, the addresses of approximately 2,000 enterprises are crawled from the "Qichacha" platform. Finally, about 2,000 university addresses were crawled from "Baidu Baike" based on the names of the undertaking schools of each university, thereby obtaining the dataset of industry-education integration resources.

2.2.2 Data pre-processing

Data preprocessing is mainly to provide a data basis for the extraction of feature words of the title and the division of the subject interest theme of the project later. This subsection uses data standardization, word splitting, and deactivation word removal for data preprocessing to eliminate the interfering data in the data and make the research content of this paper more convincing.

2.2.3 Project Subject Interest Mining Based on LDA Modeling

(1) Text feature representation

When cooperation on an industry-education integration project is established between industry and academia, both parties first determine, based on the cooperation content, whether the relevant industry-education integration resources fall within their respective areas. Since the title is limited in length and highly summarizes the cooperation content, the project that reaches cooperation must involve the user's cooperation field, so in the theme recognition of the title, the participle result of the title can be directly used as the feature word.

TF-IDF is a popular method of text classification that measures the importance of words in a document. The overall assumption is that if a term is rare in general but is frequently repeated in one particular article, then this term has the ability to represent the most important characteristics of an article. There are two parts of TF-IDF: TF and IDF. TF stands for term frequency, which is the number of occurrences of a word in a document and since the length of documents varies, this value typically needs to be normalized. Equation (1) shows the calculation:

$$\text{Term Frequency}(TF) = \frac{\text{The number of times a specific word appears in an article}}{\text{The total number of words in the article}} \quad (1)$$

IDF stands for Inverse Document Frequency, which indicates the frequency of occurrence of a word in all the texts, if the word occurs in most of the texts, the word does not represent the article features well, its importance should be low, and the value of IDF is low. The formula of IDF is shown in equation (2):

$$\text{Inverse Document Frequency (IDF)} = \log \left(\frac{\text{Total number of documents in the corpus}}{\text{Number of documents containing the term} + 1} \right) \quad (2)$$

The TF-IDF value is calculated in equation (3):

$$TF - IDF(x) = TF(x) * IDF(x) \quad (3)$$

(2) Topic Clustering

LDA topic clustering is the inverse process of article generation, which inputs articles and outputs article topics and topic words, i.e., according to a complete article to find its corresponding distribution of article-topics and topic-words, and then based on the distribution of article-topics to classify the set of articles into different topics, which also realizes the topic clustering. The goodness of the LDA topic model is usually evaluated by the degree of perplexity. Perplexity is an index that reflects the generalization ability of the model, the smaller the perplexity, the higher the prediction ability. The specific calculation formula is shown in equation (4):

$$\text{Perplexity}(D) = \exp \left\{ - \frac{\sum_{d=1}^N \sum_{n=1}^M \log p(W_n)}{\sum_{d=1}^N N_d} \right\} \quad (4)$$

where D denotes the test set in the corpus, N denotes the number of articles in the prediction set, M denotes the number of words in each article in the prediction set, N_d tabulates the number of words in the article d , and $p(W_n)$ denotes the probability of the word W_n in the article. However, as the LDA topic model is an unsupervised clustering algorithm, the decision on the number of topics based solely on perplexity can also result in the overlap between various categories. Thus, in the present chapter, further visualizations of the clustering results of LDA topic modeling are introduced and the best number of topics is defined by considering both the visualization findings and the results of perplexity.

Every industry-education integration cooperation program has one pair of cooperating partners. The title-topic classes produced by the LDA topic model can be used to get the mining outputs of interest themes of project subjects.

2.2.4 Content recommendation methods

Content-based recommendation algorithm the content-based recommendation algorithm has the feature of independence between project entities, which implies that the choice made by one project member does not affect the choice made by other members. It can also be very effective in minimizing the cold-start problem of newly-joined members. Taking an example of the content-based recommendation method whereby industry-education integration resources are recommended to industries by colleges and universities, the process consists of three steps, such as constructing the enterprise interest topic model, constructing the college interest topic model, and recommending industry-education integration resources based on the similarity between enterprises and colleges and universities.

(1) Enterprise Interest Theme Model

Once the topic model is defined, it will be possible to derive the enterprise interest topic model. The enterprise preferences on topics and their respective preference weights are expressed as a preference feature vector and its exact form is shown in equation (5):

$$U_i^c = \{(b_{1i}, w_{1i}), (b_{2i}, w_{2i}), (b_{3i}, w_{3i}), \dots, (b_{ni}, w_{ni})\} \quad (5)$$

where $b_{ni} \in B$ denotes the item theme that the i th firm is interested in, i.e., the interest theme of the firm. $w_{ni} \in [0,1]$ denotes the preference weight of the i th enterprise under the topic of interest b_n . Where i is the number of enterprises and n is the number of program themes.

(2) College Interest Theme Model

Also based on the construction of theme model, the interest theme model of universities is obtained. The preference feature vector of colleges and universities is shown in equation (6):

$$U_j^s = \{(b_{1j}, w_{1j}), (b_{2j}, w_{2j}), (b_{3j}, w_{3j}), \dots, (b_{nj}, w_{nj})\} \quad (6)$$

where $b_{nj} \in B$ denotes the program theme of interest of the j th HEI, i.e., the theme of interest of the HEI. $w_{nj} \in [0,1]$ denotes the preference weight of the j th HEI under the topic of interest b_n . Where j is the number of colleges and universities.

(3) Recommendation of teaching resources for industry-teaching integration

The larger the overlap in the research topics of enterprises and universities, the greater the preference weights associated with these overlapping topics, which implies that the possibility of recommendation has increased. Based on that, the similarity calculation formula is shown below:

$$P(c, s) = \sum_b (w_{b,c} * w_{b,s}) \quad (7)$$

where $P(c, s)$ denotes the similarity between enterprises c and colleges s , $w_{b,c}$ denotes the preference weight of enterprises c under the topic of interest b , and $w_{b,s}$ denotes the preference weight of colleges s under the topic of interest b . The higher the similarity, the higher the likelihood of recommending the same topic of interest between the enterprise and the university.

2.3 Practical training modules

According to the theory of digital twins, the practical training module is developed based on the combination of real and virtual environments where virtual supports the real and the two work together. The module considers theoretical instruction and practical application as equally important, thus enhancing the quality of industry education integration instruction and practical training effectiveness. It can be seen as a novel approach to further enhance the level of industry-education integration and collaborative development.

2.3.1 Development of software

(1) Modeling software

Currently used modeling software: Autodesk, SolidWorks, Pro/Engineer, UnigraphicsNX

and so on.

(2) Rendering software

3ds Max software operates logically, has a friendly interface, has a wealth of tutorial resources and plug-in programs, provides excellent material editing, model rendering and optimization programs, and at the same time provides a wealth of data interfaces for other three-dimensional software, which provides strong technical support to enhance the fidelity and immersion of the virtual training room.

(3) Virtual Reality Software

Virtools is a kind of development of virtual reality system - tool software, developers through the intuitive graphical development interface, as long as the required module dragged to the object can be produced complex interactive behavior, not only to meet the development needs of program designers, and even do not know the program development of the art staff can be used freely, and the two can be reasonably divided into two, can effectively shorten the development link, improve the development efficiency, Virtools is a kind of development of virtual reality system - tool software, developers through the intuitive graphical development interface, as long as the module drag to the object can be produced complex interactive behavior. Virtools is characterized by its ease of use and wide range of applications.

2.3.2 Image processing algorithms

In the practical training module, often encountered object movement, rotation, machining chip display, parts of the cutting and machine tool model of the relative relationship between the components and other issues, by virtue of Virtools itself can solve some of the problems, but in order to achieve the desired results, the need for geometric transformation, particle system, collision detection and shadow drawing and other key algorithms to optimize. The optimization and implementation of these image processing algorithms will be introduced next.

(1) Geometric Transformation Algorithm

Translation transformation refers to moving an object from its current position to a new position without changing its direction and size. Suppose the translations in the X , Y , and Z directions are T_x , T_y , and T_z , respectively. Then there are:

$$T = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ T_x & T_y & T_z & 1 \end{bmatrix} \quad (8)$$

Therefore, the new coordinates of a point (X, Y, Z) after translation are:

$$\begin{cases} X' = X + T_x \\ Y' = Y + T_y \\ Z' = Z + T_z \end{cases} \quad (9)$$

Proportional scaling transformations are those that change the size of an object by a certain proportion. Assuming that the scaling factors S_x , S_y , and S_z correspond to the (X, Y, Z) coordinate axes respectively, the transformation matrix is:

$$\begin{bmatrix} S_x & 0 & 0 & 0 \\ 0 & S_y & 0 & 0 \\ 0 & 0 & S_z & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (10)$$

Therefore, the new coordinates of a point (X, Y, Z) after scaling are:

$$\begin{cases} X' = XS_x \\ Y' = YS_y \\ Z' = ZS_z \end{cases} \quad (11)$$

Rotational transformation is a type of geometric transformation in which an object is turned about the $X/Y/Z$ with respect to the α with respect to the X axis corresponds to matrix R_x and a rotation by angle β with respect to the Y axis corresponds to matrix R_y . then a rotation by angle θ with respect to the Z axis for a transformation matrix of R_z , respectively. i.e:

$$R_z = \begin{bmatrix} \cos \theta & \sin \theta & 0 & 0 \\ -\sin \theta & \cos \theta & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 1 \end{bmatrix} \quad R_x = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos \alpha & \sin \alpha & 0 \\ 0 & -\sin \alpha & \cos \alpha & 0 \\ 0 & 0 & 1 & 1 \end{bmatrix} \quad (12)$$

$$R_y = \begin{bmatrix} \cos \beta & 0 & -\sin \beta & 0 \\ 0 & 1 & 1 & 0 \\ \sin \beta & 0 & \cos \beta & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (13)$$

(2) Particle system algorithm

The particle system is an essential component of nearly all virtual engines and is primarily applied to handle the computer-based creation and visualization of numerous macroscopic substances formed by many tiny particles moving in accordance with specific rules. Particle systems are considered to be the most successful algorithm for generating graphical simulations of irregular objects to date. The basic conception of the method is that a large number of particles with simple shapes and tiny sizes are taken as the basic elements, and then they are gathered together so as to form a system of fuzzy objects with irregular shapes and closed objects, which is the particle system.

It can be seen that each of the above steps is a process computational model, so it can be combined with all the models depicting the motion and characteristics of the object, e.g., partial differential equations can be used to describe the motion and transformation of particles. For the control of particle shapes, features and motions, some simple stochastic processes can be used to realize the stochasticity of the particle system. As for the parameters of each particle should be chosen randomly within a pre-determined range, and then its variation range is determined according to the given maximum variance and average expected value, the operational equation can be expressed as:

$$Parameter = MeanParameter + Rand() * VarParameter \quad (14)$$

where: Parameter denotes any required random parameter. MeanParameter is the mean value of the parameter. Rand() is the uniform random function in [-1,1]. VarParameter is the variance of the parameter.

(3) Collision detection algorithm

The various 3D models constructed in the practical training real-world module are independent of each other, in order to avoid objects crossing in motion, so that the scene characters are more complete, but also need to use collision detection technology. Collision detection algorithms are usually divided into two categories: spatial decomposition method and hierarchical enclosing box method, the latter is very suitable for collision detection in complex environments, which is more widely used.

Commonly used hierarchical enclosing box shown in Figure 2, compared with the AABB tree, the biggest feature of the OBB tree is the arbitrariness of its direction, because it only needs to contain the object and the direction of the hexahedron relative to the coordinate axis arbitrary. The OBB in 3D space can be expressed using the midpoint F , the half-length edges $R1/R2/R3$, and the mutually perpendicular unit vectors $Z1/Z2/Z3$ with a total of seven parameters. The expression is given below:

$$R = \{F + a R1 Z + b R2 Z + c R3 Z \mid a, b, c \in [-1, 1]\} \quad (15)$$

The algorithm utilizes the first and second order statistical properties of the object's vertex coordinates, and the enclosing box hierarchy is based on:

$$\mu = \frac{1}{3n} \sum_{i=0}^n (p^i + q^i + r^i) \quad (16)$$

$$c_{jk} = \frac{1}{3n} \sum_{i=0}^n (\bar{p}_j \bar{p}_k^i + \bar{q}_j \bar{q}_k^i + \bar{r}_j \bar{r}_k^i) \quad 1 \leq j, k \leq 3 \quad (17)$$

where: n the number of triangles that make up the model, $\bar{p}^i = p^i - u$, $\bar{q}^i = q^i - u$, and $\bar{r}^i = r^i - u$ is a 3×1 vector. $p^{-i} = (p_1^{-i}, p_2^{-i}, p_3^{-i})^T$ and C_{jk} are 3×3 covariance matrices. μ : mean value. C : covariance \bar{p} . The three vertices of the i th triangle are (p^i, q^i, r^i) .

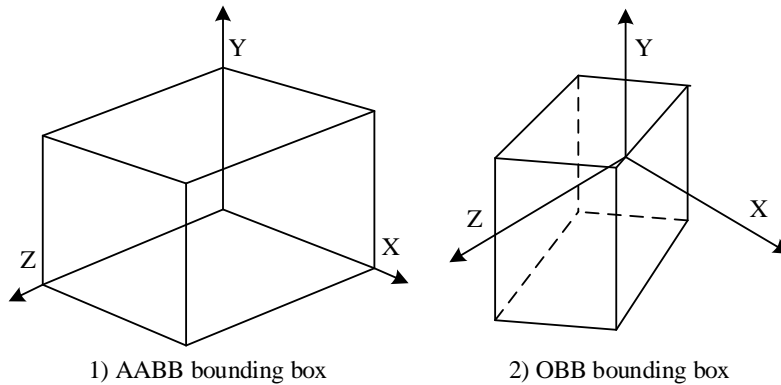


Figure 2: Commonly used hierarchical bounding boxes

(4) Shading Rendering Algorithm

Mask calculation is divided into three directions of calculation - plane normal, center point and plane X , Y direction. The formula for calculating the mask plane normal is as follows:

$$N_{maite} = \frac{\sum_{i=1}^{N_v} (V_i - V_{light})}{N_v} = \frac{\sum_{i=1}^{N_v} V_i}{N_v} - V_{light} = O_p - V_{light} \quad (18)$$

where N_{maite} represents the normal vector of the masking plane, V_i is the coordinate of the i th node of the scene, N_v is the number of nodes, O_s represents the geometric center coordinate of the scene, and V_{light} represents the coordinate of the point light source.

Project the scene onto the masking plane to obtain the masking polygon, and finally generate the masking polygon by the following transformation matrix (T_matrix). i.e:

$$V_{mate} = M_{ObjectLoadToWorld} * M_{WorldToMate} * V_{ObjectLoad} \quad (19)$$

Here, V_{mate} denotes the coordinates of the nodes after projection onto the mask surface; $M_{WorldToMate}$ denotes the transformation matrix mapping the system reference frame into the mask reference frame, $V_{ObjectLoad}$ represents the local coordinate value of any selected node in the scene; and $M_{ObjectLoadToWorld}$ denotes the transformation matrix that converts the object reference frame into the system reference frame.

2.3.3 Establishment of training scenarios

This system is based on a school CNC machining training workshop as a prototype, involving CNC lathes, CNC milling machines, machining centers and other equipment, as well as virtual machining, learning materials display, etc., the virtual scene is more complex and a large number of virtual scenarios, so this project adopts a modular scenario design ideas, to break down the complex scenarios into a number of relatively independent sub-scenes, such as: CNC lathe virtual scenarios, virtual scenes of machining centers, workshop peripheral scenes, virtual machining scenes and so on. , workshop peripheral scene, virtual machining scene and so on. Before virtual modeling, it is essential to get a comprehensive idea of the real equipment in terms of its visual aspect, size as well as internal organization and to map the actual machine tool and gather all the necessary information needed to build the model. The next step is the creation of individual component models with the help of modeling software, which are subsequently assembled and optimized correctly. The material and texture settings are then added to the model and the last step is the model rendering. This training situation eliminates the possibility of safety accidents and the breakdown of equipment that can occur during the operation in a real environment, gives students a deep and realistic environment to learn and practice the integration between education and industry, and also adds more value to the practical teaching of the CNC machining, thus enhancing the efficiency of industry-education integration collaboration

2.4 Early warning module for student management

The Student management has played a central role in the creation and future development of

schools and universities, and it will also determine if an institution is able to realize the concept of sustainable growth. In this context, the early-warning practice in student management may be viewed as one of the key top-level actions aimed at enhancing the collaborative efficiency of integration between the industry and education. The implementation of an early-warning system in student management provides an opportunity to determine the learning conditions of students, advance the process of integration between industry and education and the cooperation between school and enterprise, strictly implement early-warning and withdrawal policies, respond to changes in majors in a timely manner, focus high-quality resources on the training of talented individuals, and thereby enhance the collaborative efficiency of industry-education integration.

2.4.1 Classification of Early Warning Levels

In light of the actual conditions of student management under industry-education integration, the early-warning system is classified into four categories: red warning, orange warning, yellow warning, and green warning. Through the student management early warning neural network prediction, we will predict the probability of employment is lower than 50% of the students included in the red warning object, will predict the probability of employment is low between 50% and 60% of the students included in the orange warning object, will predict the probability of employment in 60% to 80% of the students included in the yellow warning object, for the prediction of the probability of employment is higher than 80% of the students included in the green warning object.

2.4.2 Improving LSTM networks

After the multidimensional normal-distribution feature extraction of all student data matrices is done, every matrix is sorted into either single class or regular class. The two networks process the student data matrices in each category. To train the LSTM network, which consists of adaptive activation, the corresponding data rows are used to feed the data types with high temporal correlation, like campus card usage statistics. To train the MLP network, which is based on the resilient back propagation algorithm, the relevant data rows are used to feed the data types with low temporal correlation, like the theoretical and practical scores of the students. This is followed by the combination of the outputs of the two networks using linear probability fitting to obtain network cascading and eventually get the employment probability. This is:

$$f(x) = \frac{1}{u} \frac{e^x - e^{-x}}{e^x + e^{-x}} + \frac{1}{v} \max(0, x), u + v = 1 \quad (20)$$

The original \tanh activation function is replaced with an adaptive activation mechanism in the form of a $\text{Relu}+\tanh$ weighted-average function. Each gate of the LSTM adopts this activation form for incoming data, so that information related to student card consumption can be used for training and for the warning classification of individual students, thereby generating a personalized analysis report for each student. When a high-risk warning is triggered, the corresponding warning information is obtained and then cascaded with the artificial neural network in 3 to predict the student's probability of employment.

For the parameter calculation of the adaptive activation function, the input layer is defined as a matrix with dimensions $j_1 * n$, where $j_1 < m$. Here, j_1 denotes the number of rows selected from the overall data matrix K , and in this case $j_1 = 7$. Through repeated iterative computation combined with optimal approximation, the adaptive activation function is ultimately derived, namely:

$$z = \frac{1}{v} \operatorname{relu} \left(w \frac{x^t}{t-1} \right) + \frac{1}{u} \operatorname{tanh} \left(w \frac{x^t}{t-1} \right) \quad (21)$$

The weighting coefficients $v = 0.637$ and $u = 0.363$ are best trained.

2.4.3 Iterative Training Based on Backpropagation Rprop Algorithm

The most significant advantage of the choice of resilient backpropagation algorithm is the fact that during the training of the model, the gradient of the error function affects not the extent of the weight changes but the direction of the changes. The absolute change in weights depends on the respective learning rate and is not defined by the magnitude of the gradient itself. That is, the gradient of the error function plays merely the role of signaling if the weights are to be increased or decreased and does not define the intensity of the update. If the gradient of the error function is positive, the appropriate weight value must decrease accordingly. If the gradient is negative, the associated weight must increase so that the error function slowly minimizes as follows:

$$\begin{aligned} \Delta w_{i,j} &= -\eta_{i,j}(t), \text{ if } g(y) > 0 \\ \Delta w_{i,j} &= +\eta_{i,j}(t), \text{ if } g(y) < 0 \\ \Delta w_{i,j} &= 0, \text{ otherwise} \end{aligned} \quad (22)$$

For the variation of the learning rate $\eta_{i,j}(t)$ in the resilient backpropagation algorithm, the gradient sign may change between two consecutive moments. This situation can be discussed in two cases. If the gradient direction of the error function at the current moment is different from that at the preceding moment, it indicates that the minimum point has been crossed, namely, the increment in the previous weight update was excessively large. Under this condition, $\eta_{i,j}(t)$ becomes smaller than $\eta_{i,j}(t-1)$ and the learning rate at the last step is scaled by a factor η^{up} within the interval $(0,1)$ to obtain the updated learning rate. By contrast, if the gradient directions at the two moments remain consistent, the minimum of the error function has not yet been reached, so the learning rate from the previous step is multiplied by a coefficient η^{down} greater than 1, thereby yielding the current learning rate, as expressed in Eq. (23):

$$\begin{aligned} \eta_{i,j}(t) &= \eta^{up} \eta_{i,j}(t-1), g(t-1)g(t) > 0 \\ \eta_{i,j}(t) &= \eta^{down} \eta_{i,j}(t-1), g(t-1)g(t) < 0 \\ \eta_{i,j}(t) &= \eta_{i,j}(t-1), \text{ otherwise} \end{aligned} \quad (23)$$

The system inputs to different training networks for classification operations according to the different types of student information data, and then combines the output probability results, using the form of $p*a + (1-p)*b = c$ for the fusion of results. Where p is the weight coefficient, a is the LSTM network prediction result, b is the artificial neural network prediction result, and c is the probability of employment, which ultimately results in the probability of employment of the student, and different degrees of management warning for students.

2.4.4 Network parameter configuration

The main hyperparameters of the network are the learning rate, momentum increase and the number of training iterations with their values being limited to 0.001-0.5, 0.01-4.0 and 100-1000 respectively. Calculation of the input layer: from the total data matrix K , the LSTM selects j_1 row vectors for training, then the remaining is $j_2 = m - j_1$ rows of data, then the input layer is a matrix of size $j_2 * n$. The number of nodes in the input layer is j_2 , here $j_2 = 15$, and the neurons are fully connected so the weight is 1.

Calculation of the hidden layer: hidden layer, in the learning rate $\gamma = 0.0128$ and the number of hidden layers of 8 layers when the accuracy has reached a high level but the false positive rate is also relatively high, continue to deepen the hidden layer in the learning rate of $\gamma = 0.00428$ and the number of hidden layers of 20 layers when the accuracy of the obvious decline and false positive rate is once again higher, through the elastic back propagation algorithm repeated iterations Through repeated iterations of the elastic back propagation algorithm, the optimal accuracy is obtained when the learning rate and the number of hidden layers is 10.

Calculation of the output layer: since the output result is the probability of student employment, the output layer is the number of nodes 1.

3 System module simulation and optimization

3.1 Simulation of the resource recommendation module for industry-teaching integration

Once the application effectiveness of the LDA topic model has been confirmed in mining subject interests of industry-education integration projects, it is also important to perform a comparative analysis between the content-based recommendation algorithm and the user-based recommendation algorithm to assess the effectiveness of the content-based recommendation method. To achieve this aim, simulation experiments are conducted using the text information of industry-education integration projects so as to compare the performance discrepancies between the content-based recommendation algorithm and the user-based recommendation algorithm.

3.1.1 Interest Mining Analysis of Subjects of Industry-Education Integration Projects

This subsection preprocesses the textual data of the production-teaching integration resources by vectorizing the downloaded policy text through Python's pandas library and storing it in the form of an Excel dataset. The first filtering utilizes Python's jieba lexical module to process the vectorized text of education and industry integration resources into lexical processing. Chinese literature has no prominent separating boundaries between words, and punctuation is not enough to separate the text of education and industry integration resources into topic words, and the model can only identify words with characteristic features, so this step is very important and determines the efficiency and accuracy of the LDA topic model. Next, the TfidfModel is applied to compute TF-IDF values, where the weight of a term increases with its frequency in a given document and decreases with its overall frequency across the corpus. Based on these TF-IDF scores, words occurring above a certain frequency but carrying low weights in the text of industry-education integration resources are removed, while the terms closely associated with such resources are preserved. Finally, the filtered dataset is imported into the LDA model for modeling.

The most important step in the LDA topic model is to determine the number of topics, and it is more common to determine the optimal number of topics by topic consistency and perplexity. Theme consistency, also known as theme coherence, refers to the degree of connection between words within a theme, i.e., whether the word occurs frequently within the same theme. The higher the thematic coherence, the more closely related the words are within the theme, and the higher the interpretability of the theme. Perplexity is used to measure the degree of uncertainty of the model's prediction of the text data, the lower the perplexity, the lower the uncertainty, the better the topic clustering effect, the more accurate and certain the model's generalization and prediction of the topic of the data corpus, the number of topics - perplexity folds are shown in Figure 3.

As the value of the number of topics K increases, the perplexity gradually decreases. When K belongs to (2,4), the perplexity curve gradually decreases. When K is 4, the perplexity curve decreases sharply, but the topic granularity is too large at this time. When num-topics=5, the value of perplexity is low, the clustering effect of themes is better, and the demarcation between themes is more obvious. Accordingly, the number of topics determined for industry-education integration resources is set to 5. The LDA topic model is then visualized by calling the HopPyLDAvis library, as presented in Figure 4, where T1–T30 denote the textual lexical items related to industry-education integration resources. This visualization not only provides an intuitive display of the distribution trend of textual feature-word frequencies, but also further verifies the effectiveness of the LDA model in mining the subjective interests involved in industry-education integration projects.

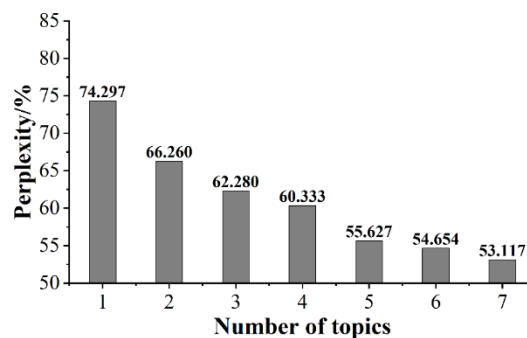


Figure 3: Topic Number - Perplexity Line

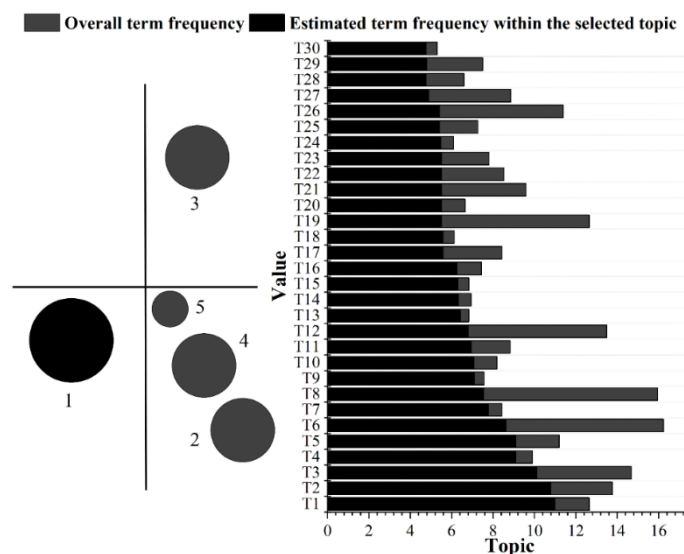


Figure 4: Visual display

3.1.2 Algorithm simulation analysis

This section compares the content-based recommendation algorithm and the user-based recommendation algorithm on the basis of their use in the context of recommending industry-education integration resources and measures the accuracy, recall and precision of both algorithms to determine their relative performance. Fig. 5 and Fig. 6 show the comparison of accuracy and recall respectively, and Fig. 7 shows the comparison of precision. A comparison of the accuracy and recall reveals that, with the increasing number of recommended industry-education integration resources, both the accuracy indicators of the content-based recommendation algorithm increase rapidly. Comparatively, the user-based recommendation algorithm requires a significant improvement in accuracy and recall, but it can be achieved only when the number of recommended resources is relatively large, and the range of values is kept between $[0, 0.4]$. Another comparison of the precision indicates that, with the rising number of recommended industry-education integration resources, the precision of the user-based recommendation algorithm reduces significantly, whereas the precision of the content-based recommendation algorithm is maintained at a relatively high level throughout. Overall, the accuracy, recall, and precision of the content-based recommendation algorithm are always no less than those of the user-based recommendation algorithm when the number of recommended industry-education integration resources increases. Furthermore, the bigger the number of recommended resources, the more apparent the performance benefit of the content-based recommendation algorithm. To put it differently, the content-based recommendation algorithm works better than the user-based recommendation algorithm. The simulation and analysis findings confirm the usefulness of the content-based recommendation algorithm in the resource module of industry-education integration and to a certain degree also support the utility of the digital twin system in terms of industry-education integration perspective, which is quite important to enhance collaborative efficacy in this sphere.

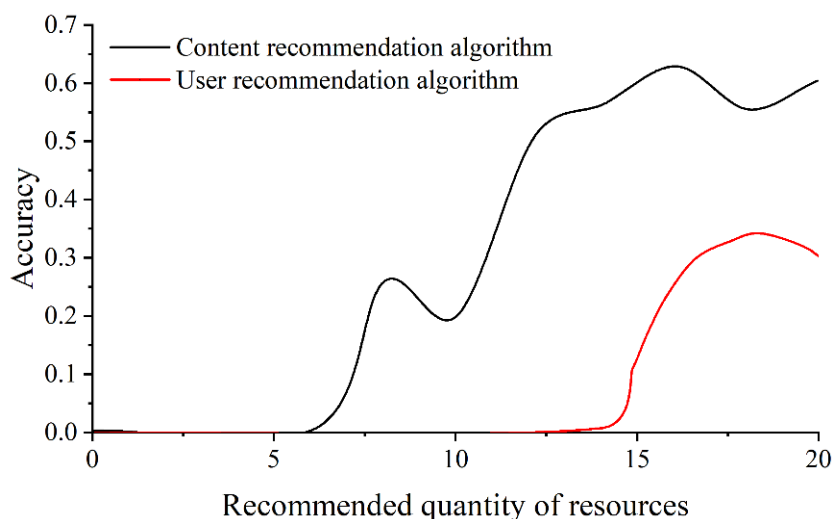


Figure 5: Comparison of accuracy rates

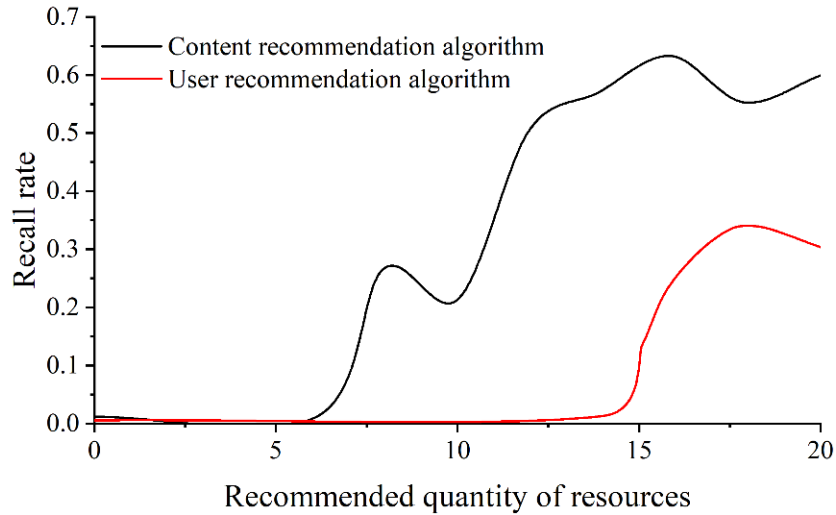


Figure 6: Recall rate comparison

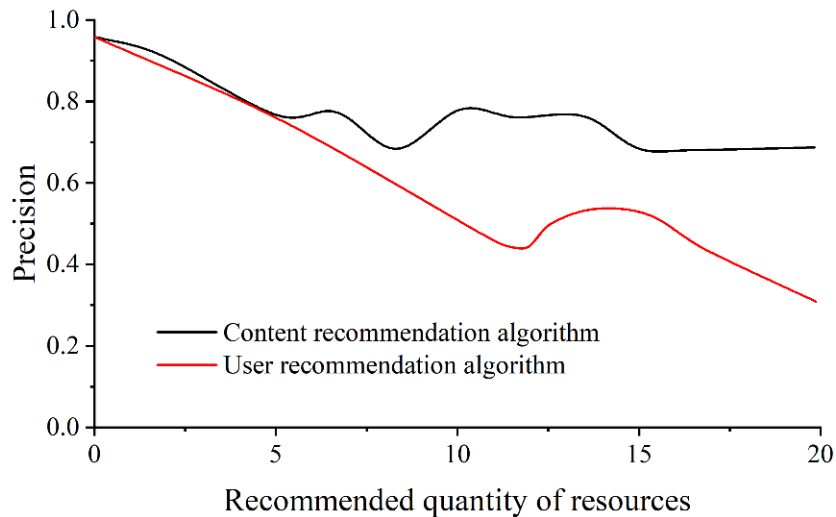


Figure 7: Precision comparison

3.2 Practical training and combat module simulation

3.2.1 Initial condition setting

The computer simulation needs to be set up initially by setting the simulation start time = 2014, simulation termination time = 2023, simulation step (DT) = 1, and time unit (UNIT) = year, and its data is derived from the data crawling program in web mining.

3.2.2 Test analysis

There is also a need to test the module after it has been created, as module testing is used to find errors so that the modeler and the user can understand the limitations of the module and improve it, and ultimately so that the module assists the user in making better decisions. Various specialized guesses are created to find flaws and improve the module, but it is not possible to prove the vulnerability of the module in every aspect, generally the following tests are performed on the module: boundary test, mental model test, quantitative consistency test, structural and behavioral test, parameter estimation test, integral error test, sensitivity test, and

extreme case test. The following further performs history test, sensitivity analysis and extreme case test on the module.

(1) Historical Test

In order to make progress in testing the effectiveness and authenticity of the module, the practical training simulation data derived from the simulation is compared with the historical practical training data, and the error rate is whether it is within the value of the error allowable range, and the results of the historical test are shown in Table 1. Most of the relative errors between the simulated real training values and the historical real training values within the process of industry-education integration from 2014 to 2023 are controlled within 5%, and the average value of the relative error rate between the simulated real training data and the historical real training data is 2.42%, and the error value is within a reasonable range. Therefore, the practical training module has excellent application effectiveness.

Table 1: Historical test results

Year	Historical training data	Practical training simulation data	Relative error value
2014	7.623	7.054	0.0807
2015	7.25	7.216	0.0047
2016	9.538	9.583	0.0047
2017	10.103	9.979	0.0124
2018	13.744	13.508	0.0175
2019	8.311	8.302	0.0011
2020	15.309	15.154	0.0102
2021	16.765	16.64	0.0075
2022	10.984	9.973	0.1014
2023	11.812	11.832	0.0017
Mean	11.1439	10.9241	0.0242

(2) Sensitivity test

Set the number of simulations of students' practical ability in the practical training module for 500 times, the sensitivity test results are shown in Figure 8, which shows that the simulation value of students' practical ability fluctuates between 0.7 and 1.0, and there are differences in the results of the run due to the different parameters, but the shape of the graph is basically the same. It shows that the practical training practical module of the students' practical ability to take the value of insensitive more stable, the model passed the sensitivity test.

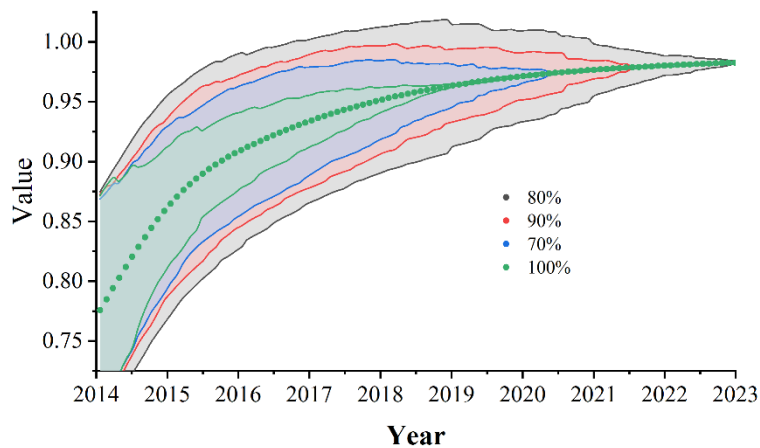


Figure 8: Sensitivity test results

(3) Extreme situation test

Set the number of students participating in the practical training practical module = 0, and carry out the module extreme case test. The results of the extreme case test are shown in Figure 9. When the number of people involved in the practical training module plummets to zero, the simulation results of the practical training module are in line with reality, and the participation in the practical training module becomes 0 in 2018, which means that the model extreme case test passes.

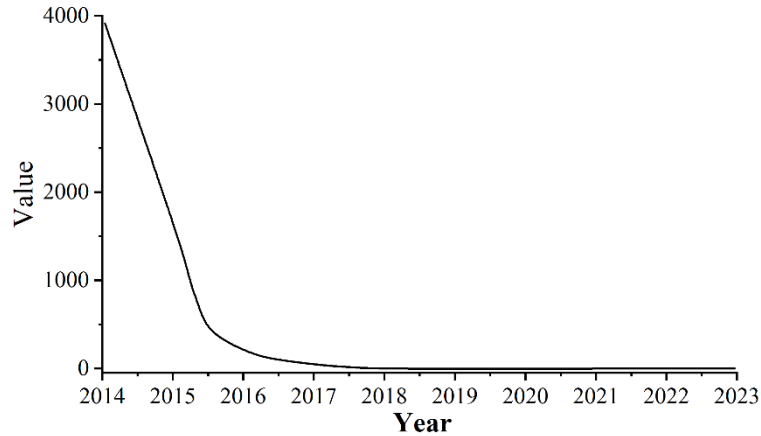


Figure 9: Extreme case test results

3.3 Simulation of Student Management Alert Module

When the student management early-warning model has been developed, there is a training set introduced to learn it. The test-set data are fed into the model after the iterative training process using the back propagation Rprop algorithm has ended, and the analysis of the student management early-warning module and the results corresponding to these are displayed in Figure 10. The data represented in the figure indicate that the difference between the simulated and the observed values of the student management early-warning model is less than 0.05, which means that the model is very highly accurate in predicting as well as very effective. This finding indicates that the proposed student management early-warning module could offer a more supportive role to the digital twin system, thus enhancing the synergistic efficacy of industry-education integration.

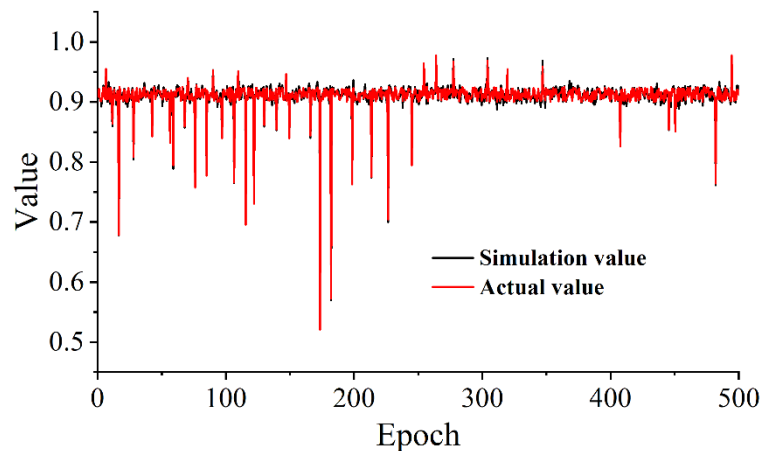


Figure 10: Simulation analysis results

To further examine the application value of the student management early-warning model in improving the synergistic effectiveness of industry-education integration, the model is applied to simulation analysis from the perspective of student employment probability, and the simulation results are presented in Table 2. According to the data in the table, during the simulation analysis of student management warning levels, the prediction errors for red warning, orange warning, yellow warning, and green warning are 0.0315, 0.0233, 0.0309, and 0.0045, respectively, all of which remain within 0.05. These results clearly demonstrate the practical value of the student management early-warning model proposed in this paper for enhancing the synergistic effectiveness of industry-education integration. The model also provides a useful reference for student early warning in colleges and universities, helping teachers identify students with low employment probability in a more targeted manner during the process of industry-education integration and carry out differentiated instruction. In this way, timely guidance and early intervention can be implemented during the learning stage, thereby effectively reducing the risk of student unemployment.

Table 2: The simulation analysis results of the model application

Student management warning level	Actual value	Simulation value	Relative error
Red alert	0.476	0.461	0.0315
Orange alert	0.558	0.545	0.0233
Yellow alert	0.744	0.721	0.0309
Green alert	0.892	0.888	0.0045

3.4 Optimization Strategies

3.4.1 Strengthening integrated leadership

The most important thing is to promote the general concept of industry-education integration, take active steps on coordinating the relevant departments in this sphere, such as education, finance, human resources and social security, as well as industry and information technology, and develop a stable joint work system of industry-education integration. This will allow forming a support system with a view to government-wide planning, scientifically-organized management and governmental support, which will also bring about a concerted mode of behavior involving interdepartmental coordination, effective interactions between higher vocational institutions, a tight connection between enterprises, and participation of many industrial associations, thus promoting the design and optimization of digital twin systems of industry-education synergy. A well-developed digital twin system that is constantly being improved can also enhance the practical skills of students and their problem-solving capacity.

3.4.2 Enhanced capacity-building for services

The accelerated development of digital twin system service capacity is also required, promoting the alignment of professional curricula with a job position at an enterprise, teaching content with occupational standards, and teaching procedures with the enterprise production process comprehensively to promote better digital twin systems that are aimed at the collaborative efficiency of industry-education integration. Through this approach, the requirements of enterprise employment will be met more effectively and more confidence will be given to enterprises to engage more actively in the integration of industry and education.

4 Conclusion

With the fast advancement of digital twin technology, the demand for deep integration between university education and industry has become higher under the background of high-quality economic development. This paper develops a digital twin system for improving the collaborative effectiveness of industry-education integration from three aspects, namely the industry-education integration resource recommendation module, the practical training module, and the student management early-warning module, and then carries out simulation and analysis for each functional module of the system.

(1) Through the subject mining of industry-teaching integration of LDA model, the number of subject generation of industry-teaching integration resources is determined to be 5, which shows a better clustering effect, i.e., it reflects the application effect of LDA model in the subject interest mining of industry-teaching integration project. In addition with the increment of the number of recommended production and education fusion resources, the content recommendation algorithm's correct rate, check all rate and accuracy rate are better than the user recommendation algorithm, which indicates the effectiveness of the content recommendation algorithm in the production and education fusion resources module.

(2) The average value of the relative error rate between the value of imitation real training and the value of historical real training within the process of industry-teaching integration from 2014 to 2023 is 2.42%, and the relative error is controlled within 5%, which demonstrates the effectiveness of the application of the practical training module in the digital twin system of this paper, which in turn promotes the high-quality development of collaborative efficacy of industry-teaching integration.

(3) The proposed model is used in the simulation analysis of student management warning levels and the results reveal that the prediction errors of red warning, orange warning, yellow warning and green warning are 0.0315, 0.0233, 0.0309 and 0.0045. The prediction errors in all cases are within acceptable limits, which validates that the student management warning module has a practical value in the digital twin system to enhance collaborative effectiveness of industry-education integration.

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References

- [1] Ren, J., Wu, Q., Han, Z., Gong, K., & Wang, D. (2018). Research on the Education of Industry-Education Integration for Geological Majors. *Educational Sciences: Theory & Practice*, 18(5).
- [2] Yu, K., & Tsao, H. J. (2024). Research on the Challenges and Paths of Industry Education Integration in Vocational Colleges. *International Journal of Education and Humanities*, 15(3), 303-307.
- [3] Xiong, L. (2025). Research on the Teaching Evaluation of Situation and Policy in Higher Vocational Colleges under the Perspective of the Integration of Industry and Education. *Educational Innovation Research*, 3(2), 29-34.
- [4] Tan, X., Cheng, Y., Tan, Y., Wei, J., & Lei, Y. (2022). Application and research on key technologies of smart campus based on 5G environment. In *Advances in Urban Engineering and Management Science Volume 2* (pp. 500-512). CRC Press.
- [5] CHEN, B., MO, Q., JI, G., HAO, T., LI, M., & WANG, J. (2025). Construction and practice of digital twin laboratory based on the industry-education integration. *Experimental Technology & Management*, 42(8).
- [6] Aguzzi, J., Chatzidouros, E., Chatzievangelou, D., Clavel-Henry, M., Flögel, S., Bahamon, N., ... & Doyle, J. (2025). A digital-twin strategy using robots for marine ecosystem monitoring. *Ecological Informatics*, 103409.
- [7] Rahman, M. A., Shahrir, M. F., Iqbal, K., & Abushaiba, A. A. (2025). Enabling intelligent industrial automation: A Review of machine learning applications with digital twin and edge AI Integration. *Automation*, 6(3), 37.
- [8] Halwani, S., Hamid, A. K., Ahmad, F. F., & Hussein, M. (2025). Comparative analysis of experimental and modelling of bifacial PV panel: a step towards digital twin. *International Journal of Thermofluids*, 101377.
- [9] Hu, P. (2023). Investigation on Smart Campus Management Platform Based on Digital Twin. *Procedia Computer Science*, 228, 937-945.
- [10] Aliyev, A. G., & Shahverdiyeva, R. O. (2023). Development of a conceptual model of effective management of innovative enterprises based on digital twin technologies. *Int. J. Inf. Eng. Electron. Bus.(IJIEEB)*, 15(4), 34-47.
- [11] Karanam, S. A. K., & Hartman, N. W. (2025). A systematic review of Digital Twin (DT) and virtual learning environments (VLE) for smart manufacturing education. *Manufacturing letters*, 44, 1597-1608.
- [12] Hazrat, M. A., Hassan, N. M. S., Chowdhury, A. A., Rasul, M. G., & Taylor, B. A. (2023). Developing a skilled workforce for future industry demand: The potential of digital twin-based teaching and learning practices in engineering education. *Sustainability*, 15(23), 16433.
- [13] Yanan, Q., & Wai Yie, L. (2025). Enhancing Engineering Competencies through Industry-

- Education Integration: Evidence from an Industrial Internet Talent Cultivation in Chinese Application-oriented Undergraduate University. *INTI JOURNAL*, 2025(10), 1-8.
- [14] Chen, Y., Li, S., & Chen, R. (2025). Impact of Industry and Education Integration on Employment Quality in Higher Vocational Colleges: Moderating Role of Faculty Qualifications and Curriculum Development Capacity. *Education Sciences*, 15(10), 1316.
- [15] Zhang, H., Wu, L., & Wang, J. (2025). Research on innovative models of industry-education integration to promote sustainable education in agricultural machinery majors. *Sustainable Futures*, 10, 101072.
- [16] Rajalo, S., & Vadi, M. (2017). University-industry innovation collaboration: Reconceptualization. *Technovation*, 62, 42-54.
- [17] Wang, Y. (2025). Industry-Education Integration: Modeling Dilemmas and Practical Tensions. *Frontiers in Economics and Management*, 6(10), 92-99.
- [18] Zhang, H. (2025). The Intrinsic Logic and Practical Pathways of Empowering Vocational Education Through Industry-Education Integration: Summary of the Session on Industry-Education Integration for Advancing High-Quality Vocational Education. *World Vocational and Technical Education*, 1(1), 38-54.
- [19] He, Z., Chen, L., & Zhu, L. (2023). A study of Inter-Technology Information Management (ITIM) system for industry-education integration. *Heliyon*, 9(9).
- [20] Lu, K., & Song, X. (2025, November). Research on the Model and Practical Innovation of Industry-Education Integration for Cultivating High-Skilled Talents in the Era of Artificial Intelligence. In *2025 International Conference on Digital Technology and Educational Psychology (DTEP 2025)* (pp. 225-234). Atlantis Press.
- [21] Tang, L., Tang, J., & Tang, Y. (2024, September). Exploration of the Construction Mode of Industry-education Integrated Curriculum System Based on Knowledge Graph. In *2024 14th International Conference on Information Technology in Medicine and Education (ITME)* (pp. 1186-1190). IEEE.
- [22] Wu, B., Li, F., & Shao, X. (2025). Construction and Optimization of Faculty Teams in Vocational Colleges under the Paradigm of Industry-Education Integration. *Journal of Computer Science and Frontier Technologies*, 1(2), 67-77.
- [23] Zhang, H. (2025). Construction of Innovation Mode of Engineering Drawing Courses Driven by Collaboration between AI and Industry-Education Integration in Application-Oriented Universities. *Frontiers in Educational Research*, 8(5).
- [24] Miao, Y., Xiao, Z., & Zhang, Y. (2025). Impact of talent cultivation model for industry education integration in vocational education by artificial intelligence and BPNN. *Scientific Reports*, 15(1), 38019.
- [25] Na, X. The Construction of Digital Teaching Curriculum Resources Based on the Integration of Production and Education. *International Journal of Educational Economy and Management*, 25.

- [26] Mohammad, A. A. S., Al-Daoud, K. I., Al Oraini, B., Mohammad, S. I. S., Vasudevan, A., Zhang, J., & Hunitie, M. F. A. (2024). Using Digital Twin Technology to Conduct Dynamic Simulation of Industry-Education Integration. *Data and Metadata*, 3, 422-422.
- [27] Acker, J., Rogers, I., Guerra-Zubiaga, D., Tanveer, M. H., & Moghadam, A. A. A. (2023). Low-cost digital twin approach and tools to support industry and academia: A case study connecting high-schools with high degree education. *Machines*, 11(9), 860.
- [28] Sepasgozar, S. M., Khan, A. A., Shirowzhan, S., Romero, J. S. G., Pettit, C., Zhang, C., ... & Liang, R. (2024). Immersive virtual environments and digital twin applications for education and training: Trends in construction, mining, and urban planning studies. In *Digital Twin Adoption and BIM-GIS Implementation* (pp. 66-109). Routledge.
- [29] Filipescu, A., Simion, G., Ionescu, D., & Filipescu, A. (2024). IoT-Cloud, VPN, and digital twin-based remote monitoring and control of a multifunctional robotic cell in the context of AI, industry, and education 4.0 and 5.0. *Sensors*, 24(23), 7451.
- [30] Meng, S., & Deng, M. (2024, July). Exploration of Information Technology Teaching Reform Based on Digital Twin Virtual Simulation Technology in the Context of Intelligent Manufacturing. In *Proceedings of the 2nd International Conference on Educational Knowledge and Informatization* (pp. 116-120).