Research on the Process Evaluation System of Higher Vocational Mathematics Driven by Big Data and AI - Guided by the Cultivation of Skilled Talents

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ABSTRACT Traditional assessment in higher vocational mathematics is often separated from the goal of skilled-talent cultivation. Summative assessment can hardly track students' mathematical application ability in dynamic engineering-learning processes, nor can it diagnose skill gaps in time for targeted intervention. This limitation is particularly evident when mathematics courses need to support applied engineering tasks such as differential equations, signal modeling, electromagnetic-field computation, and antenna-related parameter analysis. To address this problem, this paper constructs a process-oriented assessment system driven by big data and artificial intelligence. First, multi-source data from students' online learning behavior and offline classroom performance are collected and integrated through big data technology. Second, a long short-term memory network is used to dynamically model time-series learning behavior and identify weak knowledge points. Third, personalized learning paths are generated using knowledge graphs and collaborative filtering. Finally, a visual feedback mechanism transforms diagnostic results into teaching interventions, forming a closed-loop process of data collection, intelligent diagnosis, feedback, and adjustment. Experimental results show that the diagnostic accuracy of the LSTM model (RMSE = 1.66) is significantly better than that of baseline models. Personalized recommendation increases the improvement rate of weak knowledge points in the experimental group by 24.6%. The mathematical application ability score and professional project score of the experimental class reach 82.4 and 86.7, respectively, both significantly higher than those of the control class. The system realizes a shift from summative assessment to dynamic diagnosis and promotes the integration of mathematical ability with engineeringoriented professional skills.

INDEX TERMS higher vocational mathematics, process evaluation system, big data and artificial intelligence, LSTM, electromagnetic engineering education

I. INTRODUCTION

CURRENTLY, my country's vocational education is accelerating its transformation towards a skills-based talent training model, which requires higher vocational mathematics courses to integrate the complex geometric modeling of high-performance industrial structures into the cultivation of students' mathematical application abilities and problem-solving thinking. By focusing on the algorithmic calculation of tension and material density, the curriculum ensures that basic theoretical knowledge directly supports the precision requirements of advanced technical manufacturing [1,2]. However, the traditional higher vocational mathematics teaching evaluation system is still dominated by summative examinations, emphasizing formula memorization and problem-solving skills, and is difficult to dynamically track students' mathematical thinking process and application ability development in real task scenarios. This evaluation model is clearly misaligned with the goal of cultivating skills-based talents: it cannot accurately diagnose the weak links in students' transformation of mathematical knowledge into professional skills, nor can it provide effective data support for personalized teaching intervention [3]. How to construct an evaluation system that can reflect the development of students' mathematical application abilities in a dynamic and comprehensive manner has become a key issue that needs to be addressed in the current reform of higher vocational mathematics teaching. In recent years, the application of process evaluation in higher vocational teaching has received widespread attention. Li pointed out that process evaluation in high school English teaching is constrained by the system, teacher ability, and technical conditions, and proposed corresponding improvement strategies [4]. To address the lack of formative assessment in complex skills learning, Xu et al. constructed a comprehensive formative assessment framework for complex skills and verified its feasibility and effectiveness through a controlled experiment with industrial robotics students at a technical college [5]. Oh and Kwon conducted two rounds of group interviews with six high school mathematics teachers in Incheon to examine their understanding of formative assessment, implementation performance, and difficulties [6]. Solehuddin designed and evaluated the effect of a process-oriented guided inquiry learning model supported by the XPOGIEDU website on improving the programming logic thinking (branching and looping) ability of 37 tenth-grade vocational high school students [7]. However, existing studies mostly use static weighting methods such as the analytic hierarchy process or fuzzy comprehensive evaluation, which are difficult to truly reflect the dynamic changes in students' learning process; at the same time, the data sources are relatively singular, limited to homework

grades and classroom attendance, and fail to fully integrate diverse online and offline behavioral data, resulting in insufficient correlation between evaluation results and professional skills training.

In response to the above problems, related studies have begun to try to introduce data mining technology to analyze learning behavior. He et al. explored the factors influencing the effectiveness of integrating mathematics education technology in primary and secondary schools, pointed out the difficulties faced by novice teachers in application, and proposed using artificial intelligence to optimize teaching effectiveness [8]. Feng and Chen applied three types of process mining methods to educational datasets to support student learning, teacher teaching improvement, and teaching management decisions [9]. The aforementioned scholars failed to effectively capture the dynamic laws of mathematical thinking evolution, and the recommended personalized learning resources were out of sync with professional skills requirements. In view of this, this paper proposes to construct a process evaluation system driven by big data and artificial intelligence: firstly, big data technology is used to realize the collection and integration of multi-source data throughout the learning process, then long short-term memory networks are introduced to dynamically model temporal behavioral data, and finally, personalized learning path recommendations are realized based on knowledge graphs to solve the shortcomings of existing research in dynamic diagnosis and precise intervention. The main contributions of this paper are: constructing a process evaluation system for higher vocational mathematics covering the entire chain of "data collection - intelligent diagnosis - visual feedback", realizing the deep integration of evaluation and teaching; introducing LSTM models into the dynamic modeling of students' mathematical abilities, improving the accuracy of identifying weak links in skills; and designing a personalized recommendation mechanism based on knowledge graphs, so that the evaluation results can directly drive teaching intervention. The full structure of the paper is as follows: the introduction describes the research background, current status and contributions of this paper; the methodology section elaborates on the system construction methods and technical implementation; the experimental section designs comparative experiments to evaluate the system performance; and the conclusion section summarizes the research conclusions and future prospects.

Multi-source Collection and Preprocessing of Learning Behavior Data

In order to achieve dynamic tracking of the entire process of students' mathematics learning, the system first built a data collection layer covering both online and offline spaces. Online data collection relies on the log embedding technology of the learning management platform to capture in real time the duration and frequency of students watching micro-lessons, the answer trajectory of chapter tests, the activity of forum interaction, and the interactive operation records of simulation experiments. Offline data collection uses classroom sensors and mobile terminals to record students' classroom attendance, participation time in group collaborative discussions, completion progress of practical training tasks, and teachers' real-time evaluation of classroom observations [10].

The collected raw data has problems such as multi-source heterogeneity, inconsistent format, and asynchronous time, which require system preprocessing. First, the data from different ports are timestamped, and online behavior and offline performance are integrated according to teaching weeks to construct the temporal behavior sequence of each student. Then, missing values and outliers are processed: for occasional missing data, the mean of adjacent time points is used to fill in the missing data; samples with more than 30% missing data are removed; and box plots are used to identify and correct abnormal fluctuation data. Finally, all continuous features are normalized to eliminate the influence of dimensions, and categorical features are one-hot encoded to form a structured input dataset, providing a standardized data foundation for subsequent temporal modeling. To ensure the model can diagnose specific cognitive failures, the preprocessing stage maps each behavioral record (e.g., a specific test question or micro-lesson video) to a corresponding mathematical knowledge point (e.g., 'integral calculus' or 'differential equations') using a predefined curriculum metadata matrix. This allows the feature vector x_t to represent not just general activity, but interaction intensity and performance accuracy relative to specific conceptual domains [11].

A. DYNAMIC MODELING OF MATHEMATICAL ABILITY BASED ON LONG SHORT-TERM MEMORY NETWORKS

Having finished the gathering and initial data preparation of multi-source data, the system takes as the input every temporal sequence of behaviors of a student and provides an LSTM network to simulate the dynamic patterns of mathematical capabilities of students. Table 1 demonstrates the exact form and parameter settings of the LSTM network.

TABLE 1. LSTM Network Structure and Parameter Settings

Network Layer	Architecture	Parameters	Function
Input Layer	Time-series feature vector	Nodes = feature dimension	Receive normalized time-series data
Hidden Layer	Stacked LSTM	2 layers $\times$ 64 units, Dropout=0.2	Capture long-term dependencies, extract evolution features
Output Layer	Fully connected + Softmax	Nodes = number of knowledge points	Output mastery probability
Training Configuration	Adam optimizer	lr=0.001, Loss=MSE, early stopping	Optimize model, prevent overfitting

The model input layer receives a normalized feature vector x_t. Crucially, x_t is structured as a knowledge-specific state vector. For instance, 'exercise accuracy' is not treated as a global average but is decomposed into accuracy scores for specific sub-topics. The LSTM hidden layers act as a 'cognitive memory' that tracks the evolution of mastery for these sub-topics over time. The output layer is connected to a Fully connected + Softmax structure where the number of output nodes corresponds to the total number of knowledge points in the curriculum. The Softmax function outputs a probability distribution y, where each value y_i represents the predicted probability that the student has mastered knowledge point i based on their cumulative behavioral patterns. The calculation process of each LSTM unit at time step t is as follows: The forget gate determines the information to be discarded in the cell state C_{t-1} at the previous time step, as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

The input gate determines the new information to be stored in the cell state at the current input x_t, as follows:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$C_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{3}$$

The cell state update combines historical information and new input, as follows:

$$C_t = f_t * C_{t-1} + i_t * C_t \tag{4}$$

The output gate determines the output of the hidden state h_t at the current time step, as follows:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t * \tanh(C_t) \tag{6}$$

Where σ is sigmoid The function, W and b are trainable parameters. The hidden state h_T of the last time step is connected to the fully connected layer and mapped to the predicted value y of the student's mastery of each knowledge point through the Softmax function. The mean squared error is used as the loss function for model training:

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{7}$$

The parameters are updated iteratively using the Adam optimizer. An early stopping mechanism is introduced during training. Training is terminated when the validation set loss no longer decreases for 10 consecutive rounds to prevent overfitting. The diagnostic logic operates on the principle of Deep Knowledge Tracing (DKT). Finally, the trained model can receive newly generated learning behavior data in real time. By analyzing the latent state h_t, the system identifies a 'cognitive failure' when the predicted mastery probability y_i for a specific knowledge point falls below a threshold (e.g., 0.6), despite sufficient interaction time. This suggests that the student's behavior (e.g., repeated incorrect answers or re-watching specific segments) signifies a conceptual hurdle rather than a lack of engagement[12]. The model input layer receives the normalized feature vector, which includes dimensions such as online learning time, exercise accuracy, micro-lecture interaction frequency, and classroom participation. It is input into the network in sequence according to the time step. The hidden layer consists of two stacked LSTM units, each with 64 hidden nodes. Historical information related to the current knowledge point is adaptively retained and redundant or noisy information is discarded through forget gates, input gates, and output gates. At each time step, the LSTM unit outputs the student's implicit state representation of each knowledge point, which integrates historical learning trajectory and current performance. The output of the last time step of the LSTM network is connected to a fully connected layer and mapped to the student's predicted mastery of each knowledge point through the Softmax function. The model training uses mean squared error as the loss function and the Adam optimizer is used for iterative parameter updates. An early stopping mechanism is introduced during training; training is terminated when the validation set loss no longer decreases after 10 consecutive rounds to prevent overfitting.

B. PERSONALIZED LEARNING PATH GENERATION BASED ON KNOWLEDGE GRAPH

Based on the dynamic diagnosis of students' mathematical abilities by the LSTM model, the system further constructs a knowledge graph of higher vocational mathematics, establishes a connection between discrete knowledge points and professional skill requirements, and realizes intelligent recommendation of personalized learning paths. When the LSTM model diagnoses that a student has weaknesses in a specific knowledge point, the system starts the personalized path generation module. This module takes the student's current weak knowledge point as the starting point and the professional skill training goal as the guide, and searches

for the optimal learning path from the current state to the target skill in the knowledge graph. The search process comprehensively considers the pre- and post-dependent relationships of knowledge points, the difficulty gradient of learning resources, and the student's historical learning preferences, and adopts a strategy that combines collaborative filtering algorithm with graph path search. Specifically, firstly, all predecessor basic knowledge points directly related to the weak knowledge point are screened in the knowledge graph to ensure that the starting point of the path matches the student's current cognitive level; then, based on the learning trajectory of historically successful students, the effective learning order of similar students on the same weak point is mined to form a candidate path set; finally, through weighted sorting, the optimal path with moderate path length, matching resource difficulty and close association with professional skills is selected [13].

The learning path created is given to the students as a list of tasks. The nodes on the path are associated with a collection of micro-lecture video, practice, or simulated training projects. Once the learning tasks are sorted out, the system changes the diagnostic result automatically and dynamically modifies the next paths on the basis of the new mastery. This is the direct conversion of evaluation outputs into action learning interventions which converts what is initially a stagnant body of knowledge into a dynamically adaptive, personalized learning navigation delivering the accurate resources and navigation pathways to the development of talented skills.

C. VISUALIZED FEEDBACK-DRIVEN TEACHING INTERVENTION MECHANISM

The system creates a dynamically updated personal digital profile to the learner on the student side. The profile visualizes the behavioral criteria by use of a radar chart that shows how well they have mastered core knowledge modules like functions and limits, differential calculus, integral calculus and differential equations with the professional training objectives to visualize the gap between their present level and their skills. The ability trend line, which is based on the time-series forecast finding, indicates how various abilities of the students will move within the previous four weeks and offers some warnings of the future deterioration of the abilities in the forthcoming week. When students press weak areas in the radar chart, the system would automatically redirect them to a personalized learning path interface, which will display suggested microlecture videos, exercises, and simulation training projects in the form of a task list with the correspondence of each task to a professional skill point being well indicated.

The system will offer a learning progress dashboard at the teacher level in a classroom. The dashboard provides an overview of the mastery of all students on all points of knowledge, and a heat map is used to determine the most popular weaknesses, which enable the teacher to find out which areas need special attention in a short period of time. The instructors would be able to access student-level diagnostic reports, such as the warning of atypical learning behavior, ability development curves, and progress on individual learning pathways. Once the system realizes that the student has not achieved the same improvement in their diagnostic results when being tested three times in a row, or that their learning behavior has considerably deteriorated, an intervention reminder is automatically sent to the teacher. Depending on the visualized feedback, the teacher is able to make timely changes on teaching methods. To mitigate 'tool fatigue' and manage students who ignore automated prompts, the system is designed as a supplementary advisory tool rather than a mandatory barrier, allowing teachers to exercise pedagogical discretion and provide offline, face-to-face interventions when digital reminders fail to engage the learner, including arranging special lectures on the areas where students have weaknesses, setting up group tutoring sessions to learners with learning difficulties, and setting the level of difficulty of practical training activities.

D. SYSTEM DIAGNOSIS AND RECOMMENDATION PERFORMANCE EVALUATION

To evaluate the system's performance comprehensively, we designed three kinds of experiments from three dimensions, including diagnostic accuracy, recommendation accuracy, and the effect of the whole application. All the experiments selected 86 students from the second year of one vocational college's mechatronics major in one parallel class as the subjects to collect their learning behavior data for one semester. Among them, in the diagnostic accuracy comparison experiment, time-series data from all students were used for five-fold cross validation and the prediction error of LSTM model and baseline model were compared; in the recommendation accuracy comparison experiment, we selected individuals with similar knowledge weaknesses from students and randomly divided them into experimental group and control group, and then the influence of personalized recommendation on the improvement of individuals was observed; in the effect of the whole application comparison experiment, we compared the final exam scores of experimental class (using the system) and control class (traditional evaluation) to verify the effectiveness of the whole application. The statistical analysis method selected RMSE and independent samples t-tests according to the characteristics of each experiment. This study was approved by the Ethics Committee of Tieling Normal College, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

E. DIAGNOSTIC ACCURACY COMPARISON EXPERIMENT

The diagnostic accuracy comparison experiment employed a five-fold cross-validation method. Using the temporal learning behavior data of 86 students as input, the proposed LSTM model was benchmarked against a Gated Recurrent Unit (GRU) network and a Transformer-based encoder—both of which represent modern sequence modeling standards—alongside a BP neural network and linear regression to predict students' scores on the 11th interim test. The root mean square error (RMSE) was used as an indicator to compare the ability of each model to capture the dynamic changes in students' mathematical abilities, evaluating the predictive accuracy of the diagnostic module. The comparison results are shown in Figure 1:

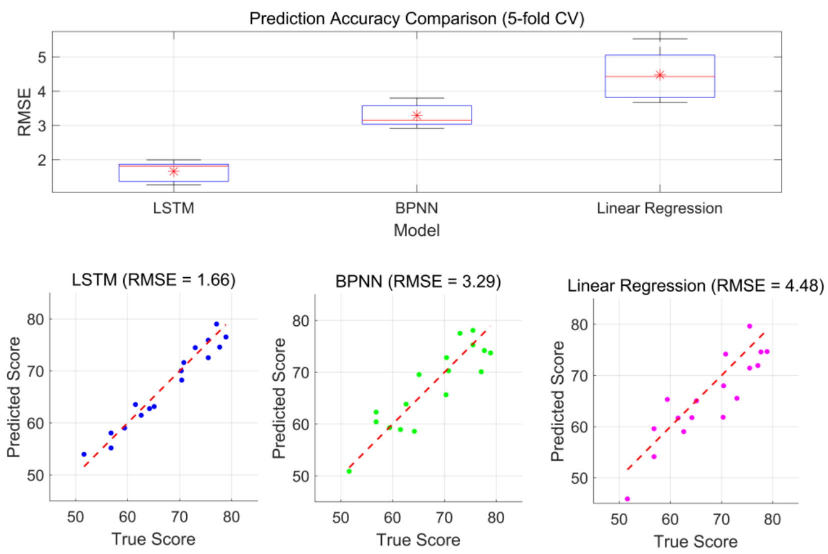

FIGURE 1. Diagnostic Accuracy Comparison

The experimental results show that the LSTM model had an average RMSE of 1.66 in the five-fold cross-validation, significantly lower than the 3.29 of the BP neural network and the 4.48 of the linear regression. This indicates that LSTM can more accurately capture the temporal dependencies of students' learning behaviors and has the smallest prediction bias for interim test scores. Its gating mechanism effectively models the dynamic evolution of mathematical abilities, providing a reliable diagnostic basis for subsequent personalized learning path recommendations. This result verifies the effectiveness and superiority of the LSTM-based intelligent diagnostic module in process evaluation.

F. COMPARATIVE EXPERIMENT ON RECOMMENDATION EFFECTIVENESS

In the comparative experiment of recommendation effectiveness, 86 students with same knowledge poor level randomly select into experimental group and control group. The experimental group got the personalized learning path recommendation based on collaborative filtering algorithm, and the control group got the random recommendation. At last, take two weeks later mastery of the weak knowledge points improvement rate as the indicator to statistic analysis and analyze the guiding effectiveness of personalized recommendation strategy.

As shown in Figure 2, after receiving personalized learning path recommendations, the average improvement rate of knowledge point mastery in the experimental group was 24.6% (standard deviation 7.8%), while the average improvement rate in the control group receiving random content recommendations was only 10.3% (standard deviation 8.2%). An independent samples t-test showed that the difference between the two groups was highly statistically significant ($t=8.29$, $df=84$, $p<0.001$). This result confirms that personalized recommendations based on collaborative filtering can accurately locate students' skill gaps and recommend suitable resources, significantly promoting the mastery of weak knowledge points and providing effective support for the targeted strengthening of mathematical application ability in the training of skilled personnel.

G. COMPARATIVE EXPERIMENT ON COMPREHENSIVE APPLICATION EFFECTS

In this study, a total of 86 students in two parallel classes of the same Mechatronics class in a vocational college were selected as experimental subjects for comparative teaching experiments in one semester. The experimental class (43 students) used the "Big Data + AI Dual-Driven Process Evaluation System" developed in this study for teaching and intervention in the entire semester, and the control class (43

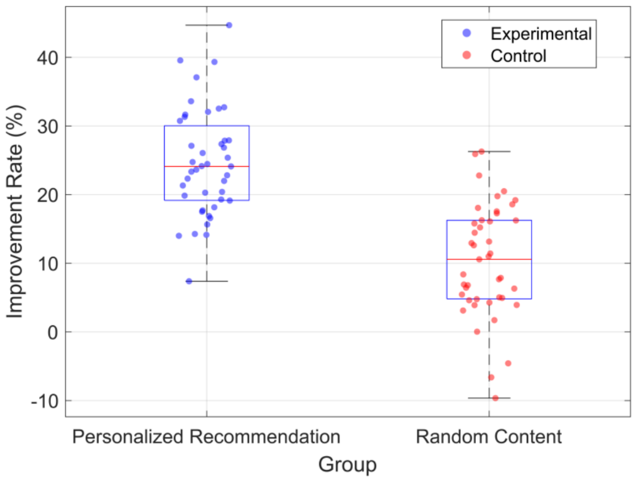

FIGURE 2. Comparison of Recommendation Effectiveness

students) used traditional summative assessment. At the end of the semester, the two classes were compared with the standard test results of mathematical application ability and the score of the project of professional course.

TABLE 2. Comparison of Comprehensive Application Effects

Assessment Indicator	Experimental Class (n=43)	Control Class (n=43)	t-value	p-value
Mathematical Application Ability Test Score	82.4 ± 6.3	71.5 ± 7.8	7.13	< 0.001
Professional Course Project Score	86.7 ± 5.2	75.3 ± 6.9	8.65	< 0.001

Table 2 shows that the experimental class's average score in the mathematical application ability test was 82.4 (standard deviation 6.3), significantly higher than the control class's 71.5 (standard deviation 7.8), t=7.13, p<0.001; in the professional course project score, the experimental class's average score was 86.7 (standard deviation 5.2), while the control class's was 75.3 (standard deviation 6.9), t=8.65, p<0.001. The results show that the process-oriented evaluation system can effectively improve the integration of quantitative problem-solving proficiency and professional skills, demonstrating significant advantages over traditional evaluation methods.

II. CONCLUSION

The process-oriented evaluation system—powered by big data and AI—developed in this study has successfully shifted higher vocational mathematics from summative assessment to a dynamic diagnosis of students' ability to model high-performance industrial structure geometries. By integrating real-time analytics of material tension calculations and structural mechanics into the feedback loop, this system ensures that mathematical proficiency directly translates into the technical precision required for advanced material manufacturing. The experimental results demonstrated that multi-source data collection and LSTM intelligent modeling can be used to identify students' skill gaps accurately and that personalized recommendation based on knowledge graphs can enhance the integration of mathematical application ability and professional skills.

The system has transformed evaluation results into visualized teaching behavior and formed a closed loop of "collection—diagnosis—feedback—adjustment," which provided an operable technical path to cultivate skilled talents. However, the research sample consisted of only 86 students from one major. While the t-test results are statistically significant, the limited sample size and the potential for the Hawthorne effect—where students or teachers perform better due to the novelty of the AI intervention—suggest that these results should be interpreted with caution. Future studies will expand the sample size across multiple institutions to mitigate these biases. In the future, the sample major will be expanded, and more advanced deep learning algorithms will be applied to improve the diagnostic model. In addition, the relationship between evaluation results and the professional competency standards for high-performance industrial engineering will be explored to advance the system's application across higher vocational colleges. By aligning mathematical assessment with the technical requirements of industrial structure geometry and material stress analysis, this framework ensures that student performance accurately reflects the specialized skills needed for advanced manufacturing.

AUTHOR CONTRIBUTIONS

Xiaoying Li designed, collected and analyzed the data, and drafted the manuscript. Xiaoying Li conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Xiaoying Li participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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HUMAN RESEARCH SUBJECTS

This study was approved by the Ethics Committee of Tieling Normal College, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form

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