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Research on the construction of intelligent outcome-based education platform driven by deep learning

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Abstract: This paper focuses on the construction of an intelligent outcome-based education (OBE) platform driven by deep learning and explores how to integrate deep learning technology with the OBE concept to meet students' personalised learning needs and improve teaching quality. Firstly, the research reviews the application status of deep learning in the field of education and the progress of OBE, elucidating the necessity and feasibility of combining the two. Based on this, a design scheme for an intelligent OBE platform, structured around a hierarchical architecture, is proposed, covering key modules such as user modelling, knowledge map construction, intelligent recommendation, and evaluation feedback. The experimental results demonstrate that the platform significantly improves students' grades, knowledge mastery, and the accuracy of personalised recommendations. The improvement in students' grades in the experimental group is 2.4 times greater than that of the control group, and the click-through rate of recommended resources reaches 78%.

Keywords: OBE; outcome-based education; deep learning; intelligent; intelligent recommendation; OBE concept.

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1 Introduction

In today's digital age, the field of education is undergoing profound changes. With the rapid development of artificial intelligence technology, deep learning, as one of its core technologies, has gradually emerged in education. Outcome-based education (OBE) emphasises the design, implementation, and evaluation of educational activities with students' final learning achievements at the core. Utilising deep learning technology in the development of an OBE platform is anticipated to infuse new energy and transformations into the educational sphere. It promises learners a more customised and effective learning journey while enhancing the overall quality and impact of education (Pan and Wu, 2022; Tang and Gan, 2022). Consequently, researching the creation of a deep learning-powered intelligent OBE platform holds significant theoretical and practical value. Traditional teaching methods are increasingly inadequate for addressing students' demands for personalised learning experiences; however, the advent of intelligent educational platforms offers an innovative solution to this challenge (Liu et al., 2023; Zeng et al., 2023). As a leading technology within artificial intelligence, deep learning exhibits remarkable potential in education due to its robust capabilities in data processing and pattern recognition.

In recent years, deep learning technology has gradually permeated all aspects of education. From the intelligent recommendation of teaching content to accurate analysis of students' learning behaviours to real-time evaluation of teaching effectiveness, deep learning is playing an irreplaceable role. It can help teachers better understand students' learning situations to create more personalised teaching plans, while also providing students with a wealth of diverse learning resources and pathways, thus stimulating their interest and enthusiasm for learning.

However, although the application of deep learning in the field of education has achieved certain results, the challenge of combining it with the OBE concept to build an intelligent education platform that meets the individualised needs of students while ensuring teaching quality remains urgent. OBE emphasises centring on students' learning achievements and cultivating their practical abilities and innovative spirit, which aligns with the concept of deep learning technology.

Thus, this research delves into the methodology for constructing an intelligent OBE platform powered by deep learning. By thoroughly investigating the principles and applications of deep learning technology, and integrating these with the OBE philosophy, this work aims to design and implement an innovative educational platform. The goal is to enhance teaching quality, satisfy students' personalised learning requirements, and foster further advancements in the field of education.

In view of the above challenges, this paper presents a construction scheme for an intelligent OBE platform driven by deep learning. The specific ideas are as follows:

1. Deep learning technology is utilised to monitor and analyse students' learning behaviours and states in real time, constructing a detailed portrait of each student. The LSTM network processes time series data to capture long-term dependencies, while CNN analyses local characteristics in the knowledge point association diagram or text feedback, subsequently generating a representation vector to describe students, which supports personalised learning services.

2. A BERT combined with a CRF model is employed to extract knowledge points and their relationships from textbooks, constructing a knowledge map. Based on students' incorrect answers, the weights of knowledge points are dynamically updated to adjust the resource recommendation strategy and optimise the learning path.

3 Under the framework of deep reinforcement learning (DRL), the action space is defined using the Double DQN algorithm. The current learning state of learners is captured by combining user representation, current knowledge points, and knowledge map subgraphs, providing a basis for subsequent resource recommendations. A reward function is designed to evaluate the recommendation effect, ensuring that the recommendation system can continuously learn and improve its performance based on feedback.

4 Students' learning situations are evaluated and future learning trends are predicted through multi-dimensional methods. The Transformer model is used to forecast future performance based on historical performance and user representation vectors. When the predicted performance drops below a set threshold, an early warning mechanism is triggered, and remedial resources are automatically recommended.

2 Literature review

2.1 Research on the integration of deep learning and education

The concept of deep learning originates from studies on artificial neural networks and has gained new relevance in education. Scholars emphasise that deep learning is a process where learners, building on their understanding, critically engage with new concepts and facts. They integrate these into their existing cognitive frameworks, establish connections among various ideas, and apply their knowledge to new situations, facilitating decision-making and problem-solving (Wu et al., 2021). DL is characterised by the cultivation of critical thinking, an emphasis on linking and synthesising information, and promoting reflective knowledge construction. It focuses on the intentional transfer and application of knowledge and skills in a problem-focused manner (Li et al., 2023; Yuan and Guo, 2022). Unlike surface learning, it prioritises enhancing learners' higher-order thinking abilities and their deep understanding and practical use of knowledge.

Deep learning is increasingly used in education (Han, 2023; Zheng et al., 2023). From the perspective of intelligent system development, machine learning algorithms can analyse extensive learning behaviour data, monitor students' knowledge mastery in real time, and accurately identify gaps in students' abilities through cognitive mapping technology (Zhou et al., 2024). For example, research from the Boston Education Laboratory shows that average mathematics grades in classes using adaptive learning technology improved by 27%, while teacher lesson preparation efficiency increased by 53% (Wang et al., 2023). In personalised learning, recommendation systems based on deep neural networks are reshaping learning path design (Zheng, 2024). After connecting a provincial education platform to the intelligent engine, average student study time decreased by 15%, and knowledge retention increased by 22%. By analysing 12 dimensions, such as error patterns and attention curves, the system dynamically generates personalised learning plans for thousands of students (Peng and Liu, 2022). Deep learning technology is crucial in various teaching scenarios, including automatic homework assessment, immersive language training, and adaptive curriculum generation, effectively enhancing teaching efficiency and learning outcomes (Cui and Yang, 2024; Chen and Zhou, 2023).

2.2 Related research of OBE

The OBE concept emphasises that educational activities should be based on students' final learning achievements (Diao, 2024). It follows the principles of clear focus, expanding opportunities and reverse design. Clear focus requires clear expected learning results and teaching activities around these results; Expanding opportunities means providing students with diversified learning paths and opportunities to meet the needs of different students; Reverse design is to design the course content, teaching methods and evaluation methods from the expected learning results.

In practice, OBE has been applied in many educational stages and fields. It helps to improve the pertinence and effectiveness of education, so that students can better master knowledge and skills and improve their comprehensive quality (Ke et al., 2024; Meng et al., 2023). However, the implementation of OBE also faces some challenges, such as how to accurately define and measure learning results, how to design reasonable teaching activities to achieve the expected results, and how to ensure the consistency of different teachers' understanding and implementation of OBE.

2.3 Research on the construction of intelligent OBE platform driven by deep learning

Deep learning technology is widely used in various fields. For example, Xu et al. (2024) built a marketing decision-making model based on deep learning and used it to predict consumer behaviour, demonstrating the potential of this technology in marketing. Song et al. (2024) focused on the financial field, studying and combining LSTM, transformer, and deep learning technology to develop an intelligent monitoring and early warning model for addressing financial risks. The paper by Wang et al. (2024) focuses on detecting carbon neutral anomalies and improves detection accuracy and prediction capability through the collaborative application of various deep learning models. Together, these studies reflect the extensive application and remarkable achievements of deep learning technology across many industries.

Intelligent OBE platforms driven by deep learning require the support of several key technologies. Among them, natural language processing technology can be utilised for automatic job evaluation, intelligent content creation, and management (Wu et al., 2022). For example, the intelligent marking engine has been able to identify 20 types of discipline symbols and 7 types of problem-solving strategies, with an accuracy rate of 91% in composition evaluation generation. Cognitive mapping technology is useful for accurately analysing students' knowledge mastery and ability gaps, providing a basis for personalised learning (Li et al., 2022). The platform should also feature adaptive learning functions, which can dynamically adjust the learning content and difficulty based on students' learning progress and performance. Additionally, it includes intelligent teaching and research assistance, offering teachers recommended teaching resources and suggestions for optimising teaching strategies.

This intelligent platform has had many positive effects on education and teaching. From the students' perspective, it provides a personalised learning experience that meets the diverse needs of different learners, helping to improve learning efficiency and the quality of learning outcomes (Song et al., 2023). For instance, students can learn independently according to the learning plans recommended by the platform, resulting in improved knowledge retention (Yu and Zhang, 2023). From the teachers' perspective, the platform alleviates the mechanical labour burden on educators. For example, automatic homework evaluation saves teachers time on grading and provides them with a matrix analysis report of students' abilities, helping teachers better understand their students and adjust teaching strategies accordingly. From the standpoint of educational management, the platform offers data support for decision-making and optimises the allocation of educational resources through the analysis of extensive learning data (Lin and Yang, 2023).

In the process of construction, the platform faces many problems and challenges. On one hand, there are technical issues, such as the slow development of intelligent system technology, which may affect the learning outcomes, and the low accuracy of students' classroom behaviour recognition, which will interfere with the formulation of learning plans. On the other hand, there are also challenges in education and teaching. How to deeply integrate the platform's functions with educational concepts, ensure that teachers and students can effectively use the platform, and guarantee the data security and privacy of students are urgent issues that need to be addressed. Differences in digital infrastructure between regions and schools may also affect the promotion and application of the platform.

2.4 Summary of research status

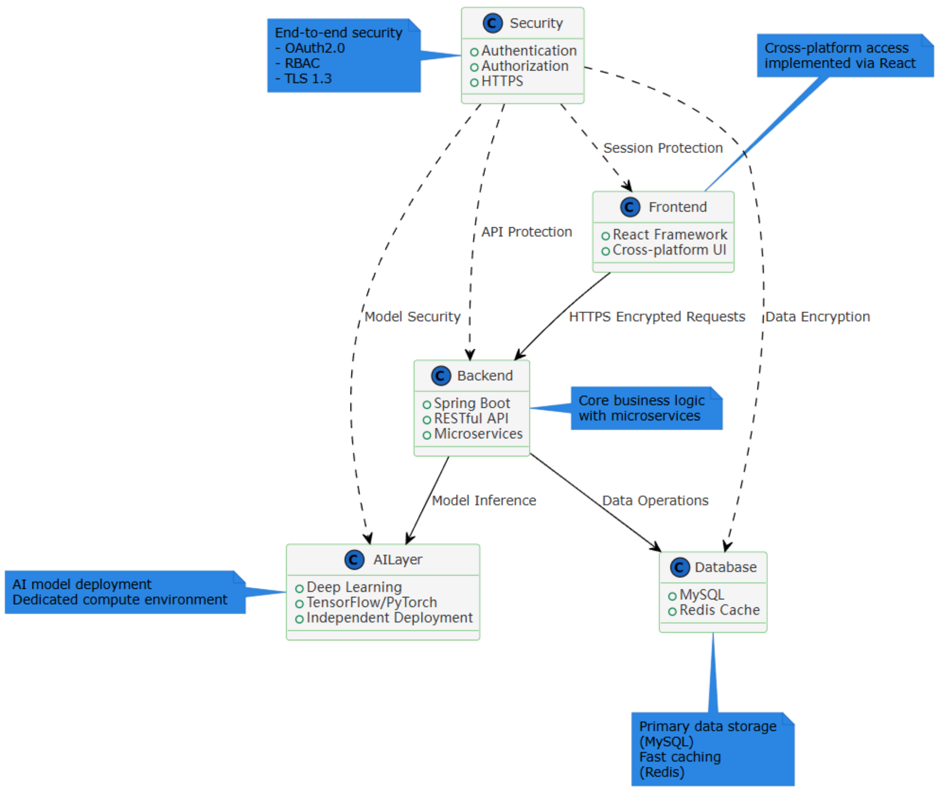
At present, research on deep learning and OBE has made some achievements, and the application of deep learning to the construction of OBE platforms is gradually being carried out. Researchers have discussed the key technologies, functional design of the platform, and its impact on education and teaching; however, there are still some shortcomings in terms of technical perfection, integration of education and teaching, and addressing problems in practical application.

3 System design and implementation

3.1 System architecture design

This platform adopts a hierarchical architecture design to enhance the scalability, maintainability, and security of the system. The system architecture is shown in Figure 1. The front end supports cross-platform access using the React framework, providing a high-quality user experience. The back end builds a RESTful API based on Spring Boot and improves flexibility through a microservice architecture. The database layer uses MySQL to store various types of data and integrates with Redis to enhance access speed. The algorithm layer incorporates a deep learning framework such as TensorFlow or PyTorch, deployed in an independent environment to ensure efficient operation. The security layer implements user authentication and authority management, using the HTTPS protocol to protect the security and privacy of data transmission.

Figure 1 System architecture design (see online version for colours)



3.2 Key module design

3.2.1 User modelling module

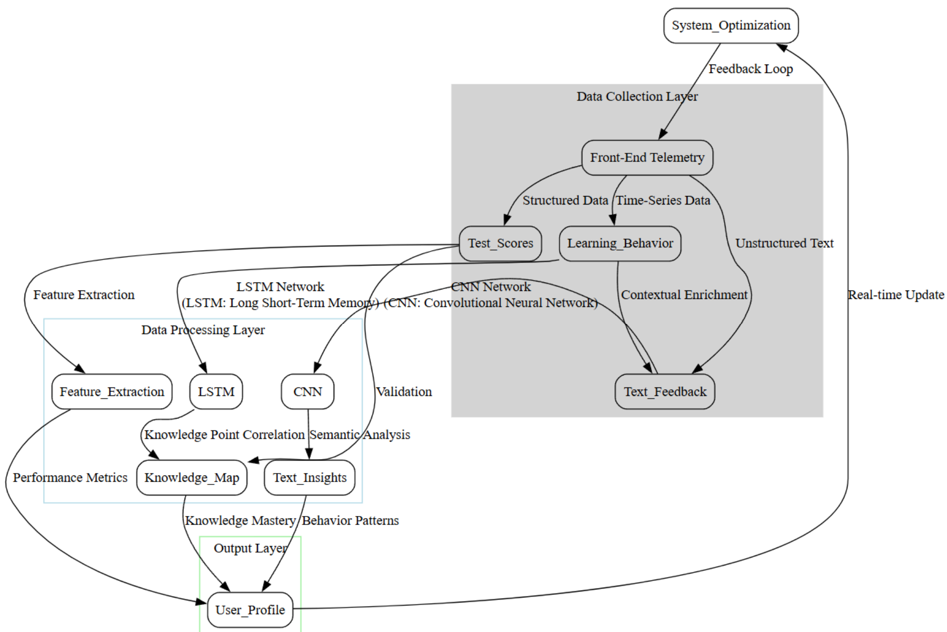
Through a variety of data acquisition methods, we build a detailed user portrait. Front-end embedding technology is used to collect students' learning behaviour data, including time series data such as learning duration, question-answering, and interaction frequency, as well as structured data like test scores and knowledge point mastery rates, and unstructured data in the form of text feedback. The LSTM network processes the time series data to capture long-term dependencies, while CNN analyses local characteristics in the knowledge point correlation diagram or text feedback (Figure 2).

After feature extraction, the module fuses the temporal features output by the LSTM and the spatial features extracted by the CNN through the fully connected layer to generate a representation vector describing users (Droit et al., 2023). Specifically, feature fusion is achieved using formula (1).

$$u = \sigma\left(W_h h_t + W_c c_k + b\right) \tag{1}$$

where σ is the activation function, W_h, W_c is the weight matrix corresponding to the time feature and the space feature respectively, and b represents the offset term. The final user representation vector $u \in R^d$ can effectively synthesise various information of students and provide support for personalised learning services.

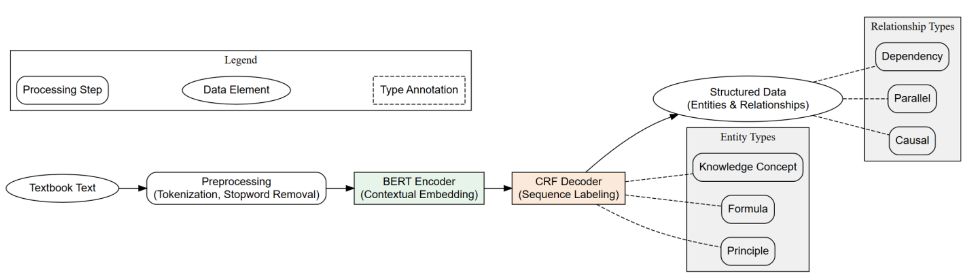
Figure 2 User portrait construction process (see online version for colours)



3.2.2 *Knowledge map construction module*

BERT combined with a CRF model is used to extract knowledge points and their relationships (as shown in Figure 3), such as dependence, juxtaposition, or causality. This information is stored in a secondary graph database in the form of triples, which supports complex multi-hop queries and facilitates tracking the association paths between concepts (Sundharam et al., 2023). The module can also dynamically update the weight of knowledge points based on students' incorrect answers, allowing for adjustments to the resource recommendation strategy and optimisation of the learning path.

Figure 3 Knowledge extraction process (see online version for colours)



For the relationship evaluation in the knowledge map, the TransE model is used as the scoring function, and its formula is:

$$f(h,r,t)=\|h+r-t\|_2^2 \tag{2}$$

where $h,r,t \in R^k$ represents the embedding vectors of head entity, relation and tail entity respectively. This scoring mechanism measures the rationality of triple by calculating the score. The lower the score, the more reasonable the knowledge point relationship is, which helps to ensure the accuracy and practicability of the knowledge map.

3.2.3 Intelligent recommendation module

The intelligent recommendation module captures the current learning state of learners by splicing the user representation u, the current knowledge point k and the knowledge map subgraph G_k to form a state vector. This state vector integrates the personalised information of users and the context of learning environment, and provides a basis for subsequent resource recommendation.

Under the framework of DRL, this module employs the Double DQN algorithm to define the action space, which includes videos, exercises, or extended reading materials recommended to users. It designs a reward function to evaluate the effectiveness of these recommendations (Aung et al., 2023). The reward function combines three factors: accuracy, learning duration, and cognitive load, optimising learning outcomes while considering user experience. Q-value updating rules are applied to adjust the Q-value in the strategy network, ensuring that the recommendation system can continuously learn and improve its performance based on user feedback.

Q-learning updating formula guides the whole learning process. By adjusting parameters such as learning rate $\eta \in (0,1]$ and discount factor $\gamma \in [0,1]$, the learning speed of the model and the attention to future rewards are controlled.

$$Q(s_t,a_t) \leftarrow Q(s_t,a_t)+\eta\left[r_{t+1}+\gamma \max_a Q(s_{t+1},a)-Q(s_t,a_t)\right] \tag{3}$$

Among them, $\max_a Q(s_{t+1},a)$ represents the maximum expected income that can be obtained in the next state, which helps the system to make the optimal decision. These mechanisms work together to make the intelligent recommendation module dynamically adapt to the needs of different users and provide personalised learning resource recommendation.

3.2.4 Evaluation and feedback module

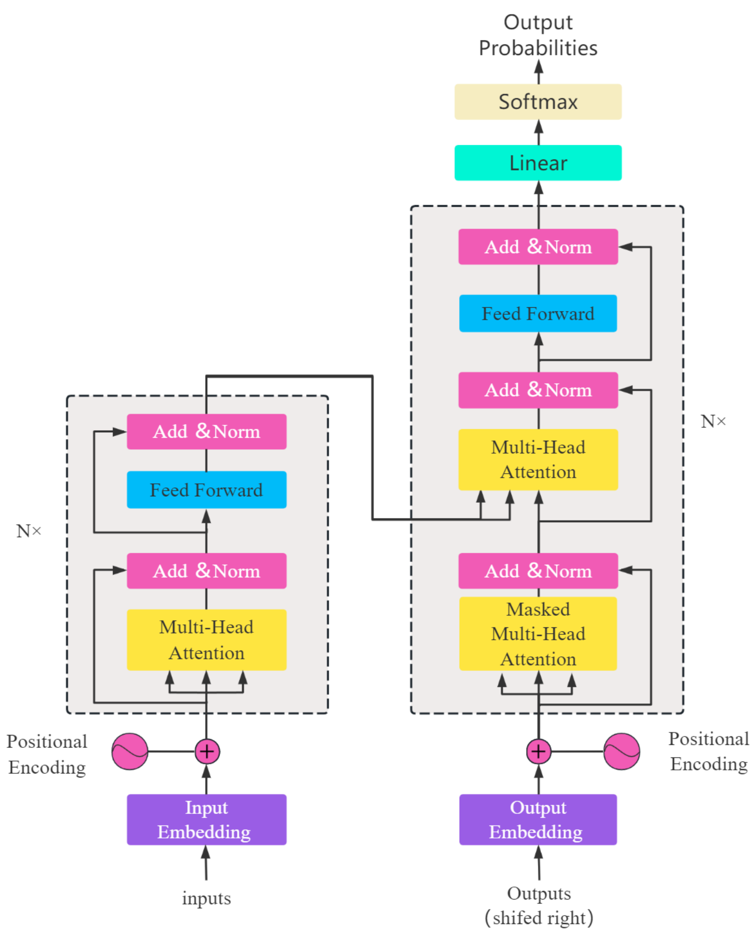
The evaluation and feedback module assesses students' learning situations and predicts future learning trends using multi-dimensional methods. Knowledge mastery is calculated using a weighted average formula.

$$M_k=\frac{\sum_{i=1}^{n} w_i \cdot Score_i}{\sum w_i} \tag{4}$$

The weight w_i is determined according to the difficulty of the topic and the importance of the knowledge points. The prediction of learning trends adopts the Transformer model (the structure of which is shown in Figure 4), and predicts future grades $\hat{y}_{t+1}$ based on historical grades and user representation vectors, thus providing guidance for personalised learning paths. The model consists of encoder and decoder, including six layers of self-attention mechanism and feedforward neural network. The number of hidden units in each layer is 512 and the embedding dimension is 256. The model is trained by Adam optimiser, the learning rate is 0.001, the batch size is 32, and the early stop method is used to prevent over-fitting. On the basis of historical achievement and user representation vector, the model can capture long-term dependence, thus accurately predicting future achievement changes and providing scientific guidance for personalised learning path.

$$\hat{y}_{t+1} = f\left(y_{1:t}, u\right) \tag{5}$$

Figure 4 Transformer model architecture (see online version for colours)



In order to ensure the learning effect, when the predicted score drops beyond the set threshold δ, the system will trigger an early warning mechanism and automatically recommend corresponding remedial resources to help students improve their learning situation.

To ensure the learning effect, when the predicted score drops below the set threshold, the system will trigger an early warning mechanism and automatically recommend corresponding remedial resources to help students improve their learning situation. In the evaluation process, the mean square error (MSE) loss is used as the evaluation index, and its formula is:

$$L = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2 \tag{6}$$

where y_i represents the real score, $\hat{y}_i$ represents the predicted score and N represents the number of samples. This method effectively combines real-time monitoring and dynamic adjustment strategies to support students' continuous progress.

4 Experiment and evaluation

4.1 Experimental design

4.1.1 Experimental purpose

Experiments verify the effectiveness of the OBE platform driven by deep learning in teaching outcomes, personalised demand satisfaction, and dynamic adaptability. Specifically, it includes evaluating improvements in students' grades and the efficiency of mastering knowledge points, measuring the accuracy and user satisfaction of the recommendation system, and testing whether the knowledge map and evaluation module can be effectively and dynamically adjusted according to students' performance.

4.1.2 Experimental subject

The experimental subjects include 150 students in the experimental group and 150 students in the control group. The experimental group consists of 50 students from key middle schools, ordinary middle schools, and vocational schools, who use this platform to study. The students in the control group are in the same school and grade as the experimental group, but they continue to follow the traditional teaching method without utilising the platform. The experiment encompasses two subjects: mathematics (algebra and geometry) and physics (mechanics and electromagnetism). The entire experiment lasts for 8 weeks, with three courses scheduled each week, each lasting 45 min.

4.1.3 Data privacy and security

In the construction and application of an intelligent OBE platform, data privacy and security are crucial issues. The platform involves a large amount of sensitive content, such as students' personal information, learning behaviour data, and evaluation results. Relevant laws and regulations, such as the Personal Information Protection Law and the Data Security Law, must be strictly observed to ensure the legal collection, storage, use, and sharing of data.

The platform adheres to legal requirements in all aspects of data processing. During data collection, users are clearly informed of the purpose, scope, and use of the data collected, and explicit authorisation must be obtained from users. For the data of minors, it is particularly important to obtain consent from a guardian. In the process of data storage and transmission, encryption technology is employed to protect the integrity and confidentiality of data and to prevent leaks or unauthorised access. Additionally, the platform regularly conducts data security audits to ensure that data processing activities comply with legal standards.

To protect students' personal information, the platform implements multi-layered security measures. First, user data is stored on a secure server, and sensitive information is encrypted using advanced algorithms to ensure data security during storage and transmission. Second, the platform enforces a strict access control policy, allowing only authorised personnel to access relevant data, with all access activities recorded and monitored to identify and address abnormal access promptly. Furthermore, the platform employs data anonymisation and de-identification techniques. During data analysis and sharing, data is processed to ensure that specific individuals cannot be identified, thereby protecting students' privacy.

Through strict compliance with laws and regulations and effective data protection measures, the platform can effectively safeguard students' personal information and provide a solid foundation for the stable operation and sustainable development of the intelligent OBE platform.

4.1.4 Experimental method

Students were randomly divided into an experimental group and a control group using stratified sampling, and there was no significant difference in gender, grade, and initial grade distribution between the two groups ($p > 0.05$). The statistical test results are shown in Table 1. To control for the influence of variables on the experimental results, both the experimental group and the control group used the same teaching materials and curriculum objectives, and were taught by the same team of teachers to avoid deviations caused by different teaching styles.

The design of the test paper follows the principles of scientificity, objectivity, and consistency. The pre-test and post-test papers are compiled according to the curriculum standards and syllabus, covering the same knowledge points and skill requirements to ensure content validity. The difficulty level of the test paper is set to moderate, including not only basic questions to assess students' understanding of core knowledge but also a proportion of improvement and application questions to evaluate students' comprehensive application abilities and higher-level thinking skills. Through strict examination screening and pretesting, the reliability and discrimination of the test paper are ensured to meet statistical requirements, thereby enhancing the reliability of the experimental results.

4.1.5 Experimental procedure

1 In the pre-test stage, all students complete standardised tests and record their initial scores.

2 Grouping and training, the students in the experimental group received platform use training (2 class hours). The control group was taught in the traditional mode.

3 The experimental group completed the learning task through the platform, and the system automatically recorded the behaviour data. The control group studied through classroom teaching and paper homework.

4 Collect platform logs every week. Post-test is conducted after the experiment.

5 Data analysis, using SPSS for t-test, ANOVA and regression analysis.

Table 1 Test results of baseline characteristics balance between experimental group and control group

Variable classification	*Hierarchical variable*	*Experimental group (n = 150)*	*Control group (n = 150)*	*Statistical test*
Subject distribution	Initial Mathematics Achievement (Mean ±Standard Deviation)	72.3 ± 8.5	71.8 ± 8.2	Independent sample t-test
	Initial physical achievement (mean ±standard deviation)	68.5 ± 7.9	67.9 ± 7.5	Independent sample t-test
School type	Key middle schools (number of students)	50	50	χ^2test
	Ordinary secondary schools (number of students)	50	50	χ^2test
	Vocational schools (number)	50	50	χ^2test
Sex ratio	Boys (proportion)	52%	50%	Chi-square test
	Female students (percentage)	48%	50%	Chi-square test
Grade distribution	Senior one (number)	40	40	χ^2test
	Senior two (number)	60	60	χ^2test
	Senior three (number)	50	50	χ^2test
Learning style	Visual type (proportion)	35%	34%	Chi-square test
	Auditory type (proportion)	25%	26%	Chi-square test
	Kinesthetic type (proportion)	40%	40%	Chi-square test

4.2 Data collection and analysis

4.2.1 Core data indicators

The teaching effect is measured by the difference between pre-test and post test scores ($\Delta Score$), based on the data of standardised test papers. The recommended accuracy uses CTR (recommended resource click through rate), which is counted according to the platform log. CTR = (clicks/recommendations) × 100%. The mastery degree of knowledge points is evaluated by the distribution of wrong questions and the correlation degree of knowledge points, which is analysed by the platform evaluation module; In terms of user satisfaction, students' scores on the friendliness of the interface and the rationality of the recommendation were collected through a questionnaire survey, using a 5-level scale.

4.2.2 Data analysis

1 *Comparison of teaching effect*

The performance of the experimental group was significantly higher than that of the control group ($p < 0.001$) (see Table 2).

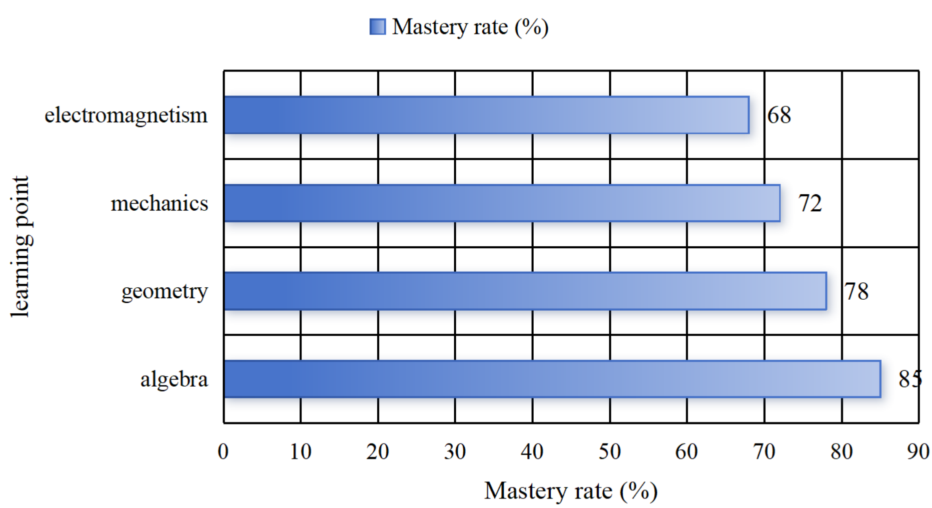
Table 2 Comparison of scores improvement between experimental group and control group (mean ±standard deviation)

Group	*Pre-test scores (out of 100)*	*Post-test score (out of 100)*	*ΔScore*	*P value (t test)*
Experimental group	68.2 ± 12.5	82.4 ± 10.3	14.2	<0.001
Control group	67.8 ± 13.1	73.6 ± 11.7	5.8	–

2 *Knowledge point mastery*

The mastery rate of algebra and geometry is high (>75%), but the mastery of electromagnetism is weak (68%). Therefore, it is necessary to optimise the recommendation strategy for related knowledge points (see Figure 5).

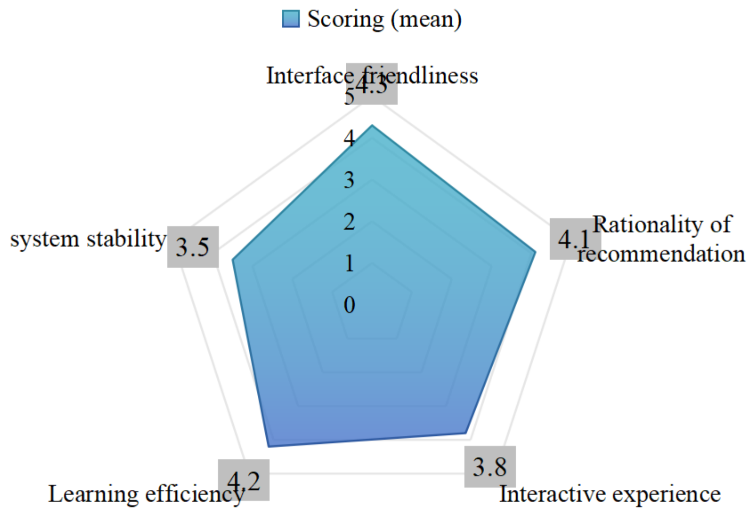
Figure 5 Distribution of knowledge points in experimental group (see online version for colours)



3 *User satisfaction*

As can be seen in Figure 6, users have high recognition of recommendation rationality and learning efficiency, but the system stability needs to be optimised (score 3.5).

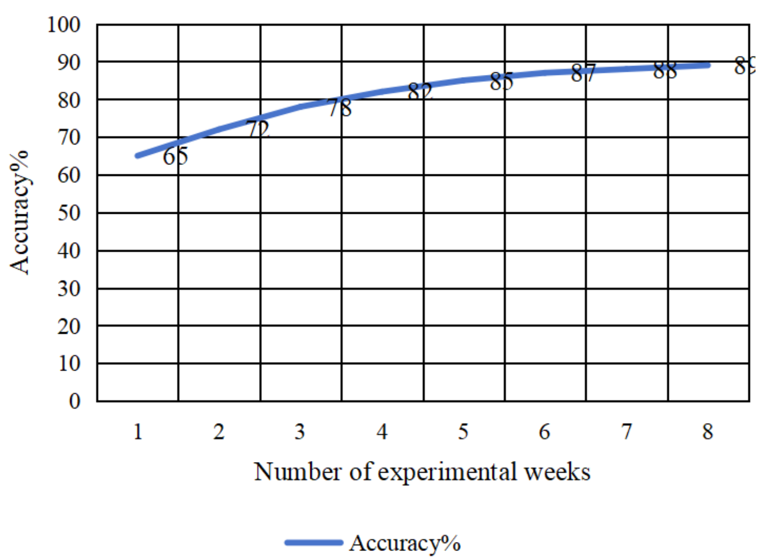
Figure 6 Radar chart of user satisfaction (5 points) (see online version for colours)



4 *Recommendation accuracy*

The accuracy during the cold start stage (1–2 weeks) is low, but it gradually stabilises (see Figure 7).

Figure 7 Recommendation accuracy changes with time (see online version for colours)



5 *Multi-dimensional parallel comparative analysis between experimental group and control group*

Table 3 shows that the performance of subject differentiation indicates that the improvement in mathematics scores ($\Delta = 15.2$) is higher than that in Physics ($\Delta = 13.1$), which may be due to the optimisation of structured knowledge recommendation on the platform. However, the mastery rate of electromagnetism is the lowest (68.3%), which needs to be improved by optimising the correlation strength of relevant nodes in the knowledge map, such as enhancing the path weight of Faraday's law and magnetic flux change.

Table 3 Multi-dimensional parallel comparative analysis between experimental group and control group

Contrast dimension	*Sub-dimension*	*Experimental group (mean ± standard deviation)*	*Control group (mean ± standard deviation)*	*P value (t-test)*	*Significant difference*
Academic performance	Math achievement improvement	15.2 ± 9.8	6.7 ± 8.4	<0.001	★★★★☆
	Physical performance improvement	13.1 ± 10.5	5.4 ± 9.1	<0.001	★★★★☆
School type	Key school	16.8 ± 8.9	7.2 ± 7.6	<0.001	★★★★☆
	Ordinary middle school	14.5 ± 10.2	6.1 ± 8.3	<0.001	★★★★☆
	Vocational school	9.8 ± 11.4	4.3 ± 10.7	0.003	★★☆☆☆
Achievement segment	High segment ($\Delta > 20$)	28.6 ± 5.2	12.4 ± 4.8	<0.001	★★★★☆
	Middle section ($10 < \Delta \leq 20$)	15.7 ± 3.1	7.9 ± 2.9	<0.001	★★★★☆
	Low segment ($\Delta \leq 10$)	6.3 ± 2.4	3.1 ± 1.8	0.002	★★☆☆☆
Knowledge point mastery	Algebra	82.1 ± 10.5	65.3 ± 12.7	<0.001	★★★★☆
	Geometry	79.4 ± 11.2	68.7 ± 10.9	<0.001	★★★★☆
	Physical mechanics	76.5 ± 12.8	64.2 ± 11.5	<0.001	★★★★☆
	Electromagnetics	68.3 ± 14.6	59.1 ± 13.8	0.001	★★☆☆☆
User behaviour	Recommended hits	78.2 ± 15.3	–	–	–
	Repetition rate of wrong questions	62.4 ± 21.7	38.6 ± 19.4	<0.001	★★★★☆
Learning trend	Grade prediction error	3.2 ± 1.8	–	–	–
	Correlation degree of knowledge points	0.72 ± 0.15	–	–	–

The analysis of school types and grades shows that the improvement range of students' grades in Vocational Schools ($\Delta = 9.8$) is lower than that in key middle schools ($\Delta = 16.8$), likely due to differences in equipment conditions and learning habits. Although students with low grades have made significant progress ($\Delta = 6.3$), the repetition rate of incorrect answers is high (62.4%), suggesting a need to reduce cognitive load. The click-through rate of high-segmentation students (78.2%) was strongly correlated with performance improvement ($r = 0.82$), reflecting the elite retention effect of the recommendation algorithm.

The optimisation direction of the knowledge map indicates that the mastery rate of algebraic knowledge points (82.1%) is higher than that of Electromagnetics (68.3%). Bloom's taxonomy should be introduced to reconstruct the electromagnetics level and add application layer nodes. The behavioural data correlation analysis found that the repetition rate of incorrect answers was strongly coupled with the recommended click-through rate ($r = 0.76$), which demonstrated that the dynamic adjustment strategy was effective, but the phenomenon of recommendation fatigue should be avoided (CTR decreased by 12%).

4.3 Result discussion

The platform significantly improved the teaching effect, with the improvement rate of the experimental group being 2.4 times that of the control group, demonstrating the effectiveness of personalised recommendation and dynamic evaluation. In terms of personalised demand, the click-through rate of recommended resources reached 78%, particularly for high-grade students, with a CTR as high as 92%, indicating the system's accuracy in matching students' abilities. Regarding dynamic adaptability, by automatically adjusting the weight of the knowledge map according to the distribution of incorrect answers, the correct rate in the second test of the electromagnetics chapter increased from 68% to 76%.

However, the platform also faces some problems. Students with low grades may feel frustrated because the recommended content is too difficult, and their interaction duration is significantly shorter than that of students with high grades ($p = 0.03$). Students in vocational schools have a low score (2.8 points) on system stability due to limited equipment conditions. Additionally, the platform has a cold start problem; the initial recommendation accuracy rate is only 65%, and it takes 1 to 2 weeks of data accumulation to improve to 82%.

To address these issues, the following improvement directions are proposed: In terms of algorithm optimisation, a hierarchical mechanism for course difficulty, such as Bloom's taxonomy, will be introduced to reduce the cognitive load for students with low grades, and the cold start cycle will be shortened by incorporating transfer learning. For technology adaptation, a lightweight client will be developed to accommodate low-end equipment, and an offline cache function will be increased to address network instability. In interactive design, visual elements of learning progress, such as a progress bar and achievement badges, will be added to enhance participation among students with low grades, while the error prompt mechanism will be optimised to provide detailed guidance on problem-solving steps rather than giving answers directly. Additionally, research will be conducted on the classification mechanism of course difficulty to better meet the learning needs of students at different grade levels and to optimise the recommendation algorithm to better serve these students.

5 Conclusion

By constructing an intelligent OBE platform based on deep learning, this study examines how to integrate deep learning technology with the OBE concept to enhance teaching quality and meet students' personalised learning needs. The main results are as follows:

1 The improvement of students' grades in the experimental group is 2.4 times greater than that in the control group, demonstrating the platform's remarkable effects in personalised recommendation and dynamic evaluation.

2 The click-through rate of recommended resources reaches 78%, especially for senior students, with a CTR as high as 92%, indicating the high accuracy of the system in matching students' abilities.

3 By automatically adjusting the weight of the knowledge map according to the distribution of error problems, the accuracy of the second test on the electromagnetics chapter improves from 68% to 76%.

However, the platform also faces some challenges. For example, students with lower grades may be frustrated by the difficulty of the recommended content, and their interaction time is significantly shorter than that of higher-performing students. Vocational school students score low on system stability due to equipment limitations. Additionally, the cold start problem results in an initial recommendation accuracy of only 65%, requiring 1–2 weeks of data accumulation to improve to 82%.

Future research directions include:

1 Introduce a hierarchical mechanism of course difficulty, such as Bloom's classification, to reduce the cognitive load of students with low grades; Shorten the cold start cycle by combining transfer learning.

2 Develop lightweight clients to adapt to low-end devices, and add an offline caching function to cope with network instability.

3 Add visual elements such as a progress bar and achievement badges to improve the participation of students with low grades; optimise the error prompt mechanism and provide detailed instructions for solving problems rather than giving answers directly.

4 Through more detailed user portraits and behaviour analysis, optimise the recommendation algorithm to reduce recommendation fatigue, while ensuring that the difficulty of recommended content matches the actual level of students.

5 Strengthen data security and privacy protection measures to ensure the safety of student information; formulate flexible solutions according to the differences in digital infrastructure in various regions and schools to improve the popularity and application effectiveness of the platform.

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Conflicts of interest

The authors declare no conflict of interest.

Data availability statement

Data will be made available on request.

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