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Research on the intelligent algorithm of personalized learning path recommendation based on machine learning

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SUMMARY: *In the present day's education, building and recommending individualised learning plans need to be carried out to improve learning efficiency and quality. Individualised learning refers to modifying the content and methods of teaching based on different needs, interests, speeds and abilities of various learners. This paper will introduce the foundation of personalised learning paths and examine how machine learning is applied in education to customise students' learning experiences, such as the construction of personalised recommendation systems and learning path design. Path recommendation is based on learner feature modeling, the construction of a learning resource database, the optimisation of recommendation algorithms, the generation of learning paths, and the guarantee of system scalability to form an intelligent algorithm framework. Test Cases for the Algorithm are shown below.*

KEYWORDS: *machine learning; personalized learning; path; recommendation; intelligent algorithm*

1 Introduction

An intelligent algorithm for personalised learning path recommendation has been developed recently to address the deficiencies of traditional learning-path systems in contemporary educational technology. The old systems usually use static content delivery and are unable to meet the changing demands of learners in an individual way. A new way has been developed in this paper to add high-end machine-learning technologies, such as reinforcement learning and deep learning, for personalised, adaptable learning experiences. Based on learners' individual traits, levels of knowledge, cognitive differences and behavioural differences, etc., the new system will provide customised materials according to these differences and also dynamically adjust to meet the learners' growing demands. This way has become a good-performing, scalable and adaptable solution in recent years, and now it is widely used in personalized education. The construction of a personalised learning path includes the multi-dimensional data modelling of learners, characteristic extraction of learning resources and semantic analysis, knowledge correlation in intelligent calculation, and dynamic adjustment of learning path optimisation strategies. The introduction of machine learning technology has greatly enhanced the intelligence of the recommendation system, and now it is based on historical learning behaviour data, adaptive learning strategies, reinforcement learning feedback mechanisms, and in-depth representations for the learning path recommendation process. Ion Learning Method achieves high relevance, strong adaptability,

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and excellent dynamic optimisation for personalised learning path recommendation.

2 The Idea of a Customised Learning Path

2.1 Meaning and Features of Personalised Learning

Personalised learning is a typical form of education technology that tailors learning plans and content based on individual differences in ability, need and interest. Intelligent algorithms for personalized learning path recommendation can be used to identify individual learners' particular needs and potential difficulties from a large volume of educational data, and based on all-round applications of various machine learning technologies, generate customized learning paths. Therefore, it is necessary to consider how much the learners have been taught so far, how quickly they have learned it, what their current level of learning ability is, and how this will change in the future. Add to this the idea of personalised learning and continuous adjustment in the learning process. Personalized learning path recommendation intelligent algorithms can dynamically adjust learning plans according to real-time data analysis to ensure that the learning activities are in line with the latest progress and feedback of the learners. This way can be used to boost students' desire to learn and self-study, enabling them to better reach their goals for academic and life development in a new kind of school. Based on the integration of advanced data mining technology and artificial intelligence, intelligent algorithms for personalised learning path recommendation continuously optimise their algorithm models to achieve more accurate learning path design and mark a new era of personalised and intelligent education.

2.2 The two will be combined to provide students with customised learning paths and personalised recommendations.

The combination of learning paths and personalised recommendations in educational technology is expected to achieve the goal of developing intelligent algorithms for learning path recommendations; a learning path is a systematic collection of learning materials that students study in an organised way to achieve their goals, with many links to lead them towards specific objectives. Personalised recommendations in learning systems are designed to meet the different requirements of individual learners in terms of ability and interest. By using advanced algorithms, these systems can push the most suitable learning content to each learner and provide a personalised educational experience. Personalized Learning Path Recommendation Intelligent Algorithm By integrating multi-dimensional data analysis, pattern recognition and predictive modelling functions of machine learning, learner profiles and learning preferences are accurately built. The above content will be used to design learning activities that match the students' different speeds of learning. The algorithm will recommend some study materials and also adjust the order in which they are presented based on how well students perform and what they need to study at that moment. Based on the above study of learning behaviour, intelligent algorithms for personalised learning path recommendation can predict problems that students will encounter in their studies and offer timely support and relevant materials in advance. Continuously improve the learning effect by dynamically adjust and predict, and provide a personalized learning-path recommendation function. Ensure that all learners receive optimal support and benefits in their learning, maximise the use of educational resources, and improve the quality of teaching outcomes. Figure 1 shows the detailed learning path and personalised recommendations.

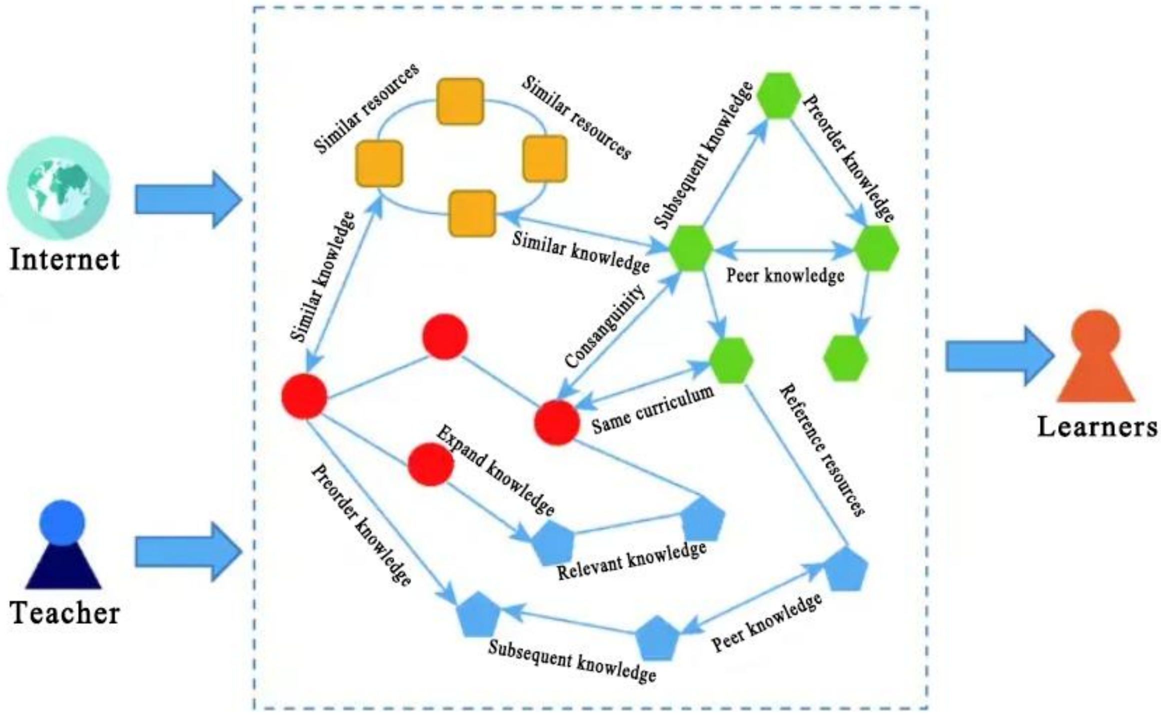

Figure 1: Learning Path and Personalised Recommendation

3 Application of Machine Learning in Personalised Learning Path Recommendation

3.1 Optimisation Strategies for Supervised Learning Algorithms

To improve both the accuracy of prediction and the generality of a model in the field of supervised learning, optimisation is required. To improve the performance of the model, the above measures will be taken to collect data, conduct data preparation (e.g., normalisation and noise reduction), and engineer features. Convolutional Neural Networks (CNN) are specifically employed in the deep learning stage for feature extraction to recognise intricate patterns within vast amounts of educational data. For example, CNNs can be used to learn the spatial relationships in students' interaction patterns and thus determine learning preferences and behavioural trends more accurately. In addition, to reduce overfitting and improve the generalisation ability of the model, dropout and batch normalisation are also employed. The above strategies can help the learning path recommendation system process all kinds of learner data normally and generate more accurate personalised recommendations. TensorFlow and PyTorch are used to conduct model training, and they are relatively resource-intensive in terms of computing power and time. After the initial training, all kinds of tests are performed on the model, such as accuracy and precision, etc., and then, based on the results of these tests, some changes are made to the model's parameters or network structure to improve its performance. Optimised Models can also be applied in practice to improve the accuracy of diagnosis and personalised treatment plans for medical images.

In the development of a personalised learning path recommendation system, to ensure both the accuracy and efficiency of recommendations, optimisation strategies for supervised learning algorithms are necessary. These algorithms learn from labelled data to predict the output of new, unseen data, and thus, their main task in optimisation is to improve the generalisation ability of the model; at the same time, reducing overfitting is required, so regularisation techniques can be used to limit the complexity of the model; by adding a regularisation term to the loss function, we can control the model's complexity and prevent it from overfitting to the training data. Another kind of relatively common optimisation is cross-validation. Divide the data into many small sets, train the model on one subset, and test the performance of this model on another to improve both the stability and accuracy of the model. Hyperparameter optimisation is another type of strategy in supervised learning, and different combinations of hyperparameters are systematically explored through grid search, random search, Bayesian optimisation, etc., to find the best model parameters. Finally, integrated learning methods, such as random forest and gradient boosting, can be used to enhance the overall prediction accuracy by combining the predictions of multiple learners; at the same time, these integration technologies improve the robustness and adaptivity of the algorithm to complex data patterns, thus meeting various personalized learning path recommendation intelligent algorithms' diverse education needs in many learning scenarios. Figure 2 shows the key point of the supervised learning algorithm.

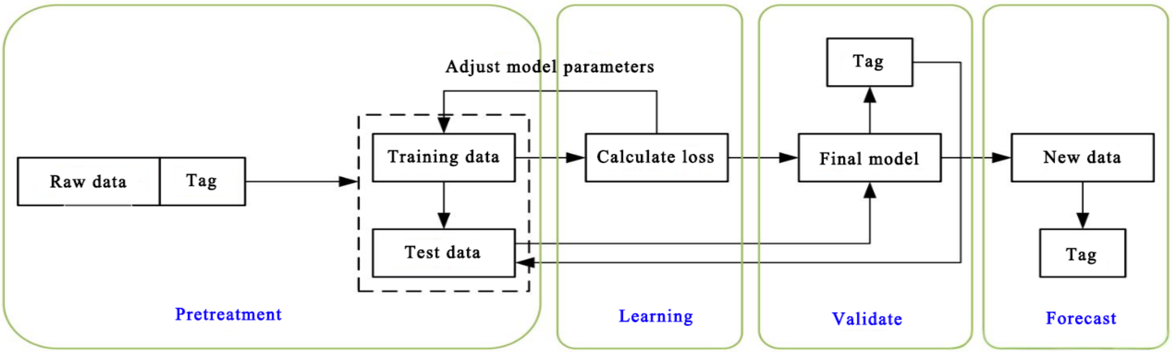

Figure 2: Main Points of the Supervised Learning Algorithm

3.2 Application of Unsupervised Learning Technology in Learning Resource Classification

Unsupervised learning automatically clusters based on similarity using clustering algorithms, such as K-means and hierarchical clustering. Classification can be based on the attributes of resource content, such as keywords and text complexity, and may also consider other factors, such as usage frequency and user engagement, to optimise repository structure and improve resource accessibility. In addition, Principal Component Analysis (PCA) is a dimension reduction technology that can extract the most significant features from a large number of attributes, reduce the complexity of the data structure by keeping only essential variables, and thus improve both the accuracy and efficiency of classification. Microsoft has achieved high-precision text-content recommendation systems through unsupervised learning; a patent for such a system has also been obtained. Therefore, more customised and relevant learning materials will be provided for the students. To show the application of unsupervised learning in learning resource classification more clearly, the following table lists simulated data analysis that includes resource features and classification results before and after clustering, as shown in Table 1:

Table 1: Data Analysis of a Simulation

resource ID	Keyword frequency	operating frequency	User engagement	Clustering tags
R1	0.75	150	0.60	C1
R2	0.50	100	0.30	C2
R3	0.65	200	0.50	C1
R4	0.85	250	0.70	C1
R5	0.30	80	0.25	C2
R6	0.55	120	0.35	C2
R7	0.90	300	0.80	C1
R8	0.20	50	0.15	C2
R9	0.40	110	0.33	C2
R10	0.80	220	0.65	C1

The table shows different resources according to keyword frequency and user engagement distribution, and then applies a clustering algorithm to assign cluster labels. It demonstrates that unsupervised learning technology can be used for the classification of learning resources and provides stable support for the data-driven classification method in personalised learning path recommendations.

3.3 Practicability of Reinforcement Learning in Dynamic Adjustment of Learning Paths

Reinforcement learning in the intelligent algorithm for personalized learning path recommendation provides an effective mechanism to dynamically adjust the learning path by employing reward and punishment signals, and thus guides the optimization of the decision-making process; according to the interaction between the environment and the agent, the agent learns and optimizes its path recommendation system; the environment is represented by learner behavior and feedback, and through trial-and-error methods based on learners' feedback, the system can adjust teaching strategies to achieve long-term educational goals. Q-learning and other types of reinforcement learning algorithms can be used to solve many complex learning problems, find the best path for learning, and adjust this path dynamically based on the learner's current ability or interest changes during study. For example, if the learners have mastered a certain subject, the system will suggest more difficult materials or introduce new topics; otherwise, it will provide additional counselling resources to help them learn better. In this way, reinforcement learning can improve the adaptability of personalised learning paths and boost the efficiency of educational resources; thus, the teaching process can better meet the individual learning needs of students and improve their learning results without diminishing their interest in learning.

3.4 Integration of Deep Learning Models in the Personalised Recommendation System

Deep learning models are now frequently employed in the construction of personalised learning path recommendation systems to improve the accuracy and adaptability of these recommendation systems through strong feature learning and non-linear expression abilities. CNNs and RNNs, as deep learning models, are used to analyze and process complex learner data and learning content for highly personalised recommendation systems. For example, an LSTM network, a particular kind of RNN, can be used to deal with and predict the time-series relationships in learner behaviour sequences, and thus adjust the learning path dynamically.

Given the sequential nature of the learner behaviour data, the state of the LSTM model can be updated according to the following formula:

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

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

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

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

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

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

In the above formula σ, representing the sigmoid W b activation function f_t , i_t and o_t representing network parameters,, and are $\tilde{C}_t$ activation C_t vectors of forgetting gate, input h_t gate and t output gate respectively, and are candidate values for cell states and new cell states, are the hidden state output at a time step. According to this series of updates, the LSTM is able to decide which information to retain, discard, and which information to output at each time step, allowing the model to adapt to the dynamic changes [1] along the learning path.

4 Design and Implementation of an Intelligent Algorithm for Personalized Learning Path Recommendation

4.1 Learner Feature Modeling

During the construction of intelligent algorithms for personalized learning path recommendation, Learner feature modeling is essential for ensuring the accuracy and adaptability of recommendation systems. By leveraging user behavior data, knowledge mastery, cognitive abilities, and learning preferences, a dynamic, multi-dimensional feature representation can be established. This approach, as demonstrated in the use of knowledge graphs and graph convolutional networks for personalized learning path recommendations, enables the accurate capture of learners' preferences and the importance of learning resources. Z_t , among, A Bayesian dynamic factor model based on hidden variable modeling t (Bayesian Dynamic Factor Model, BDFM) can effectively capture the changes in the learner behavior patterns and optimize the feature updating process, In BDFM, learner characteristics are represented by a set of hidden variables driven by historical data., These hidden variables further influence learning path recommendation decisions., The system estimates the learner's characteristic state by calculating hidden variables at each time step.:

$$Z_t = AZ_{t-1} + BX_t + \epsilon_t \tag{7}$$

Among them A, for the state transfer matrix, define $t-1$ how hidden t variables B from time to X_t time, represents the input ϵ_t characteristics of the influence of hidden variables, for random noise term, the formula through the hidden variable propagation mechanism to ensure that learners characteristics can dynamically adjust with time, make the personalized learning path recommended intelligent algorithm in the face of learners behavior change real-time adaptability.

In the personalized learning path recommendation Y_t system, the observation variables represent the current learning performance of learners, such as test Y_t Z_t scores, learning length or knowledge mastery. BDFM associates the hidden variables through the linear observation model:

$$Y_t = CZ_t + DX_t + \eta_t \tag{8}$$

Among them C, the observation matrix describes how the hidden D variables affect the observed data η_t, represents the direct contribution of the input variables to the observed values, and is a Gaussian noise term. The model framework makes the learner features constantly updated under the data-driven drive, ensuring the accuracy and personalization of the learning path recommendation.

During the training of the system, the variational Bayesian inference method is used to maximise the posterior probability distribution of the data, and a variational lower bound (Evidence Lower Bound, ELBO) is defined as:

$$L(q) = E_q(Z)[logp(Y|\ Z, X)] - D_{KL}(q(Z)|\ \ |\ p(Z)) \tag{9}$$

Among them D_{KL}, represents the Kullback-Leibler divergence $q(Z)$, measure the gap between $p(Z)$ the approximate distribution and $q(Z)$ real posterior distribution, the formula is used to optimize the variational distribution, to ensure that the characteristics of learners modeling accuracy, and can effectively avoid the data sparsity, to enhance the personalized learning path recommend intelligent algorithm generalization ability.

In practical application, the intelligent algorithm of personalized learning path recommendation makes dynamic recommendation based on the R_t results of learner feature modeling, and sets the optimization goal of learning path recommendation to maximize the learning effect. Under the Bayesian framework, the objective function can be expressed as:

$$\pi max \sum_{t=1}^{T} E_{Z_t \sim q(Z)}[R_t|\ Z_t, \pi] \tag{10}$$

Among them π, the recommendation R_t strategy represents t the learning effect of the learners in time steps. The optimization goal of the recommendation system is to dynamically adjust the learning path, thereby enhancing the learning efficiency and knowledge mastery of learners. This is achieved through the application of AI and machine learning algorithms, which enable the system to provide efficient and personalized learning path recommendations, as demonstrated in recent studies [2, 3].

4.2 Construction of the Learning Resource Database

In the design and implementation of the intelligent algorithm for personalized learning path recommendation, the construction of a learning resource database provides a strong foundation for ensuring the accurate matching of personalized learning paths;

high-dimensional, multi-modal data integration techniques are employed to learn resources, and standardization, structure, and semantic correlation of learning content are achieved to provide precise data support for the intelligent algorithm of personalized learning path recommendation; at the core of learning resource databases are knowledge hierarchy modelling, optimisation of resource labelling systems, and construction of resource retrieval indexes. Knowledge point hierarchy modeling is based on knowledge graph construction technology; split the knowledge units of learning resources into several dimensions, such as concept dependency, difficulty progression and theme correlation, to build an efficient learning path planning model; further optimisation of the resource labelling system relies on deep semantic analysis and natural language processing technology, automates the labelling of multimodal learning resources, including text, video and test questions, identifies key features through deep semantic modeling techniques such as TF-IDF, word vector embeddings (Word2Vec) and BERT, enhances the alignment of learning resources for personalised recommendation scenarios, and simultaneously needs efficient indexing mechanisms for learning resource databases; in order to support the fast retrieval and dynamic scheduling of intelligent algorithms for personalised learning path recommendation, we employed high-efficiency retrieval strategies, such as reverse indexing, hash indexing and vector similarity search, thereby improving the real-time response capability of personalised learning path recommendation [3].

4.3 Selection and Development of the Recommendation Algorithm

In the development of intelligent algorithms for personalised learning-path recommendation, the choice and optimisation of recommendation algorithms need to guarantee the accuracy, adaptability and timeliness of the learning paths. Using a combination of the above advanced recommendation models, such as collaborative filtering, matrix decomposition, deep learning and reinforcement learning, highly accurate matching of learning materials and optimised learning paths can be achieved. Collaborative filtering is particularly used to explore user preferences and improve the personalization of the learning experience based on learner behaviour data; recommended scores for learning resources are generated via user similarity or item similarity, learner interest similarity is determined using Pearson's correlation coefficient, and to enhance the accuracy of personalised learning path recommendations, matrix decomposition methods such as singular value decomposition (SVD) and non-negative matrix factorization (NMF) extract latent features by processing high-dimensional learning behaviour data and apply dimension reduction techniques; thus, the adaptability of intelligent algorithms for personalised learning path recommendation in sparse data environments is optimised. Deep learning models, such as convolutional neural networks (CNN) and long short-term memory networks (LSTM), can improve the semantic matching ability of learning resources through automatic feature learning; the CNN is good at capturing local features of the text of learning resources, and LSTM can model learners' long-term behaviour patterns, thus boosting the dynamic adjustment capacity of personalised learning paths. Reinforcement learning employs a set of reward mechanisms to enable the intelligent algorithm for personalised learning path recommendation to optimise decisions during continuous interaction; by utilising a deep Q network (DQN) in conjunction with learner feedback data, the training process implements dynamic adaptive learning path optimisation strategies to achieve optimal learning efficiency in the personalised learning path.

4.4 Learning Path Generation Mechanism

The learning path generation mechanism is based on the latest machine learning technology, deep learning and reinforcement learning, to build personalised learning paths dynamically according to real-time data and past learning records. The above mechanism predicts and adjusts for the learner's requirements and interests during study. For example, deep learning models are used to analyse the interactive behaviour and feedback of learners to obtain complex patterns, as shown by the application of deep Q-networks (DQN) for maze pathfinding in Reference 0; data relationships and recommended learning content are considered, and reinforcement learning algorithms are employed to optimise the learning path based on reward mechanisms for prolonged learning efficacy. Then, the learning path generation mechanism combines the learner's cognitive model and personal learning goals, and uses an algorithm to automatically construct a learning path that covers all aspects of learning content, from basic knowledge to advanced applications; thus, it is both goal-oriented and highly efficient at every stage of learning. The method can adjust the learning path according to changes in the environment at any time and provide the most relevant learning materials for the learner at that time. Therefore, in the following stage, some personalized elements have been introduced to provide learners with different learning materials to meet their various learning needs at different times.

4.5 Outcome Evaluation and Feedback Mechanism

Results evaluation and feedback mechanism are necessary components of the personalised learning path recommendation intelligent algorithm. Continuously optimise and adaptively reinforce the recommended learning path. A large number of indicators will be set up in both quantity and quality to evaluate how well the recommended route meets the learners' expectations. Based on real-time collection of data from learners' performance in the stage, including learning progress, achievements, knowledge depth and learning behaviour patterns, use this data to improve the capability of the recommended system for assessing the effectiveness of a learning path, and employ machine learning models such as decision trees, logistic regression and neural networks for analysis and prediction of model performance to ensure that the recommended personalised learning path aligns closely with learners' actual needs. A regular collection of user comments and other suggestions on the recommended content will also be performed in real time. Process the feedback through algorithm analysis and modify the model parameters. Through optimisation of algorithm parameters, such as the learning rate and regularization weight, continuously increase the accuracy and adaptability of recommended learning paths. The feedback mechanism also supports the function of adaptive learning and can dynamically adjust the learning path according to the progress of learners; provide additional resources or change the difficulty of the learning content when a bottleneck occurs to genuinely achieve personalised learning.

4.6 The scalability and security of the system need to meet the basic requirements of stable operation and reliable data storage for educational resources and users.

In the Design and Implementation of the intelligent algorithm for personalised learning path recommendation, scalability and security of the system are necessary to ensure long-term effective operation and user trust; scalability is particularly needed to handle an increasing number of users and higher complexity in data to maintain efficient operation and service quality. Therefore, the system architecture needs to be flexible in handling large amounts of data and complex queries; a microservice architecture and load-balancing technology will be employed to ensure that the guarantee system provides stable service under high concurrency of users, and at the same time, cloud computing resources can be used to dynamically scale capabilities and adjust computing resources and storage space according to demand, meeting the different needs of various stages in the system. For data security, a series of strategies and techniques will be used to protect user information from unauthorized access and malicious attacks, such as setting a strong password policy, providing two-factor authentication, regularly backing up data, keeping the software updated, cultivating security awareness among users, and encrypting sensitive information. Personalized learning path recommendation intelligent algorithms need to ensure the security of data collection, storage and processing by implementing enhanced data encryption protocols, adopting secure data transmission standards such as TLS, and using blockchain technology to guarantee the immutability of data; thus, the system's resistance to external threats has been improved. Access control mechanisms and authentication policies are also used to ensure that only authorized users can access sensitive data, providing a safe learning environment for users and continuously improving scalability and security. Intelligent algorithms for personalised learning paths are also being developed to adapt to and make full use of future trends in educational technology, such as the integration of AI and AR/VR, and at the same time, tailored educational services can be offered while strictly protecting user privacy and data security measures.

5 Case Study

5.1 Optimisation of Case Implementation

The personalised learning path recommendation system faced many problems in actual use of education. First of all, with a large number of users, the speed of response for the system has dropped considerably, and users have been less convenient. This problem was relatively severe at the time of high demand, and thus, timely personalised recommendations could not be provided. Second, there have been frequent problems with the security of sensitive user data; several cases of data leakage have damaged the trust placed in the institution by its users. In light of the problems above, several technical measures were introduced to increase the scale and security of the system for user data. A microservices architecture has been introduced to better support the expansion of the system by creating small, self-contained modules that can be developed and deployed independently. This way, each service can be scaled independently according to the demand, and the whole system will perform better. AES-256 bit encryption will also be used for all sensitive data, and role-based access control (RBAC) will be introduced to limit unauthorised access to data. The above technical improvements have reduced the average response time of the system from 5.5 seconds to 1.2 seconds, solved the data security problem, restored user confidence, and improved the image of the platform. Technical Improvement Measures are as follows:

(1) System scalability optimization: By introducing microservice architecture, the original monolithic application is split into multiple independent services, each processing different business logic, and deployed in independently scalable containers. Use Kubernetes to realize automatic scaling function and adjust resource allocation according to real-time load.

(2) Enhanced data security: All sensitive data, such as user personal information and learning data, is encrypted using AES 256 bit encryption technology to ensure the security of the data during storage and transmission. At the same time, role-based access control (RBAC) has been implemented to strictly restrict data access permissions, and multi factor authentication has been adopted to ensure the security of the authentication process.

5.2 Evaluation of the Optimisation Effect

The following table shows a comparison of system performance indicators and data security incidents before and after applying technological upgrades to quantify how effective the strengthening measures have been. As shown in Table 2.

Table 2: Comparison of System Performance Indicators and Data Security Events Before and After Technology Application

metric	Before the improvement	After the improvement	Increase percentage
Response Time (sec)	5.5	1.2	78%
system availability (%)	95%	99.9%	5.16%
Data breach event (second / year)	3	0	100%
User satisfaction (1-10 score)	6	9	50%

A microservice architecture has been used to reduce the response time of the personalised learning path recommendation system significantly from 5.5 seconds to 1.2 seconds. Increase will help to reduce the waiting time for users. The system has also been made more available by increasing it to 99.9%, and the general user experience is better now. In addition, AES-256 encryption and role-based access control are used to enhance the security of the data and prevent any leakage; as a result, users have gained more trust in the system and are more satisfied. The above measures will help to improve the stability and security of the system, promote the expansion of the user base, and ensure the long-term development of online education services.

5.3 Epilogue

In short, with the progress of artificial intelligence, education data analysis and intelligent computing technology, the intelligent algorithm for personalised learning path recommendation will play an ever-increasing role in the future of intelligent education. By continuously optimising algorithm design, we can improve the data processing ability and adaptability of the recommendation system, and the future of personalised learning path recommendation systems will be even more intelligent and efficient, providing strong technical support for individualised learning and promoting the all-round development of education.

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