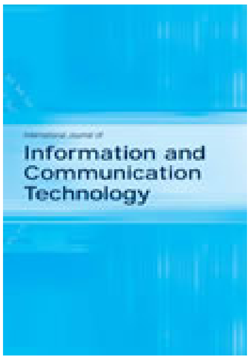

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Application of GCN-based teaching path optimisation for teachers in college education

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Abstract: Currently, optimising teachers' teaching paths using graph convolutional networks has become an important exploration direction for improving teaching quality. However, there are still issues with poor model performance and an imperfect evaluation system. To this end, this paper optimises the model algorithm to enhance the research findings of GCN-based optimisation of teaching paths for university teachers. Firstly, this paper explores the potential connections between data by redesigning convolution kernels to adapt to the complex structure of teaching data. At the same time, this paper uses efficient parameter update algorithms such as adaptive moment estimation to dynamically adjust the learning rate based on the first-order and second-order moment estimates of the parameters, in order to accelerate model convergence. The research results indicate that the improved GCN model has an accuracy of 0.97, a precision of 0.96, and a training time of 12 hours when recommending teaching resources.

Keywords: college education; teaching path optimisation; GCN model; teacher teaching; student development.

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Biographical notes: Qingsheng Liu studied at Anhui Institute of Science and Technology from 2003 to 2007 and received his Bachelor's degree in 2007. He studied in Yangzhou University from 2007 to 2010 and received his Master's degree in 2010. He worked at Huainan Normal University in Anhui Province since 2010 and studied at Perpetual University of the Philippines from 2021 to 2023, where he received his doctorate in 2023. He has published eight papers. His research interests include higher education and university student education management.

1 Introduction

In an era of rapid development of information technology, college education is in the midst of a profound change. Traditional teaching models have long adopted a 'one-size-fits-all' approach, where the teaching process often follows fixed procedures and standards, ignoring the significant individual differences among students in terms of learning ability, interests, hobbies, and knowledge base (Moallemi, 2024; Rehman and

Baig, 2024; Anggoro et al., 2024). In this model, regardless of students' learning characteristics and needs, they are given the same teaching content and teaching methods, resulting in uneven teaching results (Wong et al., 2023; Keuning and van Geel, 2021). Some students with strong learning ability may be 'underfed' and find it difficult to fully develop their potential, while students with weak learning foundation or unique learning styles may be 'indigestible' and frustrated in their learning motivation due to their inability to adapt to this unified teaching rhythm (Mazid et al., 2021; Xu and Liu, 2022; Suwastini et al., 2021). Moreover, the massive data generated in the teaching process, such as student learning behaviour data and teaching resource data, has not been fully mined and effectively utilised, which has limited the further improvement of teaching quality (AlQaheri and Panda, 2022; Khan and Ghosh, 2021). Therefore, while pursuing high-quality education, precisely grasping the learning characteristics of students and optimising teachers' teaching paths have become key issues that need to be solved in education.

In this context, the development of artificial intelligence (AI) technology has provided new ideas and methods for optimising the teaching paths of college education (Xiao and Yi, 2021; Teng et al., 2023). As a deep learning model that specialises in processing graph-structured data, graph convolutional networks (GCNs) can effectively capture the complex relationships between data and explore the patterns and laws hidden behind the data (Zhang, 2024; Lilan and Zhong, 2024). In the college education scenario, elements such as students, teachers, courses, and teaching resources are interrelated to form a complex graph structure. GCN can play its advantages in modelling and analysing these relationships (Abu-Salih and Alotaibi, 2024; Pang et al., 2023; Li et al., 2022).

However, there are still many problems in applying GCN to optimise the teaching paths of teachers in college education. On the one hand, college educational data is highly complex and diverse, including structured data (such as student grades and course information) and unstructured data (such as students' study notes and teachers' teaching reflections). Effectively integrating and processing the data to make it suitable for the input of the GCN model is a difficult problem that needs to be solved urgently. On the other hand, most of the existing GCN models are designed for general scenarios. Its direct application to education may not fully meet the special needs of teaching path optimisation, and targeted improvement and optimisation of the model are needed.

Solving these problems has essential theoretical and practical significance. From a theoretical perspective, studying the application of GCN in college education can expand its application areas, enrich the theories and methods of educational data mining and analysis, and provide new theoretical support for the development of educational AI. In practice, by optimising teachers' teaching paths, personalised and precise teaching can be achieved. The efficiency of teaching resource utilisation can be improved, and students' learning experience and learning effects can be enhanced, thus laying a solid foundation for cultivating high-quality talents that meet the needs of the new era.

This paper aims to deeply study the teaching path optimisation method of college teachers based on GCN. Through in-depth mining and analysis of college educational data, the GCN model structure is improved to better adapt to the characteristics of educational data and the needs of teaching path optimisation. The subsequent content elaborates on the relevant research methods, including data processing, model improvement, etc., as well as the research results and analysis based on these methods, to provide useful references for the education and teaching reform of colleges and universities.

2 Related work

The application research of GCN in education has attracted much attention in recent years. Zhang et al. (2023) proposed a personalised learning recommendation system based on a graph neural network, which uses students' learning behaviour data to build a graph model and achieve precise recommendations of learning resources. Li et al. (2024) used GCN to recommend dynamic teaching paths and adjust the teaching content and rhythm in real-time based on students' learning progress and knowledge mastery. In the multimodal processing of educational data, Wu et al. (2024) proposed a hybrid model that combined structured and unstructured data, incorporating data such as grades, study notes, and classroom discussions when recommending learning paths, thereby improving the precision and practicality of recommendations. Mubarak et al. (2022) optimised the GCN model based on the characteristics of educational data, improved the graph convolution operation, and enhanced the model's ability to process complex educational data. In addition to learning recommendations, the application of GCN in teaching process optimisation has also gradually attracted attention. Jiang et al. (2024) proposed a teaching path optimisation method based on GCN. By constructing a graph model of teaching activities, the relationship between teachers' teaching strategies, students' learning behaviours, and course content was analysed, thereby achieving optimal resource allocation in the teaching process.

Although there have been studies applying GCN to education, there are still many challenges. The interpretability of the GCN model is a significant difficulty. To improve its operability and acceptance in education, Lu et al. (2024) proposed an interpretable GCN model, which provided a detailed explanation of the decision process when recommending teaching paths, thereby enhancing teachers' trust in the system's recommendations. Although the application of the GCN model in education path optimisation has made some progress, it also faces problems in optimising the computational efficiency of the model and processing high-dimensional educational data. To address these challenges, Xiaoru (2024) proposed an efficient path recommendation system based on GCN, which significantly improved the efficiency and real-time performance of teaching path optimisation through parallel computing and optimisation algorithms.

In teacher teaching path optimisation, Huang and Wang (2022) proposed an optimisation framework based on GCN to construct a graph model of teachers, students, courses, and teaching resources, optimise the distribution of teaching content and strategy adjustment, and improve teaching efficiency and student learning experience. Albreiki et al. (2023) proposed a teaching activity optimisation method based on GCN, which modelled the relationship between teaching links, optimised teaching steps and activity arrangements, and improved the overall teaching effect. In the processing of multimodal educational data, Hai-tao et al. (2021) proposed an integrated GCN model that combined data sources such as student performance and learning behaviour to improve the overall performance of the model and enhance the precision and adaptability of teaching path optimisation.

Although research on educational path optimisation based on GCN has made progress, problems still exist. On the one hand, the GCN model relies on a large amount of high-quality data, but educational data often has missing data and noise, so dealing with incomplete data to ensure model stability and accuracy is a research focus. Meng et al. (2024) proposed an adaptive data filling method based on GCN to dynamically supplement missing data and effectively improve the model training effect and prediction precision. On the other hand, the problem of dynamic adjustment of teaching paths needs to be solved. In actual teaching, students' learning status and teachers' teaching strategies are constantly changing, so making the GCN model capable of real-time adjustment becomes the key to subsequent research. Gu (2025) proposed a dynamic path optimisation method based on GCN, which could adjust the teaching content in real-time according to students' learning progress and learning feedback, thereby improving the teaching effect.

In summary, the application of GCN in educational path optimisation has achieved certain results, but it still faces many challenges. Future research needs to further explore data processing, model optimisation, dynamic adjustment, etc., to promote the in-depth application of GCN in education.

3 Optimisation of teaching paths in colleges and universities

This paper focuses on the optimisation of teacher teaching paths in college education. In the research process, starting from the basic data level, the raw data from multiple channels is preprocessed. Then, the convolution kernel and graph convolution operations of the model are optimised, and the adaptive moment estimation algorithm is applied to improve the model performance. During model training and parameter optimisation, data partitioning and hyperparameter setting are performed strictly in accordance with established rules. Figure 1 presents the flow chart of the optimisation of teaching paths for college teachers in this paper.

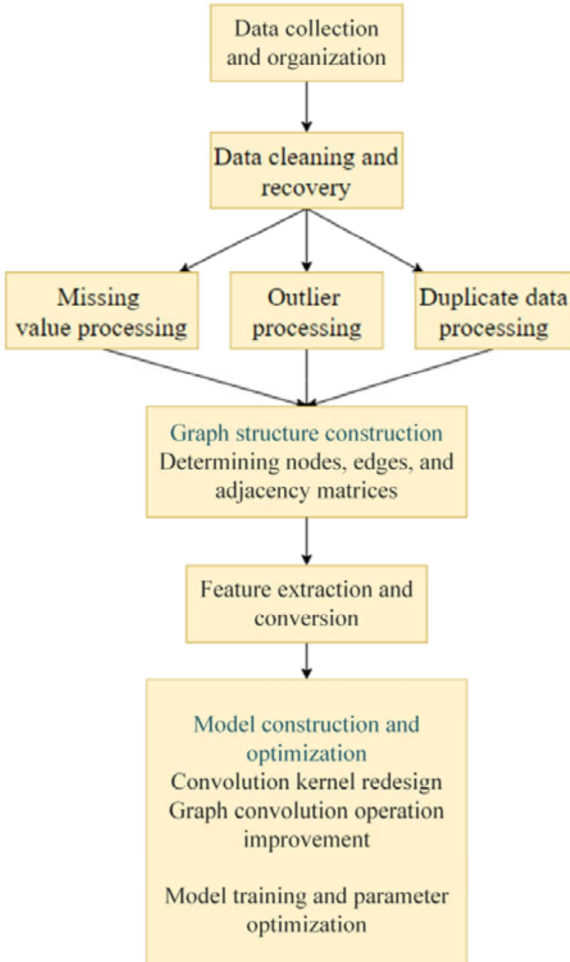
3.1 Data preprocessing

Data preprocessing is a key step to ensure that the model can learn effectively and produce accurate predictions. In the GCN-based research on the optimisation of teaching paths for college teachers, the raw data comes from multiple sources, such as student information, teacher teaching data, course content, and learning behaviour. These data are usually highly heterogeneous and complex. Therefore, before being input into the GCN model, they must go through a series of processing steps to ensure the quality and structure of the data so that they can better meet the requirements of the model.

3.1.1 Data collection and organisation

The data used in this paper primarily comes from large-scale public educational datasets and real-world university teaching data. The large-scale public educational dataset is the EdNet dataset, which contains over 100 million interactions between Korean students on a TOEIC test preparation platform, encompassing a variety of learning behaviours such as clicks, answers, and jumps. It is one of the largest public educational datasets available. This paper extracts a subset (EdNet-KT1) containing 5,000 active users, 100,000 questions, and approximately 8 million interaction records to evaluate the model's performance on knowledge tracking and resource recommendation tasks.

Figure 1 Process of optimising the teaching paths for college teachers (see online version for colours)



The real-world university teaching data comes from undergraduate computer science and technology courses at a key provincial university, covering three grades (2021 to 2023). The data covers 35 students (17 male and 18 female), five instructors, and four core courses (including 'data structures', 'operating systems', 'database principles', and 'algorithm design and analysis'). The data collection period spans two full semesters (September 2022 to June 2023), resulting in a total sample size of 10,241 learning behaviour records. Data sources include:

1 academic affairs management system: obtaining basic student information (student ID, name, grade, major), course schedule, and performance records

2 online learning platform: collecting students' online learning time, video viewing progress, chapter test scores, and homework submission records

3 teaching feedback system: collecting teachers' teaching reflection logs, classroom evaluation texts, and students' anonymous feedback; all data have been anonymised before collection.

This paper hashes and encrypts sensitive information such as students' and teachers' names, student IDs, and work IDs, and desensitises all identifiable information in all text data.

3.1.2 Data cleaning and recovery

Data cleaning is an important part of data preprocessing, and its purpose is to deal with missing values, outliers, and duplicate data in the data to ensure data quality.

- Missing value processing: for missing data, the mean filling method is used. If a student's study time is missing, the mean study time of other students in the course can be used to fill in the missing value of the student. The specific formula is:

$$x_i = \frac{1}{n}\sum\nolimits_{j=1}^{n} x_j \tag{1}$$

  Among them, x_i is the missing value, and n is the number of non-missing data.

- Outlier processing: Z-score standardisation is used to detect and correct outliers. If the Z-score of a data point exceeds a certain threshold, the data is considered an outlier. The Z-score formula is:

$$Z = \frac{X - \mu}{\sigma} \tag{2}$$

  Among them, X is the data point; μ is the mean; σ is the standard deviation.

- Duplicate data processing: duplicate records are removed to ensure that each data entity (such as students, teachers, and courses) has only one unique record.

3.1.3 Graph structure construction

GCN relies on graph data structures to handle the relationships between nodes (Yuan et al., 2023; Zhou and Zhu, 2024; Sun et al., 2021). In this study, the relationships between students, teachers, and courses are represented by nodes and edges in the graph.

- Node representation: each student, teacher, and course is a node in the graph. Student nodes represent specific students. Teacher nodes represent teaching teachers. Course nodes represent courses. Node features include student grades, study time, etc.
- Edge representation: edges represent the relationship between nodes, such as the teaching relationship between students and teachers and the association relationship between teachers and courses. The weight of the edge can represent the interaction intensity between students and teachers or the difficulty of the course.
- Adjacency matrix: the connection relationship between nodes is represented by the adjacency matrix. Element A_{ij} of the adjacency matrix represents the relationship between node i and node j. The adjacency matrix is usually normalised to improve the learning effect of GCN. The normalisation formula is:

$$\hat{A} = D^{\frac{1}{2}} A D^{-\frac{1}{2}} \tag{3}$$

Among them, A is the original adjacency matrix, and D is the degree matrix.

3.1.4 Feature extraction and conversion

Feature extraction and conversion is the process of converting structured and unstructured data into an input format suitable for the model. Teacher feedback, course content, and student learning behaviour are usually unstructured data and require feature extraction.

- Natural language processing: for text data, such as teacher teaching feedback and student learning notes, the term frequency-inverse document frequency (TF-IDF) method can be used to convert them into a vector representation. The calculation formula of TF-IDF is:

$$TF - IDF(t, d) = TF(t, d) * \log\left(\frac{N}{DF(t)}\right) \tag{4}$$

- Numerical feature standardisation: structured data (such as student grades, study time, etc.) is standardised.

  The standardisation formula is:

$$z_i = \frac{x_i - \mu}{\sigma} \tag{5}$$

  The normalisation formula is:

$$x_{new} = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{6}$$

  Through these processes, the features can be converted into a format suitable for GCN model input.

3.2 Model construction and optimisation methods

In the research on teacher teaching path optimisation based on GCN, the complexity and multimodal characteristics of educational data bring challenges to the construction and optimisation of the model. Traditional GCN models often rely on the adjacency matrix of the graph and fixed convolution operations. The relationship between teachers, students, and courses in educational data is complex and has a multi-level structure. Therefore, this paper proposes the following main optimisation methods: redesign of the convolution kernel and improvement of the graph convolution operation to effectively handle these complex data relationships and improve the model's optimisation effect. These optimisation methods and their implementation are described in detail below:

1 Redesign of the convolution kernel

  The essential convolution operation of GCN usually performs neighbourhood aggregation based on the adjacency matrix of the graph, relying on the information of direct neighbours (Qin, 2022; Luo et al., 2024; Karimi et al., 2020). However, educational data usually involves multi-level complex relationships, and there is not only one simple adjacency relationship between teachers, students, and courses. Students may have teaching interactions with multiple teachers at the same time, and these teachers may teach various courses. The relationship between courses may also be affected by other factors (such as students' historical performance, teachers' teaching style, etc.). Therefore, traditional convolution kernels cannot effectively capture these multi-level and indirect relationships.

The traditional GCN convolution operation is usually defined as:

$$H^{(l+1)} = \sigma\left(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}H^{(l)}W^{(l)}\right) \tag{7}$$

This approach only aggregates first-order neighbourhood information, making it difficult to capture the higher-order dependencies between teachers, students, and courses in the educational landscape. To model these multi-level relationships, this paper draws on the idea of higher-order graph convolution (higher-order GCN) to incorporate the node's second-order neighbourhood information into the aggregation process. Let N_i be the set of a node's direct neighbours and $N_i^{(2)}$ be its second-order neighbours. The improved convolution kernel considers both first- and second-order neighbours during aggregation:

$$h^{(l+1)} = \left(\sum_{j\in N_i} \alpha_{ij}W^{(l)}h_j^{(l)} + \sum_{j\in N_i} \beta_{ik}W^{(l)}h_k^{(l)}\right) \tag{8}$$

α_{ij} and β_{ik} are the aggregation weights of first-order and second-order neighbours, respectively. To simplify the calculation and maintain model smoothness, this paper uses the adjacency matrix power to uniformly represent multi-hop relationships. Let $\tilde{A}^{(1)} = \tilde{A}$ (first-order adjacency) and $\tilde{A}^{(2)} = \tilde{A}^2$ (second-order adjacency). The final aggregation operation can be expressed as:

$$H^{(l+1)} = \sigma\left(\left(\gamma\tilde{A} + (1-\gamma)\tilde{A}^2\right)H^{(l)}W^{(1)}\right) \tag{9}$$

$\gamma \in [0, 1]$ is a learnable mixing coefficient that dynamically balances the contributions of direct and indirect relationships. When $\gamma \in [0, 1]$, it degenerates to the standard GCN. This design enables the model to adaptively capture complex association patterns in educational data.

2 Node importance weighting mechanism

In the educational graph, the influence of different nodes varies significantly. Core courses or experienced teachers have a far greater guiding influence on the teaching path than ordinary nodes. To reflect this characteristic, this paper introduces a node importance weight ω_{ij}, which is designed based on the node's graph centrality c_i. The PageRank algorithm is used to calculate the centrality score of each node, and its iterative formula is:

$$C_i = \frac{1-\delta}{N} + \sum_{j\in N_i} \frac{c_j}{d_j} \tag{10}$$

δ is the damping coefficient ($\delta = 0.85$), and d_j is the out-degree of node j. The higher the centrality score, the more important the node is in the network. Based on this, the adjustment weight between nodes i and j is defined as:

$$\omega_{ij} = \exp\left(\eta \cdot \left(c_j - \bar{c}\right)\right) \tag{11}$$

$\bar{c}$ is the mean centrality of all nodes, and η is the scaling factor. This exponential form ensures that nodes with high centrality receive greater weights, and that weights change smoothly. Finally, ω_{ij} is combined with the adjacency matrix for weighted aggregation.

3 Multimodal graph convolution

To fuse structured and unstructured features, this paper concatenates the node's additional features F (text vectors and behavioural embeddings) with the structural features, i.e., $\tilde{H} = [H \,\|\, F]$. Graph convolution is then applied to the fused features:

$$\tilde{H}^{(l+1)} = \sigma\left(\tilde{A}_{norm} \cdot Dropout\left(\tilde{H}^{(l)}\right) \cdot \tilde{W}^{(l)}\right) \tag{12}$$

$\tilde{A}_{norm}$ is the normalised adjacency matrix, and $W^{(l)}$ is the learnable parameter matrix. By expanding the graph convolution operation, it is possible to capture deeper complex relationships in educational data.

To improve the transparency of the GCN model's decision-making process for educators, this paper further integrates the graph attention mechanism (GAT) based on the prior weights introduced based on node centrality to achieve dynamic and interpretable neighbourhood aggregation. The attention coefficient is calculated in the convolution operation:

$$\omega_{ij} = \frac{\exp\left(LeakyReLU\left(a^T\left[Wh_i \,\|\, Wh_j\right]\right)\right)}{\sum_{k \in N_i} \exp\left(LeakyReLU\left(a^T\left[Wh_i \,\|\, Wh_k\right]\right)\right)} \tag{13}$$

The attention weight ω_{ij} reflects the model's autonomously learned importance of node i to node j when making a prediction. Gradient-class activation mapping is used to perform attribution analysis on input features, identifying the feature dimensions that contribute most to the prediction results, assisting teachers in providing precise teaching interventions.

3.3 *Model training and parameter optimisation*

In the process of GCN-based teaching path optimisation, the quality of model training directly affects the accuracy and effect of the final result. To improve the model performance and ensure its generalisation ability on educational data sets, this paper adopts efficient training strategies and parameter optimisation methods to accelerate the convergence process, improve training stability, and ultimately achieve a high teaching path optimisation effect. The following is a detailed introduction to the specific methods of model training, including data partitioning, training strategies, hyperparameter optimisation, adaptive learning rate, regularisation techniques, early stopping, parameter updating, and optimisation methods, as well as loss functions and evaluation metrics.

1 Data partitioning and training set generation

Data partitioning is a crucial step in model training. Reasonable data partitioning can effectively avoid overfitting and ensure the model's generalisation ability. In this study, the collected data set is first divided into a training set (70%) and a test set (30%).

2 Training strategies and hyperparameter setting

The efficiency and performance of model training depend heavily on the appropriate training strategy and the selection of hyperparameters. During the training process, a strategy of gradually adjusting the learning rate is adopted to improve the efficiency of training. In the early stages of training, a large learning rate helps the model quickly converge to a better local optimal solution. In the later stages, gradually reducing the learning rate can avoid oscillations and ensure that the training results of the model tend to be stable.

In addition to adjusting the learning rate, this paper also uses batch gradient descent. Its update rule is:

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta J(\theta_t) \quad (14)$$

Among them, θ_t is the model parameter, and η is the learning rate. Through multiple training epochs, batch gradient descent can effectively optimise the loss function of the model.

In terms of hyperparameter tuning, this paper adopts two methods: grid search and random search. Grid search selects the best hyperparameters by traversing all possible hyperparameter combinations, while random search randomly selects a portion of hyperparameter combinations for evaluation. The main difference between the two is the computational overhead. Grid search is more comprehensive but computationally expensive, while random search reduces computational cost through random sampling. In this way, the optimal hyperparameter combination can be selected to improve model performance.

3 Adaptive learning rate optimisation

In the traditional GCN model training process, a fixed learning rate is usually used to update parameters. This method can easily lead to slow convergence or oscillation during training, especially when facing large-scale data. To solve this problem, this paper also uses an adaptive moment estimation algorithm.

The adaptive moment estimation algorithm applies estimates of the first and second order moments to each parameter when computing the gradient of each parameter. Adam adopts two important correction terms in the computing process: the correction of the first-order moment and the correction of the second-order moment. These corrections help ensure that deviations are reduced and the accuracy of parameter updates is improved in the early stages of training. The specific algorithm update rules are as follows:

The first-order moment update is:

$$m_t = \beta_1 \cdot m_{t+1} + (1 - \beta_1) g_t \quad (15)$$

Among them, g_t is the gradient at the current moment, and m_t is the estimated value of the first-order moment.

The second-order moment update is:

$$v_t = \beta_2 \cdot v_{t-1} + (1 - \beta_2) g_t^2 \tag{16}$$

The corrections to first and second-order moments are:

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t} \tag{17}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t} \tag{18}$$

The parameter update is:

$$\theta_t = \theta_{t-1} - \frac{\alpha}{\sqrt{\hat{v}_t} + \epsilon} \cdot \hat{m}_t \tag{19}$$

By adaptively adjusting the learning rate, the Adam algorithm can dynamically change the update step size of each parameter, avoiding the training instability problem caused by improper selection of the learning rate in traditional gradient descent methods. This algorithm can effectively accelerate the training process and prevent the impact of excessive or insufficient learning rates at different stages, thereby improving training efficiency and stability. Table 1 lists the parameter settings for optimising the GCN model in this paper.

4 Regularisation and early stopping

During the training process, this paper uses L2 regularisation and early stopping techniques to prevent the model from overfitting. L2 regularisation penalises the complexity of the model by adding the square sum of weights to the loss function, thereby limiting the excessive value of the model parameters. The L2 regularisation term can be expressed as:

$$L2(\theta) = \lambda \sum_{i=1}^{n} \theta_i^2 \tag{20}$$

Among them, λ is the regularisation parameter, and θ_i is the i^{th} parameter in the model. By adding the L2 regularisation term, the complexity of the model is effectively constrained, reducing the risk of overfitting.

In addition to L2 regularisation, early stopping is also a common strategy to prevent overfitting. The principle of early stopping is to terminate training early when the loss of the validation set no longer decreases over multiple training epochs. This strategy can prevent the model from overfitting on the training set and ensure the performance of the model on the test set.

Table 1 Parameter configuration information of the GCN model for teachers' teaching path optimisation

Parameter name	*Minimum value*	*Maximum value*	*Initial value*	*Step size*	*Typical value*
Learning rate	0.0001	0.01	0.001	0.0001	0.005
Number of convolution kernels	16	128	32	8	64
Size of convolution kernels	2	5	3	1	3
Number of hidden layer neurons	64	512	128	32	256
Weight decay coefficient	0.0001	0.01	0.001	0.0001	0.005
Dropout probability	0.1	0.5	0.2	0.05	0.3
Batch size	16	256	64	16	128
Adam algorithm first-order moment decay rate	0.8	0.99	0.9	0.01	0.9
Adam algorithm second-order moment decay rate	0.99	0.999	0.999	0.001	0.999
Adjacency matrix normalisation parameter	0.5	1.5	1.0	0.1	1.0

5 Parameter updating and optimisation methods

During the training process of GCN, to speed up the training, this paper adopts the adaptive moment estimation algorithm to optimise the parameters of the model. By estimating the first-order moment and second-order moment of the gradient of each parameter, the Adam algorithm can dynamically adjust the update step size of each parameter, avoiding the training instability problem caused by a fixed learning rate. The Adam algorithm can effectively accelerate the training process and improve the stability and performance of the model.

6 Loss function

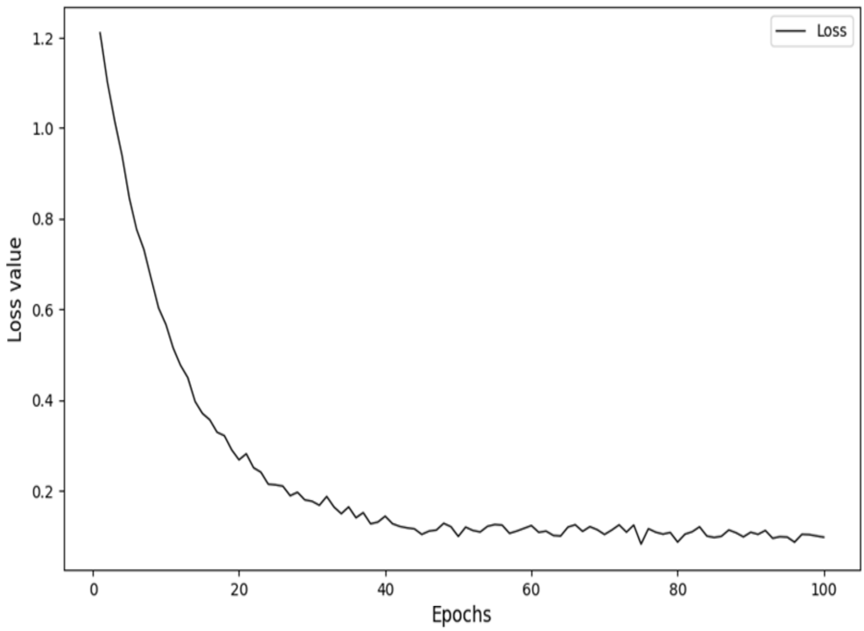
This paper chooses the cross-entropy loss function to measure the error. The function is defined as follows:

$$L_{cross} = -\sum_{i=1}^{n} y_i \log\left(\hat{y}_i\right) \tag{21}$$

Among them, y_i is the true label of the sample. $\hat{y}_i$ is the predicted probability of the model. n is the number of categories of the sample.

Figure 2 shows the changes in loss value during the model training process in this paper. In the initial stage of model training, due to the initial setting of model parameters, it is still in the preliminary exploration stage, and the loss value is relatively high at this time. As the number of training epochs increases, the model continuously optimises and adjusts its parameters based on each training, and the loss value is gradually decreasing. At around 40 epochs, the model's loss value drops to around 0.1. After that, until 100 epochs, the model loss value remains at 0.1, indicating that the model reaches convergence, and the training can be terminated.

Figure 2 GCN training iterations



4 Teaching path optimisation evaluation

To comprehensively evaluate the effectiveness and universality of the model, this paper adopts a two-track verification strategy: the EdNet public education dataset is used for benchmark testing to evaluate the model's prediction accuracy, training efficiency, and performance in different scenarios; then, the application analysis is conducted based on real teaching data to deeply explore the model's actual impact on students' learning behaviour and academic outcomes.

4.1 Comparative evaluation of teaching path optimisation model

This paper compares the optimised GCN with BN (Bayesian Network), RL (Reinforcement Learning), DT (Decision Tree), and LSTM (Long Short-Term Memory). With the goal of this paper to optimise the teaching paths of college teachers, the recall (R), F1-score, precision (P), and accuracy (A) indicators are used for evaluation. Through the use of these indicators, the actual performance of the GCN-based teaching path optimisation model in the college education scenario can be reflected, providing a basis and direction for further improvement and perfection of the model. The specific formulas are:

$$A = \frac{TP + TN}{TP + TN + FP + FN} \tag{22}$$

$$F1 = 2 \times \frac{P \times R}{P + R} \tag{23}$$

$$P = \frac{TP}{TP + FP} \tag{24}$$

$$R = \frac{TP}{TP + FN} \tag{25}$$

Figures 3 to 5 present the differences between the optimised GCN in this paper and BN, DT, LSTM, and RL models in different evaluation aspects, including student academic performance level, teaching resource recommendations, and whether students fail the course. These figures can provide relatively clear data support and strong support for subsequent research and analysis. It can be seen that when predicting the student's academic performance level in Figure 3, the A of the BN model is 0.83. The A of the GCN model is as high as 0.96, with a P of 0.95, an R of 0.94, and an F1-score of 0.94, which are much higher than those of other models, indicating that it can analyse the characteristics of student academic performance levels more precisely. In Figure 4, in terms of teaching resource recommendation, the GCN model has an A of 0.97, which is the highest among all models, much higher than BN's 0.85 and LSTM's 0.86. This shows that the optimised GCN model in this paper can more precisely push resources suitable for students and achieve personalised learning. Figure 5 shows the prediction results of whether a student fails a course. The indicators of the GCN model reach 0.97, 0.96, 0.94, and 0.95, respectively, indicating that it can deeply mine data and provide teachers with more reliable warning information on students' failure.

Figure 3 Comparison of different models in predicting students' academic performance (see online version for colours)

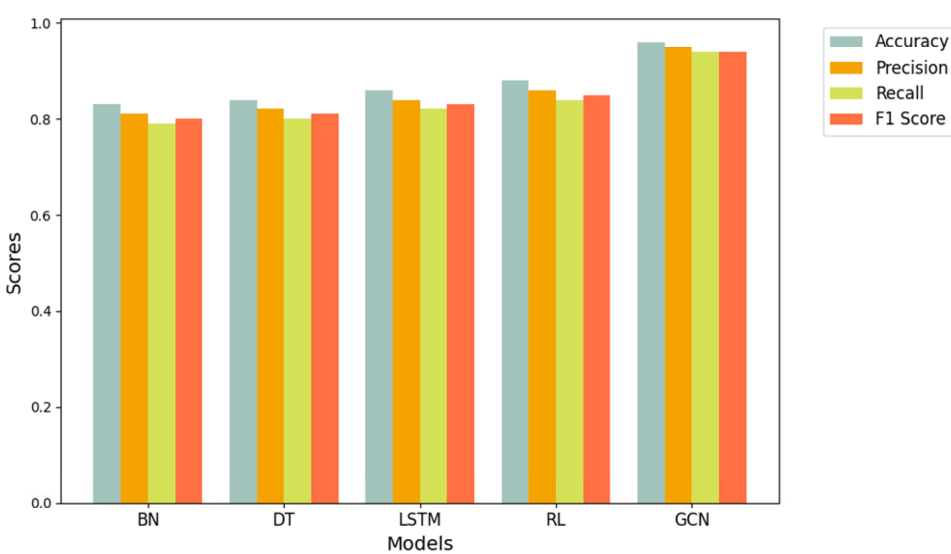


Figure 4 Performance comparison of different models in teaching resource recommendation tasks (see online version for colours)

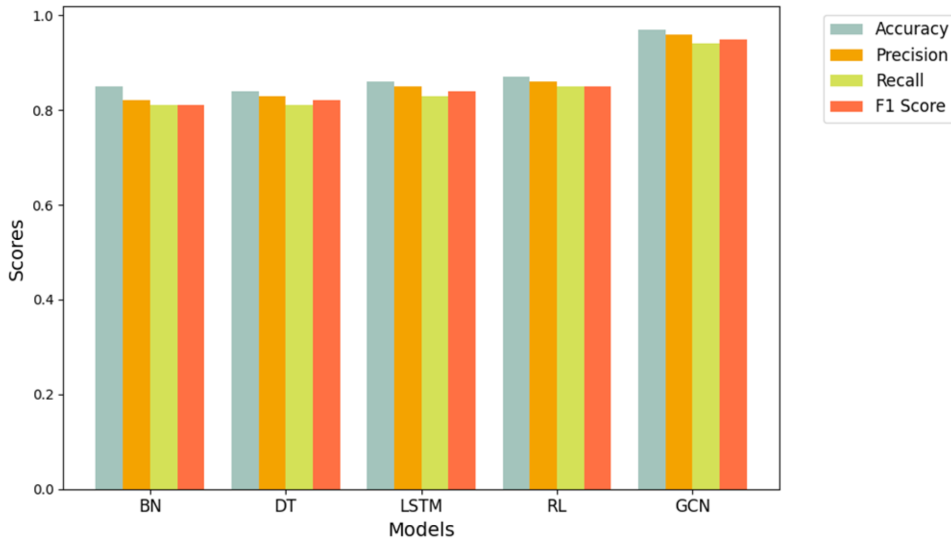
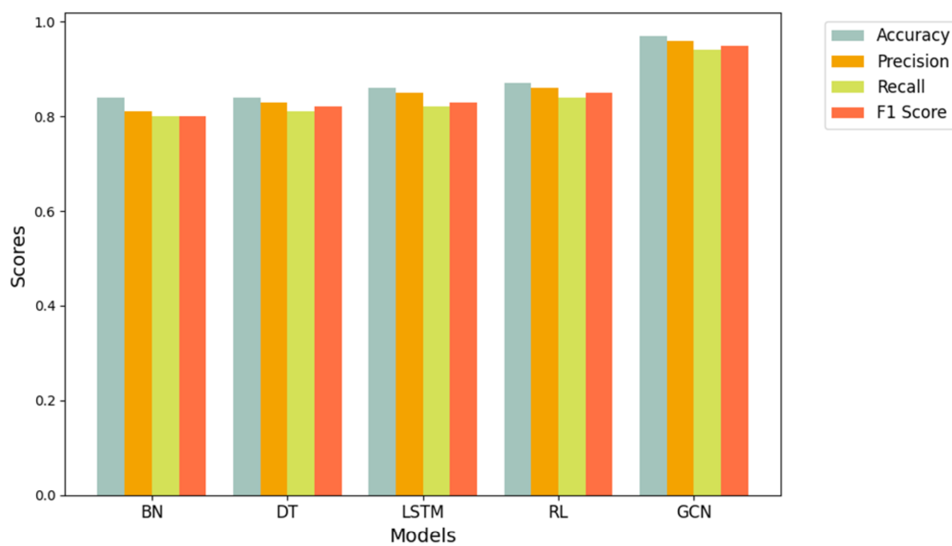


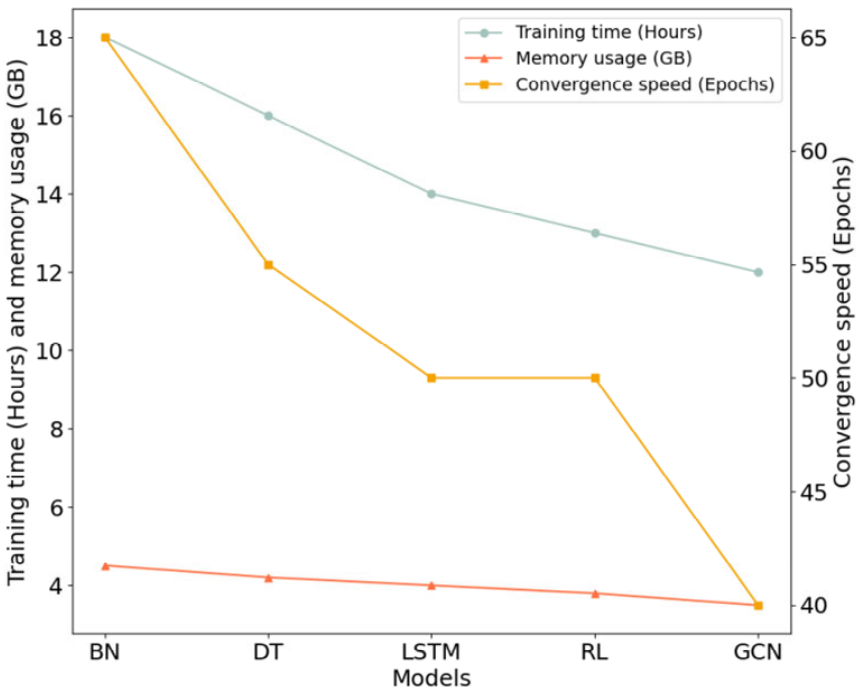
Figure 5 Performance comparison of different models in the student failure prediction task (see online version for colours)



4.2 *Performance comparison of different models*

This paper improves the convolution kernel and graph convolution operation of the GCN model. Figure 6 presents the specific data of the BN, DT, LSTM, RL, and GCN models in terms of training time, model convergence speed, and memory usage to verify the effectiveness of the improvement. In terms of training time, the BN model takes 18 hours, while the GCN model takes 12 hours, showing that GCN has apparent advantages in training efficiency and can complete the training process faster, saving a lot of time costs. In terms of model convergence speed, the GCN model can converge in 40 epochs and can reach a stable state faster compared with 65 epochs of the BN model, thus improving the timeliness of model training. In terms of memory usage, the GCN model only occupies 3.5GB, which is much lower than the 4.2GB of the DT model. This means that GCN has relatively low requirements for hardware resources, which can reduce equipment costs and operating burdens in practical applications and is more conducive to deployment and use in resource-limited environments. Combining these data, it can be found that the GCN model performs outstandingly in terms of efficiency and is more suitable for practical applications in college education scenarios.

Figure 6 Performance comparison of different models in terms of training time, convergence speed, and memory usage (see online version for colours)



4.3 *Comparison of strong baseline models*

To comprehensively evaluate the performance of the optimised GCN model in this paper, current mainstream Graph Neural Network (GNN) variants are introduced as strong baselines, include: 1) Graph Attention Network (GAT): using an attention mechanism to assign different weights to neighboring nodes, thus enhancing the model's ability to capture important relationships; 2) GraphSAGE: using a sampling and aggregation strategy suitable for large-scale graph data; 3) Graph Isomorphism Network (GIN): using a multi-layer perceptron to enhance node representation and possessing strong graph structure differentiation capabilities. Table 2 shows the performance comparison of these models in terms of accuracy, precision, recall, and F1 score. As can be seen from Table 2, the optimised GCN model in this paper outperforms the baseline model in most indicators. This is due to the redesigned convolution kernel that effectively integrates high-order neighborhood information and enhances the ability to model complex relationships in the teaching graph.

Table 2 Comparison results of strong baseline models

Model	*A*	*P*	*R*	*F1*
GAT	0.93	0.88	0.87	0.87
GraphSAGE	0.94	0.91	0.88	0.89
GIN	0.9	0.85	0.81	0.83
The model of this article	0.96	0.95	0.94	0.94

4.4 Multi-dimensional evaluation of impact of teaching path optimisation on student learning

When exploring the optimisation effect of teaching paths based on GCN, Tables 3 and 4 provide data from two different aspects. Table 3 focuses on students' learning enthusiasm, covering dimensions such as the number of active questions asked, the amount of learning materials downloaded, the duration of independent learning, learning interest scores, and homework completion rate. When GCN is not used, students ask questions 4.3 times per month. After using GCN, the number increases to 5.2 times, with an increase of 20.9%, showing that GCN stimulates students' desire to explore. The number of learning material downloads increases from 12.3 times per month to 14.7 times per month, with an increase of 19.5%. The duration of independent learning increases from 2.7 hours per week to 3.1 hours per week, with an increase of 14.8%, reflecting that students are more proactive in learning. The learning interest score increases from 6.4 to 7.6, with an increase of 18.8%, indicating that students are enthusiastic about learning. The homework completion rate increases from 82% to 91%, with an increase of 9%, indicating that students have a more positive attitude towards learning.

Table 3 Learning enthusiasm

Evaluation dimensions	*Without GCN*	*With GCN*	*Improvement (%)*
Number of active questions (times/month)	4.3	5.2	20.9
Number of learning materials downloaded (times/month)	12.3	14.7	19.5
Independent learning time (hours/week)	2.7	3.1	14.8
Learning interest score (1-10)	6.4	7.6	18.8
Homework completion rate (%)	82	91	9

Table 4 focuses on the depth of knowledge mastery, including the understanding of complex knowledge points, the excellent rate of final comprehensive grades, and the average homework grades. The understanding of complex knowledge points is 41.7% before using GCN, and it reaches 53.9% after using it, with an increase of 12.2%, which means that GCN helps students master complex knowledge. The rate of excellent comprehensive final scores increases from 10.7% to 16.3%, with an increase of 5.6%, reflecting the improvement of students' overall knowledge level. The average homework score increases from 72.4 points to 77.6 points, with a rise of 7.2%, indicating that students' ability to apply knowledge is enhanced. Overall, GCN positively impacts students' learning enthusiasm and depth of knowledge mastery significantly.

Table 4 Depth of knowledge mastery

Evaluation dimensions	*Without GCN*	*With GCN*	*Improvement (%)*
Understanding of complex knowledge points (%)	41.7	53.9	12.2
Rate of excellent comprehensive final score (%)	10.7	16.3	5.6
Average homework score	72.4	77.6	7.2

5 Conclusions

This study focuses on the core theme of optimising teachers' teaching paths in college education and uses GCN to conduct a systematic and in-depth study. After collecting experimental data, this paper processes the missing values, outliers, and duplicate data in these data. Then, the graph structure is constructed, and feature extraction and conversion are completed to make it meet the input requirements of the GCN model. On this basis, the GCN model is optimised. The convolution kernel is redesigned, and the graph convolution operation is improved. In addition, an adaptive moment estimation algorithm is applied to optimise the parameter updating process and realise dynamic adjustment of the learning rate. Through the above methods, this study has achieved certain results in optimising teaching paths. The model has high accuracy and reliability in predicting students' academic performance, which effectively helps teachers identify students with learning difficulties. Although this study has achieved certain results, there are still some areas for improvement. In the data processing stage, there is still room for further optimisation of existing processing methods to address the common problems of missing values and noise in educational data. Although some efforts have been made to improve the model's interpretability, there is still a gap from the ideal state, which, to some extent, hinders teachers' in-depth understanding and complete trust in the model's decision-making process. Future research can continue to explore more advanced and efficient data processing techniques and increase research efforts on the interpretability of models.

Declarations

All authors declare that they have no conflicts of interest.

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3 Key Educational and Teaching Reform Research Project at the University Level in 2023: Reform and Practical Exploration of Project-based Teaching Design for Primary School Science Curriculum Based on STEM Concept (2023hsjyxm10).

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