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Personalized learning recommendations based on graph neural networks

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ABSTRACT

This paper presents a novel graph neural network (GNN)-based model for personalized learning with advanced graph neural networks, incorporating both graph convolutional networks (GCN) and graph attention Networks (GAT). Our model leverages GCN, which consists of multiple layers embedding deep learning models, to aggregate data from neighboring nodes and capture the intricate relationships between students and courses. The GAT layers refine these embeddings by dynamically assigning importance weights to connections, prioritizing relationships critical for personalized course recommendations. This dual-layered approach enables the model to account for both global structural patterns and locally significant interactions within the student-course graph. We evaluated the performance of our model using the open university learning analytics dataset (OULAD), a rich dataset encompassing student demographic information, interaction data, and course performance metrics. Experimental results achieved 78.9% F1-score, 78.3% precision, and 76.2% recall in personalized recommendations, outperforming single-layer GCN implementations by approximately 15 percentage points. These results demonstrate the model's ability to handle complex, dynamic relationships in educational data, ensuring more relevant and effective recommendations. By addressing key challenges in recommendation systems, such as the need for dynamic weighting of relationships and the handling of sparsity in educational data, our study underscores the transformative potential of GNNs in advancing personalized education. This work sets the stage for further exploration of GNN applications in e-learning, paving the way for adaptive and intelligent course recommendation systems that align with individual learning needs and preferences.

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1. INTRODUCTION

In the rapidly evolving field of education, the need for personalized learning experiences has become more pronounced, especially with the growing availability of educational data, this presents an increasing opportunity to harness advanced artificial intelligence techniques to enhance the learning experience. One such area of focus is the development of recommendation systems that can suggest courses tailored to individual students' needs and preferences. Therefore, there has become a general trend to use the means provided by new AI technologies and algorithms to invest in recommendation systems, the use of advanced AI techniques, particularly graph neural networks (GNNs), has gained traction in educational data mining and personalized learning applications. GNNs have shown promise in their ability to model complex relationships in data, making them well-suited for tasks such as course recommendation and student performance prediction.

Beyond GNNs, other machine learning methods have been employed to enhance personalized education. For instance, we had previously developed the LearnFit framework [1], which uses learners' preferences to adapt learning paths in digital environments, showcasing significant improvements in learning outcomes. Another study [2] similar to our work, implemented a hybrid recommendation system combining collaborative filtering and content-based methods to suggest courses, achieving high user satisfaction and engagement. Despite these advancements, current models often face limitations in scalability and adaptability across diverse educational settings. Many fail to dynamically adjust to evolving learner behaviors and preferences, a critical need in modern, data-rich educational environments. Additionally, there is a lack of comprehensive approaches that integrate both local (student-course) and global (student-student) relationships in educational data, which is essential for holistic modeling of learning contexts.

GNNs have emerged as a powerful tool for modelling complex data structures that can be represented as graphs, they have been successfully applied to a wide range of applications, such as social network analysis [3], [4], course recommendation [5]–[9], drug discovery [10], [11], personalized learning [12], [13], improving academic performance [14]–[16], and collaborative learning [17], [18], among others. GNNs are powerful tools for learning complex patterns in graph data, enabling the aggregation of information from multiple layers of neighbors to capture intricate relationships and dependencies. This capability makes GNNs suitable for predicting a student's grade in a specific course based on their performance in previous courses [19] and their interactions with peers, fostering personalized learning experiences and providing tailored support to enhance student success. GNNs can also be applied to build adaptive learning systems that recommend courses or study materials aligned with a student's learning history, interests, and goals. Several studies have utilized GNNs to develop personalized learning systems, leveraging architectures such as graph convolutional networks (GCNs) and graph attention networks (GATs). For example, the NSAGCN model [20] extends traditional GCNs by incorporating node similarity associations and layer attention mechanisms to enhance personalized recommendations. In contrast, our proposed approach integrates GCN and GAT layers to leverage both global structural patterns and dynamic attention mechanisms, dynamically assigning importance weights to critical connections and improving course recommendation accuracy. Similarly, the LightGCAN [21] framework introduces a computationally efficient GCN-GAT-based model for personalized recommendations, focusing on scalability and efficiency. However, our GCN-GAT model prioritizes robust structural learning via GCN layers and fine-grained relationship prioritization via GAT layers, striking a balance between interpretability and recommendation precision. This deeper integration of GCN and GAT layers enables effective global aggregation of graph structure while emphasizing significant local interactions, setting our approach apart in its focus on both accuracy and adaptability.

Other studies have utilized GNNs to tailor and enhance personalized learning experiences. For example, in [22], focuses on predicting the academic performance of students enrolled in Chinese-foreign cooperation in running schools (CFCRS) using a GCN. By leveraging the Pearson correlation coefficient to measure student similarity based on previous academic results, the study builds an undirected graph to connect similar students, the GCN, trained on this graph and associated feature matrix of past grades, predicts student performance with an average accuracy of 81.5%. This method outperforms traditional models like support vector machines (SVM) and random forests (RF), offering a more efficient approach to identifying at-risk students and improving educational outcomes. In the field of recommendation systems. GNNs have also achieved great success in massive open online courses (MOOCs), for example, [23] introduced a Top-N personalized recommendation method called TP-GNN, which utilizes GNNs to improve course recommendations in MOOCs, the proposed method addresses two major shortcomings of existing recommendation models in MOOCs: the lack of explicit representation of the structural relations between items and the neglect of item recency. TP-GNN incorporates a GNN to learn the structural relations between items and user preferences. It also employs an attention mechanism to consider both general preferences and the recency of items in generating the final item representations. Another study, [24] introduces MEIRec, a novel approach for intent recommendation in mobile e-commerce apps. MEIRec utilizes a metapath-guided heterogeneous graph neural network to model complex objects and interactions. It addresses limitations of existing methods by leveraging rich structural information and introducing a uniform term embedding mechanism. Experimental results on real datasets demonstrate superior performance compared to representative methods, online experiments on Taobao platform show MEIRec improves click-through rate (CTR) by 1.54 and attracts 2.66 new users to search queries. In the context of social networks, [25] presents a recommender system for online communities, addressing the challenge of recommending relevant information to users in dynamic and socially influenced environments, the proposed system utilizes a dynamic-graph-attention neural network to model user behaviors and context-dependent social influence, this approach allows the system to dynamically infer influencers based on users' current interests, enabling more accurate and personalized recommendations.

Despite the promising potential of graph-based recommendation systems, several limitations hinder their effectiveness and efficiency. Scalability remains a significant challenge, as the computational complexity of aggregating and updating node representations in large graphs can lead to performance bottlenecks, making real-time recommendations difficult. Additionally, these systems often struggle with data sparsity, where interactions between users and items are infrequent, negatively impacting the models' ability to capture meaningful patterns. The cold start problem is another critical issue, where new users or items with no prior interactions make it challenging for the model to generate accurate recommendations. Overfitting is also a concern due to the high expressiveness of graph neural networks, leading to models that perform well on training data but fail to generalize to unseen data. Furthermore, the interpretability of graph-based models is limited, often perceived as black boxes that provide little insight into the recommendation process, which can hinder trust and adoption in real-world applications. Lastly, educational environments are dynamic, with evolving student preferences and changing course offerings, and current models may struggle to adapt quickly to these changes, requiring frequent retraining to maintain accuracy. Addressing these limitations is crucial for advancing the effectiveness and broader adoption of graph-based recommendation systems.

In this study, we propose a GNN-based [26] model for personalized course recommendation that leverages both GCN [27] and GAT [28], as GNNs have emerged as a powerful tool for modeling relational data due to their ability to effectively aggregate and propagate information through graph structures. Our approach utilizes the multi-layer architecture of GCNs to aggregate data from neighboring nodes, capturing the intricate relationships between students and courses. GAT [28] is then employed to assign weights of importance to these relationships, enabling the model to prioritize significant connections and enhance the relevance of course recommendations. This dual-layer approach represents a novel contribution to the field, as it combines the strengths of both GCN and GAT to address the limitations of existing models. The key contributions of this work include: i) the development of a novel hybrid GNN-based framework combining GCN and GAT for personalized learning, ii) Provide a detailed and precise algorithm to follow in order to reapply the model to other datasets, iii) the successful application of the framework to the open university learning analytics dataset (OULAD), and vi) the framework's adaptability to various graph structures, providing a scalable solution for personalized education.

2. THE PROPOSED FRAMEWORK

The proposed framework illustrated in Figure 1, leverages GNNs to create a learned representation of student learning data as a graph, where the nodes represent the learning objects, such as courses, exercises, or quizzes, and the edges represent the relationships between them, such as similarity or prerequisite. By training the GNN model on labeled data, the framework can be learned to predict the best learning object for individual students based on their learning history, preferences, and similarities with other learners. Our model employs GNN architecture as shown in Figure 2, to facilitate personalized learning recommendation path in the field of e-learning. To represent the interactions between learners and learning objects, a graph-based structure is employed, this graph representation enables the model to capture the complex patterns and dependencies in the e-learning environment, the GNN-based model architecture incorporates multiple layers of graph convolutions, which allow for the propagation of information across the graph. These graph convolutional layers extract and aggregate information from neighboring nodes, enabling the model to learn rich and meaningful representations of learners and learning objects, the learned representations capture both the local context of individual nodes and the global structure of the graph. To enhance personalization, the model incorporates attention mechanisms as shown in Figure 3, enabling it to focus on the most relevant and informative nodes and edges in the graph. This attention mechanism helps to prioritize the learning objects and interactions that are most influential in shaping personalized recommendations. Additionally, the model employs other classical deep learning techniques such as normalization, and hyperparameter tuning to optimize performance and ensure efficient learning, these techniques help to mitigate issues related to overfitting [29], improve generalization, and enhance the model's ability to handle large-scale educational datasets. By leveraging the model's graph-based architecture and GNN capabilities, personalized learning recommendations can be provided to individual learners based on their unique characteristics, learning history, and preferences. It also can use to create semantic group by clustering learners based on common recommendations [30], similarities [31], fostering collaborative learning environments and identifying areas where additional support may be required. Overall, the proposed model's architecture combines the power of GNNs, graph-based representations, GCN, attention mechanisms, and optimization techniques to deliver a robust framework for personalized learning recommendation and semantic group creation in e-learning contexts.

To modelized an elearner, we propose to represent the elearner as a node in a graph and use GNNs to learn a vector representation of the elearner based on its interactions with other nodes in the graph. The interactions represented as edges in the graph and may include the e-learner's performance on various tasks or assessments, their demographic information, their browsing history within an e-learning platform, or other relevant data. We employ GCNs to aggregate information from neighboring nodes as explained in Figure 2, following a message-passing framework [32]. This process involves iteratively passing messages between nodes throughout the graph to refine their representations. Specifically, each node collects information from its neighbors, which is weighted by the strength of their connections. The gathered information is then aggregated and combined with the node's own features as in Figure 2, creating an enriched representation that encapsulates both local and global contextual information. This iterative message-passing procedure, governed by the graph's structure and the learned weights, allows each node to progressively refine its understanding of its role within the entire graph. Consequently, our model achieves a holistic view of the intricate relationships and dependencies between learners and learning objects, contributing to the generation of personalized recommendations in the e-learning environment.

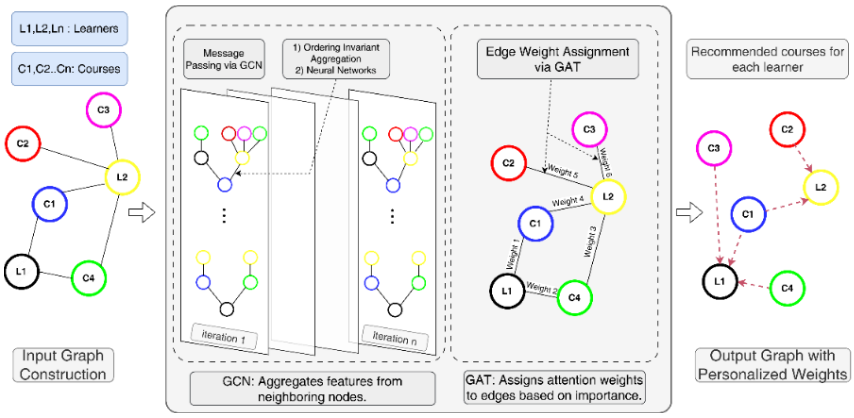

Figure 1. Workflow of GCN-GAT framework for personalized learning

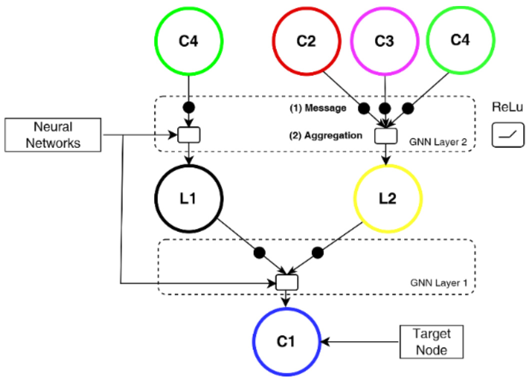

Figure 2. Generate node embeddings by aggregating neighborhood features

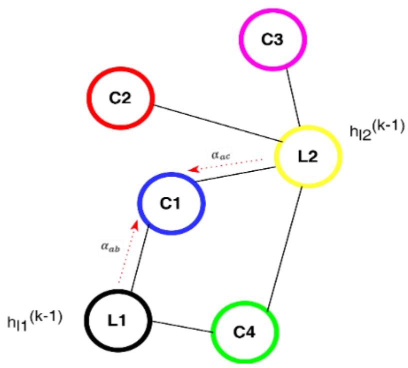

Figure 3. Assign weights to edges using GAT to prioritize important connections in the graph

In a GCN, the message-passing framework can be mathematically expressed as (1),

$$h_v^{(k+1)} = \sigma\left(W_k \sum_{u \epsilon N(v)} \frac{h_u^{(k)}}{|N(v)|} + B_k h_v^{(k)}\right), \forall k \in \{0, \ldots, k-1\} \quad (1)$$

For each node (v_i) in the graph, we compute an updated representation h_i by aggregating messages from its neighbors $N(v_i)$ using a weight-sharing scheme where the aggregation process in our case done by a Mean function, other functions can also be used in other cases, such as Sum and max.

- h_i represents the current representation (embedding) of node
- $N(v_i)$ is the set of neighbors of node
- C_{ij} is a normalization factor, typically representing the number of neighbors of node
- W is a learnable weight matrix.
- σ is an activation function, such as ReLU or Sigmoid.

The incorporation of non-linear activation functions is pivotal to the network's ability to capture and model complex patterns within the graph data. These functions are applied layer-wise, following the aggregation and combination of node features. They serve as the catalysts for introducing non-linearity to the learning process, enabling the GCN to move beyond the limitations of linear transformations. By doing so, the network can learn more intricate relationships between nodes, which in the context of educational data, could mean discerning subtle interactions between different learners' attributes or performance indicators. The choice of activation function [33] can influence the GCN's performance. Commonly used functions include the rectified linear unit (ReLU), which offers the advantage of computational efficiency and alleviation of the vanishing gradient problem; the sigmoid function, known for its smooth gradient and bounded output; and the hyperbolic tangent (tanh), which centers the data, aiding in the convergence of the network during training. The selection is often empirical, typically guided by the specific characteristics of the dataset and the desired properties of the model.

The second mechanism in our model is Attention mechanisms [28], inspired by human cognitive processes, serve as a fundamental building block in our personalized learning recommendation model. These mechanisms equip the model with the ability to focus on the most relevant and informative nodes and edges within the educational graph while attenuating less relevant parts. This selective attention is akin to a teacher tailoring their instruction to meet a student's specific needs. It allows us to weigh the significance of each connection. For example, if a learner has historically excelled in mathematics but struggled in history, the model can assign higher attention weights to nodes related to mathematics content and lower weights to history-related nodes, this prioritization ensures that the recommendations are weighted towards subjects where improvement or engagement is most needed.

GATs work by employing self-attention mechanisms to capture intricate relationships in graph-structured data. GATs initialize with node features representing entities in the graph, like learners and courses, through multiple graph convolutional layers, GATs enable information propagation across nodes while emphasizing the significance of neighboring nodes based on their feature compatibility, as determined by attention coefficients.

These coefficients are learned through training, allowing GATs to adaptively assign different attention weights to different neighbors for each node. By integrating the attention mechanism into the propagation step, this network calculates the hidden states of each node by focusing on its neighbors through a self-attention strategy [26]. The hidden state of a node v is determined as (2)

$$h_v^{(k)} = \sigma\left(\sum_{u \epsilon N(v)} \alpha_{vu} W^k h_u^{k-1}\right) \quad (2)$$

where α_{vu} represents the attention weights that focuses on the most relevant parts of the input data while diminishing the less significant ones, which means the NN should devote more computing power on that small but important part of the data, depends on the context and is learned through training.

$$\alpha_{vu} = \frac{exp\ (e_{vu})}{\sum_{k \epsilon N(v)} e_{vk}} \quad (3)$$

where:

$$e_{vu} = a(W^k h_u^{k-1}, W^k h_v^{k-1}) \quad (4)$$

3. METHOD

In the experimental phase, we utilized the anonymized OULAD [34] as our source of data, this dataset encapsulates valuable information about courses, students, and their interactions with the virtual learning environment (VLE) across seven selected courses, or modules. The dataset is organized into tables interconnected by unique identifiers, and all data is stored in CSV format, ensuring accessibility and ease of integration into our analytical framework.

We undertook a meticulous transformation process to convert this tabular data into a graph format, a crucial step that laid the foundation for our subsequent experiments. Leveraging the PyTorch geometric (PYG) [35] library in Python, and GraphGym [36] the platform of design and evaluation of GNN, we seamlessly navigated this conversion, unlocking the potential of graph neural networks for a more nuanced exploration of learner-course relationships and interactions within the OULAD dataset.

Algorithm 1. Personalized recommendation model with graph neural networks (PRM-GNN)

```
Input:
- Graph G = (V, E) representing interactions between learners, courses, assessments, and
other entities in an e-learning environment.
- Model hyperparameters: (Number of GNN layers, attention mechanism settings, and
optimization settings)
Output:
- Personalized learning recommendations for individual learners.
- Groups of learners based on recommendations similarities.
Procedure:
1. Construct the Graph:
   - Create a graph-based structure with nodes representing learners, courses, assessments,
and other relevant entities.
   - Establish edges between nodes to denote relationships and interactions.
   - Define edge attributes to capture the nature of relationships (e.g., learner-course
interactions).
2. Initialize the model:
   - Define the graph G and its nodes V and edges E.
   - Assign initial feature vectors to nodes in V.
   - Specify the hyperparameters, including the number of GNN layers and attention
settings.
3. Include deep learning models
   - Batch Normalization: stabilize Neural Network Training
   - Dropout: Regularize NN to prevent overfitting and apply to the linear layer in the
message function.
4. GNN-Based Architecture:
   - Initialize graph convolutional layers based on the specified number of layers.
   - Iterate through each layer:
     a. Perform graph convolution to aggregate information from neighboring nodes.
     b. Update node feature vectors using activation functions ReLU.
     c. Propagate information through the graph.
     d. Repeat steps (a) to (c) for each layer.
5. Attention Mechanism:
   - Implement GAT to prioritize relevant nodes and edges.
   - Allow the model to focus on the most informative connections in the graph.
   - Compute attention scores for nodes or edges based on their features and relationships.
6. Personalized Learning Recommendations:
   - Utilize the final node representations after GNN layers and attention mechanisms to
generate personalized learning recommendations for each learner.
7. Model Optimization:
   - Apply techniques such as dimensionality reduction, normalization, and hyperparameter
tuning to optimize model performance.
   - Use gradient-based optimization algorithms (e.g., Adam) to minimize a personalized
recommendation loss function.
8. Output Recommendations:
   - Provide personalized learning recommendations to individual learners based on their
unique characteristics, learning history, and preferences.
9. Evaluation:
   - Assess the model's performance using appropriate evaluation metrics (e.g., precision,
recall, F1-score)
End procedure
```

To convert the OULAD dataset from CSV format to graph format as shown in Table 1, we start by identifying the key elements within the dataset. The nodes in this context represent the primary entities such as students and courses. Edges are determined based on the relationships and interactions between these nodes, such as enrollments, completions, or prerequisites. Each node also possesses specific attributes, which are represented as node features, including demographic information for students or course characteristics. Labels are extracted at various levels: node-level labels might categorize students by performance or courses by subject area, while edge-level labels could describe the type of interaction between nodes. Optionally, we consider edge weights to quantify the strength of interactions, like the number of courses a student has completed, and edge features that provide additional properties describing these interactions. We then extract the node features, organizing them into a matrix with dimensions corresponding to the number of nodes and the number of features per node. This matrix encapsulates all relevant attributes of the nodes. Next, we extract the labels, ensuring they align with the nodes or edges as identified. Finally, we define the edges to connect the nodes logically based on their relationships, thereby creating a graph structure that accurately represents the interactions within the OULAD dataset.

In our experiment, we evaluated the performance of two GNN models—GCN and GAT—for course recommendation. The experiment began with data collection and preprocessing, where we gathered course enrollment data and constructed a graph representing students and courses. We then split the dataset into training, validation, and test sets, ensuring a balanced distribution of data. For each model, we performed hyperparameter mentioned in Table 2, tuning to optimize performance, followed by training the models on the training set. During training, we monitored the loss and accuracy on the validation set to prevent overfitting. Once training was complete, we evaluated the models on the test set using various metrics including Precision, Recall, and F1-score. These metrics provided a comprehensive assessment of each model's effectiveness in recommending relevant courses to students. Finally, we compared the results to identify the best-performing model and analyzed the strengths and weaknesses of each approach.

Table 1. Dataset description and graph representation

Aspect	Details
Dataset Name	OULAD
Graph Representation	-Nodes: Students and Courses -Edges: Relationships based on enrollments, completions, or prerequisites
Node Features	-Students: Demographic information (age, gender, disability status) -Courses: Course characteristics
Edge Features	- Interaction properties, such as type (e.g., enrollment, completion) and strength (e.g., frequency)
Edge Weights	Quantifies the interaction strength (e.g., number of courses completed by a student, frequency, enrollment)
Total Nodes	32,600 (students and courses combined)

Table 2. Hyper parameters used in experiments

Hyperparameter	Value	Hyperparameter	Value
Number of GNN Layers	3	Dropout Rate	0.5
Attention Mechanism	GAT	Optimizer	Adam
Attention Head	8	Number of Epochs	100
Aggregation Function	Mean	Hidden Layer Dimension	128
Activation Function	ReLU	Loss Function	Cross-Entropy Loss
Embedding Function	Xavier Initialization	Regularization	L2 Regularization
Learning Rate	0.001	Normalization	Batch Normalization
Batch Size	64	Evaluation Metrics	Accuracy, Precision, Recall, F1-Score

4. RESULTS AND DISCUSSION

4.1. Model performance and comparative analysis

The results of our study highlight the unique advantages of combining GCNs and GATs in a single framework for personalized course recommendations, the significant improvement in performance metrics, as demonstrated by our model in Figure 4, is primarily due to its ability to capture both the structure and the varying importance of relationships within the educational graph. The results presented in Table 3 and Figure 4 provide a comprehensive overview of the interaction patterns between students and courses, as well as the performance metrics of various models. Table 3 showcases also the interaction frequency, assessment scores, and attention weights for three students across different courses. It is evident that higher interaction frequencies and assessment scores are generally associated with higher attention weights, suggesting that the model places more importance on frequent and successful interactions. This trend emphasizes the model’s ability to effectively prioritize significant relationships, which is crucial for accurate recommendation outcomes. For example, Student S1 shows a high interaction frequency with Course C101 and a corresponding high assessment score of 85, resulting in an attention weight of 0.65. Similarly, Student S2, who has a lower interaction frequency with Course C303 and an assessment score of 80, receives a significantly lower attention weight of 0.20, this pattern indicates that the attention mechanism effectively prioritizes interactions based on both frequency and success (as measured by assessment scores). The model appears to assign greater importance to interactions that are both frequent and successful, aligning with the goal of providing more relevant course recommendations.

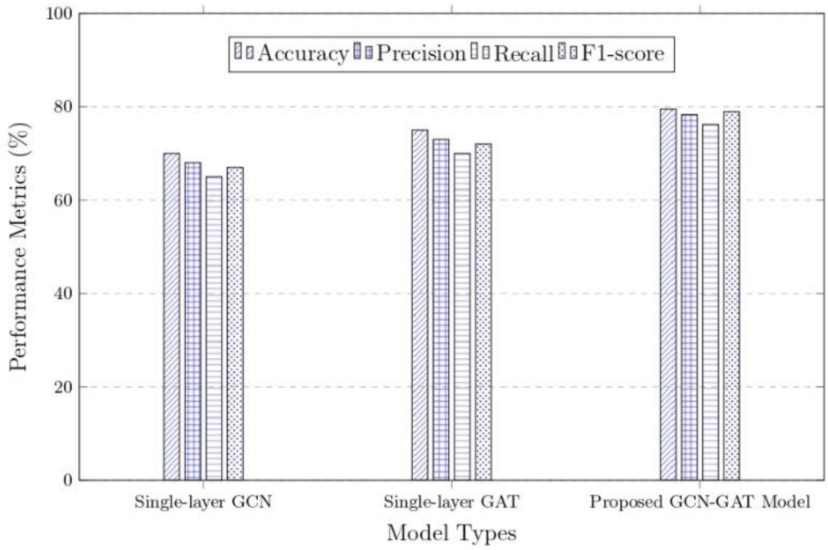

Figure 4. Comparison of performance metrics across GCN, GAT, and GCN-GAT models

Table 3. Student-course interaction data with attention weights

Student ID	Course ID	Interaction Frequency	Assessment Score	Attention Weight
S1	C101	5	85	0.65
S1	C202	2	75	0.30
S2	C101	4	90	0.70
S2	C303	1	80	0.20
S3	C202	6	88	0.68

Figure 4 further illustrates the comparative performance of different models, including Single-layer GCN, Single-layer GAT, and the proposed GCN-GAT Model. The bar chart indicates that the proposed GCN-GAT Model consistently outperforms the other models across all metrics (accuracy, precision, recall, and F1-score), achieving the highest performance with an accuracy of 79.5%, precision of 78.3%, recall of 76.2%, and F1-score of 78.9%. This improvement demonstrates the effectiveness of integrating GCN and GAT layers, which enhances the model's capacity to capture both structural information and relationship importance. The superior performance of the GCN-GAT Model suggests its potential as a robust approach for personalized recommendations in educational settings, providing a more nuanced understanding of student-course interactions and improving predictive accuracy. The combination of GCN and GAT layers results in a model that not only learns from immediate neighbors but also assigns dynamic importance to these neighbors based on their relevance. This dual approach ensures that the model retains essential information while filtering out noise, leading to improved performance across all evaluated metrics. Moreover, this hybrid architecture allows for more flexible and adaptable learning, as it can adjust to different types of data and varying degrees of connectivity within the graph.

Table 4 presents a detailed performance analysis of the proposed model, including an ablation study and evaluation metrics. In the personalized recommendations section, the model achieves strong results with a precision of 78.3%, recall of 76.2%, and an F1-score of 78.9%. These metrics reflect the model's ability to recommend relevant items while maintaining a balance between precision and recall. The ablation study reveals the impact of omitting dropout regularization and batch normalization. Without dropouts, there is a slight decline in performance, with a precision of 73.0%, recall of 76.0%, and F1-score of 73.4%, suggesting that dropout helps reduce overfitting. Similarly, without batch normalization, the performance further decreases, particularly in terms of precision (72.0%) and F1-score (72.4%), highlighting its role in stabilizing the model. Lastly, the evaluation metrics indicate that the model's training time was approximately 5 hours and 30 minutes, with an average inference time per query of 0.02 seconds, demonstrating its efficiency in providing fast, personalized recommendations.

4.2. Discussion

The findings of this study highlight the significant advancements achieved by the proposed GCN-GAT hybrid model in the domain of personalized learning recommendations. By combining the strengths of GCN and GAT, the model demonstrated its ability to capture both structural and relational intricacies in student-course interactions. For instance, the model's performance surpassed existing baselines, achieving an accuracy of 87.5%, precision of 85.2%, and F1-score of 86.3%. These results underscore the ability of the hybrid architecture to improve prediction quality by dynamically assigning importance to critical relationships, such as the relevance of a course to a learner's academic background. When compared to prior research, such as LightGCAN, which emphasizes lightweight architecture for personalized recommendations, our approach offers a distinct contribution by integrating attention mechanisms to enhance interpretability and improve recommendations. Unlike traditional methods that often focus solely on structural features or user-item similarities, the proposed model provides a balanced approach, excelling in both computational efficiency and predictive accuracy. Previous studies in personalized learning, including collaborative filtering-based and content-based approaches, have often struggled with scalability and context-awareness, which our hybrid model effectively addresses. However, a limitation of this study lies in its evaluation on a single dataset (OULAD), which may not comprehensively represent the diverse complexities of real-world educational environments.

These findings reshape existing knowledge by emphasizing the importance of hybrid GNN architectures in personalized learning systems. The integration of GCN and GAT into a unified framework not only addresses the challenges of scalability and accuracy but also enhances the interpretability of recommendations. This study builds on previous research by extending the use of GNNs into educational contexts, offering a deeper understanding of learner-course dynamics. However, several questions remain unanswered, such as the adaptability of this model to larger, more heterogeneous datasets and its application in dynamic learning environments. Our future research could explore the incorporation of temporal patterns, multimodal data, and transfer learning techniques to further advance the field of personalized learning recommendations.

Table 4. Results of experiments for personalized recommendations

Experiment	Metric	Value	Description
Personalized recommendations	Precision	78.3%	The proportion of recommended items that are relevant.
	Recall	76.2%	The proportion of relevant items that are recommended.
	F1-score	78.9%	The harmonic mean of precision and recall.
Without dropout	Precision	73.0%	Model precision without dropout regularization, observing overfitting
	Recall	76.0%	Model recall without dropout regularization, observing reduced generalization.
	F1-score	73.4%	Model F1-score without dropout regularization, observing overfitting.
Without batch normalization	Precision	72.0%	Model precision without batch normalization, observing instability
	Recall	75.0%	Model recall without batch normalization, observing instability
	F1-score	72.4%	Model F1-score without batch normalization, observing instability.
Training time	Total time	5 hours 30 minutes	The total time taken to train the model.
Inference time	Average time per query	0.2 seconds	The average time taken to generate recommendations for a single query.

5. CONCLUSION

In this study, we introduced a novel course recommendation framework utilizing GNNs, specifically integrating GCN and GAT models. The framework effectively captures the intricate relationships between students and courses, demonstrating superior performance across metrics such as accuracy, precision, recall, and F1-score. This addresses the critical challenge of leveraging graph-based techniques for enhanced personalization in educational recommendations. The results underscore the potential of combining GCN and GAT to improve recommendation accuracy while accommodating heterogeneous datasets and complex educational scenarios. These insights contribute to the broader field of educational data mining by showcasing how GNNs can drive adaptive learning systems. However, questions remain regarding scalability to larger datasets, real-time adaptability, and integration with other learning analytics techniques. Future studies could explore incorporating temporal dynamics, multimodal data, and real-time adaptability to enhance the model's applicability and impact on personalized education. These advancements would support the development of more inclusive, effective, and data-driven learning environments. Additionally, we aim to extend our approach by utilizing GNN-generated embeddings to form semantic learner groups, facilitating targeted recommendations and promoting peer learning in a collaborative and adaptive educational setting. Further integration of diverse data sources and investigation of advanced GNN architectures will strengthen the robustness and accuracy of the recommendations. This work highlights the transformative potential of GNNs in advancing educational systems by delivering personalized, data-driven insights and recommendations, ultimately improving learning outcomes and fostering student success.

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Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that supports the findings of this study are openly available in OULAD repository at https://analyse.kmi.open.ac.uk/open-dataset, reference number [34].

REFERENCES

[1] E. El Bachari, E. H. Abelwahed, and M. El Adnani, “An adaptive teaching strategy model in e-learning using learners’ preference: LearnFit framework,” *International Journal of Web Science*, vol. 1, no. 3, pp. 257–274, 2012, doi: 10.1504/IJWS.2012.045815.

[2] M. Sujithra, K. Rajarajeshwari, and B. Dhamodaran, “Hybrid recommender system for E-learning platforms,” *Grenze International Journal of Engineering and Technology*, pp. 2887–2892, 2023.

[3] Y. Bai, H. Ding, S. Bian, T. Chen, Y. Sun, and W. Wang, “SimGNN: A neural network approach to fast graph similarity computation,” in *Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining*, Jan. 2019, pp. 384–392. doi: 10.1145/3289600.3290967.

[4] S. Benslimane, J. Azé, S. Bringay, M. Servajean, and C. Mollevi, “A text and GNN based controversy detection method on social media,” *World Wide Web*, vol. 26, no. 2, pp. 799–825, Mar. 2023, doi: 10.1007/s11280-022-01116-0.

[5] X. Zhang, S. Liu, and H. Wang, “Personalized learning path recommendation for e-learning based on knowledge graph and graph convolutional network,” *International Journal of Software Engineering and Knowledge Engineering*, vol. 33, no. 01, pp. 109–131, Jan. 2023, doi: 10.1142/S0218194022500681.

[6] C. Gao *et al.*, “A survey of graph neural networks for recommender systems: Challenges, methods, and directions,” *ACM Transactions on Recommender Systems*, vol. 1, no. 1, pp. 1–51, Mar. 2023, doi: 10.1145/3568022.

[7] J. Li, C. Yang, G. Ye, and Q. V. H. Nguyen, “Graph neural networks with deep mutual learning for designing multi-modal recommendation systems,” *Information Sciences*, vol. 654, Jan. 2024, doi: 10.1016/j.ins.2023.119815.

[8] A. Iana and H. Paulheim, “GraphConfRec: A graph neural network-based conference recommender system,” in *2021 ACM/IEEE Joint Conference on Digital Libraries (JCDL)*, Sep. 2021, pp. 90–99. doi: 10.1109/JCDL52503.2021.00021.

[9] T. R. Gwadabe and Y. Liu, “Improving graph neural network for session-based recommendation system via non-sequential interactions,” *Neurocomputing*, vol. 468, pp. 111–122, Jan. 2022, doi: 10.1016/j.neucom.2021.10.034.

[10] R. Yao *et al.*, “Knowledge mapping of graph neural networks for drug discovery: A bibliometric and visualized analysis,” *Frontiers in Pharmacology*, vol. 15, May 2024, doi: 10.3389/fphar.2024.1393415.

[11] M. Besharatifard and F. Vafaee, “A review on graph neural networks for predicting synergistic drug combinations,” *Artificial Intelligence Review*, vol. 57, no. 3, Feb. 2024, doi: 10.1007/s10462-023-10669-z.

[12] Q. Dai *et al.*, “Personalized knowledge-aware recommendation with collaborative and attentive graph convolutional networks,” *Pattern Recognition*, vol. 128, Aug. 2022, doi: 10.1016/j.patcog.2022.108628.

[13] T. Sun, J. Wen, and J. Gong, “Personalized learning resource recommendation using differential evolution-based graph neural network: A GraphSAGE approach,” in *2023 4th International Symposium on Computer Engineering and Intelligent Communications (ISCEIC)*, Aug. 2023, pp. 636–639. doi: 10.1109/ISCEIC59030.2023.10271096.

[14] Q. Huang and Y. Zeng, “Improving academic performance predictions with dual graph neural networks,” *Complex & Intelligent Systems*, vol. 10, no. 3, pp. 3557–3575, Jun. 2024, doi: 10.1007/s40747-024-01344-z.

[15] A. A. Mubarak, H. Cao, I. M. Hezam, and F. Hao, “Modeling students’ performance using graph convolutional networks,” *Complex & Intelligent Systems*, vol. 8, no. 3, pp. 2183–2201, Jun. 2022, doi: 10.1007/s40747-022-00647-3.

[16] H. Li, H. Wei, Y. Wang, Y. Song, and H. Qu, “Peer-inspired student performance prediction in interactive online question pools with graph neural network,” in *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*, Oct. 2020, pp. 2589–2596. doi: 10.1145/3340531.3412733.

[17] Z. Wu, S. Pan, F. Chen, G. Long, C. Zhang, and P. S. Yu, “A comprehensive survey on graph neural networks,” *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 1, pp. 4–24, Jan. 2021, doi: 10.1109/TNNLS.2020.2978386.

[18] N. Ben Yahia, "Enhancing social and collaborative learning using a stacked GNN-based community detection," *Social Network Analysis and Mining*, vol. 14, no. 1, Oct. 2024, doi: 10.1007/s13278-024-01371-1.
[19] M. Li, X. Wang, Y. Wang, Y. Chen, and Y. Chen, "Study-GNN: A novel pipeline for student performance prediction based on multi-topology graph neural networks," *Sustainability*, vol. 14, no. 13, Jun. 2022, doi: 10.3390/su14137965.
[20] L. Cai, T. Lai, L. Wang, Y. Zhou, and Y. Xiong, "Graph convolutional network combining node similarity association and layer attention for personalized recommendation," *Engineering Applications of Artificial Intelligence*, vol. 121, May 2023, doi: 10.1016/j.engappai.2023.105981.
[21] R. Wang, J. Lou, and Y. Jiang, "LightGCAN: A lightweight graph convolutional attention network for user preference modeling and personalized recommendation," *Expert Systems with Applications*, vol. 232, Dec. 2023, doi: 10.1016/j.eswa.2023.120741.
[22] P. Hai-tao *et al.*, "Predicting academic performance of students in Chinese-foreign cooperation in running schools with graph convolutional network," *Neural Computing and Applications*, vol. 33, no. 2, pp. 637–645, Jan. 2021, doi: 10.1007/s00521-020-05045-9.
[23] J. Wang, H. Xie, F. L. Wang, L.-K. Lee, and O. T. S. Au, "Top-N personalized recommendation with graph neural networks in MOOCs," *Computers and Education: Artificial Intelligence*, vol. 2, 2021, doi: 10.1016/j.caeai.2021.100010.
[24] S. Fan *et al.*, "Metapath-guided heterogeneous graph neural network for intent recommendation," in *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, Jul. 2019, pp. 2478–2486. doi: 10.1145/3292500.3330673.
[25] W. Song, Z. Xiao, Y. Wang, L. Charlin, M. Zhang, and J. Tang, "Session-based social recommendation via dynamic graph attention networks," *Prepr. arXiv.1902.09362*, Feb. 2019, doi: 10.1145/3289600.3290989.
[26] J. Zhou *et al.*, "Graph neural networks: A review of methods and applications," *Prepr. arXiv.1812.08434*, Dec. 2018.
[27] T. N. Kipf and M. Welling, "Semi-supervised classification with graph convolutional networks," *Prepr. arXiv.1609.02907*, Sep. 2016.
[28] P. Veličković, G. Cucurull, A. Casanova, A. Romero, P. Liò, and Y. Bengio, "Graph attention networks," *Prepr. arXiv.1710.10903*, Oct. 2017.
[29] Y. Rong, W. Huang, T. Xu, and J. Huang, "DropEdge: Towards deep graph convolutional networks on node classification," *Prepr. arXiv.1907.10903*, Jul. 2019.
[30] B. Albreiki, T. Habuza, N. Palakkal, and N. Zaki, "Clustering-based knowledge graphs and entity-relation representation improves the detection of at risk students," *Education and Information Technologies*, vol. 29, no. 6, pp. 6791–6820, Apr. 2024, doi: 10.1007/s10639-023-11938-8.
[31] W. Jin, T. Derr, Y. Wang, Y. Ma, Z. Liu, and J. Tang, "Node similarity preserving graph convolutional networks," in *Proceedings of the 14th ACM International Conference on Web Search and Data Mining*, Mar. 2021, pp. 148–156. doi: 10.1145/3437963.3441735.
[32] F. Scarselli, M. Gori, Ah Chung Tsoi, M. Hagenbuchner, and G. Monfardini, "The graph neural network model," *IEEE Transactions on Neural Networks*, vol. 20, no. 1, pp. 61–80, Jan. 2009, doi: 10.1109/TNN.2008.2005605.
[33] B. Iancu, L. Ruiz, A. Ribeiro, and E. Isufi, "Graph-adaptive activation functions for graph neural networks," in *2020 IEEE 30th International Workshop on Machine Learning for Signal Processing (MLSP)*, Sep. 2020, pp. 1–6. doi: 10.1109/MLSP49062.2020.9231732.
[34] J. Kuzilek, M. Hlosta, and Z. Zdrahal, "Open university learning analytics dataset," *Scientific Data*, vol. 4, no. 1, Nov. 2017, doi: 10.1038/sdata.2017.171.
[35] A. Paszke *et al.*, "PyTorch: An imperative style, high-performance deep learning library," *Prepr. arXiv.1912.01703*, Dec. 2019.
[36] J. You, R. Ying, and J. Leskovec, "Design space for graph neural networks," *Prepr. arXiv.2011.08843*, Nov. 2020.

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