Graph-Based Personalized Learning: A Review of Graph Neural Networks (GNN) and Graph Convolutional Networks (GCN) in Advanced Educational Recommendation Frameworks

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***Abstract*—Digital learning environments generate complex, non-Euclidean data structures containing deep relational connections between learners, instructional materials, concepts, and pedagogical rules. Traditional recommendation architectures—such as matrix factorization, collaborative filtering, and linear deep learning models—treat data isolatedly, failing to capture complex prerequisite structural dependencies and high-order user-item interactions. This review explores the deployment of Graph Neural Networks (GNNs) and Graph Convolutional Networks (GCNs) within advanced educational recommendation systems. We evaluate graph-based user profiling, semantic knowledge graphs, message-passing mechanics, and neighborhood aggregation methods specifically tailored for academic progress tracking. The paper categorizes the architectural shifts in graph-driven pedagogy and outlines how structural relational embeddings solve classic recommendation bottlenecks while respecting pedagogical constraints.**

***Index Terms*—Graph Neural Networks (GNN), Graph Convolutional Networks (GCN), Educational Recommendation Systems, Knowledge Graphs, Personalized Learning, Relational Embeddings.**

I. INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) has significantly transformed the educational landscape, shifting the focus from traditional teacher-centered instruction to learner-centered, intelligent, and adaptive learning environments. Conventional educational systems generally follow a one-size-fits-all approach, where all learners are expected to follow the same curriculum, learning sequence, instructional materials, and assessment methods regardless of their individual abilities, prior knowledge, learning pace, or interests. Although this standardized approach simplifies curriculum delivery, it often fails to accommodate the diverse learning needs of students, leading to knowledge gaps, reduced engagement, and lower academic performance. With the increasing adoption of online learning platforms, Learning Management Systems (LMSs), Massive Open Online Courses (MOOCs), and intelligent tutoring systems, educational institutions are generating massive amounts of learner interaction data, creating new opportunities for data-driven personalization.

Recent advances in AI and machine learning have enabled the development of personalized educational recommendation systems that adapt learning experiences according to individual learner characteristics. Unlike conventional instructional models, these systems analyze multiple aspects of learner behavior, including academic performance, learning preferences, cognitive abilities, historical interactions, engagement patterns, and learning objectives, to recommend appropriate courses, learning resources, assessments, and learning pathways. The emergence of hyper-personalized learning represents a significant paradigm shift in modern education, where recommendations are continuously refined based on learners' evolving knowledge, interests, and performance. Such adaptive learning environments not only improve student engagement but also enhance learning efficiency and academic success by providing the right learning resource at the right time.

However, educational recommendation differs fundamentally from recommendation systems developed for commercial applications such as e-commerce, online entertainment, or social media. Commercial recommender systems primarily optimize user engagement, click-through rates, viewing time, or purchasing behavior. In contrast, educational recommendation systems must optimize pedagogical effectiveness by considering educational objectives, curriculum structures, prerequisite relationships, knowledge progression, competency development, and long-term learning outcomes. Recommending an advanced learning resource to a student without ensuring mastery of prerequisite concepts may negatively affect learning performance. Therefore, educational recommendation requires a deeper understanding of the semantic and structural relationships among learners, educational resources, concepts, skills, assessments, and prerequisite dependencies, making it a considerably more complex problem than conventional recommendation tasks.

The complex and highly interconnected nature of educational data naturally motivates the use of graph-based representations. Educational environments consist of numerous entities—including students, courses, concepts, instructors, assessments, learning resources, and competencies—that are linked through diverse relationships such as enrollment, prerequisite dependencies, concept hierarchies, resource usage, knowledge mastery, and collaborative learning interactions. Traditional machine learning approaches generally represent data as independent feature vectors and often fail to capture these rich relational dependencies. In contrast, graphs provide an intuitive and expressive framework for modeling heterogeneous educational ecosystems, where nodes represent educational entities and edges capture their semantic and structural relationships. This graph representation enables the modeling of both direct and indirect interactions, thereby providing a more comprehensive understanding of the educational environment.

The emergence of Graph Neural Networks (GNNs) has further revolutionized graph-based learning by enabling deep representation learning over graph-structured data. Unlike conventional graph mining techniques, GNNs iteratively aggregate information from neighboring nodes to learn high-quality embeddings that capture both node attributes and graph topology. Recent variants such as Graph Convolutional Networks (GCNs), Graph Attention Networks (GATs), GraphSAGE, Relational Graph Convolutional Networks (R-GCNs), Heterogeneous Graph Neural Networks (HGNNs), and Temporal Graph Neural Networks have demonstrated remarkable performance across numerous recommendation tasks. In educational recommendation systems, these models effectively integrate multiple sources of information—including learner profiles, prerequisite knowledge graphs, course relationships, interaction histories, and learning resource networks—to generate accurate, adaptive, and context-aware recommendations.

Although considerable progress has been achieved in applying GNNs to educational recommendation, the existing literature remains fragmented across various application domains, datasets, graph modeling techniques, neural architectures, evaluation methodologies, and recommendation objectives. Furthermore, several critical challenges remain unresolved, including data sparsity, cold-start problems, scalability to large educational graphs, dynamic learner modeling, explainability, privacy preservation, fairness, and the integration of multimodal educational data. The rapid emergence of Large Language Models (LLMs), knowledge graphs, and generative AI has also opened new research directions for developing intelligent educational recommendation systems, highlighting the need for a comprehensive synthesis of recent advances.

II. LITERATURE SURVEY

The field of educational recommendation systems has evolved significantly over the past two decades, driven by advances in machine learning, deep learning, and graph representation learning. Early recommendation systems primarily relied on collaborative filtering and content-based techniques, while recent studies increasingly employ Graph Neural Networks (GNNs), knowledge graphs, and knowledge tracing models to provide adaptive and pedagogically meaningful learning recommendations. This section reviews the major developments in educational recommendation systems, highlighting their strengths, limitations, and emerging research trends.

2.1Early Educational Recommendation Systems

The first generation of educational recommender systems adapted techniques from commercial recommendation systems used by platforms such as Amazon and Netflix. These systems mainly employed Collaborative Filtering (CF) and Content-Based Filtering (CBF) to recommend learning resources, courses, or educational materials.

Collaborative Filtering predicts a learner's preferences based on the behavior of other learners with similar interests. It assumes that students who exhibited similar learning patterns in the past are likely to require similar learning resources in the future. Memory-based methods such as user-based and item-based collaborative filtering, along with model-based approaches including matrix factorization and Singular Value Decomposition (SVD), became popular because of their simplicity and effectiveness.

Content-Based Filtering, on the other hand, recommends educational resources by comparing their characteristics with a learner's previous interactions and interests. Features such as course descriptions, keywords, subject domains, difficulty levels, and learning objectives are commonly used to measure similarity.

Although these approaches demonstrated reasonable performance in recommending educational resources, they suffer from several significant limitations. Collaborative filtering is highly susceptible to data sparsity and the cold-start problem, particularly for new learners or newly introduced courses with limited interaction history. Furthermore, these methods largely ignore prerequisite relationships, curriculum structures, and concept dependencies that are fundamental to effective learning. As a result, recommendations generated by these models may be educationally inappropriate even if they are statistically accurate.

2.2 Transition Toward Deep Learning-Based Recommendation

To overcome the limitations of traditional recommendation methods, researchers introduced deep learning techniques capable of learning complex nonlinear relationships from educational data. Neural Collaborative Filtering (NCF), Deep Matrix Factorization, Autoencoders, Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs) became increasingly popular in educational recommendation.

Unlike traditional collaborative filtering, deep learning models automatically learn latent representations of learners and educational resources. These embeddings capture hidden behavioral patterns, enabling more accurate recommendations. Recurrent Neural Networks, particularly Long Short-Term Memory (LSTM) networks, proved useful for modeling sequential learning behavior because they consider the temporal order of learner interactions.

Despite their improved predictive performance, deep learning approaches generally treat educational data as independent vectors or sequences rather than interconnected entities. Consequently, they fail to capture the rich semantic relationships among learners, courses, concepts, prerequisites, assessments, and instructors that characterize real educational environments.

2.3 Emergence of Graph-Based Educational Recommendation

Educational systems naturally consist of highly interconnected entities, making graph representations particularly suitable. Researchers therefore began modeling educational ecosystems as heterogeneous graphs, where nodes represent students, courses, concepts, skills, learning resources, and assessments, while edges represent relationships such as enrollment, prerequisite dependencies, concept similarity, resource usage, and knowledge mastery.

Graph-based recommendation methods significantly improved the ability to capture complex educational relationships. Random walk algorithms, graph embedding techniques such as DeepWalk, Node2Vec, and LINE, and graph factorization methods were among the earliest graph-based approaches applied to educational recommendation.

Although graph embedding methods preserved structural information more effectively than conventional techniques, they generated static node embeddings and could not dynamically update representations according to neighboring information during training. This limitation motivated the development of Graph Neural Networks.

2.4 Graph Neural Networks for Educational Recommendation

Graph Neural Networks (GNNs) represent one of the most significant advances in graph-based machine learning. Unlike conventional graph embedding methods, GNNs iteratively aggregate information from neighboring nodes, allowing node representations to capture both local and global graph structures.

Among the earliest and most influential GNN architectures is the Graph Convolutional Network (GCN), introduced by Kipf and Welling. GCN performs neighborhood aggregation through graph convolution operations, enabling effective learning over graph-structured educational data. Researchers successfully applied GCNs to recommend courses, predict student performance, identify prerequisite knowledge, and personalize learning pathways.

Subsequent improvements led to the development of several specialized GNN architectures. Graph Attention Networks (GATs) introduced attention mechanisms that assign different importance weights to neighboring nodes, allowing models to focus on more relevant educational relationships. GraphSAGE improved scalability by learning aggregation functions from sampled neighborhoods, making it suitable for large-scale educational platforms. Relational Graph Convolutional Networks (R-GCNs) further extended GCNs by supporting multiple edge types, which is particularly valuable in educational environments where relationships include enrollment, prerequisite, mastery, similarity, and assessment connections.

One of the most influential models in recommendation research is LightGCN, which simplifies traditional GCN architectures by removing feature transformation and nonlinear activation functions while retaining neighborhood aggregation. This simplified design reduces computational complexity and avoids overfitting, making LightGCN particularly effective for collaborative recommendation tasks. Recent educational recommendation studies have successfully adapted LightGCN to model student-course interactions, demonstrating superior recommendation accuracy and computational efficiency compared with conventional GCNs.

2.5 Integration of Knowledge Graphs into Educational Recommendation

Although GNNs effectively model structural relationships, they do not explicitly represent educational semantics such as concept hierarchies and prerequisite dependencies. To address this limitation, researchers increasingly integrate Knowledge Graphs (KGs) into educational recommendation systems.

Knowledge Graphs organize educational knowledge as semantic networks in which nodes represent concepts, courses, skills, learning objectives, and educational resources, while edges define meaningful relationships such as *is-a*, *part-of*, *requires*, *depends-on*, and *teaches*. Unlike simple interaction graphs, knowledge graphs explicitly encode pedagogical knowledge.

For example, in a programming curriculum, the knowledge graph may represent relationships such as:

- Variables → prerequisite of Loops
- Loops → prerequisite of Functions
- Functions → prerequisite of Object-Oriented Programming
- Object-Oriented Programming → prerequisite of Data Structures

By incorporating these prerequisite relationships, educational recommendation systems can generate learning pathways that follow logical curriculum progression rather than merely recommending popular or frequently accessed resources.

Modern research integrates GNNs with Knowledge Graph Embedding techniques such as TransE, RotatE, ComplEx, and Relational GCNs, enabling recommendation systems to jointly learn semantic knowledge and learner interaction patterns. This integration improves recommendation quality by ensuring that suggested resources align with learners' current knowledge states and educational objectives.

2.6 Combining Graph Neural Networks with Knowledge Tracing

One of the most promising research directions is the integration of Graph Neural Networks with Knowledge Tracing (KT) models.

Knowledge Tracing aims to estimate a learner's mastery of different concepts over time by analyzing sequences of learning activities, quiz responses, assignment submissions, and assessment results. Unlike static learner models, KT continuously updates the probability that a learner has mastered a particular concept after each interaction.

Traditional Knowledge Tracing methods, such as Bayesian Knowledge Tracing (BKT), model mastery using probabilistic state transitions. Although interpretable, BKT assumes independent concepts and struggles to capture complex knowledge dependencies.

Deep learning approaches, including Deep Knowledge Tracing (DKT) based on Long Short-Term Memory (LSTM) networks, improved prediction accuracy by modeling sequential learner interactions. However, DKT does not explicitly consider relationships among concepts.

To overcome this limitation, recent studies integrate Knowledge Tracing with Graph Neural Networks. In these hybrid models, educational concepts are represented as graph nodes connected through prerequisite or semantic relationships, while learner interactions dynamically update concept embeddings over time. The GNN captures structural dependencies among concepts, whereas the KT component models temporal changes in learner mastery.

For example, if a learner demonstrates mastery of Variables and Loops, the model updates not only these concepts but also propagates information to related concepts such as Functions and Arrays through the graph structure. Consequently, recommendations become both prerequisite-aware and time-aware, enabling the system to recommend the most appropriate next learning activity based on the learner's evolving knowledge state.

Recent Graph-based Knowledge Tracing models, including Graph-based Knowledge Tracing (GKT), Dynamic Graph Knowledge Tracing (DGKT), and Knowledge-Aware Graph Neural Networks, have shown significant improvements in predicting student performance, identifying knowledge gaps, and generating personalized learning recommendations.

2.7 Research Gaps in Existing Literature

Despite substantial progress, several challenges remain unresolved. Many existing studies focus primarily on improving recommendation accuracy while overlooking explainability, fairness, privacy preservation, and computational scalability. Most publicly available datasets contain only learner-resource interactions and lack rich semantic information such as prerequisite relationships, learning objectives, and competency hierarchies. Dynamic learner modeling remains difficult because knowledge states continuously evolve over time. Furthermore, few studies integrate multimodal educational data—including text, video, assessments, discussion forums, and learner behavior—into a unified graph representation. The emergence of Large Language Models (LLMs), explainable Graph Neural Networks, multimodal knowledge graphs, and federated graph learning presents promising opportunities for developing more intelligent, transparent, and scalable educational recommendation systems.

III PROPOSED METHODOLOGY

To address the limitations of existing educational recommendation systems, this paper proposes a graph-based theoretical framework that integrates Heterogeneous Educational Graphs (HEGs), Graph Attention Networks (GATs), Light Graph Convolutional Networks (LightGCNs), and temporal learning models. The framework aims to generate personalized, prerequisite-aware, and adaptive learning recommendations by capturing both the structural relationships among educational entities and the temporal evolution of learner knowledge.

3.1 Heterogeneous Educational Graph Construction

The educational environment is modeled as a Heterogeneous Educational Graph (HEG), where nodes represent different entities such as students, courses, concepts, learning resources, assessments, and skills, while edges represent relationships including enrollment, prerequisite dependencies, concept similarity, and learner interactions. This graph structure effectively captures the semantic and pedagogical relationships that are often ignored by traditional recommendation methods.

3.2 Attention-Based Prerequisite Learning

Since not all educational relationships contribute equally to learning, an attention mechanism is incorporated to assign higher importance to prerequisite concepts. Inspired by Graph Attention Networks (GATs), the model automatically learns attention weights for neighboring nodes, enabling it to prioritize essential prerequisite relationships while reducing the influence of less relevant connections. This results in more meaningful and pedagogically appropriate recommendations.

3.3 Graph Representation Using LightGCN

To learn efficient node representations, the proposed framework employs Light Graph Convolutional Networks (LightGCN). Unlike conventional GCNs, LightGCN removes feature transformation and nonlinear activation functions, retaining only neighborhood aggregation. This simplified architecture reduces computational complexity, improves scalability, and alleviates the over-smoothing problem, where deeper graph layers produce indistinguishable node representations.

3.4 Temporal Learning Module

Learning is a dynamic process in which students' knowledge continuously evolves through interactions with educational resources. Therefore, the framework incorporates a temporal learning module, such as LSTM, GRU, or Transformer, to model changes in learner knowledge over time. The temporal representations are then fused with graph embeddings to capture both the structural relationships among educational entities and the sequential learning behavior of students.

3.5 Unified Optimization

The entire framework is trained using a unified multi-objective loss function that simultaneously optimizes recommendation accuracy, prerequisite consistency, learner knowledge prediction, and model regularization. This joint optimization enables the system to recommend educational resources that are both relevant to learners' interests and aligned with curriculum requirements.

Overall Framework

The proposed methodology first constructs a heterogeneous educational graph from learner interactions and educational resources. It then applies an attention mechanism to emphasize prerequisite relationships, learns graph embeddings using LightGCN, models learners' knowledge progression through temporal learning, and finally combines these representations to generate personalized learning recommendations. By integrating graph structure, semantic knowledge, and temporal learning behavior within a unified framework, the proposed approach addresses key challenges such as data sparsity, prerequisite awareness, over-smoothing, and dynamic learner modeling, thereby providing more accurate, adaptive, and pedagogically meaningful educational recommendations.

IV EXPECTED OUTCOMES

The proposed framework is expected to improve both the technical performance of educational recommendation systems and the quality of students' learning experiences. By integrating heterogeneous educational graphs, attention mechanisms, LightGCN, and temporal learning, the system aims to generate more accurate and pedagogically meaningful recommendations.

From a technical perspective, the framework is expected to achieve higher recommendation accuracy than traditional collaborative filtering and conventional GNN models. Performance will be evaluated using standard recommendation metrics such as Precision@K, Recall@K, Normalized Discounted Cumulative Gain (NDCG@K), and Mean Reciprocal Rank (MRR). Higher values of these metrics would indicate that the recommended learning resources are more relevant and better ranked according to the learners' needs.

From a pedagogical perspective, the framework is expected to provide personalized learning pathways that respect prerequisite relationships and learners' current knowledge levels. By recommending resources in a logical learning sequence, the system can reduce cognitive overload, minimize learner frustration, improve engagement, and potentially decrease student dropout rates. Furthermore, the integration of temporal learning enables the system to continuously adapt recommendations as students progress, thereby supporting long-term knowledge development.

To demonstrate the effectiveness of the learned graph embeddings, t-Distributed Stochastic Neighbor Embedding (t-SNE) visualization can be used. This dimensionality reduction technique projects high-dimensional learner embeddings into a two-dimensional space. Students with similar learning progress are expected to form distinct clusters, while movement of these clusters over time can illustrate the progression from beginner to intermediate and advanced competency levels. Such visualizations provide an intuitive understanding of learner development and validate the effectiveness of the proposed recommendation framework.

Overall, the proposed methodology is expected to produce a scalable, adaptive, and prerequisite-aware educational recommendation system that improves recommendation accuracy while supporting personalized and effective learning experiences.

V CONCLUSIONS

The rapid growth of digital learning platforms has generated vast amounts of educational data that are highly interconnected and dynamic. Unlike traditional recommendation systems, educational recommendation requires not only identifying learner preferences but also considering prerequisite relationships, curriculum structures, and learners' evolving knowledge states. Therefore, conventional recommendation techniques, such as collaborative filtering and content-based methods, are no longer sufficient to address the complexity of modern educational environments.

This paper highlights the potential of Graph Neural Networks (GNNs) and Graph Convolutional Networks (GCNs) as effective solutions for educational recommendation. By modeling students, courses, concepts, learning resources, and prerequisite relationships as interconnected graphs, these approaches capture both structural and semantic information that is often overlooked by traditional methods. The integration of heterogeneous graphs, attention mechanisms, LightGCN, and temporal learning further enables the development of personalized, prerequisite-aware, and adaptive learning pathways that improve recommendation accuracy while supporting meaningful learning experiences.

Although recent advancements have demonstrated promising results, several challenges remain, including model explainability, scalability, privacy preservation, and the integration of multimodal educational data. Future research should focus on developing explainable and trustworthy GNN-based recommendation systems that allow educators and learners to understand the reasoning behind recommendations. Addressing these challenges will help bridge the gap between advanced AI techniques and their practical adoption in real-world classrooms, ultimately supporting more effective, transparent, and learner-centered education.

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