PERSONALIZED LEARNING PATH GENERATION USING KNOWLEDGE GRAPHS AND NEURAL RECOMMEN SYSTEMS

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ABSTRACT

This dissertation presents a hybrid model for personalized learning path generation using knowledge graphs and neural recommendation systems. The proposed approach integrates semantic reasoning from knowledge graphs with the predictive power of deep neural networks—specifically Graph Neural Networks (GNNs) and Transformer architectures—to recommend adaptive, individualized learning sequences. By modeling both conceptual relationships and learner behavior, the system dynamically adjusts to users' evolving knowledge levels. Experimental results on educational datasets such as EdNet and ASSISTments demonstrate significant improvements in accuracy and personalization compared to traditional methods. The model also enhances explainability through attention mechanisms and graph-based reasoning. This research contributes to the development of AI-driven adaptive education systems, offering a scalable and interpretable framework for next-generation intelligent tutoring platforms.

1.1 Introduction

The evolution of personalized learning has been deeply influenced by advancements in artificial intelligence, particularly in knowledge representation and recommendation systems. Traditional learning management systems often fail to capture the complex semantic relationships between learning concepts and student profiles. The integration of **Knowledge Graphs (KGs)** and **Neural Recommendation Systems (NRS)** represents a transformative shift toward **adaptive, data-driven learning environments.** This literature review explores the theoretical and empirical foundations of this integration, focusing on research between 2020 and 2025 that leverages **Graph Neural Networks (GNNs), Neural Collaborative Filtering (NCF),** and **Transformer-based models** for educational personalization.

1.2 Personalized Learning Systems: Concept and Evolution

Personalized learning refers to the adaptation of educational content, pacing, and instructional strategies to align with each learner's unique profile (Holmes et al., 2021). Early adaptive systems primarily relied on rule-based logic or Bayesian networks, which limited their scalability and flexibility. The transition to **data-driven models,** supported by large-scale learner interaction data, enabled the emergence of recommender systems in education (Drachsler & Kalz, 2020). Recent studies emphasize **AI-driven personalization,** where algorithms continuously analyze learner behavior to optimize instructional sequences. For instance, Yang et al. (2021) demonstrated that integrating learning analytics with deep recommendation techniques can improve engagement and retention by more than 20%. then, these systems still struggle with knowledge interpretability and contextual reasoning—challenges that knowledge graphs are particularly well-suited to address.

1.3 Knowledge Graphs in Education

Knowledge Graphs (KGs) are structured representations of entities and their semantic relationships, typically modeled as nodes and edges. In education, KGs map **learning concepts, skills, and dependencies** to provide a structured ontology of knowledge domains (Huang et al., 2020).

Educational Knowledge Graphs (EduKGs) enable:

- **Concept dependency modeling** (e.g., prerequisite structures);
- **Curriculum design automation;**
- **Knowledge tracing and skill gap analysis** (Zhang & Li, 2022).

Several frameworks have been developed to formalize educational KGs. For instance, **EduGraph** (Luo et al., 2021) and **LearnKG** (Wang et al., 2022) utilize semantic embeddings to connect learning objectives, assessment items, and learner progress. A major strength of KGs is their interpretability, which contrasts sharply with the “black box” nature of deep neural networks.

Nevertheless, standalone KGs often lack dynamic adaptability; they represent *what should be learned* but not *how learners actually learn*. This limitation has led to hybrid architectures combining KGs with **neural recommender systems.**

1.4 Neural Recommendation Systems in Learning Environments

Neural recommendation systems (NRS) employ deep learning to capture complex non-linear patterns between users and items—in this case, learners and learning resources. **Neural Collaborative Filtering (NCF)**, proposed by He et al. (2017), marked a significant departure from linear matrix factorization by replacing inner product interactions with multi-layer perceptrons.

In educational contexts, NCF has been used to:

- Predict learner preferences for specific resources;
- Estimate performance outcomes;
- Sequence learning modules dynamically (Xie et al., 2021).

Conventional NCF-based recommenders treat learning items as independent entities, ignoring the hierarchical and semantic relationships inherent in educational content. The fusion of NCF with **knowledge graphs** addresses this limitation by embedding structural information into the recommendation process.

1.5 Hybrid Knowledge Graph–Neural Recommender Models

Hybrid models combining KGs and NRS have become the dominant paradigm for personalized education systems since 2020. These models typically include three layers:

1.Knowledge Representation Layer – encodes educational content and concept dependencies in a KG structure.

2.Behavioral Embedding Layer – learns user–item interaction patterns using deep neural architectures.

3.Fusion or Reasoning Layer – integrates semantic reasoning with learned embeddings to generate adaptive recommendations.

For example, Chen et al. (2020) proposed a **Knowledge-Aware Recommendation Framework (KARF),** which enhanced recommendation accuracy by integrating concept-level reasoning into deep user–item models. Similarly, Huang et al. (2021) developed **EduKGR,** a system that applies graph convolutional networks to infer missing relationships in educational datasets.

Such systems show consistent performance improvements, with F1-score and Recall@10 gains of 10–15% compared to baseline collaborative filtering approaches. However, scalability and real-time adaptability remain challenges, particularly in dynamic learning environments with continuous user feedback.

1.6 Graph Neural Networks (GNNs) in Personalized Learning

Graph Neural Networks (GNNs) have revolutionized the way relationships and structures are modeled in AI. GNNs can learn embeddings for nodes (concepts, students, or materials) while preserving the topological dependencies in the KG. In personalized learning, this means the system can **infer both explicit and implicit relationships** between learning concepts and learners' progression.

Recent works include:

- **Wang et al. (2021):** Proposed a **Graph Attention Network (GAT)** for recommending next-step learning activities based on concept importance.
- **Tang and Wang (2021):** Used **GraphSAGE** for curriculum sequencing, demonstrating better generalization to new learners.
- **Sun et al. (2021):** Conducted a comprehensive survey of GNN applications in recommender systems, highlighting their suitability for knowledge-aware personalization.

GNN-based approaches outperform conventional NCF models because they capture **contextual learning dependencies** rather than relying solely on behavioral similarity. Furthermore, GNNs enhance explainability through attention coefficients that quantify the importance of specific knowledge edges.

1.7 Transformer-Based Models in Learning Path Generation

The introduction of **Transformer architectures** (Vaswani et al., 2017) has significantly impacted sequence modeling in personalized learning. Unlike GNNs, Transformers excel at capturing **temporal learning dynamics**—the order and evolution of learner activities.

Models such as **EduTransformer** (Kim et al., 2022) and **LearnFormer** (Xu et al., 2023) have applied self-attention mechanisms to predict optimal next learning steps based on historical interactions. These models outperform recurrent architectures (LSTM, GRU) by capturing long-range dependencies in student behaviors.

When combined with knowledge graphs, Transformers can align **semantic dependencies (KG)** with **temporal patterns (Transformer),** creating a dual-context personalization mechanism. This hybridization offers the potential to build systems that are not only accurate but also *contextually and temporally aware*.

1.8 Explainability and Ethical Considerations

Explainability is critical in educational AI systems. Learners and educators must understand *why* specific learning paths are recommended. The **explainable AI (XAI)** movement, as discussed by Luo & Cheng (2022), emphasizes transparency through interpretable KG reasoning and attention visualization. Hybrid models combining symbolic reasoning (KG) and deep learning (NRS) offer a balanced trade-off between performance and interpretability.

Ethical concerns also emerge, including data privacy, algorithmic bias, and the risk of over-personalization (Holmes et al., 2021). Federated learning and privacy-preserving graph computation are emerging solutions that enable personalization without compromising learner data integrity

1.9 Conclusion

The literature reveals a clear trajectory toward integrating symbolic and neural AI approaches for educational personalization. Knowledge graphs contribute structured semantic knowledge, while neural recommenders add adaptability and learning dynamics. Graph Neural Networks and Transformer architectures represent the next frontier in combining these paradigms, offering systems that are both contextually rich and responsive to individual learner progress.

The subsequent chapters of this dissertation will build upon these insights by proposing a novel **KG–GNN–Transformer hybrid framework,** implementing it on educational datasets, and evaluating its impact on personalization accuracy and explainability.

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