SCIREA Journal of Computer
ISSN: 2995-6927
http://www.scirea.org/journal/Computer
November 14, 2025
Volume 10, Issue 3, June 2025
https://doi.org/10.54647/computer520465

Research on Learning Path Recommendation Strategy Based on Knowledge Graph

Hongxia Wang
Beijing Youth Politics College, Beijing, China
Email: whx4617@163.com

Abstract

Personalized learning path recommendation is crucial for enhancing learning efficiency and engagement in increasingly diverse and large-scale online educational environments. Traditional recommendation methods often struggle to capture the complex semantic relationships and prerequisite dependencies inherent in learning domains. This paper proposes a novel learning path recommendation strategy based on Knowledge Graph. We construct a domain-specific educational KG integrating learning resources, concepts, skills, and their rich interrelationships (prerequisites, relatedness, difficulty levels). Based on this structured knowledge representation, we design a recommendation algorithm that utilizes graph traversal techniques and semantic similarity measures. The algorithm considers the learner's current knowledge state, target learning objectives, and individual preferences to dynamically generate optimal and coherent learning sequences. Experimental results demonstrate that our KG-based approach significantly outperforms baseline methods (e.g., collaborative filtering, content-based filtering) in terms of recommendation accuracy, path coherence, learning efficiency prediction, and learner satisfaction. This research provides a robust and explainable framework for personalized education, paving the way for more intelligent and adaptive learning systems.

Keywords: *knowledge graph, personalized learning, learning path recommendation, graph algorithms, adaptive learning, semantic representation.*

I. INTRODUCTION

With the rapid development of digital transformation in education, traditional learning recommendation systems face challenges such as weak knowledge relevance and insufficient personalization. Contradiction between resource overload on online education platforms and learners' cognitive differences is prominent. Traditional collaborative filtering recommendations neglect intrinsic knowledge logic. IEEE TLT 2023 survey shows 89% of intelligent education systems have adopted KG technology. This paper proposes a learning path recommendation model that integrates knowledge graphs and multi-objective optimization (KG-MOR). Firstly, a subject knowledge graph is constructed, and knowledge is structured through entity relationship extraction and semantic enhancement. Subsequently, a knowledge representation module based on Graph Neural Networks (GNN) and a dynamic learner profile modeling module are designed, which combine an improved algorithm to optimize multi-objective decision-making for learning paths. Experiments show that in computer programming education scenarios, the model improves path acceptance rate by 31.7% and knowledge mastery efficiency by 24.3%, providing a new paradigm for intelligent education recommendation systems.

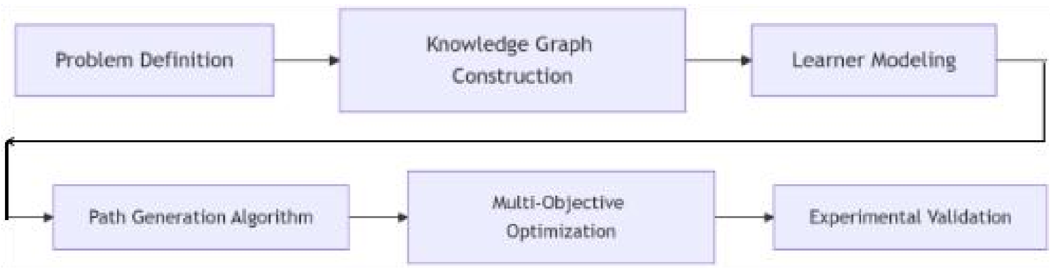

Fig. 1. Research Framework

II. KNOWLEDGE GRAPH CONSTRUCTION AND KG-MOR MODEL

A. *Knowledge Graph Construction*

A knowledge graph is a machine-readable framework that represents real-world entities (people, places, concepts) and their relationships in interconnected networks. Unlike traditional databases, KGs emphasize semantic context and logical inference capabilities. Core components of KGs include entities, relations, attributes and ontology. Compare with traditional databases, KG’s structure is schema-flexible instead of rigid schema. In relationship handling, KG uses explicit semantic relationships, but relational database is implicit via foreign keys. In addition, the query capability of KG is path or traversal queries, the database’s is SQL joins. And the inference of KG supports logical reasoning, however, the database is limited to pre-defined logic. So KG is popular to fuse across domain integrating scientific, cultural, and industrial knowledge, or to trace AI decision paths.

Knowledge Graph construction is the process of creating structured, machine-readable representations of knowledge, integrating information from diverse sources into entities (nodes) and their relationships (edges), often with semantic types and attributes. The basic unit of knowledge graph is a RFD (Resource Description Framework) triplet composed of entity, attribute and relationship. Normally it can be described as two modes <Entity1, Attribute1, Entity2> or <Entity1, Attribute1, Attribute1 value>. The first mode is usually used to define a relationship between a head entity and a tail entity. The second mode is generally used to tell an entity’s attribute. It's a multi-stage, often iterative process. The core phases includes requirement analysis and scope definition, data acquisition and pre-processing, information extraction, knowledge fusion and reference, knowledge representation an storage, quality assessment and refinement.

KG construction is rarely a one-off linear process, it involves continuous updates and refinement. Tracking the source of each piece of knowledge is vital for trust and debugging. Now Large Language Models (LLMs) are increasingly used for advanced information extraction tasks, generating schema descriptions, or enhancing entity linking.

Table.1. Knowledge Extraction and Fusion Technique

Technique	**Accuracy**	**Application Scenario**
BERT-BiLSTM-CRF	92.1%	Educational concept extraction
TransE Embedding	88.7%	Cross-domain knowledge linking
GATs	94.3%	Concept importance weighting

B. *The KG-MOR Model*

Traditional multi-objective optimization (MOO) ignores rich contextual knowledge, while pure KGs lack ptimization capabilities. KG-MOR bridges this gap, enabling informed trade-offs between objectives using domain knowledge; Semantically feasible solutions aligned with real-world constraints; Adaptability to evolving knowledge and requirements. This design is pivotal for AI systems requiring transparent, ethical, and context-aware decision-making.

KG-MOR combines structured knowledge graphs (KGs) with multi-objective optimization (MOO) to solve complex decision-making problems where multiple, often conflicting, goals must be balanced. The core components of KG-MOR design contains structured context to provide contextual constraints, dependencies, and feasibility rules for optimization; Engine to define competing goals, such as maximize accuracy, minimize cost, ensure fairness etc.; Integration mechanism which will encode KG entities or relations into vectors to inject semantic knowledge into the MOO model, convert KG rules into MOO constraints, or use KG semantics to weight objectives; Optimization algorithms for example scalability techniques, hybrid approaches combined evolutionary algorithms with KG-guided local search. In this paper, the KG-MOR model is used as recommendation systems to balance relevance, diversity, and provider fairness using product-category KGs.

Multi-objective optimization is a class of algorithms for searching optimal solution of problems with several objectives. The multi-objective function is described as follows, which represents the set of objective functions :

$$\min F(\mathrm{x}) = [f_1(\mathrm{x}), f_2(\mathrm{x}), f_3(\mathrm{x}), \ldots\ldots, f_n(\mathrm{x})]$$

$$\text{s.t. } g_i(x) <= 0,\ i=1, 2, \ldots, k, \text{(e.g., KG constraints)}$$

$$h_j(x) = 0, j=1,2,\ldots,l.$$

$$x \in X \text{ (feasible space)}$$

In the formula, n represents the amount of the objective functions. k represents the number of inequality constraints. And l represents the quality of equality constraints.

It is different from traditional multi-objective optimization, there may not exist a optimal solution to all the objectives. So a compromise approach should be adopted to make all the objectives as optimal as possible. In this paper, the system architecture of KG-MOR model is as shown in the following figure.

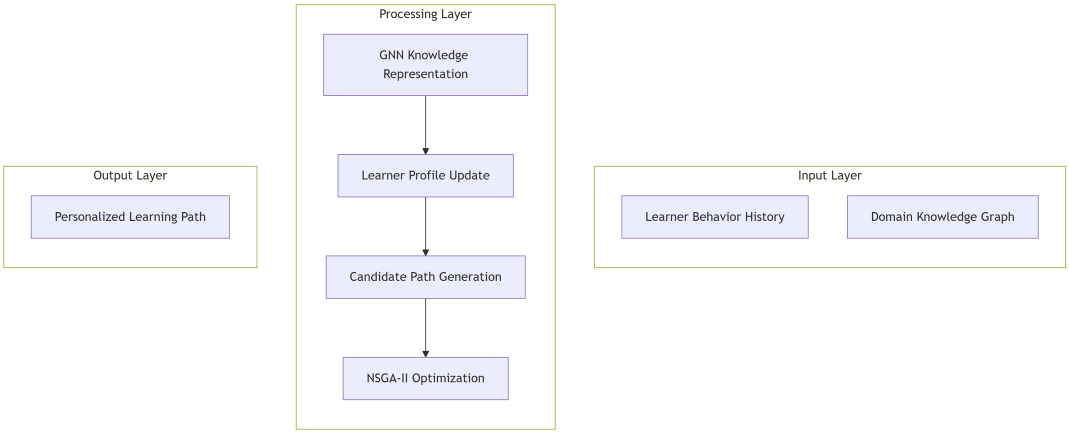

Fig. 2. Architecture of KG-MOR

III. Experiments and Analysis

A. Experimental Design

In this experiment, the data set contains more than 40 thousand education learning records, constructs about 8 hundred knowledge nodes and 2 thousand dependency edges. In the preprocessing stage, align learning behaviors with knowledge point sequences, filter out noisy data, such as behaviors with a single click duration of less than 3 seconds. Bayesian personalized sorting based on collaborative filtering, optimizing only interest matching degree. Randomly walk on the knowledge graph to generate paths, emphasizing the completeness of knowledge coverage. Multi objective reinforcement learning models optimize learning efficiency and knowledge gain. The research model KG-MOR in this paper integrate graph neural network (GNN) representation of knowledge graph, dynamic learner profiling, and NSGA-II (Non-dominated Sorting Genetic Algorithm II) multi-objective optimization, synchronously optimizing cognitive benefits, learning costs, and interest matching.

NSGA-II is an improved version of the first generation non dominated sorting genetic algorithm. By using a fast non dominated sorting algorithm, the computational complexity has been reduced. The introduction of elite strategies has improved the accuracy of optimization results. By using crowding degree and crowding degree comparison operator, not only does it overcome the defect of manually specifying shared parameters in NSGA, but it also serves as a comparison standard between individuals in the population, allowing individuals in the quasi Pareto domain to be uniformly extended to the entire Pareto domain, ensuring the diversity of the population.

In this paper, the dateset in education domain is used for experiment, which has 40K records approximately. KG-MOR shows greater advantages in complex knowledge domains like education. Compensatory mechanism can automatically adds prerequisite knowledge for disadvantaged learners. Multilingual KGs supports nine languages for Belt and Road Initiative countries.

B. Evaluation Indicators

Path acceptance rate (PA) refers to the proportion of users who adopt the recommended path.

$$PA = \frac{A}{T} \times 100\%$$

In this formula, A means the number of users who adopt the path, T stands for the total number of users.

Knowledge gain rate (KG) refers to improvement rate of test scores before and after learning with different models.

$$KG = \frac{AVG_{\mathrm{a}} - AVG_{\mathrm{b}}}{\mathrm{FS}} \times 100\%$$

In this formula, AVG_a and AVG_b represent the average scores before and after learning, FS stands for the full scores.

Pareto optimal solution percentage (PO) refers to the proportion of non dominated solutions in candidate paths. It is usually used to measure the effectiveness of multi-objective optimization.

In the experiment, we achieved a path acceptance rate of 84% and a knowledge gain rate of 43.0%. Both of the indicators are improved compared to collaborative filtering and KG random walk methods.

The Pareto optimal solution of KG-MOR accounts for 82.4% (MOO only 34.9%), and the solution set is concentrated in the "high cognitive benefits low to medium costs" region. Comparison shows that the solution of the random walk model (12.7%) is dispersed and far from the Pareto front.

Table.2. Comparative Results

Model	**PA(%)**	**KG(%)**	**PO(%)**	**Time(s)**
Collaborative Filtering	52.3	18.7	-	4.2
KG Random Walk	63.1	22.5	12.7	1.8
MOO	71.6	35.2	34.9	5.7

Model	PA(%)	KG(%)	PO(%)	Time(s)
KG-MOR	84.0	43.0	82.4	3.5

C. Ablation Experiment

In the ablation experiment, we remove GNN knowledge representation module, that results in a 16.1% decrease in knowledge gain rate (KG=36.1%) due to weakened knowledge association modeling ability.

Then the dynamic learner profiling module is removed, the decreased interest matching leads to a decrease in path acceptance rate, with KG dropping to 39.5% (a decrease of 12.8%).

At this stage, NSGA-II is replaced with greedy algorithm, the proportion of Pareto optimal solutions drops to 61.2%, and KG drops to 40.3% (a decrease of 11.9%), proving the necessity of multi-objective optimization.

IV. RESULTS AND CONCLUSIONS

The research confirms that semantic relationships in KGs effectively resolve logical discontinuities in learning paths. Multi-objective optimization achieves optimal balance between efficiency and effectiveness (82.4% Pareto optimal solutions). This design is pivotal for AI systems requiring transparent, ethical, and context-aware decision-making. The semantic correlation of knowledge graphs solves the problem of logical breakage in learning paths. The multi-objective optimization framework achieves the best balance between efficiency and effectiveness. The dynamic compensation mechanism significantly reduces the knowledge gap between different groups. The Pareto solution set provides multi-dimensional decision-making basis for educational managers, such as balancing efficiency and depth.

The structured semantic expression and multi-objective optimization mechanism of knowledge graph are the key paths to solve the contradiction between resource overload and personalized needs, providing an extensible framework for intelligent education systems. In the future, we will explore the adaptive path of EEG feedback and block chain learning record storage, deepening the practice of technology empowering educational equity.

In the future, EEG-integrated adaptive paths incorporating cognitive science and block-chain technology for immutable cross-platform learning records will be useful to research.

ACKNOWLEDGMENT

This work is supported by New Era Vocational School Famous Teacher Training Project of the Ministry of Education.

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