

Research on Algorithm-driven Subject Knowledge Graphs Empowering Graduate Precision Teaching Mode

Xia Tao, Weiwei Huang, Shang Xu*

School of Marxism Wuhan Institute of Technology, Wuhan, Hubei, China

**Corresponding Author.*

Abstract: The integration of AI and big data has revitalized precise teaching. Knowledge graphs, driven by algorithms, structure knowledge and integrate teaching resources, offering more precise content for graduate education. Applied to graduate teaching, they can solve the problems of generalized teaching content and difficulty in meeting individual student needs in traditional modes. This paper takes the "Principles of Education" course as an example. It builds and applies knowledge graphs, considers graduate teaching needs, and proposes a precise teaching model based on knowledge graphs. This model aims to optimize educational resource allocation and maximize teaching effectiveness.

Keywords: Knowledge Graph; Graduate Education; Precise Teaching; Teaching Model; Principles of Education

1. Introduction

1.1 Research Background

Graduate education, the pinnacle of higher education in China, directly impacts national talent-cultivation quality. With the swift progress of AI and big data, the education sector is undergoing profound digital transformation. Policies like "China Education Modernization 2035" and the "Education Informatization 2.0 Action Plan" advocate "technology + education" integration and innovation, urging the exploration of intelligent and personalized teaching models in higher education. Consequently, graduate education must break free from traditional homogeneous teaching and move toward precision and adaptability.

1.2 Current Status and Challenges of Graduate Education

The current graduate education model shows

significant problems in large-scale talent cultivation. Mainly, there is a disconnection between educational content and student needs. Now, graduate education often has "homogeneous output", with uniform courses ignoring student differences. Teaching content also updates slowly, lagging behind disciplinary frontiers, creating a big gap between what students learn and practical demands. This disconnection reduces students' learning interest, motivation, and restricts their innovation ability development.

Teaching methods lack personalization. Traditional lecture-based and rote-learning methods dominate, ignoring students' individual learning styles, paces, and abilities. This "one-size-fits-all" approach fails to motivate students and doesn't meet the graduate-stage requirements for developing their self-study and research skills^[1].

At this point, knowledge graphs, with their dynamic relevance, knowledge visualization, and intelligent recommendation features, offer new solutions to these problems.

1.3 Research Purpose

This study focuses on the "Principles of Education" knowledge domain, aiming to build a precise teaching model based on knowledge graphs. The innovations are reflected in three aspects:

(1) Creating a knowledge - graph - empowered precise teaching model for graduate education. It systematically organizes teaching information in "Principles of Education", incorporates cases and research, and enables precise and personalized content delivery.

(2) Meeting individualized learning needs. It offers personalized learning paths and methods based on students' differences and experiences. Supported by knowledge graphs, it helps students quickly acquire knowledge, understand connections, and fosters innovation and practical abilities.

(3) Promoting graduate education reform. It

provides a new teaching model and explores digital transformation in education. The knowledge - graph - empowered model can steer graduate education toward refinement and adaptability, improving its quality and effectiveness, and supporting the cultivation of high - quality talents to meet social needs.

2. Theoretical Foundations of Knowledge Graphs and Precision Teaching

2.1 Definition of Knowledge Graph

In May 2012, Google first introduced the concept of "Knowledge Graph"^[2]. In the era of big data, knowledge graphs, as a key knowledge representation method, connect elements such as entities, concepts, relationships, and attributes in a structured way. Their main purpose is to describe entities and their relationships in the objective world.

Since Google introduced knowledge graphs in 2012, their applications in general fields have become increasingly mature, with significant progress in areas such as agriculture, medicine, aerospace manufacturing, and social media. They have become a bridge for artificial intelligence to move from the perception stage to the cognitive stage^[3]. With the upgrading of educational informatization, knowledge graphs, as a key technology for knowledge organization and representation in AI^[4], offer new opportunities for the high-quality development of smart education in the context of building a strong educational nation^[5].

2.2 The Role of Algorithms in Building Subject Knowledge Graphs

The construction of knowledge graphs involves the entire process from knowledge extraction and modeling to application, with algorithms being the core driving force for their intelligence. In particular, in the generation and optimization of subject knowledge graphs, algorithms endow the graphs with stronger subject characteristics and scalability through data mining, pattern learning, and dynamic reasoning. The following explains the specific functions and principles of algorithms in the key links of knowledge graph construction and application: Rule-based Entity Relationship Recognition Algorithm: According to professional knowledge and grammar rules in the field of pedagogy, a series of matching rules are set to

identify entities and relationships in the text. For example, the relationship between educational theories and their proposers can be identified by matching rules such as "... is put forward by ...".

2.3 The Connotation and Requirements of Precision Teaching

Precision Teaching (PT) was first proposed by Ogden Lindsley in the 1960s, based on Skinner's behaviorist learning theory. It is a teaching model that uses digital tools to collect and analyze data for personalized instruction^[6]. PT focuses on changes during students' learning and uses standard celeration charts for educational decision - making to promote student learning^[7]. Early PT relied on manual recording, which was restrictive and hindered its development. In 2016, Professor Zhuzhitong introduced information technology into PT in China^[8], revitalizing it and marking a new starting point in the field.

2.4 The Integration of Algorithm-driven Knowledge Graphs and Precision Teaching Mode

The integration of knowledge graphs and precision teaching brings new opportunities and challenges to education. Knowledge graphs, which integrate and represent knowledge, strongly support precision teaching.

(1) Knowledge Representation and Personalized Learning: Knowledge graphs structure complex knowledge to offer students personalized learning paths. They help understand students' learning needs for precision teaching. Ying et al. (2024) proposed CourseKG, an education knowledge graph based on course information, which uses AI and deep learning to improve teaching quality^[9]. By building a proper and comprehensive course knowledge system, CourseKG promotes the formation of personalized learning paths.

(2) Knowledge Modeling and Instructional Design: Knowledge graphs provide new ideas for instructional design. Through knowledge modeling, they help better organize and present teaching content. Choi et al. (2023) presented a model to extract optimal knowledge components from knowledge graphs for educational knowledge concept maps^[10].

(3) Constructing Learning Paths: Precision teaching using knowledge graphs has been proven to significantly enhance teaching efficiency. Zhang Hua's research shows that by using subject knowledge graphs to deconstruct ability elements and plan dynamic learning paths, learners' core

literacy indicators can be improved by an average of 28.4%^[11].

3. Construction of Knowledge Graphs

3.1 Concept Definition and Construction Approach

A Knowledge Graph (KG) is a technical framework that represents knowledge and complex relationships using a graph model. It originates from semantic network and ontology research and was first introduced by Google in 2012 to enhance search engine semantic understanding. At its core, a KG stores knowledge in a graph structure using "node-edge-property" triples. Nodes represent entities or concepts, edges describe semantic relationships (e.g., "is a" or "depends on"), and properties provide additional details about nodes or relationships (e.g., "difficulty level" for knowledge points or "target audience" for resources). This framework aims to make knowledge machine-readable and enable intelligent reasoning.

Constructing a KG involves extracting and refining relationship data represented by Resource Description Framework (RDF) triples^[12]. The process combines manual and automated methods, integrating top - down and bottom - up approaches. As shown in Figure 1, using "Principles of Education" and teaching outlines as data sources, data is collected, organized, and integrated to build a subject knowledge framework. Then, entity, property, and relationship classes are defined with expert input to establish the ontology structure. Next, knowledge extraction and fusion techniques transform multi-source, heterogeneous data into structured knowledge triples, forming the instance data layer. Finally, the knowledge is stored in a graph database like Neo4j to complete the KG construction, with updates mainly affecting the data layer while the ontology structure remains stable.

The construction process emphasizes consistency, standardization, scalability, updatability, knowledge quality, and verifiability. Ontology is built manually and with tools like Protégé to define educational concepts and relationships accurately. Knowledge extraction involves identifying entities and relationships using rule-based algorithms, while knowledge fusion includes entity alignment, relationship integration, and

property fusion to filter and merge knowledge. For storage, a graph-suitable database is chosen to build and import the knowledge graph, ensuring its quality.

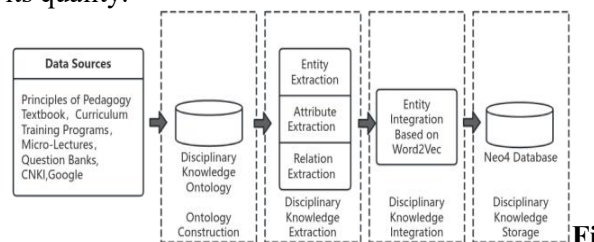


Figure 1. Flow Chart of Subject Knowledge Map Construction

3.2 Algorithm-Driven Construction of Subject-based Knowledge Graphs

3.2.1 Determining construction objectives and data scope

The construction of knowledge graphs aims to achieve precise teaching, meet diverse student learning needs, and enhance teaching quality. Using the textbook "Principles of Education" and its teaching outline as data sources, we collect and organize textbook content, teaching materials, official syllabi, relevant literature, and cases. This clarifies the course's teaching objectives, key points, difficulties, and class hour arrangements. Data sources are then integrated into a single document or database for subsequent processing and analysis.

3.2.2 Building the subject ontology

Ontologies, which provide a shared and consistent semantic framework for defining and organizing domain-specific concepts, attributes, and relationships, guide subsequent knowledge extraction^[13]. Constructing a high-quality subject ontology is crucial for building a comprehensive and accurate knowledge graph, requiring strict data quality with an emphasis on consistency, standardization, scalability, updatability, knowledge quality, and verifiability^[14].

In this study, ontologies are built manually with the Protégé tool, defining entity types, attributes, and relationships under the guidance of subject matter experts. This process focuses on key educational concepts such as "educational principles", "teaching methods", and "learning theories". Manual construction, combined with expert guidance, effectively enhances the accuracy of the ontology.

3.2.3 Subject knowledge extraction

A crucial step in building a subject knowledge graph, knowledge extraction comprises entity, relationship, and attribute extraction. Rule - based

algorithms define matching rules to identify and extract these elements from text.

Entity extraction involves identifying relevant knowledge and skill points from subject data and forming "entity-relationship-entity" triples^[15]. It focuses on extracting key concepts, theories, figures, and events from the textbook. Relationship extraction identifies relationships between entities, such as "containment" and "causality". Rule-based entity relationship recognition algorithms offer high accuracy and interpretability, especially suitable for domains with rich knowledge and fixed text formats. Combining manually defined rules with expert guidance improves the precision of entity and relationship identification.

3.2.4 Knowledge fusion

A high-level knowledge organization method, knowledge fusion filters and merges knowledge based on entity and relationship extraction^[16]. It mainly involves entity alignment, relationship integration, and attribute fusion.

Entity alignment unifies different expressions of the same entity from various chapters or sources, such as standardizing "constructivism" and "constructivist theory" to "constructivist learning theory". Relationship integration merges similar or duplicate relationships, standardizing their expressions for consistency and accuracy in the knowledge graph. Attribute fusion consolidates entity attribute information from diverse sources, eliminating redundant or conflicting values to form complete entity descriptions.

3.2.5 Knowledge storage

Knowledge fusion involves calculating entity similarity, using BERT for data classification and cleaning, and Word2Vec for semantic

similarity assessment based on word distance to achieve entity alignment. Finally, the extracted and fused knowledge triples are stored in a Neo4j graph database using the Cypher language^[17]. In Neo4j, entities are nodes, relationships are edges, and attributes are property values of nodes or edges, forming a structured knowledge semantic network. This facilitates subsequent functionality and performance optimization. The imported data is also validated for integrity and correctness to ensure knowledge graph quality.

This study constructs a subject knowledge graph primarily using "Principles of Education" and course plans. After ontology construction, knowledge extraction, and fusion, the data is stored in a Neo4j graph database, as shown in Figure 2.

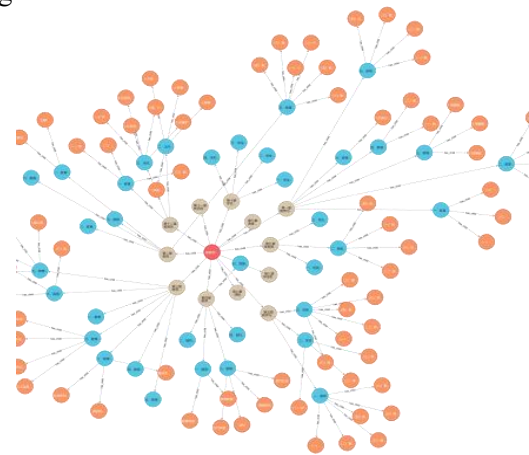


Figure 2. Map of the Principle of Pedagogy

4. Construction of Precision Teaching Model

The precision teaching model based on knowledge graph construction consists of three phases: precise teaching-goal positioning, exact teaching-process implementation, and accurate teaching-result evaluation, as shown in Figure 3.

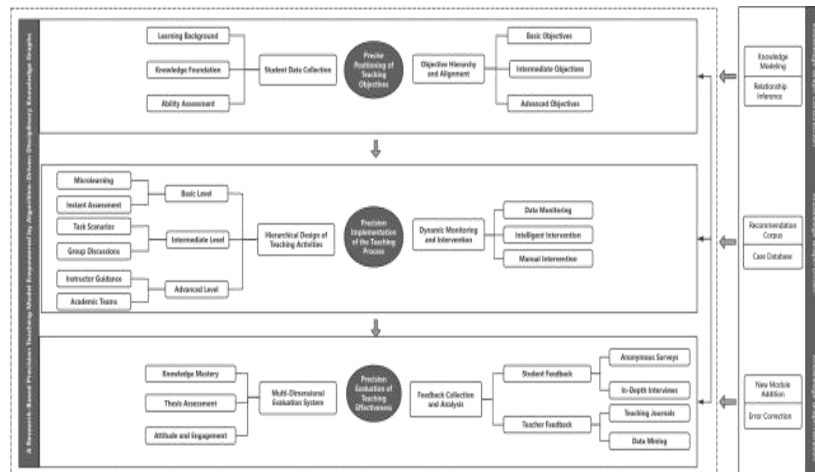


Figure 3. Accurate Teaching Pattern Diagram Constructed Based on the Knowledge Graph

4.1 Precise Teaching-Goal Positioning

In this research, the positioning of teaching goals begins with data collection on students' backgrounds, including their undergraduate majors and research orientations, to grasp their existing knowledge base and capabilities. Next, it involves learning knowledge modules and the logical relationships between knowledge points through the knowledge graph. Finally, by leveraging data-driven approaches, the teaching goals are matched with students' individual needs. The teaching goals are categorized into three tiers^[18]. The primary goal is for students to master the core concepts of the "Principles of Education" course via the learning content provided by the knowledge graph. The secondary goal is to enable students to apply theories in analyzing real-world educational issues. The advanced goal is to have students independently complete the writing of a course paper on the "Principles of Education" through this mode of study.

4.2 Teaching Process Implementation

The implementation of the teaching process, the second and core phase of the precision teaching model based on knowledge graph construction, centers on dynamically matching resources and activities using the knowledge graph to achieve precise teaching. First, the knowledge graph drives intelligent resource recommendations, such as pairing "Educational Equity" with "The Coleman Report" and the Finnish curriculum reform case^[19]. Second, teaching activities are designed in a hierarchical manner. The basic level emphasizes knowledge input through micro-lectures and instant quizzes on the Learning-through platform, which are automatically graded and provide feedback. The intermediate level focuses on capability application, with group discussions on related concepts like "Educational Equity vs. Efficiency" from the knowledge graph, and task simulations such as writing policy analysis reports, which require calling up the "Policy Evaluation Model" knowledge module. The advanced level is centered on research innovation, with mentors guiding students in topic selection and academic groups assisting in paper writing. During these stratified teaching activities, student learning behaviors are monitored via the Learning-through platform. Based on the monitoring results, learning

interventions are implemented. Smart interventions involve the knowledge graph pushing remedial resources to students who fail knowledge-point quizzes and the Learning-through platform sending reminders to students with lagging progress. Human interventions involve teachers adjusting teaching priorities according to data.

4.3 Teaching Effect Evaluation

The core task of the teaching effect evaluation stage is to continuously optimize the knowledge graph and teaching strategies through multi-dimensional evaluation and feedback. Initially, standardized tests, including short-answer questions, are employed to assess students' mastery of knowledge graph nodes. Subsequently, students' research abilities are evaluated by combining their course paper scores with their classroom participation. Upon the completion of the teaching process, feedback is collected from students via questionnaires and in-depth interviews with some students, while teachers reflect on the teaching process through their teaching journals and by analyzing the backend data of the Learning-through platform. This forms a closed loop for continuous improvement, ensuring that the knowledge graph is refined and modules are added based on student feedback and teacher reflection, recommendation algorithms are enhanced, and the teaching model is optimized.

5. Conclusion and Reflection

This study developed a graduate precise teaching model driven by algorithms, supported by knowledge graphs, and assisted by the Learning-through platform. This model embodies the teaching philosophy of "goal-oriented, knowledge graph-driven, student-centered, and teacher-led." Teachers design teaching processes to promote student self-study and collaborative learning, thereby enhancing their knowledge and research abilities. The model's effectiveness has been verified through teaching practice, student feedback, and research results. However, several issues were also identified and reflected upon.

5.1 Limitations in Knowledge Graph Construction

Firstly, it is difficult to accurately determine the associations between knowledge points, especially in interdisciplinary or advanced knowledge contexts, where the relationships

between different knowledge points are not linear or unique. Secondly, the construction of knowledge graphs relies on course content in various forms, such as textbooks, presentations, and videos, which may contain biases or be time-sensitive. This can result in inaccuracies in the constructed knowledge graph, thereby affecting the reliability of recommendation results.

5.2 Limitations in Dynamic Updating of Knowledge Graphs

Knowledge graphs are static or semi-dynamic and cannot timely reflect students' cognitive changes. For example, they may fail to promptly adjust recommendation strategies when students experience sudden changes in learning status due to emotional fluctuations or temporary interest shifts. Additionally, excessive standardization of knowledge modules in knowledge graphs may stifle students' creativity and hinder the development of their research abilities, as seen when recommended learning resources are too fixed, limiting students' autonomous exploration.

5.3 Over-reliance on Technology May Affect Fairness and Teacher Roles

Over-reliance on algorithms in precise teaching models may diminish teachers' roles and raise fairness issues. Firstly, it might weaken teachers' leading role in teaching, reducing their decision-making flexibility and creativity. Secondly, algorithmic bias can trap low-performing students in a "low-level learning cycle" by continually recommending simple knowledge, restricting their potential, exacerbating learning inequality, and worsening educational inequity.

Acknowledgments

This paper is supported by the 2024 Wuhan Institute of Technology Postgraduate Education and Teaching Reform Research Project "Construction and Application of Precision Teaching Model for Postgraduates Based on Learning Analytics" (No. 2024JYXM12); 2023 Annual Ministry of Education Humanities and Social Sciences Fund for Young Scholars Project: "Research on the Construction and Application of a Credibility Index System for Third-Party Evaluation Agencies in Higher Education" (No.23YJC880098); 2024 Annual Hubei Provincial Department of Education General Project for Humanities and Social Science Research: "Research on the Influencing

Factors and Enhancement Paths of Scientific and Technological Innovation Capacity of Universities in the Yangtze River Economic Belt" (No.24Y082)

References

- [1] Xu YR, Liu Jian, Su Linqin, et al. Investigation and countermeasure recommendations on the current status of graduate education in Chinese research institutions. *Academic Degrees & Graduate Education*, 2024, (08): 23–29.
- [2] Pujara J. Probabilistic models for scalable knowledge graph construction. University of Maryland, College Park, 2016.
- [3] Shao H, Zhang Kai, Li Fangyuan, et al. Constructing knowledge graphs from scratch: Technologies, methods, and case studies. China Machine Press, Beijing, 2021.
- [4] Zhu ZT, Xu QX, Wu YH. Standards requirements and action recommendations for new infrastructure in educational informatization. *Distance Education in China*, 2021, (10): 1–11, 76.
- [5] He WB, Dong YQ, Zhao CJ, et al. A Study on the Construction of Educational Knowledge Service Model Based on Subject Knowledge Graphs. *Digital Education*, 2022, 8(06): 21-28.
- [6] Binder C. Precision teaching: measuring and attaining exemplary academic achievement. *Youth policy*, 1988, 10(07): 12-15.
- [7] Lindsley OR. Precision teaching: discoveries and effects. *Journal of Applied Behavior Analysis*, 1992, 25(1): 51-57.
- [8] Zhu ZT, Peng HC. Efficient knowledge-based teaching supported by information technology: Activating precision teaching. *China Educational Technology*, 2016, (1): 18–25.
- [9] Li Y, Liang Y, Yang R, et al. Course KG: an educational knowledge graph based on course information for precision teaching. *Applied Sciences*, 2024, 14(7): 2710.
- [10] Choi H, Lee H, Lee M. Optimal knowledge component extracting model for knowledge-concept graph completion in education. *IEEE Access*, 2023, 11: 15002-15013.
- [11] Zhang H, Li SY, Wang JG. Design and practice of a precision teaching model based on knowledge graphs: A case study of the mechanics unit in high school physics. *China Educational Technology*, 2023, (5): 54–62.

- [12]Lin J, Ke QC, Huang ZH, et al. Dynamic generation of subject knowledge graphs and their application in intelligent resource organization. *Distance Education Journal*, 2022, 40(04): 23–34.
- [13]Zhang XX, Tang YQ, Zhao W, Ma H, Tang WS. Personalized learning resource recommendation based on knowledge graphs and graph embedding. *Computer Systems & Applications*, 2023, 32(05): 180–187.
- [14]Sun YS, Peng MY, Liu T. Subject knowledge graphs and their construction mechanisms. *Science & Technology Management Research*, 2022, 42(20): 157–162.
- [15]Li CY, Wu YQ, Tang ZK, Lin WJ, Tang Y. Personalized learning resource recommendation integrating knowledge graphs. *Mini-Micro Computer Systems*, 2024, 45(02): 285–292.
- [16]Xu XK, Fang DW, Jiang X, et al. Granular representation and standardization of knowledge in knowledge organization. *Library & Information Knowledge*, 2014, (06): 101–106+90.
- [17]Dong M. Personalized learning path recommendation strategy based on subject knowledge graphs. *Modern Information Technology*, 2024, 8(20): 117–122.
- [18]Li K. Application of hierarchical teaching methods in junior high school mathematics. *Learning Weekly*, 2025, (08): 110-112.
- [19]Ma YZ. Research on smart teaching applications based on course knowledge graphs. *Henan Education (Higher Education)*, 2024, (02): 84–86. *Education (Higher Education)*, 2024, (02): 84–86.