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Review

A Survey of Knowledge Graph Approaches and Applications in Education

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Abstract: This paper presents a comprehensive survey of knowledge graphs in education. It covers the patterns and prospects of research in this area. A total of 48 relevant publications between 2011 and 2023 were collected from the Web of Science, Scopus, and ProQuest for review. The findings reveal a sharp increase in recent years in the body of research into educational knowledge graphs which was mainly conducted from institutions in China. Most of the relevant research work adopted a quantitative method, such as performance evaluation, user surveys, and controlled experiments, to assess the effectiveness of knowledge graph approaches. The findings also suggest that knowledge graph approaches were primarily researched and implemented in higher education institutions, with a focus on computer science, mathematics, and engineering. The most frequently addressed objectives included enhancing knowledge representation and providing personal learning recommendations, and the most common applications were concept instruction and educational recommendations. Diverse data resources, such as course materials, student learning behaviours, and online encyclopaedia, were processed to implement knowledge graph approaches in different scenarios. Relevant technical means employed for the implementation of knowledge graphs dealt with the purposes of building knowledge ontology, achieving recommendations, and creating knowledge graphs. Various pedagogies such as personalised learning and collaborative learning are supported by the knowledge graph approaches. The findings also identified key limitations in the relevant work, including insufficient information for knowledge graph construction, difficulty in extending applications across subject areas, the restricted scale and scope of data resources, and the lack of comprehensive user feedback and evaluation processes.

Keywords: knowledge graph; learning recommendation; technology-mediated learning; educational technology

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1. Introduction

Advances in technologies have facilitated the development of innovative ways to represent and organise vast amounts of information and knowledge in a structured format. A knowledge graph is one of such innovations which has been increasingly used in both industry and academia [1]. A knowledge graph refers to a graph of data with nodes representing entities such as objects and abstract concepts and with edges showing relationships between the entities [2,3]. As an artificial intelligence technology, knowledge graphs have been adopted in a wide range of applications, from information retrieval, integration, and management to recommendations and question answering [4]. Since their introduction in the 2010s, knowledge graphs have become an effective and efficient approach to knowledge organisation, visualisation, and management [5–7].

In the education domain, knowledge graphs have been incorporated into various tools to enhance teaching and learning, such as recommending personalised learning resources based on learning styles and preferences [8], predicting learning performance [9], facilitating question generation process [10], and reducing time to retrieve teaching materials [11]. They have also been used to support course management and curriculum improvement by enhancing course–teacher matching, course offerings, and curriculum coherence [12]. The application of knowledge graphs can be seen in various academic disciplines, such as computer science [13,14], mathematics [15,16], and medicine [17].

Despite the broad range of studies on knowledge graphs in education, there are only a handful of review studies reporting related works [18–20]. These reviews have focused on some specific areas of knowledge graphs or covered limited works in the literature only. To obtain a holistic view of the status of development in this area, this paper presents a comprehensive survey of knowledge graph approaches and applications in education. It systematically summarises the features, patterns, and prospects of research and practice in this area. Specifically, this survey focused on the following research questions:

1. What are the patterns of publications on knowledge graphs in education?
2. What are the educational contexts of knowledge graph applications?
3. What are the objectives, application categories, data sources, technical means, and pedagogical issues for knowledge graph approaches and applications in education?

2. Related Work

A range of review studies with respect to knowledge graphs have been performed over the years. Some of the reviews focused on the overall development of knowledge graphs. For example, Chen et al. [21] explored the status and trends of research in knowledge graphs. Their results show that there has been a tremendous increase in the amount of relevant research, particularly in China. The main research focuses cover areas such as knowledge graph embedding, knowledge graph-based search and query, and the use of knowledge graphs for intangible cultural heritage. Similarly, Wang and He [22] performed a bibliometric analysis of knowledge graph research between 2013 and 2022 and found six frequently explored dimensions, including ontology modelling, knowledge extraction, multi-modal knowledge graphs, knowledge-aware applications, knowledge graph embedding, and representation.

There have been reviews which focused on specific knowledge graph techniques. Wang et al. [23], for example, investigated publications on knowledge graph embedding in terms of its model designs and training procedures in order to provide insights into how relevant techniques contributed to knowledge graph completion, relation extraction, and question answering. Rajabi and Etminani [24] surveyed the ways in which knowledge graphs were applied in explainable artificial intelligence systems. They found that knowledge graphs have been widely used for pre-modelling for the systems to extract features, entities, and relations for inferencing and reasoning purposes, with neutral-network-based machine learning techniques being the most commonly used. Tian et al. [25] identified three types of knowledge reasoning methods, which are based on logic rules, representation learning, and neural networks, respectively. Moreover, they conducted a comparison of knowledge hypergraph representation methods, taking into account factors such as problems, solutions, and categories.

Reviews on knowledge graphs also addressed its application in specific domains. Abu-Salih [26] presented an analysis of knowledge graph construction research in seven domains—including healthcare, education, information and communication technology, science and engineering, finance, society and politics, and travel—with respect to knowledge graph usage, construction algorithms, knowledge graph resources, embedding techniques, evaluation measures, and limitations. Chiu et al. [27] summarised how knowledge graphs were constructed and applied in e-retailing, in terms of its design methods, coverage of structured and unstructured data, and application areas such as question answering, customer service optimisation, inventory management, and supply chain visibility. The study by Wang et al. [28] reviewed the use of knowledge graphs for medical imaging and identified the major application areas, with disease classification being the most widely examined followed by report generation, disease localisation and segmentation, and image retrieval. In a similar vein, Abu-Salih et al. [29] analysed how knowledge graphs were used in the healthcare area, in terms of the types of methods, knowledge bases, and evaluation protocols.

Regarding the use of knowledge graphs in education, however, there have been very limited reviews on relevant work. Among the few related reviews, Abu-Salih and Alotaibi [18] examined knowledge graph applications across five domains in education, such as personalised learning, curriculum design, concept mapping, semantic search and questioning answering, and other relevant applications (e.g., educational management, knowledge integration, and link prediction). In each domain, they summarised the knowledge graph functionalities, types, resource requirements, construction methods, evaluation criteria, and limitations. Elkaimbillah et al. [19] provided a comparative study of knowledge graph models in the education domain based on related studies, highlighting the purposes, techniques, data sources, evaluation measures, and limitations. Fettach et al. [20] reviewed the knowledge graph applications in education and for employability. They identified the main categories of applications in education, namely instructional conception, knowledge management, personalised learning, questioning answering, and educational assessment. For employability, relevant applications range broadly from job recommendation to job-skill matching and talent intelligence.

Nevertheless, these reviews on knowledge graphs in education are limited by the focuses (e.g., specifically on analysing the relationships among knowledge graph, education, and employability as in Fettach et al. [20]) and sources of data (e.g., covering only seven publications as in Elkaimbillah et al. [19]). Related reviews have yet to provide a comprehensive overview of relevant work on knowledge graphs in education, such as their research scopes, research methods, pedagogy issues, and research trends. These limitations are addressed in the present paper, which presents a systematic survey of relevant research publications.

3. Methodology

3.1. Data Collection

For this study, research articles on knowledge graphs in education were collected from the Web of Science, Scopus, and ProQuest. These three publication databases were chosen for their comprehensive coverage of the literature and their popularity as data sources for reviews of various topics [30–32]. The keywords ["knowledge graph" and "education"] were used for searching the relevant literature from the databases. Only journal articles were covered. The publication period was set for 2011–2023 to cope with the introduction of knowledge graphs in the 2010s [5].

Figure 1 illustrates the procedures for the search and selection of relevant articles for review based on the PRISMA framework. The initial search across the three databases yielded 289 results, which were reduced to 181 records after removing duplicates. The abstract of each paper was scrutinised and any records that did not meet the inclusion criteria were excluded, including those which were not empirical studies, not related to education, or not clearly relevant to the application of knowledge graphs. This screening process resulted in 88 records.

After removing the articles for which their full text could not be accessed, 71 records remained. The next phase involved thoroughly examining the full texts of these articles to assess their eligibility. This process led to the exclusion of 23 records which did not meet the defined criteria, such as not being written in English, not being journal articles, or not illustrating the design and implementation of an educational system or programme based on knowledge graphs. Additionally, articles which did not report the impacts of knowledge graphs on pedagogy, learning environments, and/or learning outcomes were excluded.

Finally, a total of 48 articles were selected for review and analysis, representing the most relevant research on knowledge graph construction and application in the educational domain.

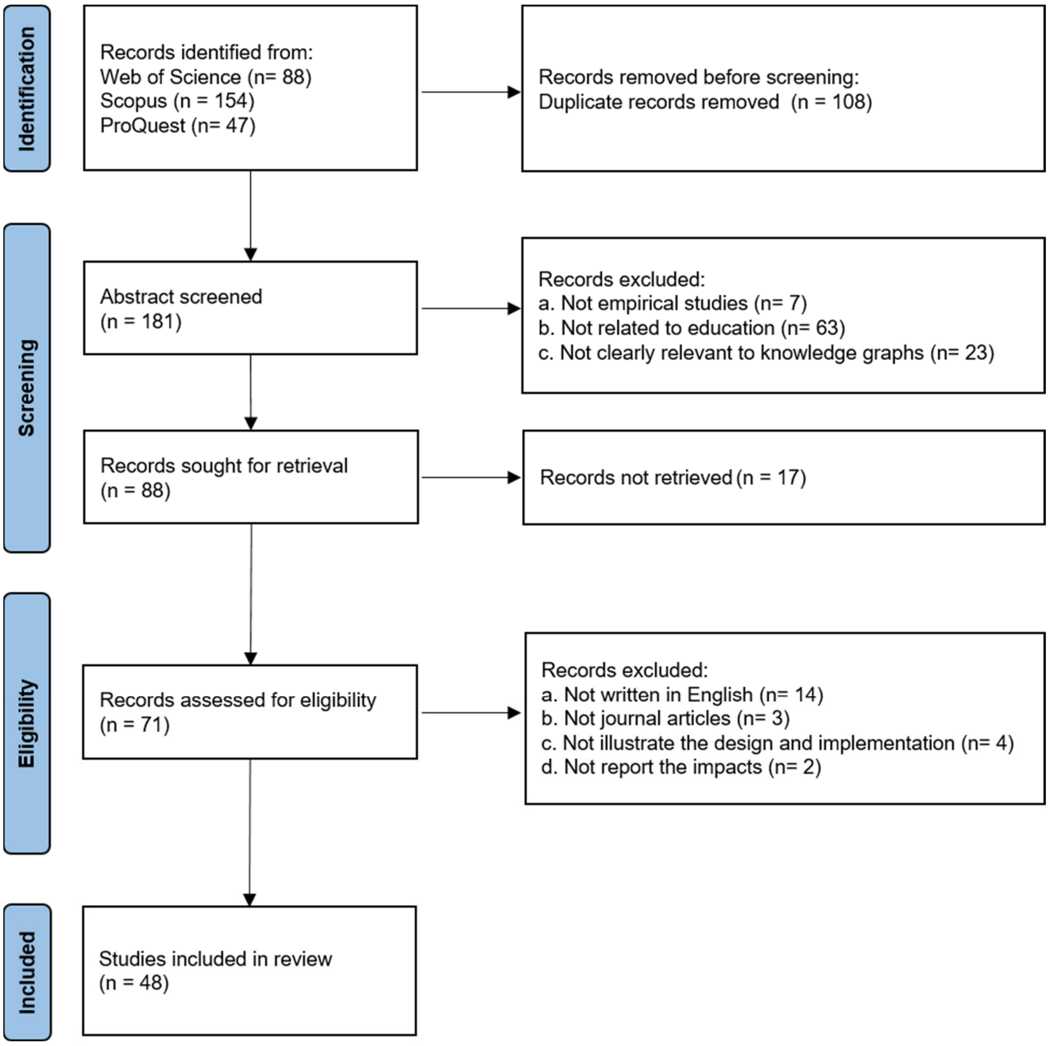

Figure 1. Procedures for search and selection of relevant publications.

3.2. Data Analysis

Content analysis was performed for the selected articles. Information relevant to the research questions was identified from each of the articles and categorised, including the research methods, educational levels, subject disciplines, objectives, application categories, knowledge graph resources, technical means, pedagogies, and limitations. The coding and categorisation of the information were first performed by a researcher and then checked by another researcher. Differences between the judgements of the two researchers were discussed until an agreement was reached. Based on the processed data, the features and patterns of research and practice on knowledge graphs in education were analysed.

4. Results

4.1. Overview of the Publications

4.1.1. Year of Publication

Figure 2 shows the distribution of the publications between the years 2011 and 2023. The results suggest that knowledge graphs were not used for education purposes in the first few years after it was introduced in the 2010s [5]. Relevant publications on knowledge graphs in education have been published starting from 2018. Then, there has been an increasing trend of publications, and the number of publications increased rapidly from 2 in 2018 to 22 in 2023. These results echo those of Chen et al. [21], namely that there has been a growing interest in research into knowledge graphs in education in recent years.

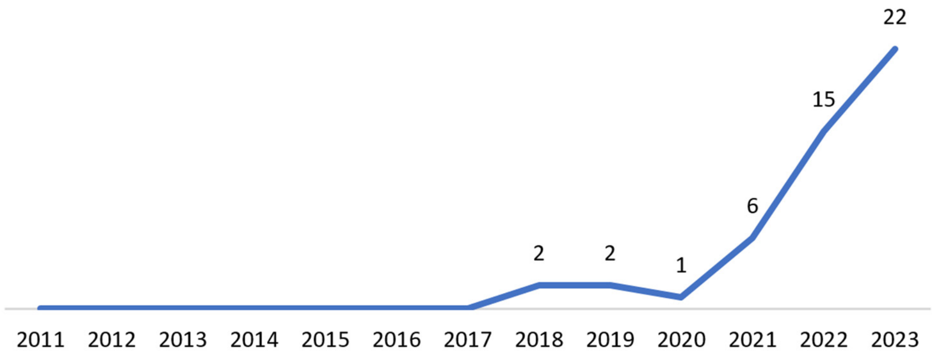

Figure 2. Distribution of the publications between 2011 and 2023.

4.1.2. Country/Region of Authors' Affiliations

Figure 3 presents the countries/regions of authors' affiliations in the publications. A large proportion of publications (42%) were generated from affiliations in China, followed by the United States with 11%. There were 5% of the publications from Korea, and 4% from Greece, Vietnam, Spain, Italy, and India. Each of the other countries, such as Malaysia, Germany, Switzerland, and Russia, contributed about 2% of the publications. These results reveal that knowledge graphs have been studied and applied in education in a wide range of countries/regions. These results also resemble those of Chen et al. [21], in which China is the primary region for knowledge graph research.

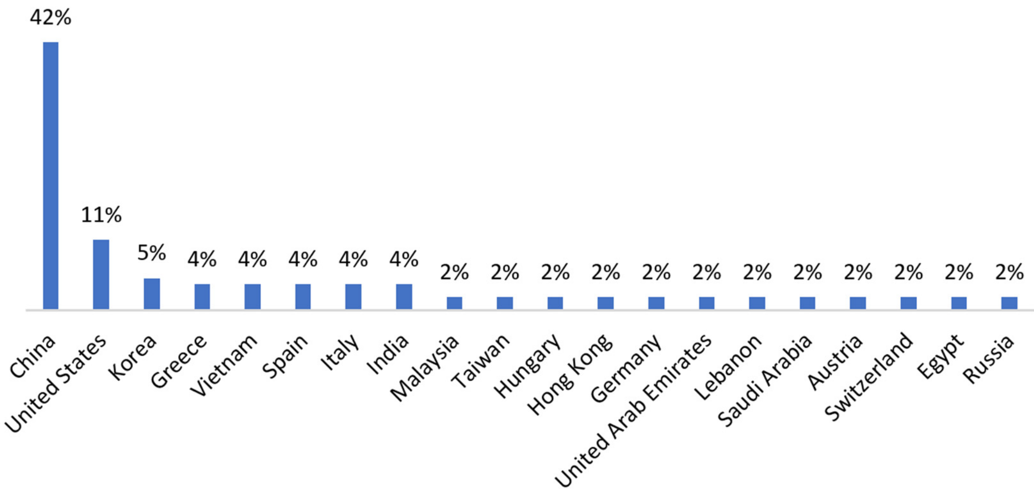

Figure 3. Distribution of the countries/regions of authors' affiliations.

4.1.3. Research Methods

Figure 4 shows the research methods used in the studies on knowledge graphs in education. Most of the studies (78%) adopted quantitative methods. As shown in Figure 5, the studies involved a total of five types of quantitative methods, including assessing the model/system performance through evaluation metrics (e.g., Hits@N, Accuracy, Precision, Recall, and F-measure); comparison experiments; questionnaire surveys on user experience, perception, or satisfaction; tests on student learning performance; and social network analysis, among which evaluation metrics were the most frequently used quantitative measures. A small proportion (2%) of the studies used qualitative methods, such as interviews and focus groups, to conduct in-depth analyses of participants' responses. The remaining (20%) refers to the use of mixed methods, combining both quantitative and qualitative ways of collecting and analysing the data.

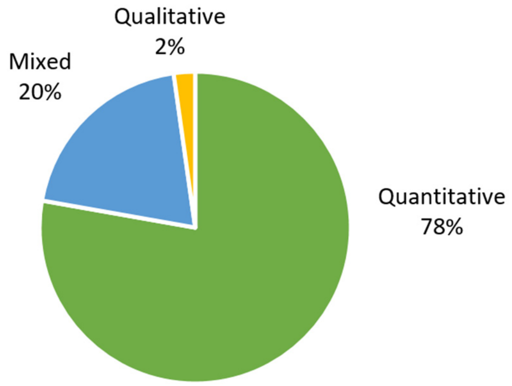

Figure 4. Research methods adopted in the studies.

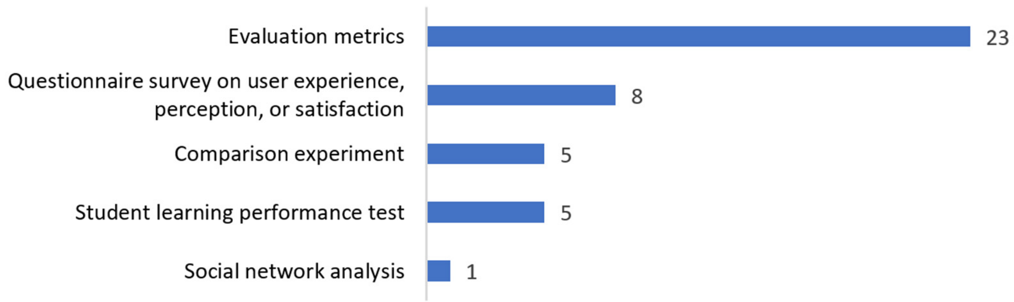

Figure 5. Types of quantitative methods.

4.2. Contexts of Knowledge Graph Approaches

4.2.1. Level of Education

Figure 6 shows the levels of education involved in the applications of knowledge graphs. A majority of publications were focused on the tertiary level of education (86%). The secondary and primary levels of education have much smaller percentages, i.e., 10% and 4%, respectively. The distribution of publications suggests that knowledge graph approaches were primarily being implemented and researched in higher education institutions, with a lesser focus on secondary and primary education.

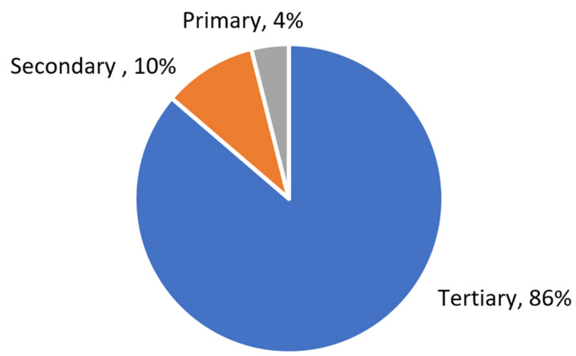

Figure 6. Levels of education for the studies.

4.2.2. Subject Disciplines

Figure 7 presents the subject disciplines covered in the publications. A total of nine subject disciplines were identified. Overall, computer science was the subject discipline with the largest proportion (49%), followed by mathematics (15%) and engineering (12%). Subject disciplines such as language as well as commerce and management have a relatively smaller proportion of publications (6%). The smallest percentage of publications (3%) was found in subject disciplines including political science, medicine, education, and the arts.

These results indicate that knowledge graphs have been applied in a broadening spectrum of subject disciplines in recent years.

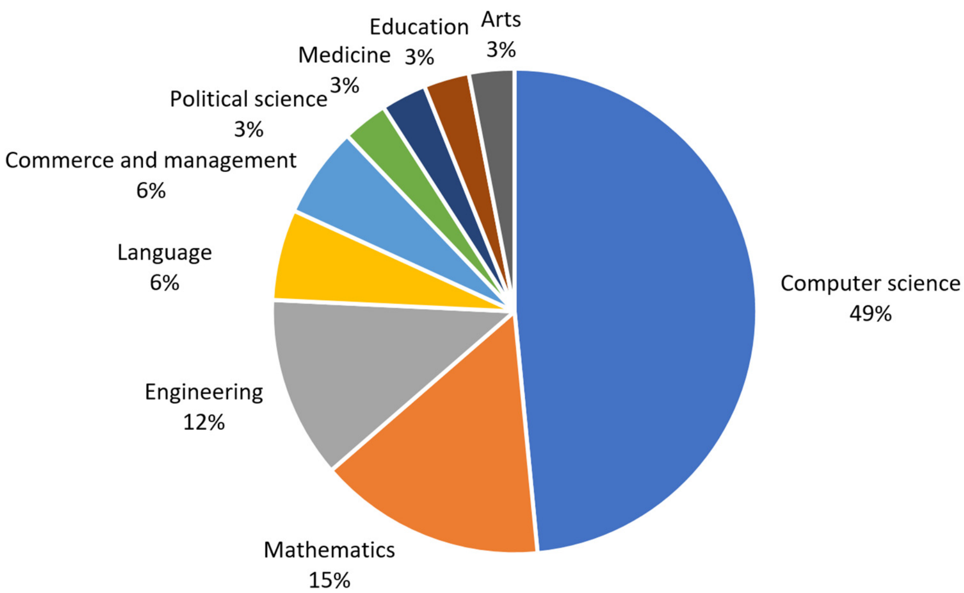

Figure 7. Distribution of subject disciplines in the publications.

4.3. Implementation of Knowledge Graph Approaches

Table 1 provides a summary of the implementation of knowledge graph approaches reported in the reviewed articles. It includes details on the objectives, application categories, data resources used to construct knowledge graphs, technical methods employed, pedagogical approaches, and key limitations identified.

Table 1. Summary of articles based on objectives, application categories, knowledge graph resources, technical means, pedagogies, and limitations.

Ref.	Objectives	Application Categories	Knowledge Graph Resources	Technical Means	Pedagogies	Limitations
[8]	Enhance personalised educational content recommendation.	Educational recommendation	Learning resources, learner attributes, and preferences	Cosine similarity	Personalised learning	• The need for consistent updates and upkeep of the knowledge graph.
[10]	Facilitate question generation for instructors.	Question generation	Textbooks	Semantic networks	N/A	• Evaluation covered limited learning topics. • Unclear influence of machine-generated content on ratings. • Small sample size of instructors. • Lack of standard question generation model datasets.
[15]	Find a meaningful knowledge-concept path.	Concept instruction	Student log data	Feature selection using Elastic Net (LASSO) + RF algorithm	Personalised learning	• The final knowledge component set size was arbitrarily selected.
[14]	Empower a question-answering Chabot to respond to queries.	Question answering	Wikipedia	The Wit.ai NLP model	N/A	• Inconsistent performance due to TF-IDF document content limitations or need for fine-tuning.
[33]	Enable semantic querying, predictive modelling, and reasoning for student behaviour analysis.	Prediction of educational outcomes	LMSs (Moodle, COCO Udemy, Open University)	OWL 2 ontology	N/A	• There is a need to align with ontologies from different domains like social networks, health behaviours, and demographics.

Table 1. *Cont.*

Ref.	Objectives	Application Categories	Knowledge Graph Resources	Technical Means	Pedagogies	Limitations
[34]	Support collaborative knowledge building.	Educational recommendations and educational assessment and feedback	Online discussion transcripts	BERT-BiLSTM-CRF	Collaborative learning	• Limited sample size. • Focused on only one learning domain. • Investigated limited variables.
[35]	Improve collaborative learning performance.	Educational recommendations and educational assessment and feedback	Online discussion transcripts	BERT-BiLSTM-CRF and BERT-Random Forest	Collaborative learning	• Limited sample from a single university. • Focused on one learning task only.
[36]	Promote knowledge elaboration.	Educational assessment and feedback	Online discussion transcripts	BERT-BiLSTM-CRF	Collaborative learning	• Small sample size and short study duration. • Single task environment and text-only interactions. • Limited to post-test data.
[37]	Predict students' mastery of knowledge based on their learning activity.	Prediction of educational outcomes	English problem-solving record data from EdNet and ASSIST2017	Graph neural network	Personalised learning	• Did not utilise relationships among knowledge components like prerequisites or similarities. • Unable to leverage relationships between students for social-based recommendations. • Limited usage of textual exercise data.
[38]	Improve the recommendation of learning activities.	Educational recommendations	Textbooks, student learning activities	Similarity measures	Personalised learning	• Only explored one method (path-based) for knowledge graph recommender systems.
[39]	Help students find out courses and knowledge related to graduation requirements.	Learning resources searching	Syllabi, teachers' lesson plans, and webpages	Ontology construction, Large Language Models	Personalised learning	• There is a need to build a search engine.
[40]	Offer learners a semantic representation of domain concepts.	Concept instruction	Learning materials, Wikipedia, and Dbpedia	SqueezeBERT, word and sentence embeddings	Personalised learning	• Limited evaluation of knowledge graph accuracy.
[41]	Visualise the knowledge construction process.	Concept instruction	Lecture slides, Wikipedia, and videos	N/A	Immersive learning, collaborative learning	• Lack of discussion on the process and techniques of knowledge graph construction.
[9]	Identify students at risk of failing a course.	Prediction of educational outcomes	Course information, student historical features and performance	Ontology mapping	N/A	• Limited dataset. • Lack of user feedback.
[16]	Help learners efficiently memorise and learn concepts.	Concept instruction	Textbooks, Baidupedia, and students' classroom responses (collected using sensors)	Graph convolutional network (GCN), BiLSTM-CRF	Personalised learning	• Unclear standards for knowledge points relationships, division, and visualisation.
[42]	Support knowledge sharing and learning in groups.	Concept instruction	DBpedia, Wikidata, and YAGO3	Embedding-based knowledge map fusion algorithm	Collaborative learning	• Lack of demonstration on how the group knowledge graph is constructed based on individual knowledge graphs.
[43]	Predict and analyse student educational outcomes.	Prediction of educational outcomes	The Linked Data for Education dataset (learning resources), the Open Academic Graph dataset, DBpedia, and MOOC platforms	Feature selection using LSTM_GOA algorithm	N/A	• Lack of discussion on knowledge graph construction based on data collected.
[44]	Show the logic between knowledge.	Concept instruction	Individually constructed knowledge graphs by teachers and students	Knowledge fusion	Project-based learning, collaborative learning	• Lack of discussion on knowledge graph construction algorithm.
[45]	Assist students in reviewing lectures and comprehending course material.	Learning resources searching	Textbooks	Ontology Rela-Ops model	N/A	• There is a need to develop more functions to support many kinds of queries.
[46]	Represent relations of knowledge components and retrieve contents of queries.	Learning resources searching	Textbooks and workbooks	Ontology Rela-Ops model	N/A	• The system lacks integration with functionalities like student evaluation or personalised learning recommendations.

Table 1. *Cont.*

Ref.	Objectives	Application Categories	Knowledge Graph Resources	Technical Means	Pedagogies	Limitations
[47]	Enables learners to perform non-linear navigation of learning contents.	Concept instruction	Video lectures	Speech-to-text techniques and semantic analysis	N/A	• Lack of adaptive and personalised features.
[17]	Help students quickly and systematically grasp the framework and key content of video lectures.	Concept instruction	Video lectures	BERT, name entity recognition, and YOLOv3	N/A	• Omission of key images and handwriting in the video lectures. • Lack of relationship weights between nodes.
[48]	Estimate students' proficiency in knowledge concepts.	Prediction of educational outcomes	Online tutoring system and E-learning platform	Recurrent neural network	N/A	• Explored factors limited to final grade and discussion.
[12]	Improve the curriculum system in higher education institutions.	Curriculum design and management	Course syllabi in the current university and the benchmarking top universities, teacher information	Latent Dirichlet Allocation	N/A	• Lack of intelligent algorithms and databases for automated curriculum improvement.
[13]	Construct meaningful connections between social media and formal learning.	Curriculum design and management	Course information, social media (Facebook, Twitter)	Semantic mediawiki	Collaborative learning	• Biased by single course domain and student background. • Lack of professors' perspectives on knowledge graph tools. • Students underutilised social features compared to online platforms. • Lack of analysis of the implications of crowdsourcing ontology concepts.
[49]	Provide concept visualisation and promote cognitive engagement.	Concept instruction	Course materials	Named-entity recognition and NLP	Problem-based learning	• There is a need to develop downstream applications like curriculum design and learning recommendations.
[50]	Provide semantic search for reskilling and upskilling options.	Educational recommendations	Education providers' Webpages	Resource Description Framework, slot filling	N/A	• Lack of apprenticeship providers and cost–benefit analysis for education recommendation.
[51]	Manage and present various modes of educational resources.	Knowledge management	Online education resources (e.g., Baidu entries), offline education resources (e.g., PowerPoints and class audios)	BERT-BiLSTM-CRF	N/A	• Limited educational resource integration. • Small-scale knowledge graphs.
[11]	Minimise the time instructors have to spend looking for teaching material.	Educational recommendations	DBpedia Knowledge Graphs, instructor's teaching plans	Semantic similarity	N/A	• Semantic data extraction challenges feasibility and scalability.
[52]	Provide a comprehensive resource for students.	Learning resources searching	National Science Foundation, Survey of Earned Doctorates Restricted Data Analysis System, and Wikidata	Semantic Extract Transform and Load-er	N/A	• Incomplete data source coverage. • Insufficient coverage of diverse groups.
[53]	Enhance online course recommendations to address user characteristics.	Educational recommendations	Two public datasets (Movielens-20M, Book-Crossing) and an industrial dataset	Graph convolutional network, Collaborative filtering algorithms	Personalised learning	• Static user modelling ignores attribute correlations (age, knowledge level). • A need to improve the recommendation accuracy.
[54]	Predict appropriate resources with the highest ranking linked to the learner's interests.	Educational recommendations	E-content (e.g., E-Library, Coursera), user selections out of these materials	NLP	Personalised learning	• Potential to improve predictions using deep learning techniques.
[55]	Help students build complex knowledge structures.	Concept instruction	Educational resources, learning behaviour	Node feature extraction method	N/A	• Lack of evaluation of the proposed method.
[56]	Help students access learning resources accurately and efficiently.	Educational recommendations	Learning behaviours, course information	Collaborative filtering algorithms, similarity measures	Personalised learning	• Limited analysis of user factors.

Table 1. *Cont.*

Ref.	Objectives	Application Categories	Knowledge Graph Resources	Technical Means	Pedagogies	Limitations
[57]	Present knowledge units in a semantically well-organised manner.	Concept instruction	Textbooks	NLP	N/A	• It uses a general lexical database (WordNet) which could be improved with domain-specific ontologies. • The model has only been applied to Computer Science textbooks so far.
[58]	Communicate knowledge logically and coherently.	Concept instruction	N/A	Entity extraction, relation extraction, and attribute extraction	N/A	• Insufficient information provided about the data sources and technical implementation of the knowledge graph construction process.
[59]	Improve the course recommendation accuracy for music education	Educational recommendations	Audio, sheet music, chants, and metadata	Resource Description Framework	Personalised learning	• A need to improve the recommendation accuracy.
[60]	Enable students to seek out and examine educational resources that align with their interests.	Learning resources searching	Textbooks	Wikipedia Miner, NLP	Networked learning	• Only text-based data resources included.
[61]	Provide personalised learning content according to the skill set of learners.	Educational recommendations	Learning assessment, course materials	Named-entity recognition	Personalised learning	• Lack of evaluation of the proposed method.
[62]	Predict students' learning behaviour in order to provide feedback on the teaching effect.	Question answering	Subject materials and syllabi	Conditional Random Fields, TF-IDF	Problem-based learning, cognitive learning	• Deep learning is needed to improve problem understanding accuracy.
[63]	Effectively provide information in response to searches for content that is useful to learners.	Learning resources searching	Webpages	Bi-LSTM model	N/A	• Lack of in-depth system evaluation. • No algorithm performance comparison or technical support.
[64]	Recommend personalised exercises to students in an appropriate order.	Educational recommendations	Textbook, Wikipedia, and testing behaviour of students	Collaborative filtering	Personalised learning	• Prerequisite relationships between knowledge points are recognised manually. • Limited testing behaviour data types.
[65]	Provide personalised content for learners.	Educational recommendations	N/A	Collaborative filtering	Personalised learning	• Fails to adequately discuss or describe the data sources.
[66]	Effectively recommend learning resources to learners.	Educational recommendations	Webpages	Collaborative filtering	Personalised learning	• A need to improve the recommendation accuracy.
[67]	Support students in constructing and expanding their knowledge structure.	Concept instruction	Student-generated knowledge graphs	N/A	Collaborative learning	• Lack of discussion on knowledge graph construction method and process.
[68]	Provide a well-structured overview of knowledge in nuclear power engineering.	Concept instruction	DBpedia	Semantic Similarity Measure, Resource Description Framework	N/A	• Limited data sources.
[69]	Enhance scientific retrieval efficiency.	Knowledge management	Three scientific databases: Web of Science, Engineering Village, and EBSCO	Machine-learning algorithms	Problem-based learning	• The scale of the knowledge graph should be expanded to cover more domains. • More advanced algorithms are required.
[70]	Support personalised teaching services and adaptive learning solutions.	Concept instruction	Standard curriculum data and learning assessment data	Gated recurrent unit network, probabilistic association rule mining algorithm	Personalised learning	• Limited scope of relations identified. • Lack of semi-supervised learning to utilise unlabelled data.

4.3.1. Types of Objectives

Figure 8 illustrates the objectives of knowledge graph approaches in the studies. The most frequent objective was enhancing knowledge representation, such as demonstrating the relationship between knowledge to aid comprehension and memorisation. Another common objective was providing personal learning recommendations, where course resources, learning paths, or learning activities were recommended according to students' interests or characteristics. Other objectives are related to the learning process, such as improving learning efficiency, predicting learning behaviours or outcomes, promoting collaborative learning, and offering accurate responses to learning queries. Some objectives aimed to support staff, such as facilitating instructors' organisation of learning resources and assisting with knowledge/course management.

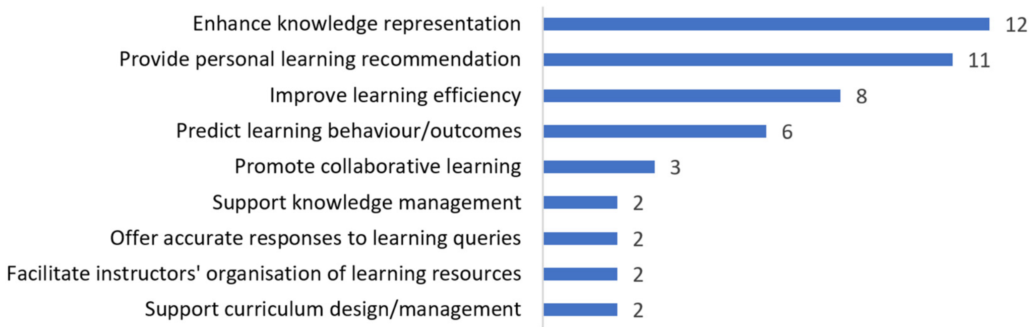

Figure 8. Types of objectives of knowledge graph approaches.

4.3.2. Types of Application Categories

Figure 9 summarises the application categories of knowledge graph approaches. The most common approach was concept instruction, followed by educational recommendations. Other common types of applications include learning resource searching, the prediction of educational outcomes, and educational assessment and feedback. In addition, knowledge graphs have also been employed to aid in curriculum design and management, knowledge management, question answering, and question generation.

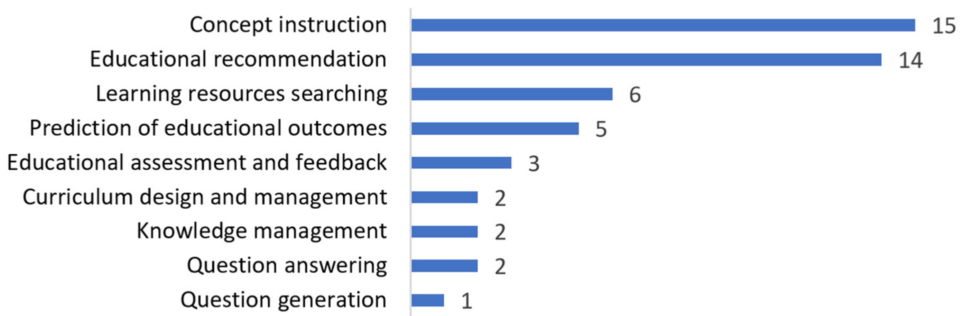

Figure 9. Application categories of knowledge graph approaches.

4.3.3. Types of Knowledge Graph Resources

Figure 10 presents the types of knowledge graph resources utilised in the studies. The most commonly used resources were course materials, such as textbooks, PowerPoint slides, syllabi, course videos, lecture notes, lab manuals, and exam questions. Other frequently utilised resources include specific datasets (e.g., Wikidata, DBpedia, and scientific databases) and data related to student learning behaviours (e.g., login to learning platforms, the selection of or access to materials, and testing behaviour data during the process of answering questions). These were followed by online encyclopaedias (e.g., Wikipedia and Baidupedia), student performance (e.g., scores of homework assignments, quizzes, midterm exams, and final exams), learning management systems or learning platforms, webpages (e.g., education providers' webpages), and online discussion transcripts. Some types of resources were used relatively infrequently, including course information, MOOC platforms, learner attributes, teacher information, and social media.

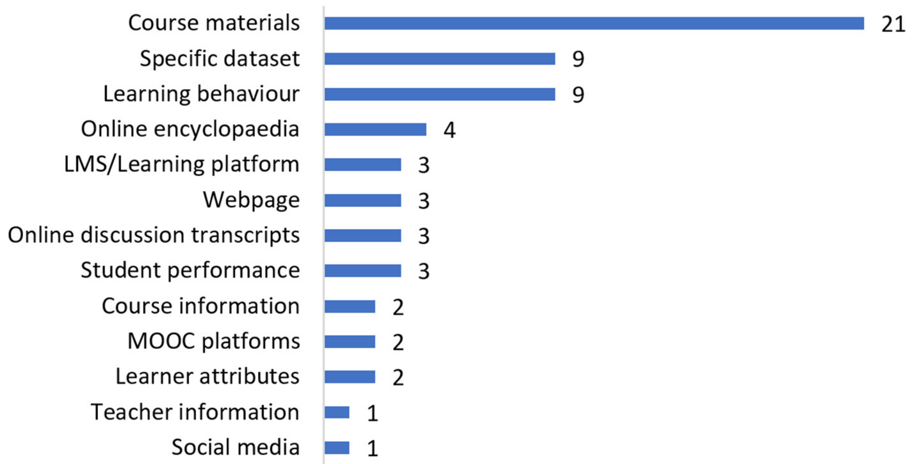

Figure 10. Types of knowledge graph resources.

4.3.4. Types of Technical Means

Figure 11 depicts the technical means employed to implement knowledge graph approaches for education. For building knowledge ontology as the data model for knowledge graph, machine learning techniques such as Graph Neural Networks (GNNs), Bidirectional Encoder Representations from Transformers (BERTs), and Latent Dirichlet Allocation (LDA) were the most frequently used means. This was followed by semantic web technologies such as Resource Description Framework RDF and OWL 2 ontology, and natural language processing techniques such as named-entity recognition. For achieving recommendations based on the knowledge graph, collaborative filtering algorithms such as matrix factorisation were most frequently used, followed by similarity measures such as cosine similarity, graph algorithms such as SPARQL, and correlation coefficients such as Spearman's rank correlation. For the creation of knowledge graphs, graph database management systems such as NEO4J were the most commonly used means. Other means include knowledge embedding toolkits such as OpenKE and bibliometric visualisation and analytics tools such as CiteSpace.

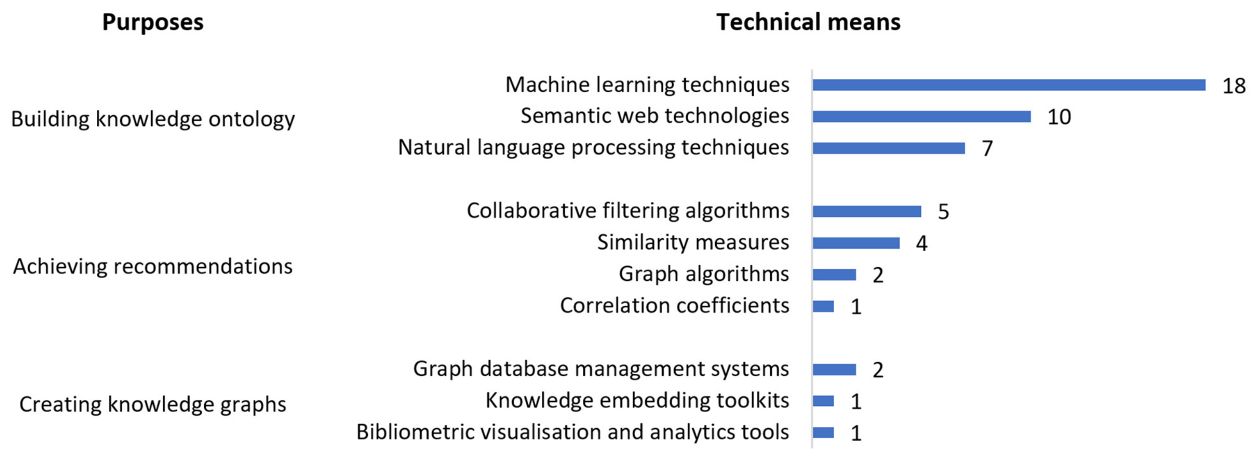

Figure 11. Types of technical means used for implementation of knowledge graph.

4.3.5. Types of Pedagogies

Figure 12 shows the pedagogies supported by knowledge graph approaches. The most frequent pedagogy was personalised learning, achieved through the recommendation of adequate learning activities or appropriate learning resources for students. This was followed by collaborative learning, where knowledge graph approaches were applied to improve group knowledge building. Problem-based learning was adopted in three studies. There were also a few types of pedagogy which were used only in one practice, such as networked learning, project-based learning, immersive learning, and cognitive learning.

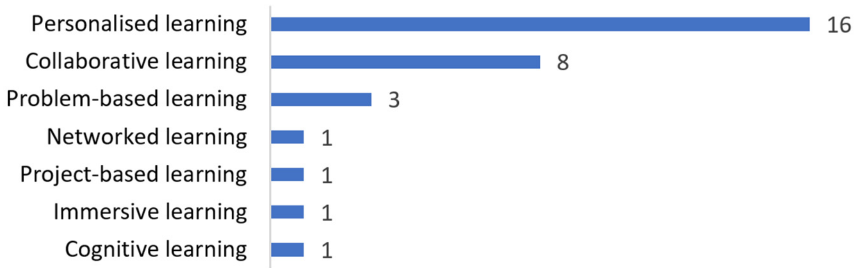

Figure 12. Types of pedagogies supported by knowledge graph approaches.

5. Discussion

The findings of this study illustrate the features of research and the application of knowledge graphs in education. They contribute to supplementing relevant work on knowledge graphs and revealing the current state of development in this area and future research needs.

The overall patterns of the publications covered in this study are consistent with those of related reviews [21,22,71]. They show a sharp increase in the amount of relevant work in recent years, and most of the work was contributed by institutions in China. The results reveal the rapid development in this area, particularly in China where knowledge graphs have been highlighted in its development plan [72]. The results also suggest a need for promoting inter-regional collaborations for exchanges relevant to the use of knowledge graphs in education among institutions across countries.

In terms of the research methods used in the studies, the results show the popularity of quantitative methods for testing the applicability, stability, and effectiveness of knowledge graph applications. Commonly used methods for evaluating the effectiveness of knowledge graph approaches in education include performance evaluations based on metrics, user experience surveys using questionnaires, and controlled experiments comparing traditional and proposed approaches. Qualitative data mainly include perceptions of students, teachers, and experts towards the knowledge graph approaches collected from interviews, focus groups, and open-ended questionnaires. Both the standardised evaluation metrics and user feedback serve as important data sources for assessing the effects of knowledge graph approaches on educational outcomes.

The findings regarding the education levels and subject disciplines suggest that knowledge graph approaches have been primarily implemented and researched in higher education institutions, with a focus on computer science, mathematics, and engineering. This is consistent with previous research that has highlighted the advantages of knowledge graphs in these fields [26]. Overall, the results indicate that knowledge graphs have been applied in a broadening spectrum of subject disciplines in recent years, and there is potential for further exploration of their use in various educational contexts.

The objectives of knowledge graph approaches addressed in the publications are intimately linked to their respective application categories. For example, the most common objective of enhancing knowledge representation is closely tied to the application category of concept instruction, which was the most frequent application. By structuring and interconnecting educational concepts, relationships, and resources into a coherent knowledge graph, these approaches aim to provide a comprehensive and intuitive representation of the subject matter, facilitating better understanding and learning for students. Similarly, the objective of providing personal learning recommendations is closely associated with the application category of educational recommendations, which was the second most common application category. Educational recommendation involves the use of knowledge graphs to suggest course resources, learning paths, or activities based on students' interests or characteristics, which can help personalise the learning experience and improve student engagement. From the instructor's perspective, the objective of supporting staff in organising learning resources and assisting with knowledge/course management is closely related to the application categories of knowledge management and curriculum design and management, which utilise knowledge graphs to organise and manage educational resources and facilitate course management. Overall, the findings regarding the objectives and application categories demonstrate that knowledge graph approaches have been primarily used to facilitate learners' cognitive processes and streamline educational management.

The diverse range of resources utilised in the studies highlights the adaptability of knowledge graphs in accommodating various types of data. As evidenced by the extensive coverage of online resources, the majority of relevant work was conducted within the context of online learning. This may be due to several factors. Firstly, online learning is often self-directed and personalised, with learners possessing distinct backgrounds, interests, and learning styles that require them to navigate and explore content independently. Knowledge graphs can provide a visual and interactive interface that enables learners to explore the relationships between concepts, uncover new information, and generate customised learning paths and recommendations based on learners' interactions with the system. Secondly, knowledge graphs are scalable and capable of handling vast amounts of data and intricate relationships, rendering them well suited for online learning, which frequently encompasses a broad range of subjects and domains.

A wide array of technical means were identified for the implementation of knowledge graph applications in education. The selection of these methods was based on various purposes covering building knowledge ontology, achieving learning recommendations, and creating knowledge graphs. Consistent with previous studies, machine learning algorithms have become increasingly popular for entity recognition, relation extraction, and concept linking [18], and collaborative filtering is a widely recognised method for providing recommendations [73]. Given the most frequently identified research prospect on the incorporation of novel techniques, approaches, and tools to enhance the effectiveness and functionality of the proposed model/system, it is expected that a greater variety of technical means will be employed in future work.

The findings also highlight the potential of knowledge graph approaches to support various pedagogies in education. Personalised learning, which prioritises students' autonomy and responsibility in directing their own learning, was effectively facilitated via knowledge graph applications, which served to meet the diverse needs of learners by providing them with tailored information such as learning resources and recommended courses. Knowledge graph approaches can also be commonly employed to support collaborative learning activities, such as group discussions, peer review, and knowledge sharing, by providing a structured and interconnected representation of course content.

Based on the results summarised in Table 1, four research limitations are commonly shown in the relevant studies on knowledge graphs in education. Firstly, there is insufficient information on the knowledge graph construction process and methods, making it challenging to replicate or adapt proposed solutions to specific contexts or domains. Secondly, there is difficulty in applying the knowledge graph approaches to other subject areas. As educational domains vary in terms of aspects such as content, structure, pedagogical approaches, and learning objectives, the techniques and strategies employed in constructing knowledge graphs and extracting relevant information may be influenced by the unique characteristics and requirements of a specific domain. Additionally, there is a restricted scale and scope of the resources utilised for knowledge graphs. The data sources are often confined to particular subject areas, educational levels, or institutions, limiting the generalisability of the resulting knowledge graphs. Moreover, many studies focus primarily on factual knowledge, overlooking other essential aspects of education such as pedagogical strategies or learner profiles. Lastly, there is a lack of comprehensive user feedback and evaluation processes. User feedback is crucial for assessing the actual impact and usefulness of knowledge graph-based solutions from the perspectives of educators, learners, and other stakeholders. Conducting iterative feedback cycles is essential for refining and improving the solutions, ensuring they effectively address diverse educational requirements. These limitations should be addressed in future research to enhance the development and application of knowledge graphs in education.

6. Conclusions

This study surveyed the publications on knowledge graph in education and synthesised the features of relevant research and practice. It contributes to providing an overview of the development in this area and offering insights into the potential of knowledge graph approaches to support various pedagogies in education, as well as the prospects for future research in this field. The findings address the research questions of this study:

RQ1: What are the patterns of publications on knowledge graphs in education? The publication patterns show a rapid increase in recent years, indicating a growing interest in this area. China is the primary contributor, followed by the United States. Quantitative methods, particularly performance evaluation metrics, are most commonly used, while qualitative and mixed methods are less prevalent. This suggests that more inter-institutional and inter-regional studies, as well as qualitative approaches, could be explored.

RQ2: What are the educational contexts of knowledge graph applications? Knowledge graph applications are primarily focused on tertiary education, with less emphasis on the secondary and primary levels. They have been applied across various disciplines, with computer science, mathematics, and engineering being the most common. There is potential for further exploration of the use of knowledge graph in various educational contexts.

RQ3: What are the objectives, application categories, data sources, technical means, and pedagogical issues for knowledge graph approaches and applications in education? The most frequently addressed objectives include enhancing knowledge representation and providing personal learning recommendations. The common applications are concept instruction and educational recommendations. Diverse data sources, such as course materials, student learning behaviours, and online encyclopaedia, are used in different scenarios. Technical means are employed to deal with the purposes of building knowledge ontology, achieving recommendations, and creating knowledge graphs. Various pedagogies such as personalised learning and collaborative learning are supported by the knowledge graph approaches.

The findings of this study also highlight the prospects for future work, including incorporating novel techniques and tools, applying knowledge graphs to other domains, and expanding data sources to enhance coverage. Addressing the limitations of the present study, such as the small sample size and strict inclusion criteria, is essential. Future reviews could expand the search to capture a broader range of publications. Moreover, as this survey only examined the use of knowledge graphs in education, future research could also cover the work on non-educational knowledge graphs in order to examine the similarities and differences between the knowledge graph in the two aspects, as well as the methodologies and techniques from non-educational knowledge graph which could be used in the educational aspect.

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