Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 8, 1464-1497
2025
Publisher: Learning Gate
DOI: 10.55214/2576-8484.v9i8.9644

Knowledge graphs for domain-specific teaching and learning - a systematic review of the construction models and evaluation methods

Akinyinka Tosin Akindele[1]*, Sunday O. Ojo[2]
[1,2]Department of Information Technology, Faculty of Accounting and Informatics, Durban University of Technology, Durban 4001, South Africa; 22290481@dut4life.ac.za (A.T.A.) sundayo1@dut.ac.za (S.O.O.).

Abstract: Knowledge Graphs are structured representations of knowledge that capture concepts and their relationships, facilitating informed decision-making, enhancing efficiency, and enriching learning experiences across various educational contexts. Although interest in Knowledge Graphs (KGs) for teaching and learning (T&L) is increasing, systematic reviews of the latest models, baseline comparisons, and evaluation methods remain limited. This systematic literature review (SLR) aims to address this gap by analyzing the underlying models, baseline algorithms, and evaluation techniques used in the field. Following PRISMA guidelines, a comprehensive search was conducted across five major databases—Scopus, Web of Science, ScienceDirect, ACM Digital Library, and IEEE Xplore—resulting in the identification of 34 relevant articles published between 2018 and 2024. These articles focus on domain-specific KGs applied explicitly to T&L activities. The applications of KGs are categorized into three main areas: Recommendation and Personalized Learning, Concept Mapping and Knowledge Organization, and Information Retrieval and Question Answering. The synthesis of results indicates that deep learning models—particularly BERT and its variants, BiLSTM, and Conditional Random Fields (CRF)—are predominant in knowledge extraction processes. Additionally, Knowledge Graph Embedding (KGE) techniques and Graph Neural Networks (GNNs), such as Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs), are extensively utilized. The review also highlights several limitations, including data scarcity, issues with generalizability, and a lack of standardization. To advance the development of educational KGs, future research should focus on automated data extraction from heterogeneous sources, standardized approaches for entity extraction, consistent evaluation and benchmarking methods, improved interoperability and scalability, as well as enhanced explainability and privacy-preserving techniques.
Keywords: *Deep learning, Education, Graph neural network, Knowledge graph, Ontology.*

1. Introduction

The last decade has witnessed an increased interest in Knowledge Graph (KG) research and its applications across various fields. A Knowledge Graph is a structured representation of knowledge that delineates and maps concepts or terms and their interrelations within a specific subject domain through graphs [1] It represents real-world data, aiming to capture the relationships between the entities of the data via a graph. In a knowledge graph, the entities are represented as nodes while the relationship between them is represented as edges linking one node with another. As such, KG can be viewed as a graph-structured data model used to store and manage linked data while outlining the semantics of the relationships between data entities. [2]. Figure 1a depicts a generic structure of a KG, and an instance of a KG is illustrated in Figure 1b, depicting the structure of nodes and the relationship between the terms. A Knowledge Graph can be represented mathematically as:

History: Received: 18 June 2025; Revised: 5 August 2025; Accepted: 8 August 2025; Published: 25 August 2025
* Correspondence: 22290481@dut4life.ac.za

$$G = (V, E, R)$$

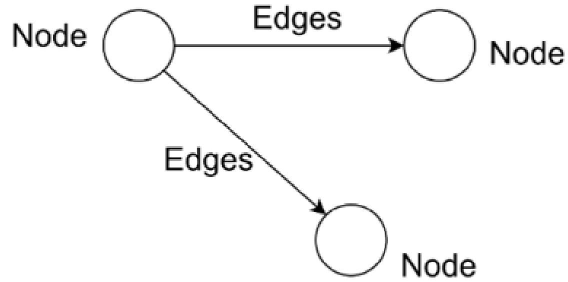

Figure 1a.
Node and Edges.
Note: Where: G: Knowledge Graph.
V: Set of vertices (entities, concepts).
E: Set of edges (relationships).
R: Set of relationship types (labels).

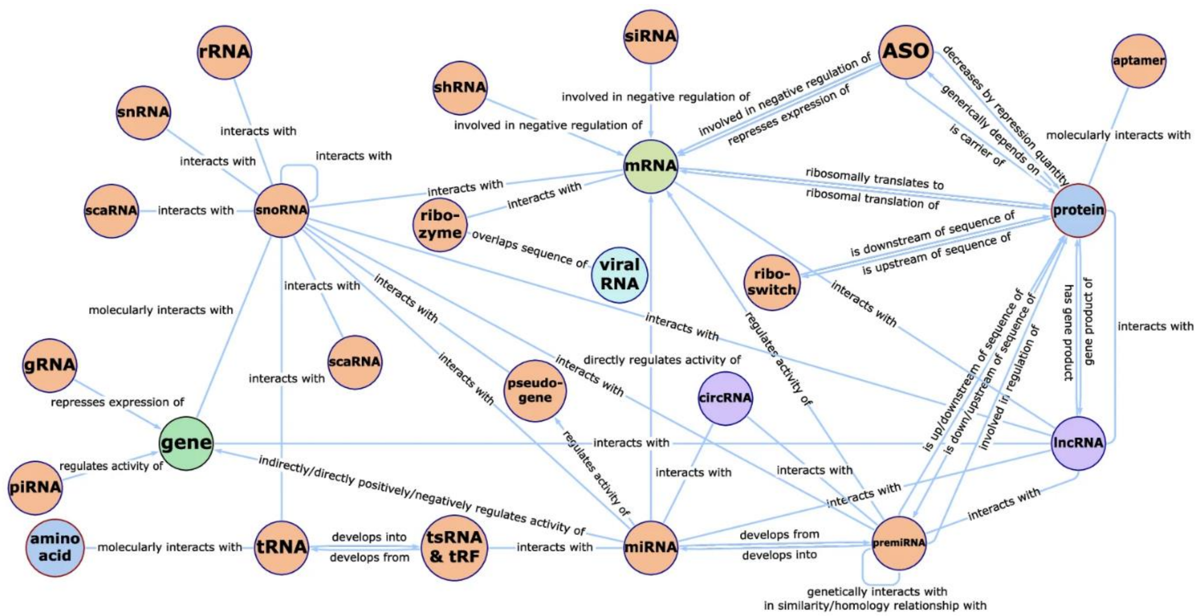

Figure 1b.
KG depicting concepts and relationships between RNA molecules [3].

Knowledge Graphs are practical tools for structuring and representing knowledge in a machine-readable format, establishing it as a significant technology within the Semantic Web[4]. Knowledge Graphs (KGs) have emerged as a transformative technology, revolutionizing several sectors and disciplines by facilitating informed decision-making, fostering innovation, and improving efficiency in synthesizing and contextualizing diverse data. For example, knowledge graphs have been used in the healthcare sector for disease diagnosis, health risk prediction, treatment recommendations, and personalized medicine [5-7]. In finance, KGs facilitate intelligent audit risk management, compliance monitoring, investment analysis, and credit scoring [8, 9]. KGs also enable data-informed policy formulation and crisis management in the governmental and public sectors [10], as well as providing

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 8: 1464-1497, 2025
DOI: 10.55214/2576-8484.v9i8.9644

public service information, and open data governance [10-12] . In Cybersecurity, KG has proven helpful for improving threat detection, vulnerability assessment, and access management [13, 14]. Knowledge Graphs are also utilized in media and entertainment for content recommendations [15] ; retail and e-commerce for customer profiling and product recommendation [16]; transportation for route prediction, route optimization, and traffic management, amongst others [17, 18].

Within the field of education, KG has been utilized for diverse tasks such as teaching and learning, administration, analytics, and other aspects of education. Notable KGs for teaching and learning include KG for precision teaching based on personalized or adaptive learning [19] Intelligent tutoring systems [20, 21] question-answering [22-24] information retrie [25] curriculum design and management, and recommendation systems in which KGs suggest learning paths [26] reskilling and upskilling options [27] but primarily for recommending relevant resources such as videos, articles, and podcasts for teachers and students [28]. Likewise, in the areas of assessment and learners' evaluation, KGs have been used to generate self-tutorials [29] and practice questions from the course resources [30]. In addition, KG has been utilized for data mining and learning analytics, offering insights into student performance, predicting grades, and identifying improvement areas. However, these applications are not explicitly tied to teaching and learning. Other non-explicit applications of KG vary, including educational administration, such as resource and course allocation [31] research-related activities such as cross-language plagiarism detection [32] literature review automation [33] related literature visualization, amongst others.

Some reviews and survey studies have been done on different aspects of KG for education, such as systematic reviews [34-37] and surveys by Abu-Salih [38] and Qu, et al. [39]. While these studies have provided valuable insights into the applications and limitations of KGs in education, they have largely overlooked the underlying models and baselines used in different phases of KG development. Notably, [37] highlighted the variability in models used by researchers in KG development and proposed an overall process for KG development, a comprehensive examination of the diverse models remains largely unexplored. This gap hinders the advancement of KG research, as developers may waste time exploring inefficient models and approaches. This Systematic Literature Review (SLR) addresses this issue by concisely analyzing state-of-the-art construction models, baseline approaches for comparison, and evaluation methods used in KG development.

The rest of this article is structured as follows: Section 2 covers the methodology behind this SLR, including the databases searched, keywords utilized, and the inclusivity and exclusivity criteria applied. In section 3, an overview of the architecture of a Knowledge Graph is presented, establishing a foundational understanding of the subject. The results of the SLR are presented in Section 4, a synthesis of the various applications of KGs in teaching and learning contexts with particular emphasis placed on the domains represented, the construction and baseline methods employed, and the limitations identified. A tabular summary of the reviewed literature within the respective use cases accompanies each of the identified teaching and learning application categories. Section 5 presents a summary and classification of different methods and construction models considered to be state-of-the-art in KG development. Section 6 critically examines the limitations inherent in each study, highlighting the corresponding research gaps and open issues in KG development. Finally, section 7 proposes directions and recommendations for future KG research development, which may address the identified gaps and limitations.

2. Methods

The applications of KG in education go beyond teaching and learning; it also includes its use for education administration, data analytics, research development, process or event scheduling, and other areas that require decision-making. This study exclusively considered KGs utilized primarily or explicitly for teaching and learning activities. We examined the architecture of these KGs in terms of the knowledge domain, data models, construction and baseline models, evaluation methods, and respective specific purposes. With an increasing body of scholarly work on Knowledge Graphs, it was observed that a significant number of KG articles are devoid of adequate documentation regarding specific methods and elements of the KG's architecture, such as the models, frameworks, and tools utilized in the design and deployment of Knowledge Graphs. Thus, the motivation behind this SLR effort is to comprehensively synthesize the different methods used to design KGs, from the initial stage of knowledge acquisition to the evaluation of the KG-specific purposes. Overall, this SLR aims to present the state-of-the-art models utilized in KG construction methods and the corresponding baseline approaches used to compare results in teaching and Learning. By identifying the most effective models employed in diverse research, this study aims to guide future researchers in selecting the optimal models for their KG development while avoiding wasting time and resources.

This SLR focuses on articles published within the past seven years (2018–2024) to ensure relevance and currency. The review adheres to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework for guidance. To assemble the initial set of articles, on 7th September, 2024, an extensive search was conducted across five (5) databases: Scopus, Web of Science, Science Direct, ACM Digital Library, and IEEE Xplore Digital Library. Scholar. The search was limited to English-language articles and employed this set of keywords in the database query: Knowledge Graph AND "Domain-Specific" OR Subject OR Course AND "Teaching OR Learning OR Training". Amidst several applications of KG within the educational setting, we focused on KGs with specific domains or subject domains utilized for explicit teaching and learning (T&L). As such, KGs designed for academic data analysis, results predictions, and other administrative tasks were exempted.

The review articles were categorized based on their specific applications for explicit T&L, and each of the selected articles was examined through the lens of four key areas: Coverage and Source, Construction Methods, Evaluation Methods, and Limitations. Each of these Research Focus (RF) was examined by unique research questions that a prospective article must answer to be considered eligible; they serve as a reference point in result dissemination and discussion. The RFs and their respective questions that guided this systematic review are presented below.

RF1: Coverage and Sources

i. What specific knowledge domains, especially the subjects or courses, were primarily targeted in knowledge graph construction, and at which level of education?
ii. What datasets were utilized in the KGC, and the sources of the datasets

RF2: Construction Methods

i. What design approaches were employed, and was the design of the KG automatic, semi-automatic, or manual?
ii. Which models or frameworks were used in the Entity Recognition (ER), Entity Extraction (EE), and Knowledge embedding (KE) phases of the knowledge graph construction, and how practical are these approaches in capturing complex relationships?

RF3: Evaluation Methods

i. Which evaluation methods and metrics have been used to assess the performance of knowledge graphs at each phase of the KGC?

RF4: Limitations

i. What were the limitations encountered when the authors tested the effectiveness of the KG applications in real-world scenarios?

Figure 2 illustrates the article selection procedure using the PRISMA framework. Initially, through the keyword-based search, 232 articles were identified from the Web of Science database, 182 from Scopus, 157 from ACM, 136 from IEEE, and 51 from Science Direct, aggregating 762 articles from databases. A screening phase was executed to eliminate superfluous or irrelevant articles. The title and abstract of each paper were scrutinized to verify adherence to the inclusion criteria. Consequently, 321 records were omitted at this phase. Several papers predominantly discussed KG embeddings about established KGs rather than concentrating on developing and utilizing educational KGs. Several authors examined the development of knowledge graphs in domains beyond education while referencing education as a pertinent instance of knowledge graphs used in industrial settings. Following the screening process, an eligibility evaluation was performed by an exhaustive examination of the entire text of the surviving articles. This action led to the elimination of 124 records that did not satisfy the specified criteria. In the final stage of the systematic literature assessment, 91 papers were determined as eligible for inclusion in this comprehensive analysis of knowledge graph construction in the educational domain

3. Architecture of a Knowledge Graph

The architecture of a Knowledge Graph (KG) denotes the conceptual, logical, and physical framework that underlies the design, construction, and deployment of a KG. It encompasses the structural organization, schema, and ontologies governing the representation, integration, and management of heterogeneous knowledge sources and the interfaces, protocols, and APIs facilitating access, querying, and reasoning over the KG's knowledge assets. The architecture of a KG, depicted in Figure 3, is complex and multi-layered. Still, overall, it provides a blueprint for how the KG's knowledge is represented, integrated, stored, managed, and queried, enabling various applications of the KG.[40-42].

The foundation of a KG is the data layer. This layer aggregates diverse raw data formats from various sources, including structured databases, semi-structured formats like XML or JSON, and unstructured sources like text documents. On top of the data layer lies the knowledge representation layer, also known as the ontology layer, which defines the structural framework of the KG. This layer establishes the schema, specifying entities, attributes, and the relationships between them, thus providing the blueprint for integrating disparate datasets. This layer also guides the unification process, ensuring that the KG presents a coherent and consistent view of the data. The next layer is the integration layer, which is responsible for harmonizing data from various sources. This layer resolves inconsistencies, duplicates, and conflicts that could have arisen during the integration process. Techniques such as Knowledge fusion and knowledge embedding are employed to ensure the consistency and accuracy of the KG. The integration layer creates a unified data view, enabling the KG to represent the targeted knowledge domain comprehensively and accurately.

The storage layer is responsible for storing or hosting the KG; Graph databases are typically used for this purpose. Graph databases are designed to efficiently query and traverse the graph's intricate connections, making them well-suited for the storage and management of KG. A query layer is required to interact with the knowledge graph, which provides mechanisms to retrieve knowledge by analyzing data from the KG. This layer supports query languages like SPARQL, GREMLIN, CYPHER, amongst others, enabling users to pose complex questions and extract meaningful insights from the graph's interconnected data. The query layer bridges the stored knowledge and its practical application. Finally, the application layer leverages the knowledge graph's capabilities for various use cases. From powering semantic search engines and recommendation systems to aiding in natural language understanding and decision support, this layer translates the graph's potential into tangible benefits for users.

3.1. KG Construction Processes and Phases

Knowledge Graphs can be developed using either top-down or bottom-up approaches [35, 43]. The top-down approach involves conceptualizing the domain and refining it into a detailed representation of entities and their relationships, aligning with W3C standards and meeting specific research needs. This process includes defining the subject domain, developing a conceptual model, creating logical and physical models, selecting appropriate programming languages, and deploying the knowledge graph as an application or service [43]. The ontology (or data schema) is defined first, and knowledge is extracted based on the ontology. The Bottom-Up approach leverages existing data sources like literature and crowd-sourced information to create the KG. This method effectively analyzes large volumes of unstructured or semi-structured data, revealing patterns and relationships that may not be immediately apparent through traditional methods. As such, the KG reflects the complexities of the

DOI: 10.55214/2576-8484.v9i8.9644

domain being represented [35, 43]. Some research works, such as those reported byHu, et al. [44] and Zhang, et al. [45] combined both top-down and bottom-up strategies for ontology mapping, leveraging the strengths of both approaches.

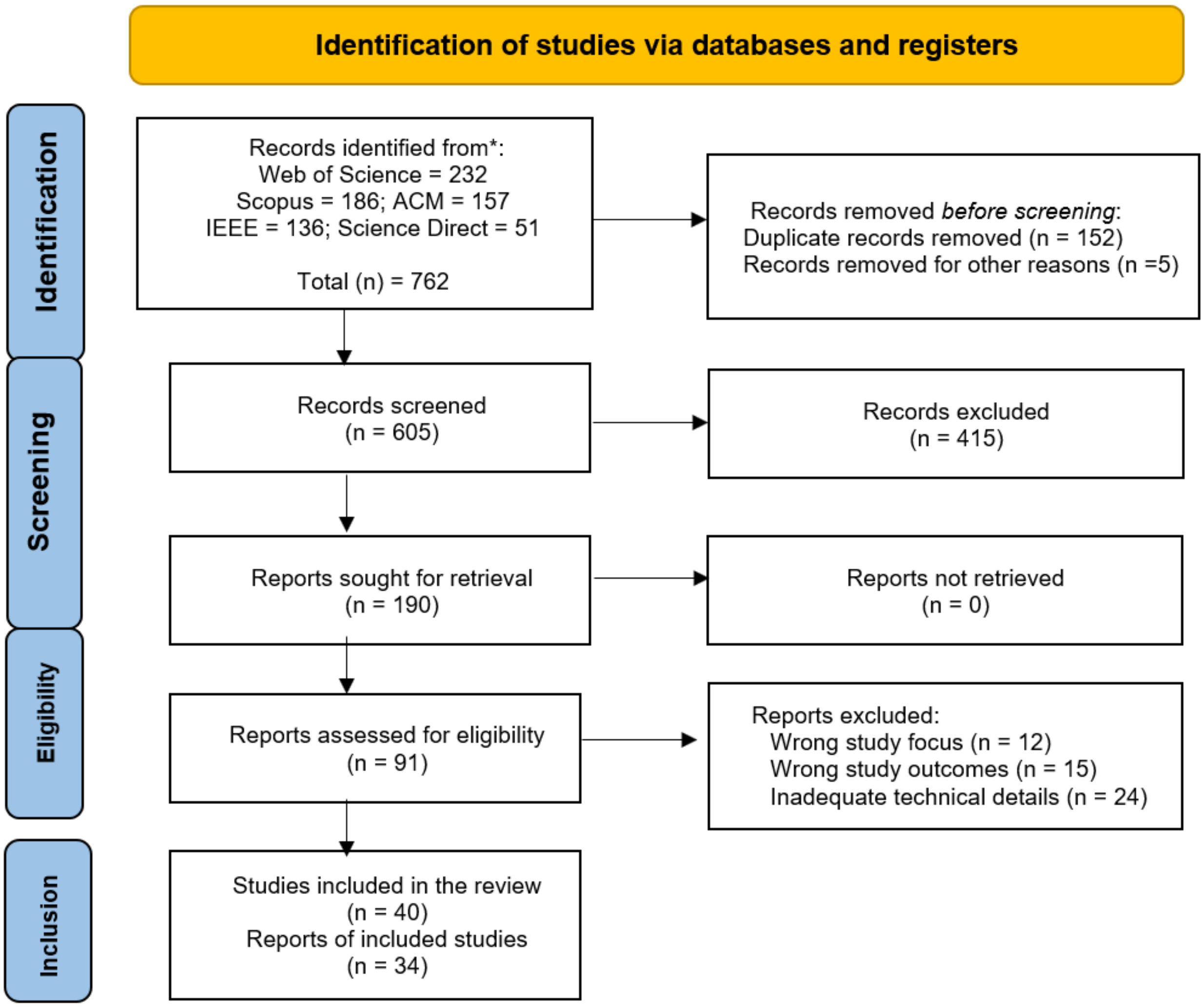

Figure 2.
SLR paper screening and selection using the PRISMA model Page, et al. [46].

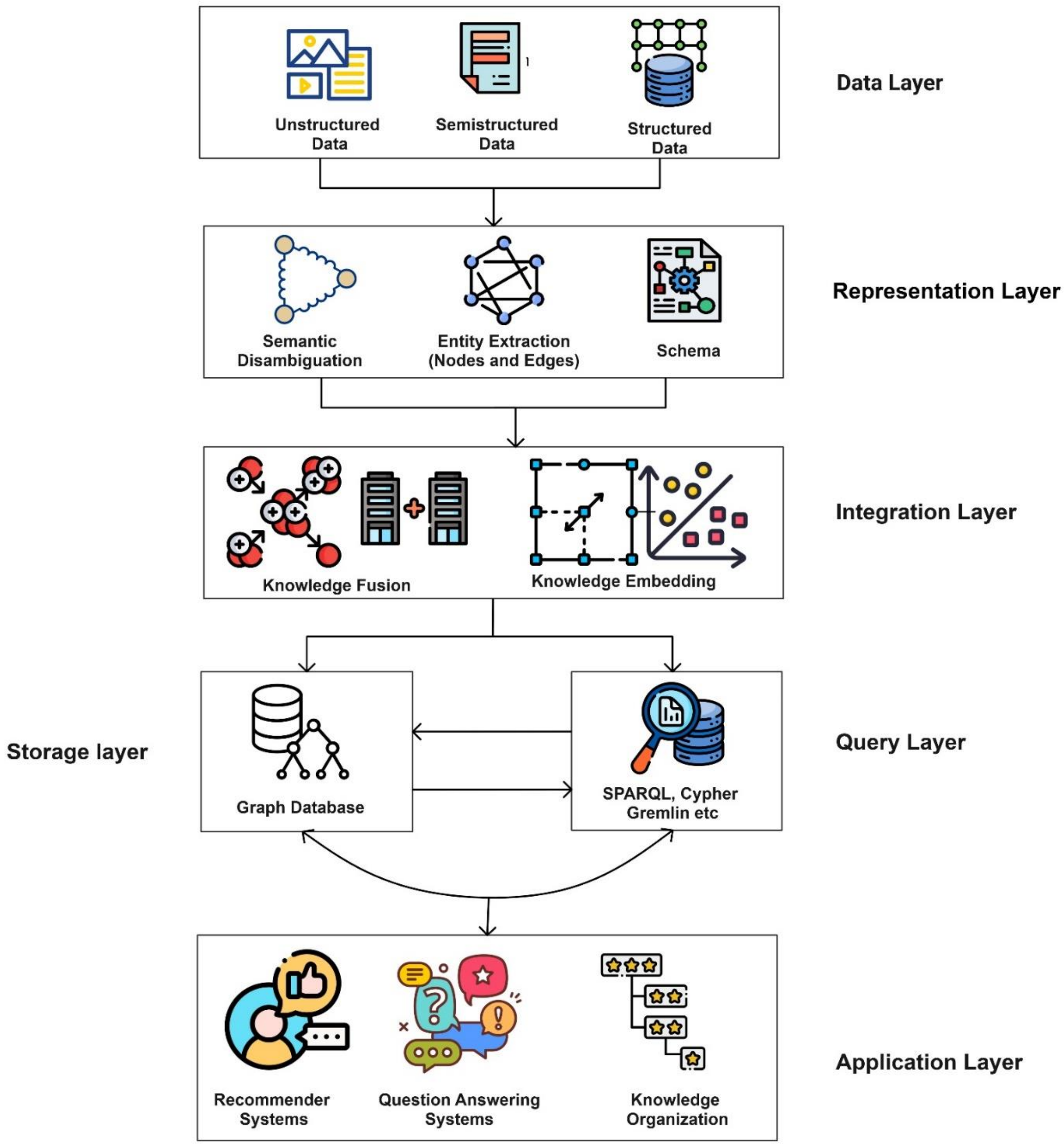

Figure 3.
Multilayer Architecture of KG.

Aside from a KG top-down, bottom-up, or hybrid development approach, the architecture of a KG also encompasses the models or algorithms behind each step of the construction methods and corresponding models. The choice of the model is dependent on the methodology behind the design and development. Details on the state-of-the-art construction models are summarized in Section 5. However, regardless of the method behind the construction of a Knowledge Graph (KG), the phases or stages, summarized in Table 1, include the Planning and Design phase, followed by Data or Knowledge Acquisition, then Entity Recognition and Extraction, Relation and Attributes Extraction, Knowledge Embedding and Fusion. The KG is then validated, and the quality is checked for refinement. Finally, the KG is deployed, maintained, and updated regularly. Each phase of KG development has multiple steps or tasks, and the specific activities will vary depending on the KG construction project's scope, goals, and methodology.

4. Results

This section summarizes the identified Knowledge Graphs used for teaching and learning, the classification of their specific purposes, the architecture, evaluation methods, and limitations. In the context of KG use in Teaching and Learning, seven primary pedagogical tasks were identified for which KGs are utilized: Recommendations, Question Answering, Semantic Search, Information Extraction, Adaptive Learning, Precision Teaching, and Concept Mapping. The specific meaning or purpose of each teaching and learning task is summarized in Table 2, while the mind map and distributions are illustrated in Figure 4 and Figure 5, respectively.

Table 1.
Phases of KG Construction with the respective actions and deliverables.

S/N	Phases	Actions and Deliverables
1.	Planning and Design	Define the scope and goals of the KG Identify the target audience and use cases Determine the relevant domains and entities to be included Establish a data model and governance framework for the KG
2.	Data Acquisition and Integration	Identify and collect relevant data sources (e.g., databases, files, web pages) Integrate data from multiple sources into a unified format Handle data quality issues (e.g., duplicates, missing values) Transform and normalize data into a suitable format for the KG
3.	Entity Recognition and Disambiguation	Identify and extract the required entities from the collected data Disambiguate entities with similar names or identifiers Assign unique identifiers to each entity Create entity profiles with relevant attributes and relationships
4.	Relation, Attributes Extraction and Modeling	Extract relationships between entities from the collected data Model relationships using ontologies, taxonomies, or other frameworks Define relationship types and properties (e.g., symmetric, transitive, hierarchical) Create relationship instances between entities
5.	Knowledge Embedding and Fusion	Create a graph data structure to represent the entities and relationships as numerical vectors in a high-dimensional space. Use graph algorithms to optimize the graph structure and reduce complexity Perform graph-based reasoning and inference to derive new knowledge
6.	Validation and Quality Assurance	Perform data quality checks and handle errors or inconsistencies Evaluate the KG against relevant metrics and benchmarks Refine and update the KG based on feedback and evaluation results
7.	Deployment and Maintenance	Deploy the KG in a suitable environment (e.g., database, file system, cloud) Develop real-world applications and interfaces to interact with the KG Monitor and maintain the KG to ensure data freshness and accuracy Update the KG with new data and knowledge sources as needed
8.	Evaluation and Refining	Continuously evaluate the KG against relevant metrics and benchmark Define and update the KG based on feedback and evaluation results Identify areas for improvement and optimize the KG accordingly Explore new use cases and applications for the KG

Table 2.
Teaching and Learning Tasks and their respective meaning

T&L Tasks	Meaning or Specific Usage
Recommendations	To provide individualized recommendations, such as resources, curriculum, or paths of instruction to learners based on their unique profiles
Question Answering	Allows learners to ask questions and access the precise and relevant answers to the inquiries.
Semantic Search	It is a search through provided instructions utilizing search queries' understanding, meaning, and context rather than just matching keywords.
Information Extraction	To automatically extract relevant information from unstructured or semi-structured learning materials.

Upon meticulous examination of the identified T&L tasks, employing human cognizance and AI tools such as meta-AI, considerable parallels and overlaps were identified, and this served as a basis for the reclassification of identified teaching and learning tasks. Both Precision Teaching and Recommendation entail customizing educational experiences to meet the specific needs of individual students, rendering them compatible for integration. Adaptive systems represent a personalized learning methodology, warranting their classification within the same category. Similarly, Information Retrieval, Semantic Search, and Question Answering entail extracting and providing pertinent information to facilitate learning, rendering them appropriate for integration in these tasks. As such, the identified KGs were reclassified into three categories:

i. KG for Recommendation and Personalized Learning: This category integrates precision teaching and learning, recommendation systems, and adaptive technologies. Knowledge graphs in this category help tailor learning experiences to individual students' needs.
ii. KG for Concept Mapping and Knowledge Organization: This category focuses on concept mapping and knowledge organization, which includes the use of KG to generate
iii. taxonomies and ontologies and for concept clustering, all of which can be used to support learning, teaching, and knowledge management.
iv. KG for Question Answering and Information Retrieval: This category merges information extraction, question answering, and semantic search or information retrieval. Knowledge graphs in this category facilitate the retrieval and provision of relevant information to support learning

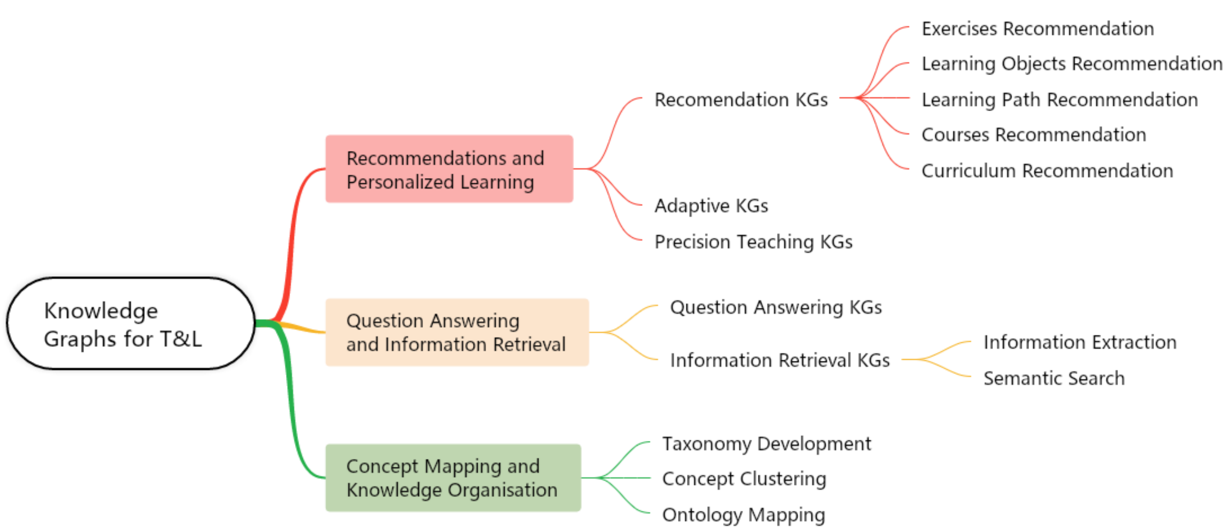

Figure 4.
A mind map of KG for T&L pedagogical tasks

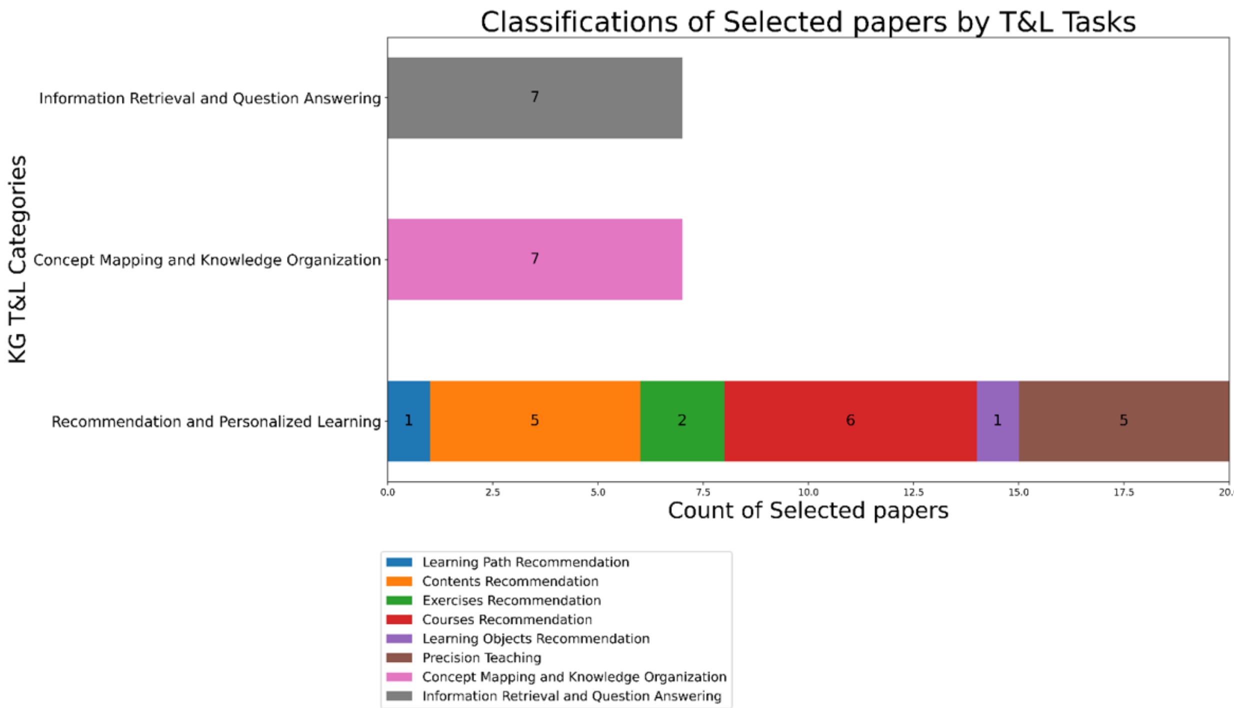

Figure 5.
Distributions of T&L pedagogical tasks of Selected Papers.

4.1. KG for Recommendation and Personalised Learning

A recommendation system is designed to facilitate the mining of user preferences by leveraging the semantic relationships and available contextual information to generate tailored, personalized, and relevant recommendations that meet the needs and interests of users [47]. A KG-based recommendation system uses a graph-based data model to capture entities and their relationships, algorithms such as Graph Neural Networks (GNN) or other Machine Learning techniques are used for the system to dynamically adapt to the evolving learning profiles of students to optimize and select educational resources that will suit users (learners or teachers) individual needs and preferences[13, 15, 48, 49]. The rich semantic information embedded within the KG allows the recommendation system to better understand the underlying factors influencing user decisions, thereby addressing issues of data sparsity, cold start problems, and incompleteness commonly encountered in traditional recommendation approaches while also capturing a more holistic view of a user's multifaceted preferences[50]. KGs can be used to represent various educational concepts, including learners, learning resources, knowledge components, learning pathways, and pedagogical strategies [19, 26, 29, 50, 51] This structured representation allows for the development of intelligent systems that can reason about learning processes, tailor content recommendations, and provide personalized feedback [53]. Likewise, the paths within a recommender KG that connect users to items can serve as explanatory mechanisms, elucidating the rationale behind specific recommendations and enhancing the interpretability of the recommendation process [26, 52] .

The SLR synthesis identifies several key applications of KGs relating to recommendation systems and personalized learning. Notable specific purposes of these KGs include Precision Teaching [19, 53-55] diverse forms of recommendations such as learning path recommendations [19], [26], course recommendations[30, 48, 51, 56, 57] exercise or assessment recommendations [53, 58], learning resources, and multimedia learning object recommendations [28, 59] amongst others, and Systems for Adaptive teaching and learning [60]. For instance, [19] designed CourseKG to enhance precision teaching by creating personalized learning paths. The study proposes a new framework that targets the shortcomings of current general-purpose knowledge graphs by combining a pre-trained BERT model [53]

Other notable KGs used in precision teaching are the works of [53-55] which are summarized in Table 3. Huang, et al. [55] propose WERECE, an unsupervised method that extracts educational entities based on word embedding refinement. WERECE incorporates a manifold learning algorithm to modify a pre-trained model for extracting educational concepts while considering the geometric information in the semantic computation. Using the EDU-DT and EDUTECH-DT datasets, the model performance was compared to 5 baseline alternative approaches - Text Rank, TF–IDF, Isolation Forest, K-means clustering, and one-class Support Vector Machine (SVM). WERECE outperformed these baselines with 85.9% precision, 87.0% recall, and 86.4% F1 score. Huang, et al. [55] credited WERECE's enhanced performance to the optimization of pre-trained word embeddings and the application of a discriminant function in their knowledge graph construction. However, the authors also acknowledged the limits of the KG design concerning the generalisability of the utilized corpora and the possibility of a mismatch between the extracted concepts and the specific domain semantics. Yuan et.al [53], developed a knowledge graph for higher mathematics knowledge extraction. This study employs a Graph Convolutional Network (GCN) and an Attention Mechanism (AM) to construct an entity recognition model. Attention-Guided Graph Convolutional Network (AGGCN) was utilized for relation extraction, and a Graph Convolutional Network (GCN) based model for text classification [54]. The authors contrasted the GCN model with different techniques used in prior similar research, such as BiLSTM-CRF. While the results indicated that GCN attained superior accuracy, recall, F1 score, and p-values relative to other models, the authors also recognized the constraints of the study, including the necessity for extensive labeled datasets for training and the difficulty of accurately encoding advanced mathematical knowledge as a precise graph structure [54].

In addition to the precision teaching from knowledge concept extracts, it is also possible to auto-generate assessments, such as quizzes, from a KG. This approach precisely conforms assessments to a specific resource made available to learners. The authors of Ma and Ma [53] introduced a framework for automatically generating questions from subtitles of video-based instructional content in Massive Open Online Courses (MOOCs). The framework extracts information from subtitles utilizing a knowledge graph and then uses a template-driven approach to formulate questions. The authors utilized the SimpleQuestions dataset, which comprises question-answer pairs derived from Freebase. The authors correlated Freebase with WIKIDATA and employed BLEU as the parameter for assessing question quality. Their proposed method attained a BLEU score of 0.48, surpassing baseline methods (0.40) and MP Triples TransE++ (0.46).

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 8: 1464-1497, 2025
DOI: 10.55214/2576-8484.v9i8.9644

Table 3.
Selected KG for Precision Teaching and Learning.

Ref.	KG Specific Purpose	Knowledge Domain/Subject	Dataset(s)	Nature of Data	KG Data Model	Construction model(s)	Baseline model(s)	Evaluation Metrics	Limitations
Weichselbraun, et al. [27]	To structure and integrate course data, establish a comprehensive curriculum knowledge system, and individualize learning paths.	Computer Science Domain C Programming	Digital Teaching Materials CourseGrading and Educoder	Unstructured Semi-structured and Structured	Ontology	N-LTP and Co-word Analysis BERT-BiGRU-MHSA-CRF Cosine Similarity	BERT-BiLSTM-CRF BERT-GRU-CR	Accuracy Precision, Recall, F1-Score	The study overly relies on textual data and neglects multi-modal data like videos and audio; the study used only the C programming courses dataset, which limits generalizability.
Aliyu, et al. [31]	To enhance the understanding of mathematical concepts, provide teachers with effective teaching strategies, and offer personalized feedback to their students.	Higher Mathematics	Mathematics textbooks & Network resources Baidu Encyclopedia	Unstructured	Ontology	GCN BiLSTM-CRF	AGGCN, AM, Word2vec HMM, CRF, BiLSTM, BERT-CRF and BERT softmax	Accuracy Precision, Recall, F1-Score P-Value	• Imbalanced and limited dataset size; • Existing word embeddings are not designed for the targeted use case • Lack of clear standards for relationships and knowledge points.
Sahlab, et al. [33]	For educational concept extraction & enhancing targeted instructions	Education MOOC	EDU-DT and EDUTECH DT Source - MOOCCube	Unstructured	NA	K-means Clustering, Manifold Learning Distance-based Discriminant Function	TF-IDF; TextRank K-Means Clustering Isolation Forest and One Class SVM	Precision, Recall, F1-Score	• Lack of gold-standard datasets • Imbalanced distribution of samples • Sensitivity to sample distribution and generalizability issues.
Abu-Salih and Alotaibi [34]	Extracts pertinent facts from video subtitles for the automatic generation of quiz questions	MOOC	SimpleQuestions and an unnamed MOOC video from xuetangX Wikidata	Unstructured	NA	MediaWiki API TF-IDF	MP Tripples TransE++ RNN	BLEU	• The BLEU score may not accurately reflect task performance • A limited number of questions are generated due to the training set's inadequate relationships

Course Recommendation: Research has shown that students sometimes struggle to choose a course, especially in online MOOC platforms, where there are too many courses to pick from; students may find it overwhelming to select the most appropriate to their learning styles, goals, and interests [61]. A course recommendation system helps to mitigate this problem by recommending courses to learners based on their demographics, preferences, and goals. The study by Ma, et al. [30] proposed the SRACR method, which considers the semantics of courses and their relationships. In the study, authors use Latent Dirichlet Allocation (LDA) to extract fine-grained semantics of each course as a topic vector, mapped course relationships into a course knowledge vector using the TransE knowledge embedding method and with Linear Upper Confidence Bound (LinUCB), combined both course topic and knowledge vectors into a feature vector. The KG design contextually estimated student preference and balanced exploration and exploitation during recommendation.

Another KG on course recommendation is the KG-based data repository for career goal-based course recommendations developed by Nguyen, et al. [56]. This study focused on IT careers and employed a Labelled Property Graph (LPG), with three major concept layers. There is a layer for the course, a layer for the career, and another for competency. The models employed are Deep Learning models (Bi-LSTM + CRF, BERT, XLNET) to extract entities and handle data duplication. The KG was implemented using Neo4j to store it. Sometimes, a course recommendation needs improvement. Authors of [52] used Reinforcement Learning with an MOOC KG to generate explainable course recommendation paths. The study approach to the KG design is to formalize the course recommendation problem as a Markov Decision Process (MDP). Using Reinforcement learning, user interaction with the KG was simulated to generate an interpretable course recommendation path. The authors compared the results of this approach to other baseline methods such as User-based Collaborative Filtering (U-CF) and Deep Q-Network (DQN) to estimate the performances of each approach based on the Normalized Discounted Cumulative Gain (NDCG) that evaluates the ranking of recommended courses and Hit Rate (HR) to measure the percentage of recommendations that match user's interests.

Ma, et al. [62] proposed Contrastive Learning and Graph Convolution Network-based Attentive Decay Network (CLGADN) to help improve course recommendation fairness by considering the learner's knowledge background and mitigating popularity bias. Their research used a Graph Convolution Network to capture learners' knowledge backgrounds, while the Monotonic Attention Decay Mechanism accounts for the knowledge forgetting curve. The performance evaluation metrics - Precision, Recall, and F1 score of CLGADN are higher in comparison to models that used MLP, NeuMF, Wide & Deep, DIN, BST, KGAT, HG-GNN, HRL, and GADN.Nguyen, et al. [56]. In another study method, the KSCR - Knowledge-aware Sequence modelling for Course Recommendation was introduced Deng, et al. [48] the technique incorporates heterogeneous course information and employs BiLSTM and CNN to capture point-wise and collective sequential dependency in sequence modelling. Knowledge Embedding method TransD was used to obtain course representation vectors, and an MLP to predict the probability of a user learning a candidate course. More studies on KG for course recommendations employ varied approaches for incorporating KGs into course recommendation systems. While some prioritize recommendation accuracy, others focus on fairness and explainability. Each study leverages different KG construction methods, modelling techniques, and evaluation strategies, which are summarized in Table 4.

Exercise Recommendation: Another form of recommendation is exercises or assessment recommendations. For instance, KG4Ex is an exercise recommendation KG employed to match students with suitable exercises and provides clear explanations for the recommendations [58]. KG4Ex knowledge graph comprises three key entities - students, knowledge concepts, and exercise nodes, and their interrelationships, enabling personalized exercise recommendations and detailed explanations of the reasoning behind those recommendations. The study experimented with KG embedding models, TransE, TransE-adv, and RotatE, to acquire entity and relationship embeddings, alongside traditional Collaborative Filtering recommendation approaches - EB-CF, SB-CF, KGEB-CF; Content-Based

Filtering (CBF) and Hybrid Recommendation Model (HB-DeepCF). Three authentic datasets (ASSISTments 2009, Algebra 2005, and Statics 2011) were used to train and test the proposed method, and the results indicated KG4Ex's efficacy and interpretability, attaining performance on par while offering an explicit rationale for recommendations [58].

With KGs, recommendations of exercises could be customized and linked to a specific area of educational content. The study conducted by Li, et al. [63] examined the efficacy of KGs for linking exercises to educational content using Cosine Similarity. The research sought to autonomously associate digital textbooks in Swedish across three distinct subjects and two categories of exercises (quizzes and study questions) with pertinent information utilizing embeddings derived from pre-trained language models. The research employed ConceptNet Numberbatch KG embeddings with contextual embeddings from SBERT and ADA-002 (a substantial language model) in various ensembles. The findings demonstrated that employing contextual embeddings from ADA-002 yielded enhanced performance in Recall@3 and MRR, surpassing other models and ensembles [63].

Multimedia Learning Objects Recommendations: Teaching and Learning Resources, including Multimedia Learning Objects (MLO), Documents, or any other forms of resources, could be recommended with KGs. In an extended abstract by Zhu, et al. [59] the authors proposed using an Attentive Composition-based Graph Convolutional Network (ACGCN) model to enhance the recommendation process for learning objects. In the study, the ACGCN model has three layers, the first being the heterogeneous educational graph that categorizes entities into three types: learners, learning objects (LO), and other supplemental entities (such as schools, teachers, and concepts). The second layer is responsible for updating and maintaining the KG, while the third is the recommendation layer. Inspired by existing models like CompGCN, ACGCN employs an attention mechanism-optimized Composition-Based Graph Convolutional Networks, to encode representations of entities and relations. The authors experimented with the model with MOOCCube datasets and achieved an accuracy of 84.42% and an F1 score of 84.55%, which was higher by 1.4% and 1.3%, respectively, when compared to the existing baseline models (CompGCN, HAKE, ROtatE, TukER, DeepFM, Wide&Deep, DCN, and TENTF). Another resource recommender KG is the works of Liang, et al. [50] which utilized Deep Learning methods, specifically Graph Convolution Networks (GCN) and Reinforcement Learning techniques. In addition to GCN and RL, the model that the authors termed the Multi-path Enhanced User-centric Recommendation (MEUR) model incorporated Multipath fusion, reasoning path templates, and user ser-centric search strategy to improve reasoning accuracy [50]. Sometimes, recommendations might be linked to content and specific areas within the content [63]. Beyond the afore-mentioned subcategories of KG-based recommender systems, other forms of recommendations are reported in Table 4.

4.2. KG for Concept Mapping and Knowledge Organization: Knowledge Graph

A Concept Map (CM) is a diagram that illustrates the relationships between interconnected ideas, predominantly consisting of shapes representing ideas and interconnected lines that denote the relationships between the ideas. Concept Maps, Mind Maps (MM), and Knowledge Graphs are often confused; however, there are essential differences in their structure, information hierarchy, and practical uses. With several overlaps in the structures, Knowledge Graphs can be used to generate concept maps autonomously [64], mind maps [65] Concept clusters and ontologies of specific knowledge domains. Concept maps function as effective instruments for learning, teaching, and assessment, facilitating the integration of complex concepts [66]. Concept Clusters (CC) are closely related to concept maps, in which groups of related concepts, ideas, or keywords that share common characteristics, themes, or meanings form clusters. While concept maps emphasize the relationships between concepts, highlighting the context and meaning of each idea, concept clusters identify patterns, themes, and relationships within a set of concepts, grouping the concepts into clusters. The KG presented by Chen, et al. [67] and Huang, et al. [68] proposed to extract instructional concepts and relationships from different data sources automatically. For the instructional concept extraction, [68] applied Neural network-based sequence labeling models, specifically GRU and LSTM, to well-curated pedagogical resources such as curriculum standards, textbooks, and course tutorials.

The authors chose these models as they capture dependencies in sequential data well. The results were compared with CRF, and the authors reported that neural networks outperform the traditional CRF method. On the other hand,[69] employed a rule-based NER to extract the course concepts from course outlines, and POS tagging was performed using the Language Technology Platform (LTP) designed for Chinese texts. In the study, authors also utilized course video captions as part of the data sources; however, the extraction of video captions, the NNGP approach, which integrates neural networks and graph propagation, was used. The approach's efficacy was compared with the confidence propagation algorithm, resulting in a 10% enhancement in accuracy.

KG is also used for knowledge organizations, especially when several hierarchical entities are involved. Zhang et al.'s work is a typical example [28] which focuses on course clustering and uses KG to represent the relationships between faculties, majors, courses, and knowledge points. The study seeks to effectively group courses based on their knowledge points, thereby addressing issues such as the repetition of knowledge points and the illogical sequencing of courses. For the construction of the KG, the authors employed TF-IDF to create the courses' feature vectors, which were derived from the knowledge points, and then a K-means clustering algorithm was used to group the courses. The authors evaluated the clustering quality using the Silhouette Coefficient, which measures the tightness within the course clusters and the separation between them to determine the optimal clusters [28].

Sometimes, concept mapping is not the only feature incorporated in such KG-based applications; it could also be designed such that concept-level representations are linked to instructional resources [70] or with visualization capability for visualizing knowledge while managing learning resources, which facilitates efficient learning [60]. Thaker, et al. [70] connected educational materials to concept-level representations obtained from domain-specific content and external knowledge bases like Wikipedia. In the study, two models were proposed: C2V-Tb and C2V-Kb. The C2V-Tb model acquires concept embeddings from domain-specific educational resources by employing a neural network approach, effectively capturing the semantic representations of concepts. The C2V-Kb model enhances the C2V-Tb by utilizing external knowledge graphs, notably Wikipedia, to establish a concept-to-Wikipedia mapping. They utilize Concept Skip-Gram (CSK) to get concept embeddings derived from the interconnections between concepts and Wikipedia articles. The proposed models were compared to baseline methods such as LDA, Word2vec, and Doc2vec for linking tasks, while the performance was measured using NDCG and MAP metrics. The authors conclude that concept-level representations, especially C2V-Kb, surpass conventional methods in linking tasks, highlighting the advantages of integrating external knowledge.[70]. Another form of KG used for concept mapping is the work of Gupta, et al. [71] which automatically extracts meaningful information from NLP research papers and structures it into a Scientific Knowledge Graph (SKG). Table 5 summarizes several KGs used for Concept and Knowledge Mapping.

ISSN: 2576-8484
Vol. 9, No. 8: 1464-1497, 2025
DOI: 10.55214/2576-8484.v9i8.9644

Table 4.
Selected KG for Diverse forms of Recommendations.

Refs.	KG Specific Purpose	Knowledge Domain/ Subject	Dataset(s)	Nature of Data	KG Data Model	Construction model(s) or Algorithm(s)	Baseline Model(s)	Evaluation Metrics	Limitations
Liu, et al. [26]	To recommend structured learning paths and enhance communication between learners and teachers.	Information Technology (High School)	Book Chapter ("Information Processing")	Unstructured	RDF	NCT PageRank MI-SA-PSO BiLSTM+CRF model	LSTM BiLSTM LSTM+CRF	NA	Limited adaptability across different disciplines; Efficiency of feedback needs further evaluation and refinement; The System suffers from insufficient compatibility with mobile devices
Li, et al. [63]	To recommend educational content by linking exercises to relevant textbook sections	Biology, Social Science & Physics	Swedish digital textbooks and associated exercises	Semi-Structured	NA	Cosine similarity using various Embedding models, including ensembles and domain filtering.	ConceptNet Numberbatch (CN-NB), SBERT, ADA-002	Recall@3, MRR	Limited to textbook section-level recommendations; recommendations on other granularities not explored.
Liang, et al. [50]	To provide a diverse array of educational materials for users and to clarify the rationale behind these recommendations.	online courses on MOOCs	MOOCCube bsed on Xuetang X	Structured	Property Graph	GCN with multi-path fusion, RL with user-centric search.	BPR, FM, MLP, FISM, NAIS, NASR, MEUR-NoUCR and MEUR-NoMP	HR@K, (k=5,10,20) NDCG@K, MRR	Integration of user feedback into the agent's learning process for more tailored recommendations to be explored.
Ma, et al. [30]	To enhance the course recommendations	online courses on MOOCs	MOOCCube	Semi-Structured	Property Graph	CE = LDA KE =TransE LinUCB	Random E-Greedy UCB SACR RACR	NA	The study used only coarse-grained student feedback and did not consider social relationships between students.
Zhang, et al. [51]	To improve the relevance and interpretability of the course recommendations provided to learners	online courses on MOOCs	MOOCCube	Semi-Structured	Property Graph	RL Node2Vec Markov Decision Process (MDP) Policy Network and Value Network.	DQN U-CF	NDCG HR	Limited Evaluation Metrics; limited path length to 3 for explainability; future work to integrate multiple data sources (e.g., student comments) to improve generalizability

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 8: 1464-1497, 2025
DOI: 10.55214/2576-8484.v9i8.9644

Zhang and Mariano [57]	To enhance the prediction of student grades and facilitate practical course recommendations	Software Engineering Courses	Students' grades across 52 courses	Semi-Structured	NA	K-means Clustering LTSM KE =TransH Cosine Similarity	User-Based Collaborative Filtering	RMSE MAE	Limited Data from a single major course at only one university was used; the scope of evaluation is also limited, and a single baseline method was used for comparison; potential for bias or overfitting in course clustering.
[29]	Generates personalized tutorials by organizing users' multimodal information and establishing relationships among resources	Hospital Network Architecture Planning and Design	MOOC-Course MOOCCube	Unstructured Multimodal (text, image, video, audio)	Ontology	Cyclic RL	MLP NeuMF HRL GMF	Precision@10 Recall@10 F1@10 NDCG@10	Limited scope and generalizability; scalability issues as users and content increase; over-dependence on explicit user preferences and limited consideration of learner diversity and complexity
Nguyen, et al. [56]	To recommend online courses to users based on their desired IT career goals	Information Technology	MOOC	Semi-Structured	Labeled Property Graph (LPG)	BERT	Bi-LSTM + CRF XLNet	Precision, Recall, and F1 score	The model only focused on IT careers and may not apply to other careers; the study relied on manual validation, which is time-consuming and may not be scalable.
Zhu, et al. [59]	Recommendation of learning objects (LOs) to learners	MOOC (Positive psychology)	MOOCCube	Semi-Structured	NA	ACGCN DFOAN	CompGCN HAKE ROtatE TukER DeepFM Wide&Deep DCN TENTF	Precision Recall F1 Score Accuracy AUC LogLoss	Only one type of LO was used, which might not work well with other kinds; the study lacks insights into the reasoning behind recommendations; the study was conducted in a controlled environment with a small dataset and may not be generalizable to real-world settings with a large dataset.
Zhang, et al. [28]	To create a personalized learning resource recommendation system for online platforms, based on students' needs and preferences.	Education	SCHOLAR, IMOOC datasets	Structured	NA	Preference Propagation KGCN	PLRec-KGGE, KPRN, RippleNet, and KGNNLS	Accuracy AUC	Limited to exploring relationships within single subjects; The study did not address temporal aspects of learning; Reliance on interaction data, which may be sparse or unavailable.

Alatrash, et al. [52]	For personalized and explainable recommendations of knowledge concepts to learners in a MOOC environment.	MOOC	Inspec dataset SemEval2017 dataset	Unstructured: Text content of slides and learning materials, Wikipedia abstracts of concepts	Property Graph	SingleRank SBERT GCN	An adapted version of LightGCN	ResQue framework Time performance comparison Precision@5	Small Dataset: user study data (N=31) and reliance on a single MOOC platform; Limited Exploration of GCN Architectures; The study focuses on cognitive aspects; motivational factors are not considered; Limited Evaluation of Explainability
Ma, et al. [62]	to represent the knowledge background of learners to enhance the fairness and accuracy of course recommendations in MOOC	MOOC	XuetangX	Structured	Property Graph (Implicitly Inferred)	CLGADN Monotonic Attention Decay Mechanism	MLP, NeuMF HRL, DIN, BST CKE, LightGCN, KGAT, HG-GNN GADN	HR@K NDCG@K MRR @K TotalScore@K Recall	Limited Dataset Scope; Lack of User-Centric Evaluation of Fairness; The study lacks direct feedback from learners on their perception of recommendation fairness.
Deng, et al. [48]	Integrate heterogeneous Course information to improve the accuracy of online course recommendation by modelling learning sequences.	Online Courses	NA	NA	NA	TransD BiLSTM CNN MLP	CB, LG, NB, DNN, ATT KPCR MKCR FKGCF FKG	HR@K NDCG@K MRR @K (K = 1,2,5 &10)	The study KG points focused on user interests, and not on learning outcomes; Learning sequences may have irrelevant courses; Limited use of course data, and applicability limited to online course recommendation
Guan, et al. [58]	To identify suitable exercises for students based on their learning states and historical interactions, and provides explanations for these recommendations.	Mathematics and related subjects	ASSISTments 2009, Algebra 2005, and Statics 2011	Structured	Property Graph (implied)	LSTM TransE-adv KCP-ER	RotatE, TransE EB-CF SB-CF KGEB-CF CBF HB-DeepCF	Accuracy (Mean and Std) Novelty (Mean and Std)	Unable to handle intricate interactions, the effectiveness of KG4Ex recommendations relies heavily on the quality and quantity of historical learning interaction data.

Xue [72]	To power a personalized course recommendation system for lifelong learners	Lifelong Education	sourced from a learner activity tracker tool known as the Experience API (xAPI).	Unstructured (Implied as learners provide the data)	NA	EE& RE = TF-IDF, Doc2Vec Improved K-means Clustering CNN	Word2Vec Traditional K-means SVM Naive Bayes KNN Fuzzy Logic	Accuracy Precision Recall F1-Score RMSE MAP	With a limited dataset scope, the study used student-provided data, which might not fully capture individual characteristics; the study doesn't detail specific ontology attributes or Neo4j implementation choices.
Yang, et al. [49]	To deliver precise and tailored legal document recommendations for expert users, tackling issues inherent to legal information retrieval and recommendation.	Legal Domain	Real-World Legal Information System Data, such as user interaction, search history, clicks, queries, and a large-scale KG manually annotated data	Semi-Structured	Property Graph (implied)	BERT TransR Multi-relational GNN SDAE	BPR, LightGCN, KGAT, CFKG, GATNE-T, GATNE-I. ACCM, NFM, NRMS, NRHUB	HR NDCG	The study used a proprietary legal dataset that is not accessible to the public, constraining the reproducibility of the findings and the comparisons with alternative methodologies. The model fails to incorporate temporal variations in user interests explicitly.

Table 5.
Selected KG for Concept Mapping and Organization.

Refs	KG Specific Purpose	Knowledge Domain/Subject	Dataset(s)	Nature of Data	KG Data Model	Construction model(s) or Algorithm(s)	Baseline Model(s)	Evaluation Metrics	Limitations
Gupta, et al. [71]	To automate the extraction and organization of contributions from scientific publications	NLP Research	NCG dataset; SciERC dataset; SciClaim dataset; AASC dataset	Semi-structured	NA	BERT-CRF BERT Rule-based extraction	BioNLP ECNUICA ITNLP	NA	Limited Exploration of Additional Scaffold Tasks; NCG Dataset Anomalies
Chen, et al. [67]	For representing the relationships between instructional concepts in subjects or courses	Education Mathematics	Pedagogical and educational sources such as curriculum standards, textbooks, and course manuals	Semi-structured	NA	RNN specifically GRU CRF	LSTM	Precision, Recall, F1-Score	The study is limited to a single subject, and may not apply to other subjects; the score rate as a proxy for knowledge mastery may not be completely accurate.

Thaker, et al. [70]	To link educational resources through concept-level representation	Education	textbooks and publications Wikipedia	Semi-structured	NA	TFIDF-NP. CSK C2V-Tb & C2V-Kb Cosine similarity	TF-IDF LDA Word2vec Doc2vec	NDCG MAP	The study does not explicitly address the differentiation between the prerequisite and explained concepts.
Zhang, et al. [28]	To merge online and offline resources to address unreasonable course settings, such as repetition of KPs	Software Engineering	Course catalogs (online and offline)	Unstructured, Semi-structured	Property Graph	TF-IDF K-means clustering	NA	Silhouette Coefficient	Limited dataset size, as only course catalogs were used; Clustering results may be too granular, and some courses must be combined into broader categories.
Su and Zhang [73]	To represent the interconnected structure of subject knowledge to support various educational applications, such as learning assessment, and personalized learning resources	Computer Science & Physics	teaching resources, Open and online encyclopedia	Semi-Structured	NA	Regular Expressions, Semantic Similarity (context-based), PMI and NGD. BERT-BiLSTM-CRF	CRF BiLSTM-CRF	Precision (P) Recall (R) F1 Score	The method's threshold sensitivity can impact results, potentially excluding relevant Knowledge points (KP), and its incremental expansion may limit KG growth, potentially leading to stagnation.
Li, et al. [63]	To provide and visualize a structured representation of the knowledge related to database courses.	Database Management Systems	Wikipedia Database course textbook	Semi-Structured	Property Graph (Implied) Ontology-based model (Top-Down)	EE- Manual Curation & TF-IDF RE - K-means Clustering	NA	NA	Relationships extracted using K-means clustering are not always precise; the recommendation function is limited due to sequential relationship reliance; An Absence of formal evaluation of KG's impact on learning outcomes.
Han, et al. [69]	to automatically construct a structured representation of course concepts and their relationships	Computer Science & Economics	MoocData, Open course outlines and Video Captions	Structured and semi-structured	NA	Rule-based NER - POS Tagging with LTP CPM with NNGP BERT-BiLSTM-CRF	NLTK, POSTagger & ANST CRF RNN PMI	Precision Recall	Limited scope of relations as only inclusion relations between course concepts were considered; Data sources are primarily course outlines and video captions; Limited KG evaluation: Quantitative evaluation focused on concept extraction, no evaluation of the KG itself.

4.3. KG for Question Answering, Information Retrieval, and Semantic Search

An essential aspect of teaching and learning is Question Answering (QA), usually done traditionally by verbal interactions between teachers and their respective learners. However, with increased interest in self-study, numerous open and online learning paradigms, and even times when teachers are not readily available, an automated question-answering system is a viable and effective alternative that could perform the same role, thereby reducing time, cost, and burden on the teachers, especially in large classes.[24, 74, 75]. A QA system could also recommend relevant follow-up questions to the user based on the topics of the initial queries [76]. One of the popular approaches to designing automated QA systems is via knowledge-powered systems. KG used for QA can provide precise and user-friendly answers to both explicit and open-ended questions asked by users [23, 69, 77]. It could also infer the user's intentions and provide answers that meet the user's personalized needs [23, 78]. Likewise, some KG for QA could also generate on-demand, expandable explanations [77] provide diverse learners with quick personalized feedback on the subject [25, 78, 79] and improve learners' independent learning efficiency [25, 78]. Identified approaches used to design KG for QA include ontology [80, 81] transformer architectures such as BERT[79, 82, 83] RoBERTa [82, 84] and sometimes an existing KG could be aided by a pre-trained T2T language model such as the Text-to-Text Transfer Transformer (T5) for Graph Embedding [84, 85] . In a study by Zhao, et al. [86] the authors employed Graph Reasoning Transformers (GRT) to address the limitations of conventional approaches, such as the inability to capture triplet-level relational semantics and the modality gap between text and KGs. GRT utilizes a triplet-level graph encoder for semantic triplet and spatial position embeddings and a representation alignment pretraining process for text-triplet matching and masked language modelling. Finally, a cross-modal information fusion module with attention bias was used to facilitate effective interaction and fusion between language and KG information [86].

Graph neural networks (GNNs) such as graph attention networks (GATs) have also contributed immensely to KG due to their ability to capture relational semantics and handle complex reasoning in KG-based QA systems [72, 87-89]. For instance, [89] employed Stanford's Open Information Extraction (OpenIE) and heuristic rules to dynamically construct a KG within an interactive text-based game environment. Using information extracted from game observations and the agent's actions, the constructed KG is processed using a GAT, which learns meaningful representations of the graph by attending to relevant nodes and their relationships, enabling the agent to understand the game world. The output from the GAT was further encoded into a fixed-length vector representation using a transformer encoder, making it compatible with other components of the QA system. Finally, a Deep Q-Network (DQN) agent, a reinforcement learning algorithm, used the information from the GAT to learn an optimal policy for answering questions and navigating the game environment. Similarly, in another study [87] a muLti-task semAntic parSing with trAnsformer and Graph atteNtion nEtworks (LASAGNE) model was designed specifically for complex conversational question answering over a large-scale KG like Wikidata. This model employs a multi-task learning framework with a transformer model and a GAT for semantic parsing. The transformer translates the conversational input into a sequence of actions (a logical form) to represent the question's meaning. An entity recognition module identifies and links entities in the conversation to the KG, further filtering and permuting them based on context and logical form. The GAT in LASAGNE focuses on learning meaningful representations of entity types and predicates in the KG by exploiting their correlations. These representations are then combined with the transformer's output to predict the correct types and predicates for the logical form, facilitating accurate answer extraction [87].

Knowledge Graphs for Information Retrieval and Knowledge Graphs for Semantic Search are relatively identical to Knowledge Graphs for question-answering, as the trio incorporates semantic search as an essential feature. For a KG to be able to perform these tasks, NLP and ML techniques are usually required to comprehend the intent and context of a query, facilitating the retrieval of information or answers pertinent to the user's needs. In information retrieval, semantic search facilitates the retrieval of documents relevant to a specific topic or entity, whilst, in question answering, it aids in identifying the most appropriate response to a user's inquiry. This implies that the models to be used in the KG design must encapsulate the semantic links among entities and allow interrogation via semantic search methods [90, 91]. Table 6 summarizes different approaches and models to develop KG for question answering, Information retrieval, and semantic search.

5. Summary of KG Construction Models and Discussion

In the previous sections that explored the architectures of identified Knowledge Graphs designed for diverse purposes within the context of teaching and learning, it was observed that knowledge graph is an area of growing interest for powering systems used in different aspects of education due to their ability to turn data into machine-interpretable knowledge. It is a perfect technology for implementing Natural Language Processing Systems. The identified KG depicted in Tables 4-7 shows the utilization of KG for precision teaching and learning. These adaptive systems personalize and recommend learning resources such as learning objects, curriculum, concepts, etc., based on the learner's knowledge gaps and provide adequate, timely feedback. KGs were also used for question answering, information retrieval, and semantic search, which ensures that learning inquiries on unclear areas can be clarified.

With the emphasis of this SLR being primarily on the various models and algorithms, the respective authors of identified KGs used to design and develop their KGs and the baseline methods that were used to compare their proposed models, the most identified methods used are Ontology, Rule-based approaches, Machine Learning, and Deep Learning. Deep Learning is the dominant approach for knowledge extraction (entities and relation extraction), evidenced by the frequent use of deep learning models and algorithms across the surveyed studies.

Named Entity Recognition (NER), a crucial step in knowledge extraction, has seen a notable transition from manual curation to conventional machine learning techniques and rule-based approaches and is now dominated by deep learning models. The cited studies regularly emphasize the efficacy of deep learning models such as BERT, BiLSTM, and CRF in Named Entity Recognition tasks, ascribing deep learning's capability in identifying intricate linguistic patterns to attain superior performance over other methods [92]. Sometimes, these models were hybridized to achieve the utmost accuracy and precision. Deep Learning architectures such as BERT and CNN also greatly enhance relative extraction. Sources show that BERT-based models occasionally integrate with other architectures, such as BiGRU and CRF, which are exceptionally effective for relation extraction due to their ability to model complex relationships between entities, frequently surpassing conventional methods [54, 92].

In most KG development, the knowledge extraction phase (entity, relation) is followed by a form of knowledge fusion and embedding, depending on the specific purpose of the KG application. For instance, in some KGs for recommendations, Knowledge Graph Embedding (KGE), which learns and utilizes dense vectors in a high-dimensional space for entities and relations representation, is employed to calculate the semantic similarities between users and the resources, thereby, facilitating diverse downstream tasks such as knowledge graph completion, relation prediction, and link prediction. These models can predict links between users and resources or any other outputs they might be interested in, forming the basis for recommendations.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 8: 1464-1497, 2025
DOI: 10.55214/2576-8484.v9i8.9644

Table 6.
Selected KG for Question Answering, Semantic Search, and Information Retrieval.

Refs	KG Specific Purpose	Knowledge Domain/Subject	Dataset(s)	Nature of Data	KG Data Model	Construction model(s) or Algorithm(s)	Baseline Model(s)	Evaluation Metrics	Limitations
Zhang, et al. [23]	facilitation of precise answers to medical inquiries in the Chinese language and furnishing users with dependable medical information.	Healthcare	EHRs and the 39 Health Network,	Semi-structured	OWL Ontology	Bootstrapping Annotation DNN Context Bridges MemNN CNN Bi-LSTM+CRF	SVM Decision Tree CRF Bi-LSTM Bi-LSTM+CRF (w/o context bridge) BERT (SVM-classifier) Attention+Bi-LSTM	Precision and F1 Score	Shortage of data with good quality and availability; Complexity of medical languages and dependence on Knowledge Base; KG evaluation is limited to Precision and F1 Score
Veena, et al. [92]	to assist farmers with inquiries concerning different agricultural practices, disease control, and high productivity	**Agriculture**	Self-curated corpus from agriculture websites (30,000 sentences)	Unstructured	NA	Semi-supervised NER, Bootstrapping, Dependency parsing, Extended BERT, LDA, TuckER	NA	Accuracy, precision, recall, and F1-score Hits@N, Mean Reciprocal Rank, and Mean Rank	Lack of benchmark datasets in the agriculture domain; Dependency parse may produce errors with out-of-vocabulary words; The study does not explore the system scalability for a larger dataset
Cheng [80]	For QA and IR that could assist programmers with technical questions and C programming concepts.	C Programming Language	C programming textbooks, papers, multimedia, syllabi, etc.	Structured and Unstructured	Property Graph	Ontology construction	NA	NA	Detailed evaluation metrics or benchmarks are not provided; Scope of datasets is limited to C programming; User interaction with the QA system may depend on users' query formulation approach.
Li [93]	A framework for enhancing the accuracy and efficiency of responses to questions by utilizing the reasoning abilities of Large Language Models.	General Knowledge (using Wikidata as the knowledge base)	LC-QuAD 2.0 and WebQSP dataset	Structured	RDFs (implied)	Schema Tree MRC: TASE_IO + SSE JointGT	Qanswer, Platypus GRAFT-Net, PullNet UniQORN, EmbedKGQA, and NSM	Hits@1 Hits@5	Limited to answering simple factual questions and may not be effective for complex reasoning; The study does not explore the scalability of the approach to larger knowledge bases.
Lan, et al.	to facilitate the	Chinese Recipes	DuIE1.0	Unstructured	NA	BERT + Adversarial	Bert + Bi-LSTM	Precision	Constrained to a particular

[94]	extraction of relational triples from unstructured text on Chinese recipes to answer queries about these recipes and their respective components		dataset Recipe_Chinese (custom-built dataset)			Training + Cascaded Binary Tagging + Bi-LSTM (BertAdvCasLSTM)	Bi-LSTM + CNN + Dense CasRel BertCasLSTM	Recall F1-score	domain and language (Chinese cuisine), the model's generalization capability to alternative domains or languages is not considered.
Nair, et al. [79]	for automated QA providing structured, accurate, and relevant responses and feedback to learners' queries with consideration for non-native learners	Remote Education	SQUAD Dataset Eng-Hin Dataset	Unstructured	NA	NLP techniques (dependency parsing and sentence segmentation) BERT LSTM	NA	NA	Limited information on the KG evaluation; Future work to include more language, mobile device compatibility, and personalized learning
Yu, et al. [25]	For enhancing intelligent QA capabilities within the domain of entrepreneurship education.	Entrepreneurship Education	MOOCCube and a Custom-built dataset of entrepreneurship education questions and answers.	Structured and Unstructured	NA	TFIDF and Flair embedding BERT GCN BiLSTM	SW Algorithm SA Reader GA Reader BERT Reader AFS Graph Reader	Paragraph Recall (PR) Prediction Accuracy Loss Function	The study focused on the domain of entrepreneurship education, and the transferability of the model to other educational domains was not explored.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 8: 1464-1497, 2025
DOI: 10.55214/2576-8484.v9i8.9644

Researchers have utilized and compared numerous KGE models, including TransE, TransD, TransH, TransR, RESCAL, RotatE, DistMult, and ComplEx, and the authors eventually relied on the embedding technique with the best result for the KG development [51, 95]. The appeal of KGE approaches stems from their capacity to represent complex knowledge efficiently, facilitate various downstream activities, and integrate semantic information. This improves query performance and enhances reasoning and inference, improving the usability and precision of produced knowledge graphs.

Graph Neural Network is another popular approach used to leverage the structured knowledge within a KG to connect users with relevant resources. GNNs operate directly on the graph structure of the KG, propagating information through nodes and edges to learn representations [50, 52] . GNNs can effectively capture complex relationships and dependencies between users, resources, and other entities in the KG. Examples of GNN models include Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs). Research has employed hybrid models by combining KGE and GNNs, in an attempt to leverage the strengths of both techniques. For example, a model might use KGE to learn initial entity embeddings and then employ a GNN to refine these embeddings based on graph structure and user interactions. Zhang, et al. [28] introduces a model (CLGADN) that integrates contrastive learning with GAT for course recommendation, showcasing the efficacy of hybrid methodologies.

6. Limitations and Open Research Issues in KG Development

The benefits and roles of knowledge-powered systems for teaching and learning have been substantiated. However, as indicated in the references, many of the KGs or the studies that develop them face various obstacles and constraints that hinder or at least limit the development and deployment of KGs across multiple disciplines. The limitations could be in the form of performance restrictions, domain generalizability issues, limited domain-specific datasets, absence of standardized procedures or data formats, and evaluation difficulties.

Data Limitations: Several researchers whose KGs are for educational purposes struggle with several dataset-related issues. Typical constraints include data sparsity or inadequacy of related datasets for knowledge extraction, model training, and KG populating. In many cases, the researchers had to settle for unstructured data as structured educational data from repositories are rare, and when they do, they exist in independent silo, which may not be open source. Unlike the healthcare domain, where platforms such as CDE Repository (Common Data Elements), Clinical Data Interchange Standards Consortium (CDISC), Bioportal, Havard DataVerse, and several repositories and research labs have structured data on clinical studies that are already in machine-readable formats, such educational data, especially on contents are rarely available. Most available datasets are usually limited, either in terms of single domain-based, unstructured, sparse, or unlabelled data. This hinders effective machine learning or deep learning model training for classification tasks like NER and relation extraction. Alas, the scarcity of annotated data forces researchers to devote significant manual effort and time. Another data limitation or constraint is the lack of standardized benchmarks in specific domains, such as agriculture, which complicates evaluating and comparing different KG construction methods. Furthermore, the heterogeneity of data sources poses a challenge, as the knowledge used in education is in various forms, including text, images, and videos. This heterogeneity necessitates the development of robust methods capable of handling multimodal data effectively. In addition, real-world data is often noisy, incomplete, and prone to errors. These issues can propagate through the KG, impacting the accuracy of downstream tasks and potentially leading to biased or unreliable insights from the KG developed on erroneous data.

Construction Models Limitations - The performance of a KG largely depends on the KG construction techniques employed. At every step involved in KG construction, the algorithms' limitations subject the KG developed to the same limitations and potential biases. For example, Dependency parsing, a crucial component in relation extraction, can introduce errors due to the complexity and ambiguity of natural languages in the KG, which could lead to inaccurate or incomplete representation of the relationship between the entities, ultimately affecting the overall quality and reliability of the KG. Additionally, the performance of deep learning models for NER and relation extraction is often limited by the maximum input length, and for KG, which involves knowledge embedding, the computational complexity of the specific KGE embedding techniques employed can be a concern, especially when dealing with large-scale KGs [92, 96].

Inadequate Technical Documentation: KG construction is done in phases, and for every phase, specific algorithms or methods are used to accomplish the task or objective of that phase. Unfortunately, many researchers failed to report or were vague in reporting the technical procedures involved in KG construction. These include insufficient information on datasets such as the sources, collection techniques, pre-processing stages, and annotation rules utilized for their datasets. In KG constructed by ML or DL techniques, it could be a limited description of model architectures and hyperparameter tuning, primarily when authors might not explain the chosen deep learning model architectures, including the reasons for certain design choices. Additionally, specifics about hyperparameter tuning, such as the search space, optimization techniques, and evaluation metrics employed, can be omitted or insufficiently presented. This lack of transparency can make comprehending the model design's and hyperparameters' impact on the stated performance challenging. Furthermore, ambiguous descriptions of knowledge extraction and relation extraction methods are common. Authors might not adequately describe the precise knowledge and relation extraction strategies, including the chosen algorithms, pre-trained models, and any rule-based heuristics employed. A lack of clarity in presenting these technical details can make it tough to reproduce the work, comprehend the limitations of the chosen methodologies, and build upon the study. It also fosters transparency and enables a more critical examination of the strengths and limits of the proposed approaches.

Limited KG Evaluation and Performance Comparison: Researchers are usually expected to try different approaches in their studies and pick the model or methods with the best results; however, several KGs were developed from the author's supposed view only, without consideration or comparison with other related approaches, which could serve as baselines. Sometimes, authors could have compared, but there are insufficient details on critical components like splitting tactics, chosen measures, or statistical significance tests. A lack of transparency in reporting the evaluation methodologies can create issues about the trustworthiness and generalizability of the author's conclusion on results [71]. In addition, most KGs evaluated only the knowledge extraction (NER and RE) phase, using confusion matrix metrics such as Precision, Accuracy, and F-1 Score, the specific purpose or applicability of the KG, such as personalized learning, recommendation of resources, or Question Answering capabilities of the KGs, are rarely evaluated. Other forms of evaluation, like KG Data Quality [97] or KG Structural Quality [98] and their respective dimensions, are seldom considered.

Lack of Standardization: Another significant challenge is the lack of standardized methodologies, standardized KG data models or schema, and standardization of datasets, making it difficult to establish best practices and evaluate different approaches fairly. There is a need for clear standards in areas like concept extraction, where subjective interpretations and the absence of widely accepted definitions can hinder consistency and reproducibility. Standardized methodologies would help to introduce fairness and transparency from the user's perspective, especially in applications involving recommendations, where biases related to knowledge background or popularity of elements involved can lead to unfair outcomes. The need for explainable KG-based systems is also emphasized, as transparency in the decision-making process can enhance user trust and acceptance.

Interoperability Challenges: KGs are expected to be a promising technical solution for adopting the FAIR Principles, which promote data findability, accessibility, interoperability, and reuse [99, 100]. However, several KGs find it challenging to integrate and exchange knowledge with one another seamlessly. The heterogeneity of data sources and varying data representation formats have been identified as significant interoperability barriers. In education, knowledge might be text, images, or videos, and integrating these disparate data sources into a single KG requires multimodal data processing approaches. The same applies to different KGs, which could contain different data modes, making their integration challenging. Different KGs' vocabularies, acronyms, and semantic representations could differ across specializations even within a single data medium like text. Many domain-specific concepts often involve subjective interpretations, and integration of different KGs with the same concepts without resolving these conflicts could lead to inconsistencies and hinder the development of robust and generalizable methods [55]. As such, the making, merging, linking, and querying such KGs are challenging without a common knowledge representation language.

Generalizability and Scalability Constraints: Many datasets used in KG development are tailored to specific domains, e.g., cancer datasets or textbooks on C programming. Generalizability refers to the ability of a KG and the respective construction methods to perform well on unseen data and different specializations or domains. Several authors indicate that despite their impressive performance, deep learning models are often limited in their generalizability. For example, while effective in specific domains, pre-trained language models like BERT may require significant adaptation to perform well on data from other domains. This adaptation can be computationally expensive and time-consuming, limiting the scalability of deep learning-based KG construction methods [92]. In the same light, robust KGs are often trained on extensive datasets from multiple sources, making the management, processing, and updating of the KG in real time computationally intensive. KG based on Deep Learning and graph convolutional networks for relation extractors usually require substantial computational resources for training and inference. This may restrict scalability, particularly in resource-constrained environments. As the size of knowledge graphs increases, tasks like knowledge graph completion and path-based reasoning become more intricate, time-intensive, and costly [101, 102].

Knowledge Representation, Trust, and Privacy Issues: The various constraints usually encountered in Knowledge Engineering apply to KG development. For instance, an expert is typically required to develop and maintain ontologies that accurately capture domain knowledge. When experts or the data used are biased, the KG applications reflect the biases present in the underlying data. Also, knowledge evolves, and KGs must adapt to changes in the concepts and their respective relationships. Continuous amendment of knowledge in a KG and keeping up with the latest trends is intensive. Regarding trust, KG models should be explainable to mitigate bias, ensure fairness, and promote responsible use. KGs may contain sensitive personal information, raising privacy concerns about data storage, access control, and potential misuse. While anonymizing data in KGs is excellent, it is challenging due to the interconnected nature of the information, and removing or obfuscating specific data points can compromise the graph's structure and weaken the graph. To address these concerns, data provenance and federated learning practices are recommended. With data provenance, the origin and usage of the data within the KG are tracked, allowing for the ease of verifying its accuracy and compliance with privacy regulations. Federated learning also alleviates privacy issues by ensuring that models are trained on decentralized datasets without sharing the raw data [103].

7. Future Research Directions in KG Development

The open research issues in KG development have exposed a lot of future research directions that could be explored to solve or mitigate the identified limitations. This includes, but is not limited to, developing automated and robust methods for extracting structured information from diverse unstructured data sources, including text, images, and videos, to overcome data scarcity. Research into few-shot[104, 105] zero-shot [106] extraction techniques and state-of-the-art deep learning models [107] could help build KGs with limited annotated data. Furthermore, establishing standardized benchmarks and evaluation metrics that assess the utilization of KGs for specific downstream tasks beyond simple link prediction is needed. To improve interoperability, future work should focus on developing common ontologies and data models across domains and creating methods for seamless KG merging and linking, perhaps by leveraging and extending semantic web standards. Addressing scalability requires research into more efficient KGE models and graph processing techniques for handling large-scale KGs. Finally, enhancing trust and explainability through explainable AI (XAI) - based KG models such as SHapley Additive exPlanations (SHAP) or Local Interpretable Model-Agnostic Explanations (LIME) would be beneficial towards deploying responsible KG. Future research can also investigate how privacy-preserving KG construction and application methods like federated learning and prominent cryptographic techniques, such as Differential Privacy (DP), Secure Multi-Party Computation (SMPC), and Homomorphic Encryption (HE), can complement federated learning to protect sensitive information during knowledge graph (KG) queries [108, 109].

Abbreviations:

The following abbreviations are used in this manuscript:

AASC	ACL Anthology Sentence Corpus
ACCM	Attentive Collaborative Contextual Model
ACGCN	Attentive Composition-based Graph Convolutional Network
AFS-GR	Axiomatic Fuzzy Set Graph Reader
BPR	Bayesian Personalized Ranking
BST	Behavior Sequence Transformer
C2V-Kb	Concept-to-Vector Knowledge Base
CFKG	Collaborative Filtering with Knowledge Graph
CKE	Collaborative Knowledge Base Embedding
CLGADN	Contrastive Learning-based Graph Attention Network for Course Recommendation
CPM	Confidence Propagation Model
CSK	Continuous Skip-gram model
DFOAN	Deep Feature Operation-Aware Network
DIN	Deep Interest Network
EB-CF	Exercise-Based Collaborative Filtering
EHR	Electronic Health Records
FISM	Factorized Item Similarity Model
FM	Factorization Machine
GADN	Graph Convolution Network-based Attentive Decay Network
GAR	Gated-Attention Reader
GATNE-I	Graph Attention Network Embedding for Inductive Learning
GATNE-T	Graph Attention Network Embedding for Transductive Learning
GMF	Generalized Matrix Factorization
HG-GNN	Heterogeneous Global Graph Neural Network
HR	Hit Rate
HRL	Hierarchical Reinforcement Learning
KGAT	Knowledge Graph Attention Network
KGEB	Knowledge Graph Embedding-based Collaborative Filtering
KGNNLS	Knowledge Graph Neural Network with Linkage Structure.
KP	Knowledge Points
KPRN	Knowledge Graph-based Path Recommendation Network.
KSCR	Knowledge-aware Sequence Modeling for Course Recommendation
LightGCN	Light Graph Convolutional Network
LinUCB	Linear Upper Confidence Bound
LTP	Language Technology Platform
MAE	Mean Absolute Deviation
MAP	Mean Average Precision
MEUR-NoMP	Multi-path Enhanced User-centric Recommendation without Multi-path
MEUR-NoUCR	Multi-path Enhanced User-centric Recommendation without User-Centric Reasoning
MI-SA-PSO	Simulated Annealing Particle Swarm Fusion Algorithm for Multiple Iterations
MLP	Multi-Layer Perceptron
MOOC	Massive Open Online Courses
MRC	Machine Reading Comprehension
MRR	Mean Reciprocal Rank
NAIS	Neural Attention-based Item Similarity
NASR	Neural Attention-based Sequential Recommendation
NCG	NLP Contribution Graph
NCT	Node Centrality Theory
NDCG	Normalized Discounted Cumulative Gain
NeuMF	Neural Matrix Factorization

NFM	Neural Factorization Machine
NGD	Normalized Google Distance
NNGP	Neural Network and Graph Propagation
NRHUB	Neural Recommender with Heterogeneous User Behavior
NRMS	Neural Recommender Model with Multi-Head Self-Attention
PLRec	Personalized Learning Recommendation.
PMI	Pointwise Mutual Information
RACR	Relationship-Aware online Course Recommendation
RL	Reinforcement Learning
RMSE	Root Mean Square Error
SACR	Semantic-Aware online Course Recommendation
SAR	Stanford Attentive Reader
SB	Student-Based Collaborative Filtering
SDAE	Stacked Denoising Autoencoder.
SWA	Sliding Window Algorithm
TFIDF-NP	Term Frequency-Inverse Document Frequency with Noun Phrase
UCB	Upper Confidence Bound

Funding:
The Research Office, Postgraduate, Durban University of Technology, supported and funded this work.

Transparency:
The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

References
[1] A. Sheth, S. Padhee, and A. Gyrard, "Knowledgegraphs and knowledge networks: The story in brief," *IEEE Internet Computing*, vol. 23, no. 4, pp. 67-75, 2019. https://doi.org/10.1109/MIC.2019.2928449

[2] Y. Li and L. Zou, "gbuilder: A scalable knowledge graph construction system for unstructured corpus," *arXiv preprint arXiv:2208.09705*, 2022.

[3] E. Cavalleri *et al.*, "An ontology-based knowledge graph for representing interactions involving RNA molecules," *Scientific Data*, vol. 11, no. 1, p. 906, 2024. https://doi.org/10.1038/s41597-024-03673-7

[4] N. Heist, S. Hertling, and H. Paulheim, "Kgreat: Aframework to evaluate knowledge graphs via downstream tasks," presented at the Proceedings of the 32nd ACM International Conference on Information and Knowledge Management, Birmingham, United Kingdom, 2023.

[5] P. Chandak, K. Huang, and M. Zitnik, "Building a knowledge graph to enable precision medicine," *Scientific Data*, vol. 10, no. 1, p. 67, 2023. https://doi.org/10.1038/s41597-023-01960-3

[6] H. Parshotam and S. Nel, "Diagnosis prediction using knowledge graphs," *The South African Journal of Industrial Engineering*, vol. 34, no. 3, pp. 111-125, 2023. https://doi.org/10.7166/34-3-2941

[7] X. Tao *et al.*, "Mining health knowledge graph for health risk prediction," *World Wide Web*, vol. 23, no. 4, pp. 2341-2362, 2020. https://doi.org/10.1007/s11280-020-00810-1

[8] H. Zhong, D. Yang, S. Shi, L. Wei, and Y. Wang, "From data to insights: the application and challenges of knowledge graphs in intelligent audit," *Journal of Cloud Computing*, vol. 13, no. 1, p. 114, 2024. https://doi.org/10.1186/s13677-024-00674-0

[9] I. Naja, M. Markovic, P. Edwards, W. Pang, C. Cottrill, and R. Williams, "Using knowledge graphs to unlock practical collection, integration, and audit of ai accountability information," *IEEE Access*, vol. 10, pp. 74383-74411, 2022. https://doi.org/10.1109/ACCESS.2022.3188967

[10] M. Chen, Z. Tao, W. Tang, T. Qin, R. Yang, and C. Zhu, "Enhancing emergency decision-making with knowledge graphs and large language models," *International Journal of Disaster Risk Reduction*, vol. 113, p. 104804, 2024. https://doi.org/10.1016/j.ijdrr.2024.104804

[11] R. Promikyridis and E. Tambouris, "Using knowledge graphs to provide public service information," presented at the Proceedings of the 23rd Annual International Conference on Digital Government Research, Virtual Event, Republic of Korea, 2022.

[12] Y. Liu, J. Zhang, and Z. Ge, "Construction and application of knowledge graph of government policy based on deep neural network," in *2020 5th International Conference on Information Science, Computer Technology and Transportation (ISCTT)*, 2020,https://doi.org/10.1109/ISCTT51595.2020.00135.

[13] Y. Jia, Y. Qi, H. Shang, R. Jiang, and A. Li, "A practical approach to constructing a knowledge graph for cybersecurity," *Engineering*, vol. 4, no. 1, pp. 53-60, 2018. https://doi.org/10.1016/j.eng.2018.01.004

[14] L. Li, F. Qiang, and L. Ma, "Advancing cybersecurity: graph neural networks in threat intelligence knowledge graphs," presented at the Proceedings of the International Conference on Algorithms, Software Engineering, and Network Security, Nanchang, China, 2024.

[15] A. Breitfuss, K. Errou, A. Kurteva, and A. Fensel, "Representing emotions with knowledge graphs for movie recommendations," *Future Generation Computer Systems*, vol. 125, pp. 715-725, 2021. https://doi.org/10.1016/j.future.2021.06.001

[16] A. G. Regino, R. O. Caus, V. Hochgreb, and J. C. d. Reis, "Leveragingknowledge graphs for e-commerce product recommendations," *SN Computer Science*, vol. 4, no. 5, p. 689, 2023. https://doi.org/10.1007/s42979-023-02149-6

[17] D. Yuan, K. Zhou, and C. Yang, "Architectureand application of traffic safety management knowledge graph based on neo4j," *Sustainability*, vol. 15, no. 12, p. 9786, 2023. https://doi.org/10.3390/su15129786

[18] Y. Tang, Z. Zhao, W. Deng, S. Lei, Y. Liang, and Z. Ma, "Routekg: A knowledge graph-based framework for route prediction on road networks," *arXiv Preprint* 2023.

[19] Y. Li, Y. Liang, R. Yang, J. Qiu, C. Zhang, and X. Zhang, "Coursekg: An Educational Knowledge Graph Based on Course Information for Precision Teaching," *Applied Sciences*, vol. 14, no. 7, p. 2710, 2024. https://doi.org/10.3390/app14072710

[20] G. Ding, P. Yi, and X. Feng, "Constructing a knowledge graph for the chinese subject based on collective intelligence," *International Journal on Semantic Web and Information Systems (IJSWIS)*, vol. 19, no. 1, pp. 1-19, 2023. https://doi.org/10.4018/IJSWIS.327355

[21] L. Li and Z. Wang, "Knowledge graph-enhanced intelligent tutoring system based on exercise representativeness and informativeness," *International Journal of Intelligent Systems*, vol. 2023, no. 1, p. 2578286, 2023. https://doi.org/10.1155/2023/2578286

[22] T. Bui *et al.*, "Cross-data knowledge graph construction for llm-enabled educational question-answering system: A case study at HCMUT," presented at the Proceedings of the 1st ACM Workshop on AI-Powered Q&A Systems for Multimedia, Phuket, Thailand, 2024.

[23] L. Zhang, X. Yang, S. Li, T. Liao, and G. Pan, "Answering medical questions in Chinese using automatically mined knowledge and deep neural networks: an end-to-end solution," *BMC Bioinformatics*, vol. 23, no. 1, p. 136, 2022. https://doi.org/10.1186/s12859-022-04658-2

[24] B. Zylich, A. Viola, B. Toggerson, L. Al-Hariri, and A. Lan, "Exploring automated question answering methods for teaching assistance," in *In Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics*, Cham, 2020: Springer International Publishing, https://doi.org/10.1007/978-3-030-52237-7_49.

[25] H. Yu, E. Wang, Q. Lang, and E. Wang, "Intelligent retrieval and comprehension of entrepreneurship education resources based on semantic summarization of knowledge graphs," *IEEE Transactions on Learning Technologies*, vol. 17, pp. 1198-1209, 2024. https://doi.org/10.1109/TLT.2024.3364155

[26] C. Liu, H. Zhang, J. Zhang, Z. Zhang, and P. Yuan, "Design of a learning path recommendation system based on a knowledge graph," *International Journal of Information and Communication Technology Education (IJICTE)*, vol. 19, no. 1, pp. 1-18, 2023.

[27] A. Weichselbraun, R. Waldvogel, A. Fraefel, A. van Schie, and P. Kuntschik, "Building knowledge graphs and recommender systems for suggesting reskilling and upskilling options from the web," *Information*, vol. 13, no. 11, p. 510, 2022. https://doi.org/10.3390/info13110510

[28] J. Zhang, S. Jing, and S. Liang, "Research on personalized learning resource recommendation based on knowledge graph," in *2023 3rd International Conference on Electronic Information Engineering and Computer Communication (EIECC)*, 2023. https://doi.org/10.1109/EIECC60864.2023.10456638

[29] X. Wu, E. Wang, Y. Zhang, B. Zou, and H. Hong, "A Tutorial-generating method for autonomous online learning," *IEEE Transactions on Learning Technologies*, vol. 17, pp. 1532-1541, 2024. https://doi.org/10.1109/TLT.2024.3390593

[30] D. Ma, E. Wang, M. Chen, and J. Shen, "SRACR: Semantic and relationship-aware online course recommendation," in *2021 IEEE International Conference on Engineering, Technology & Education (TALE)*, 2021. https://doi.org/10.1109/TALE52509.2021.9678921

[31] I. Aliyu, A. Kana, and S. Aliyu, "Development of knowledge graph for university courses management," *International Journal of Education and Management Engineering*, vol. 10, no. 2, p. 1, 2020. https://doi.org/10.5815/ijeme.2020.02.01

[32] J. Stegmüller, F. Bauer-Marquart, N. Meuschke, T. Ruas, M. Schubotz, and B. Gipp, "Detecting cross-language plagiarism using open knowledge graphs," *arXiv Preprint* vol. 1, 2021.

[33] N. Sahlab, H. Kahoul, N. Jazdi, and M. Weyrich, "A knowledge graph-based method for automating systematic literature reviews," *Procedia Computer Science*, vol. 207, pp. 2814-2822, 2022. https://doi.org/10.1016/j.procs.2022.09.339

[34] B. Abu-Salih and S. Alotaibi, "A systematic literature review of knowledge graph construction and application in education," *Heliyon*, vol. 10, no. 3, 2024. https://doi.org/10.1016/j.heliyon.2024.e25383

[35] X. Ma, "Knowledge graph construction and application in geosciences: A review," *Computers & Geosciences*, vol. 161, p. 105082, 2022. https://doi.org/10.1016/j.cageo.2022.105082

[36] M. M. Akter and M.-M. Rahoman, "A systematic review on knowledge graphs classification and their various usages," *Artificial Intelligence Evolution*, pp. 187-215, 2023. https://doi.org/10.37256/aie.4220233605

[37] G. Tamašauskaitė and P. Groth, "Defining a knowledge graph development process through a systematic review," *ACM Trans. Softw. Eng. Methodol.*, vol. 32, no. 1, p. Article 27, 2023. https://doi.org/10.1145/3522586

[38] B. Abu-Salih, "Domain-specific knowledge graphs: A survey," *Journal of Network and Computer Applications*, vol. 185, p. 103076, 2021. https://doi.org/10.1016/j.jnca.2021.103076

[39] K. Qu, K. C. Li, B. T. M. Wong, M. M. F. Wu, and M. Liu, "A survey of knowledge graph approaches and applications in education," *Electronics*, vol. 13, no. 13, p. 2537, 2024. https://doi.org/10.3390/electronics13132537

[40] Z. Zhao, S.-K. Han, and I.-M. So, "Architecture of knowledge graph construction techniques," *International Journal of Pure and Applied Mathematics*, vol. 118, no. 19, pp. 1869-1883, 2018.

[41] A. Hogan, "Web of data," in *The Web of Data*. Cham: Springer International Publishing, 2020, pp. 15-57.

[42] A. Hogan *et al.*, "Knowledge graphs, ser," *Synthesis Lectures on Data, Semantics, and Knowledge. Morgan & Claypool*, no. 22, 2021. https://doi.org/10.2200/s01125ed1v01y202109dsk022

[43] F. Li, W. Xie, E. Wang, and Z. Fan, "Research on optimization of knowledge graph construction flow chart," in *2020 IEEE 9th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, 2020, vol. 9, https://doi.org/10.1109/ITAIC49862.2020.9338900.

[44] J. Hu *et al.*, "Development and application of Chinese medical ontology for diabetes mellitus," *BMC Medical Informatics and Decision Making*, vol. 24, no. 1, p. 18, 2024. https://doi.org/10.1186/s12911-023-02405-y

[45] Y. Zhang, J. Liu, and K. Hou, "Building a knowledge base of bridge maintenance using knowledge graph," *Advances in Civil Engineering*, vol. 2023, no. 1, p. 6047489, 2023. https://doi.org/10.1155/2023/6047489

[46] M. J. Page *et al.*, "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," *bmj*, vol. 372, 2021. https://doi.org/10.1136/bmj.n71

[47] J. Lu, D. Wu, M. Mao, W. Wang, and G. Zhang, "Recommender system application developments: A survey," *Decision Support Systems*, vol. 74, pp. 12-32, 2015. https://doi.org/10.1016/j.dss.2015.03.008

[48] W. Deng, P. Zhu, H. Chen, T. Yuan, and J. Wu, "Knowledge-aware sequence modelling with deep learning for online course recommendation," *Information Processing & Management*, vol. 60, no. 4, p. 103377, 2023. https://doi.org/10.1016/j.ipm.2023.103377

[49] J. Yang, W. Ma, M. Zhang, X. Zhou, Y. Liu, and S. Ma, "Legaignn: Legal information enhanced graph neural network for recommendation," *ACM Transactions on Information Systems*, vol. 40, no. 2, p. Article 33, 2021. https://doi.org/10.1145/3469887

[50] Z. Liang, L. Mu, J. Chen, and Q. Xie, "Graph path fusion and reinforcement reasoning for recommendation in MOOCs," *Education and Information Technologies*, vol. 28, no. 1, pp. 525-545, 2023. https://doi.org/10.1007/s10639-022-11178-2

[51] Y. Zhang, Y. Zhang, X. Cao, and H. Yu, "Interpretable MOOC course recommendations based on reinforcement knowledge graph," in *2024 2nd International Conference on Big Data and Privacy Computing (BDPC)*, 2024, https://doi.org/10.1109/BDPC59998.2024.10649286.

[52] R. Alatrash, M. A. Chatti, Q. U. Ain, Y. Fang, S. Joarder, and C. Siepmann, "Conceptgcn: Knowledge concept recommendation in MOOCs based on knowledge graph convolutional networks and SBERT," *Computers and Education: Artificial Intelligence*, vol. 6, p. 100193, 2024. https://doi.org/10.1016/j.caeai.2023.100193

[53] L. Ma and Y. Ma, "Automatic question generation based on MOOC video subtitles and knowledge graph," presented at the Proceedings of the 2019 7th International Conference on Information and Education Technology, Aizu-Wakamatsu, Japan, 2019.

[54] R. Yuan, H. Li, Z. Sun, and H. Zhang, "Application of graph convolutional network in the construction of knowledge graph for higher mathematics teaching," *Sensors & Materials*, vol. 35, 2023.

[55] J. Huang *et al.*, "WERECE: An unsupervised method for educational concept extraction based on word embedding refinement," *Applied Sciences*, vol. 13, no. 22, p. 12307, 2023. https://doi.org/10.3390/app132212307

[56] T. Nguyen, N. Vu, and B. Ly, "An approach to constructing a graph data repository for course recommendation based on IT career goals in the context of big data," in *2022 IEEE International Conference on Big Data (Big Data)*, 2022. https://doi.org/10.1109/BigData55660.2022.10020436

[57] Y. Zhang and V. Y. Mariano, "A grade prediction model using knowledge graph and time series," in *2023 IEEE 15th International Conference on Advanced Infocomm Technology (ICAIT)*, 2023, pp. 428-433. https://doi.org/10.1109/ICAIT59485.2023.10367307

[58] Q. Guan *et al.*, "KG4Ex: An explainable knowledge graph-based approach for exercise recommendation," presented at the Proceedings of the 32nd ACM International Conference on Information and Knowledge Management, Birmingham, United Kingdom, 2023.

[59] Y. Zhu *et al.*, "Recommending learning objects through attentive heterogeneous graph convolution and operation-aware neural network (extended abstract)," in *2024 IEEE 40th International Conference on Data Engineering (ICDE)*, 2024. https://doi.org/10.1109/ICDE60146.2024.00505

[60] J. Bai and L. Che, "Construction and application of database micro-course knowledge graph based on Neo4j," presented at the The 2nd International Conference on Computing and Data Science, Stanford, CA, USA, 2021.

[61] M. J. Gomez, M. Calderón, V. Sánchez, F. J. G. Clemente, and J. A. Ruipérez-Valiente, "Large scale analysis of open MOOC reviews to support learners' course selection," *Expert Systems with Applications*, vol. 210, p. 118400, 2022.

[62] W. Ma, W. Chen, L. Lu, and X. Fan, "Integrating learners' knowledge background to improve course recommendation fairness: A multi-graph recommendation method based on contrastive learning," *Information Processing & Management*, vol. 61, no. 4, p. 103750, 2024. https://doi.org/10.1016/j.ipm.2024.103750

[63] X. Li, A. Henriksson, M. Duneld, J. Nouri, and Y. Wu, "Evaluating embeddings from pre-trained language models and knowledge graphs for educational content recommendation," *Future Internet*, vol. 16, no. 1, p. 12, 2024. https://doi.org/10.3390/fi16010012

[64] J. Hernandez, D. Golpayegani, and D. Lewis, "An open knowledge graph-based approach for mapping concepts and requirements between the eu ai act and international standards," *AI and Ethics*, pp. 1-12, 2025.

[65] Y. Wen, Z. Wang, and J. Sun, "Mindmap: Knowledge graph prompting sparks graph of thoughts in large language models," *arXiv Preprint* 2023. https://arxiv.org/abs/2308.09729

[66] B. A. Schwendimann, "Concepts maps as versatile learning, teaching, and assessment tools," in *Learning, Design, and Technology: An International Compendium of Theory, Research, Practice, and Policy*, M. J. Spector, B. B. Lockee, and M. D. Childress Eds. Cham: Springer International Publishing, 2020, pp. 1-64.

[67] P. Chen, H. Lu, V. W. Zheng, X. Chen, and B. Yang, "KnowEdu: A system to construct knowledge graph for education," *IEEE Access*, vol. 6, pp. 31553-31563, 2018. https://doi.org/10.1109/ACCESS.2018.2839607

[68] C. Huang, Q. Li, Y. Chen, and D. Zhan, "An effective method for constructing knowledge graph of online course," presented at the Proceedings of the 2021 4th International Conference on Big Data and Education, London, United Kingdom, 2021.

[69] Y. Han, B. Zhan, B. Zhang, C. Zhao, and S. Yan, "An efficient transformer-based model for chinese question answering," presented at the Proceedings of the 2024 8th International Conference on Intelligent Systems, Metaheuristics & Swarm Intelligence, Singapore, Singapore, 2024.

[70] K. M. Thaker, P. Brusilovsky, and D. He, "Concept enhanced content representation for linking educational resources," in *2018 IEEE/WIC/ACM International Conference on Web Intelligence (WI)*, 2018. https://doi.org/10.1109/WI.2018.00-59

[71] K. Gupta, A. Ahmad, T. Ghosal, and A. Ekbal, "A bert-based sequential deep neuralarchitecture to identify contribution statements and extract phrases for triplets fromscientific publications," *International Journal on Digital Libraries*, vol. 25, no. 4, pp. 1-28, 2024. https://doi.org/10.1007/s00799-023-00393-y

[72] Y. Xue, "Knowledge graph based recommendation by adversarial learning algorithm in application of lifelong education data classification," in *ACM Transactions on Asian and Low-Resource Language Information Processing*, 2023. https://doi.org/10.1145/3595636

[73] Y. Su and Y. Zhang, "Automatic construction of subject knowledge graph based on educational big data," presented at the Proceedings of the 2020 3rd International Conference on Big Data and Education, London, United Kingdom, 2020.

[74] J. Jayaraman and J. Black, "Effectiveness of an intelligent question answering system for teaching financial literacy: A pilot study," in *The Learning Ideas Conference*, 2021: Springer, pp. 133-140.

[75] M. Almotairi and F. Fkih, "Developing a semantic question answering system for e-learning environments using linguistic resources," *Journal of Education and e-Learning Research*, vol. 9, no. 4, pp. 224-232, 2022. https://doi.org/10.20448/jeelr.v9i4.4201

[76] R. Sheng *et al.*, "Knowledge compass: A question answering system guiding students with follow-up question recommendations," presented at the Adjunct Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology, San Francisco, CA, USA, 2023.

[77] F. Sovrano, K. Ashley, P. L. Brusilovsky, and F. Vitali, "How toimprove the explanatory power of an intelligent textbook: A case study in legal writing," *International Journal of Artificial Intelligence in Education*, 2024. https://doi.org/10.1007/s40593-024-00399-w

[78] K. Shi, Y. Fan, Z. Zhuang, and M. Tong, "Intelligent question and answer system based on course knowledge graph," in *2023 5th International Conference on Computer Science and Technologies in Education (CSTE)*, 2023. https://doi.org/10.1109/CSTE59648.2023.00035

[79] L. S. Nair, M. K. Shivani, and Jo Cheriyan, Sr., "Enabling remote school education using knowledge graphs and deep learning techniques," *Procedia Computer Science*, vol. 215, pp. 618-625, 2022. https://doi.org/10.1016/j.procs.2022.12.064

[80] Y. Cheng, "An intelligent question and answering system for the c programming language based on knowledge graph," in *2023 10th International Conference on Dependable Systems and Their Applications (DSA)*, 2023. https://doi.org/10.1109/DSA59317.2023.00096

[81] Z. An, J. Huang, G. Jiao, L. Liu, and C. Feng, "Chat-Easyedu: an education field intelligent question-answering system based on knowledge graphs," in *2023 10th International Conference on Dependable Systems and Their Applications (DSA)*, 2023. https://doi.org/10.1109/DSA59317.2023.00075

[82] S. Sengupta, C. Heaton, S. Cui, S. Sarkar, and P. Mitra, "Towards efficient methods in medical question answering using knowledge graph embeddings," in *2024 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, 2024. https://arxiv.org/abs/2401.07977

[83] L. S. Nair and K. S. M, "Knowledgegraph based question answering system for remote school education," in *2022 International Conference on Connected Systems & Intelligence (CSI)*, 2022. https://doi.org/10.1109/CSI54720.2022.9924128

[84] D. Banerjee, P. A. Nair, R. Usbeck, and C. Biemann, "GETT-QA: Graph embedding based t2t transformer for knowledge graph question answering," in *In C. Pesquita, J. E. Ruiz, J. M. Fernández, D. Moussallem, A. Dattolo, R. Troncy, & S. Hellmann (Eds.), The Semantic Web*, Cham, 2023: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-33455-9_17

[85] S. Sarkar and P. Singh, "Combining the Knowledge Graph and T5 in Question Answering in NLP," Singapore, 2023: Springer Nature Singapore. https://doi.org/10.1007/978-981-19-5443-6_30

[86] R. Zhao, F. Zhao, L. Hu, and G. Xu, "Graph reasoning transformers for knowledge-aware question answering," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 38, no. 17, pp. 19652–19660, 2024. https://doi.org/10.1609/aaai.v38i17.29938

[87] E. Kacupaj, J. Plepi, K. Singh, H. Thakkar, J. Lehmann, and M. Maleshkova, "Conversational question answering over knowledge graphs with transformer and graph attention networks," *ArXiv*, vol. abs/2104.01569, 2021. https://api.semanticscholar.org/CorpusID:233025411

[88] A. G. Vrahatis, K. Lazaros, and S. Kotsiantis, "Graph attention networks: A comprehensive review of methods and applications," *Future Internet*, vol. 16, no. 9, p. 318, 2024. https://doi.org/10.3390/fi16090318

[89] R. Cohen, *The role of graph attention networks in interactive question answering systems*. University of Cape Town South Africa: Part of the QAit Project, 2021.

[90] Y. Tu, R. Qiu, and H.-W. Shen, "A versatile information retrieval and analysis framework for academic papers with semantic knowledge graphs," *arXiv Preprint* 2023.

[91] L. Aryan, K. Thingbaijam, P. V. Prasad, B. Mallala, and S. Patil, "Incorporating knowledge graphs in semantic search," in *In 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT 2024), IEEE*, 2024.

[92] G. Veena, D. Gupta, and V. Kanjirangat, "Semi-supervised bootstrapped syntax-semantics-based approach for agriculture relation extraction for knowledge graph creation and reasoning," *IEEE Access*, vol. 11, pp. 138375-138398, 2023. https://doi.org/10.1109/ACCESS.2023.3339552

[93] Y. Li, "Knowledge base question answering based on machine reading comprehension," in *2024 IEEE 6th Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC)*, 2024. https://doi.org/10.1109/IMCEC59810.2024.10575550

[94] A. Lan, Y. Zhu, Q. Zhang, Y. Cui, and Q. Mao, "Joint extraction model of chinese recipe entities and relations based on adversarial training and cascaded binary tagging," in *2022 2nd International Conference on Algorithms, High Performance Computing and Artificial Intelligence (AHPCAI)*, 2022. https://doi.org/10.1109/AHPCAI57455.2022.10087617

[95] L. Halilaj, T. Richardsen, A. Dittberner, F. Wauro, and K. N. Nguyen, "Semi-supervised construction of domain-specific knowledge graphs," in *CEUR Workshop Proceedings. Aachen*, Germany, 2023.

[96] M. Stewart and W. Liu, *An end-to-end neural model for domain agnostic knowledge graph (not text graph) construction from text*. Berlin, Germany: Explosion AI, 2020.

[97] H. Chen, G. Cao, J. Chen, and J. Ding, "A practical framework for evaluating the quality of knowledge graph," in *China conference on knowledge graph and semantic computing*, 2019: Springer.

[98] S. Seo, H. Cheon, H. Kim, and D. Hyun, "Structural quality metrics to evaluate knowledge graphs," *ArXiv Preprint* 2022.

[99] L. Vogt, M. Konrad, and M. Prinz, "Knowledge graph building blocks: An easy-to-use framework for developing fairer knowledge graphs," *ArXiv*, vol. abs/2304.09029, 2023. https://api.semanticscholar.org/CorpusID:258187474

[100] M. D. Wilkinson *et al.*, "The fair guiding principles for scientific data management and stewardship," *Scientific Data*, vol. 3, no. 1, p. 160018, 2016. https://doi.org/10.1038/sdata.2016.18

[101] X. Guo *et al.*, "ACE-ADP: Adversarial contextual embeddings based named entity recognition for agricultural diseases and pests," *Agriculture*, vol. 11, no. 10, p. 912, 2021. https://doi.org/10.3390/agriculture11100912

[102] D. He, B. Dong, and P. Jiang, "A heuristic grafting strategy for manufacturing knowledge graph extending and completion based on nature language processing: Knowtree," *IEEE Access*, vol. 9, pp. 90847-90862, 2021. https://doi.org/10.1109/ACCESS.2021.3092019
[103] J. Ao, S. Dinakaran, B. Yang, D. Wright, and R. Chirkova, "Trustworthy knowledge graph population from texts for domain query answering," in *2021 IEEE International Conference on Big Data (Big Data)*, 2021. https://doi.org/10.1109/BigData52589.2021.9671514
[104] B. Dong, B. Yang, J. Liu, and X. Qin, "Few-shot relation extraction through prompt with relation information and multi-level contrastive learning," *IEEE Access*, vol. 12, pp. 123352-123361, 2024. https://doi.org/10.1109/ACCESS.2024.3452720
[105] M. Qu, T. Gao, L.-P. Xhonneux, and J. Tang, "Few-shot relation extraction via bayesian meta-learning on relation graphs," in *International conference on machine learning*, 2020: PMLR.
[106] D. Li, L. Zhang, J. Huang, N. Xiong, L. Zhang, and J. Wan, "Enhancing zero-shot relation extraction with a dual contrastive learning framework and a cross-attention module," *Complex & Intelligent Systems*, vol. 11, no. 1, p. 42, 2024. https://doi.org/10.1007/s40747-024-01642-6
[107] T. Zengeya and J. Vincent Fonou-Dombeu, "A review of state of the art deep learning models for ontology construction," *IEEE Access*, vol. 12, pp. 82354-82383, 2024. https://doi.org/10.1109/ACCESS.2024.3406426
[108] C. Sandeepa, T. Senevirathna, B. Siniarski, E. Wang, and M. Liyanage, "Navigatingexplainable privacy in federated learning," in *2024 IFIP Networking Conference (IFIP Networking)*, 2024. https://doi.org/10.23919/IFIPNetworking62109.2024.10619875
[109] N. Sharma and R. Bhatt, "Privacy preserving knowledge graph for healthcare applications," in *Journal of Physics: Conference Series*, 2022: IOP Publishing.

DOI: 10.55214/2576-8484.v9i8.9644