Domain-specific Knowledge Graphs: A survey

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Abstract

Knowledge Graphs (KGs) have made a qualitative leap and effected a real revolution in knowledge representation. This is leveraged by the underlying structure of the KG which underpins a better comprehension, reasoning and interpreting of knowledge for both human and machine. Therefore, KGs continue to be used as a main driver to tackle a plethora of real-life problems in dissimilar domains. However, there is no consensus on a plausible and inclusive definition to domain KG. Further, in conjunction with several limitations and deficiencies, various domain KG construction approaches are far from perfection. This survey is the first to provide an inclusive definition to the notion of domain KG. Also, a comprehensive review of the state-of-the-art approaches drawn from academic works relevant to seven dissimilar domains of knowledge is provided. The scrutiny of the current approaches reveals a correlated array of limitations and deficiencies. The set of improvements to address the limitations of the current approaches are introduced followed by recommendations and opportunities for future research directions.

Keywords: Knowledge Graph; Domain Knowledge Graph; Knowledge Graph Embeddings; Knowledge Graph evaluation; Domain Ontology; Survey

1. Introduction

KGs, as one of the key trends which are driving the next wave of technologies [1], have now become a new form of knowledge representation, and a cornerstone for several applications span from generic to specific industrial use cases [2]. This ever-increase interest in this technology is leveraged by its underlying abstract structure which effectively facilitates domain conceptualization and data management, and further used as a main driver for several Artificial Intelligence applications. In particular, the KG depicts an integrated collection of real-world entities which are connected by semantically interrelated relations. In this essence, data are given formal semantics via data annotation and manipulation in a machine-readable format, thereby reducing ambiguity and deriving meaningful information that is specific to an application’s domain. Therefore, the incorporation of KGs has extended the existing data models depicted by domain ontologies and established a new form of data analytics that is able to capture semantically interconnected large-scale data sets.

Beyond the generic and open-world KGs such as Google KG [3], most of the currently constructed KGs are domain-specific that are designed over certain underlying ontologies [4]. In conjunction with the lack of ‘one-size fits all’ schema or ontology that is well-suited to address real-life problems, efforts to establish, polish, and
augment domain KGs are continuing to circulate over several domains of knowledge [5]. However, this ongoing interest on domain KGs poses a question on the quality and robustness of such KGs and whether adequate evaluation measures are undertaken, particularly on those propagated from mix-quality data sources. Also, the dynamic nature of domain knowledge is highly correlated to contextual situations, and various facts that describe entities might change over time. Neglecting the dynamic nature of knowledge harms the quality and correctness of facts attained in the KGs and might lead to poor decision making that is merely based on such data sources. Therefore, it is significant to conduct an inclusive review to the current state-of-the-art approaches for domain KG construction so as to highlight such issues and present solutions to tackle them.

In this survey, we provide an inclusive definition to domain KG. Further, we discuss various notable KG construction approaches in seven dissimilar domains of knowledge. These approaches are reviewed and a summary is provided for each domain that indicates the mechanism followed to construct the KG in each designated approach, the resources from which the KG is constructed, whether any of the KG embedding techniques is incorporated, the measures used to evaluate the KG construction approach, and the limitations and deficiencies of such techniques. Further, this survey provides a recapitulation to the main issues inferred from the conducted analysis. At the same time, we highlighted uncharted territories on the research map to tackle the indicated issues in the literature and open directions for future research. The contribution of this paper is summarized as follows:

- To the best of our knowledge, this is the first paper that provides an inclusive definition to domain knowledge graph.
- We conduct a thorough analysis to more than 140 papers on KG construction approaches in seven dissimilar domains.
- The paper highlights research gaps in the area of domain KG construction and opens venues for future research.

The rest of this paper is organised as follow: Section 2 discusses the methodology followed in this survey. Section 3 establishes the necessary ground for this survey by indicating important preliminaries and relevant terminologies. Section 4 analyses the KG construction approaches in seven different domains followed by a thorough discussion on the findings of this survey as well as the research gaps. Finally, concluding remarks are summarised and presented in Section 7.

2. Methodology

The papers collection strategy was initiated by indicating the set of domains involved in the study. There are seven dissimilar domains have been chosen, namely: Healthcare, Education, ICT, Science and Engineering, Finance, Society and Politics, and Travel. The examined papers in this survey were obtained by screening recent volumes of both conference proceedings of relevant series (such as ACM SIGKDD, ACM WSC, WWW, ICWE, ISWC, etc.) and high-quality journals (such as Knowledge-based Systems, Expert Systems with Applications, IEEE Access, Journal of Web Semantic, etc.) for papers that are relevant to the predefined domains. Further, we used certain keywords such as "knowledge Graph for Engineering", "Knowledge Graph for healthcare", etc. to search for articles in Google Scholar.

We examined more than 140 research articles that appeared between 2016 to 2020 in high-quality computer science and information systems publication venues. Figure 1 illustrates the number of papers collected for the survey. As it can be conveyed from the figure, there is a notable consideration in domain-specific KGs as the number of papers have increased dramatically over the recent years.
This survey paper is different from other similar works. For examples, the current important researches in this arena either focus on generic and domain-independent KGs such as [6-8], or slightly addressed and discussed domain-specific KGs [5, 9]. To the best of our knowledge, this is the first attempt to provide both an inclusive definition to the domain KG term as well as a thorough analysis to various domain-based KG construction approaches. This survey further highlights the deficiencies in the examined approaches and proposes solutions to tackle them.

3. Preliminaries

3.1 Generic Knowledge Graphs

Generic KGs (a.k.a. open-world, cross-domain, or domain-independent) graphs have been continuously constructed even before coining the “Knowledge Graph” term. In fact, since the invention of the Semantic Web, generic KGs have been associated with the Linked Data as being a natural representation for entities interlinking [10]. Nevertheless, the term has gained the sheer momentum recently as it has fostered the computing paradigms by shifting from traditional databases to knowledge-bases [11]. Ironically, there is no consensus on the definition of the term despite the few attempts to provide a reasonable description. For example, Ehrlinger and Wöß [10] perceive the KG as the process of acquiring and correlating knowledge to an Ontology and applying a reasoner to infer knowledge. A further technical depiction to the term is provided by Wang et al. [8] in which the KG is conceived as a multidimensional graph encompassed of entities/nodes and relations/edges. Entities are interconnected using relations which are the edges of the graph, and facts are commonly represented as triples (subjects, predicate, object). Intuitively, two entities connected by a relation form a fact in the KG. For example, the following fact: “Tim Berners-Lee has invented the World Wide Web” comprises two entities/nodes, namely “Tim Berners-Lee” and “World Wide Web”, and the relation “has invented” forms the triple “Tim Berners-Lee, hasInvented, World Wide Web”.

![Figure 1. Number of studied papers per year.](image)
Examples of various steadily evolving open-world KGs include: Freebase\(^1\), Semantically-Interlinked Online Communities (SIOC\(^2\)), YAGO\(^3\), Dublin Core (DC\(^4\)), Simple Knowledge Organization System (SKOS\(^5\)), and DBPedia\(^6\) knowledge base. In fact, various of these massive publicly-available data islands have been harvested from the Web as being a key source of knowledge to benefit numerous Artificial Intelligence and smart systems [12], such as recommender systems [13], decision support systems (DSSs) [14], and intelligent QA systems [15].

3.2 Domain-specific Knowledge Graphs
Despite the extensive use of the generic and open-world KGs to tackle a wide variety of domain-independent tasks, constructing KGs from domain corpora to benefit domain-specific problems is of high significance [16]. This is because domain KGs have relevant and semantically interlinked applications with domain-specific problems. Intuitively, the notion of domain-specific KGs also lacks an agreement on an inclusive and a well-established definition considering that it still comparatively a new territory and an under-explored frontier [17]. Nevertheless, some studies perceive the domain KG as a special type of KG that is used to represent a specific and complex domain [4, 18, 19]. Others reported domain KGs as the process of enriching an underlying domain ontology [5]. This inadequacy to provide an inclusive definition to the domain KG has driven us to frame a definition to the term as follows:

"Domain Knowledge Graph is an explicit conceptualisation to a specific subject-matter domain represented in terms of semantically interrelated entities and relations"

This comprehensive definition addresses three core aspects, namely: (i) formal conceptualisation: which indicates the logical design of the KG depicted by a specific and predefined domain ontology, (ii) subject-matter domain: this frames the domain KG to be firmly contextualised to address a particular subject-matter knowledge, and (iii) semantically interrelated entities and relations: which indicate the physical design of the domain KG depicted in form of a labelled graph in which the semantics of data is enriched with a specific conceptual representation of entities and relationships between these entities.

3.3 Knowledge Graph Construction
KG was introduced as being an efficient and smart approach to tackle the continuous propagation of various forms of unstructured text (e.g. Web data) and other structured or semi-structured sources [6]. However, harvesting meaningful knowledge from this diversity data format is not a trivial task; it includes extracting facts in terms of entities and potential relations between them, which requires a correlated array of various Information Extraction (IE) techniques and sophisticated Natural Language Processing (NLP) approaches. Examples of techniques used for entities recognition and relations extraction are: Conditional Random Field (CRF) [20], machine learning models (e.g. SVM), neural network models such as Bidirectional Long Short-Term Memory

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1 https://developers.google.com/freebase
2 http://sioc-project.org/
3 http://www.foaf-project.org/
4 https://www.dublincore.org/
5 http://www.w3.org/2004/02/skos/
6 https://wiki.dbpedia.org/
(BiLSTM) \cite{21}, Hidden Markov Models (HMM) \cite{22}, and off-the-shelf NLP tools (e.g. spaCy\textsuperscript{7}, Stanford CoreNLP\textsuperscript{8}, AllenNLP \textsuperscript{9}, IBM Watson NLU\textsuperscript{10}, etc.).

Various efforts have been undertaken in an attempt to tackle the KG construction problem. These endeavours can be categorised in four groups based on the selection of data sources and ontology \cite{23, 24}; namely: (i) methods that incorporate the structural nature of Wikipedia by using the predefined ontology model (e.g. DBpedia \cite{25}) or by inferring the ontology schema from the underlying structured data (e.g. YAGO \cite{26}); (ii) IE approaches that rely on the openness nature of the Web so as the information is collected using various knowledge extraction techniques with no consideration to a unified ontology design (e.g. \cite{27}); (iii) techniques in which the knowledge is obtained based on a predetermined ontology, as well as facts gathered from the Web (e.g. KnowledgeVault \cite{23}, NELL \cite{28}); and (iv) techniques that build taxonomies (hierarchy) attained based on information from the Web \cite{29}.

3.4 Knowledge Graph Embedding

KG Embedding (KGE) is the process of creating propositional feature vector representations of the constituents of a KG (entities and relationships) \cite{8} so as to apply numeric techniques resulting scalable besides of effective \cite{30}. This is evident because KGE techniques can simplify resolving various complex real-life graph problems in which using conventional graph presentation (i.e. adjacency matrix) is inadequate and inferior. This can be indicated in the current extensive use of KGE to tackle problems such as KG completion, entity recognition, and link-based clustering \cite{31-33}.

The intuitive idea behind KGE is to create a vector for each entity and each relation in the KG, then define a set of score functions that are used to measure the space distance of two entities relative to the type of the relation in the low-dimensional embedding vector space. The aim is to capture latent properties of the semantics in the KG so as alike entities and alike relations will be represented with similar vectors, and those not semantically connected are detached. Embedding a KG is learned via training a neural architecture over a KG, and commonly includes three main steps \cite{34}, namely; (i) encoding entities into dispersed points in the semantic space, and encoding relations as vectors; (ii) scoring function or model-specific function that is used to assemble the information combing from a triple; and (iii) optimization procedure represented by the loss function which in which the objective is defined and minimised during the KG embedding process. Example of KGE models include, but not limited to; Translating Embedding (TransE) \cite{35}, DistMult \cite{36}, Complex Embeddings (ComplEx) \cite{37}, Holographic Embeddings(HoE) \cite{38}, Convolutional 2D KG Embeddings (ConvE) \cite{39}, Convolution-based model (ConvKB) \cite{40}, etc.

3.5 Knowledge Graph Evaluation

The proliferation of massive constructed KGs poses a question on the quality of the embedded knowledge (i.e., entities and relations), and whether these facts do precisely depict the intended real-world concepts and interlinked via their relationships. Therefore, acknowledging the completeness and correctness of the constructed KG is crucial to determine the KG’s “fitness of purposes” \cite{41} on various downstream applications, and further assist to tackle uncertainty in the data quality \cite{42}.

\textsuperscript{7} https://spacy.io/
\textsuperscript{8} http://corenlp.run/
\textsuperscript{9} https://allennlp.org/
\textsuperscript{10} https://www.ibm.com/cloud/watson-natural-language-understanding
In domain KG, the absence of a complete and accurate KGs represents a challenge to the evaluation process. This is because collecting all true facts of a certain domain of interest is not a trivial task (if not impossible). Therefore, various attempts, commonly known as KG Augmentation/Completion techniques, have been undertaken to augment the KG with new facts depicted by new potential entities and/or new relations. To ensure data quality, these efforts are subject to correctness and completeness evaluation measures. In particular, according to the new and known true facts, the evaluation can be carried out by using classification accuracy and ranking metrics such as Hits@N and Mean Reciprocal Rank (MRR), Accuracy, Precision, Recall, and F-score [5, 43]. These metrics are amongst various other measures that have been currently incorporated to evaluate the KG construction and completion in terms of the factuality of the embedded entities as well as their relations. The evaluation of KG construction has been also varied out using case studies and domain expert evaluation [44, 45].

4. Domain-specific KGs

This section reviews various domain-based KGs that were discussed in the literature. These domains are Healthcare, Education, ICT, Science and Engineering, Finance, Society and Politics, and Travel. Appendix A includes seven tables, each with a summary of the literature for each designated domain. These tables demonstrate the specific KG usage, KG construction algorithm(s), the resources used to feed the KG, whether KG embedding techniques were incorporated, the evaluation approach, and the limitations of each designated work.

4.1 Healthcare

Recently, Healthcare sector has gained much attention, particularly with coronavirus 2019 (COVID-19) pandemic continues to rattle the world. Therefore, there is a notable consensus in both industry and academia to consolidate efforts to overcome the challenges of this vital sector [46]. KGs offer the healthcare sector technical means to derive meaningful insights from voluminous and heterogeneous healthcare data [47, 48]. For example, Rotmensch et al. [49] constructed a KG that captures diseases and symptoms related entities form 273,174 electronic medical records. The authors incorporate Google Health Knowledge Graph (GHKG) and created a KG that embodies diseases and symptoms and relationships between them. Rastogi et al. [50] framed the personal health KG as a combination of context, personalization, and integration with other knowledge-bases. Their study indicated that the literature on personalised health-related KGs is inadequate and lacks a unified standard representation to depict the designated domain. Incorporating health KGs for Query Answering (QA) system was discussed by Sahu et al. [51]. The authors offered a system that can be used to search for various health-based KGs to obtain a set of healthcare-related response sub-graphs. Incorporating KG in the medical domain to benefit QA applications was also discussed in [52].

Health data mining by means of a KG approach was also followed in the literature. Gatta et al. [53] presented a library in R that was developed for process mining in the medical domain. The library is designed to encode the extracted processes in the form of directed graphs, which can be then interpreted and visualised by domain experts. Constructing KGs that can describe depression was provided by Huang et al. [54]. In particular, they attempted to generate a sub-graph, that describes depression disorder, obtained by parsing a variety of large knowledge sources such as PubMed, Medical Guidelines, DrugBank, Unified Medical Language System (UMLS) etc. Another important effort that integrated plausible reasoning with fine-grained biomedical ontologies to tackle data incompleteness problem in health domain was undertaken by Mohammadhassanzadeh et al. [45]. The authors proposed Semantics-based Data analytics (SeDan) framework that performs an exploratory and plausible analysis of the KG using plausible OWL extension and query rewriting algorithm. The framework incorporates various knowledge bases include the DrugBank, Disease Ontology, and the large-scale semantic MEDLINE database (SemMedDB).
Constructing a KG to benefit health management and to address current health-related problems and chronic diseases were proposed in the literature [55-58]. For example, Huang et al. [55] suggested a KG construction model that benefits people seeking knowledge regarding a healthy diet. The authors proposed a domain ontology as an underlying structure of a diet KG. The KG was then enriched with entities extracted from a set of healthcare websites using Conditional Random Fields (CRF), Support Vector Machine (SVM) and Decision Tree (DT) algorithms. Another effort was carried out by Haussmann et al. [56] who proposed an integrated KG (FoodKG) that embodies knowledge on healthy food, recipes, and nutrition. The authors ensured the credibility of the obtained knowledge by adopting RDF Nanopublication specification [59]. On the same research direction, an inclusive healthy diet KG was also constructed by Chi et al. [57]. The reported KG integrated five key concepts that included food material, dish, nutritional element, symptom, and the crowd. Through semi-automatically extraction approach, the proposed model was capable to collect and import entities captured from a set of online resources using various NLP and machine learning algorithms. Modeling food domain KGs were also implemented in [60-62]. Further, tackling challenges in healthcare systems leveraging KGs technologies was discussed in [63-65].

Evaluating the robustness of a constructed KG in healthcare is of utmost significance to ensure the quality of the inferred knowledge in this sensitive domain. In this context, Chen et al. [66] presented a methodology to measure and evaluate the robustness of knowledge in terms of diseases and symptoms captured from existing health knowledge graphs as well as records of patient visits to Beth Israel Deaconess Medical Center (BIDMC). Addressing the temporal dimension in KG creation is an important dimension in healthcare. Ma et al. [67] established a temporal KG that can be used for cognitive episodic memory. This temporal KG was initially derived from the Integrated Conflict Early Warning System (ICEWS) dataset as well as Global Database of Events, Language and Tone (GDELT). Their work was different from other seminal works by generalizing four significant static KGs embedding to 4-dimensional temporal/episodic KGs. Also, two novel generalizations of RESCAL were proposed and discussed. Application of KGs in healthcare and medical domains was demonstrated in other relevant tasks such as fraud, waste, and abuse Detection [68], drugs similarity [17], drug repurposing [69], clinical decision support systems [70], and medical recommender systems [71, 72].

4.2 Education

The construction and usage of educational KGs have been extended recently due to the significance of KGs application to the learning systems as well as the abundance of pedagogical data [73]. Further, the KGs have proven ability to foster learning [74] and been used in popular massive open online course (MOOC) platforms [75, 76].

Chen et al. [77] presented K12EduKG, a KG constructed based on K-12 educational subjects. Domain-specific educational data (Chinese curriculum standards of mathematics) was the source of knowledge that was used in K12EduKG. Concepts and relations are identified and imported into K12EduKG using CRF model and probabilistic association rule mining. Su and Zhang [78] designed a KG schema that can accommodate educational Big data. Their KG was enriched by using two large datasets, namely subject teaching resources and an online encyclopedia resource. Another attempt has been undertaken to build a KG (MathGraph) that can be used to solve high school mathematical exercises including mathematical derivation and calculation [79]. The authors of [79] used MathGraph, that was initially constructed with the help of crowdsourcing, to embody dissimilar mathematical objects, operations and constraints. KnowEdu [75] is one of the important efforts in educational KG design and construction. By using standard curriculum and learning assessment data as data sources, and by using neural network models for concepts and relations identification, KnowEdu is created to facilitate learner's cognitive and
educational process. Aliyu et al. [80] presented an approach for implementing a KG to be used for course allocation scheduling. Although the evaluation of the constructed KG was inadequate, the work is promising toward this important research direction. Liu et al. [81] and Lian et al. [82] provided approaches that adopted graph-based relational learning for concept prerequisite learning in education domain. The former introduced an automatic technique for prerequisites prediction by inferring directed graph at the course and concept levels. The latter incorporated active learning to the concept prerequisite learning problem. Modelling internal control in higher education using KG technology was discussed in [83]. The author proposed a KG that can conceptualise the internal control policy in the higher educational institutions. Despite the author’s attempt to demonstrate the utility in a visualisation task, the overall mechanism to construct and evaluate the designated KG is inadequate and inferior. Applying KGs to benefit education domain was also outlined in [84].

Designing a KG that can be used to depict academic networks was discussed in [85]. The authors proposed a model of scientific publication management that can integrate scientific metadata in terms of academic entities. The model embodies a KG which conveys the relationship between research entities and research topics. Incorporating KG embedding techniques in the process of constructing the educational KGs is inadequate, particularly those leverage the rich literals of the designated KGs, thus Yao et al. [86] attempted to tackle this issue by reporting on a model for embedding learning of educational KGs. With the use of three experimental KGs in the education domain, the authors demonstrated the significance of the proposed model when processing educational KGs. In particular, authors of [86] presented a method that can jointly learn embeddings built on pre-trained structural (i.e. TransE) and literal embedding vectors (i.e. BERT). Evaluating the utility of the educational KG by means of visualisation analysis was rarely discussed in the literature. An attempt in this direction was undertaken by Sun et al. [87] who integrated an education KG and demonstrated its utility by carrying out visual analysis so as to provide a better understanding to its topological structure.

4.3 ICT

KGs have been widely used to benefit several applications related to Information and Communication Technology. In Cybersecurity, detecting and preventing cyberattack is inevitable to ensure providing continuous and uninterrupted services. Interestingly, various cybersecurity-related KGs have been introduced and developed. For example, [88] presented a practical approach for cybersecurity. They first developed a domain ontology that put forward a technique to construct the cybersecurity KG. Then they proposed a quintuple model that was used to obtain new knowledge using the path-ranking algorithm. Deng et al. [89] discussed another cybersecurity-related KG that was constructed to serve students who seek concepts in this domain. Despite the Adhoc mechanism to construct their KG and the absence of a benchmark comparison for utility evaluation, the line of research is important per se; providing KGs that facilitate personalized learning and benefit education is highly recommended [90]. Kiesling et al. [91] followed a bottom-up approach to build their cybersecurity KG using National U.S. Vulnerability Database (NVD) and set of security online references. The authors demonstrated the effectiveness of the developed KG by means of two case studies in vulnerability assessment and intrusion detection systems. Cybersecurity KGs were also reported in [92-94].

Software development is a sophisticated process that encompasses an array of challenges and decisions to be made in a timely manner [95]. Hence, the software engineering domain has also benefited from the propagational use of domain KGs due to their efficacy to store and manage relevant entities and relations of high complexity. For example, Nayak et al. [96] developed a KG that was used to extract test cases that would assist in the functional requirements gathering process. As a backbone schema, the authors designed an ontology for software testing and applied a series of NLP tools including Constituency Parse Tree (CPT) to mine and populate
the KG with test cases. Schindler et al. [97] introduced a KG (SoftwareKG) that embodies information pertaining to the software mentioned in academic articles of social science. SoftwareKG depicts various aspects of the software including its availability, source and links with other knowledge repositories. Designing a framework to industrial software design and development processes was proposed by [98]. The authors applied a knowledge-driven QA system for parameters searching and can be also used for carrying out variable calculation and ontology reasoning. The proposed model integrated the constructed KG with an SQL database and efficiency is demonstrated in certain industrial scenarios. Fu et al. [99] made use of IT crowdsourcing services to construct a KG (ITServiceKG) to improve existing IT services IR system. The authors implemented a learning-to-rank model (Gradient Decision Tree) that was leveraged to re-rank the obtained results, thereby attaining much relative search results. Constructing KGs to improve software engineering practices and internal processes were also addressed in [100-103].

Defining and conceptualizing the structure of telecommunication networks can be explicitly delivered through incorporating KGs. Aumayr et al. [104] benefited from the unique structure of KG to build a graph that can be used to solving issues that confront telecom operators. The authors populated the KG with entities captured form community knowledge in forms of telecom and products documentations, online sites, engineering reports, etc. The aim was to build an automated system to improve network incident management processes and to provide better customer service. Krinkin et al. [105] proposed a telecommunication network monitoring model by means of incorporating a domain KG at the top of the telecommunications service domain ontology. In particular, the authors encompass an array of components that are integrated into monitoring cable television operator networks. These components are: the billing model, user access rights, network topology and application hierarchy, and the cable television operator network service model. In the Internet of Things (IoT), integrating heterogeneous access of electronic devices poses a momentous challenge. Hence, the underlying structure of the KG offers a promising solution to bridge the gap between IoT devices. For example, Xie et al. [106] proposed an IoT KG that was used in a new layer to map IoT devices, thereby unifying the communications of all devices. Many studies further elaborated on KGs and their advantages to IoT ecosystem [107-109].

4.4 Sciences and Engineering
Applying semantic web technologies and ontologies in natural sciences has proven successful leveraging the formal knowledge representation and the semantic web languages that can model rich and complex knowledge of natural sciences [110-114]. For example, the utility of semantic analytics has been validated in providing a formal representation to chemical data, thereby increasing the sharing and interoperability of such data [115]. Incorporating KG has extended these endeavours and provided a platform where information can be integrated from multiple chemical kinetic systems, and offered an automatic method to comprehend chemical mechanisms to perform complex chemical-related semantic queries [116]. For example, [117] proposed an integrated system that used KG to demonstrate interoperability in cross-domain applications that compass combustion as well as to address the problem of data inconsistencies in chemical reaction mechanisms. Krdzavac et al. [118] designed a domain ontology (OntoCompChem) as an underlying structure of a KG that was used to demonstrate quantum chemistry calculations. In Biology, Choi et al. [119] carried out benchmark comparison amongst a selection of KG embedding models in a relational discovery task. Prior to the implementation of the incorporated KG embeddings, the authors constructed a domain KG that was populated with entities and relations captured from heterogeneous public data sources. These bio-related data sources are PubMed database11, Comparative

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11 http://www.ncbi.nlm.nih.gov/PubMed/
Toxicogenomics database (CTD)\textsuperscript{12}, The Biological General Repository For Interaction datasets (BioGRID)\textsuperscript{13}, and the human disease database: (MalaCards)\textsuperscript{14}. In Geology, incorporating KGs on geological data has proven effectiveness and enhance the interconnectivity between such data sets. Zhu et al. \textsuperscript{120} showcased the use of KG in an intelligent system for deep mining of geological data. The authors constructed the KG using Baike.com and local geological documents. Constructing a KG from geoscience documents was discussed in \textsuperscript{121}. The authors made use of an integrated corpus composed of a geology dictionary and the \textit{Terminologies and Classification Codes of Geology and Mineral Resources} (TCCGMR) \textsuperscript{122} to enrich the KG incorporating CRF-base geological word segmentation model. The utilisation of KG to conceptualise geosciences were further detailed in \textsuperscript{123-125}.

More advanced technical solutions have been also importing KGs to build sophisticated systems in various fields of engineering \textsuperscript{126}. For example, Myklebust et al. \textsuperscript{127} demonstrated the implication of using a domain KG and KG embeddings to improve the ecotoxicological effect prediction in the Norwegian Institute for Water Research (NIVA). In particular, the authors designed TERA KG to integrate information captured from dissimilar resources relevant to ecotoxicology and risk assessment domain (e.g. ECOTOXicology database (ECOTOX)\textsuperscript{15} and NCBI taxonomy\textsuperscript{16}). The construction of TERA KG was carried out by using LogMap ontology alignment system \textsuperscript{128} to index and align the ECOTOX and NCBI vocabularies. Yan et al. \textsuperscript{129} designed KnowIME (KG’s Intelligent Manufacturing Equipment), a knowledge-based integration system for manufacturing equipment such as lathes, conveyors and robots. A domain KG was constructed and augmented using CRF method from heterogeneous equipment-related data. Industrial adoption to KGs to enhance customer satisfaction and user experience was undertaken by \textsuperscript{130}. The authors designed two KGs for evolutionary Smart Product– Service System (Smart PSS) development. The constructed KGs resulted from data obtained from open-source knowledge, prototype specifications, and user-generated textual data. The KGs were then used to bringing expert knowledge, thereby solving issues related to cost-effectiveness that exist in the current knowledge supply for Smart PSS.

Electric power artificial intelligence systems have also contributed to the KGs construction and augmentation. For example, Fan et al. \textsuperscript{131} proposed an approach to construct the dispatch KG for the power grid to semantically describing behavior of dispatchers. They follow semi-automated labelling to construct a power corpus, then BiLSTM-CRF model was used to extract entities and indicate the dispatching behavior relationship patterns. Yang et al. \textsuperscript{132} also leveraged the KG schema to collect and integrate data from various power assets. They aimed to deliver a unified multi-source heterogeneous knowledge base that contains power transmission and transformation assets. Engineering is a wide spectrum of domains that have found KGs advantageous in several important applications. This is evident in various other engineering fields such as, nuclear engineering \textsuperscript{133}, marine engineering \textsuperscript{134}, Photonics engineering \textsuperscript{135}, Nanotechnology Engineering \textsuperscript{136}, Ceramics engineering \textsuperscript{137}, and Geomatics engineering \textsuperscript{138}.

4.5 Finance

The finance sector is a pillar of any successful business. It is the driver for businesses to take opportunities and make revenue. Accordingly, researchers commonly draw great attention to this domain by discovering new venues for continuous improvements. Intuitively, KGs, as being a powerful tool for various applications, have

\textsuperscript{12} http://ctdbase.org/
\textsuperscript{13} https://thebiogrid.org/
\textsuperscript{14} https://www.malacards.org/
\textsuperscript{15} https://cfpub.epa.gov/ecotox/
\textsuperscript{16} https://www.ncbi.nlm.nih.gov/taxonomy
been constructed to benefit several aspects of finance [139]. For example, Liu et al. [140] leverage a domain KG to carry out stock market forecasting on the renowned companies. Their work also comprised a deep learning approach and proven effectiveness when integrated with the constructed KG on the prediction task. Another attempt was commenced by Fu et al. [141]. The authors introduced a stochastic optimisation algorithm, genetic programming, and generalised crowding which are all integrated into a model for market return prediction using financial KG. Cheng et al. [142] proposed KG-based event embedding framework that is designed for event-driven quantitative investment. In particular, the constructed KG (named FinKG) and the implemented embeddings perform learn informative representations based on both the relations of event argument and the lead-lag relations amongst the entire KG. Liu et al. [143] demonstrated the use of a KG embedding framework to predict stock prices using news sentiment analysis. Although the authors did not provide much discussion on the validity of the mechanism followed to construct the KG, the utility was demonstrated in the prediction task. In the same line of research, Long et al. [144] integrated trading data, public market information and investor's records to construct a KG that is incorporated to model the market and its features. The KG was then embedded using node2vector approach and used in a deep neural network model for forecasting trends in stock prices. Authors of [145] depicted the relevance of using a knowledge-empowered model on event representation and stock prediction. Zhang et al. [146] supported the aforementioned endeavours by propounding an approach to detect short-term stock price movement. The authors developed an enterprise KG and designed a top-up power vector model and influence propagation model. The aim was to compute the effect of a specific relationship from the relevant enterprise. The construction of the KG involved incorporating Named Entities Recognition (NER) and Neural Relation Extraction (NRE) for entities extraction and Convolutional Neural Network (CNN) for relation inference. Stock management and stock prediction tasks have been also discussed in [147-151].

Financial fraud detection is another application of financial KG in the investment domain. KGs have been leveraged to establish approaches that can be used to stop such criminal activity. For example, Wang et al. [152] used a finance KG as a basis for label propagation algorithm to detect online fraud. Their model embodies a partition algorithm that is used to distinguish fraudulent groups of users. They argued that fraudulent users tend to position a close distance, whereas normal users commonly exist in isolated tense or firmly connected groups. Zhan et al. [153] also proposed a model that was applied in the fraud detection domain. In particular, the authors designed a call network KG that is enriched with call historical data and loan transactional data. Although the mechanism followed to construct the KG and the evaluation metrics are inadequate and inferior, the research topic is important and emphasises the significance of combining KGs with machine learning techniques to detect fraud in finance [154, 155].

4.6 Society and Politics
The current advances in information and communication technologies have made a qualitative leap and have created new venues where people can exchange thought, ideas and interest [95, 156, 157]. This ICT revolution is embodied into various electronic means embodied by the emergence of social media. The data created by such platforms are propagating posing questions on the quality of the data being generated by these platforms [158-161]. Hence, there is a vital need to study these platforms and provide ground truth of trustworthy data sets [160, 162-164]. Tchechmedjiev et al. [165] introduced ClaimsKG, a knowledge graph of fact-checked claims originated from International Fact-Checking Network (IFCN). The purpose of ClaimsKG is to enable users searching for true facts of a certain entity. Similarly, it can be used to infer false facts of people, organisations, etc. Nguyen et al. [166] created a KG that embodied social events decomposed from social media using Independent Component Analysis (ICA) and the SocioScope Knowledge Graph (SKG) model. ICA is used to cluster social events obtained
from a matrix of collected hashtags. This was followed by using the SKG model do automatically construct event-driven KGs from Twitter data.

Processing social data to infer domain knowledge that can be used to design a domain-specific KG was also discussed in the literature. For example, our previous work [167] developed a credibility-based Politics and applied various KG embedding techniques to validate the KG’s utility. In particular, BBC politics ontology was incorporated and extended as a backbone schema for the Politics KG. Then, various domain knowledge inference tools were used to enrich the KG with political entities captured from the collected datasets. Finally, several KG embedding models were implemented and tested over a set of link prediction, clustering, and visualisation tasks. The work proposed by [168] crossed with the former model as both efforts emphasized the significance of adding trust aspect in the process of designing and constructed a KG. Laufer and Schwabe [168] presented POLARE, an ontology that conceptualised the political system, and built a KG based on the provided ontology schema so as to be used for a better understanding the existing relations between agents in the political system in Brazil. Another attempt to detect and infer Political ideology was proposed by [169] whereby the authors introduced an opinion-aware KG that was used for conducting political ideology forecasting. The model integrated knowledge captured from social media, DBpedia and ideological books corpus. Huang et al. [170] reported a KG that can be used in social media to detect entity morphs (aliases that are commonly used to conceal the identity of a certain entity). The developed KG includes the real entity linked with all identified morphs mansions. A topic modelling algorithm (i.e. CorrLDA2), as well as SVM models, were used in the KG construction process. Various comparative studies were undertaken to demonstrate the effectiveness of the proposed approach.

Rudnik et al. [171] made use of Wikidata to semantically annotating news articles. The annotated articles were then fed into a predefined event-oriented KG that was used for semantic-based search engine. News recommendation by means of a KG was also examined in [172]. The authors applied a filtering method to eliminate irrelevant relations from the currently incorporated and propagated KG. Microsoft Satori KG was used as a backbone knowledge-based and enriched with entities captured from MSN news corpus. Also, the authors introduced article topic entities and the collaborative edges as two new categories of information to be embedded in the original graph. Mehdi et al. [173] designed a KG embedding approach based on socio-scholarly KG which embodies scientific artifacts on social good. The developed system incorporated various KG embedding approaches so as to retrieve, for a given entity (i.e., publication, author, domain and venue), all related and semantically-matched entities. Other studies were further established systems over KGs to benefit news and journalism domain [174-176].

Modelling culture and history of societies have been also conceptualised using domain KGs. For example, Liu et al. [177] developed a KG that depicts ancient Chinese history and culture. The author constructed the KG employing Baidu Encyclopedia as the knowledge source, BiLSTM-CRF for entity recognition, and DeepKE (developed by Zhejiang University) for relation inference. Constructing cultural knowledge bases that benefit from domain ontology and cultural KGs was elaborated further in [178-180].

4.7 Travel
Travel is one of the key domains which availed from the growing use of KGs. This is evident because KGs have been constructed and used in touristic QA systems [181] or in tourism recommender systems to recommend personalized attractions [182] and the best accommodation prices [183]. For example, Kärle et al. [183] gathered data about Tirol region at Austria and constructed “Tirol Tourism” KG to benefit applications such as eCommerce.

17 https://baike.baidu.com/
The constructed KG was fed by entities and relations extracted from Destination Management Organizations (DMOs) and Geographical Information Systems (GIS) and other tourism and accommodation-related websites. Establishing a touristic KG for China was introduced in [184]. The authors designed the domain-specific KG by using data obtained from Chinese encyclopedia KG and unstructured web pages. For entity alignment, the authors made use of Skip-Gram Model to fit relative entities during the knowledge acquisition phase. Another attempt to construct a KG for Chinese tourism was undertaken by [181]. The aim was to build a QA system based on the implemented KG of tourism. The authors followed a proposed entity recognition algorithm for entity extraction and utilised CNN model for relation inference. In a different context, Calleja et al. [185] created “DBtravel” KG over the Spanish entries of Wikitravel[18]. The authors followed GATE19 pipeline that encompasses three internal processes, namely: (1) tokenizer, (2) sentence splitter and (3) named entity recognition. Employing KGs in the tourism domain has been highly active recently and used in various applications [186-188].

Applying KGs in transportation and traffic has also obtained much attention recently due to the population growth, air pollution, and other sophisticated embedded issues that require intelligent systems to resolve them efficiently [189]. For example, Zhou et al. [190] introduced a model to predict urban traffic congestion. In this model urban KG was constructed from miscellaneous static and dynamic raw urban data. The authors applied CNN to model spatio-temporal correlation between each indicated region. One of the well-known KGs that was applied to the US transportation system is ATMGRAPH [191] which was built at the top of the NASA ATM Ontology (ATMONTO) [192]. M. Keller [191] in ATMGRAPH combined an array of structured aviation data obtained from the large part by US federal agencies. The developed KG conceptualises the US National Airspace System by incorporating entities describing, airspace infrastructure, flights, and flight operating conditions. Detecting traffic events by employing KG was proposed in [193]. The authors built a KG named ITSKG (Imagery-based Traffic Sensing Knowledge Graph) that was used to comprehend traffic patterns based on stationary traffic camera imagery data. Further, Wang et al. [194] followed a semi-automated KG construction approach based on China railway electrical accidents data. The purpose of the work is to analyse and identify the faulty equipment of railway electrical accidents in China as well to infer patterns and trends from such data. In a different context, Zhang et al. [195] have expanded the exertions in the maritime transportation by applying KG to build a knowledge representation of the regulations depicted by International Maritime Dangerous Goods Code (IMDG Code). They aimed to facilitate the access and retrieval of detailed guidelines embedded in IMDG. Knowledge-based models in transportation domain were also benchmarked [196] and others were used in travel-related intelligent systems to facilitate information sharing and interoperability [197, 198].

5. Findings from the Survey

The review of KG construction approaches which are drawn from academic works in seven domain reveals a correlated array of limitations and deficiencies related to the following summarised points:

A) KG data quality, privacy, and credibility: The examined papers have shown discrepancies in attaining standardized and proper data quality measures, particularly with the construction of large-scale KGs. Various approaches imported data collected from noisy and less quality data sources (such as social media) with a lack of consideration to the credibility or privacy of generated facts. This can be also indicated in electronic medical records in which data is relatively hard to be collected due to the privacy constraints. This poses a question on the quality and robustness of KGs that are constructed from such

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18 https://wikitravel.org/
19 https://gate.ac.uk/
data lakes. Despite some attempt to tackle data quality issue [41, 44], the endeavours in this direction are inadequate. Hence, methodologies are required that exert best practices toward maintaining the quality of constructed KGs.

B) **Knowledge resources and semantic expansion:** Semantic Web technologies and Linked Open Data (LOD) have opened the door wide to improving several domain applications [199]. KGs are extensions to these efforts and commonly associated with the LOD projects as they enrich the semantics of data by providing conceptual representation to concepts and entities [10]. Therefore, the interoperability of information is facilitated by relevant entity interlinking obtained from other KG repositories, thereby constructing multi-modal KGs. However, the studied approaches in the designated domains have demonstrated limitations in attaining interoperability of information. In particular, semantic expansion/broadening techniques were insufficiently incorporated to benefit from the openly available vocabularies and curated semantic repositories. Intuitively, the underlying structure of KGs is designed to pave the way for data integration, unification, and information sharing and usability. Research in this direction should be reinforced to attain the essence of KGs that adhere to FAIR (Findable, Accessible, Interoperable, Reusable) principles.

C) **KG construction algorithms:** The scrutiny conducted on the incorporated papers indicates limited discussions on techniques used for entity recognition and/or relation extraction. Most of these studies either neglected to specify the algorithm(s) used in the KG construction including techniques for entity and relation extraction (e.g. [132, 141, 152]) or presented an inadequate elaboration and poor rationale on using such techniques (e.g. [53, 88, 105, 142]). Based on the conducted analysis, we also identify an existing research gap in providing consolidated methodologies for automating the process of constructing a domain-specific KG that facilitate the selection of suitable algorithms to the designated techniques (involving both NLP methods and data-driven approaches [200]). Adopting such methodologies not only improves the KG construction practices, rather it will be making the knowledge broadly available to be accessed by both humans and machines.

D) **Time-aware KGs:** The dynamic nature of knowledge is highly correlated to contextual situations, and various facts that describe entities might change over time. Hence, the temporal dimension should be assimilated. Various currently propagated KGs are static but highly ephemeral and do not consider the time aspect [201]. This applies to both open-world and domain-specific KGs. Neglecting the dynamic nature of knowledge harms the quality and correctness of facts attained in the KGs and might lead to poor decision making that is merely based on such data sources. Consequently, despite some exceptions such as Wikidata and YAGO in which certain facts are already endowed with the time information, the construction of KGs should consider the validity period of facts [202].

E) **KG evaluation:** The process of constructing KGs might involve capturing incorrect facts in terms of entities and/or relations. This process is prone to errors, particularly those propagated from mix-quality data sources. As mentioned previously, it is vital to consider the credibility of the data source, yet evaluating the overall construction process is another important consideration. In fact, KG evaluation has been indicated as one of the most indicated weaknesses amongst the examined studies. For example, some studies carried out a superficial and subjective evaluation to the KG construction with no incorporation

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20 https://www.go-fair.org/fair-principles/
to concrete evaluation metrics [131, 141, 193]. Another thread of efforts attempted to involve theoretically proven evaluation metrics to systematically measure KG completion and KG correctness approaches. The former approaches were commonly measured using recall, precision, and f-measure [55, 57, 78, 88]. The later incorporated accuracy and/or area under the ROC curve (AUC) [7, 66, 144]. Nevertheless, our study endorses the survey conducted by [7] in that providing holistic techniques which simultaneously improve the quality of KGs in dissimilar domains is still an open research problem. Further, the absence of testbeds and benchmark datasets has prevented the community form undertaking a proper and fair evaluation of techniques used for KG creation [203]. Last but not least, the evaluation methodologies should consider various other data quality indicators including completeness, believability, relevancy, objectivity, consistency, understandability, etc. [204].

F) Computing performance in Big KGS: There is a notable consensus amongst the research society that the conventional technologies used to process and analyse the continuous propagation large-scale datasets are no longer adequate [205]. Machine Learning and Artificial Intelligence have become the preferred method to process and analyse Big data whereby obtaining the hoped-for added value. Large-scale KGS (i.e. those includes trillions of triples) adhere to various Big data features. Volume is not the only feature for Big KGS, they can be described by the variety in data sources, the velocity in data generation, veracity in data quality, volatility in data currency and availability, etc. Despite some growing efforts to integrate large-scale KGS in Big data processing [206], deeper and congruent integration of Big data technology infrastructures and sophisticated statistical models is deemed necessary for reasoning over domain KGS, and this remains an open research venue.

G) Domain KG Reasoning: KG reasoning aims to provide new interpretations and conclusions from constructed KGS. It is a mechanism in which new facts can be inferred from existing KG [207]. KG embedding-based approaches (including tensor decomposition, distance, and semantic matching models) have gained considerable attention in the literature due to their scalability and efficiency to accommodate large-scale KGS so as to deduce a generalizable context about the KG that can be included to infer new relations [8, 208]. This study discloses rare incorporation to KG embedding techniques into the examined approaches. Applying KG embeddings extends these efforts and tackles the deficiencies that might occur in the KG construction process which leads to incomplete graphs. To address this issue and to establish a technical ground for conducting relational reasoning in AI systems, KG embeddings should be integrated and implemented in domain KG construction models.

6. Conclusion

The widespread use and the prevalence of the Internet have led to the rapid increase in data volume which necessitated the development of advanced data analytics that are capable to handle the propagation and the heterogeneity of such data. Knowledge graphs continue to dominate as a distinctive form of data representation and knowledge inference, and a core activity for several industrial applications. This notable interest in this technology has arisen due to its underlying structure that is built on a formal conceptual representation that is depicted by a domain ontology. Therefore, domain KGS have been constructed and used to tackle several real-life problems in dissimilar domains. Yet, there is no unified definition to the notion of domain KG, also the current practices to construct and evaluate domain knowledge graphs are far from perfection.
This survey is the first to present an inclusive definition to domain KG. Further, an in-depth analysis of the current state-of-the-art knowledge graph construction research in seven domains of knowledge is provided. The undertaken efforts in each research domain are discussed followed by pointing out the deficiencies and limitations of these efforts along with future research opportunities which we hope to motivate researchers in this designated area.
## Table A.1: Overview of KG approaches in healthcare domain

| Ref. | Sub-domain       | KG Usage                                                                 | Construction Algorithm(s)              | KG Resource(s)       | Embedding Technique(s) | Evaluation Measure(s) | Limitation(s)                                                                                   |
|------|------------------|--------------------------------------------------------------------------|----------------------------------------|----------------------|------------------------|-----------------------|---------------------------------------------------------------------------------------------|
| [49] | Diseases         | Identification of diseases and symptoms across the collected medical records | LR, NB and Bayesian network modeling   | Custom, GHKG         | N/A                    | Precision and Recall   | • Inadequate to infer correct causal relations,                                            |
|      |                  |                                                                          |                                        |                      |                        |                       | • concept extraction requires further elaboration                                           |
| [53] | Generic          | Medical process mining                                                  | Markov Models and Careflow Mining      | Event logs           | N/A                    | Case study            | • Inadequate evaluation,                                                                   |
| [54] | Depression disorder | QA                                                                      | NLP tools                              | PubMed, DrugBank, DrugBook, and UMLS | N/A                    | Use cases              | • inadequate discussion on the KG construction approach                                    |
|      |                  |                                                                          |                                        |                      |                        |                       | • Lack of proper evaluation,                                                               |
| [55] | Healthcare management | Healthy diet recommendation                                             | CRF, SVM and DT                       | Healthcare websites  | N/A                    | Precision, Recall, and F1-score            | • Limited to food and dietary,                                                             |
|      |                  |                                                                          |                                        |                      |                        |                       | • Chinese language only,                                                                  |
| [56] | Healthcare management | Food recommendation, and QA systems                                      | Lexical similarity and string matching | DBpedia, USDA, Recipe1M and FoodOn KG | word2vec, and FastText | Case study and F1-score             | • inadequacy to prove utility in link prediction and other knowledge discovery tasks      |
|      |                  |                                                                          |                                        |                      |                        |                       | • Lack of evaluation on both KG constructions and incorporated embeddings techniques,     |
| [57] | Healthcare sustainability | Food recommendation                                                      | NLP tools, CRF, SVM, NB, LSTM, and KNN | China Food Composition and Online health websites, | N/A                    | Precision, recall, F1-measure, and Questionnaire            | • inadequate meaningful representations for food recommendation                           |
|      |                  |                                                                          |                                        |                      |                        |                       | • Limited data sources,                                                                  |
|      |                  |                                                                          |                                        |                      |                        |                       | • lack of proper recommendations,                                                          |
|      |                  |                                                                          |                                        |                      |                        |                       | • directed solely for the Chinese context                                                  |
| Ref. | Sub-domain | KG Usage | Construction Algorithm(s) | KG Resource(s) | Embedding Technique(s) | Evaluation Measure(s) | Limitation(s) |
|------|------------|----------|----------------------------|----------------|------------------------|-----------------------|---------------|
| [77] | Generic    | K-12 Education | CRF and probabilistic association rule mining | Chinese curriculum standards of mathematics | N/A | AUC | • Insufficient evaluation, • narrow scope of the proposed KG and its applications |
| [85] | Teaching and classroom resources | Decision-making in academia | NLP tools, SVM, NB, and LR | Web of Science, Engineering Village, and EBSCO | N/A | F-score | • The limited scope of KG (can be expanded to include instructors and their metadata), • no domain ontology is provided as a base for the proposed KG, • limited evaluation measures |
| [78] | Teaching and classroom resources | Learning assessment and recommendation | Bootstrapping construction strategy and BERT-BILSTM-CRF | Subject teaching resources, Baidu Encyclopedia, and DBPedia | N/A | Precision, Recall and F1 measure | • Limited demonstration on the utility of the constructed KG including assessment of student learning, etc. |
| [86] | Educational Technologies | Link Prediction | Adhoc | Knowledge Forest, Wikipedia | TransE and BERT | Mean Rank and Hits@10 | • Insufficient structural and literal embedding models were used |
| [79] | Teaching and classroom resources | Solving high school mathematical exercises | Complex, Triangle, Conic and Solid | Crowdsourcing and domain experts | N/A | Accuracy, Precision, Recall and F1 measure | • Limited resources used for KG construction, • limited targeted audience |
| [75] | Teaching and classroom resources | Learning assessment | RNN and probabilistic association rule mining | Pedagogical data and learning assessment data | N/A | AUC, Precision, Recall and F1 measure | • Lack of elucidating the effects of KG in other settings, • their schema is relatively hard to be provided for conducting benchmark comparison |
| [80] | Education management | QA and course allocation scheduling | Adhoc | Structural educational information system | N/A | Case study | • Poor evaluation measures, • limited KG resources, • narrow scope |
| [83] | Education management | Internal policy control conceptualization and visualization in higher education | Adhoc | CNKI database | pTransE | mean Silhouette | • Limited data sources, • limited application scope, • poor evaluation metrics, • KG embedding was not properly demonstrated and evaluated |
| Ref. | Sub-domain | KG Usage | Construction Algorithm(s) | KG Resource(s) | Embedding Technique(s) | Evaluation Measure(s) | Limitation(s) |
|------|------------|----------|---------------------------|----------------|------------------------|-----------------------|---------------|
| 88   | Cybersecurity | Cyberattack detection | Stanford NER | Enterprise data and security websites | N/A | Precision, Recall, and F1 | • Narrow KG construction approaches,  
• limited evaluation with current state-of-the-art KGs in the designated domain |
| 89   | Cybersecurity | QA and RS for education | Adhoc and NLP tools | Wikipedia | N/A | Case study and survey | • Limited data sources,  
• no benchmark comparison,  
• no backbone ontology schema |
| 91   | Cybersecurity | Vulnerability Assessment and Intrusion Detection | Adhoc and RML Rules  
21 | NVD and security online sites | N/A | Case studies | • No benchmark comparison,  
• inadequate rationale on the construction approach |
| 96   | Software | Test cases extraction | CPT and CRF | Software documents, requirement statements and test reports | FastText algorithm | Accuracy, Precision, Recall, F1 | • Transfer learning can replace the incorporated NER model, thereby using pre-trained datasets instead,  
• Inadequate validation to the collected requirement statements and past test reports |
| 97   | Software | Investigating Software Usage in the Social Sciences | bi-LSTM and bi-LSTM-CRF | DBpedia and PLoS | N/A | Case study | • Narrow to PLoS which affected the target domain,  
• evaluation is inadequate as no benchmark comparison was undertaken,  
• the automatic linking process with DBpedia requires a further scrutiny |
| 99   | Software | Info. Retrieval (IT crowdsourcing services) | Adhoc | StackOverflow, Wikipedia and crowdsourcing platforms | N/A | MRR, P@K, Recall | • Ranking modeling system can be enhanced with incorporating neural networks |
| 98   | Software | Industrial software design and development processes | Adhoc | Generic(public databases and unstructured data sources) | N/A | Case study | • Limited domain-based data sources,  
• unable to provide recommendation in complex and domain-specific situations,  
• poor retrieval performance |
| 104  | Telecom | Telecom incidents managements | NLP tools | Network incident documents | N/A | Case study on information reduction and discovery | • No discussion on the effectiveness of the incorporated algorithms/tools for KG construction,  
• no benchmark comparison with similar state-of-the-art |
| 105  | Telcom | Television operator network monitoring | Adhoc | Data obtained by monitoring systems | N/A | Case study | • Limited discussion on KG construction and propagation,  
• no rationale on using the designated ontology schema,  
• inadequate evaluation method |
| 106  | IoT | Bridging gaps between e-devices in IoT | Adhoc | oneM2M | N/A | Case study | • Inadequate discussion on concept and relation extraction approaches,  
• limited in data sources and application scope |

21 https://github.com/carml/carml  
22 https://www.onem2m.org/component/rsfiles
| Ref. | Sub-domain | KG Usage | Construction Algorithm(s) | KG Resource(s) | Embedding Technique(s) | Evaluation Measure(s) | Limitation(s) |
|------|------------|----------|---------------------------|----------------|------------------------|-----------------------|---------------|
| [117] | Chemistry | Combustion chemistry modelling | J-Park Simulator | Linked open data | N/A | Query and simulation systems | • Limited data sources, • lack of human and machine-interaction tools |
| [119] | Biology | Biodata relational discovery | Manually | PubMed, CTD, BioGRID, and MalaCards | TransE, PTransE, TransR and TransH | Hits@10 | • Poor KG construction approach, • unsatisfactory evaluation of the incorporated KG embedding models |
| [120] | Geology | Geological IR system | HanLP23 and association rule analysis | Baike.com | N/A | Case study | • Limited data sources, • undefined underlying structure, • inadequate evaluation to the utility of KG. |
| [121] | Geology | Chinese geology Knowledgebase | CRF | Geology dictionary and TCCGMR | N/A | Case study | • Limited data sources, • inadequate concept and relation extraction, • no benchmark comparison with similar state-of-the-art |
| [129] | Manufacturing engineering | Intelligent manufacturing equipment recommendation | CRF | Equipment-related data (e.g. Baidu Encyclopedia, etc.) | N/A | Case study (Information richness and effectiveness) | • Limited to level of stand-alone equipment, • scattered manufacturing data that harden data acquisition, • poor accuracy |
| [130] | Design engineering | Evolutionary Smart Product–Service System Development | Domain experts and NLP toolkits | Smart PSS prototype, user generated textual data, misc. medical websites | N/A | Showcase | • Proposed solutions for the personalized requirements are someway generic and oversimplified, • unoptimized incorporated algorithms that led to poor complexity in terms of time and space |
| [127] | Environment engineering | Ecotoxicological effect prediction | LogMap | ECOTOX, NCBI and Wikidata | TransE, DistMult, and HolE | Accuracy, Precision, Recall, and F-score | • Limited data sources; can be enhanced with information about species and compounds |
| [131] | Electrical engineering | Improving power dispatching process. | BiLSTM-CRF | Power dispatching texts | N/A | Subjective evaluation | • Small, static and non-diversified dataset, • poor evaluation mechanism |
| [132] | Electrical engineering | Improving utilization of power assets information | Adhoc | PMS and ERP | N/A | Case study | • Limited evaluation measures, • limited data sources, • limited KG structure and application |
| [209] | Oil and gas | Intelligent search engine for oil and gas | BiLSTM-CRF | Center of Oil and Gas | N/A | Precision and Recall | • Limited data sources, • lack of optimization to the embedded search engine. |

23 https://javalibs.com/artifact/com.hankcs/hanlp
| Ref. | Sub-domain | KG Usage | Construction Algorithm(s) | KG Resource(s) | Embedding Technique(s) | Evaluation Measure(s) | Limitation(s) |
|------|------------|----------|---------------------------|----------------|------------------------|-----------------------|---------------|
| [140] | Investment | Stock market prediction | Adhoc | Tomson Reuters, CNN | word2vec, TransE, Neural network | Accuracy and F1-score | • Limited resources led to insignificant scale of the trained dataset,  
• vague KG construction approach (no algorithm is indicated),  
• reporting the utility of the KG embedding was inadequate |
| [141] | Investment | Market return prediction | Adhoc | Shanghai Stock Exchange and WIND Financial Terminal | N/A | Subjective evaluation based on 29 component stocks | • KG construction in terms of entities and relations was not properly addressed,  
• missing KG schema,  
• poor evaluation to the resultant KG |
| [153] | Financial risk management | Fraud Detection | Adhoc | Loan transaction data and call history | word2vec | Precision Acceleration-Recall curve | • Challenging data acquisition and might lead to poor KG construction and prediction performance accordingly,  
• poor evaluation to the implemented KG |
| [152] | Financial risk management | Fraud Detection | N/A | Orange Finance | N/A | AUC, Precision, Recall and F1 measure | • Unindicated KG construction mechanism/algorithm,  
• inadequate demonstration to the KG schema |
| [142] | Investment | Event-driven quantitative investments | OpenIE v5.1 | Financial news websites | N/A | Micro − F1, Weighted − F1 | • Poor discussion on KG construction mechanism/algorithm,  
• lack of justification on the use of customized evaluation metric |
| [143] | Investment | Stock price volatility prediction | Rule-based named entity recognition | Financial news websites and UQER | TransR | Accuracy (prediction task) | • Large scale KG that can affect the performance of TransR embedding model,  
• the KG construction validity was not scrutinized prior using it in the prediction task |
| [144] | Investment | Stock price trend prediction | Adhoc | Chinese securities companies | node2vec | AUC | • KG modelling was neither illustrated nor validated,  
• sentiment analysis can be integrated to obtain better performance results |
| [146] | Investment | Stock price movement direction prediction | NER, NRE, and CNN | Online financial news | N/A | Acc, MCC, and FM | • Lack of temporal dimension,  
• limited data sources,  
• discussion on KG construction is inadequate |
## Table A.6: Overview of KG approaches in the social science domain

| Ref. | Sub-domain | KG Usage | Construction Algorithm(s) | KG Resource(s) | Embedding Technique(s) | Evaluation Measure(s) | Limitation(s) |
|------|------------|----------|----------------------------|----------------|------------------------|----------------------|----------------|
| [165] | Social science | QA (fact-checked claims) | TagMe tool | International Fact-Checking Network websites | N/A | Case study | • Limited data sources, • poor KG construction algorithm, • limited evaluation metrics |
| [166] | Social science | Detecting and tracing social events. | SKG model | Social media (Twitter) | N/A | Precision, Recall, and F-measure | • Complexity can be improved by increasing periods and applying ICA on other cases, • limited data sources, • schema of the KG is inadequate to properly representing the relationships |
| [173] | Social science | Social good recommender system | Adhoc | Academic research papers | TransE, ComplEx, TransH, TransR, TransD, DistMult and RESCAL | Mean rank and hits@k | • Limited conceptual presentation of the KG in terms of entities and relations, • results can be improved by using reinforcement learning |
| [167] | Politics | Link prediction, clustering, and visualisation | Adhoc using IBM Watson NLU | BBC Politics ontology, Wordnet, Google KG and light-weight ontologies. | TransE, DistMult, ComplEx, HolE, ConvE, and ConvKB, | Hits@N, MMR, Accuracy, Precision, Recall and F-score | • Limited discussion on the utility of the KG in a practical real-life example, • limited discussion on the KG construction algorithms. |
| [170] | Social science | Identify Entity Morphs | CorrLDA2 and SVM | DBpedia, Yago, and Freebase | N/A | Precision, recall, and F-measure | • Too many useless generate morphs can be avoided by adopting certain heuristic algorithms, • morphs can be also extended to cover not only people but events and other entities |
| [171] | Social science | News articles retrieval | SpaCy | Wikidata | N/A | N/A | • Limited data sources, • evaluation metrics were not provided |
| [169] | Politics | Political ideology detection | Holistic lexicon-based approach | DBpedia, Twitter and ideological books corpus | N/A | Accuracy | • Imperfect use of evaluation strategy and metrics, • no KG Embedding was undertaken, thus, no rationale provided on the benchmark comparison, • limited data sources |
| [172] | Politics | Politics news recommendation | Adhoc | MSN News corpus and Microsoft Satori | TransE | AUC, NDCG @10, and F1-Score | • Sophisticated model construction that hardens the process of usability and interoperability |
| [168] | Politics | Trustworthy claims fact in the political system | Adhoc/nanopublication model24 | Se Liga na Politica(SLNP) | N/A | Case Study | • Limited direct relations between political organizations, • lack of fine-grained patterns in the political agent domain, • the utility of the incorporated provenance dimension was not properly validated |
| [177] | Culture | QA and RS for Chinese ancient history and culture. | BILSTM-CNN-CRF2S and DeepKE | Baidu Encyclopedia | N/A | Precision, recall, and F1-score | • Inadequate use of named entity extraction techniques, • limited data sources |

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24 http://nanopub.org/wordpress/
25 BiLSTM-CNN-CRF: Short-Term Memory-Convolutional Neural Networks-Conditions Random Field
| Ref.  | Sub-domain       | KG Usage                                               | Construction Algorithm(s) | KG Resource(s)                                | Embedding Technique(s) | Evaluation Measure(s) | Limitation(s)                                                                                     |
|-------|------------------|--------------------------------------------------------|---------------------------|-----------------------------------------------|------------------------|-----------------------|-----------------------------------------------------------------------------------------------|
| [183] | Tourism          | Touristic IR system for Tirol at Austria               | Adhoc wrapper software    | DMOs, GISs, Feratel\(^{26}\), Infomax\(^{27}\), web maps\(^{28}\), Outdooractive\(^{29}\) and waldhart\(^{30}\) | N/A                    | Case Study            | • Scalability; hard to provide a wrapper for each source when it maps to Schema.org,            |
|       |                  |                                                        |                           |                                               |                        |                       | • data collection is subject to error- prone,                                                   |
|       |                  |                                                        |                           |                                               |                        |                       | • poor KG construction evaluation                                                               |
| [184] | Tourism          | Chinese tourism-domain knowledge service               | NLP - Skip-Gram Model     | Sogou-T\(^{31}\), Chinese Wikipedia dump\(^{32}\), and Zhishi.me\(^{33}\) | N/A                    | Accuracy              | • Inadequate evaluation measures,                                                                |
|       |                  |                                                        |                           |                                               |                        |                       | • lack of benchmark comparisons with other related KGs                                          |
| [181] | Tourism          | KG-QA in tourism                                       | Adhoc entity recognition algorithm and CNN | Manual collection and NLPCC2016KBQA dataset\(^{34}\) | N/A                    | Accuracy              | • Inadequate discussion on rationale on entity and relation extraction,                         |
|       |                  |                                                        |                           |                                               |                        |                       | • limited evaluation metrics                                                                     |
| [185] | Tourism          | Spanish tourism-oriented knowledge service             | Adhoc based on GATE pipeline | Wikitravel                                   | N/A                    | Precision, recall and F-measure                  | • Construction of the KG led to import noisy data,                                              |
|       |                  |                                                        |                           |                                               |                        |                       | • limited data sources                                                                          |
| [190] | Traffic          | Urban traffic congestion                              | Adhoc                     | Beijing traffic data and meteorological data. | N/A                    | Accuracy, and F1     | • Limited discussion on KG construction including entity and relation extraction approaches     |
| [195] | Transportation   | Knowledge integration of maritime dangerous goods      | Adhoc                     | IMDG Code                                    | N/A                    | Case study                         | • Poor discussion on entity and relation extraction algorithms,                                  |
|       |                  |                                                        |                           |                                               |                        |                       | • lack of proper evaluation metrics to validate the utility of the proposed KG                    |
| [193] | Traffic          | Traffic image feature extraction                      | Adhoc                     | Imagery data                                 | N/A                    | Subjective evaluation | • Poor evaluation approach,                                                                    |
|       |                  |                                                        |                           |                                               |                        |                       | • traffic cameras are prone to errors (weather, lighting, maintenance, etc.)                   |
| [194] | Traffic          | Railway Electrical Accident Analysis                   | Adhoc and BiLSTM-CRF      | China Railway electrical accidents data       | N/A                    | Precision, Recall and F1                  | • Limited data sources,                                                                       |
|       |                  |                                                        |                           |                                               |                        |                       | • inadequate discussion on utility of the constructed KG                                        |
|       |                  |                                                        |                           |                                               |                        |                       | • lack of benchmark comparison                                                                 |

\(^{26}\) https://www.feratel.com/
\(^{27}\) https://www.infomax.de/
\(^{28}\) https://general-solutions.eu
\(^{29}\) https://www.outdooractive.com
\(^{30}\) https://www.waldhart.at/
\(^{31}\) https://www.sogou.com/labs/resource/t.php
\(^{32}\) https://dumps.wikimedia.org/zhwiki/
\(^{33}\) http://openkg.cn/dataset/zhishi-me-dump
\(^{34}\) https://github.com/huangxiangzhou/NLPCC2016KBQA
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