IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 1 March 2024, accepted 11 March 2024, date of publication 18 March 2024, date of current version 22 March 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3378514

TOPICAL REVIEW

Investigating the Challenges and Prospects of Construction Models for Dynamic Knowledge Graphs

MAHA FARGHALY[1], MAHMOUD MOUNIR[2], MOSTAFA AREF[2], AND SHERIN M. MOUSSA[2,3]

[1]Information Systems Department, Faculty of Computers and Information Technology, Future University in Egypt, Cairo 11835, Egypt
[2]Faculty of Computer and Information Sciences, Ain Shams University, Cairo 11566, Egypt
[3]Laboratoire Interdisciplinaire de l'Université Française d'Égypte (UFEID Lab), Université Francaise d'Égypte, Cairo 11837, Egypt

Corresponding author: Maha Farghaly (maha.farghaly@fue.edu.eg)

ABSTRACT Recently, Dynamic knowledge graphs (DKGs) have been considered the foundation stone for several powerful knowledge-aware applications. DKG has a great advancement over static knowledge graph with the ability to capture the dynamicity of knowledge. The correctness and completeness of DKGs strongly affect the accuracy of the dependent application, in which many factors may have an impact, including data sources, graph construction model, and evaluation methods. Despite the increasing attention to DKGs, the literature of DKG construction is not comprehensively investigated, and the limitations are not fully revealed. In this paper, a comparative study is conducted for the emerging construction models of DKG. An extensive analysis is provided for each of the three main phases of DKG construction: entity extraction, relationship extraction and graph completion. For the different phases, we investigated the employed techniques, the used data sources, as well as the associated challenges, limitations, and evaluation metrics of each model. The learning approach is introduced as a novel categorization perspective for the employed techniques in the DKG construction. Finally, the encountered challenges and limitations are inspected to deduce the possible future directions that can be adopted for effective and advanced DKGs construction. It was found that 100% of the investigated models lack the key aspects of dynamicity in DKGs, 75% suffer from insufficient training features, 58% have a clear exposure to bias, 33% are vulnerable to changes, 25% have a performance and efficiency concerns, while lack of evaluation and comparison represented 25% and 17% of the models respectively.

INDEX TERMS Dynamic knowledge graph, learning approaches, knowledge graph completion, knowledge graph construction.

I. INTRODUCTION

Recently, there has been growing recognition of the importance of analyzing and exploring disparate data sources as unified and integrated. Integrating real-time data from multiple sources is extremely challenging, due to the enormous amount of data, continuous updates, and messy data structures [1]. These common challenges of integrating data in different domains obstruct the way for utilizing the collected data in real-world applications. Knowledge graphs (KGs) grabbed a great attention in the research communities as a unified knowledge integration model that is capable of not only providing an integrated unified view of data, but also enriching the integrated data with semantics that could be very valuable [2].

Knowledge graph (KG) construction is the process of building a unified knowledge view extracted and integrated from various data sources. The construction process involves the extraction and structuring of information into a set of knowledge triplets (h, r, t), where h is a head entity, t is a tail entity and r is the relationship between them [3]. The set of knowledge triplets forms the KG, the entities represented as graph nodes and relationship between the head and tail entities on each knowledge triplet is represented as a directed

The associate editor coordinating the review of this manuscript and approving it for publication was Laxmisha Rai.

TABLE 1. Released well-known knowledge graphs.

Knowledge Graph Name	Domain	Main Data Source		Number of Entities/ Instances	Number of Relationships	Types of Relationships	Applications
DBpedia [11], [12]	Generic	- Wikipedia		7,470,000	127,800,000	1355	- Recommendation systems [13] - Power Equipment Management [14]
YAGO [15], [16]	Generic	- Wikipedia	- WordNet	4595,906	25,946,870	N/A	- Personalized search
MOOC Knowledge Graph [17]	Education	- Coursera - EDX XuetangX	- ICourse, Wikipedia	52 779	281,180	11	- Prerequisites Mining [17]
BabelNet [18], [19]	Generic (Multilingual)	- Wikipedia	- WordNet	13,110,067	1,617,548,336	22	- Search engine enhancement (Understanding Users Intent) [20]
Graph of Things [1], [21]	IoT	- SSN Ontology [22] - LinkedGeoData - Geonames - DBPedia	- Facebook - Twitter - YAGO	N/A	N/A	N/A	- Real-time search engine for IoT [1]
Google Knowledge Graph [23]	Generic	- CIA World Factbook	- Wikipedia	570,000,000	18,000,000,000	35,000	- Google Search Engine - Google Assistant
ConceptNet [24], [25]	Generic (Multilingual)	- DBpedia [11] - Wiktionary	- WordNet - OpenCyc	8000,000	32,755,210	34	- Recommendation System for Domain Modeling [26] - Image Retrieval [27]
AliCoCo [28]	E-commerce	- ConceptNet	- Alibaba e-commerce platform	8,215,339	400,000,000,000	N/A	- Shopping Guide [29] - Product Question Answering System [29] - E-commerce Recommendation System [30]

edge between the two entity nodes [4]. The extracted knowledge triplets form a static KG. Although static KG solves many of the aforementioned challenges, it cannot capture the dynamic nature of real-world data and their continuous flow and evolution in most of the domains that usually change or increment over time, leading to the incompleteness of static KGs [5]. Therefore, the constructed graphs need to be updated and completed dynamically [6].

As a consequence, dynamic knowledge graphs (DKGs) have gained much attention, due to their capability of completion and adaptability to the evolution of the integrated data over time [7], as well as temporal KGs as a special type of DKGs, with the additional capability to hold a timestamp for each piece of knowledge, imposing consistency of the graph content with respect to time and considering the time-validity of data [8].

Many general and domain-specific KGs have been presented and employed in various applications, and continuously updated. Table 1 summarizes the main well-known KGs, at several domains, together with data sources, the key applications employed these graphs, and the observed counts of entities, relationships, and classes of relationships as per the latest access date of these KGs, as most of them have been modified several times since their first release.

The recent research efforts on DKGs can be categorized into construction-based and employment-based studies. The construction process of DKGs can mainly be phased into entity extraction, relationship extraction and graph completion [6], [9]. The correctness and completeness of the constructed DKGs pave the way for powerful knowledge-aware applications [10], arising the importance of investigating the emerging construction models considered for the DKGs to discover their limitations and challenges, and hence, advance DKGs.

In this paper, an extensive analysis is conducted to evaluate the emerging construction models of DKGs, the challenges and limitations of each, as well as the key domains and applications adopted DKGs. Thus, the main contributions of this study are summarized as follows:

- A phased manner investigation is adopted to comprise the employed techniques, challenges, and limitations of each phase in DKG construction models.
- The learning approach is introduced as a novel categorization perspective for knowledge extraction in DKG construction.
- The novelty of the considered categorization perspective of knowledge extraction models adopted in both KG construction from raw data and extraction-based knowledge graph completion.

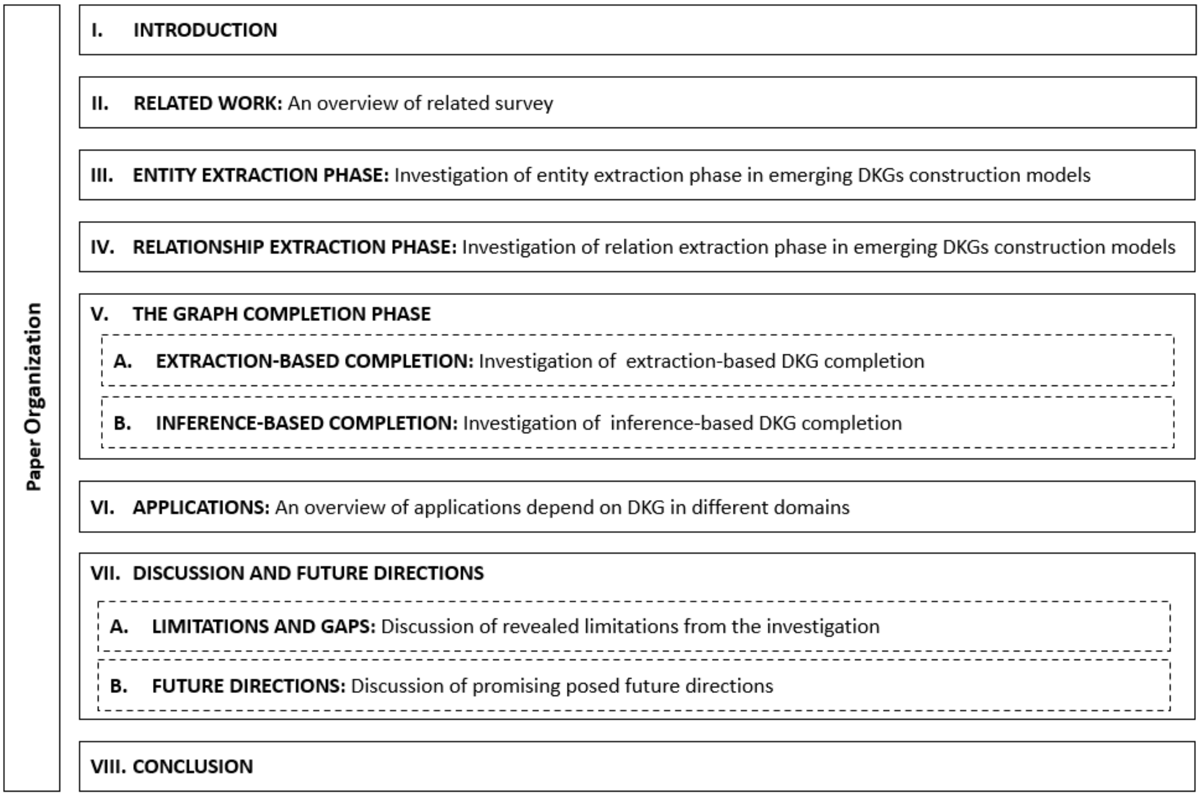

FIGURE 1. The article organization.

- A comprehensive novel list of limitations and challenges of DKG construction models is deduced, considering different assessment parameters.
- Inferring novel future directions and open research gaps that will be promising to address for effective DKGs construction.

As shown in Fig. 1, the reminder of this paper is organized as follows. Section II provides an overview of related surveys, highlighting the uniqueness of our study. Sections III, IV and V conduct a comprehensive study of the emerging DKG construction models, organized into the entity extraction phase, the relationship extraction phase and the graph completion phase respectively, discussing the employed techniques and the learning approach at each phase. Section VI explores the various domains and applications that adopted DKGs, whereas section VII poses the future research directions and gaps that would be promising to be further considered. Finally, section VIII concludes our findings and insights of this study.

II. RELATED WORK

Many surveys have been conducted on KGs. Authors in [10] studied the domain-related KGs in seven domains. They categorized the construction methods into four categories and briefly named the algorithms in each category. In [31], a systematic review was performed for the representation learning models in KGs, categorized based on the employed features on the learning process, whether it is confined to the graph content or additional external semantic information. Another review was conducted in [32] over the encoders and decoders employed for representation learning. In [33], the authors focused on multimodal construction models. They investigated KGs constructed from both text and image. In [34], the main concern was the completion process of temporal KGs. The authors focused on the methods ability to discover the knowledge evolution by utilizing the time dimension of facts. While in [35], the reasoning of static, temporal, and multimodal KGs were investigated for KG completion. Authors in [6] studied the representation learning methods for knowledge acquisition and discussed temporal KGs and their applications from various aspects. Other surveys have been conducted on task-specific applications that utilize KGs [36], [37], [38].

In this study, we conduct a phased study for the emerging construction models of DKGs, their employed techniques, challenges, limitations, and applications. The employed techniques are considered from their learning approach perspective. The learning approach of the construction models varies mainly between traditional models, transfer learning-based models, reinforcement learning-based models, and embedding learning-based models. Transfer learning is the process of migrating a learnt task or parameters to perform a new near-similar task. It is widely utilized in case of the insufficiency of labelled training sets, or in purpose of reducing the model's training time [39]. Reinforcement learning is concerned with how intelligent a model can perform a task in an environment in order to maximize the notion of cumulative reward [40], [41]. Embedding learning, also termed as Feature Learning, is the process of projecting raw data into a representation space to discover and extract latent features [42].

In the following sections, a phase-based intensive study is discussed for the emerging construction models of DKGs with respect to their learning approach. Fig. 2 presents the phases and the categorization of our study. As illustrated in the figure, the study is partitioned into knowledge graph construction from raw data sources with knowledge extraction, and graph completion to obtain knowledge dynamicity in the constructed KG. The main tasks of knowledge extraction are entity extraction and relationship extraction, studied based on their learning approach. Graph completion is categorized based on the new knowledge source and the employed learning features source, whether extracted from external raw sources or inferred from the graph itself.

III. ENTITY EXTRACTION PHASE

Entity Extraction mainly employs natural language processing techniques to automatically locate and label structured concepts from unstructured data sources [43]. The extracted entities are considered as the KG nodes. Entity extraction accuracy highly affects the accuracy of the constructed KG, due to the dependency of the consequent phases on the extracted entities [44].

In [40], the authors built an interpretable DKG of integrated financial data, challenging the limited publicly accessible labelled data in finance domain to train a knowledge extraction model. They overcame this challenge by constructing an initial KG and enriching it with financial information by training an extraction model with standard labelled dataset and further transferring the learnt task for the graph completion. Investigating the construction of the initial KG from entities extraction perspective, a list of companies was obtained from a structured data sources as main graph entities, and their attributes along with crawled relevant information from structured and semi-structured data sources, to form the entities networks with the aid of Tushare tool. However, the authors shallowly explained the construction of the initial graph, without explaining what features they utilized and how the entities' network were extracted and linked to the companies' entities from the semi-structured data sources and did not evaluate the initial graph.Another entity extraction model adopting the transfer learning approach employed BiLSTM and CRF in [9], combined with a self-attention mechanism to improve BiLSTM in order to deal with dependent features that are apart in sentences. Transfer learning was adopted by training the model with labelled corpus from People's Daily. The learnt model parameters were then migrated to extract enterprise entities from a corpus of news compiled from People's Daily, Encyclopedia, and other crawled corporate news. Although the authors experimented the effect of transfer learning on the employed model, but their experiments were insufficient, as there were no comparisons to other models following transfer learning. Another limitation is that the crawled time-based news may expose the constructed graph to bias [45].

Authors in [46] constructed DKG from user-generated reviews on an e-commerce website in order to be employed for fake reviews detection. Investigating the entity extraction of their model, they proposed the embedding-based entity extraction model sentence vector/twin-word embedding conditioned Bi-LSTM (ST-BiLSTM). The model was trained using a public available dataset that is crawled and extracted from the official GroupLens website. The twin-word embedding captures the word-level semantic features of entities, the sentence vector captures the sentence-level semantic features, and Bi-LSTM was trained using both to extract the entities. Since the entities extracted out of social feed data, the existence of bias should have been examined and mitigated if exists.

In [47], another embedding-based model was introduced that extracts entities from a scene video of robot manipulation task based on Seq2Seq architecture. The model starts with splitting the video into frames, then extracts the features from the frames using a vision-language model of ImageNet-pretrained CNN. Following, two consequent LSTMs were applied to encode the features and decode the entities with their relationships, respectively. Yet, the explanation of relationship extraction at this DKG construction model was very poor. The dependency between the vision language model and the construction model, and the possibility of error propagation between the two models should be investigated. Besides, employing temporal features could enhance the efficiency of entity extraction.

IV. RELATIONSHIP EXTRACTION PHASE

A knowledge graph edge consists of a specific type of semantic relationships between a pair of entities, directed from an object to a subject [6]. Given a pair of entities, relationship extraction tries to detect the existence of an edge between the given pair beside its label [48]. Various studies have been conducted to extract relationships and identify their classes efficiently and completely. In [46], the relationship extraction problem was considered as an entity association problem. They defined the comprehensive correlation value (CCV) to measure the correlation between entity nodes, based on the Entity-to-Entity relation mutual information (EER-MI). An edge between two unconnected graph entity nodes, a and b, exists, if the measured CCV between these nodes is greater than a specific threshold, where CCV of the two nodes defined in (1):

$$CCV\ (a, b) = EERMI_{e_1}\ (a, b) \oplus EERMI_{e_2}\ (a, b) \oplus \ldots \oplus EERMI_{e_n}\ (a, b) \quad (1)$$

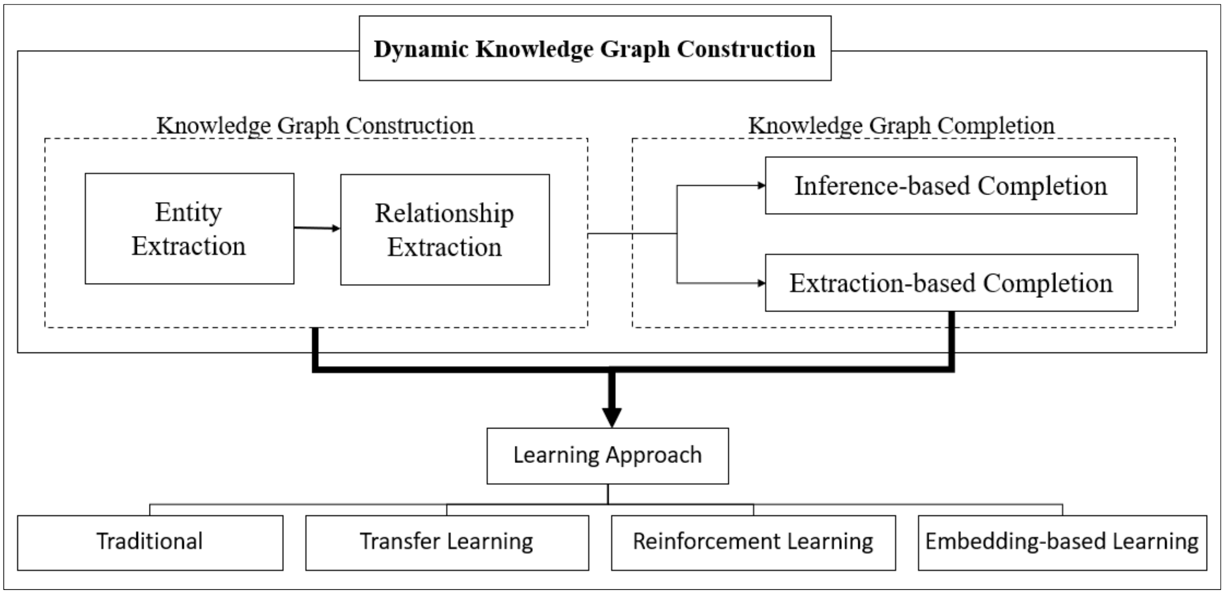

FIGURE 2. Learning approaches categorization of DKG construction phases.

where $e_1, e_2, \ldots, e_n$ are common directly connected graph nodes to a and b, n is the number of common directly connected graph nodes to a and b, and $EERMI_{e_1}(a, b)$ is the association between two indirectly connected entity nodes a and b, which calculated by (2).

$$EERMI_{e_1}(a,b) = I(e_1,a) + I(e_1,b) - \sqrt{[I(e_1,a).I(e_1,b)]} \quad (2)$$

where e_1 is directly connected graph node to a and b, a and b are not connected in the graph, $I(e_1, a)$ is the MI between a and e_1, and $I(e_1, b)$ is the MI between b and e_1. There is a concern in the relationship extraction phase at this DKG construction model, which is the user-provided thresholds that may affect the correctness and completeness of the DKG. Another limitation is the model's capability of discovering the existence of a relationship between two graph nodes without identifying the relationship class.

Authors in [9] stated that entity attributes can be considered as a type of relationship. Thus, they targeted the extraction of semantic attributes, time, and relation features. BiGRU-Incep and BiGRU-CNN models were employed to obtain the embeddings of entities and extract the aforementioned features, which furtherly input to the soft max classifier to obtain the relationship. The authors did not evaluate the relation extraction phase on their DKG model, creating a concern around the model efficiency.

Another approach named KGPool was developed in [48] to extract relationships for a set of entities, depending on the sentence-wise context information. The approach consisted of three consecutive stages: heterogenous graph construction, context graph obtainment, and context aggregation. The heterogonous graph is composed of the embedding of all graph entities, their context attributes and sentences words obtained from Wikidata and Freebase KGs and represented using Bi-LSTM embedding. Context pooling was then performed over the heterogenous graph to enrich the nodes with neighbors' contextual features via Graph Convolutional Network (GCN). Following, the resultant graph nodes were filtered based on the calculated self-attention score to exclude the less relevant nodes, and hence, obtain the context graph. The context graph representation was aggregated with entities embedding and sentence embedding in order to learn new relationships. However, a concern is raised about how KGPool deals with multi-context and generic context graphs, and whether the extraction will be biased to the selected context [45]. An open question regarding the model capability to be employed for DKG completion and to cover the dynamicity of knowledge over time.

V. THE GRAPH COMPLETION PHASE

KG completion is the process of dynamically adding and updating an existing KG with new instances. The new added instances can be nodes, edges, attributes, or a complete knowledge triplet [49]. This newly added piece of knowledge may be extracted from external sources and merged into an existing KG or inferred from the latent knowledge features of the graph components [50]. In the following subsections, the main knowledge graph completion models are elaborated and categorized based on the method of the new knowledge acquirement.

A. EXTRACTION-BASED COMPLETION

The KG completion based on the extraction of new knowledge can be thought of as constructing a new KG via knowledge extraction from external data sources and linking this new KG to an existing one by fusing the newly extracted knowledge into the existing KG [9]. The extracted knowledge for completion is not necessarily a full knowledge triplet, as it can be entities, relationships, or even semantic attributes [50].

In [40], the concept of extraction-based completion was adopted to build a financial DKG by building an initial graph from structured and semi-structured data sources, and then extracting the financial knowledge from different data sources to be fused into the initial graph. BERT_BiLSTM_CRF was proposed and applied to extract financial entities. The model consisted of successive stages of BERT, Bidirectional Long-Short Term Memory, and Conditional Random Field models. The model was trained with standard dataset, and the learnt task was transferred with finetuning the model using a financial dataset constructed with aid of the Standers CoreNLP tools to recognize financial entities from unstructured financial data.

For relationship completion, the extraction task was considered as a relationship classification task, with a special class named ''Not Available'' if two entities have no relationship. The training set was filtered by an instance selector before training BERT model for the classification task. The filtration and the classifier training processes were done in a reinforcement learning-manner. Then, the obtained knowledge was linked to the standard KG based on the similarity of three feature types: (i) the syntactic word features, computed by a pre-trained Word2Vec model and Jaccard similarity, (ii) the context features, computed by trained Doc2Vec model and pretrained BERT model, and (iii) corpus features, obtained at the extraction phase. Finally, an SVM classifier was fed by the computed features to link the new financial entities to the initial KG. Although this model overcame the challenge of the scarce labelled data to construct a financial DKG, but there is a limitation in the relation extraction phase, that is the instance selector filters the training set by selecting only the sentences that contain a paired entities at the initial KG, indicating that the relationship extraction was trained on the sentence level only, without considering other levels of features to discover relationships. Another main concern is about the accuracy of the constructed dataset used to fine-tune the entity extraction model, and whether it is biased or not, as well as the model performance and accuracy, especially that they did not compare their results with any other models for verification. In addition, a concern is raised whether the constructed KG holds dynamic aspects such as deletion of outdated facts, and spatio-temporal validity of knowledge.

Authors in [51] proposed PolarisX as a completion model that expands ConceptNet KG with new extracted knowledge triplets. Their challenge was to update ConceptNet with unprecedented words or concepts. PolarisX crawls social media and news and extracts keywords from the crawled data, using the probabilistic Latent Dirichlet Allocation algorithm (LDA) [52]. Next, a BERT-based model was trained to extract relationships between the obtained set of keywords. The multilingual BERT model was fine-tuned using TACRED dataset to generate a specified relationship that pairs an object to a subject. Using a string-matching algorithm, the graph was searched for a node that matches the discovered object. If found, the node is connected to the new related subject, otherwise, a new node is created in the expanded KG with the discovered object and connected to the related subject. With the possibility of error propagation from the extracted entities to the relation extraction process, if exists, the limitation of this work is that the performance of LDA for entity extraction was not evaluated. Moreover, the model only considers the addition of new knowledge, neglecting other forms of knowledge evolution such as deletion of invalid knowledge from the graph. Besides, there is a concern about the completed KG whether it is biased as a result of completing the graph from social media data, which may introduce a bias [45].

Table 2 summarizes the discussed extraction models employed in DKG construction models, either for KG construction or for the graph completion, in terms of their domain, data sources, entity extraction, relation extraction, evaluation metrics, challenges and limitations.

B. INFERENCE-BASED COMPLETION

Inference-based completion mainly relies on discovering new knowledge from the graph itself, either hidden knowledge or knowledge inferred from the entity's semantics [50].

In [9], the constructed KG dynamicity was maintained by continuous knowledge reasoning. The MultiNet model was adapted for graph completion by obtaining the representation of the timed events, entities, their attributes, and neighbor entities semantics, to be utilized for predicting the presence of new entities or relationships as a multiclassification problem. A loss function was applied to balance the multiclassification task of entities and relationships. A concern is raised; whether the timed events influenced the constructed DKG and caused existence of bias [45]. Moreover, the constructed KG is partial dynamic where only the addition of new knowledge was considered.

The time dimension of the constructed KG was employed in [46] by introducing a new algorithm that infers the existence of new relationships between the graph nodes based on the integrated time information, but it is limited to discover the existence of a relationship between a pair of nodes without identifying the relation type. The model suffers from a lack of employed features for relationship discovery and completion, as only the time feature was employed for completion. Partial completion was performed, in addition to considering only the addition of new relationships, resulting partial dynamicity of the KG.

Entity attributes-level completion was performed in [47] to the constructed KG, employing a robot-specific ontology to enrich the graph nodes with semantic attributes and values. For each entity node in the graph, the assigned attributes and values are queried from the ontology and integrated to the entity at the KG. Yet, the authors did not evaluate the completion process and the enriched attributes, in which no evidence is proven for their positive impact on entities and relations completion if utilized. Another raised concern is whether considering the structural features of the static

TABLE 2. A summary of the main knowledge extraction models in DKGS.

Ref. No.	Domain	Data Sources	Training set	Challenges	Entity Extraction		Relationship Extraction		Evaluation Metrics	Limitations	Applications
					Model	Learning Approach	Model	Learning Approach			
[40]	Finance	- A-share companies - Snowball - CN-DBPedia - Baidu Encyclopedia - Dongfang Finance	- SIGHANBakeoff2006 - Wikipedia Corpus	- Complexity and diversity of financial data sources - Necessity of interpretability - Availability of labelled training data	BERT_BiLSTM_CRF	Transfer learning	Instance selection +CNN	Reinforcement learning	- Marco-F1 - Accuracy	- Poor explanation of initial graph construction. - Sentence-level relation extraction and partial dynamicity. - Concerns about accuracy of the constructed dataset used by the extraction model. - Absence of comparisons to other models.	A website for financial KG with readable visualization to observe dynamicity in finance domain and aid user decisions.
[9]	Enterprise	- People's Daily Corpus	- Encyclopedia - Baidu Encyclopedia	- Big data in enterprise domain - Rigorous specifications and diversity of enterprise risk knowledge	SA-BiLSTM-CRF	Transfer learning	BiGRU-CNN BiGRU-Incep Soft max	Embedding-based learning	- Accuracy - F1 score - Recall - MRR - Hit@k	- Insufficient experiments and comparisons to other transfer learning-based models. - Exposure to bias due to crawled news. - Relationship extraction was not evaluated.	Risk-event question answering framework
[46]	E-commerce	- Amazon - Netflix - Movielens - Webdata	- A crawled dataset from GroupLens - TMDB	- Considering the correlation between time and semantics of the review text	ST-BLSTM	Embedding-based learning	MI	Traditional	- Accuracy - Recall - F1 score - Rand index - Jaccard coefficient - Fowlkes& Mallows index	- Social feed data expose the constructed graph to bias. - User-defined thresholds on relationship extraction is an efficiency concern. - Existence of a new relationship is inferred without relationship type.	Fake reviews detection on e-commerce websites.
[47]	Robotics	- The Robot Semantics Dataset	- ImageNet	- Interpret semantic knowledge into robot manipulation tasks	Seq2Seq -based model (CNN+LSTM)	Embedding-based learning	Seq2Seq -based model (CNN+LSTM)	Embedding-based learning	- BLEU 1-4 - ROUGE-L - METEOR - CIDEr	- Poor explanation of the relationship extraction. - Possible error propagation between vision language and construction models. - Temporal features to be employed for efficient entity extraction.	Robot manipulation tasks
[51]	Generic	- Twitter crawling - APIs and news crawling	- TACRED	- Language dependency - Neologisms	LDA [52]	Traditional	Pretrained multilingual BERT	Transfer learning	- BLEU score - Precision - Recall - F1 score - Relationship's count - Relationship types count	- LDA was not evaluated. - Social feed data exposed to bias. - Partial dynamicity by considering only addition of new knowledge.	Enhanced search engine
[48]	Generic	- NYT Freebase - Wikidata	- NYT Freebase - Wikidata	- Graph pooling due to divergent number of adjacent nodes in the graph	-	-	KGPOOL	Embedding-based learning	- Precision - Recall - F1 score	- A concern regards dealing with generic or multi-context KGs. - Possibility of bias. - Covering dynamic aspects.	-

graph will have an impact over the attribute-level completion. However, the constructed KG was partial dynamic.

The authors of [53] developed KG-BERT as a textual encoding model for knowledge graph completion tasks. The model starts with considering head (h) and tail (t) entities and relationship (r) in a knowledge triplet (h, r, t) and their description sentences as a single textual sequence. The sequences contextual embeddings for all knowledge triplets were obtained and fed into a pre-trained BERT model to score the triplets using a sigmoid-based function. Two versions of KG-BERT were developed, in which the first version performed two completion tasks: triplets' plausibility as a next-sentence prediction task, and entities prediction, by computing the plausibility score for each knowledge triplet produced by examining each entity in the knowledge graph at a time. The second version predicts the relationship between two entities, head, and tail, by scoring the plausibility of each knowledge triplet produced by examining each existing relationship type in the knowledge graph. The model limitation is not utilizing the graph structural information and surrounding triplets' information in the completion. Also, the performance of entities prediction and relationships prediction tasks is expected to be very poor on a large-scale knowledge graph completion with large numbers of entities and relationships. Moreover, the completion model neglected the temporal evolution of knowledge resulting partial dynamicity.

In [42], a fusion-based embedding model was proposed for KG completion named G2SKGE. The model utilized the entities' surrounding information, in addition to the entities and relations for embedding learning rather than learning from entities and relations independently. Each entity and its surrounding relations were considered as a subgraph structure, then selected randomly N number of in-relations and N number of out-relations, obtained their embeddings, concatenated them and all fused following the Graph2Seq architecture in Graph Neural Network (GNN) into one embedding vector with attention mechanism. The embeddings of all triplets were employed to train the prediction model with binary cross entropy function to predict new triplets. Although the model utilized the graph structural information in the learning process but selecting randomly a fixed number of surrounding relations for all entities to be utilized was inefficient and would cause loss of information. The non-selected relations could be more important to predict a triple than the selected relations. However, the model lacks the ability to utilize other types of features (e.g., contextual, semantic, etc.) to be fused to train the prediction model. Also, the model only considers the addition of new knowledge triplets, neglecting other dynamic aspects such as the deletion of nonvalid knowledge and the topological graph changes. Besides, a concern is raised about the model performance over sparce KGs.

Both the structural embedding and textual embedding paradigms were combined in [54], proposing the Structure Augmented Textual Representation (StAR) completion model. For each knowledge triplet, the tail is separated from the rest of the triplet components, forming two parts. The encoding vectors of each part were obtained by a transformation-based encoder, and dually utilized to score the textual and structural information parallelly. For the textual embedding score, the embedding vectors of the two parts were interactively concatenated and fed into a multilayer perceptron-based binary classifier. For the structural embedding score, the vectors were translated into a space, and the distance between them was measured as the structural score. The textual and structural scores were fed into binary cross entropy loss and margin-based hinge loss, respectively, for training. Finally, the trained loss functions were employed for the inference model for KG triplets' completion. The main limitation was considering the spatial distance only between the entities to score the structural information, while other structural features (e.g., common relations) could be informative. A concern is raised regarding the constructed DKG validation over time.

Unlike the above models, [55] challenged the completion over sparce KGs, in which the relations between entities were insufficient. A model named DacKGR was proposed, consisting of two phases: dynamic anticipation and completion. As for the anticipation, the Markov Decision Process (MDP) was employed and augmented with LSTM to embed the historical path and obtain the needed anticipation scores to guide the training of completion. Following the reinforcement learning approach, the anticipation scores were fed into the completion learning to add new relations to entities. The new additional relations along with entities were fed into the pre-trained embedding model to obtain a vector of probabilities of each entity in the graph to be the missing tail in an uncomplete knowledge triplet. A drawback of this model was that these embedding-based scores did not hold any contextual or structural information, which is expected to be more efficient to utilize. Moreover, the model neglected the possible changes in entities and attributes meanings over time.

Authors of [5] introduced their model learning TDG2E, utilizing a different type of knowledge features for KG completion. The triplets embedding along with its timestamp embedding was obtained using TransE. The time information was then utilized to capture the evaluation features of the KG triplets by snaping the DKG into a sequence of static KGs. Each snap holds the triplets of a time bin that maintains the structural information of the triplets, determined by a developed gate added to the gated recurrent units in order to project the triplets of the snap graph into a hyper-plane. All the hyperplanes of the DKG were fed into the training of completion model to capture the evolution of knowledge. However, the model did not capture the contextual semantics of entities and relational information which are valuable features for training the model to enrich and complete the DKG. An open question is raised whether the resulted DKG suffers from a time-based bias [45], and whether it considers the changes in entities and attributes meanings over time.

Temporal features were also considered by authors of [56]. They developed a model based on Recurrent Neural Network (RNN) architecture, which learns the evolving knowledge triplets' embeddings, taking into consideration the relation-based dependency among the knowledge triplets over time. They proposed a score function that incorporated structural and temporal features of the KG. The network-based model inferred missing facts and missing timestamp for a given fact. Although the model considered both the structural and temporal knowledge features, it neglected the textual triplets' features. The model suffered from partial dynamicity, due to neglecting that entities meanings or attributes may change over time. A concern was raised regarding the model's efficiency with inadequate temporal facts and whether the resulted DKG suffered from a time-based bias [45].

Table 3 summarizes the discussed knowledge inference-based completion models employed in DKG construction models, in terms of their domain, data sources, knowledge completion, evaluation metrics, challenges and limitations.

VI. APPLICATIONS

With the ability to model the real-world dynamicity and heterogeneity and to enrich knowledge with semantics, DKGs proved to be a main stone for building powerful knowledge-aware applications at different domains:

- In linguistics and cross language modelling, the novelties of language were modelled in [51] using a DKG, in purpose of enhancing the search results of search engine and better understanding of user intent.
- In finance, the authors of [40] published a website for financial knowledge graph visualization. The website allows the user to interact by searching entities, view entity details, and displaying a readable, time-lined, integrated, and updated financial data. such functionalities allow the user to have accessibility to integrated financial data, observe the dynamicity in finance domain and aid user decisions.
- In enterprises domain, with DKG ability to adapt to big data environment, the authors of [9] introduced an iterative framework for risk-event Question Answering QA based on enterprise event DKG. The framework iteratively asks the user questions till fully understanding user intent, the risk event that the question revolves around, its entities and attributes. Following, the DKG

TABLE 3. A summary of inference-based completion models.

Ref. No.	Domain	Data Sources	Training sets	Challenges	Completion	Evaluation Metrics	Limitations
[9]	Enterprises	People's Daily Corpus	Encyclopaedia, Baidu Encyclopaedia	Maintaining the interpretability of enterprise knowledge with completion	ResNet	Accuracy, F1 score, Recall, Hit@k, MRR	· Exposure to bias. · Partial dynamicity.
[46]	E-commerce	Amazon, Netflix, Ovielens, Webdata	A dataset crawled from the official GroupLens website and TMDB	Considering the correlation between time and the semantics of the review text	Introduced an algorithm utilizing time information for relationship inference	Accuracy, Recall, F1 score, Rand index, Jaccard coefficient, Fowlkes, and Mallows index	- The completion infers only the existence of a new relationship between a pair of entities without the type of the relationship. - Insufficient employed features for completion. - Partial dynamicity.
[47]	Robotics	The Robot Semantics Dataset	ImageNet	Interpret semantic knowledge into robot manipulation tasks	Simple entity matching-attribute retrieval		- Completion not evaluated. - Attribute-level dynamicity only and ignoring the structural features of the static graph at the completion task.
[53]	Generic	WN11, WN18RR, FB15K, FB15K-237, UMLS	BooksCorpus, Wikipedia	Weighting triples' reasonability	KG-BERT	Accuracy, MR, Hits@k	- Excessive time-cost and performance for large scale KGs. - Ignorance of structural information. - Partial dynamicity.
[42]	Generic	WN18, WN18RR, FB15K, FB15K-237	WN18, WN18RR, FB15K, FB15k-237	Utilizing graph structure for prediction learning	G2SKGE	MRR, Hit@k	- Loss of information due to the fixation of the number of entity's surrounding relations to utilize. - Random selection of utilized entity's surrounding relations. - Insufficient features for completion and partial dynamicity - Concern about the performance over sparce KGs.
[54]	Generic	WN18RR, FB15K-237, UMLS, NELL-One	WN18RR, FB15k-237, UMLS, NELL-One	Considering both structural and textual features for completion learning	StAR	MR, MRR, Hits@k	- Considering only the spatial distance between the entities as structural information. - Partial dynamicity.
[55]	Generic	Several datasets based on FB15K-237, NELL23K, WD-singer, and Wikidata	Several datasets based on FB15K-237, NELL23K, WD-singer, and Wikidata	Inference with sparsity in KGs	DacKGR	MRR, Hits@k	- Poor explanation of the feature types utilized and employed at the reinforcement-based reasoning. - Partial dynamicity.
[5]	Generic	YAGO11k, Wikidata12k	YAGO11k, Wikidata12k	Considering the changes in KG structure over time	TDG2E	MR, Hits@k	- Ignoring semantic features of the KG in the learning process. - Exposure to bias and partial dynamicity.
[56]	Generic	GDELT ICEWS	GDELT ICEWS	Considering knowledge evolution over time in learning knowledge inference	Know—Evolve	MAR, Hits@k, Standard Deviation for MAR	- Ignoring textual features of the knowledge triplet in the learning process - Exposure to bias and partial dynamicity. - A concern regarding the model performance with non-temporal facts.

queried to retrieve the matching entities and attributes to compute the answer to the user.

- For e-commerce, [46] constructed a DKG using user generated data to detect the fake reviews on e-commerce websites. The DKG utilized a time dimension and revealed the hidden connections between the reviewer, the store, the commodity, and the review, which enabled the authors to define four new metrics for identifying fake reviews with high accuracy. The framework is compatible for any review-based applications at other domains.
- Robotics domain also has its share in DKG literature, where [47] constructed a DKG that model the surrounding environment sensed objects and visually captured manipulation tasks. The model helps robotics to understand and perform manipulation commands. The authors of [57] inspired by human memory, designed a memory model based on DKG to aid robots understanding and learning capabilities. The memorized knowledge partitioned into experience memories and new sensed memories that are interconnected as main concepts and objects respectively.
- In the smart cities and Internet of Things (IoT) domain, Graph of Things (GoT) [1] is a live-updated DKG that has been constructed and published on purpose of creating a real time search engine [21]. GoT integrates and unifies multisource, heterogenous data sensed using IoT sensors or crawled from news and social media. The authors of [58] constructed an urban knowledge graph using datasets obtained from OpenStreetMap, Google APIs and Baidu as the base for analytical application. They presented a framework to analyze the causes of traffics and pollution in a city.
- In Animations, [59] developed a framework to generate a 3D animation from an image, utilizing the knowledge of human to object interactions with respect to time and space which integrated in a DKG. The framework generates a scene of animated interactions driven from the environment, objects, or other clues appeared in the given image.

VII. DISCUSSION AND FUTURE DIRECTIONS

Upon evaluating the different construction models proposed for DKGs, a vision of possibly unexplored gaps, and inadequately covered concerns can be posed. In this section, we highlight the main limitations revealed through our conducted study, considering different assessment parameters, followed by our vision of future directions and the challenges that would increasingly face the construction models of DKGs.

A. LIMITATIONS AND GAPS

In this subsection, we explore the limitations of the investigated DKGs construction models, as well as how they would impact the overall usefulness and quality of the constructed DKGs. It is possible to quantify the impact of incorrectness and incompleteness of DKGs on the dependent applications, but it is very challenging, as the consequences of the exposed limitations on the relying applications depend on multiple factors. These factors include: the application's task, functionalities, and performance, as well as the DKG's complexity, domain, and scale. We herein clarify the specifications of each limitation and discuss its impact, as well as its potential consequences over the relying applications as follows.

1) PARTIAL DYNAMICITY

a: LIMITATION SPECIFICATIONS

The investigated DKG construction models fail to clearly explain or fully cover the crucial dynamicity aspects of DKGs. For all the investigated models, the dynamicity is partially achieved through manual run of the knowledge completion phase to update a static KG in terms of addition of new knowledge into the graph to obtain an updated KG, neglecting either one or more of other dynamic aspects such as topological structure changes, addition or deletion of entities and relationships, changing the meaning of entities over time, removing outdated facts, and attribute information changes.

b: LIMITATION IMPACT

Partially considering the dynamic aspects could produce an incomplete or inaccurate KG, due to neglecting changes in entities semantic, attributes, or topological structure changes. The constructed graph could also be outdated or inconsistent as a result of considering the addition of new facts only, while neglecting the removal or update of outdated facts.

c: POTENTIAL CONSEQUENCES

Partial dynamicity of the constructed DKG could cause the relying application to produce inaccurate output or suboptimal solution, due to the missing or outdated facts in the DKG. The application may fail to adapt to the evolving user or market needs.

2) INSUFFICIENT FEATURES

a: LIMITATION SPECIFICATIONS

Regarding the employed features for construction and completion learning, the feature types can be specified into semantic features, textual features, structural features, contextual features, and temporal features. Eight out of the eleven construction models neglected more than one valuable type of features and suffered from insufficient types of features employment, representing 75% of the construction models.

b: LIMITATION IMPACT

Training the construction model with insufficient features would limit the model ability to predict missing knowledge, and hence, it may produce an incomplete DKG. It also may cause the model to perform inaccurate predications, leading to an inaccurate DKG.

c: POTENTIAL CONSEQUENCES

Relying on an DKG constructed using a model trained with insufficient features may limit the application ability of generalization. It may also cause the application to perform poor analysis due to the incompleteness or incorrectness of the constructed DKG.

3) POSSIBILITY OF BIAS

a: LIMITATION SPECIFICATIONS

All the construction models did not examine the existence of bias in the constructed graph, although six of the eleven models were exposed to bias due to social media and temporal resources [45], representing 58% of the construction models.

b: LIMITATION IMPACT

Exposure to bias may yield to a skewed DKG topology. The constructed graph could be subjective to a specific domain, time, attribute, or representation, leading to an inaccurate constructed DKG.

c: POTENTIAL CONSEQUENCES

Relying on a biased DKG would reduce the application's efficiency, limit the diversity of the presented solutions, and produce biased outputs, exposing the user to a poor experience.

4) VULNERABILITY TO CHANGES

a: LIMITATION SPECIFICATIONS

Vulnerability to changes is concerned with the construction model not being robust to changes, such as the graph context, domain, scale, or knowledge features adequacy, which was suffered by three of the models, representing 33% of the models.

b: LIMITATION IMPACT

Model vulnerability to changes would risk the graph adaptability to unseen schema, in which a sudden shift in the model's performance may occur. This threatens the constructed graph reliability if the model frequently needs to be fixed to adapt to changes. It also may threaten the graph's consistency and accuracy over time if the model is unable to efficiently update the graph.

c: POTENTIAL CONSEQUENCES

Vulnerability of the construction model to dynamics may cause performance instability of the relying application. This would increase the failure risk and the maintenance overhead of the application to ensure the continuity of the application's functionality.

5) PERFORMANCE & EFFICIENCY CONCERN

a: LIMITATION SPECIFICATIONS

Regarding the performance and efficiency of the constructed DKG, many concerns were raised due to fixating the parameters, user-specified thresholds, or possibility of error propagation between the construction phases. This was detected in three of the models, representing 25% of the construction models.

b: LIMITATION IMPACT

Fixating the model's parameters would limit the model's robustness to the dynamics, as the fixed parameters may became outdated, or less effective over time, which may produce an inaccurate or incomplete DKG. User-specified thresholds in the construction model may cause the constructed DKG to be subjective, biased, and less adaptable to the dynamics. In addition, such user-specified thresholds may introduce human error to the construction process. Error propagation between the construction phases of DKG would produce an inaccurate DKG, due to the dependency between phases.

c: POTENTIAL CONSEQUENCES

Fixating the parameters of the construction model and the user-specified threshold would limit the adaptability of the relying applications to changes. The constructed inaccurate or incomplete DKG would impact the accuracy and relevancy of the relying application's output.

6) LACK OF EVALUATION AND COMPARISON ABSENCE

a: LIMITATION SPECIFICATIONS

Some efforts in the research community were directed to the metrics and methods of KG evaluation [60], [61], [62]. All the investigated models considered the evaluation of merely the model's performance, but none of them evaluated the graph as a whole. Moreover, many proposed construction models conducted insufficient experiments, either by the lack of evaluating a specific phase, or the absence of comparing the results to baseline models, representing 25% and 17% of the construction models respectively.

b: LIMITATION IMPACT

The evaluation and comparison of the construction models are considered a development aspect, as they assess the quality of the constructed DKG and help to identify its weaknesses and possible improvements. The lack of evaluation and absence of comparison to baseline models may produce a suboptimal DKG, limit the possibility of improvement, as well as limit the user's reliability and trustiness.

c: POTENTIAL CONSEQUENCES

Relying on a constructed DKG without evaluation or comparison to baseline models would cost the relying applications the user's trustiness and the competitive advantage in the market. It may cause unintended consequences on the accuracy of the application output. The application may suffer from unidentified weaknesses and suboptimal performance.

7) POOR EXPLANATION

a: LIMITATION SPECIFICATIONS

Some models neglected or inadequately explained the phases of their construction models, obtained outputs, or employed training features, limiting the advantageousness of their work in the literature. This limitation represented 25% of the models.

b: LIMITATION IMPACT

Poor explanation of the construction models would complicate the interpretability of the constructed DKG, which may lead to the underutilization of the graph. It would also hinder its customization and its possibility of improvement.

c: POTENTIAL CONSEQUENCES

Applications relying on inadequately explained DKGs are exposed to difficulties in debugging, limited improvements, as well as narrow innovation opportunities.

Table 4 summarizes the limitations revealed through the investigation of DKG construction models, whereas Fig. 3 quantifies the percentage of construction models that face each of these limitations. The aforementioned limitations formulated a vision of future prospects that would be promising to address for efficient DKGs construction.

B. FUTURE DIRECTIONS

Despite the rich efforts done in the literature to advance KGs, there remains multiple promising prospects to be addressed as follows:

1) AUTOMATIC KNOWLEDGE DYNAMICITY

In real world scenarios, integrated data continually changes over time. These changes may include presence of new knowledge, absence of previous knowledge, or changes in the meanings or attributes of existing knowledge. The velocity and repetition of updates are usually unknown [35]. This diversity in the forms of knowledge changes, and velocity of updates over time calls for automating the dynamic updating of KG, considering the KG topological structure level, knowledge meaning level, and spatio-temporal knowledge validation.

2) KNOWLEDGE FEATURES COLLABORATION

The research community utilized variant types of KG's features to learn completing missing knowledge in a KG. The types of features can be categorized into semantic features,

TABLE 4. A summary of the limitations of DKGS construction models.

Ref. No.	Partial Dynamicity	Insufficient Features	Possibility of Bias	Vulnerability to Changes	Performance & Efficiency Concern	Lack of Evaluation	Comparison Absence	Poor Explanation
[40]	√	√	√				√	√
[9]	√		√			√	√	
[46]	√	√	√		√			
[47]	√	√			√	√		√
[51]	√		√			√		
[48]	√		√	√				
[53]	√	√		√				
[42]	√	√		√	√			
[54]	√	√						
[55]	√	√						√
[5]	√	√	√					
[56]	√	√	√	√				

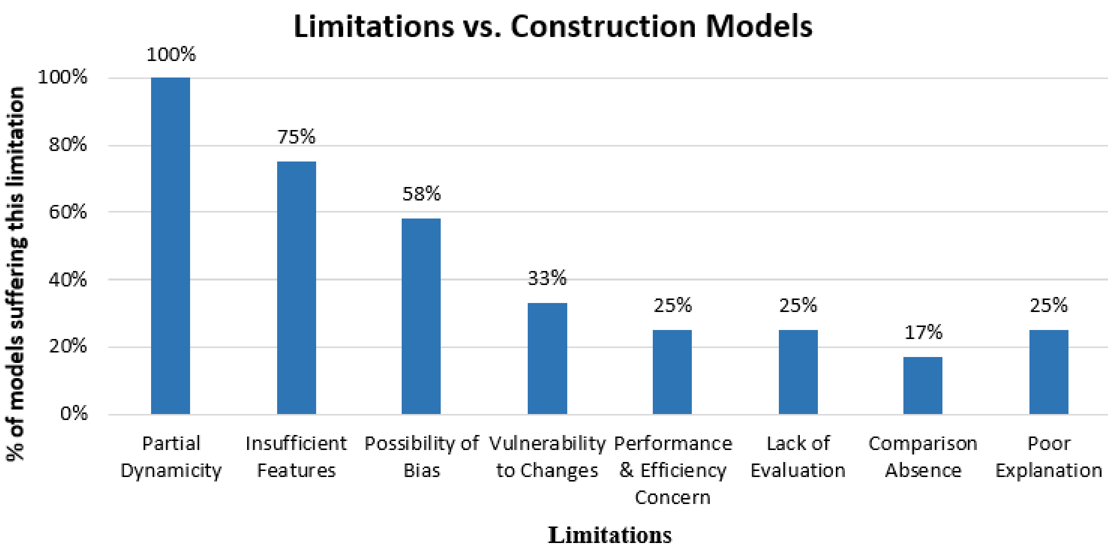

FIGURE 3. Percentages of faced limitations in DKGs construction models.

textual features, structural features, contextual features, and temporal features, as clarified below.

Semantic features present the meaning and characteristics of entities and relations in a KG, which can be utilized in training the model to discriminate whether an entity or a relation is semantical consistent in a knowledge triplet, and hence, predicting missing knowledge [53]. Enriching the KG with semantics of entities and relations or employing external semantic ontologies would optimize the utilization of semantic features.

Textual features are the natural language definitions, descriptions, or mention of entities and relations in unstructured text, which makes the completion problem remodeled into a natural language processing problem [53]. Employing large language models, natural language processing techniques, or leveraging rich textual corpus with an efficient entity disambiguation algorithm between the graph's entities and their mention in the corpus would advance the potential of textual features.

Structural features in a KG refer to the graph's topology and information of neighboring connected entities and relations in the graph, which can be leveraged to learn the connectivity and relational patterns in order to decide the topological plausibility of a knowledge triplet and to infer missing knowledge [54]. The utilization of structural features can be optimized by the capabilities of graph neural networks and graph embedding-based techniques to learn the graph's topology.

Contextual features point to the context meta data of entities and relations, which can be utilized to measure the plausibility of a knowledge triplet, where the likelihood of a relation between two entities is conditioned by their mutual context [48]. Leveraging pretrained language models to understand, embed or predict the context of entities and relations would optimize the employment of contextual features.

Temporal features include the timestamps indicating when a relationship occurred, which can be leveraged to understand the KG evolution to capture missing or future knowledge [34]. Recurrent unit-based architectures with the capability of sequential processing and time-aware embedding can optimize the temporal-based completion.

Accordingly, each of the aforementioned types of knowledge features has a vital role to reach the completeness and correctness of DKG that cannot be neglected, calling for the collaboration of all knowledge features for completion.

The collaboration of knowledge features is suggested to be optimized either by early fusion, late fusion, or model-level fusion of the knowledge features. Early fusion is associated with combining all features at the input level, which is challenging due to the features heterogeneity. Late fusion is associated with fusing the output of multiple completion models, where each model is trained with different knowledge features. The main potential challenges of late fusion are knowledge alignment and model complexity. Model-level fusion is concerned with training the model to jointly consider the different knowledge features in the model's score function or using attention mechanisms. This is probably associated with the challenging interpretability and complexity of the model. Thus, the suggested fusion techniques and their challenges pose multiple future research directions to be addressed to advance DKGs.

3) DYNAMIC KNOWLEDGE GRAPH BIAS

Minor research has addressed the bias of KGs. Authors in [63] focused on debiasing implicit user-specified relations, while authors in [64] focused on detecting bias on the data sources. In [45], the authors focused on the causes that originate bias into KGs, which includes the data source and the construction model, whereas in [65], they focused on detecting the bias on the knowledge embedding. Analyzing the investigated construction models of DKGs, none of them has examined the existence of bias in the constructed DKG. Hence, an interesting direction that can be further investigated is to examine the possible biases that may arise from both constructing and dynamically updating DKGs, the potential bias detection metrics, as well as avoiding or mitigating a bias if exists.

4) MODEL ADAPTABILLITY TO CHANGES

DKGs differ in several characteristics, such as the graph scale, dynamicity speed, context, and domain. The DKGs may be built over scarce [40] or rich sources of semantics [53]. It can be a contextualized DKG [17] or aggregates multi-contexts [8]. It may hold time information [34] or not [42]. These variations raise another concern about the adaptability of the investigated construction models to diversity, whether they are applicable to efficiently construct variant DKGs or they would be vulnerable to changes.

5) DYNAMIC KNOWLEDGE GRAPH SCALABILITY

DKG evolves over time due to continuously integrating the flow and updates of data into the graph [35]. Although this dynamic nature is more efficient and powerful than static KGs for knowledge-aware applications [7], but it raises a serious concern about the graph's scalability after a long duration of continuous integrations, and whether the current construction models would be still applicable and robust with larger scales of DKGs, or this would cost excessive time and performance.

Handling the evolving and growing graph scale also calls for multiple novel research directions, which includes: (i) considering memory management features to manage the scale of DKGs and their frequent updates, (ii) continual preserved re-scaling of the DKG, (iii) distributed parallel handling of the DKG, (iv) designing incremental strategies to handle the evolving nature of DKG rather than reprocess the entire graph, and (v) building a scale-adaptable models that optimize the utilization of DKG in their processing.

6) HYBRID LEARNING APPROACHES

The DKGs construction process consists of consecutive phases. Having novel learning approaches that can maintain the performance and accuracy of DKG with different graph scales, or domains, is another research gap to be investigated.

The impact of hybridizing learning approaches in a DKG construction model also needs to be investigated, whether it will lead to a completer and more correct DKG due to the additional learning and noise filtration through the different learning approaches, or it will lead to a less complete and incorrect DKG due to the possibility of error propagation between the consecutive diverse learning phases.

Other concerns are raised over the potential complications that may be introduced by hybrid learning approaches in a construction model, such as hard interpretability, increasing complexity, more vulnerability to the growing graph scale, excessive runtime, growing computational overhead, a challenging number of hyperparameters to be tuned, and requiring inconsistent knowledge representation through the consecutive phases, which calls for efficient entity disambiguation and alignment.

VIII. CONCLUSION

In this paper, an investigative study is conducted over the emerging construction models of dynamic knowledge graphs (DKGs), in order to explore the challenges and limitations of each, as well as the main applications that adopted DKGs at different domains. The uniqueness of this paper relies in (i) conducting the investigation through the construction phases of DKGs; entity extraction, relationship extraction, and graph completion, (ii) categorization of the completion phase based on the acquisition of new knowledge, as extraction-based and inference-based completion, (iii) novel categorization of the knowledge extraction models employed in DKGs construction models with respect to the learning approach, as traditional, transfer learning-based, reinforcement learning-based, and embedding learning-based models, and (iv) the conducted analysis considers various parameters, revealing critical limitations on the studied models and opens up multiple novel future directions.

It can be inferred from our detailed analysis that automatic DKG construction, with considering all aspects of dynamicity is an open research direction in which 100% of the construction models lack the flexibility of automatically fully updating the KG. The impact of utilizing temporal, textual, semantic, along with structural information for DKGs construction needs to be investigated in the future, as well as investigating the existence of correlation between these features in different domains, in which 75% of the construction models suffer from utilizing insufficient features. Moreover, to the best of our knowledge, there is no single study that examined bias in DKGs and its causes, and whether it is different than bias in static KGs, although 58% of the construction models had a clear exposure to bias. Other open questions were raised about the scalability of DKGs over time, and the capability of DKG completion models to deal with large-scale KGs, as well as their adaptation to the diversity of knowledge in different domains. The impact of hybridizing learning approaches between the construction phases over the correctness and completeness of the constructed DKGs needs to be further explored. DKGs can be also examined to facilitate regression testing and test cases generation for large scale systems [66], [67]. We believe that the revealed research gaps would pave the way for more efficient and useful construction models for DKGs.

In future, we plan to investigate other learning approaches such as continual learning, online learning, and lifelong learning, and the level of dynamicity they consider, besides their impact over the correctness and completeness of DKGs. Inspired by [68], we intend to study the dynamic changing structural dependencies in KG and how it could be optimized in DKG completion.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

REFERENCES

[1] D. Le-Phuoc, H. N. M. Quoc, H. N. Quoc, T. T. Nhat, and M. Hauswirth, "The graph of things: A step towards the live knowledge graph of connected things," *J. Web Semantics*, vols. 37–38, pp. 25–35, Mar. 2016.

[2] N. Maghawry, S. Ghoniemy, E. Shaaban, and K. Emara, "Weighted entity-linking and integration algorithm for medical knowledge graph generation," *Int. J. Intell. Comput. Inf. Sci.*, vol. 23, no. 1, pp. 1–17, 2023.

[3] G. Assem, A. Salah, S. El-Sayed, and M. Othman, "Visual question answering: A survey," *Future Comput. Informat. J.*, vol. 8, no. 1, pp. 1–20, 2023.

[4] S. Gupta, S. Tiwari, F. Ortiz-Rodriguez, and R. Panchal, "KG4ASTRA: Question answering over Indian missiles knowledge graph," *Soft Comput.*, vol. 25, no. 22, pp. 13841–13855, Nov. 2021.

[5] X. Tang, R. Yuan, Q. Li, T. Wang, H. Yang, Y. Cai, and H. Song, "Timespan-aware dynamic knowledge graph embedding by incorporating temporal evolution," *IEEE Access*, vol. 8, pp. 6849–6860, 2020.

[6] S. Ji, S. Pan, E. Cambria, P. Marttinen, and P. S. Yu, "A survey on knowledge graphs: Representation, acquisition, and applications," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, no. 2, pp. 494–514, Feb. 2022.

[7] L. Yang, Z. Xiao, W. Jiang, Y. Wei, Y. Hu, and H. Wang, "Dynamic heterogeneous graph embedding using hierarchical attentions," in *Proc. Eur. Conf. Inf. Retr.*, 2020, pp. 425–432.

[8] Y. Liu, W. Hua, K. Xin, and X. Zhou, "Context-aware temporal knowledge graph embedding," in *Proc. Web Inf. Syst. Eng.*, 2019, pp. 583–598.

[9] B. Yang and Y.-M. Liao, "Research on enterprise risk knowledge graph based on multi-source data fusion," *Neural Comput. Appl.*, vol. 34, no. 4, pp. 2569–2582, Feb. 2022.

[10] B. Abu-Salih, "Domain-specific knowledge graphs: A survey," *J. Netw. Comput. Appl.*, vol. 185, Jul. 2021, Art. no. 103076.

[11] S. Auer, C. Bizer, G. Kobilarov, J. Lehmann, R. Cyganiak, and Z. Ives, "DBpedia: A nucleus for a web of open data," in *Proc. Int. Semantic Web Conf.* Berlin, Germany: Springer, 2007, pp. 722–735.

[12] *Knowledge Graphs*. Accessed: Sep. 29, 2023. [Online]. Available: https://www.dbpedia.org/resources/knowledge-graphs/

[13] S. Haussmann, O. Seneviratne, Y. Chen, Y. Ne'eman, J. Codella, C. H. Chen, D. L. McGuinness, and M. J. Zaki, "FoodKG: A semantics-driven knowledge graph for food recommendation," in *Proc. Int. Semantic Web Conf.* Auckland, New Zealand: Springer, 2019, pp. 146–162.

[14] Y. Tang, T. Liu, G. Liu, J. Li, R. Dai, and C. Yuan, "Enhancement of power equipment management using knowledge graph," in *Proc. IEEE Innov. Smart Grid Technol.*, May 2019, pp. 905–910.

[15] T. P. Tanon, G. Weikum, and F. Suchanek, "YAGO4: A reasonable knowledge base," in *Proc. Int. Semantic Web Conf.* Heraklion, Greece: Springer, 2020, pp. 583–596.

[16] *Yago-Knowledge*. Accessed: Sep. 20, 2023. [Online]. Available: https://yago-knowledge.org/

[17] F.-R. Dang, J.-T. Tang, K.-Y. Pang, T. Wang, S.-S. Li, and X. Li, "Constructing an educational knowledge graph with concepts linked to Wikipedia," *J. Comput. Sci. Technol.*, vol. 36, no. 5, pp. 1200–1211, Oct. 2021.

[18] R. Navigli and S. P. Ponzetto, "BabelNet: The automatic construction, evaluation and application of a wide-coverage multilingual semantic network," *Artif. Intell.*, vol. 193, pp. 217–250, Dec. 2012.

[19] *Babelnet*. Accessed: Sep. 20, 2023. [Online]. Available: https://babelnet.org/

[20] N. BhagwantKamat and G. Varkey, "Understanding users intent by deducing domain knowledge hidden in web search query keywords," *Int. J. Comput. Appl.*, vol. 67, no. 15, pp. 17–20, Apr. 2013.

[21] *The Graph of Things*. Accessed: Sep. 20, 2023. [Online]. Available: http://graphofthings.org/

[22] M Compton, P Barnaghi, L Bermudez, R. Garcia-Castro, O. Corcho, S. Cox, J. Graybeal, M. Hauswirth, C. Henson, A. Herzog, and V. Huang, "The SSN ontology of the W3C semantic sensor network incubator group," *J. Web Semantics*, vol. 17, pp. 25–32, Dec. 2012.

[23] *Google Knowledge Graph*. Accessed: Sep. 20, 2023. [Online]. Available: https://developers.google.com/knowledge-graph/

[24] R. Speer and C. Havasi, "ConceptNet 5: A large semantic network for relational knowledge," in *Proc. People's Web Meets NLP*, 2013, pp. 161–176.

[25] *ConceptNet*. Accessed: Sep. 20, 2023. [Online]. Available: https://conceptnet.io/

[26] H. Agt-Rickauer, R.-D. Kutsche, and H. Sack, "DoMoRe—A recommender system for domain modeling," in *Proc. 6th Int. Conf. Model-Driven Eng. Softw. Develop.*, 2018, pp. 71–82.

[27] M. H. de Boer, P. Brandt, M. Sappelli, L. M. Daniele, K. Schutte, and W. Kraaij, "Query interpretation—An application of semiotics in image retrieval," *Int. J. Adv. Softw.*, vol. 8, pp. 435–449, Jan. 2015.

[28] X. Luo, L. Bo, J. Wu, L. Li, Z. Luo, Y. Yang, and K. Yang, "AliCoCo2: Commonsense knowledge extraction, representation and application in e-commerce," in *Proc. ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, 2021, pp. 3385–3393.

[29] F. L. Li, H. Chen, G. Xu, T. Qiu, F. Ji, J. Zhang, and H. Chen, ''AliMeKG: Domain knowledge graph construction and application in e-commerce,'' in *Proc. Int. Conf. Inf. Knowl. Manag.*, 2020, pp. 2581–2588.

[30] X. Luo, L. Liu, Y. Yang, L. Bo, Y. Cao, J. Wu, Q. Li, K. Yang, and K. Q. Zhu, ''AliCoCo: Alibaba e-commerce cognitive concept net,'' in *Proc. ACM SIGMOD Int. Conf. Manag. Data*, 2020, pp. 313–327.

[31] Y. Dai, S. Wang, N. N. Xiong, and W. Guo, ''A survey on knowledge graph embedding: Approaches, applications and benchmarks,'' *Electronics*, vol. 9, no. 5, p. 750, May 2020.

[32] S. M. Kazemi, R. Goel, K. Jain, I. Kobyzev, A. Sethi, P. Forsyth, and P. Poupart, ''Representation learning for dynamic graphs: A survey,'' *J. Mach. Learn. Res.*, vol. 21, no. 1, pp. 2648–2720, Mar. 2020.

[33] X. Zhu, Z. Li, X. Wang, X. Jiang, P. Sun, X. Wang, Y. Xiao, and N. J. Yuan, ''Multi-modal knowledge graph construction and application: A survey,'' *IEEE Trans. Knowl. Data Eng.*, vol. 36, no. 2, pp. 715–735, Feb. 2024.

[34] B. Cai, Y. Xiang, L. Gao, H. Zhang, Y. Li, and J. Li, ''Temporal knowledge graph completion: A survey,'' 2022, *arXiv:2201.08236*.

[35] K. Liang, L. Meng, M. Liu, Y. Liu, W. Tu, S. Wang, S. Zhou, X. Liu, and F. Sun, ''Reasoning over different types of knowledge graphs: Static, temporal and multi-modal,'' 2022, *arXiv:2212.0576*.

[36] J. Chicaiza and P. Valdiviezo-Diaz, ''A comprehensive survey of knowledge graph-based recommender systems: Technologies, development, and contributions,'' *Information*, vol. 12, no. 6, p. 232, May 2021.

[37] J. Wang, X. Wang, C. Ma, and L. Kou, ''A survey on the development status and application prospects of knowledge graph in smart grids,'' *IET Gener., Transmiss. Distrib.*, vol. 15, no. 3, pp. 383–407, Feb. 2021.

[38] M. Yani and A. A. Krisnadhi, ''Challenges, techniques, and trends of simple knowledge graph question answering: A survey,'' *Information*, vol. 12, no. 7, p. 271, Jun. 2021.

[39] Y. Kawashti, D. Khattab, and M. Aref, ''Exploring self-supervised pretraining datasets for complex scene understanding,'' *Int. J. Intell. Comput. Inf. Sci.*, vol. 23, no. 2, pp. 62–73, Jun. 2023.

[40] R. Miao, X. Zhang, H. Yan, and C. Chen, ''A dynamic financial knowledge graph based on reinforcement learning and transfer learning,'' in *Proc. IEEE Int. Conf. Big Data*, Dec. 2019, pp. 5370–5378.

[41] N. H. Alharbi, R. O. Bameer, S. S. Geddan, and H. M. Alharbi, ''Recent advances and machine learning techniques on sickle cell disease,'' *Future Comput. Informat. J.*, vol. 5, no. 1, pp. 46–59, 2020.

[42] W. Li, X. Zhang, Y. Wang, Z. Yan, and R. Peng, ''Graph2Seq: Fusion embedding learning for knowledge graph completion,'' *IEEE Access*, vol. 7, pp. 157960–157971, 2019.

[43] T. Al-Moslmi, M. Gallofré Ocaña, A. L. Opdahl, and C. Veres, ''Named entity extraction for knowledge graphs: A literature overview,'' *IEEE Access*, vol. 8, pp. 32862–32881, 2020.

[44] Z. Pan, C. Su, Y. Deng, and J. Cheng, ''Video2Entities: A computer vision-based entity extraction framework for updating the architecture, engineering and construction industry knowledge graphs,'' *Autom. Construction*, vol. 125, May 2021, Art. no. 103617.

[45] J. Gerritse, F. Hasibi, and A. P. de Vries, ''Bias in conversational search: The double-edged sword of the personalized knowledge graph,'' in *Proc. ACM SIGIR Int. Conf. Theory Inf. Retr.*, 2020, pp. 133–136.

[46] Y. Fang, H. Wang, L. Zhao, F. Yu, and C. Wang, ''Dynamic knowledge graph based fake-review detection,'' *Int. J. Speech Technol.*, vol. 50, no. 12, pp. 4281–4295, Dec. 2020.

[47] C. Jiang and M. Jagersand, ''Bridging visual perception with contextual semantics for understanding robot manipulation tasks,'' in *Proc. IEEE 16th Int. Conf. Autom. Sci. Eng. (CASE)*, Aug. 2020, pp. 1447–1452.

[48] A. Nadgeri, A. Bastos, K. Singh, I. O. Mulang, J. Hoffart, S. Shekarpour, and V. Saraswat, ''KGPool: Dynamic knowledge graph context selection for relation extraction,'' in *Proc. Findings Assoc. Comput. Linguistics, ACL-IJCNLP*, 2021, pp. 535–548.

[49] Z. Chen, Y. Wang, B. Zhao, J. Cheng, X. Zhao, and Z. Duan, ''Knowledge graph completion: A review,'' *IEEE Access*, vol. 8, pp. 192435–192456, 2020.

[50] H. Paulheim, ''Knowledge graph refinement: A survey of approaches and evaluation methods,'' *Semantic Web*, vol. 8, no. 3, pp. 489–508, Dec. 2016.

[51] S. Yoo and O. Jeong, ''Automating the expansion of a knowledge graph,'' *Exp. Syst. Appl.*, vol. 141, Mar. 2020, Art. no. 112965.

[52] D. M. Blei, A. Y. Ng, and M. I. Jordan, ''Latent Dirichlet allocation,'' *J. Mach. Learn. Res.*, vol. 3, pp. 993–1022, Mar. 2003.

[53] L. Yao, C. Mao, and Y. Luo, ''KG-BERT: BERT for knowledge graph completion,'' 2019, *arXiv:1909.03193*.

[54] B. Wang, T. Shen, G. Long, T. Zhou, Y. Wang, and Y. Chang, ''Structure-augmented text representation learning for efficient knowledge graph completion,'' in *Proc. Web Conf.*, Apr. 2021, pp. 1737–1748.

[55] X. Lv, X. Han, L. Hou, J. Li, Z. Liu, W. Zhang, Y. Zhang, H. Kong, and S. Wu, ''Dynamic anticipation and completion for multi-hop reasoning over sparse knowledge graph,'' in *Proc. Conf. Empirical Methods Natural Lang. Process. (EMNLP)*, vol. 2020, pp. 5694–5703.

[56] R. Trivedi, H. Dai, Y. Wang, and L. Song, ''Know-evolve: Deep temporal reasoning for dynamic knowledge graphs,'' in *Proc. Int. Conf. Mach. Learn.*, 2017, pp. 3462–3471.

[57] M. Sukhwani, V. Duggal, and S. Zahrai, ''Dynamic knowledge graphs as semantic memory model for industrial robots,'' 2021, *arXiv:2101.01099*.

[58] N. Zhang, H. Chen, X. Chen, and J. Chen, ''Semantic framework of Internet of Things for smart cities: Case studies,'' *Sensors*, vol. 16, no. 9, p. 1501, Sep. 2016.

[59] W. Song, X. Zhang, Y. Guo, S. Li, A. Hao, and H. Qin, ''Automatic generation of 3D scene animation based on dynamic knowledge graphs and contextual encoding,'' *Int. J. Comput. Vis.*, vol. 131, no. 11, pp. 2816–2844, Nov. 2023.

[60] S. Issa, O. Adekunle, F. Hamdi, S. S. Cherfi, M. Dumontier, and A. Zaveri, ''Knowledge graph completeness: A systematic literature review,'' *IEEE Access*, vol. 9, pp. 31322–31339, 2021.

[61] E. Huaman, ''Steps to knowledge graphs quality assessment,'' 2022, *arXiv:2208.07779*.

[62] A. Hogan, C. Gutierrez, M. Cochez, G. D. Melo, S. Kirrane, A. Polleres, R. Navigli, A.-C. N. Ngomo, S. M. Rashid, and L. A. O. Schmelzeisen, ''Quality assessment,'' in *Knowledge Graphs*. Cham, Switzerland: Springer, 2022, pp. 119–125.

[63] K. Janowicz, B. Yan, B. Regalia, R. Zhu, and G. Mai, ''Debiasing knowledge graphs: Why female presidents are not like female popes,'' in *Proc. Int. Semantic Web Conf.*, 2018, pp. 1–5.

[64] D. Keidar, M. Zhong, C. Zhang, Y. Raj Shrestha, and B. Paudel, ''Towards automatic bias detection in knowledge graphs,'' 2021, *arXiv:2109.10697*.

[65] J. Fisher, D. Palfrey, C. Christodoulopoulos, and A. Mittal, ''Measuring social bias in knowledge graph embeddings,'' 2019, *arXiv:1912.02761*.

[66] P. Kandil, S. Moussa, and N. Badr, ''Regression testing approach for large-scale systems,'' in *Proc. IEEE Int. Symp. Softw. Rel. Eng. Workshops*, Nov. 2014, pp. 132–133.

[67] R. Elghondakly, S. Moussa, and N. Badr, ''A comprehensive study for software testing and test cases generation paradigms,'' in *Proc. Int. Conf. Internet Things Cloud Comput.*, Mar. 2016, pp. 1–7.

[68] Q. He, H. Fang, J. Zhang, and X. Wang, ''Dynamic opinion maximization in social networks,'' *IEEE Trans. Knowl. Data Eng.*, vol. 35, no. 1, pp. 350–361, Jan. 2023.

MAHA FARGHALY received the B.S. degree in computer and information sciences from the Faculty of Computer and Information Sciences (FCIS), Ain Shams University (ASU), Cairo, Egypt, in 2018, where she is currently pursuing the M.S. degree in computer and information sciences. She has been a Teaching Assistant with the Information Systems Department, Faculty of Computers and Information Technology, Future University in Egypt, since 2019. Her research interests include data mining, natural language processing, knowledge representation, and artificial intelligence.

MAHMOUD MOUNIR received the B.S., master's, and Ph.D. degrees from the Information Systems Department, FCIS, ASU, Cairo, Egypt. Subsequently, he transitioned into a Teaching Assistant with the Information Systems Department, FCIS, ASU. He is currently an Assistant Professor with the Information Systems Department, FCIS, ASU, specializing in machine learning, artificial intelligence, and bioinformatics.

MOSTAFA AREF received the Ph.D. degree in engineering science from The University of Toledo, Toledo, OH, USA, in June 1988. He is currently a Professor of computer science with FCIS, ASU, Cairo, Egypt. He has more than 50 journals and conference publications. His research interests include natural language processing, knowledge representation, object-oriented programming, ontology, and real-time strategy games.

SHERIN M. MOUSSA received the Ph.D. degree in conjunction with the University of Illinois Urbana–Champaign, Champaign, IL, USA, in 2010.

She was the Director of the Quality and Accreditation Unit, FCIS, the Foreign Affairs Consultant of the Research and Development of Projects Center, and the Director of the Grants and International Collaboration Office, ASU. She is currently a Full Professor with FCIS, ASU. She is also on a national mission to Université Française d'Égypte, Cairo, Egypt, as the Deputy Vice President of the Research and Postgraduate Studies, and the Head of the Information Technology and Communications Department. She is a consultant to many organizations, with industrial experience. In addition to her teaching, research contributions and publications in highly ranked international journals and conferences, she has more than 24 years of experience in IT multiple/complex national/regional projects. Her research interests include the Internet of Things, service-oriented computing, big data analytics, software engineering, data mining, bioinformatics, and data privacy preservation and publishing. She is the Founder and the Executive Director of the Next Generation Scholar (NGS) Research Group, the co-organizer of several international workshops and conferences, and the guest editor and a recognized reviewer at many reputable journals.