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Exploiting Knowledge Graphs in Industrial Products and Services: A Survey of Key Aspects, Challenges, and Future Perspectives

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Abstract: The rapid development of information and communication technologies has enabled a value co-creation paradigm for developing industrial products and services, where massive heterogeneous data and multidisciplinary knowledge are generated and leveraged. In this context, Knowledge Graph (KG) emerges as a promising tool to elicit, fuse, process, and utilize numerous entities and relationships embedded in products and services, as well as their stakeholders. Nevertheless, to the best of the authors' knowledge, there is scarcely any comprehensive and thorough discussion about making full use of KG's potentials to solve pain points of product development and service innovation in the industry. Aiming to fill this gap, this paper conducted a systematic survey of KG exploitations in industrial products and services and the customizations towards higher adaptability to practices. The authors selected 119 representative papers (up to 10/03/2021) together with other 27 supplementary works to summarize the technical and practical efforts and discuss the current challenges of exploiting KG in industrial products and services. Meantime, this work also highlights enhancing KG's availability and boosting its productivity in industrial products and services development as the core future perspectives to explore. It is hoped that this work can provide a basis for the explorations and implementations of KG-supported industrial product and services development, and attract more open discussions to the exploitation of KG-enabled industrial information systems.

Keywords: knowledge graph; product development; service innovation; knowledge management; product-service systems; review

1. Introduction

Since IBM Watson has won the Jeopardy in 2011, Knowledge Graph (KG) has gained incremental research interest due to its capability of storing knowledge, structured or unstructured, elicited from heterogeneous domains, and further querying them to realize question answering. Formally, Knowledge Graph is *a graphical knowledge base that consists of a set of interconnected typed entities and their attributes and has an ontology as its schema defining the vocabulary used in it* [1]. This idea is not completely new and can be date back to Semantic Network and Linked Data [2], which express knowledge with interconnected nodes and edges and enable cross-level relationships among them. However, with less time and manpower consumed in the evolutionary construction, and higher flexibility of knowledge utilization empowered by the arbitrary linkage among entities [3], now KG has shown its promising prospects in many sectors, and it has been widely recognized as the core element of the next-generation industrial information systems [4].

Demonstrating stronger capabilities of propelling productivities in multiple industries, KG attracts widespread research interests in recent years. Tentatively applied in designing, manufacturing, maintenance, and other tasks, KG empowers industrial products and services, and their development process, mainly in two aspects. Firstly, by providing a semantic-based and in-depth knowledge management manner, KG can save time and manpower costs while improving accuracy and efficiency in domain knowledge retrieval for the tasks of requirement analysis, solution design, and operation and maintenance management [1, 5]. More important, KG is capable to further deduct and predict new relationships and attributes based on the stored multidisciplinary domain knowledge, so as to generate originative concepts and ideas that strongly support the involved stakeholders of products and services to complete these creative tasks [6, 7].

However, studies on KG-enabled industrial products and services development have not been systematically performed yet. Most researchers still regard KG as a medium for providing information in some web-based services and only focus on the performance of KG itself to develop faster, more robust, more accurate algorithms [8-10]. Concerns and contributions on customizing, enhancing, and integrating KG for industrial products and product-based services are far beyond adequate. Besides, some industry pain points in product and service development, which can be effectively mitigated or even productively tackled by KG's advantages, have not been fully discussed, such as risk prediction and information distillation [11-13]. Thus, a gap is deemed to exist between KG exploitation and demands of industrial products and services.

Aiming to fill the gap, this paper has conducted a review of 119 recent peer-reviewed publications that apply KG to industrial products and services and enhance current KG techniques to fit them into practical exploitations, and further outlined the main challenges and prospective research directions in the field. The rest of this paper is organized as follows. Section 2 states the systematic literature review process and gives a statistical result. Based on the selected literature, a holistic relook of KG utilization in industrial products and services is elaborated in Section 3. Moreover, the main challenges are highlighted in Section 4. Correspondingly, perspectives of future studies are suggested in Section 5. The scientific contributions of this review are summarized at last.

2. Systematic literature review

The systematic literature selection process and the statistical review result are depicted in this Section. The first-round basic search was conducted on the Web of Science Core Collection, which covers a wide range of all major peer-reviewed academic articles.

2.1 Search and filtrate

The literature selection process is depicted in Fig.1. The search sentence is written as "Topic = (knowledge graph) AND Topic = (application OR industrial OR products OR services); Time Span: 2017 – 2021; Language: English". 972 items were found through this first-round searching (accessed on 10/03/2021). Then a second-round search was conducted by excluding the articles that are not within the industrial fields (e.g. mathematics) and merely selecting the academic journals and conferences, remaining 492 items. At the last, authors went through the contents and references, and filtrated items containing the keywords "knowledge" or "graph" but not truly discussing Knowledge Graph exploitations in industries (e.g. knowledge collaboration, graph neural networks). Besides, four items are added according to the suggestions of domain experts during the review process. Finally, 119 items are selected as the foundation for this survey.

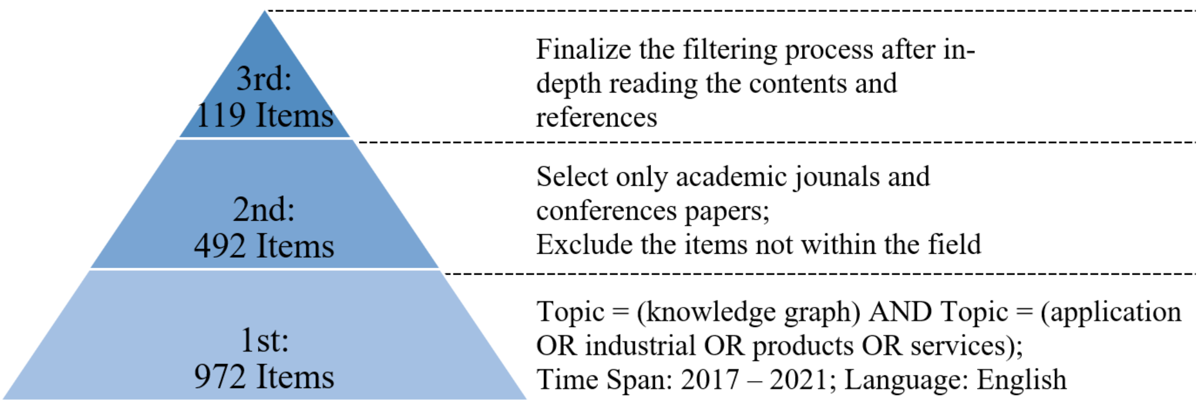
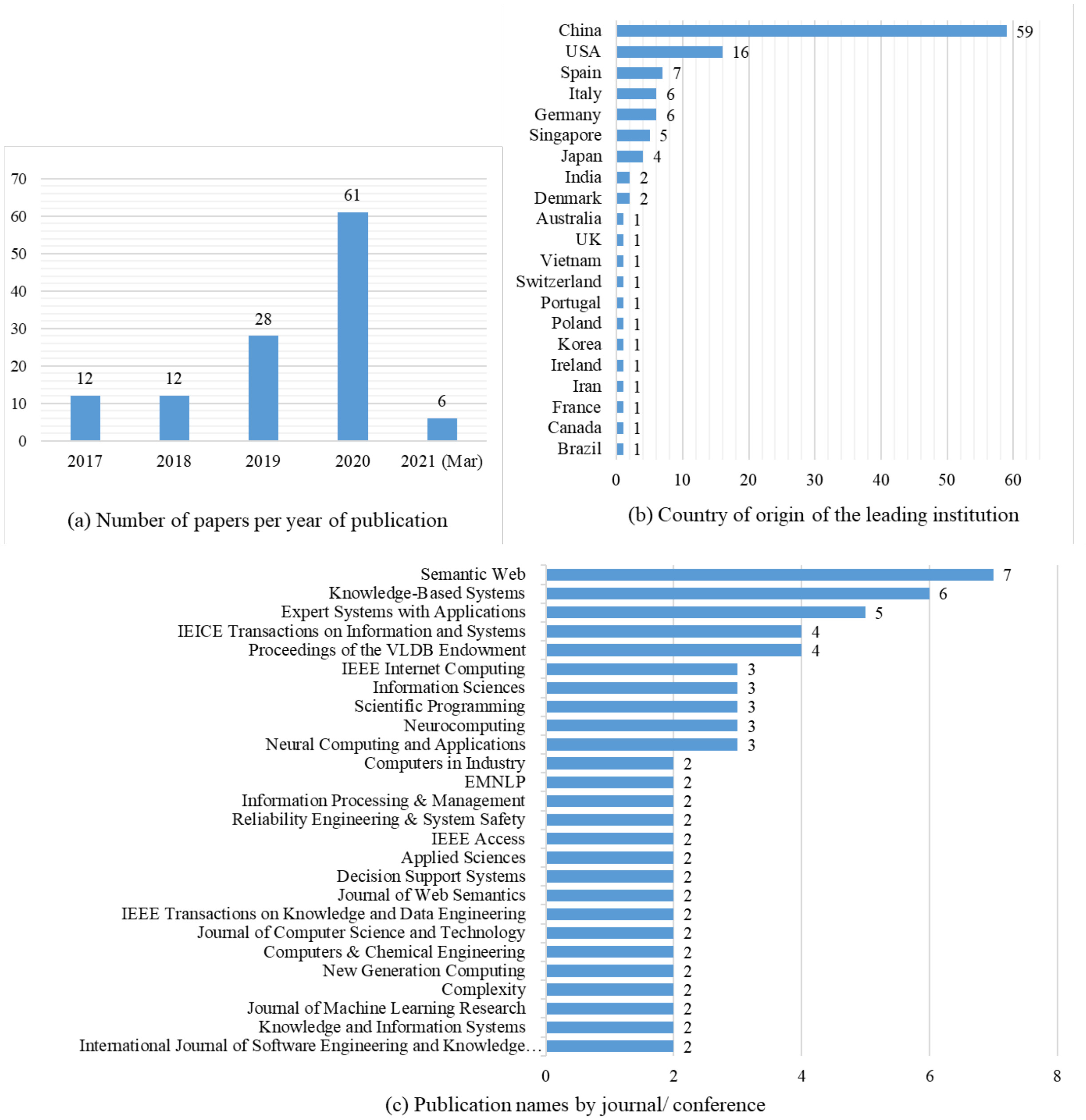


Fig. 1. The systematic literature selection process

2.2 General analysis of the selected papers

A general analysis is conducted based on the 119 selected papers, including the year of publications, journals or conferences of the publication, original countries of the leading institutes to show the mainstream of relative researches in recent five years. The result is shown in Fig. 2.



(a) Number of papers per year of publication

(b) Country of origin of the leading institution

(c) Publication names by journal/ conference

Fig. 2. The analysis result of the selected publications

It can be seen from Fig. 2(a) that there is an increasing trend of KG studies in industries during the past five years. This can be regarded as a signal indicating the bloom of KG exploitations in the 2020s, considering the remarkable elevating requirements of novel smart technologies ignited by the labor constraints due to COVID-19. Meanwhile, among all the selected publications, most are from China, USA, and European countries, as shown in Fig. 2(b). The result is in line with the scale and vitality of the internet servitization enterprises and digital economy in those respective countries. Moreover, from Fig. 2(c), one can find that *Semantic Web*, *Knowledge-Based Systems*, and *Expert Systems with Applications* are the major publishers in this area (only Journals/Conferences that have published more than 2 articles are shown). The published journal/conference papers are mainly dispersed in various computer science domains, which reveals an active synthesis of multiple information technologies in KG construction and exploitation. However, the lack of major publishers in other traditional engineering disciplines, such as mechanical engineering, civil engineering, and energy & environmental engineering, reveals a shortage of KG exploitations in diverse industrial products and services.

3. Exploit KG in industrial products and services

Based on the systematic literature review process, this section provides an analysis of exploiting KG in industrial products and services from two key perspectives:

1. What efforts have been conducted on customizing and enhancing KG to fit in industrial products and services?
2. What industry pain points in products and services development have been mitigated by KG?

3.1. Efforts on customizing and enhancing KG

Considering huge gaps between knowledge exploitation manners in different industries, the general KG has been customized and enhanced in its exploitation, so as to fit in various scenarios of industrial products and services. To this end, this section conducts a review of the efforts that have been made. According to different concerns in KG exploitation, the reviewed efforts are divided into three periods, as shown in Fig. 3.

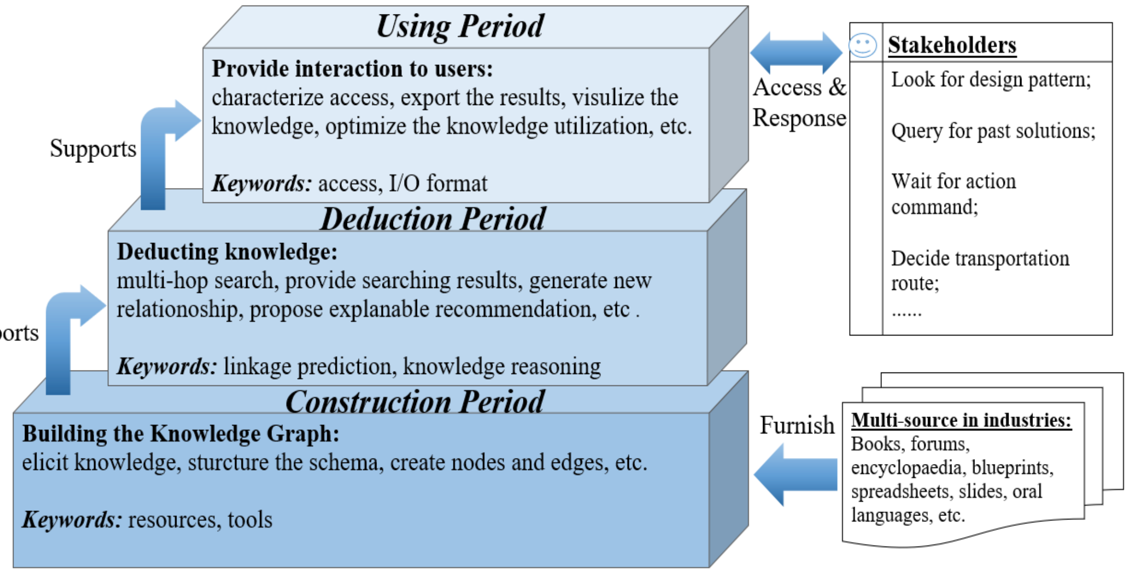


Fig. 3. Three periods concerning KG exploitation

The Construction period aims to build a high-quality KG from massive data generated and leveraged in industrial products and services, in which the major efforts involve adopting proper tools to elicit and process multidisciplinary knowledge from multi-source in industries. The Deduction period generates recommendations and results for the design and operation process based on the existing KG, where the efforts concentrating on executing multi-hop semantic searching and knowledge reasoning. The Using period interacts with stakeholders to accept queries and export knowledge outcomes, and its efforts emphasize adapting the heterogeneous interactions from stakeholders of industrial products and services. It is worth noting that the subsequent periods sometimes co-exist with the previous ones, though they start later and rely on the previous outcomes.

3.1.1 Construction period

Knowledge of industrial products and services are majorly embedded in diverse forms of user-generated contents and sensing records. Therefore, the construction period integrates multiple text mining and machine learning tools to process the raw data, and hence formalize the triples of <*head*, *relation*, *tail*> for the KG. As shown in Table 1, Natural Language Processing (NLP) techniques and toolkits are frequently adopted to automatically extract entities from semi-structured or unstructured knowledge resources [14-17]. Some advanced deep learning techniques, like Convolutional Neural Networks (CNN) and Bi-directional Long Short Term Memory (BiLSTM), are also used to execute accurate relationship extraction and knowledge fusion from multidisciplinary knowledge [18-20].

Table 1 Tools for formalizing knowledge in industrial products and services

Task	**Key techniques and toolkits**	**Ref.**
Word segmentation and Part-of-speech (POS) tagging	HanLP standard tokenizer; Language Technology Platform; BERT model	Zhu et al., [21] Zhou et al., [22]
Co-reference resolution; Syntactic analysis	Deep neural networks; Text chunking; Stanford NLP tool	Cudre-Mauroux et al., [23] Nizzoli et al., [24] Kertkeidkachorn et al., [25] Liu et al., [16] Shan et al., [26]
Elements classification	Neural network; Bidirectional LSTM (BiLSTM) ; Supervised predictor	Chen et al., [20] Wu et al., [18]
Identify inference factors	Deep tensor; Attention network	Fuji et al., [27] Song et al., [28]
Identify, extract entities and relations	Stanford core NLP toolkits; Deep learning; Iterated Dilated Convolutional Neural Networks (ID-CNN); Seed entity set expansion	Li et al., [8] Dou et al., [29] Chen et al., [17] Abad-Navarro et al., [30] Vogt et al., [10]
Semantic context learning	Word2Vec; NLTK; Convolutional Neural Network; Bidirectional LSTM (BiLSTM)	Sarica et al., [31] Huang et al., [32] Long et al., [19] Ristoski et al., [33]
Semantically clustering words	Deep learning; Latent Dirichlet Allocation (LDA)	Wang et al., [14] Wang et al., [34] Guo et al., [15]

Besides the heterogeneous user-generated contents and sensing records, some open-access knowledge repositories can be utilized to enhance the constructed KG for industrial products and services. As shown in Table 2, online encyclopedias and domain repositories can be served as some supplementing knowledge resources, which provide instructive and validated solutions for industrial products and services.

Table 2 Utilized open-access knowledge repositories for enhancing KG

Repository	Description	Character	Ref.
DBpedia [35]	A crowd-sourced community effort to extract structured content from the information created in various Wikimedia projects.	Evolves as Wikipedia changes; multilingual	Peroni et al., [11] Palumbo et al., [36] Nizzoli et al., [24] Kertkeidkachorn et al., [25]
WordNet® [37]	A large lexical database of English developed by Princeton University.	More than 200 languages; extension of a dictionary and thesaurus	Li et al., [8] Wu et al., [18]
YAGO [38]	A large knowledge base with general knowledge about people, cities, countries, movies, and organizations.	Extracted from Wikipedia, WordNet, GeoNames; linked to the DBpedia ontology and the SUMO ontology	Ignacio et al., [39] Wenige et al., [40] Wu et al., [18]
BabelNet [41]	A multilingual encyclopedic dictionary and a semantic network with about 16 million entries.	Linking Wikipedia to WordNet	Dalle et al., [3] Wang et al., [34] Wu et al., [18]
Freebase [42]	A large collaborative knowledge base developed by Metaweb, consisting of data composed mainly by its community members.	Both commercial and non-commercial use; composed mainly by its community members	Bakhshi et al., [43] Huang et al., [32]
ChEBI [44]	A freely available dictionary of molecular entities focused on 'small' chemical compounds.	Specialize in Bio-chemical engineering	Kushida et al., [45] Hastings et al., [44]

Among the reviewed researches, Neo4J [46] gained remarkable favor in the reviewed studies as a tool to store the KGs [8, 26, 30]. Additionally, the document-oriented database Mongo could also be an option in some studies [10].

3.1.2 Deduction period

Different from the ordinary usage of KG that simply delivers some existing knowledge items, knowledge demands in industrial products and services require higher synthesis and creation. Meanwhile, to fit for the concurrent and iterative teamwork by multiple aspects of stakeholders, knowledge deduction in KG should be enhanced to be transdisciplinary, context-aware, and flexible.

Table 3 provides some enlightening efforts that aim to fulfill the above requirements. Knowledge deduction could be further categorized into attribute deduction and relationship deduction [19, 27, 47, 48], corresponding to the node modification and edge creation in the graphs. More specifically, considering diversified problem-solving contexts, attributes and relations are vectorized according to the semantical and topological features, hence the deduction processes are transformed into matrix manipulations [8, 49-51]. For example, based on a KG built with the product data and the usage contexts, the dynamic relationship between end-users and products can be modeled via the linear transformation to the latent space that shares the same dimensionality, and hence it can be inferred with a solid logic through entity soft matching on the KG [51].

Table 3 Enhanced knowledge deduction for industrial products and services

Deduction	Ref	Key techniques and toolkits	Task
Attribute	Long et al., [19]	BiLSTM prediction	Predict the target's price movement direction and its trend
Relationship	Wang et al., [47]	Attention-based Deep Reinforcement Learning(ADRL); Markov decision	Learning multi-hop relational paths;
	Fuji et al., [27]	Deep Tensor combined with Knowledge Graph	Identify inference factors by Deep Tensor; Connect the factors in KG to form a basis
	Nizzoli et al., [24]	Spelling-based expansion; Latent semantic expansion; Topological expansion	Retrieve the largest set of geographic entities related to the starting one
	Zhao et al., [52]	Embedding model using tensor decomposition based on SimplE	Generates axioms through rule learning and injects them into the embedding representation of a knowledge graph to enhance reasoning
Attribute & Relationship	Wang et al., [49]	Attention-based LSTM; Multi-Head Dot Product Attention	Interact and update the memories embedded in the memory system for reasoning purposes
	Abraham et al., [50]	OWL Axiom-based Classifier; Forward Chaining Reasoner; Hybrid Reasoner	Identify type of problem; adds qualitative and quantitative knowledge; Solve problem qualitatively and quantitatively
	Li et al., [8]	Four Knowledge Graph-Aided Concept–Knowledge Operators: C-K, C-C, K-C, C-C	C-K& C-C: Propose relevant entities; K-C& K-K: Map, evaluate and update generated relationship and concept
	Ai et al., [51]	Dynamic Relation Embedding Model	Create a dynamic knowledge graph based on both the multi-relational product data and the context of the search session

3.1.3 Using period

The usage period refers to the interaction with users, including accessing methods and input & output formats. The major concern of this period is to provide flexible interaction capability to ensure a user-friendly experience to multi-aspect stakeholders of industrial products and services.

Some tentative efforts in this aspect have been conducted. For example, in a showcase of a KG-enabled nursing bed, the mobile app accepting queries and exporting usable knowledge can be served as an easy-to-use channel for patients, nursing staff, and maintenance engineers [8]. Other sorts of human-machine interfaces, like chatbots [53], visualized graphs [29], and system interfaces[12], also prove their usability in several industrial cases. However, these interaction modes are still similar to the conventional knowledge-based systems, and demonstrate insufficient novelties in adapting the value co-creation paradigm in the current industrial products and services [54]. Frankly speaking, there is still a rather long way to go before a satisfying methodology for KG usage is achieved.

3.1.4 Summary

To sum up, most of the current customization and enhancement on KG contribute to constructing a KG using multiple sources and forms of industry records, and proposing semantic-based and topological-based algorithms to conduct knowledge deduction in multiple problem-solving contexts. However, few efforts are paid to improve user interactions, and demonstrate inadequate adaptiveness to the state-of-the-art paradigms of industrial products and services. Besides, as the iteration of industrial products and services becomes more frequent and user-oriented, the continuous enrichment to KG itself should be emphasized to guarantee its availability.

3.2. KG-mitigated industry pain points in products and services development

KGs are customized and enhanced to fit in industrial products and services, and it conversely mitigates the pain points in their development process. A pain point in the industry is a persistent or recurring problem that frequently inconveniences stakeholders and slacks their satisfaction. Identified from the reviewed literature, five representative industry pain points are discovered along with the lifecycle stages of products and services, as shown in Fig. 4. The existence of these pain points in disparate industries is also briefly introduced in Table 4, which will be elaborated in the following subsections.

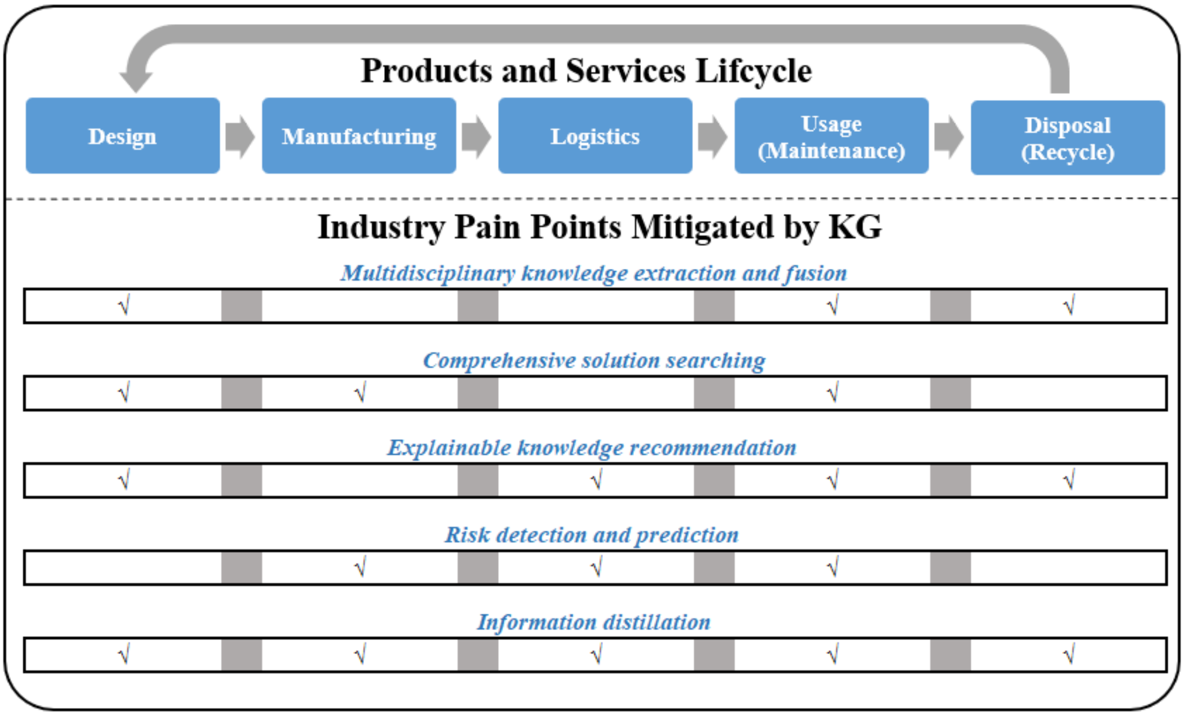


Fig. 4. Industry pain points in products and services development

Table 4 Industry pain points that KG could mitigate

Pain points	Objective	Ref.	Industries
Multidisciplinary knowledge extraction and fusion	Automatically extract information from heterogeneous resources and various formats, then fuse them into proper analytical models.	Zhu et al., [55] Wu et al., [56] Sun et al., [57] Zhu et al., [21] Yuan et al., [58] Liu et al., [59] Eibeck et al., [60] Farazi et al., [61] Zhou et al., [62]	Bio-medical engineering; Software engineering; Cybersecurity Chemical industry
Comprehensive solution searching	Fast and faithful question answering with relevant information provided as reference.	Morton et al., [63] Rasmussen et al., [64] Zhou et al., [22] Xie et al., [65] Zhou et al., [66]	Bio-medical engineering; Construction; Energy and power
Explainable knowledge recommendation	Proactively provide reasonable recommendations with intelligent options.	Lin et al., [67] Fernandez-Tobias et al., [39] Bhatt et al., [68] Munoz et al., [69]	Software engineering; Bio-medical engineering

Risk detection and prediction	Predict potential risks based on the collected information like workers' location and/or machines' status and generate preventative methods	Liu et al., [70] Jia et al., [71] Shi et al., [12] Zhao et al., [6] Liu et al., [72]	Manufacturing; Energy and power; Aerospace; Cybersecurity; Railway operation
Information distillation	Utilize the solid knowledge base to provide creative and user-friendly support to help stakeholders achieve their tasks easier.	Dou et al., [29] Abad-Navarro et al., [30] Peroni et al., [11] Ławrynowicz et al., [7] Wu et al., [73] Wu et al., [74]	Agriculture engineering; Fast fashion; Software engineering; Product development

3.2.1 Multidisciplinary knowledge extraction and fusion

The first pain point in industrial product and service development is extracting and fusing multidisciplinary knowledge to accomplish a synthetic target. It is most evident in the design and usage (maintenance) stages of the lifecycle since massive engineering knowledge and human factors coexist that it is hard to organically integrate them into conducive deliverables. For instance, designing bio-medical products needs multidisciplinary knowledge in high quality and quantity [58]. The terminology and taxonomy in different domains are rather isolated, which requests experienced professionals and a great time to link-up and verify. KG provides a novel knowledge representation method by connected nodes and edges that coreference and disambiguation could be better solved by vertical calculating of the relationships and referring to the relevant attributions. Automatic methods of knowledge extraction and fusion that only need little supervision have been explored in several studies that benefit the designing and usage stages in the lifecycle [21, 58, 59]. Though great progress has been made to processing textual information [59, 75, 76], more effort could be made to processing visual information such as videos and pictures.

3.2.2 Comprehensive solution searching

Comprehensive solution searching is a crucial demand in design, manufacture, and usage stages due to the high standard of precision in the industry practices. Stakeholders need comprehensive and descriptive solutions to their encountering problems, rather than just mapping the keywords and give a monotonous answer. In the design stage, designers may query the knowledge base very often to inspire and verify their ideas. In the manufacturing and usage stages, manufacturers and end-users need a fast and accurate question-answering approach to solve their issues independently. Thus accuracy, speed, and comprehensiveness are all highly required in industrial activities. KG takes advantage of the knowledge reasoning and customizable query patterns based on multi-hop semantic search to achieve better question answering results. Technically, KG enhanced by NLP and deep learning techniques better considers the semantic meanings and topological relations simultaneously, hence it achieves conspicuous success in understanding the industrial problems and retrieving corresponding solutions. For example, Morton et al. [63] presented Reasoning Over Biomedical Objects linked in Knowledge Oriented Pathways (ROBOKOP) as an abstraction layer and user interface to query KGs easier, and to store and rank the results. Platforms like J-Park Simulator are designed based on KG to carry out process simulation and optimize the process in the energy industry [66]. Efforts are also made to enable both online and offline running to ensure the searching demand is fulfilled [22].

3.2.3 Explainable knowledge recommendation

Knowledge recommendation could achieve better automation in industrial products and services, augmenting the efficiencies in almost all the lifecycle stages and related development tasks. Further, the explainable recommendation is crucial to stakeholders since products and services are built upon reasonable logic chains. They may not be willing to adopt the machine recommended result directly without convincing and sufficient reasons. For example, product managers may feel hard to make decisions on selecting the most proper logistics routes and disposal options, without a solid knowledge-based explanation. Based on question answering with comprehensive answers, making explainable recommendations is a further achievement by KG. A typical case is conducted by integrating a software KG with the intelligent development environment, utilizing the evolving KG's data parsing and semantic search capability to assist intelligent recommendation in software engineering [67]. In other studies, explainable knowledge recommendation is utilized in architecture and construction [64], biochemical engineering [69], and software engineering [68]. To achieve better explainable knowledge recommendation, Knowledge Graph Embedding (KGE) and path-based KG-aware are emphasized in insightful studies [5, 36, 77-79].

3.2.4 Risk detection and prediction

Risks are concealed in every step in the manufacturing process, as well as many key steps in logistics and usage stages. The coverage of human inspection limited the risk detection and prediction in enormous manufacturing plants and long logistics period that automatically risk prediction and detection are heavily needed by the industries. Safety risks could be affected by various factors in the lifecycle of products and services, including people's role, behavior, organization, machine status, apparatus and equipment [80]. Building a robust knowledge base and then utilize the capability of knowledge reasoning, question answering, and knowledge recommendation, it is possible to achieve prediction proposals and proactive risk detections in both the physical and cyber environments [6, 12, 71]. For instance, Liu et al. [70] proposed a paradigm to apply the KG into smart factories to support safety management in the manufacturing process. The research proposes the KG to be adopted not only to take actions based on the diagnosis of issues, but also to predict potential risks based on the collected information like workers' location and/or machines' status and generate preventative methods.

3.2.5 Information distillation

In the lifecycle of products and services, there is a huge gap between massive heterogeneous knowledge resources in the information systems and the system users' limited cognitive ability [81, 82]. In the practice, holistic but not specific information is often useless or even confusing for one single user. It hence requires the information system to distill proper information at the proper time to the users who are executing specific activities. As shown in Fig. 4, information distillation affects all the stages in the lifecycle of products and services, as well as all involved stakeholders. Benefiting from the capabilities of novel knowledge representation and knowledge deduction, KG could mitigate this pain point. For example, a KG-based system for hybrid information management is well-operated in Imperial Fashion, one of the most important fast-fashion companies in Italy [11]. It showcased the KG-based system could achieve good performance to deliver the proper information even in a multilanguage environment, with employees holding less technical background. Li et al., [8] developed a mobile app based on KG to distill targeted articles concerning the different patients' situations. Some KG-enabled information systems are also implemented to smartly deliver creative ideas to support users in generating novel designs [7, 73]. These KG-based functions provided friendly user interaction and achieved great user experiences in both products and services by distilling useful information to users with limited cognitive capabilities.

3.2.6 Summary

To sum up, by utilizing their flexible knowledge representation and in-depth deduction methods, the enhanced KGs are proved to benefit multiple industry pain points in lifecycle stages and also reveal the promising prospect in more kinds of industrial products and services [6, 8, 12, 83]. However, to generalize the exploitation of KG to more industrial scenarios, the barrier between multiple KGs or KG-enabled information systems largely impedes the reusability and transferability of previously developed techniques. The assorted portfolio and ecosystem [3, 11, 19, 59] hence emerge as a novel challenge. In fact, seen from the reviewed studies, KG is still a prevailing technique in industries, rather than a mature productivity tool for stakeholders of industrial products and services.

4. Challenges

According to the review, remarkable achievements have been made to enhance KG to fit in products and services, and mitigate the industry pain points in their lifecycle stages. Nevertheless, KG still faces several challenges in its practical exploitations, and there are several vacancies in potential prospects that could be studied to fill the gap. To better concentrate on the aspects of industrial products and services and conduct more practical KG exploitations, three challenges of the interaction with stakeholders, continuous enrichment, and assorted portfolios and ecosystems are discussed. As shown in Fig. 5, these challenges consider the interactions between KG and KG-enable information systems with stakeholders, knowledge resources, and peer industrial systems, which are the main concerns in the managerial perspective [74, 84]. However, pure theoretical challenges that merely improve the performance of KG, like similarity ranking precision [43, 85-87], database & storage optimization [88-91], noise curation [92-95], are not the key points here.

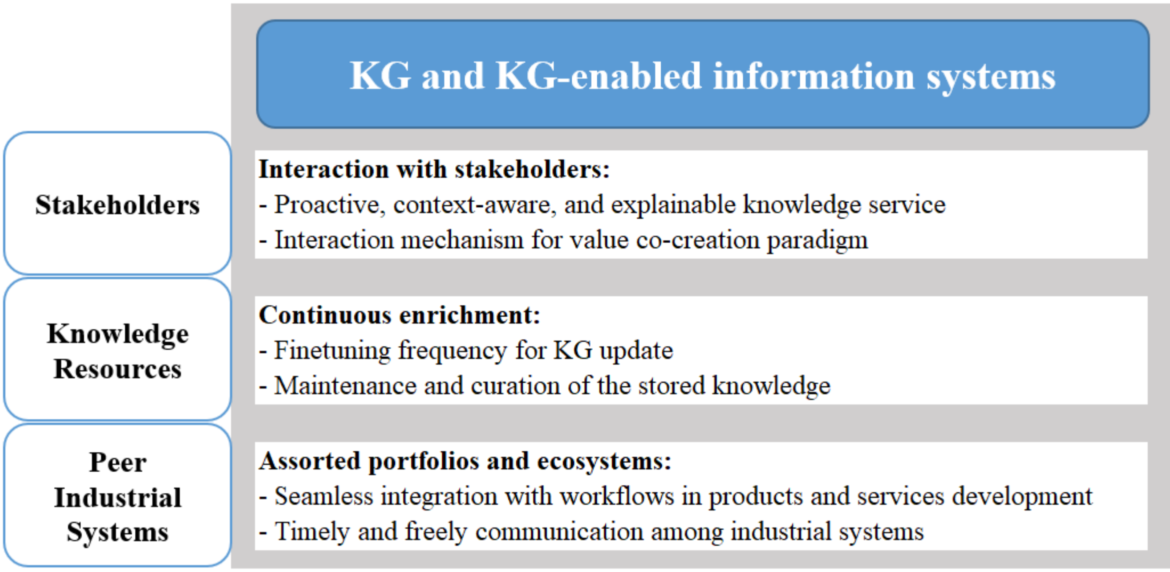


Fig. 5. Three managerial challenges aiming to more practical KG exploitations

4.1 Interaction with stakeholders

According to the review in Sec 3.1, most efforts are paid to the optimization of the accuracy and efficiency of knowledge reasoning [96-98], but user interaction is not emphasized. In fact, design and optimization for user interactions are mostly considered to be a business and management activity, which is seldom concerned in researches of computer science disciplines. To fully exploit KG's advantages in knowledge representation and knowledge deduction to better support stakeholders in products and services development, the KG-stakeholder interaction needs further enhancement. The challenge in this aspect lies in two-folds. One is a proactive, context-aware, and explainable knowledge service based on a KG storing the social networking, concerning when, how, and why to deliver proper information to which stakeholders of products and services involved in the workflow [99-101]. The other one is an open-to-all and bi-directional knowledge interaction mechanism fitting for the value co-creation paradigm of the product and service development, so that all the stakeholders can participate in the development process with more timely and accurate supports from KG.

4.2 Continuous enrichment

New knowledge is always being generated during the iterative development of industrial products and services, requiring the evolvement of knowledge extraction, knowledge fusion, and schema designing in KG construction [102-105]. To this end, continuous enrichment of KG faces challenges from two aspects as elaborated below:

Frequency of update: Adaptive to different stakeholders, the stored knowledge, as well as the demand of knowledge, will update with different frequencies. For example, product designers need up-to-date knowledge and concepts to ensure the products are creative and competitive. However, the operation management staff cares more about stableness and consistency and may not need such immediate knowledge or information [11]. Therefore, a stakeholder-centric balance between new knowledge update and existing knowledge resource usage should be achieved in the KG-enabled information systems [106-108]. Beyond merely focusing on the efficiency of new knowledge extraction, the robustness of knowledge representation, and the accuracy of knowledge reasoning, a frequency finetuning method considering industry workflows should be concerned in constructing KG and KG-enabled information systems [9, 109, 110].

Maintenance and curation: In industrial scenarios, the quality of knowledge weighs more heavily than quantity. Development activities driven by inaccurate knowledge may cause even worse consequences than not having knowledge. In this case, knowledge discovered or deducted by KG needs to be delicately verified and curated. Currently, researchers are keeping working on improving the accuracy of knowledge reasoning by utilizing subgraphs and deep attention [111, 112], but the involvement of human labor is still unavoidable to reach a final judgment. Thus, there is another balance need to be achieved between maintaining the high accuracy of the system and keeping low loading of the experts to verify and correct the newly generated knowledge. Utilizing experts' effort on ontology evolution rather than miscellaneous entity verification could be a prospective direction [113-115]. Other novel knowledge curation mechanisms between KG-enabled information systems and domain experts or other potential contributors, such as crowdsourcing, also need to be well-considered.

4.3 Assorted portfolios and ecosystems

Enhanced by sorts of advanced NLP and Machine Learning techniques, KG is currently well-performed in multidisciplinary knowledge extraction and fusion tasks [116-119]. In industrial enterprises, it also demonstrates strong capabilities to reform the existing management information systems (MISs) and operate as the core of the next-generation information system [4]. However, due to a lack of KG-involved assorted portfolios and ecosystems that seamlessly integrate with workflows in products and services development procedures, Information Silo that widely existed among enterprise MISs still re-occurs (i.e. unable to timely and freely communicate with other sorts of KG or KG-enabled information systems). As industrial products and services require higher stability and more smooth transitions to ensure the robustness of themselves, challenges of assorted portfolios and ecosystems, like unified portal and platform [10, 31], database fusion methods [44, 120-122], workflow migration [112], should be highlighted to mitigate this issue.

4.4 Summary

To sum up, although KG techniques are robust enough to set up a solid knowledge base and timely offer necessary information, challenges still lie in further enhancing the practical usability and operability in multiple industrial scenarios, and delivering ideal supports and outcomes for product and service development. Further efforts are required to improve the interactions between KG and stakeholders, KG and knowledge resources, and KG and other industrial systems, thus achieving a closer collaboration in the scenario of industrial products and services.

5. Future perspectives

To cope with the raised challenges, this section proposes and highlights several promising future perspectives on better exploiting KG in industrial products and services, so as to motivate more open discussion and in-depth studies in the near future.

5.1 Enhancing KG's availability for industrial products and services

To fulfill the challenge of continuous enrichment and enhance the availability of KG itself in industrial products and services, subsequent studies can work on three perspectives, i.e., improving self-adaptability on knowledge update, uncovering tacit knowledge, and co-working with experts.

5.1.1 Improving self-adaptability on knowledge update

The frequencies of knowledge evolvement and the timeliness of knowledge demands are different in various knowledge exploitation scenarios. Belated knowledge update in the knowledge base may cause out-of-style design for a new product. However, the unnecessary high frequency of updates may cause an extra burden for the system, and may even cause unpredictable issues in some manufacturing industries with strict process restrictions. Thus self-adaptability, which directs the KG and KG-enabled information systems to react to the changes in ever-evolving environments with context-awareness, is highly recommended. Potential self-adaptability may base on 1) Setting threshold quantity for a new keyword existence; 2) Ranking of the information resource; 3) Frequency of query to the keyword; 4) Will the update of knowledge impact the current working process? 5) Current usage of system resources; 6) Reliability of the new knowledge [123].

5.1.2 Uncovering tacit knowledge

Massive tacit knowledge in the enterprises still remains undiscovered and inaccessible, since many stakeholders haven't systematically recorded their valuable experience yet or even do not know how to conclude them into records [124, 125]. To solve this, KG could help to match knowledge expressions to their efficient behaviors to uncover the tacit knowledge embedded under their unconscious actions. Aiming at enhancing the KG complement capability, the studies on tacit knowledge discovery and knowledge reasoning could be conducted to support such works. Tackling tacit knowledge may also rely on the contribution of information distillation since some knowledge is unknown for specific stakeholders only because they are not familiar with the context beyond their professions. Current studies have achieved remarkable results in coreference processing and characteristic output that could contribute to enhancing the information distillation and better understanding the users' behaviors [3, 126-131]. Further research could be conducted based on those works on cognizing users' professions and behavior modes, as well as correlating multi-users behaviors to achieve tacit knowledge uncovering.

5.1.3 Co-working with domain experts

The new knowledge captured from outsource or deducted by the KG and KG-enabled information systems may need to be verified by the domain experts before adopting it. But diverse knowledge may need different levels of experts' interactions. For example, the transportation route recommended from knowledge deduction may need little authentication, contrarily the mechanical engineering knowledge needs serious cross-check from senior engineers. Crowdsourcing via verification channels, monetary intensive knowledge correction, and regular verification are usual methods to achieve the correction and accuracy maintenance of the knowledge base. The authors would like to highlight the interactions with domain experts because their opinions have the most value. Current current systems such as protégé [132], metaphactory [133] have provided valuable platforms that allow experts to manipulate KGs, while the proposals regarding new knowledge and interaction methods still need to be developed, considering domain experts' IT skills of operating KGs. The explainable recommendation capability based on KG is recommended to be further developed to address the efficiency of proposing queries to the experts, so as to bridge the gap between the collaboration of human intelligence and artificial intelligence. Some rising methods such as graph-embedding techniques are worthy to be considered [134-137].

5.2 Boosting KG's productivity in products and services development

To provide better user interactions to the stakeholders of industrial products and services and boost KG's productivity in the development process, the exploitation of KG should be refined towards the goal of seamless KG-based portfolios and ecosystems. This section highlights three representative industrial scenarios that can be further explored in products and services development, i.e., demand forecasting and requirement analysis, smart engineering solution design, and automatic risk detection and issue handling.

5.2.1 Demand forecasting and requirement analysis

In industries, demand forecasting and requirement analysis are initial and crucial topics to product and service development, which need massive information input and a proper analysis model to make better predictions. Processing multi-source information and conducting logical knowledge reasoning are two major strengths of KG and KG-enabled information systems. Several attempts, such as [19, 59, 138, 139], have shown the capability of KG to collect massive information from online technical forums and portal websites to capture the latest trend of the market and other events that may impact the demands. The logical inference could be conducted through the knowledge deduction in KG to provide robust calculations [50, 59]. The explainable capability of knowledge reasoning and recommendation enabled by KG can be valuable for demand forecasting and requirement analysis, since the ordinary output results may only be a reference in the business environment while stakeholders care more about the insights and logic behind the results.

5.2.2 Smart engineering solution design

A typical solution design process includes 5 steps: 1) Problem recognition; 2) Cause analysis; 3) Knowledge retrieval; 4) Solution creation; 5) Solution verification [140, 141]. KG and KG-enabled information systems could help the first 4 steps that leave human efforts mainly focus on the last verification step, which could save a lot of time and would be more efficient. 1&2) Take advantage of the novel knowledge representation method to better "understand" the problems more "humanly" and analyze the cause based on the knowledge in KG; 3) Retrieve knowledge in the KG by multi-hop searching; 4) Conduct knowledge deduction and clustering similar relationships to create derivative knowledge and assemble solutions. Solution design of products or services empowered by KG would benefit both time and labor-consuming, which improves efficiency [142-145]. Besides, KG also mines the surplus-value in the solution design phase by utilizing the unadopted ideas: When applying KG-based solution design systems, not only the optimal solutions generated by the system would be saved and stored automatically, but even the initial ideas that didn't compose complete solutions could be stored in the system. These solutions and ideas stored as knowledge in the KG could build a holistic and robust knowledge base for the enterprise, keep enhancing the healthy lifecycle of the solution design of new products and services.

5.2.3 Automatic risk detection and issue handling

Detecting risks or safety threatens by humans is based on experience and logical inferences. The experience provides the knowledge on what is risk, inference based on domain and common knowledge leads to logical judgment on whether a thing is a risk. By utilizing KG-based technologies, the system could help in both ways of risk detections. Firstly, KG extraction and fusion methods could help to process the knowledge and build a robust knowledge base as an experience repository. More importantly, information collected by sensors could be utilized by the knowledge reasoning process in KG to identify if the current situation matches any specific rules in the knowledge base thus make a logical judgment on whether there is a risk. Some studies have provided valuable experience in building KG and KG-enabled information systems for risk detection by focusing on specific domain risks [6, 70, 146]. It is worth noting that common knowledge of safety management will be contained during the construction of KG, rather than only the specific domain knowledge that covers the existing situations.

Meanwhile, through a better understanding of the relationship among Function-Behavior-Structure (FBS) with proper knowledge representation, the KG-based issue handling system could actuate the smart components to adjust themselves to solve problems [12]. When the information collected from ubiquitous sensing networks is identified to be risks or issues by knowledge reasoning, the system could take the next action to keep digging and deducting the cluster of knowledge to generate one or several issue-handling resolutions. Then the resolutions with the highest rankings could be executed automatically. Besides, authorizations could be set ahead accordingly to the hazard level, emergency, or the smart components to be actuated, to differentiate whether the actions should be taken by the system automatically or announce and suggest human workers judging and taking actions.

6. Conclusions

Knowledge Graph, as an emerging tool to manage numerous entities and relationships, has been ever-evolvingly developed among academics. Nevertheless, the majority of KG-related researches in industries still regard KG techniques as a medium for providing industrial information, and they predominantly focus on the theoretical methodologies of improving the algorithm's performance. There still lacks comprehensive and thorough discussions about making full use of KG's potentials to solve pain points of product development and service innovation in the industry. To identify the limitations of current KG methods when applying to practical applications and propose some future research perspectives, this paper conducted a holistic relook at 119 academic articles that contribute to enhancing the availability and productivity of KG technologies in industry products and services.

The main findings and contributions of this study can be summarized into three aspects below:

Provided a holistic review of publications on KG exploitations in industrial products and services. Through a review of 119 recent papers, this study outlines three enhancements to fit in industrial products and services, which are dispersed in KG construction, deduction, and using periods. Five industry pain points in industrial products and services development that can be mitigated by KG are also discovered and summarized, i.e., multidisciplinary knowledge extraction and fusion, comprehensive solution searching, explainable knowledge recommendation, risk detection and prediction, and information distillation.

Illustrated the current challenges of KG and KG-enabled information systems to be applied to industrial products and services. Towards a more operative and productive KG exploitation manner, the gaps between the actual system-using preference and the exploited capabilities of KG in the scenario of industrial products and services are identified. Three practical challenges of KG exploitation in industrial products and services are further discussed in the managerial perspective, i.e., interaction with stakeholders, continuous enrichment, and assorted portfolios and ecosystems, aiming to improve the interactions between KG and KG-enabled information systems with stakeholders, knowledge resources, and peer industrial systems.

Proposed the future perspectives of promoting KG's availability and productivity for industrial products and services. To make the full exploitation of KG's capability on managing and processing knowledge, it is recommended that KG practitioners can further enhance KG's availability in industrial products and services with three possible directions, i.e., improving self-adaptability on knowledge update, uncovering tacit knowledge, and co-working with domain experts. For industrial product and service developers, three representative industrial scenarios are also highlighted to boost KG's productivity in the development process, i.e., demand forecasting and requirement analysis, smart engineering solution design, and automatic risk detection and issue handling.

The authors hope this research can be regarded as the basis for both academics and industries in their explorations and implementation of KG-supported industrial product and services development. Also, this work is hoped to attract more open discussions and provide useful insights for the practical exploitations of industrial KG and KG-enabled industrial information systems in the near future.

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