Requirements for the Application of Knowledge Graphs in Automotive Manufacturing

Jan Michael Spoor
Team Digital Factory Sindelfingen
Mercedes-Benz Group AG
Sindelfingen, Germany
jan_michael.spoor@mercedes-benz.com

Christian Graewe
Automotive Connected Customer Journey
NTT DATA Deutschland AG
Erfurt, Germany
christian.graewe@nttdata.com

Jens Weber
Mechanical Engineering Department
DHBW Lörrach
Lörrach, Germany
weberj@dhbw-loerrach.de

***Abstract*—The application of knowledge graphs drives in particular the development of Digital Twins. Thus, the creation of knowledge graphs becomes an important objective in automotive manufacturing. In the current literature, multiple requirements are given. In this paper, we conduct a categorization of these requirements. In addition, we evaluate expert interviews to enable a comparison of the requirements mentioned by practitioners with the requirements mentioned in the literature. While the industry experts agree with most challenges and requirements from the literature, some requirements differ. Most notably, real-time monitoring is not seen as a high priority by the practitioners. The application of predictive maintenance is seen as a subsequent application and not as a fundamental feature. Lastly, the integration of external partners such as suppliers is seen as controversial between the industry experts. This conducted evaluation provides a foundation to further develop use cases and implementation concepts in automotive manufacturing. In future work, we plan to add technical implementation requirements and conduct first use cases of knowledge graphs.**

***Index Terms*—Cyber-Physical Systems, Knowledge Based Systems, Production Engineering**

I. Introduction

Within the highly automated Body-In-White (BIW) assembly of the automotive industry, an improved representation, documentation, and production connectivity as well as planning knowledge are required to further drive the automation level. For this purpose, knowledge graphs are developed for manufacturing applications. A knowledge graph is defined by Ehrlinger and Wöß [1] as a system which acquires and integrates information into an ontology and applies a reasoning to derive new knowledge. In their review, Buchgeher et al. [2] list among others knowledge fusion, creation of Digital Twins (DT), automated process integration, and program generation as use cases for knowledge graphs. Thus, the development of knowledge graphs is an essential part of the development of DTs and as such highly relevant in the current development and implementation of DTs within the automotive industry, in particular the BIW assembly. In addition, Spoor et al. [3] highlight the importance of knowledge representation within the BIW assembly for inference procedures of fault detection.

In order to drive the development of DTs and to improve existing ontologies, Mercedes-Benz decided to run an evaluation of the requirements for the applications of knowledge graphs. Objective of the initiative is the discussion of applications, requirements, and future use cases of knowledge graphs with senior staff members and industry experts. Thus, the academic view of knowledge graphs is complemented by the view of industry experts. This enables a refinement of the requirements for an application in the BIW assembly line. The results of the conducted interviews and the comparison of the results with the academic point of view are presented in this paper.

In Section II, an overview of the current literature is provided and the requirements from the literature are grouped and categorized. In Section III, the methodology of the interview process is described. Subsequently, the results of the interviews are presented and contrasted with the requirements from the literature in Section IV. To summarize the paper and to provide a future outlook, a conclusion is given in Section V.

II. Literature Review

As structure for the requirements of knowledge graphs, we use the ISO/IEC 25010 criteria [4]. In particular, we use the quality model characteristics and add specific technical requirements of knowledge graphs in the automotive industry per category. The sub-characteristics of ISO/IEC 25010 still apply as evaluation criteria of the requirements but are not additionally discussed. The ISO/IEC 25010 criteria are discussed in the literature and considered to be useful for the evaluation of software architectures [5]. The derived requirements for knowledge graphs from the literature review and the respective ISO/IEC 25010 characteristics are summarized in Figure 1.

Functionality As first step of the application of knowledge graphs, a suitable data preprocessing is necessary. This includes a check for redundancy and preprocessing in order to counteract this since duplication is a rather common problem in knowledge graphs [6]. In addition, it is necessary to have comprehensive data validity checks and conduct an extensive *Data Cleansing* prior to the import and storage of data since Machine Learning (ML) and Artificial Intelligence (AI) require solid databases for the training. Thus, Josko et al. [7] propose a data defects ontology for knowledge graphs. Weikum [8] states that it is crucial to think judiciously about data source discovery and data quality assessment.

As second requirement, the overall *Relation Modeling* using an ontological model as well as a query engine to access this information is necessary. Ontologies are developed by,

 ISBN: 978-1-68558-049-0

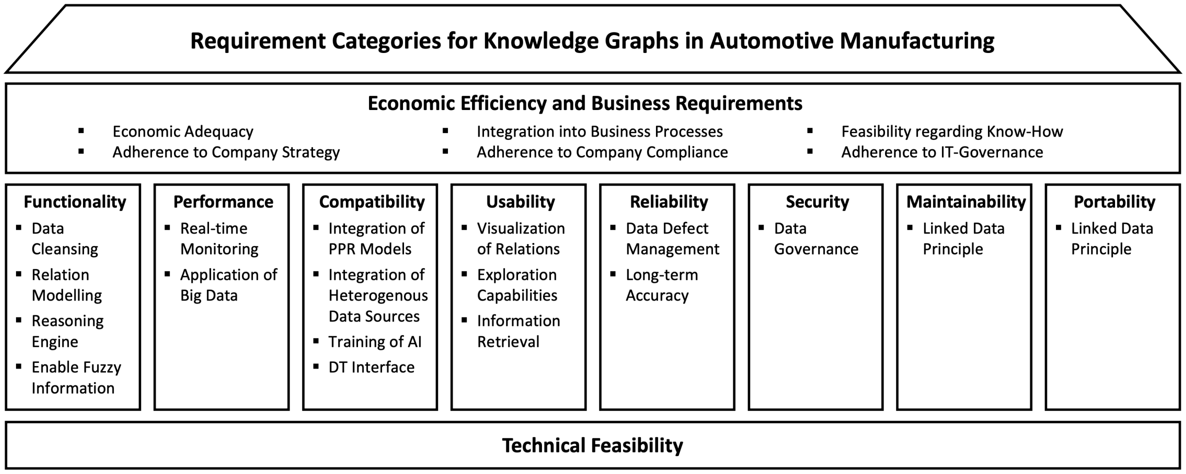

Fig. 1. Overview of the different requirement categories. Adapted from ISO/IEC 25010, we identified important requirements along the eight categories [4]. Business requirements are a cross-section to be taken into account in all vertical categories. All requirements rely on the technical feasibility of the concept.

e.g., Giustozzi et al. [9]. Most common in the automotive industry are product, process, and resource (PPR) models, e.g., by Ferrer et al. [10]. Yahya et al. [11] list as a requirement for ontologies that the scope should not be too application-specific and applicable in all areas of the production. Currently available semantic model-based ontologies are limited regarding this requirement.

Furthermore, the knowledge graph should provide an as-is-model as well as a defined to-be-model. Spoor et al. [3] see the knowledge graph as method for inference procedures and fault detection. Bellomarini et al. [12] differentiate a knowledge base management system from a knowledge graph management system since the latter includes Big Data and analytics capabilities. Ehrlinger and Wöß [1] describe the knowledge base and reasoning engine as components of a knowledge graph. Thus, the capabilities of the *Reasoning Engine* is a core functional requirement of knowledge graphs.

Since knowledge graphs most commonly use the Resource Description Framework (RDF) consisting of subject, predicate, and object, these relations have an uncertainty in case of inconsistencies within the applied datasets [13] and the data cleansing will not be able to resolve all inconsistent information. Thus, a knowledge graph should *Enable Fuzzy Information* and be applicable for fuzzy inferences. Noy et al. [14] state that each entity may have multiple types and specific types matter in different scenarios.

Performance Firstly, *Real-time Monitoring* and the speed of integration of new or changed data is a performance-specific requirement for knowledge graphs. In the literature, often a real-time data availability and processing is demanded [11].

Secondly, the integration and *Application of Big Data* is required [12]. Combined with real-time monitoring, this highly affects the ISO/IEC 25010 performance sub-characteristics of time behavior, resource utilization, and capacity.

Compatibility In this category, the main requirement is the *Integration of PPR Models* including existing, currently developed, and future ontologies. A knowledge graph should enable a problem-free integration of all systems related to the management of ontologies [11]. Different knowledge domains in manufacturing often use different systems and thus, an efficient integration of heterogeneous data from knowledge domains such as factory, building, system, resource, process, product, strategy, performance, and management is required [15]. This includes different applied systems within the production line, all relevant data management software applications, and also systems of external partners such as suppliers [16]. Thus, the knowledge graph has to be able to manage the *Integration of Heterogenous Data Sources* and extract knowledge from multiple structured and unstructured sources [14]. This results in interoperability requirements that are difficult to implement.

Knowledge graphs should in addition be able to provide data for the *Training of AI Models*. In particular, they improve explainability by applying the knowledge graph's reasoning capabilities [17] and function as fundamental source for the development of DTs by providing a direct *DT Interface* [2]. It should be noted that the boundary between knowledge graphs and DTs is rather blurred and implemented knowledge graphs themselves are sometimes considered as DTs [18]. However, knowledge graphs are most certainly important foundations for any DT development. Thus, there is a high relevance in the co-existence criteria between subsequent applications such as the DT or AI models and the knowledge graph.

Usability Within the context of scientific knowledge graphs, Auer et al. [19] name the development of methods for exploration, retrieval, and visualization of knowledge graph information as future challenges in the development of knowledge graphs. Thus, an appropriate *Visualization of Relations*, the *Exploration Capabilities* for finding new causal relations among the industrial data, and the possibility for an *Information Retrieval* of difficultly accessible knowledge are specific requirements. Although the original proposal is in the context of scientific knowledge graphs, these requirements are also relevant for the BIW assembly, the automotive industry, and manufacturing in general.

Reliability Data in real-world scenarios often lack reliability and thus, ontologies often contain errors, redundancies, inaccuracies, or contradicting relations in particular if different domain ontologies from different data sources are merged [8]. This results in a reduction of reliability of the applied knowledge graph. Thus, it is important to detect, identify, and mark potential reliability issues and inform users about these problems. Therefore, an applied knowledge graph must provide information about its own reliability and errors for users and industry experts to later correct these instances. Hence, a *Data Defect Management* for users to handle errors, redundancies, inaccuracies, or contradicting relations is a relevant feature of applied knowledge graphs.

A further aspect of the reliability of knowledge graphs is its *Long-term Accuracy* since the knowledge base continuously changes over time. Noy et al. [14] state that it is critical to manage changing schemas and type systems, without creating inconsistencies. In practical applications, a system needs to change organically based on changing input data due to, e.g., company mergers or splits, scientific discoveries, and organizational changes of divisions.

Security The ISO/IEC 25010 sub-characteristics are important for knowledge graph management systems. However, the application of a suitable *Data Governance* for the knowledge graph is most relevant as part of the overall IT Governance of the company [16]. This includes among others data security, data consistency for an improved decision making by users, profitable use of the data, and most notably an organizational concept for the accountability of the data quality [20]. Thus, applied knowledge graphs should also contain concepts for organizations and users to manage, improve, and correct data quality. This is related to the data cleansing and data defect management but differs since it focuses not on applications and systems themselves but the overall organization and company guidelines. In addition, this includes the organizational decision on the confidentiality of data and ontologies within a knowledge graph since malicious users could potentially use the exploration and information retrieval aspects of knowledge graphs to gain access to sensitive and business-relevant data.

Maintainability Regarding maintainability, the aspects of re-usability and modifiability can be improved by following the *Linked Data Principle* as stated by Yahya et al. [11] as an important future development task for improved knowledge graphs. These principles are as following: 1) the use of Uniform Resource Identifiers (URI) as names for entities, 2) the use of HTTP URIs, 3) the provision of useful information when searching a URI, using standards such as RDF or SPARQL, and 4) the inclusion of links to further URIs. The application of linked data is often difficult since the data owners are different organizations (or sub-organizations within a company), different URIs are used for the same real-world entity, complementary information exists across different datasets, the data is erroneous, out-of-date, or conflicting, and different conceptualizations of the domain for each dataset apply [21]. However, following the linked data principle enables a high maintainability and scalability.

Portability Using the same rationale as in the category of maintainability, the linked data principle also ensures an adaptability and replaceability of knowledge graphs within organizations. Thus, the linked data principle is a core requirement for maintainability as well as portability.

In addition to the requirements based on the ISO/IEC 25010 characteristics, overarching business and economic requirements have to be met within an application in automotive manufacturing. In general, the development, implementation, and use of a knowledge graph should follow economic adequacy. This includes development and running costs compared to the usage benefits such as among others reduced production costs, reduction of complexity, or faster production planning and development. This is realized by a prior development of a business case to ensure an economic cost and benefit consideration. Further, not only the technical implementation and integration into the IT systems but also the integration into the business processes must be considered. In addition, a company which wants to develop a knowledge graph should carefully consider their current know-how and availability of their IT workforce. If the development and maintenance of a knowledge graph cannot be conducted by current internal capacities, external capacities or an investment in internal capacities should be considered. Furthermore, the knowledge graph should be in adherence to the company's strategic direction, compliance guidelines, and IT governance. The business and economic requirements should be evaluated as a cross-section over the relevant vertical categories.

In conclusion, the technical feasibility of the proposed knowledge graph should also be evaluated since some requirements currently lack extensive use cases so that a feasibility assessment is not always completely possible. The technical feasibility should also cover the analysis of the current hardware and software of the IT landscape and the interoperability of these systems. Server capacities or applications of cloud or hybrid cloud solutions should be evaluated regarding available storage capacities, performance, and interfaces.

III. Methodology

Building on the developed categorization from the literature, guided and quantitative expert interviews were conducted. The methodology of the interview process can be structured into six consecutive phases. An overview of the six phases of the interview process is given in Figure 2.

The first phase of the used methodology is the development of the interview guideline and of a quantitative questionnaire. This includes questions regarding all identified special requirements. Within the guided expert interview the focus was the precise definition of the requirements from an industry perspective. Guided interviews were selected since they enable the interviewee to add necessary details and further ideas, concepts, or requirements not covered by the conducted literature review. The quantitative questionnaire was in addition designed to query the approval or rejection by the interviewee of individual sub-aspects. For all questions, the approval was measured using a five-level Likert scale.

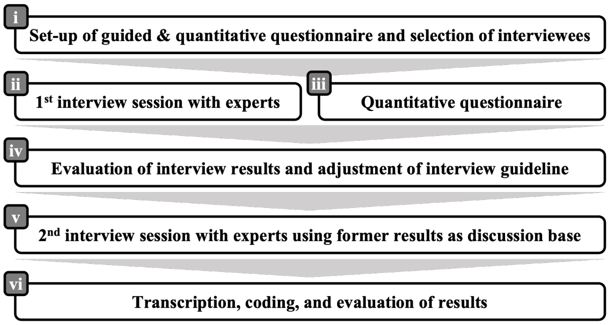

Fig. 2. Sketch of the applied methodology along six phases for the conduction of the interviews with industry experts from automotive manufacturing.

The first phase includes the selection of relevant industry experts. Only manufacturing industry experts with a high seniority levels of >10 years of industry expertise and either experience within data and knowledge modeling of the BIW assembly or prior experience with the development, application, or implementation of knowledge graphs were selected. This was checked via a pre-screening of potential interviewees and only interviews with relevant industry experts were conducted. Disadvantageously, this resulted in a rather small set of interviewed experts. In total, the whole described interview process was conducted with twelve industry experts (N=12) from German automotive BIW manufacturing departments.

After the first interview sessions were conducted, each expert completed a quantitative questionnaire. Subsequently, the results of the guided interviews and the quantitative questionnaire were aggregated to flesh-out relevant questions regarding the requirements and identify the most controversial opinions or opposing statements. Using the updated set of questions, a second round of guided interviews was conducted. In particular, the interviewees were confronted with statements from the literature or other interviewees contradicting their former assertions and asked to clarify their statements. Thus, the most relevant questions were discussed in greater detail and the assessment of requirements was further fleshed-out.

Concluding, the interview transcripts were evaluated using as coding categories the ISO/IEC 25010 characteristics and as sub-categories the derived requirements from the literature. We separated within the coding of the transcripts factual statements and opinion statements. After the first coding of the interviews, the requirement categories from the literature were adjusted so that literature and interview structure aligned along the new set-up requirements. These are the requirement categories listed in Section II. Subsequently, a second coding of the interview transcripts using the updated coding logic was conducted. The resulting statements were then analyzed, evaluated, and compared with the statements from the literature.

IV. Results

The results of the interviews are presented by descending order starting with the most mentioned categories. While this might not reflect the technical difficulties, it shows the focus within the practical application in the automotive industry.

The most mentioned and discussed category during the interviews was the *Integration of Heterogenous Data Sources*. The main concerns of the practitioners are the compatibility of different sources as well as the applications that access information of the knowledge graph. Applications which access the data from the knowledge graph are, e.g., Microsoft PowerBI and other analytics tools. Often, multiple analytics applications are in use within the same organization. Thus, multiple Application Programming Interfaces (API) are required for an integration within the IT landscape of the automotive industry. Important input data sources are the Internet of Things (IoT) applications and sensor data. A major challenge in particular is how to keep data within a knowledge graph up-to-date. The concern is often that the data sources need to be adapted prior to the implementation of the knowledge graph in association with a high level of necessary manual effort. Furthermore, data sources exist in different organizationally separated units within an enterprise such as production, maintenance, research & development, or sales, in particular aftersales. Thus, the German automotive industry sees the development of industry standards as a crucial part of a knowledge graph development. The integration of heterogenous data sources is discussed in the literature [16] and also a well-know current limitation and future challenge in the development of knowledge graphs [14]. Thus, the perception from the literature and by the industry experts match regarding this topic.

The next relevant topic is the applied *Data Governance*. Most interviewed industry experts and practitioners have referred to directives already in force within their company. Thus, the topic has already a high visibility within the German automotive industry. However, the details of the application are still part of a discussion. Multiple experts name data democratization, the idea of providing all employees with the necessary data, as a core principle for the management of the information generated by the knowledge graph. Other experts state that access control and access rights should strictly apply since a knowledge graph contains critical information. In addition, the access of suppliers, whose efficiency in providing solutions to businesses would be greatly improved as a result by the knowledge graph, is seen as a potential risk of losing internal company knowledge. Thus, the role of knowledge graphs needs further discussion within management science regarding the level of data democratization and integration of external partners and suppliers. While the literature states high benefits in the integration of external partners [16], this has yet not been sufficiently discussed in application.

Within the topic of *Relation Modeling*, the integration of contextual information and implicit knowledge by employees are perceived as important topics. While the context and implicit knowledge is perceived as highly relevant to understand the application, possible faults, and presented data, there is a lack of ideas on how to integrate the implicit knowledge and how to manage or update implicit knowledge. Since not all users share the same technical terms within large organizations such as German automotive companies, it is crucial to enable an identification of entities by multiple, sometimes ambiguous,

 ISBN: 978-1-68558-049-0

terms. An exemplary case of ambiguous terms is the diversity of variants which are sometimes referred to as the same car model but in other instances strictly distinguished. Unfortunately, the embedding of implicit knowledge is considered necessary and knowledge graphs without this information might be of no value to users. Implicit knowledge is a well-know challenge in the literature [14].

Regarding *Data Cleansing*, there is a consensus among the experts that manual data correction processes are doomed to fail. The knowledge graph should provide functionality to automatically check redundancies, validate the logic of the RDF information of new or changed entities, check for currency of the data, and identify data defects. This is important since industrial process data and decision-making processes are highly susceptible to error and the current data sources are often inadequately prepared. This matches with the recognized challenges from the literature [8] and highlights the need to develop concepts for data validation.

The implementation of knowledge graphs according to the *Linked Data Principle* is very important to the experts and is discussed in the practical application. The usage of URI, RDF, and SPARQL is recognized by all experts as an important factor for the maintenance and modifiability of the system by software suppliers, as well as the connection with the supply chain. All experts promote a collaboration within the German manufacturing industry to align standards and ontologies. Projects within initiatives such as AutomationML are currently conducted and first results evaluated.

Regarding usability, *Information Retrieval* was mentioned the most. The idea to search multiple connected queries at once is seen as a core advantage of knowledge graphs compared to commonly used databases. Currently used databases are seen as opaque with a lot of unused data and as a hurdle to extract the necessary data. However, the experts are highly critical if the knowledge graph should display the full complexity to all users. The experts fear that users may not be able to find their way around and that too many functions and displayed data might be a hurdle regarding usability. Thus, the capabilities should be limited for certain users for an improved usability. This should encourage academics to further research and develop concepts in the field of user experience of knowledge graphs. The resulting transparency by a knowledge graph is seen as an important feature. This feature is enabled by user interfaces with refined information retrieval capabilities.

Most noteworthy, an application of *Real-time Monitoring* is seen as controversial among the industry experts. Although real-time capabilities are considered to be potentially useful, experts have doubts about the technical feasibility with the given IT infrastructure since currently implemented systems struggle regarding real-time data processing. Using a cost-benefit consideration, all interviewees list real-time monitoring as a subsequent, secondary, or optional requirement. This is in contrast to the literature such as Yahya et al. [11] and results mostly from the technical feasibility.

Similar to the information retrieval, the *Visualization of Relations* should only contain the most useful data and context information. Links to other entities should be displayed and the network visualized but the information should also be reduced to only the most relevant data for the given user type. However, the industry experts struggle to provide best practices and examples. Thus, it is concluded that data visualization is still a relevant future research topic.

The application of a *Reasoning Engine* is also not seen as highly important since other tools are already in place. The knowledge graph should be capable of adding more context to currently identified problems but not necessarily act as a separate reasoning engine. Thus, the knowledge graph as proposed by the industry experts is more similar to a knowledge base since Ehrlinger and Wöß [1] describe the reasoning as core differentiation between a knowledge base and a graph. Thus, practitioners see the knowledge graph as a method to add further context to already identified errors. The error detection is conducted in a separate application.

Regarding the *Integration of PPR Models*, the interviewees note that a knowledge graph should use current PPR models but PPR data are currently even within the same organization heterogenous and not aligned. Thus, it is important to merge, classify, and semantically enrich current models. One interviewee proposed to first build up a new narrow graph and steadily further develop and enlarge its knowledge base using additional PPR data. This is also acknowledged by the literature as a challenge and as a necessary requirement for the development of knowledge graphs [11].

The wide-scale application and *Training of AI* in production engineering is currently not achieved and seen as too far from a practical application in the automotive industry production. However, the knowledge graph is seen as a foundation of a useful database for future applications of AI and its explainability and thus, the necessary data quality and machine-readability should be ensured. More important is currently the *DT Interface* since the contextual information across multiple systems is an important success factor of the DT development.

An unsolved aspect is the *Long-term Accuracy* of a knowledge graph. An autonomous development and updating of the knowledge graph are seen as necessary but currently no solution for this topic exits. For example, if a part is changed, repaired, or updated during maintenance work, this should be noted and recorded accordingly within the knowledge graph. These updates of input data are frequent and thus, this processes must be automatically connected. Furthermore, with long-term use changes of the domain ontologies will occur and should trigger an automated update of the graph structure.

A second unsolved challenge is the *Data Defect Management*. It is unclear for the interviewees how problems in the database of the knowledge graphs should be managed. Proposals range from technically capable users as product owners, over rule-based consistency checks, to ML methods.

The interviewees see the necessity for an *Application of Big Data* since, e.g., an interviewee states that an exemplary manufacturing cell generates 37 GB data per day. Another expert states that a processing of 1 TB production data per day per factory location is currently feasible. As the amount

 ISBN: 978-1-68558-049-0

of cells per factory goes into the hundreds, either data and features have to be selected prior or further Big Data capabilities must be implemented to provide additional functionality for large scale pattern detection and data mining. Solutions are in particular hybrid clouds where high-risk data is stored locally.

The industry experts are uncertain on how to *Enable Fuzzy Information* since some knowledge is not a priori known but predicted and fuzzy categorized. However, the knowledge graph should primarily display confirmed factual information. In addition, context might shift dynamically over time creating fuzzy transitions. Overall, the knowledge graph should act as a cross-section between predictions, assumptions, and facts.

The *Exploration Capabilities* were not a focus of the practitioners but the analytic deep-dive capabilities are recognized. The infrequent mentioning of this topic might be due to a focus on operation and not analytics aspects of most interviewees.

In conclusion, the economic benefits are named as cost reduction due to process optimization, improved product quality to ensure competitiveness, and an enabling of cross-functional and organizational collaboration on production data. Current IT governance and strategies are already in place to enable a development of knowledge graphs. However, internal competencies are still under development and communities within an organization are necessary for the education and training of employees in the application of knowledge graphs.

V. Conclusion and Future Work

This contribution lists the most relevant requirements for a knowledge graph implementation within the automotive industry and proposes a useful categorization for these requirements. In addition, the requirements from the body of literature and from industry experts are listed and compared.

While most requirements match between literature and practitioners, most notably, the real-time capabilities and reasoning engine are seen as a secondary priority since the knowledge graph should primarily enable users and subsequent applications to gain contextual information. In addition, the aspect of data governance and access rights for users and external partners such as suppliers are highly controversial. Thus, management science should focus on data governance concepts in the context of knowledge graphs in future research.

This manuscript is limited by the small amount of interviewed experts and due to the focus on the German automotive industry. In subsequent work, more international experts should be interviewed and their opinion compared to the here given results. In addition, we want to evaluate the technical requirements and implementation of knowledge graphs in the automotive industry in future research projects.

Acknowledgment

A special thanks to all interviewees for their time and the information provided. We also thank all colleagues and former colleagues who provided data, concepts, and development support of the research work within Mercedes-Benz Group AG and the University of Applied Sciences Zwickau.

Funding by Mercedes-Benz Group AG and NTT DATA Deutschland AG. All authors contributed equally.

References

[1] L. Ehrlinger and W. Wöß, "Towards a Definition of Knowledge Graphs," In: SEMANTiCS, vol. 48, pp. 1-4, 2016.

[2] G. Buchgeher, D. Gabauer, J. Martinez-Gil and L. Ehrlinger, "Knowledge Graphs in Manufacturing and Production: A Systematic Literature Review," In: IEEE Access, vol. 9, pp. 55537-55554, 2021.

[3] J.M. Spoor, J. Weber, S. Hagemann, F.S. Bäumer, "Concept of an Inference Procedure for Fault Detection in Production Planning," The Fourteenth International Conference on Pervasive Patterns and Applications (PATTERNS'22), Barcelona, pp. 10-17, 2022.

[4] ISO/IEC 25010, "Systems and software engineering: Systems and software Quality Requirements and Evaluation (SQuaRE)-System and software quality models," International Organization for Standardization, Geneva, 2011.

[5] M. Haoues, A. Sellami, H. Ben-Abdallah, L. Cheikhi, "A guideline for software architecture selection based on ISO 25010 quality related characteristics," In: Int. J. Syst. Assur. Eng. Manag., vol. 8, no. 2, pp. 886-909, 2017.

[6] M. Galkin, S. Auer, H. Kim and S. Scerri, "Integration Strategies for Enterprise Knowledge Graphs," 2016 IEEE Tenth International Conference on Semantic Computing (ICSC'16), Laguna Hills, pp. 242-245, 2016.

[7] J.M.B. Josko, L. Ehrlinger, and W. Wöß, "Towards a Knowledge Graph to Describe and Process Data Defects," The Eleventh International Conference on Advances in Databases, Knowledge, and Data Applications (DBKDA'19), Athens, pp. 57-60, 2019.

[8] G. Weikum, "Knowledge graphs 2021: A data odyssey," In: Proceedings of the VLDB Endowment. vol. 14, no. 12, pp. 3233-3238, 2021.

[9] F. Giustozzi, J. Saunier, and C. Zanni-Merk, "Context Modeling for Industry 4.0: an Ontology-Based Proposal," In: Procedia Computer Science, vol. 126, pp. 675-684, 2018.

[10] R.B. Ferrer, B. Achmad, D. Vera, A. Lobov, R. Harrison, and J.L. Martínez Lastra, "Product, process and resource model coupling for knowledge-driven assembly automation," In: Automatisierungstechnik, vol. 64, no. 3, pp. 231-243, 2016.

[11] M. Yahya, J. G. Breslin, and M.I. Ali, "Semantic Web and Knowledge Graphs for Industry 4.0," In: Appl. Sci. 2021, vol.11, article 5110, 2021.

[12] L. Bellomarini, G. Gottlob, A. Pieris, E. Sallinger, "Swift Logic for Big Data and Knowledge Graphs," In: Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence (IJCAI'17), pp. 2-10, 2017.

[13] G. Li, W. Li, H. Wang, "Querying Fuzzy RDF Knowledge Graphs Data," 2020 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Glasgow, pp. 1-8, 2020.

[14] N. Noy, Y. Gao, A. Jain, A. Narayanan, A. Patterson, J. Taylor, "Industry-scale Knowledge Graphs: Lessons and Challenges: Five diverse technology companies show how it's done," Queue, vol. 17, no. 2, pp. 48-75, 2019.

[15] K. Agyapong-Kodua, C. Haraszkó, and I. Németh, "Recipe-based Integrated Semantic Product, Process, Resource (PPR) Digital Modelling Methodology," In: Procedia CIRP, vol. 17, pp. 112-117, 2014.

[16] M. Galkin, A. Auer, M.-E. Vidal, S. Scerri, "Enterprise Knowledge Graphs: A Semantic Approach for Knowledge Management in the Next Generation of Enterprise Information Systems," In: Proceedings of the 19th International Conference on Enterprise Information Systems (ICEIS'17), vol. 2, pp. 88-98, 2017.

[17] G. Futia, A. Vetrò, "On the Integration of Knowledge Graphs into Deep Learning Models for a More Comprehensible AI-Three Challenges for Future Research," In: Information, vol 11, no. 2, article 122, 2020.

[18] A. Banerjee, R. Dalal, S. Mittal, K.P. Joshi, "Generating Digital Twin Models using Knowledge Graphs for Industrial Production Lines," In: Proceedings of the 2017 ACM on Web Science Conference (WebSci'17), New York, pp. 425-430, 2017

[19] S. Auer, V. Kovtun, M. Prinz, A. Kasprzik, M. Stocker, M.E. Vidal, "Towards a Knowledge Graph for Science," In: Proceedings of the 8th International Conference on Web Intelligence, Mining and Semantics (WIMS'18), Novi Sad, pp. 1-6, 2018.

[20] M. Al-Ruithe, E. Benkhelifa, K.A. Hameed, "Systematic literature review of data governance and cloud data governance," In: Pers. Ubiquit. Comput., vol. 23, pp. 839-859, 2019.

[21] M. Mountantonakis, Y. Tzitzikas, "Large-scale Semantic Integration of Linked Data: A Survey," In: ACM Comput. Surv., vol. 52, no. 5, article 103, 2019.

 ISBN: 978-1-68558-049-0