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Overcoming Fuzziness with Semantic Modeling and AI

Frank Mueller [1,*] and Wolfgang Ziegler [2,**]

[1)] Liebherr-IT Services GmbH
St. Vitus 1, 88456 Kirchdorf/Iller
Germany

[2)] Karlsruhe University of Applied Sciences
Moltkestrasse 30, 76133 Karlsruhe
Germany.

Corresponding author:
[*] frank.mueller.lis@liebherr.com
[**] wolfgang.ziegler@h-ka.de

Abstract. Today, customer service in mechanical engineering struggles with a wide variety of challenges when it comes to providing relevant information for specific use cases. The information requirements of service technicians, on the other hand, have increased enormously. On the one hand due to increasingly complex products, but also due to the growing shortage of trained specialists. Fast and efficient provision of relevant information is essential. Remote assistance systems and portal solutions are being used to meet these challenges. A heterogeneous information landscape, characterized by data silos, makes this difficult. In a preliminary study, the authors have developed an approach based on the formalization of knowledge in knowledge graphs that bridges the data silos and thus enables efficient information provision by linking information based on use cases. However, this approach requires high data quality and suitable metadata concepts. Inaccuracies in classification systems create unwanted fuzziness when linking information. The study based on this shows how the fuzziness can be eliminated by supplementary modeling of context information and by extended modeling methods in the form of so-called DynaRules. The authors also compare how AI methods and DynaRules can be used to check the plausibility of deep links with potential fuzziness.

1 INTRODUCTION

In this applied research, we consider the use case of providing service information in the construction equipment industry. We investigate semantic technologies and AI as a means to improve information quality for information recipients. The authors build on the publication [1], which showed the influence of data quality on the success of semantic technologies. The study focuses on the following aspects:

- Analyze additional generic contextual information for certain use cases.
- Manually extend the Semantic Correlation Rules with contextual information.
- Dynamic query of contextual information using DynaRules.
- Extension of the processing of the question/answer in the microservice.
- Dynamic check of the plausibility of suggested links by means of a context analysis with artificial intelligence methods with appropriate processing in the microservice and call of external functions.

2 INITIAL SITUATION

The study looks at use cases relating to two important applications in customer service: Content Delivery Portal (CDP) and Spare Parts Catalog (SPC). These applications use information from different data domains. Semantic technologies can be used as a bridge between domains to dynamically generate deep links to relevant information for a specific use case in service portals. The corresponding modeling based on existing information models of the data silos can be successful if the quality of the data is sufficient. In contrast, insufficient data quality can prevent this or at least create fuzziness.

Two data and classification domains are relevant for the use cases of the study: The domain of content engineering and the domain of product engineering. Both domains use different classification systems to categorize product-related data. In the content engineering domain, content topics are categorized using functional assembly groups (a component-oriented classification) and information classes. This methodology, known as PI classification [2], is used in many industrial implementations. In the product engineering domain, items in a bill of materials are labeled with a parts classification from master data management.

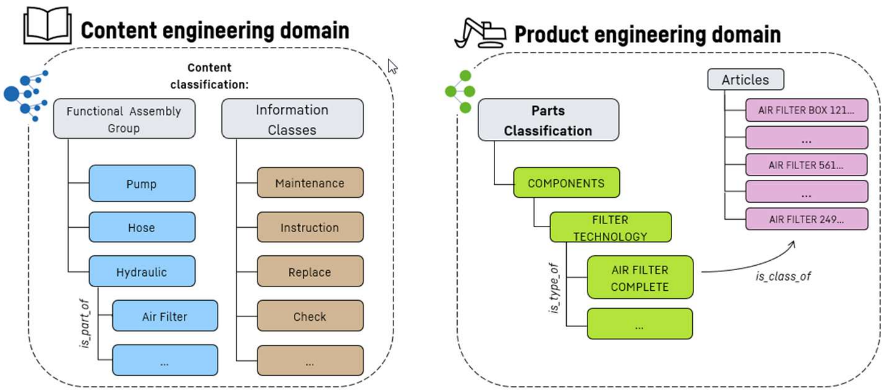

FIGURE 1. Content engineering data domain vs. product engineering data domain

Semantic Information Models (SIM) can be used to link metadata from the different domains, express their relationship and describe the dependencies between information in the systems. This creates a formalized representation of previously hidden knowledge, an additional logical layer that can be used independently of the data domains. The formalized knowledge is made available to different applications to support multiple use cases, such as linking related content.

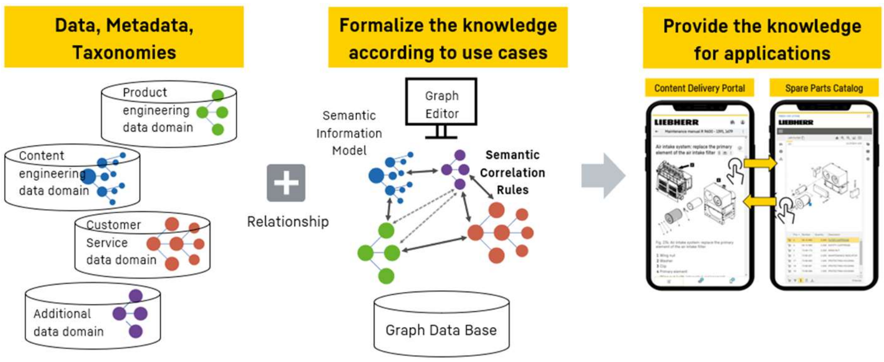

FIGURE 2. Formalize knowledge with Semantic Information Model

Semantic Correlation Rules (SCR) [3] were modeled in the Semantic Information Model for various use cases in customer service, e.g. the exchange of components. Metadata from the different domains correlate.

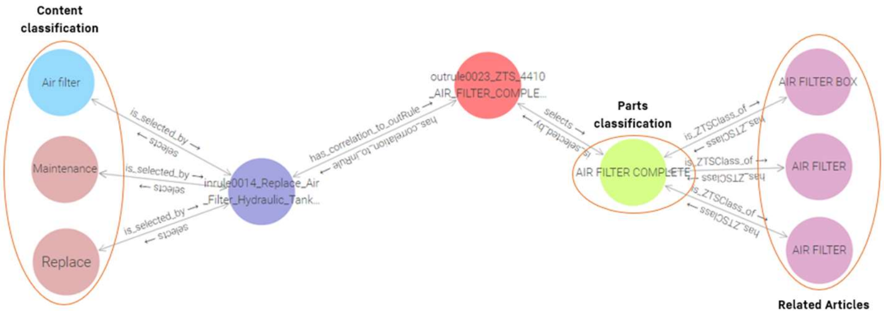

FIGURE 3. Semantic Correlation Rule 1.0 with incoming metadata selected by the inRule and output metadata selected by the outRule

The links to correlated content are visualized on the user interface of the application. This is done dynamically by a user activity (as when selecting the content object).

In the study, 19 typical use cases in customer service were modeled as Semantic Correlation Rules. Correct links were generated for 11 use cases. In 8 use cases, some of the links led to information that was in a different context, which means they were incorrect.

Most of the incorrect links were caused by the classification in product engineering, which proved to be too imprecise in the use case described. The options for intervening in this classification are very limited or excluded. product engineering is involved in a series of dependencies that only allow substantial changes to classification systems to a limited extent. This challenge is the driver for this study. The authors show non-disruptive approaches that make it possible to eliminate fuzziness in product engineering despite the existing classification system.

3 CONSIDERED USE CASE

In our study, the authors focus on ways to avoid existing fuzziness by additive modeling of context information in the semantic information model. Alternatively or additionally, the fuzziness is to be detected by a plausibility analysis without explicit modeling of context information.

The aim is for information architects to be able to apply different procedures and best practices by default as soon as a potential for fuzziness is identified in certain use cases.

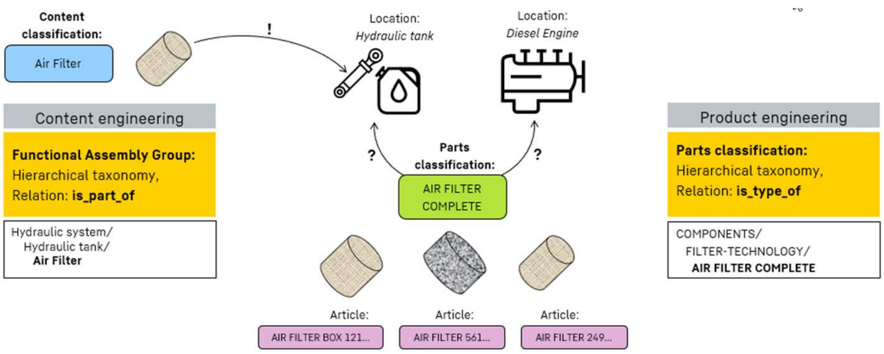

FIGURE 4. Fuzziness with parts classification

Figure 4 illustrates the problem with the existing parts classification. The current taxonomy of parts classification does not allow any conclusions to be drawn about the installation location. The relationships between the classes within this taxonomy are "is_type_of". The structure path describes the "AIR FILTER COMPLETE" as a type of "FILTER-TECHNOLOGY" but not where the air filter is installed. On the other hand, the classification of the content engineering domain is fortunately unambiguous because the taxonomy includes the context. The objects within this taxonomy have the relationship "is_part_of". The structure path shows that the "Air filter" is part of the "Hydraulic tank".

Other classifying structures in product engineering were also examined in the study, but these did not provide a decisive advantage over the parts classification.

4 METHODOLOGY

As described above, we have an open question or an unclear initial situation regarding the context when using the parts classification. Therefore, the first approach is to close this gap with additional context information. The first step is to examine which context information is suitable and which is available in the semantic information model.

In the content engineering domain, the context in the taxonomy is unique due to the "is_part_of" logic.
Example: "Hydraulic system / Hydraulic tank / Air filter".

In the Product Engineering domain, the contexts of the related articles can be examined using the bill of materials (BOM). The BOM paths of these articles can be specified as a structure path.

- "path": "LIEBHERR-MACHINE / R9600-1391 / BASIC MACHINE / UPPERCARRIAGE / HYDRAULIC TANK INSTALLATION / AIR FILTER INSTALLATION / **AIR FILTER BOX**"
- "path": "LIEBHERR-MACHINE / R9600-1391 / BASIC MACHINE / UPPERCARRIAGE / POWER PACK PP2 / AIR FILTER UNIT / **AIR FILTER**"
- "path": "LIEBHERR-MACHINE / R9600-1391 / BASIC MACHINE / UPPERCARRIAGE / HYDRAULIC TANK INSTALLATION / AIR FILTER INSTALLATION / **AIR FILTER**"

The structure paths in the BOMs provide information about where a part (in this case an air filter) is installed. In contrast to the taxonomy of parts classification, the BOMs contain an implicit relationship "is installed in". Example "AIR FILTER BOX" is installed in "HYDRAULIC TANK INSTALLATION", which is installed in "UPPERCARIAGE". Whereas the "AIR FILTER" is installed in "POWER PACK PP2". This implicit "is installed in" information from the BOM can serve as context information.

The task now is to include and evaluate this available context information in the existing semantic correlation rules. It remains to be decided on a case-by-case basis which higher-level assembly is best suited as context information. In this approach, the context information should also be explicitly modeled in the semantic correlation rule.

A second approach is intended to enable a context check without additional modeling. For this purpose, structural paths from the bill of materials are to be semantically compared with the structural path from the content engineering taxonomy in order to check the plausibility of the articles determined. Here, the authors use text analysis by applying AI methods from natural language processing (NLP).

- "reference path": "Hydraulic system / Hydraulic tank / Air Filter", "similarity": 100.0
- "path": "LIEBHERR-MACHINE / R9600-1391 / BASIC MACHINE / UPPERCARRIAGE / HYDRAULIC TANK INSTALLATION / AIR FILTER INSTALLATION / AIR FILTER BOX", "similarity": **?**
- "path": "LIEBHERR-MACHINE / R9600-1391 / BASIC MACHINE / UPPERCARRIAGE / POWER PACK PP2 / AIR FILTER UNIT / AIR FILTER", "similarity": **?**
- "path": "LIEBHERR-MACHINE / R9600-1391 / BASIC MACHINE / UPPERCARRIAGE / HYDRAULIC TANK INSTALLATION / AIR FILTER INSTALLATION / AIR FILTER", "similarity": **?**

The idea is therefore to use AI methods to find out how similar the BOM paths are to the reference path from the content engineering taxonomy. From the value of the similarity, conclusions could be drawn as to which item is in the correct context. The task now is to select the appropriate AI methods, integrate the verification by AI methods and evaluate them.

5 SEMANTIC CORRELATION RULES 1.2 AND DYNARULES

The previous study proved that Semantic Correlation Rules (SCR) is a very simple and efficient method for building a bridge between data domains on specific use cases. Therefore, this study is based on an extension of this proven method. With the introduction of DynaRules, Semantic Correlation Rules can be designed more flexibly. In contrast to the simple selection of objects or classes, DynaRules can be used to call more complex functions. The encapsulation of functions also enables simpler SPARQL queries on the implementation side and their processing in the microservice.

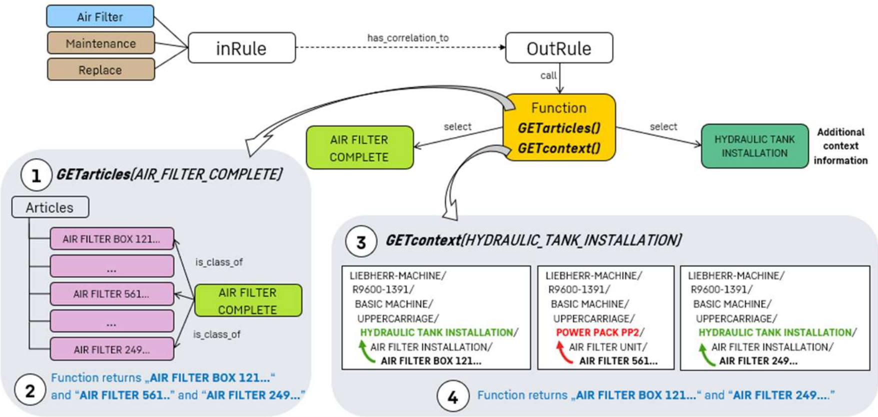

FIGURE 5. Schematic call of functions

The SCR shown in Fig. 5 contains the DynaRule function *GETarticles()* and function *GETcontext()*. In order to be able to check the context, the additional context information (here "HYDRAULIC TANK INSTALLATION") is modeled via a select relationship. First, related articles are determined via the parts classification and output (steps 1 and 2). The context is then checked by searching the structure paths of the related items for the context information (step 3). The function then only returns the articles in the correct context (step 4). The fuzziness is thus eliminated.

6 AI METHODS

Processing triggered by DynaRules

DynaRules are also used in the application of AI methods. The big advantage is that external functions can now be called. The SCR shown in Fig. 6 contains the DynaRule function *GETarticles()* and function *USE_AI()*. First, related articles that are related to the selected parts classification are determined via a SPARQL query and output (steps 1 and 2). With a further function call, the structure paths of the related articles and the reference path from the content classification are determined and sent to an AI service endpoint (step 3). The request also contains instructions on which AI method and which AI model should be used. The AI service performs the comparison and returns a value for the similarity to the reference path for each path (step 4).

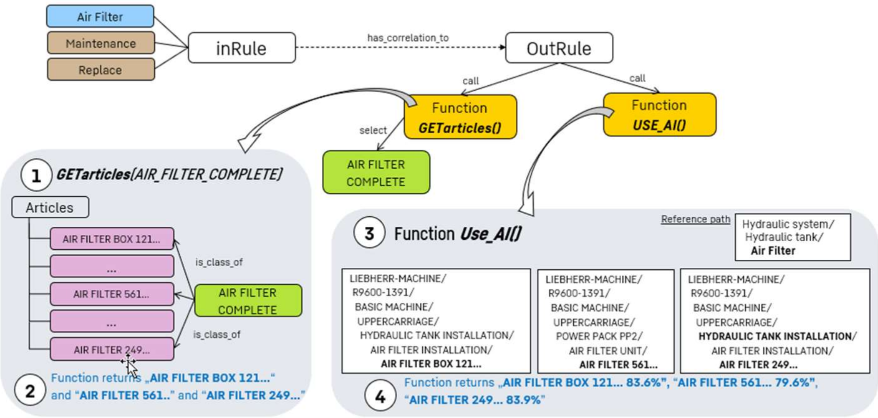

FIGURE 6. DynaRules calls internal and external functions (AI Service)

Embedding

The embedding method is often used to compare words, texts or entire documents. The input texts are converted into tokens and then vectors are formed in a vector space. The closer the vectors are to each other, the more similar the original content is. The authors apply this principle to the structural paths of the individual taxonomies and data.

The following open source embedding models were tested in the study:
- "intfloat/multilingual-e5-large"
- "intfloat/e5-large-v2"
- "sentence-transformers/multi-qa-distilbert-cos-v1"
- "sentence-transformers/paraphrase-multilingual-MiniLM-L12-v2"

Example result with "intfloat/e5-large-v2"
- "reference path": "Hydraulic system / Hydraulic tank / Air Filter", "similarity": 100.0
- "path": "LIEBHERR-MACHINE / R9600-1391 / BASIC MACHINE / UPPERCARRIAGE / HYDRAULIC TANK INSTALLATION / AIR FILTER INSTALLATION / AIR FILTER BOX", "similarity": **83.6**
- "path": "LIEBHERR-MACHINE / R9600-1391 / BASIC MACHINE / UPPERCARRIAGE / POWER PACK PP2 / AIR FILTER UNIT / AIR FILTER", "similarity": **79.6** (lowest value is correct)
- "path": "LIEBHERR-MACHINE / R9600-1391 / BASIC MACHINE / UPPERCARRIAGE / HYDRAULIC TANK INSTALLATION / AIR FILTER INSTALLATION / AIR FILTER", "similarity": **83.9**

The results of the individual models varied. In most use cases, "intfloat/e5-large-v2" produced the best results. The lowest similarity was always correctly determined for the structure path with the wrong context.

Large Language Models (LLM)

A prompt was developed for the use of LLMs that describes the task as precisely as possible. Here too, the AI service receives the structure paths via a request, which were previously determined using a SPARQL query. The method and corresponding models can be specified in the request. After the LLM has performed the comparison, the values for the similarities are returned.

Prompt: *"You are an efficient content analyst. Your task is to compare different paths of taxonomies and evaluate the similarity of the paths with a probability in percent. The paths consist of a hierarchical sequence of English assembly designations of a construction machine. The upper assemblies in the hierarchy give the context of the deepest assembly in the hierarchy. Consider this in your comparison. The assembly designations are separated by slashes. Evaluate the similarity by comparing the assembly designations semantically based on the actual meaning of the* *words. Below you will see different paths. Path 1 is the outgoing path. Compare all other paths with path 1. Evaluate the similarity of the other paths with path 1 using a probability in percent and create the result in JSON format. Do not add remarks or notes into the result. Do not change the paths."*

The following open source models were tested

- "Llama-2-13b-chat"
- "leo-hessianai-13b-chat"

Example result with „Llama-2-13b-chat":

- " reference path": "Hydraulic system / Hydraulic tank / Air Filter", "similarity": 100%
- "path": "LIEBHERR-MACHINE / R9600-1391 / BASIC MACHINE / UPPERCARRIAGE / HYDRAULIC TANK INSTALLATION / AIR FILTER INSTALLATION / AIR FILTER BOX", "similarity": **90%**
- "path": "LIEBHERR-MACHINE / R9600-1391 / BASIC MACHINE / UPPERCARRIAGE / POWER PACK PP2 / AIR FILTER UNIT / AIR FILTER", "similarity": **80%**
- "path": "LIEBHERR-MACHINE / R9600-1391 / BASIC MACHINE / UPPERCARRIAGE / HYDRAULIC TANK INSTALLATION / AIR FILTER INSTALLATION / AIR FILTER <u>HOUSING</u>", "similarity": **70%**

Again, the results were different. Conspicuous in both models were implausible results and manipulations to the structure paths in the output. The LLM has replaced the term "AIR FILTER" with "AIR FILTER HOUSING" in the last path of this example.

7 IMPLEMENTATION

After the semantic modeling and the design of the Semantic Correlation Rules, the research group implemented a corresponding IT architecture [4] as shown schematically in Fig. 7. The two applications Spare Parts Catalog and Content Delivery Portal send requests to a REST API webservice. The webservice takes care of the preprocessing, the querying into the graph data base, the postprocessing and the calling of an AI Service. Finally, the applications receive the response and display the links on the user interface.

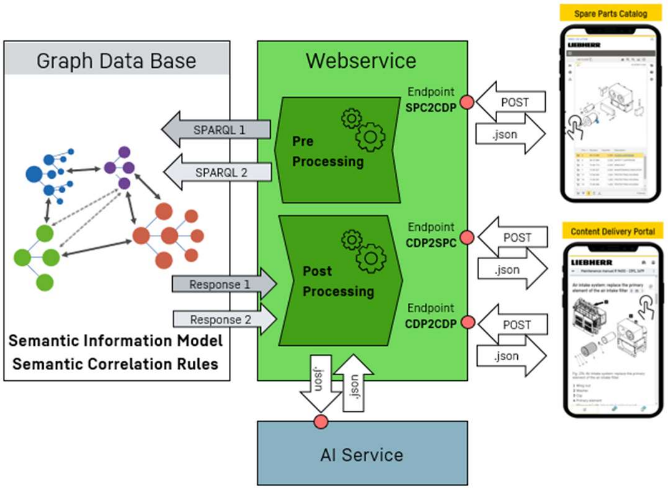

FIGURE 7. Schema of the IT architecture and processes

FIGURE 8. Results of the implementation: Dynamically generated links to correlated content are displayed on the user interface

The related links to correlated content are being visualized on the applications user interface. This is done dynamically by a user activity (as in selecting the content object). The links are only visible, if the graph data base delivers a response according to a request. We decided to display each of the three methods of overcoming fuzziness in the user interface. The first section, the red outlined rectangle in Fig. 8, displays now only the correct links according to the context information in the semantic correlation rules. The second and third section, the blue outlined rectangle, displays the links of all related articles with the similarity values.

8 FINDINGS

We can show that an explicit extension of the Semantic Correlation Rules and DynaRules with context information, overcomes the fuzziness. With this method, we now get links that link relevant information for a specific use case in the right context. We see that knowledge graph technology and semantic modeling can provide reliable and comprehensible results. We can explain why exactly these links are displayed and others are not. The use of DynaRules has now also been successfully implemented from the user's point of view. It's clear that modeling requires an extra effort. This must be considered. Semantic modelling also needs new roles in the organization [5].

In this context, it is interesting to look at AI methods to answer the question if it is really a low-effort alternative to manual modeling. The study shows that the task can certainly be performed by AI methods, especially since we are moving in the field of natural language analysis. Depending on the embedding model plausible results emerge from the first tests. However, the similarity values of the other paths were often close to each other (e.g., 83.6%, 79.6%, 83.9%). For an automatic evaluation to eliminate the false links, a threshold value would have to be defined. However, the results do not allow this. Thus, the similarity value can only indicate a trend as to which link is most likely to be incorrect.

The use of large language models shows the well-known challenge of generative AI. The results are rather inaccurate, not comprehensible, and not reliable. Overall, the results were not satisfactory. In principle, the task was performed correctly by the LLMs. However, the similarity values determined deviated from the actual similarity. For example, a path in the wrong context was rated higher than a path in the right context. In addition, typical behaviors of LLMs were detected. The values are not always reproducible. In some cases, the structure paths were changed in the output, although this was exclusively prohibited in the prompt ("Do not change the paths!"). It is possible that commercial LLMs such as GPT4.0 can solve this problem better. Optimization of the prompt or a combination of embedding and LLM could also improve the results. However, no further tests were carried out as part of the study. Further developments in LLM must be awaited and tested if necessary.

Overall, the quality of the data to be examined must also be considered when using AI methods. The sometimes different and cryptic terminology and unclear abbreviations in the structural paths are a challenge for a linguistic analysis. We can see that today's AI methods do not sufficiently cope with the task at hand with this particular type of text.

In the study, we achieved our goal of overcoming fuzziness. We have developed a reliable method through additional semantics via explicit modelling and the DynaRules in the SCR methodology. We can draw good comparisons to AI methods.

9 CONCLUSION

This study has once again confirmed that explicit semantic modeling of implicit knowledge in the form of Semantic Correlation Rules supports many use cases that bridge data silos. Inadequacies in the quality of data and metadata can also be circumvented through clever modeling without having to change existing structures in the source systems. From today's perspective, AI methods should be taken seriously as a supplement or support, but not yet at the level of maturity required to fully take on the task (considering the existing data quality). The highly dynamic development of AI models may require a new assessment in the foreseeable future.

The following outlook for productive use in an industrial environment can be derived from the experiences of the study:

- Anchoring semantic technologies such as knowledge graphs in an enterprise architecture and in a data governance initiative
- Provision of flexible microservices for communication with applications and services
- Gradual expansion of knowledge graphs into a digital information twin
- Use of DynaRules for a wide range of use cases (in affected business areas)

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