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Integration of product development data for further ontological utilization

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Abstract

The amount of data within the product development process requires a structured approach to coordinate them. Knowledge management solutions, such as ontologies, are a suitable way of linking data and representing semantic relationships. However, making all relevant data usable to ensure their target-oriented application is still a challenge. Thus, this contribution presents an approach to identify and classify heterogeneous data in product development. Besides this single ontology approach, interface solutions for data integration into an ontology are proposed.

Keywords: ontology, product development, data management, interface solution

1. Introduction

Within the product development process, a multitude of heterogeneous data is generated, which must be considered in design decisions. This product development data is stored in various data bases or knowledge representations, which often stand alone with missing linking for the further use of the data. On the one hand, considering necessary data and verifying its completeness is challenging, since suitable approaches for their identification are lacking. On the other hand, the large number of existing heterogeneous data sources in product development poses a fundamental challenge for data linking. These sources impede central access and, therefore, the meaningful use of the available data (Bittel, 2014). For this reason, it is required to transfer the data into a uniform format. Thus, knowledge management systems were established to access the heterogeneous data and make them usable for, e.g., decision-making situations. In this context, the use of ontologies, which have been defined as an explicit specification of a conceptualization (Gruber, 1993), is recommended as they function as a knowledge management solution where they provide a semantic link between the data and open up connections between the classes. This contribution aims to solve the interface problems between heterogeneous data in product development and ontologies. For this purpose, existing data is analyzed and classified so that suitable interface solutions can then be proposed.

2. Background and state of the art

These challenges can be solved by utilizing existing work. Thus, chapter 2.1 addresses various knowledge representation approaches that enable the analysis and classification of product development data. In addition, chapter 2.2 deals with ontologies as a knowledge management solution for unifying information.

2.1. Knowledge representation and classification in product development

Due to the multifaceted knowledge in product development, it is challenging to organize the product development data in a suitable way to ensure that the relevant data can be utilized. Therefore, the modeling of product knowledge has been studied by a literature review addressing various ontology-based frameworks for product modeling and their architecture (Lyu et al., 2017). To structure the comprehensive product data, classification features and associated exemplary expressions of product models are illustrated in (Kohn, 2014), whereby the knowledge base is described in an ontology. The author provides a step-by-step method with rules and instructions for accessing the required user-specific knowledge, which is supported by checklists, templates and correlation matrices. Rachuri et al. (2008) aimed at adapting especially product lifecycle management (PLM) data formats, such as the Standard for the Exchange of Product Data (STEP) or the System Modeling Language (SysML). Therefore, Rachuri et al. (2008) attached them graphically to the individual steps of the product life cycle as well as complementary aspects of the information (divided into product, process and enterprise services). In this approach, a basic classification of standards was presented, whereby a multiple assignment of data types to the phases as well as the information is plausible. In contrast to the classification of specific data standards, a categorization of the different types of knowledge into their so-called units (pictorial, symbolic, linguistic, virtual and algorithmic) represents a more general grouping of the knowledge elements within the product development, since no concrete data formats are specified (Owen and Horváth, 2002). To expand the approach of (Owen and Horváth, 2002), their knowledge units are classified with examples, e.g. mathematical equations were assigned to the algorithmic unit (Chandrasegaran et al., 2013). In order to use or extend existing approaches to knowledge representation and its classification schemes, knowledge management solutions, such as ontologies, are required.

2.2. Usage of ontologies in product development

Ontologies use specifically designed languages. The Resource Description Framework (RDF) was developed by the World Wide Web Consortium (W3C) and represents a data model in a graph structure (Schreiber and Raimond, 2014). Since it exclusively contains information, the ontology language Web Ontology Language (OWL) was released on this basis, which links this information to represent knowledge based on description logics (Imane et al., 2021). Classes are defined, which in turn group individuals and are connected by properties to the previously defined classes (Hitzler et al., 2008).

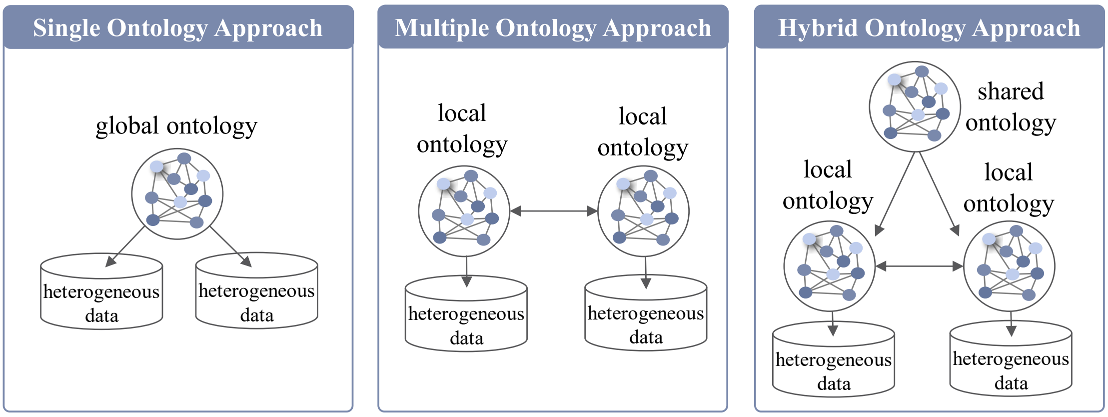

Figure 1. Ontology approaches according to (Fahad, 2023)

Ontologies should not only structure existing knowledge and data, but also identify semantic relationships. This enables the identification of untapped relationships or the consideration of multi-criteria requirements. Besides, there are different approaches for linking knowledge by means of ontologies. Figure 1 illustrates the basic schemes of the Single, Multiple and Hybrid Ontology Approach. The Multiple and Hybrid Ontology Approach combine holistic, already existing ontologies (Wache et al., 2001), which can be accomplished with established interlinkage approaches. In contrast, the focus of the Single Ontology Approach is on a singular global ontology that incorporates various heterogeneous data sources (Subhashini and Akilandeswari, 2011). In this context, an existent product development ontology is regarded as the basis into which the data has to be integrated.

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Thereby, the challenge lies in the identification of relevant data and the integration into this ontology via an interface.

3. Need for action and research question

The utilization of heterogeneous product development data and their different formats is challenging. Existing approaches focus on the representation and classification, but are neither oriented to established product development processes nor intended to analyze and categorize the data considering interface solutions. Nevertheless, classifying the data creates a basis for finding appropriate interfaces between product development data and knowledge representation for a data category and uncovers potential research gaps. However, the underlying overviews for data classification are only partially usable in the context of data identification.

With regard to the use of ontologies for knowledge representation in product development, (Štorga et al., 2010) present a fundamental design ontology as a basis for knowledge exchange and management. Ahmed and Štorga (2009) pursue the approach of comparing the theoretical Engineering Design Integrated Taxonomies ontology (EDIT) with the practice-oriented Design Ontology (DO) with regard to their concepts and relationships to subsequently design a template ontology in the product development domain through merging. However, the focus of (Ahmed and Štorga, 2009) was placed on the conceptualization of independent ontologies in this domain and not on the coordination of the necessary interfaces for such existing ontologies. Therefore, there is a lack of approaches, which support the user in integrating relevant product development data into an ontology.

So, an overall concept is needed that ensures the identification and classification of the corresponding data and offers suitable interface solutions. Accordingly, this paper aims for an approach to integrate heterogeneous product development data in ontologies based on the Single Ontology Approach. Thus, the focus is on integrating data with interfaces instead on developing an overarching, holistic product development ontology. Taking these aspects into account, the following research question is raised and will be answered in this contribution: How can existing product development data be integrated for further use in an ontology according to the Single Ontology Approach?

To answer the raised question, knowledge representation schemes in product development are first analyzed, whereas the approach of (Owen and Horváth, 2002) offers a suitable basis for transferring the relevant data into a generic context for further use and to classify them. This is applied to the product development process according to (Verein Deutscher Ingenieure, 2019). The process serves as a reference for a subsequent assignment of data to the sub-activities and ensures the completeness of the identified data types. The classified data is used as the basis for identifying possible interface solutions for integrating product development data into an ontology.

Therefore, the remainder of the paper is structured as follows: Chapter 4 proposes an approach for product developers to manage the integration of product development data into ontologies. Then, chapter 5.1 introduces a classification of these heterogeneous data, which is the basis for the assignment of existing interface solutions in chapter 5.2. Finally, the discussion of the approach in chapter 6, followed by a summary and an outlook in chapter 7.

4. Approach for data integration in ontologies

Figure 2 shows the the proposed approach for integrating product development data into an end-user ontology including a step-by-step description. First, the Ontology Approaches (Single, Multiple, Hybrid) should be analyzed and the appropriate one should be selected for the specific use case. The following process described within this contribution is based on the Single Ontology Approach, since the findings are easily transferable to the other mentioned approaches. Then, the relevant data for the integration into the ontology has to be identified and classified by following the procedure and classification scheme described in chapter 5.1. Before integrating the data, it has to be determined whether unrestricted access to the identified data can be provided and which data protection guidelines, if one exists, must be observed. To manage the integration of the identified product development data into an ontology, the proposed classification can be used for the definition of appropriate interface

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solutions, whereby the mapping overview in chapter 5.2 is a sufficient starting point helping to evaluate, whether new interface solutions have to be developed.

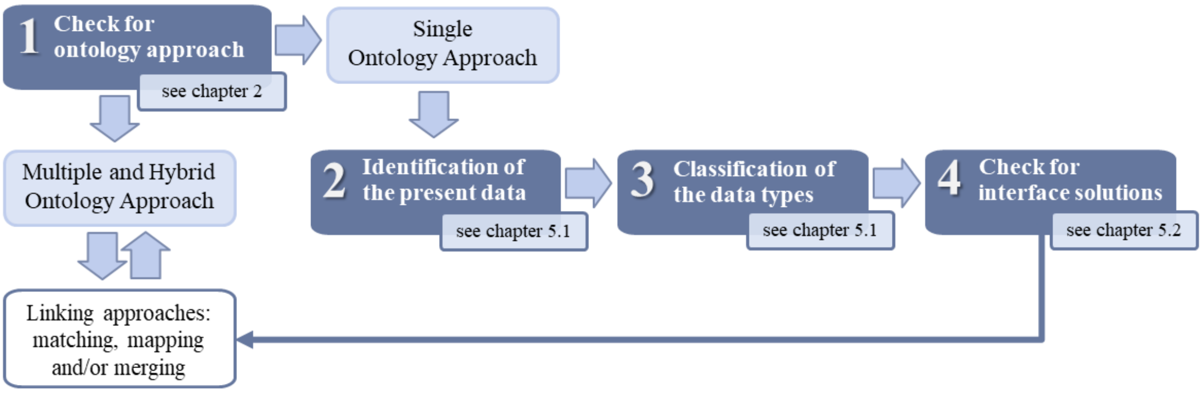

Figure 2. Approach for product development data integration in ontologies

5. Classification of data and overview of interface solutions

In order to obtain an overview of the heterogeneous data available in product development, the data formats of the product development process are first identified and then categorized. This categorization aims to find classes among the numerous individual data formats, which enable easy linking to an ontology by higher-level interface solutions. Finally, these solutions are summarized.

5.1. Heterogeneous data in product development

While identifying the product development data, the focus is on explicit, documentable knowledge within product development, since implicit knowledge is mostly experiential knowledge, which is bound to single persons and difficult to communicate (Verein Deutscher Ingenieure, 2009). Therefore, data has to be considered as a baseline in the first step. The identification of the data is supported by the categorization of (Owen and Horváth, 2002), who divide the data types in product development into the five classes pictorial, symbolic, linguistic, virtual and algorithmic. This ensures that the data can be identified and classified into data types for which interface solutions can be used later on. To assign specific formats to these categories, the output data of the product development process, described by (Verein Deutscher Ingenieure, 2019), is analyzed. Moreover, the data is categorized according to its dimensionality, see Figure 3. This leads to a clear and transparent structure that enables a straightforward categorization of the data types. Furthermore, overlaps can be easily identified, when new data formats are added. This supports the expandability of the data classification.
For 1D formats, text based documents, for example the bill of materials are used. These can be assigned to the linguistic class, in this context, better referred to as **textual** data. In addition, **algorithmic** descriptions, which include mathematical expressions, and the **symbolic** unit for logical representations, such as evaluation schemes, are one-dimensional data. Within the product development also **pictorial** representations arise, which are assigned to the 2D format. These include drawings, such as technical drawings, as well as principle sketches. **Graph** representations, usually applied in functional models or module lists, cannot be assigned directly to the schema according to (Owen and Horváth, 2002). Thus, it is extended by a new subcategory within the 2D formats, since every graph can be transformed into a 2D adjacency matrix. Finally, the 3D formats are differentiated into **meshes** (both volume and surface meshes), as they are used in Finite Element Analysis (FEA) simulations, and **volume models**. These include BREP (Boundary Representation) and CSG (Constructive Solid Geometry) data. Linguistic content is not considered here, since the examples taken up by (Owen and Horváth, 2002) such as taped verbal or typed textual communication are already classified under the class textural. Videos, for example, could be considered as a fourth dimension, although they are not a main outcome of the product development process.

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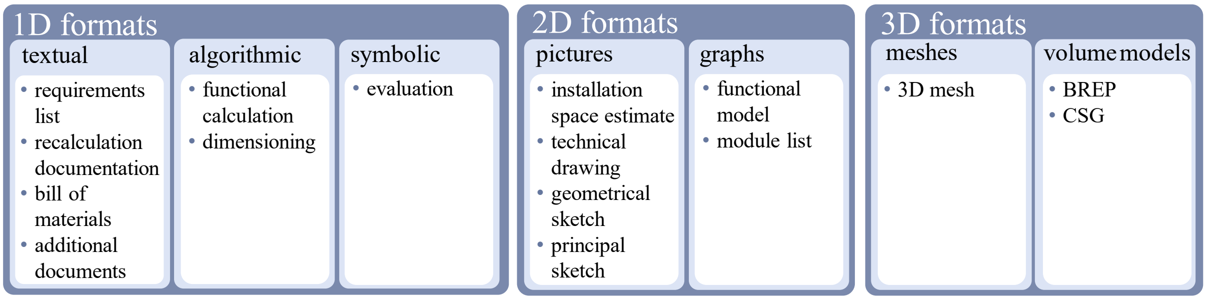

Figure 3. Assignment of data within the product development process to their format types

Based on the classification of (Verein Deutscher Ingenieure, 2019), the left side of Figure 4 picks up the activities, their tasks and the results of the sub-steps and assigns the classified data types and their dimensions to that context. Some elements encompass several subtasks of the process, being relevant for various steps or are partly revised and adapted and, thus, run through multiple iteration loops.

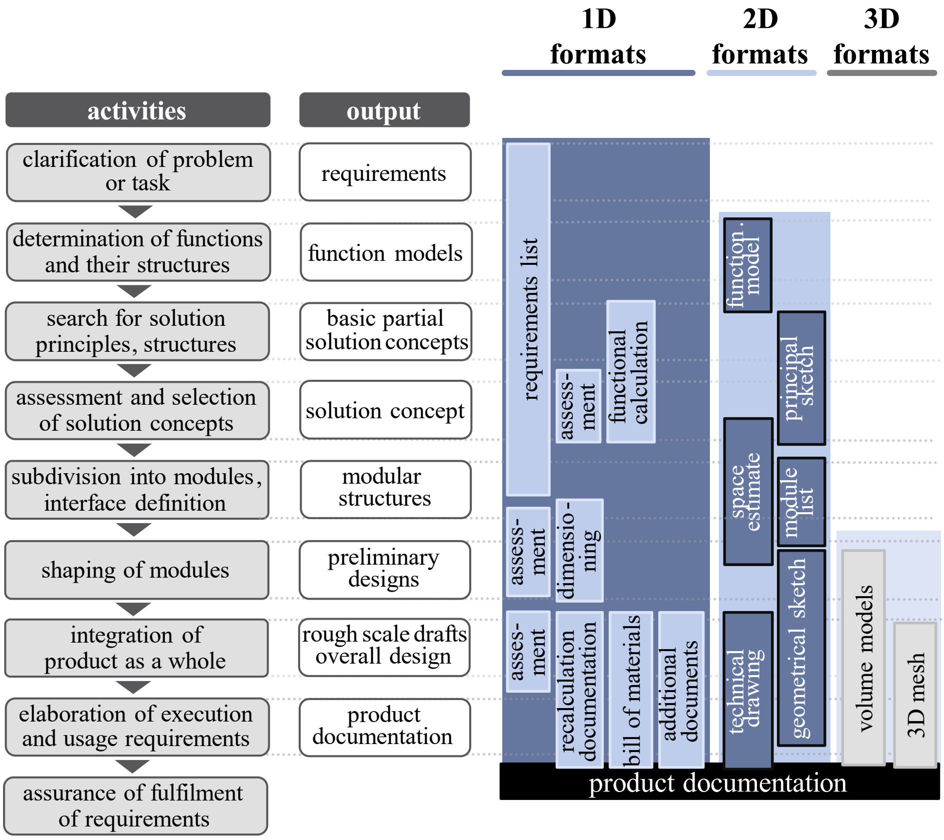

Figure 4. Product development process according to (Verein Deutscher Ingenieure, 2019) with the assigned data

During data integration, it is important that the latest version of data is always available to the ontology and not redundant. The increase in information over the steps of the product development process is reflected by the fact that only one-dimensional formats are present at project initiation, whereas the largest dimension (3D) is used in the final subtasks. Within the proposed approach, the granularity of the data is adapted for further use in analyzing interface solutions. For example, the subdivision of the volume models into their software-specific file formats is not useful. In contrast, higher-level approaches to interface integration should be developed, referring, for instance, to standard exchange formats. In addition, newly emerging file formats can be equally assigned to the higher-level groups for which, at best, interface solutions already exist. This classification degree reduces consequently the

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development expenditure. Insofar, the overview serves an examination of the data to raise awareness of possible interface problems and for the examination of the available data on their completeness, so that no relevant contents remain unconsidered. In the next step, based on this and by assigning the use case-specific data to the superordinate classes, solutions can be found for the respective integration options.

5.2. Integration of product development data into an ontology

The previously introduced classification scheme and their categorization according to the data types enables the description of the integration into an ontology, see overview in Table 1. In the one-dimensional domain, various interface solutions are available for textural data. For the integration of Excel data, the **Cellfie** plugin for the well-established ontology editor Protégé (Musen, 2015) represents a promising option by specifying transformation rules and axioms for the data provided to guarantee integration into the ontology (Protégé Project, 2022). Furthermore, Buitelaar et al. (2008) published a system for ontology-based information extraction from heterogeneous data resources (**SOBA**) that integrates plain text into an ontology based on Natural Language Processing (NLP), but also takes content such as table and image captions as well as duplicates into account. In this way, a meaningful description of images can already be used to integrate initial pictorial information. Using Artificial Intelligence (AI) approaches, specifically NLP, Korel et al. (2022) present their proposed **Text-to-Ontology Mapping** that enables integrating textual data by applying artificial neural networks and classifiers. Ahmad and Gillam (2005) introduce an attempt to automatically integrate **unstructured text** into ontologies by utilizing algorithms to analyze keywords, extract them, and transform them into a semantic network based on frequently used words. Accordingly, the application focuses on the preliminary generation of ontologies and their classes. The overview shows that there are various approaches for the integration of text data, for which likewise a multiplicity of modified and adapted publications exists and the methods represented here embody no complete listing in consequence. However, it should be noted that the ones presented here are based on elementary approaches.

For the representation of dimensions and calculations, the approach of Natho (2005) can be used, which aims at creating an ontology by means of a **semantic analysis of mathematical language** and its structures. This is implemented by applying predicate logic and axiomatic set theory, which forms a terminological model for deriving mathematical concepts.

To make abstract symbolic representations usable, the **symbolic Artificial Intelligence** (AI) system became established. This transforms a series of logic-like reasoning steps into linguistic representations based on relationships between objects as well as inference rules, and has the capabilities to identify features in high-resolution data through Deep Learning (Garnelo and Shanahan, 2019). Bordes et al. (2011) present an approach built on the symbolic AI system to obtain the original data and embed the symbolic representations into a vector space, allowing the knowledge bases to be represented as graphs. Interface solutions for these graphs can be found in the following paragraph.

Since ontologies are a formal representation of knowledge, it initially proves to be non-trivial to integrate images and their information. A first approach is formed by Buitelaar et al. (2008), who analyze initial descriptions through image captions and subsequently integrate them in an ontology. However, this is not a fully comprehensive approach to fundamentally exploit the information indeed represented in images. For this purpose, the information stored in images must be transferred into formal language to incorporate it into an ontology. By means of classification of images, they can be annotated to assign semantic information to the information source (Wache et al., 2001). Liu et al. (2005) use features from digital camera metadata as well as those from image content for this purpose and employ the linear discriminant analysis (LDA) algorithm in their contribution, which implements linear combinations between fixed features and generates newly combined features. In the application domain of biomechanics, Temal et al. (2008) present the integration of medical images into an ontology through the use of **image annotation**, performed by humans or computer programs. The transfer of the approach to the topic area of product development seems feasible due to the generally valid approach to describe the image contents and by the proven integration into a medical ontology.

In contrast to images, the integration of two-dimensional data types into an ontology also requires the consideration of graphs. Knowledge Graphs can represent information via the Resource Description Framework (RDF) format, which is the basic data format of the Semantic Web (Imane et al., 2021). The

graphs are defined by nodes and their connections and are represented in so-called triples, which have the following structure: <subject> <predicate> <object> (Schreiber and Raimond, 2014). As an example of this structure, the following context could be defined: <ontologies> <own> <classes>. If the RDF format is already available, this can be directly integrated into an ontology editor such as Protégé (Musen, 2015) to represent a simple ontology. In addition, Horst (2005) presents an approach to the **semantic extension of RDF Scheme**, so that this can also be applied to the OWL vocabulary.
For the integration of simulation data, (Kestel et al., 2019) proposed a **text and data mining** based approach, which transfers the data elements from simulation documents such as reports, guidelines, conference and journal contributions into an ontology. This part of the approach can be assigned to the one-dimensional textual format and is therefore not in the focus of 3D data analyzed here. Also, an interface solution for the data transformation of the three-dimensional simulation models is being examined. To enable their further use, an intermediate step is taken that transform them into a subordinate dimension. The simulation models are converted into structured reports using the report generation tool of the CAE (Computer Aided Engineering) system ANSYS Workbench, the contents of which can then be integrated into an ontology using text and data mining. The resulting reports contain, for example, contact settings between the existing elements as well as geometric and material information, the convergence of simulation results, outcomes such as the maxium mises stress and scripting commands for the application of special modeling operations.
In contrast, Boussuge et al. (2019) present an approach whose basis is a knowledge-based CAE model that provides analysts with knowledge to describe the 3D simulation model in a **simulation intent ontology** in addition to geometric representations. In this context, cellular modeling intends the segmentation of the three-dimensional space and the assignment of simulation attributes.
In addition to the segmentation of the volume model, geometry simplifications and design updates as well as material data, loads and boundary conditions are included. In contrast, **OntoBREP** represents a practical approach to translate topological and geometric entities into OWL, which is implemented using semantic processing of the Boundary Representations (BREP) of volume models (Perzylo et al., 2015). For the further use of volume models, the National Institute of Standards and Technology (NIST) provides a tool called **OntoSTEP**, available as a Protégé plugin, which semantically extends the data in the standard STEP exchange format and translates it into an OWL-DL (OWL description logics) based on the creation of a terminology (TBox) and an assertion component (ABox) (Barbau et al., 2012). The **SeED approach** similarly pursues the semantic integration of volume model data into an ontology, built up in different steps to decompose and segment the model at hand (Dworschak et al., 2019). In this approach, the data is represented in a 1D array and stored as an xlsx file, which can preferably be integrated into the ontology using the previously presented Cellfie plugin (Protégé Project, 2022).

Table 1. Identified interface approaches for the integration of product development data

xD	Data	Interface Approaches	Source
1D	Textual	Cellfie	(Protégé Project, 2022)
		SOBA	(Buitelaar et al., 2008)
		Text-to-Ontology Mapping	(Korel et al., 2023)
		Unstructured Text	(Ahmad and Gilliam, 2005)
	Algorithmic	Semantic analysis of mathematical language	(Natho, 2005)
	Symbolic	Symbolic artificial intelligence	(Bordes et al., 2011)
2D	Graphs	Image annotation	(Temal et al., 2008)
	Pictures	Semantic extension of RDF Scheme	(Horst, 2005)
3D	Meshes	Text and data mining	(Kestel et al., 2019)
		Simulation intent ontology	(Boussuge et al., 2019)
	Volume models	OntoBREP	(Perzylo et al., 2015)
		OntoSTEP	(Barbau et al., 2012)
		SeED approach	(Dworschak et al., 2019)

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6. Discussion

With the help of the presented step-by-step approach according to Figure 2, the research questions could be answered as follows. The research question focuses on how product development data can be integrated in an ontology. The user can now use an approach to manage the interface challenges between heterogeneous product development data and ontologies. Based on previous schemes, the data was classified and the data types and their dimensions were assigned to the product development process. On the one hand, it provides an overview to enable decision-making considering the relevant data. On the other hand, the classification and identification build a basis for identifying solutions for integrating similar product development data into a knowledge representation solution such as ontologies. In chapter 5.2, interface solutions were analyzed and presented in an overview, assigned to the previously developed classes. Appropriate interface solutions were identified for each class of product development data. However, some approaches such as OntoSTEP (Barbau et al., 2012) or text and data mining (Kestel et al., 2019) for the integration of simulation data are based on the principle of transforming the data back into a subordinate dimension, usually as textual data.

Possible loss of data can occur during the transformation. This was not specifically mentioned by the authors, but should be the focus of further research. In the elaboration of the existing solutions for data integration, the diverse use of data-driven methods became clear. Data mining approaches offer significant potential, mainly in the processing of one-dimensional data. In future steps, other interfaces have to be analyzed for the advanced application of data-driven methods.

Beyond this, the contribution focuses on the Single Ontology Approach for integrating heterogeneous data, whereby the Multiple and Hybrid Ontology Approach were not addressed. In the further procedure, the Single Ontology Approach serves as a basis, which should be extended by linking further ontologies or migrating them to a shared one. This can be done by applying established linking approaches, which allows to use the integrated heterogeneous data in a superordinate context. For this purpose, the following methods can be used: matching, where relationships between entities of the different ontologies are searched (Euzenat and Shvaiko, 2013), mapping, which aims to find semantic matches between ontologies (Mao, 2007) or merging, where mapped parts are merged into an overall concept (Amrouch and Mostefai, 2012).

In addition, the data should be prioritized based on its role in decision-making situations to ensure that only use case specific elements are included in the ontology. To avoid excessive accumulations of data in the ontology that are leading to a lack of clarity, it must be checked whether data must be entirely integrated. For the elimination of redundant information in the ontology, intentional forgetting approaches could be pursued (Kügler et al., 2018).

7. Conclusion and outlook

Ontologies represent a solid and flexible knowledge management solution in which existing data can be centralized and made usable through their semantic representation. The introduced approach provides a classification of data formats that ensures their completeness and serves as a basis for the description of further, newly developed data formats in product development, facilitating their integration into ontologies. Due to the developed identification and classification of the data in Figure 4, the complexity of handling the various heterogeneous data can be reduced by using the assigned interface solutions. These results should be integrated into a broader approach to consider additional issues, discussed in the previous chapter, for the further use of product development data within an ontology.

With regard to data interfaces, further research could focus on the design of prefabricated and integrable interface solutions or plugins such as Cellfie (Protégé Project, 2022) or OntoSTEP (Barbau et al., 2012) by elaborating methodological approaches. These facilitate data management, promising to save time in the design of product development ontologies. In addition, the use of data-driven methods for (partially) automated data integration should be enforced. Therefore, the classification approach serves as a suitable foundation for implementing ontology learning approaches.

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References

Ahmad, K. and Gilliam, L. (2005), “Automatic Ontology Extraction from Unstructured Text”, *On the Move to Meaningful Internet Systems 2005: CoopIS, DOA, and ODBASE, Agia Napa, Cyprus, October 31 - November 4, 2018, Lecture Notes in Computer Science, Vol. 3761, pp. 1330-1346. Springer, Berlin Heidelberg.* https://doi.org/10.1007/11575801_25

Ahmed, S. and Štorga, M. (2009), “Merged ontology for engineering design: Contrasting empirical and theoretical approaches to develop engineering ontologies”, Artificial Intelligence for Engineering Design, Analysis and Manufacturing, Vol. 23 No. 4, pp. 391–407.

Amrouch, S. and Mostefai, S. (2012), “Survey on the literature of ontology mapping, alignment and merging”, *International Conference on Information Technology and e-Services, Sousse, Tunisia, March 24-26, 2012*, IEE, pp. 1–5. https://doi.org/10.1109/ICITeS.2012.6216651

Barbau, R., Krima, S., Rachuri, S., Narayanan, A., Fiorentini, X., Foufou, S. and Sriram, R.D. (2012), “OntoSTEP: Enriching product model data using ontologies”, *Computer-Aided Design*, Vol. 44 No. 6, pp. 575–590. https://doi.org/10.1016/j.cad.2012.01.008

Bittel, V. (2014), *Semantische Informationsintegration - Konzeption eines auf Beschreibungslogiken basierenden Integrationssystems für die Produktentwicklung, [PhD Thesis]*, Karlsruher Institut für Technologie (KIT). https://doi.org/10.5445/IR/1000041607

Bordes, A., Weston, J., Collobert, R. and Bengio, Y. (2011), “Learning Structured Embeddings of Knowledge Bases”, *Proceedings of the Twenty-Fifth AAAI Conference on Artificial Intelligence, San Francisco, USA, August 7-11, 2011, AAAI Press, Palo Alto*, pp. 301–306. https://doi.org/10.1609/aaai.v25i1.7917

Boussuge, F., Tierney, C.M., Vilmart, H., Robinson, T.T., Armstrong, C.G., Nolan, D.C., Léon, J.-C. and Ulliana, F. (2019), “Capturing simulation intent in an ontology: CAD and CAE integration application”, *Journal of Engineering Design*, Vol. 30 No. 10-12, pp. 688–725. https://doi.org/10.1080/09544828.2019.1630806

Buitelaar, P., Cimiano, P., Frank, A., Hartung, M. and Racioppa, S. (2008), “Ontology-based information extraction and integration from heterogeneous data sources”, *International Journal of Human-Computer Studies*, Vol. 66 No. 11, pp. 759–788. https://doi.org/10.1016/j.ijhcs.2008.07.007

Chandrasegaran, S.K., Ramani, K., Sriram, R.D., Horváth, I., Bernard, A., Harik, R.F. and Gao, W. (2013), “The evolution, challenges, and future of knowledge representation in product design systems”, *Computer-Aided Design*, Vol. 45 No. 2, pp. 204–228. https://doi.org/10.1016/j.cad.2012.08.006

Dworschak, F., Kügler, P., Schleich, B. and Wartzack, S. (2019), “Integrating the Mechanical Domain into Seed Approach”, *Proceedings of the 22nd International Conference on Engineering Design (ICED19), Delft, Netherlands, August 05-08, 2019*, Cambridge University Press, Cambridge, pp. 2587–2596. https://doi.org/10.1017/dsi.2019.265

Euzenat, J. and Shvaiko, P. (2013), *Ontology Matching: Second Edition*, Springer, Berlin Heidelberg. https://doi.org/10.1007/978-3-642-38721-0

Fahad, M. (2023), “Ontology-based Mediation with Quality Criteria”, *8th International Conference on Business Intelligence (CBI 2023), Istanbul, Turkey, July 19-12*, 2023, Springer Nature Switzerland, Cham, pp. 1–15. https://doi.org/10.48550/arXiv.2307.00830

Garnelo, M. and Shanahan, M. (2019), “Reconciling deep learning with symbolic artificial intelligence: representing objects and relations”, *Current Opinion in Behavioral Sciences*, Vol. 29, pp. 17–23. https://doi.org/10.1016/j.cobeha.2018.12.010

Gruber, T.R. (1993), “A translation approach to portable ontology specifications”, *Knowledge Acquisition*, Vol. 5 No. 2, pp. 199–220. https://doi.org/10.1006/KNAC.1993.1008

Hitzler, P., Krötzsch, M., Rudolph, S. and Sure, Y. (2008), *Semantic Web*, Springer, Berlin Heidelberg. https://doi.org/10.1007/978-3-540-33994-6

Horst, H. J. ter (2005), “Completeness, decidability and complexity of entailment for RDF Schema and a semantic extension involving the OWL vocabulary”, *Journal of Web Semantics: Science, Services and Agents on the World Wide Web 3*, Vol. 3 No. 2-3, pp. 79–115. https://doi.org/10.1016/j.websem.2005.06.001

Imane, Z., Souhail, S., Ibtissam, E.-H., El-Moukhtar, Z. and Mohammed, D. (2021), “Using Ontologies to Improve New Product Development Process - Case Study”, *Proceedings of the 11th International Conference on Integrated Design and Production, Fez, Morocco, October 14-16, 2019*, Springer Cham, pp. 249–260. https://doi.org/10.1007/978-3-030-62199-5_22

Kestel, P., Kügler, P., Zirngibl, C., Schleich, B. and Wartzack, S. (2019), "Ontology-based approach for the provision of simulation knowledge acquired by Data and Text Mining processes", *Advanced Engineering Informatics*, Vol. 39, pp. 292–305. https://doi.org/10.1016/j.aei.2019.02.001

Kohn, A. (2014), *Entwicklung einer Wissensbasis für die Arbeit mit Produktmodellen, [PhD Thesis]*, Lehrstuhl für Produktentwicklung, Technische Universität München.

Korel, L., Yorsh, U., Behr, A.S., Kochkmann, N. and Holeňa, M. (2023), "Text-to-Ontology Mapping via Natural Language Processing with Application to Search for Relevant Ontologies in Catalysis", *Computers*, Vol. 12 (1) No. 14. https://doi.org/10.3390/computers12010014

Kügler, P., Kestel, P., Schon, C., Marian, M., Schleich, B., Staab, S. and Wartzack, S. (2018), "Ontology-based Approach for the Use of Intentional Forgetting in Product Development", in Proceedings of the 15th International DESIGN Conference, 21.-24.05.2018, Faculty of Mechanical Engineering and Naval Architecture, University of Zagreb, Zagreb, pp. 1595–1606. https://doi.org/10.21278/idc.2018.0402

Liu, X., Zhang, L., Li, M., Zhang, H. and Wang, D. (2005), "Boosting image classification with LDA-based feature combination for digital photograph management", *Pattern Recognition*, Vol. 38 No. 6, pp. 887–901. https://doi.org/10.1016/j.patcog.2004.11.008

Lyu, G., Chu, X. and Xue, D. (2017), "Product modeling from knowledge, distributed computing and lifecycle perspectives: A literature review", *Computers in Industry*, Vol. 84, pp. 1–13. https://doi.org/10.1016/j.compind.2016.11.001

Mao, M. (2007), "Ontology Mapping: An Information Retrieval and Interactive Activation Network Based Approach", *Lecture notes in Computer Science Vol. 4825, Busan, Korea, November 11-15, 2007,* Springer Berlin Heidelberg, pp. 931–935. https://doi.org/10.1007/978-3-540-76298-0_72

Musen, M.A. (2015), "The Protégé Project: A Look Back and a Look Forward", *AI Matters*, Vol. 1 No. 4, pp. 4-12. https://doi.org/10.1145/2757001.2757003

Natho, N. (2005), *Eine semantische Analyse der mathematischen Sprache für ein computergestütztes Information Retrieval System, [PhD Thesis]*, Technische Universität Berlin.

Owen, R. and Horváth, I. (2002), "Towards product-related knowledge asset warehousing in enterprises", *Proceedings of the TMCE 2002, Wuhan, China, April 22-26, 2002,* pp. 155-170.

Perzylo, A., Somani, N., Rickert, M. and Knoll, A. (2015), "An ontology for CAD data and geometric constraints as a link between product models and semantic robot task descriptions", *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Hamburg, Germany, September 28 - October 02, 2015,* IEEE, pp. 4197–4203. https://doi.org/10.1109/IROS.2015.7353971

Protégé Project (2022), *Cellfie Plugin.* [online] GitHub. Available at: https://github.com/protegeproject/cellfie-plugin (accessed 10.09.2023).

Rachuri, S., Subrahmanian, E., Bouras, A., Fenves, S.J., Foufou, S. and Sriram, R.D. (2008), "Information sharing and exchange in the context of product lifecycle management: Role of standards", *Computer-Aided Design*, Vol. 40 No. 7, pp. 789–800. https://doi.org/10.1016/j.cad.2007.06.012

Schreiber, G. and Raimond, Y. (2014), *RDF 1.1 Primer.* [online] W3C OWL Working Group Note. Available at: https://www.w3.org/TR/rdf11-primer/ (accessed 15.10.2023).

Štorga, M., Andreasen, M.M. and Marjanović, D. (2010), "The design ontology: Foundation for the Design Knowledge Exchange and Management", in Journal of Engineering Design, Vol. 21, pp. 427–454. https://doi.org/10.1080/09544820802322557

Subhashini, R. and Akilandeswari, J. (2011), "A Survey on Ontology Construction Methodologies", *International Journal of Enterprise Computing and Business Systems*, Vol 1. No. 1, pp. 60–72.

Temal, L., Dojat, M., Kassel, G. and Gibaud, B. (2008), "Towards an ontology for sharing medical images and regions of interest in neuroimaging", *Journal of Biomedical Informatics*, Vol. 41 No. 5, pp. 766–778. https://doi.org/10.1016/j.jbi.2008.03.002

VDI (2009), VDI 5610-2: Wissensmanagement im Ingenieurwesen - Wissensbasierte Konstruktion (KBE), Verein Deutscher Ingenieure, Berlin.

VDI (2019), VDI 2221-1: Entwicklung technischer Produkte und Systeme: Modell der Produktentwicklung, Verein Deutscher Ingenieure, Berlin.

Wache, H., Vögele, T., Visser, U., Stuckenschmidt, H., Schuster, G., Neumann, H. and Hübner, S. (2001), "Ontology-based Integration of Information - A Survey of Existing Approaches", *Proceedings of the IJCAI 2001 Workshop on Ontologies and Information Sharing, Seattle, USA, August 4-5, 2001, pp. 108-117*.