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Review

Digital Engineering Methods in Practical Use during Mechatronic Design Processes

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Abstract: This work aims to evaluate the current state of research on the use of artificial intelligence, deep learning, digitalization, and Data Mining in product development, mainly in the mechanical and mechatronic domain. These methods, collectively referred to as "digital engineering", have the potential to disrupt the way products are developed and improve the efficiency of the product development process. However, their integration into current product development processes is not yet widespread. This work presents a novel consolidated view of the current state of research on digital engineering in product development by a literature review. This includes discussing the methods of digital engineering, introducing a product development process, and presenting results classified by their individual area of application. The work concludes with an evaluation of the literature analysis results and a discussion of future research potentials.

Keywords: digital engineering; product development; data mining; machine learning; data-driven methods; system design; system integration; implementation; validation

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1. Introduction

The terms artificial intelligence, deep learning, digitalization and Data Mining are widely used when talking about the next disruptive technologies, changing our lives as well as the way we work or develop new products. In the area of product development, the consistent evaluation and use of existing data applying these methods is subsumed under the term digital engineering [1]. Nevertheless, the integration of those methods in currently established product development processes in small- and medium-sized enterprises is not widely spread [2]. Even though there are already some use-cases in industry and science, those contributions are rather isolated and a consolidated overall view of the current state of research is missing. The ontology AI4PD provides a framework to store and search use-cases for product development [3]. Unfortunately, AI4PD only provides a framework for use-case coverage but gives no overview of available solutions. Therefore, the aim of this work is to evaluate the current research state and summarise those applications for product development processes. Overall, the following research question is answered using the literature study:

- Which use-cases of digital engineering methods are currently available for the application in product development?

In order to reflect potentials of digital engineering applications, the required basic knowledge is given in the next section. There, the major methods of digital engineering such as Machine Learning and Data Mining are discussed. Additionally, a wide-spread methodical product development process is introduced. Afterwards, the methodology of the literature review with its search strings is discussed. In the fourth chapter, the results are presented, classified by their individual area of application during the presented product development process. A result evaluation and discussion of future research potentials completes the contribution.

2. Materials and Methods

In order to be able to analyze and discuss the methods of digital engineering in the context of product development practice, the widely used methodical product development process VDI 2206 is first presented. Afterwards, fundamentals of digital engineering methods are explained.

2.1. Product Development Process According to VDI 2206

Product development in engineering practice must reflect the increasing interactions between mechanics, electronics and software [4]. Therefore, VDI 2206 provides a suitable methodological method framework, see Figure 1.

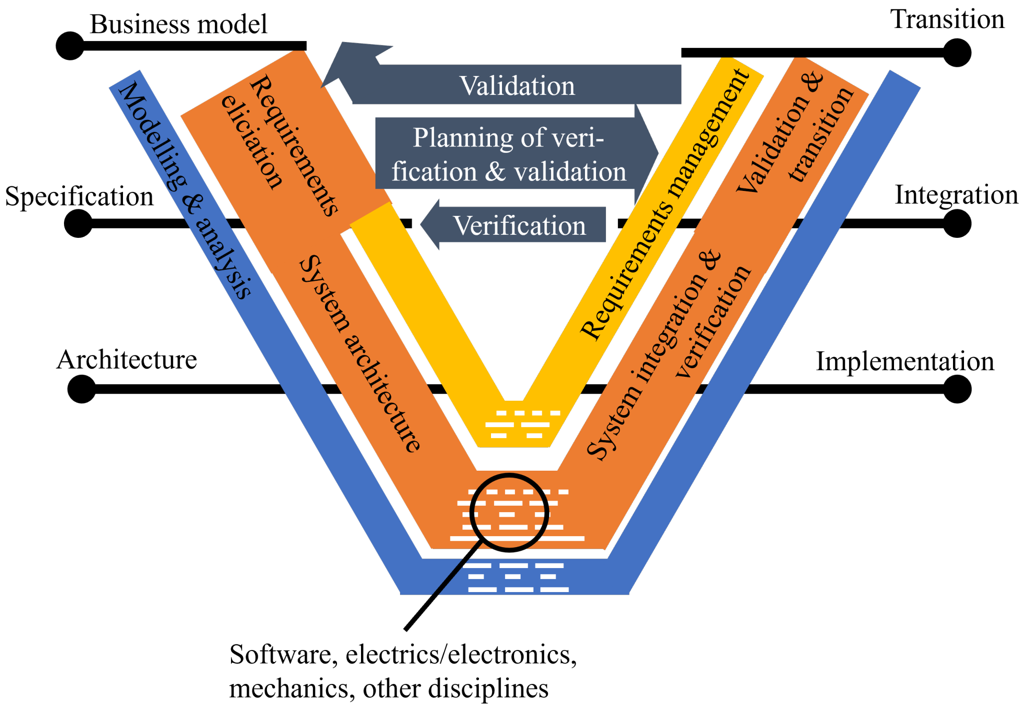

Figure 1. V-Model for development of mechatronic systems according to [4].

In the left branch, requirements engineering and the building of the basic system architecture is conducted. Afterwards, the domain-specific implementation is carried out in the bottom of the V. Lastly, as shown on the right branch, the system integration and validation are conducted. Between the two branches of the V, the properties are continuously verified and validated. Within recent years, the usage of digital engineering in product development has become increasingly important [3].

2.2. Digital Engineering

In digital engineering, a consistent knowledge and information extraction from design, testing or operation data is conducted with the help of data-driven methods. The insights are used during the whole engineering process. Based on this, products are optimised and knowledge is used in earlier phases of product development. Since the difference to the established virtual engineering is not directly clear, a short distinction according to the derivation from a previous publication [2] is given.

Virtual engineering, also known as virtual product development, is a term used to describe the process of creating physical objects in virtual environments. Over the years, it has gained prominence as a means of computer-aided modelling. The main objective of virtual engineering is to digitally represent a product and its characteristics, as stated by Pahl et al. [5]. However, Vajna et al. [6] have extended this definition to include the prediction or determination of all relevant product properties during the development phase, without the need for the physical existence of the product or its components. This extension emphasises the evolving nature of virtual product development. Virtual product development typically starts with a computer-aided design (CAD) model, which is then analysed using computer-aided engineering (CAE). Validation of virtual products often starts with the CAD model. It is important to distinguish virtual product development from digital engineering, and the following definitions provide clarity on this distinction. Schumann et al. [7] were among the first to define digital engineering as the continuous use of digital methods and tools throughout the product development and manufacturing process. This approach aims to improve product quality and process control throughout the lifecycle. Extending the definition of Schumann et al. [7], Künzel et al. [8] incorporate essential requirements into the concept of digital engineering. A crucial aspect is the traceability of all data, especially with regard to change and variant management. In addition, data are used for the optimisation and further development of products. This requires the systematic transfer of knowledge from later phases of the product lifecycle to earlier phases, a key element of future engineering. Duigou et al. [9] also place digital engineering within the framework of a comprehensive view of existing data across the entire product development process. Drawing on the characteristics of both virtual and digital engineering, the authors argue that digital product development can be seen as a logical progression from virtual product development, as Schumann et al. [7] have previously stated. However, the authors see digital engineering as being completed at the end of process planning and the start of production, as this is where the term "digital production" becomes applicable. In particular, the consistent evaluation and use of existing data from design, testing and real-world operation are novel features of digital engineering compared to virtual product development. In summary, the transition from virtual product development to digital engineering occurs when knowledge and information are consistently extracted from data and applied to the product development process. This shift represents the evolution of virtual engineering into a broader and more advanced discipline that leverages data throughout a product's lifecycle.

A data-driven method enables autonomous decisions based on data and corresponding models [10]. Data-driven methods are divided into Data Mining and Machine Learning (ML), which will be further evaluated in the next paragraphs.

The term Data Mining emerged in the early 1990s from the broader topic of Knowledge Discovery in Databases (KDD) and today describes the application of special algorithms for extracting patterns from data as a sub-step of the KDD process [11]. Data mining is highly relevant because the accumulating data in most companies can no longer be meaningfully processed without computer support and a large part of implicit knowledge within the data remains unused in existing database systems, although it is readily available. According to Tan et al. [12], there are three main steps in a KDD process: preprocessing, processing, and postprocessing. In preprocessing, the step of data preparation, the input data are unified, cleaned and, if necessary, also normalised, so that structured data are available. In the second step, processing, these structured data are processed by Data Mining methods and used to generate predictive models or metamodels. In the final step, post-processing, the predictions from the models are evaluated and interpreted. In addition to the KDD process described by Tan et al. [12] for the use of Data Mining, two other processes have become established in the meantime. These are the KDD process according to Fayyad et al. [11] and the Cross-Industry Standard Process for Data Mining (CRISP-DM) [13]. The KDD process according to Fayyad et al. [11] consists of nine steps, whereas the CRISP-DM is divided into six phases. In the steps six and seven (Select Data Mining method & Data Mining) according to Fayyad et al. [11] and phase four according to CRISP-DM (Implementation), the actual Data Mining methods are used. In recent years, the programming language Python and other software tools such as Weka [14] have been used for the operational implementation of Data Mining.

An important distinction to the field of Data Mining is that in Machine Learning (ML), the algorithm learns itself and does not just build on existing data sets trying to find patterns. In addition, Data Mining often uses statistical methods. In ML, the system learns until a termination criterion or a certain prediction quality is reached based on existing data [15]. ML methods can be divided into three groups. These are unsupervised learning, supervised learning, and reinforcement learning [15]. For further use of ML in the context of digital engineering, supervised learning methods are most suitable, as these methods can be used to generate predictive models that are capable of forecasting [6]. Algorithms such as linear or polynomial regression, decision trees, or artificial neural networks are usually used. In supervised ML there exist mainly two tasks which can be addressed: regression and classification. In regression, the task is to predict a previously unknown value from a new parameter configuration based on an initial dataset often created via a parameter study, e.g., predicting the maximum forming force during the manufacturing of a part [16]. In classification, the aim is to classify a new datapoint with respect to given classes of datapoints, also based on an initial dataset. For example, requirements for a given product can be classified into different classes, e.g., organisation, function, technology, as well as overarching boundary conditions [17]. One problem of the application of supervised learning methods is that the trained model learns only the training data by role and thus learns the pure data points rather than the correlations in data. As a result, the model can no longer react adequately to new datapoints. To put it in short, the model is not able to generalise or handle new data. This phenomenon is called overfitting and must be avoided by choosing appropriate training parameters [15].

3. Literature Review

Several use-cases and methods of data-driven methods and their application in product development exist. However, as presented in the introduction, no overview covering the whole development process according to VDI 2206 is available and only studies concerning small parts of the whole process exist. This makes it hard to identify potentials and research needs, especially when looking at cross-phase use-cases. Therefore, a literature analysis of existing integrations of data-driven methods along the development process according to VDI 2206, which was conducted to analyze existing approaches. The aim is to research the link between digital engineering methods and the product development process, particularly with regard to possible application scenarios. For a structured review, the product development process according to VDI 2206 was divided into four review areas as shown in Figure 2. The first one is system design, which deals with the left branch of the V-model. The second area is system implementation, dealing with the V's bottom while the third aspect is system integration in the right branch of the V. The last one is validation addressing the connection between the two branches. The distinction into the four areas was created since they can be seen as the four main problem areas of the development process as visualised by the shape of the V.

For the literature study, the **P**referred **R**eporting **I**tems for **S**ystematic Reviews and **M**eta-**A**nalyses (PRISMA) (http://prisma-statement.org/, accessed 13 June 2023)-method was used. PRISMA is an evidence-based system for systematic reviews with a focus on transparent reporting. The search was conducted using the Scopus literature database. The search string was varied depending on the focus area, but always contained uniform basic terms. Table 1 provides an overview of the keywords used. The character "|" represents the keyword OR, the character "&" the keyword AND. The results are limited to the subarea Engineering (ENGI) and the languages German and English. Since English descriptions and abstracts are available for the German articles, the use of English-only search terms was possible. The area "construction" was also excluded from the search, since this keyword was used mainly by civil engineering research, which was not in the scope of this research. Overall, four searches where conducted, combining the Area General with one of the four defined research areas. For the first search, no specific timeframe was defined.

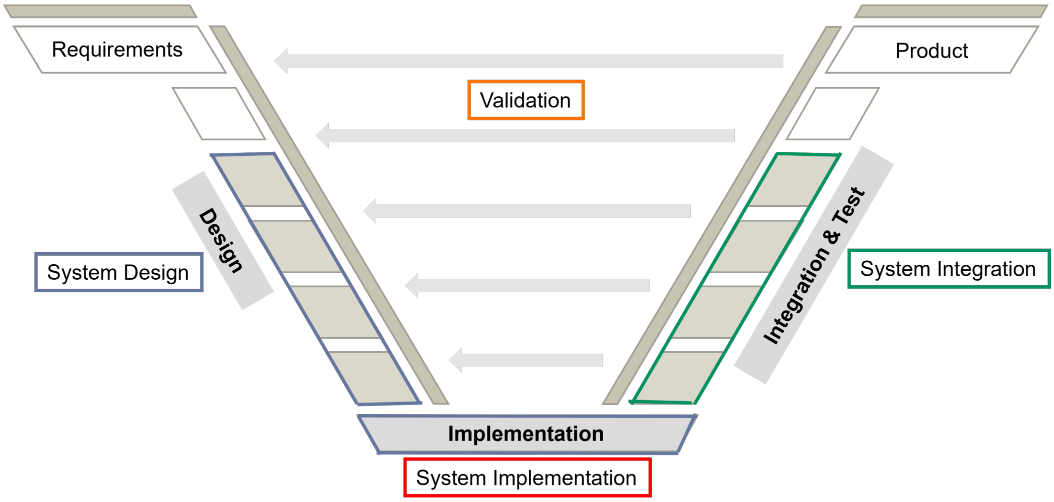

Figure 2. Assignment of the research areas of the literature review in the V-model according to VDI 2206.

Table 1. Search string definition.

Area	**Keywords**
General	"data mining" ǀ "machine learning" ǀ "data-driven" ǀ "digital engineering" & "product development" & NOT "construction" AND
System Design	"requirement" ǀ "concept" ǀ "system design"
Implementation	"design" ǀ "application" & "domain specific" ǀ "subsystem" ǀ "mechatronics" & "development" & "method" ǀ "product"
System Integration	"system integration" ǀ ("component" & "integration" & "system") & "method" ǀ "product"
Validation	("data-driven" ǀ "machine learning" ǀ "data mining") & ("design" ǀ "application") & ("development" & (method* ǀ "product") & "assurance") & NOT "construction"

The first search yielded a total of 632 results. This was further refined in two prescreening cycles according to abstract and title. Contributions were excluded if their abstract and title had no connection to digital engineering methods such as Data Mining or Machine Learning, or if they were not in the context of product development or the four previously defined research areas. Moreover, contributions were excluded that did not correspond to the actual objective after fulltext evaluation. A total of 115 results were considered relevant to the research objective about the use of data-driven methods in product development. The evaluation was conducted by the first four authors, each an expert at the application of data-driven methods in one of the four research areas. Possible biases of this research method are elaborated in detail in the discussion section. The total numbers are shown in Figure 3.

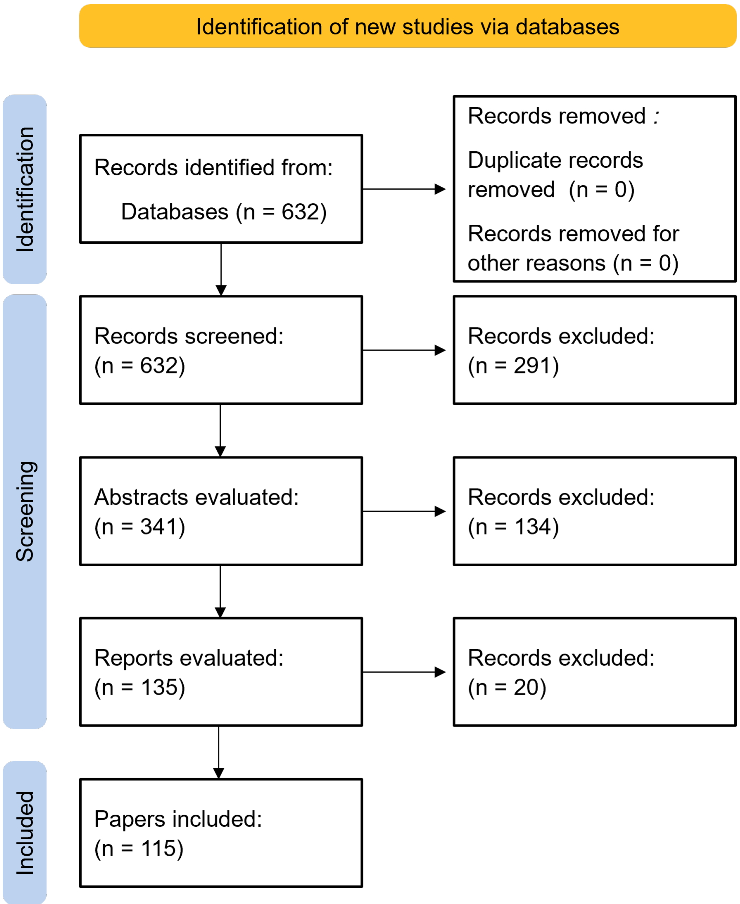

Figure 3. PRISMA Flowchart of literature review.

4. Results

In the following section, the identified use-cases of data-driven methods in the research areas are presented. The resulting papers of the literature review are categorised into the four areas with the following additional categories: use-case (realization of an explicit problem), method (higher-level approach), review (analysis of existing solutions of data-driven methods), and concept (planning/concept for solving a problem), see Figure 4. A subdivision in terms of algorithms used etc. was deliberately omitted, as algorithms strongly depend on the actual task, so that it is difficult to derive universal best practices.

The overview in Figure 5 shows the number of publications in respect to their publication year from 1996 to 2021. The time series is divided into the four research categories: System Design, Implementation, System Integration and Validation.

From 1996 onward, there was a gradual increase in publications across the categories. In 1998, one publication was recorded in Implementation, and System Integration, while Validation had its first publication in 1996. In the subsequent years, the number of publications varied, with occasional peaks and declines in different categories. Notably, 2019 had the highest number of publications across all categories, with eight in System Design, five in Implementation, three in System Integration, and eight in Validation.

Overall, the time series shows a gradual increase in publications in Digital Engineering, with different emphases and stages of development. The increasing number of publications reflects the growing importance of digital engineering in recent years, especially in System Design and Implementation. This goes along with the continuous development and integration of digital technologies in engineering in this time series.

The central result of the analysis is that previous research work primarily relates to the areas of system design and implementation. System integration, in particular, is found in the literature, but takes up a small share of the total sources. In the following, the central findings of the respective areas are discussed in more detail.

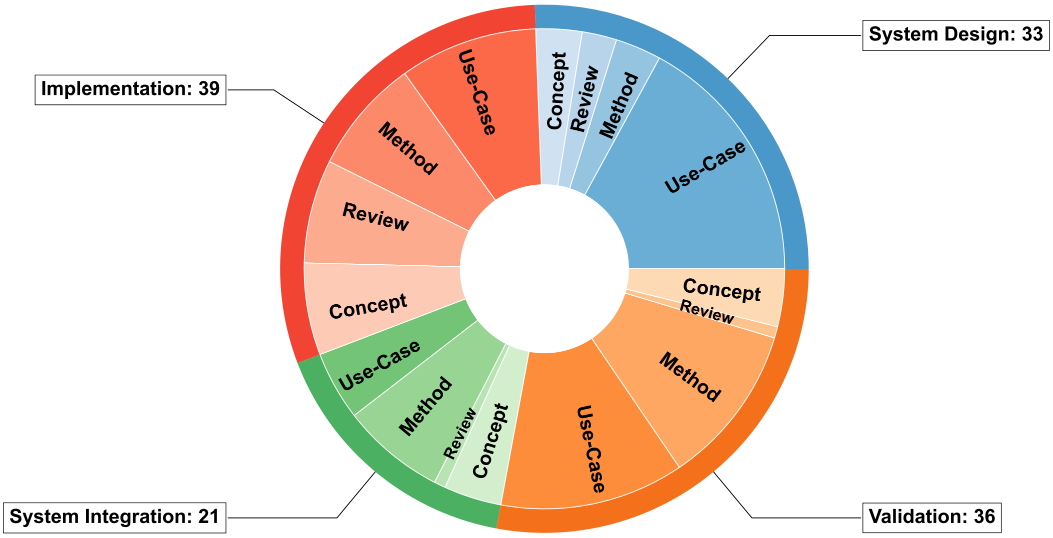

Figure 4. Distribution of the included papers among the four research areas. Some papers are assigned to two categories.

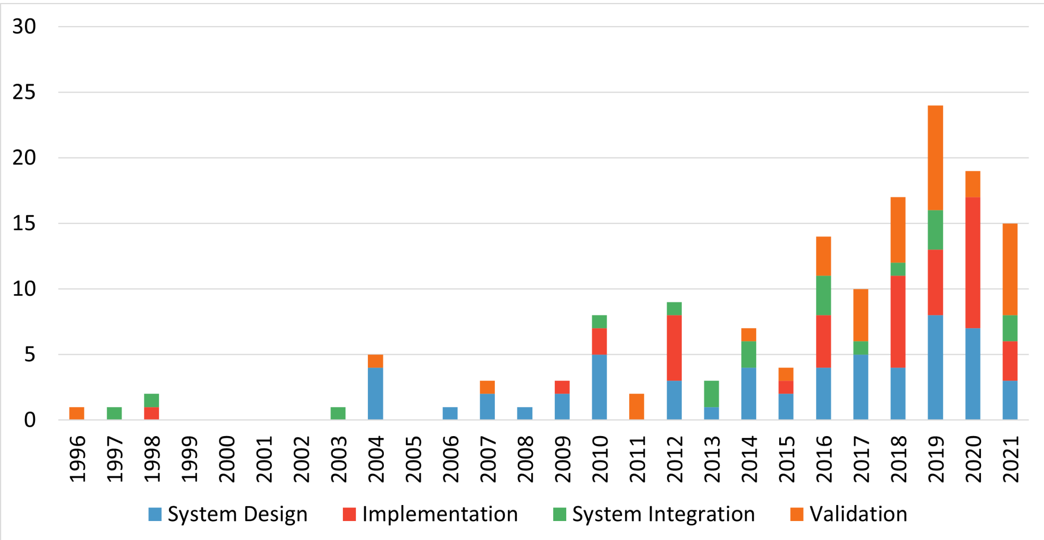

Figure 5. Distribution of the identified papers among the publication years.

4.1. System Design

In system design, there have been significant advances in the application of data-driven methods, particularly in the form of use-cases. Researchers such as Bertoni et al. [18] have demonstrated the potential of Data Mining for decision support in the early stages of product development. Similarly, Menon et al. [19] have focused on the benefits of text mining for predicting quality and reliability. As new digital products require innovative product development processes that incorporate data-driven capabilities, Li et al. [20] proposed an integrated process model based on the classical product development model and CRISP-DM. Their model emphasises the fuzzy early system design phase.

Numerous literature reviews have also been conducted in specific areas of system design. Shabestari et al. [21] explore the use of machine learning in the early stages of product development, while Breitsprecher et al. [22] and Burggräf et al. [23] investigate knowledge-based problem solving and Data Mining in modern product development processes. Trauer et al. [24] evaluate industrial climate system developers and identify several opportunities for data-driven design throughout the product development process, with a particular focus on system design. Various methods have been developed to support system design using data-driven approaches. In the domain of requirements engineering, researchers have addressed challenges [25] and presented automated techniques for selecting requirements from diverse digital sources [26]. Dworschak et al. [1] even generate new geometries based on changing part requirements.

While current system design support systems struggle to address the goals of green products, approaches that combine artificial intelligence, multi-criteria decision support, expert systems, and life cycle assessment have emerged to address this gap [27]. Patent analysis is another critical task in the early stages of new product development; however, this can be time-consuming. To tackle this issue, digital engineering methods such as text mining combined with ontologies have been employed to automatically generate patent summaries [28]. Furthermore, sketching plays a crucial role in communicating new ideas during system design. To assist inexperienced designers, AI-based pedagogical support tools have been developed to facilitate idea development through sketching [29].

Other applications support the concept phase by providing suggestions for later manufacturing strategies [30], manufacturing capabilities [31,32], and assembly [33]. Additionally, product configurations [34,35] and product family management [36] have been explored as use-cases as well as concept analyses [37–40]. There are also attempts to influence product reliability during system design using test and field data [41]. For companies dealing with low-volume, high-complexity, and long-life products, as well as spare parts producers, cost estimation support is of particular relevance [42]. Since customer attitudes and perceived quality significantly impact sales, Gussen et al. [43] have developed an approach to predict the perceived quality of surface materials, which can be utilised during system design. Lindemann et al. [44] have defined a method to integrate perceived quality evaluations into the product development process. Furthermore, data-driven prediction and analysis are used to consider physical interactions between users and products [45].

Customers often express their opinions online through comments and product reviews. Text mining combined with Kansei Engineering has been employed to analyze customer requirements based on these expressions [46]. Additionally, Lutzenberger et al. [47] propose a method to combine product usage information with data-based models, leveraging text mining algorithms on quality reports during requirement engineering. Wang and Zhang [48] address the semantic gap between well-defined product specifications and customer needs by proposing a machine learning mechanism based on classification algorithms. In the field of gear design, [49] employ Data Mining techniques to perform uncertainty quantification focused on noise, vibration, and harshness characteristics.

In summary, there is a wide range of use-cases available for data-driven methods in system design, addressing various relevant problems. These use-cases provide starting points for the development of a generalised concept for the application of these methods in this field.

4.2. Implementation

The field of domain-specific implementation is primarily divided into manufacturing engineering, automotive engineering, and aerospace engineering sectors. Within each sector, there are subdivisions that focus on concepts, methods, literature reviews, and use-cases.

In the domain of mechanics, there are several noteworthy concepts being introduced. For instance, Przystałka et al. [50] propose an expert system concept for the coal mining industry to support decision-making in determining the optimal location for new coal mines. Another concept by Pasqual and de Weck [51] involves network analysis to aid in change management within the mechanical engineering domain. In the domain of informatics, research primarily centers around hardware and circuit design [52]. Tine et al. [53] present an expert system for near real-time simulation of circuit design, while Qin and Ji [54] develop a hyperparameter optimization toolkit for ML models using parallel strategy parameter selection. In the context of Industrial Internet of Things (IIoT), Liu et al. [55] leverage artificial intelligence (AI) methods to optimise security systems in high-speed railways. For human-machine interfaces (HMI), Czauski et al. [56] introduce a domain-specific language (NERD) for the Internet of Things (IoT) that facilitates HMI definition in production control systems. Sartori et al. [57] employ ML and HMI techniques in a use-case involving smart control of prosthetics. In the aerospace industry, Horoschak et al. [58] propose a concept to reduce the return-to-service time for space equipment. Additionally, Daiker et al. [59] explore a broader range of applications, specifically in the development of safety-critical systems for NASA. Regarding method usage, data-driven methods like machine learning (ML) find extensive application in manufacturing engineering. For example, Fredin et al. [60] utilise ML to optimise tools, while Ozer et al. [61] employ ML to support product development in flexible electronics. Settaluri et al. [62] utilise reinforcement learning, a novel ML approach, for designing analogue circuits. Murrell et al. [63] propose a supervised learning-based method for reducing sensor data. In the domain of informatics, data-driven methods often focus on pattern recognition algorithms. Li and Wu [64] develop a text mining-based approach to support reliability analysis and design failure mode and effect predictions. Luo et al. [65] employ fog computing, a form of edge computing, to facilitate process monitoring in larger production plants using a data-driven design process. In the early stages of product development, Ivezic and Garrett [66] utilise ML to support collaborative design through co-simulation. Bork [67] investigates meta-approaches by analyzing domain-specific conceptual modeling methods using a metamodel approach, facilitating the application of use-case-specific modeling methods. In the aerospace field, Martin et al. [68] focus on ML-based control models for contamination in extraterrestrial space.

Literature reviews and studies within the automotive industry mainly revolve around the automation of routine activities [69] and the use of computer-aided design (CAD) tools [70]. In "classical" mechanical engineering, there are initial investigations into integrating data-driven methods such as ML and Data Mining into mechanical-mechatronic component development [71]. Verhagen et al. [72] conducted a literature review on knowledge-based engineering, which serves as a predecessor to data-driven and digital engineering, focusing on identifying research questions in this area. In materials science, Pilania [73] explores the application of ML methods for discovering and developing new materials. Menezes et al. [74] conducted a comprehensive review to identify the potentials of Industry 4.0 and smart operations within the manufacturing domain. IoT is often utilised for condition-based maintenance of products, and Prajapati et al. [75] surveyed condition-based maintenance methods that frequently employ ML to predict dangerous conditions. Simonetto et al. [76] explored the state-of-the-art time-dependent optimization methods, which have broad applications in mechatronic products.

In terms of use-cases, condition-based maintenance and condition monitoring are prominent areas. Shan and Li [77] developed a data-driven system to support smart bridge management and maintenance, while Grishin [78] focused on intelligent algorithms for handling errors and deviations in condition monitoring systems. ML and data-driven methods are also being investigated for production optimization and control [79]. Geiger et al. [41] explored the use of Data Mining methods to test existing products for reliability and optimise future products based on this analysis. Hui et al. [80] present a use case involving boiler design. Schreiber et al. [81] propose an ML and data-driven approach for building cooling management system design. Lützenberger et al. [47] demonstrate an approach for improving product-service-systems (PSS) using data from the usage phase. Bertoni et al. [82] combine ML and value-driven design to create a decision support system for product design. Kayama et al. [83] evaluate the usefulness of model-driven thinking in academic teaching institutions. In aerospace engineering, Wei et al. [84] present an AI and ML-based control system for failure detection, while Kalita and Thangavelautham [85] combine design optimization and evolutionary algorithms for microsatellite design.

4.3. System Integration

In the system integration phase, the developed system elements are combined into bigger systems and finally the overall system. To overcome problems, it is closely interlinked with the implementation phase. Another element is the interaction with verification to ensure the overall system fulfils its requirements and the prediction of system properties to achieve this [4]. For system integration, there are few literature results that use the term according to VDI 2206. This is mainly caused due to the spare use of the system integration phase itself in engineering-related publications. The identified papers can mainly be divided into three categories. In product development, data-driven methods can be used to simplify the integration of components into systems by simulating their behaviour [86]. Another use-case is the implementation of data-driven methods into products, either existing or under development. There it can be used for predictive maintenance applications [87]. The last category is the use for production preparation and surveillance, where these methods can act as a connection between development and production [33,88].

Modern development projects often make use of a holistic development approach. This includes the storage of all data produced during the development, e.g., from simulations, testing and field data, in a data management system. As part of digital development, this data-driven development enables the planning of reliability tests and thus optimises the product and component testing during the system integration phase [89]. This becomes especially important when the level of integration and therefore challenges related to product manufacturability and reliability increase [90]. Because of the integration of multiple-disciplinary fields, such as mechanical, electro-mechanical, digital, etc., system integration is getting more and more complex. An approach to connect these fields is by reorganizing the data management system, including support for agile methods. Therefore, a framework has been developed to illustrate the benefit of agile methods for multidisciplinary integration tasks [91]. Key tasks during system integration are positioning and dimensioning of components in combination with verifying the solutions. This is supported by object-oriented multidisciplinary modeling and related languages [92]. In today's companies, there is often a huge number of similar products available, which could be used as carry-over parts. The complex task of portfolio analysis can be acheived through a data-driven approach, which utilises metamodels [93].

When it comes to testing of system elements, information about their usage and life cycle data is needed. To allocate this information and enable methods, such as X-in-the-loop, which help during the development cycle and provide testing techniques for hardware and software, methods of Data Mining are applied [20,94]. While Data Mining has become useful to gain information in maintenance, it is not solely usable as a stand-alone technique. Therefore, Data Mining products are shifting from stand-alone technology to be integrated in relational databases. The right deployment of this technique enables optimised maintenance decisions [87,95]. An important part of the system integration is to ensure that the overall system meets its requirements. For this topic, assembly planning and design for assembly have to be considered. Data mining techniques are also used to gather information about the expected assembly effort and cost, as well as to gain clarity about the test requirements themselves [33,96–98]. They are also used for monitoring, planning, fault analysis, etc., and are directly integrated into production systems [74,99,100]. This includes, for example, the prediction of assembly processes and thus the verification of the system integration process [101].

4.4. Validation

Out of the total of 36 publications identified in the field of validation, around one-third, see [96,102–111], are strongly related to manufacturing, while an equally large proportion, see [112–124], stems from the field of automotive and aerospace development. Still, five contributions, see [125–129], contemplate the development and production of integrated circuits. Besides two contributions that focus on advancements in material science [130] and medical technology [131], only four articles address product development on a more general, abstract level:

Kano et al. [106] focus on the improvement of quality and yield, especially for new products in the advent of increasingly short life cycles, and propose a corresponding data-based methodology. Li et al. [132] go one step further regarding new product development and address the number of necessary verification, validation, and accreditation cycles of the V-Model with a Model-Based Systems Engineering integration and an explicit extension towards data-driven features. On a slightly lower but equally important level, Shao et al. [133] realised that current data-mining approaches regarding historical simulations are often limited to specific and isolated engineering challenges and neglect overall performance evaluation. Therefore, they present a data-mining approach to discover interrelations between erstwhile singular design parameters and improve overall performance estimations. The earliest identified publication was released in 1996 and aims at enhancing the use of Quality Function Deployment (QFD). The crux of QFD lies in the necessity of estimating a large number of values based solely on the subjective and potentially inaccurate experiences of the developers in charge. To mitigate the lack of accurate data input, the paper suggests a machine-learning approach to determine the required data by learning from examples in a white-box process that represents the actual terms of the respective application [134]. In a similar machine-learning-based approach, Li and Wu [64] utilise text mining to classify failure modes and failure causes in FMEA analyses and therefore unveil the most economical improvement activities. However, they have not investigated the potential interrelationships between failure modes and failure causes, yet.

This aforementioned pattern suggests that digital methods for validation have so far been considered primarily on a rather application-specific basis. When new methods are presented in these works, as in [115,117,119,125,134–136], they mostly refer to the context of manufacturing, e.g., [96,104,106,107,109,126]. Considering the share of manufacturing within the entire overarching development process, this subtopic seems to be over-represented in the given context. On the contrary, only a single publication [119] explicitly targets the vertical aggregation of data across the entire second half of the V-model. Another paper [20] addresses horizontal verification and validation between product, model, and data life cycles in this same context. Particularly with regard to general approaches and recommendations for action, the topic of validation across the product development process still lacks further assistance of a generic nature.

5. Discussion

Using a comprehensive view and broad approach for a complete overview, the general use of digital engineering in individual sections of the product development process has been shown. Different companies and, thus, researchers refer to different process models for product development that are tailored to their individual and specific use cases. The authors chose the V-model as a flexible approach to cater to different needs in product development. Although there is a limitation regarding the search terms due to the utilization of the V-model and its specific terminology for the literature review, the selection was made because the V-model has found its way into VDI 2206 [4] as the leading process model used by different companies and for numerous studies. Articles that failed to properly situate themselves within the context of the product development process or neglected to employ the appropriate keywords were excluded from the dataset and subjected to subsequent analysis. As a result, the analysis focused solely on a specific sector of ongoing research, thereby limiting the scope of the investigation. Furthermore, the restriction to English and German publications leads to a language bias. To overcome this bias, an international research consortium covering all the major world languages is needed. Another bias is a lack of publications elaborating industrial use-cases in detail. This is because companies do not want to publish their innovative solutions to keep the competitive advantage. However, this leads to the fact that there are digital engineering solutions in practice that cannot be covered by scientific research. An industry survey would have to be carried out to record use-cases and best practices. However, the significance of such a study can also be questioned due to the companies' intention to maintain secrecy, as explained above.

Considering the aforementioned scope of the analysis, the initial research question can be answered as follows: In the early and concept phases of the product development process, digital engineering is widely used. Especially in system design and implementation, several best-practices and use-cases as well as first literature studies which can be used as a first application database are known. According to the authors, this is particularly due to the fact that conceptual data rather than engineering data are preferred in these phases. This results in easier accessibility of data, since proprietary engineering data must usually first be made usable via exchange formats such as point clouds or data tables. In the next product development process steps, especially in system integration, the share of digital-engineering use-cases is much lower. Use-cases for linking the individual areas and also for validation or verification are also still hardly known and researched.

Further potential aftermarket application possibilities of data-driven methods are given. In the areas such as marketing, user-centered design [137] or education [138], digital engineering methods could provide beneficial insights or process automation support. In user-centered design, mass customization is a big new area of interest. Here, companies try to make products as individual as possible and customise it to the individual customer needs. A first approach of combining Industry 4.0 methods with mass customization is available, using augmented reality to visualise those customizations [139]. Digital Engineering may open up the opportunity of generating those customised products automatically based on Machine Learning or generative design.

The results of the literature review presented in Figure 5 depict the evolution of publications in the field of Digital Engineering over time. The data show fluctuations in the number of publications across different categories, indicating varying research focuses within the field. These findings provide insights into the trends and advancements within Digital Engineering and can serve as a basis for further analysis and understanding of the field's development.

Furthermore, manufacturing-focused publications are highly represented in the findings, although they were not the main research-focus. A possible reason for this bias is an easier data-acquisition and availability in manufacturing. Manufacturing machines can be extended with IoT sensors, enabling easy data generation during the manufacturing process. Since data generation and provision is one of the biggest hurdles in the application of digital engineering methods, this is a significant advantage that promotes its spread in the manufacturing sector. In order to exploit this opportunity in the field of upstream product development and gain initial experience more easily, data-driven approaches that utilise production data and incorporate them back into product development are a good first step for companies to introduce digital engineering. Future research should therefore focus on this area just as much as on simplified data acquisition in the actual development context.

From a research perspective, there is often a lack of reliable and realistic data. This highlights the need for enhanced collaboration with the industry. To facilitate this cooperation, public funding opportunities that explicitly support technology transfer between research and industry are desirable. On the industry side, integrating such partnerships brings about greater complexity to the problem at hand. This is because a multitude of factors and their corresponding data need to be mapped and identified. Accomplishing this task without expert assistance from the research community can be challenging. Both of the aforementioned aspects hold significant potential for further research activities and should be focused on.

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