Facilitating the Implementation of Data-Driven Processes in Product Development

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Abstract: The use of Data-Driven Design (DDD) plays a pivotal role in transforming the design and development processes within various industries. The purposeful use of data can extract valuable insights to foster innovation. This paper explores the current application of data management throughout the product lifecycle, focusing on identifying underutilized data and missed innovation opportunities. Our research focuses on the challenges in incorporating data-driven applications in multidisciplinary development processes, aiming to assist companies in effectively navigating, choosing, and implementing data-driven strategies within product development. Through a systematic literature review and industry insights, we present twelve data-driven applications, classified by lifecycle phases and linked with relevant data sources. Based on this, a guiding framework utilizing data science and AI is proposed, enhancing data empowerment and efficiency in industrial practices. Finally, the findings are validated through a case study, providing a structured path from theoretical exploration to practical implementation of DDD.

Keywords: data-driven design, support methodology, artificial intelligence, product development, systems engineering

1 Introduction and problem clarification

In the current industrial landscape, the trend of digitalization signifies a transition towards more data and its subsequent processing. This is amplified by significant advances in information and communication technologies (ICTs), which enhance sensor capabilities while also reducing costs, thereby fostering increased utilization in products (Liu et al., 2018; Zheng et al., 2021). The phenomenon has led to a rapid growth in the amount of data available within companies, prompting a need for effective management and utilization (Briard et al. 2021). The concept of Data-Driven Design (DDD) emerges as a pivotal strategy in leveraging this data to refine the design and development processes, extracting valuable insights to facilitate innovation (Kim et al., 2017).

In addition, the rise of new technologies, notably artificial intelligence (AI), presents unprecedented opportunities for automated data processing and knowledge acquisition, further emphasizing the necessity of adept data management (Meyer et al. 2022; Langley et al. 2022). Despite the evident potential and increasing adoption of data-centric approaches in various industries, a significant gap persists. Companies, particularly within engineering domains, struggle with harnessing the full value of their data, mainly due to an absence of a coherent digitalization strategy or a clear understanding of data-driven application use cases (Paliyenko et al., 2022; Dausch et al., 2023; Müller et al., 2023).

This deficiency is not merely operational but fundamental, affecting the core structures of data processing in companies. There is an evident disconnect in the end-to-end chain of data handling across the product lifecycle, leading to underutilized data and underexploited areas of innovation. Despite industry acknowledging the benefits that data can offer for both internal and external processes, such as in the realms of Industry 4.0, Product Service Systems (PSS), and Cyber-Physical Systems (CPS), a structured approach to integrating data-driven applications is still lacking. The challenges extend beyond mere data acquisition., rather, the underutilization and inefficient handling of data are to be observed, particularly in multidisciplinary processes (Paliyenko et al. 2023; Huikolla et al. 2022; Liu et al. 2018). This underscores the necessity of structured frameworks that do not only assist companies in identifying and implementing relevant data use cases but also in aligning these with their respective product lifecycles, thereby maximizing efficiency and innovation (Opazo-Baséz et al., 2023; Ganz et al., 2021).

Aligning data-driven applications along the Product Lifecycle (PLC) may significantly enhance developmental and operational efficiency, as well as foster innovation in internal and external value creation. Additionally, the creation of a guiding framework for structuring data-driven applications could support decision-making in product development, delineating necessary actions, and data processing requirements. Furthermore, the implementation of a checklist or questionnaire for self-assessment could streamline the initiation of data-driven use cases, enabling organizations to better identify and leverage potential applications. Thus, the research questions (RQ) posed are: RQ1: *How can data-driven applications be structured to unlock untapped potential in product development?* RQ2: *What approaches can be taken for the practical initiation of data-driven use cases in companies?*

The overarching subjective of this research is to assist companies in navigating, selecting, and implementing data-driven processes within product development. This entails providing comprehensive support in aligning data-driven applications with phases of the product lifecycle, considering the current state of the art, and understanding the implications and opportunities presented by AI in data utilization. Through addressing these focal areas, the study aims to bridge the gap between theoretical data capabilities and practical application, thereby fostering a more efficient, innovative, and data-empowered industrial environment.

2 Methodology

Through a multifaceted approach to research, this paper systematically investigates the potential of data-driven design in product development. By combining theoretical exploration with practical insights and validation, the research not only underscores the importance of data-driven methodologies but also provides a structured approach to implementing these strategies in industry settings. The subsequent sections will delve deeper into the results and discussions, providing a detailed exposition of how data-driven design can lead to enhanced innovation and efficiency in product development.

The research commenced with a comprehensive literature review to establish a foundational understanding of the key domains relevant to our study: data-driven design and systems engineering. This preliminary review aimed to identify existing theories, methodologies, and gaps within the field, facilitating the formulation of a comprehensive research framework. The domains were explored through various academic databases and journals, with the intent to gather a broad spectrum of perspectives and methodologies.

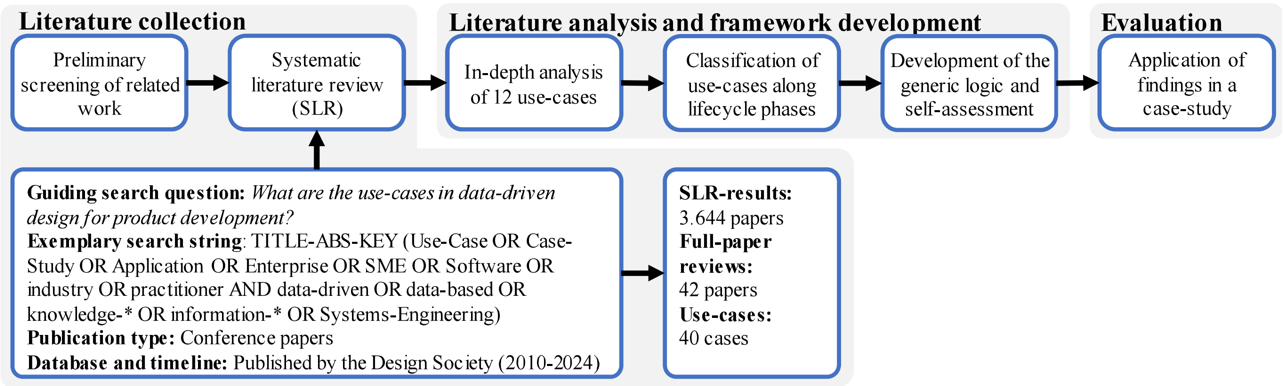

Figure 1. Research procedure

Following the preliminary review, a more focused systematic literature review was conducted. The central guiding question, which remains specifically articulated to address the overarching RQ of this paper, directed this review phase. The selection of literature was governed by clearly defined criteria as depicted in Table 1, ensuring the relevance and quality of the sources. To handle the extensive body of literature, a multistage analysis approach was employed. Initially, an automated AI-based screening tool (Pital AI) was used to filter through the publications based on predefined keywords and relevance to the topics. Subsequent to this automated screening, manual analysis by the authors was conducted to ensure the nuanced aspects of data-driven applications were adequately captured. This dual-layered screening process allowed for a comprehensive and thorough exploration of the literature.

The identified use cases were meticulously analyzed and categorized based on various criteria. These criteria, while specific to the needs and context of the research, typically encompass factors such as the stage of product development they impact, the type of data utilized, and the action they aim at. The classification was done according to the stages of the product lifecycle, adhering to established models in the field. For such structuring, a universal framework is essential.

The lifecycle model serves this purpose well, guiding practitioners on the relevance and timing of data-driven applications at each stage of the lifecycle. This understanding forms the basis for initiating these applications. Nevertheless, numerous lifecycle models exist, detailing the phases that products or services undergo. It is crucial to adopt a model that holds general validity across various industries to ensure the broad applicability of the findings. Consequently, it becomes necessary to consolidate existing models. Qureshi et al. (2014) conducted an analysis of 64 lifecycle and development models to identify universally accepted phases in product development, leading to the proposal of a meta lifecycle model. This meta model aligns with well-established development models for CPS development or smart service design (cf. Peruzzini and Wiesner, 2020; DIN SPEC 33453, 2019; VDI/VDE 2206, 2021). Drawing from the work of Qureshi et al. (2014), we adopt a transdisciplinary lifecycle model with five phases:

Phase 1 - Planning: This initial phase begins with strategic planning, where market analysis and forecasting are conducted to identify potential customers and their needs. This insight informs the business case definition and design. Following this, operational planning takes place, which includes design coordination and continuous requirements management.

Phase 2 - Development: The development phase starts with the generation of initial realization ideas during the conceptual design stage, which are then refined in the embodiment design phase. The process leads to the detailed design stage, where the solution is finalized. Production planning is integrated into this phase to allow for a seamless transition from product development to production. Clarifying this transition is crucial to avoid any confusion regarding the categorization of data-driven applications linked to work planning. Concurrently, if relevant, the development of associated services should align with the product to ensure integrated design.

Phase 3 - Production: This phase transitions development concepts into tangible products or services. It starts with procurement to gather all necessary inputs, followed by the manufacturing and assembly of components. Systems integration is a pivotal step, ensuring that the combined hardware, software, and service components function reliably and meet targeted specifications.

Phase 4 - Operations: Once the product or service is produced, it moves into operation. After sales and distribution, installation and initial configurations set the stage for actual usage. During this phase, ongoing services such as support, training, maintenance, and repairs are provided to enhance the user experience.

Phase 5 - End of Life: The lifecycle concludes with the retirement of the product and service. This phase focuses on various strategies for reusing, recycling, and recovering, commonly known as the "R-Strategies." More detailed information on these strategies can be found in the research literature, for example, Kirchherr et al., (2017).

Based on the comprehensive insights gathered through literature and case studies, an industry-oriented guiding framework was developed. This generic logic serves multiple purposes: it acts as a self-assessment for companies to gauge their current utilization of data-driven design, and it aids in structuring the application of data-driven techniques within their design processes. The development of this logic was informed by both the academic and practical findings of the study, ensuring its relevance and applicability in real-world settings.

Finally, to validate the research findings, they were tested through a practical application in a case study. This approach was designed to evaluate the effectiveness of data-driven design methodologies in improving product development processes. In this case study, we utilized the generic logic to model a real-world application (*Decent Espresso DE1 Pro*), creating a data-driven use case around the operation of an espresso machine. By gathering and analyzing real-time operational data from the espresso machine, we were able to transform this data into actionable knowledge regarding its use by consumers. This transformation process facilitated the derivation of clear, actionable steps that could be implemented in the product development cycle. The findings from this case study not only confirmed the results of our research but also enriched them by integrating industry insights. Feedback from this practical application was integrated back into the research, enhancing the overall conclusions and providing a robust validation of the data-driven design methodologies employed.

3 Findings

3.1 Analysis of data-driven use-cases

Our literature analysis identified 40 potential use cases, out of which 12 were selected due to their pivotal roles in product lifecycle stages, as depicted in Figure 2. These use cases were meticulously chosen based on criteria, such as their representativeness, detailed descriptions, and the diversity of data types used for implementation. Each use case exemplifies the integration of various data sources, demonstrating their practical applicability across different stages of the product development process.

The primary focus of this study is to extract actionable insights that help in refining data-driven product development strategies. A key aspect of our analysis was to highlight the specific actions driven by the underlying data within each use case. This approach does not only clarifies the functional role of data in enhancing product development but also strengthens the understanding of how data can be strategically used to drive innovation and efficiency. Additionally, we adopted a classification system for the data based on its source of origin. This classification helps in understanding the dynamics and context of data generation, which is crucial for ensuring the reliability and relevance of the data in practical applications. By emphasizing the origin and context of the data, we aim to provide a more nuanced understanding of how different data types can be optimally utilized throughout various phases of the product lifecycle. This classification further facilitates the systematic exploration of data potentials and limitations in the context of product development.

The use cases depicted in Figure 2 illustrate a diverse array of data generated at various stages of the product lifecycle, each tailored to specific developmental phases and operational needs. During the **planning phase**, a multifaceted assortment of data sources is employed, including controlling data, PLC data, product configurations, sales data, insights from market trends, patent databases, and expert data. This rich blend of data supports early-stage decisions and strategic planning. In the **development phase**, the focus shifts to leveraging existing designs, sensor data from operational equipment, simulation outputs, and experimental data. These data types are crucial for refining product designs and enhancing functionality through iterative testing and simulation. **Production-**oriented use cases predominantly rely on manufacturing data and product sensor data, which are vital for optimizing production processes and ensuring product quality. During the **operation phase**, there is an opportunity to validate customer requirements, analyze user-generated content, and monitor the overall system performance. This phase is critical for ongoing support and adaptation of the product based on real-world usage and feedback.

Data-driven design represents applications where decision-making in design and development is mainly guided by data analytics. These comprehensive data sources foster a variety of data-driven use cases, such as the creation of digital twins, automation in design processes, identification of customer needs, and extensive market or patent screenings. Each use case leverages data to transform insights into actionable strategies and innovations, thus enhancing product value and operational efficiency.

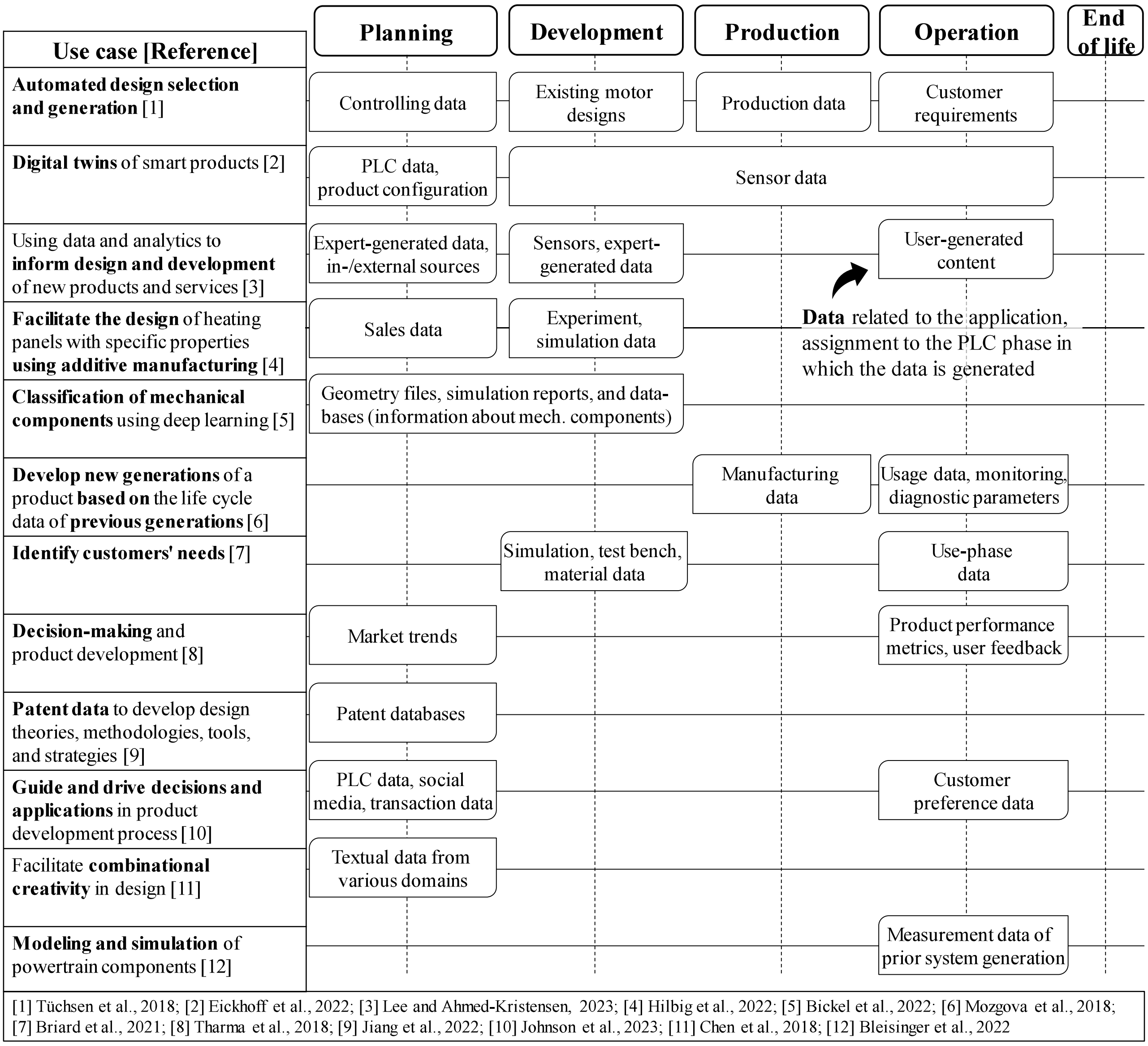

Figure 2. Selected data-driven use cases and their collected data along the product lifecycle

3.2 Logic for the deployment of data driven design

Despite the diverse nature of the depicted use cases, a generic logic in their emergence and transformation processes can be observed upon closer inspection. This is achieved by applying the principles of North's data-knowledge staircase (North and Kumta, 2018), which illustrates the step-by-step transformation of raw data into actionable knowledge, thereby showcasing the potential of data science and artificial intelligence in practical applications.

We have chosen five distinctive use cases that are both well-described and also provide a rich data-set to demonstrate the overall similarities among them. This same reasoning can be applied to the other seven use cases, and it remains valid. However, due to spatial constraints, we forgo their depiction. By mapping the data-driven use cases onto the knowledge staircase (Figure 3), it becomes evident that the use-cases share similarities. Each process begins with raw data. This data is then processed through various methods, including machine learning techniques, to produce structured data sets that yield insights. These insights become knowledge when augmented with context, experience, or foresight, typically through the development of models or systems, which may include AI technologies. Consequently, this knowledge is embedded within systems, which can either assist humans in tasks or, in the case of AI, handle tasks autonomously.

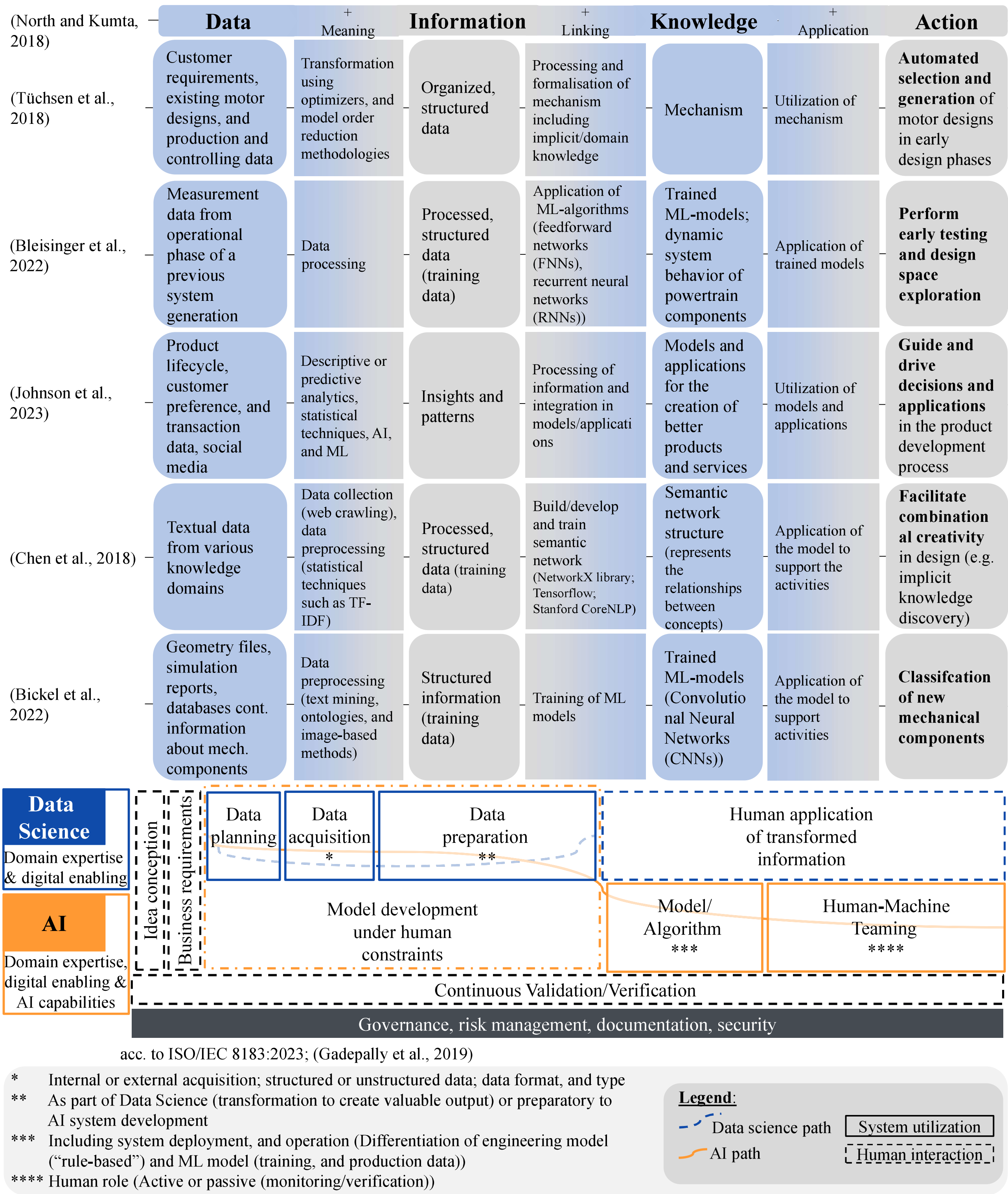

Figure 3. Use-case mapping and logic for utilizing DDD

The similarities across these five use cases are underscored by referencing established models from academic literature. For example, aligning with the Data lifecycle framework of ISO/IEC 8183:2023, this schema encompasses stages from the initial conception of ideas and business requirements through to data processing phases such as data planning, acquisition, preparation, model building, system deployment, operation, and ultimately, system or data decommissioning. These stages are subjected to continuous validation and verification to ensure the efficiency of both the model and the system. In a simplified representation, Figure 3 traces these processes via an AI pathway marked in orange.

According to Gadepally et al. (2018), who explored functional relationships in AI systems and emphasized Human-Machine teaming, critical phases like model building, system deployment, and operation are redefined in Figure 3. With the evolution of AI technologies, system deployment could lead to fully automated tasks, including decision-making processes. The role of human oversight in the development and utilization of AI systems is crucial, as it demands specific AI skills and resources. These aspects of AI system development are further elaborated in ISO/IEC 22989, which not only supports the data lifecycle framework but also expands on other elements of the comprehensive AI system lifecycle relevant to DDD. If an AI system is not involved, the machine's role in data processing within the knowledge staircase is limited to transforming data into information or knowledge. In this context, human intervention is necessary to further process and apply the output in practical activities, as illustrated by the "Data Science Path" shown in blue in Figure 3.

It is noteworthy to mention that this approach aligns well with international standards, such as those outlined by ISO/IEC. A comparative analysis with these standards indicates a strong correlation with the data lifecycle models employed in machine learning, which validates the robustness and applicability of our data-handling methodologies. Such alignment does not only confirm the efficiency of our approaches but also broadens the interoperability of our data-driven solutions across various industrial and technological platforms.

Building on these insights, we derived several key questions that can guide and enhance the implementation of use cases throughout the development process. These questions, which aim to streamline the adoption and optimization of DDD strategies, are discussed in detail in the subsequent chapter. This structured inquiry not only deepens our understanding of data-driven applications but also aids in the strategic implementation of AI-enhanced processes within industry frameworks.

3.3 Status quo assessment for deploying DDD

This section presents a method to evaluate the preparedness of these use cases for business implementation. To facilitate this assessment, specific questions have been outlined in Table 1, distributed across seven distinct categories. These questions not only assess readiness, but also highlight areas that require attention to facilitate use case implementation.

The questions are based on the data lifecycle framework outlined in ISO/IEC 8183 and the fundamental requirements for the use of artificial intelligence as described in ISO/IEC 5259. In Table 1, the "References" column indicates the applicability of each question to the use cases discussed in Sections 3.1 and 3.2. Initially, questions were developed based on insights gathered from the analyzed use cases. Similar questions were then grouped according to the specific perspectives they addressed. Subsequently, these clusters were compared with existing literature and guidelines, particularly ISO/IEC 8183 and ISO/IEC 5259. These standards provide the criteria for focusing the assessment. Additionally, the self-assessment process was reviewed by the authors and refined based on insights gained from industry projects.

Table 1. Guiding questions for the assessment of DDD deployment

Category	Questions [references]
Data availability & data quality	Is the necessary data readily available for analysis? [1,2,3,4,5,6,7,8]
	Is the quality, accuracy, and completeness of the data verified? [1,2,3,4,5,6,9,10]
Scalability, security, and compliance	Has scalability for the introduced use case been part of the considerations? [2,5]
	Which measures ensure compliant and secure data handling? [10]
	How is access management achieved? [10]
	Are data governance policies and procedures established?
	Is compliance with privacy regulations ensured (e.g., GDPR, CCPA)?
Stakeholder engagement and infrastructure	Are all relevant stakeholders (IT, market research, etc.) included in discussions about the use case? [5,10]
	Is additional hardware infrastructure required? [4,5,9,11]
	Are additional systems required? [2,5,7,9]
Performance metrics and impact measurement (KPI):	Are relevant metrics and key performance indicators (KPIs) for evaluating the success of these use cases defined? [11,12]
	How will the impact on engineering processes caused by the use case be continuously measured? [5,6,11]

Integration and risk mitigation	How will the use case integrate with existing engineering workflows and systems? [2,5,6,9,11]
	What are potential disruptions during implementation? What are the risks associated with implementing the use case? [11]
	How will continuous learning and adaptation of the use case be ensured? [2,5]
	How will user feedback and acceptance be tracked? [8,11]
Organizational readiness	Was a specific user interaction concept specified and evaluated? [1,9]
	What efforts are necessary to qualify employees? [2,4,7,8,9]
Strategy and function	Are problems to be solved as well as the approach, which is in scope of the use case well defined? Have requirements been created to further detail the use case? [6,7,8,9,12]
	How is the data-driven use case linked to the business and enterprise strategy? [5,9]
References: [1] Mozgova et al., 2018; [2] Jiang et al., 2022; [3] Bleisinger et al., 2022; [4] Chen et al., 2018; [5] Lee and Ahmed-Kristensen, 2023; [6] Hilbig et al., 2022; [7] Bickel et al., 2022; [8] Eickhoff et al., 2022; [9] Briard et al., 2021; [10] Tharma et al., 2018; [11] Johnson et al., 2023; [12] Tüchsen et al., 2018	

The information in Table 1 highlights that data availability and data quality are critically important for the use cases discussed. It also shows that integrating these use cases into existing engineering workflows and the capability to monitor efficiency are key to their success. Additionally, clearly defining the problem that needs resolution is essential for devising a data-driven strategy to support development. However, the aspects of organizational and security-aspects, like establishing robust data governance, have not been adequately emphasized. In industrial settings, considerations such as security, compliance, and governance are fundamental for the successful implementation of a use case. These elements are also considered in our assessment outlined above.

4 Case-Study

To demonstrate the effectiveness of the support tools introduced, they were applied in a case study involving a smart espresso machine, specifically to detect user operating errors. The *Decent Espresso DE1 Pro* machine, controlled by a user via a tablet interface, allows for full customization of the espresso extraction process in terms of temperature, pressure, and water flow over time. For easier use, these parameter settings can be saved as different extraction profiles. To make an espresso, users grind espresso beans into a portafilter, tamp the ground espresso, insert the portafilter into the machine, and start the extraction. The machine, equipped with separate pumps for hot and cold water, adjusts the water to the desired temperature via a mixing manifold before it flows through the espresso in the portafilter. The machine contains several sensors that monitor and record temperature, pressure, and water flow data, which are then stored for analysis.

In this case study, the objective was to identify potential user errors during operation to identify areas for product improvements and ideas for new accessory products. Following the framework outlined in Figure 3, data planning started by identifying available data: in this case, operational data collected from sensors due to the specific relevance of objective data. This data from one machine located in an office kitchen used by approximately 60 users, provides a representative sample of diverse user interactions, allowing for broad conclusions from the analysis. Other data like online product reviews or service requests were not considered due to their subjectivity and potential inaccuracy in reflecting user errors.

The sensor data, along with the user-defined extraction profiles, are displayed in real-time on the tablet and recorded in a structured text file (called espresso "shot file"), which logs parameters such as pressure at various timestamps as illustrated in Figure 4. These time steps refer to the values of the parameters, here pressure. For example, after 0.539 seconds, the pressure has reached 0.37 bar. In addition, the shot file stores the pre-set extraction profile chosen by the user. To make further use of the shot file data, it is stored and visualized using a simple proof-of-concept workflow. The shot files are then transferred via OneDrive to a file converter that transforms them into JSON format for easy import into Excel. From Excel, the data is visualized using Power BI, which displays the changes in parameters over time for each espresso extraction. This setup also facilitates further analysis, such as the frequency of specific profiles used over a certain period.

Since the data is stored, all previous espresso shots can be analyzed. To identify operator errors, a database was created to correlate potential errors with temperature, flow, and pressure graphs. To gain an understanding of how potential user errors would reflect in the recorded data, benchmark data was created: A series of controlled experiments was conducted to simulate every potential operating error identified through a root-cause analysis, such as issues with grind size, tamping pressure and angle, portafilter attachment, and cleanliness of machine parts. Each error was induced separately to allow for clear differentiation in the data. The experiments were limited to one preset profile to reduce variation and maximize the relevance of findings to the most commonly used settings. Since the beans, water, and room conditions remained unchanged, non-user-defined variables were minimized.

The data analysis revealed that the graphs of errors caused by very coarse or very fine grinds were distinctly differentiable in the flow rate data. Specifically, a very fine grind resulted in almost no water flow due to overly compacted espresso grounds, whereas a very coarse grind allowed too much flow due to insufficient resistance. This is visualized in Figure 4 by the section of reference data: the top graph (too coarse) and the bottom graph (too fine) are clearly distinguishable. This data enabled the identification of incorrect grinder settings directly from historical data, where approximately 28% of all shots were identified with a too-coarse grind and 8% with a too-fine grind. Altogether, this represented over a third of all shots made with incorrect grinder settings, providing crucial insights into the most common operational errors.

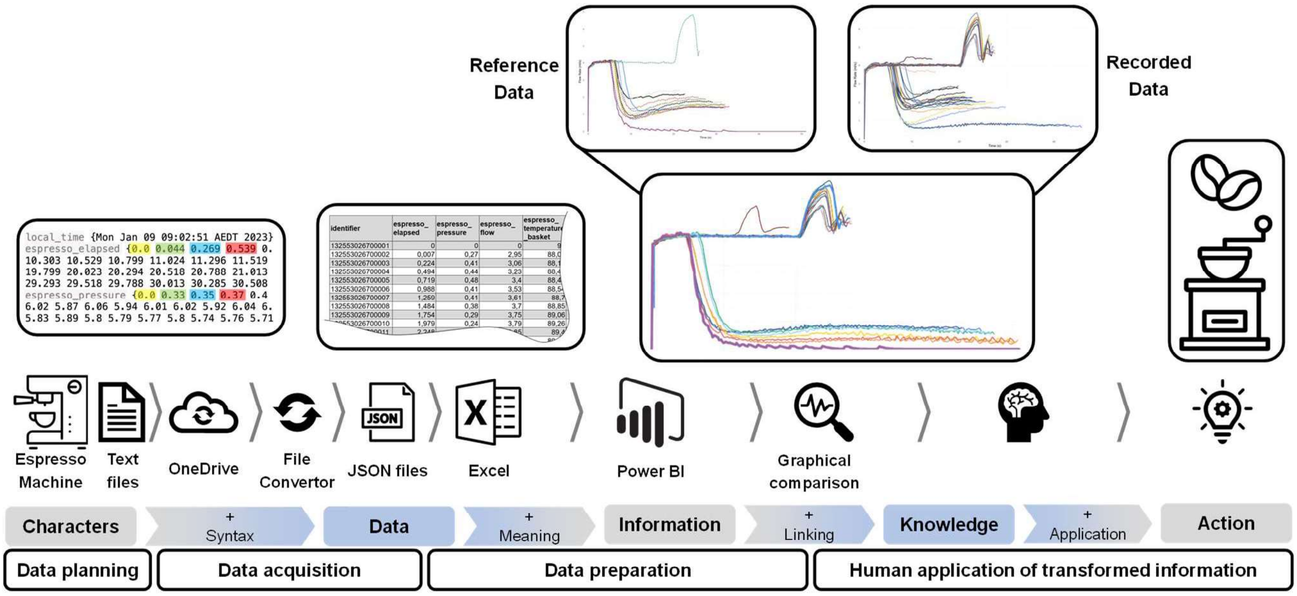

Figure 4. Excerpt from the case study

Looking at the future implications for product design and applying the knowledge acquired in accordance with the described knowledge staircase, a promising product improvement would be to assist customers in preventing operational errors due to incorrect grinder settings. This improvement necessitates a system where feedback on each espresso shot is analyzed to potentially adjust the grinder settings. To facilitate this, each data file documenting an espresso shot must include a value for the grinder setting to link the results of the extraction process to the grind coarseness. The assessment of the grinder setting post-extraction could be managed in two ways: either the user is shown a comparison between a standard example and their own shot graph on the tablet for self-evaluation, or the software analyzes the shot graph and provides recommendations on whether and how the grinder setting should be adjusted. The necessary modifications could be transmitted directly to the grinder for automatic adjustments, or through a notification on the tablet's user interface, allowing the user to manually adjust the grinder. While the development of such a solution falls outside the scope of this paper, the case study has demonstrated the significant value added through the application of data-driven tools as proposed.

5 Reflective conclusion and outlook

Data-driven design supports a bidirectional perspective on development, benefiting both the creation process and the end value delivered to customers. The first dimension of a data-driven approach involves the identification and exploitation of existing data sources. By assessing available data, organizations can uncover insights that were previously unknown or inaccessible. This process involves not only tapping into existing data pools but also enhancing the ability to interpret this data to foster informed decision-making. The derived insights enable organizations to tailor their development strategies, ensuring they are aligned with real-time evidence and trends. Conversely, the design process might start with a predefined objective or a specific use case in mind. In such a case, the challenge shifts to determining the necessary data requirements to support this objective. This entails defining what data is needed, sourcing it effectively, and setting up robust mechanisms for ongoing data acquisition and analysis. This proactive approach in establishing data sources ensures that the design and development process is grounded in data from the outset, enhancing the accuracy and relevance of the solutions developed.

Internally, data-driven design significantly optimizes the company's development processes. For instance, by integrating real-time data analytics, companies can streamline iteration cycles, thus accelerating time to market. Furthermore, predictive analytics can be employed to anticipate and mitigate potential production flaws or bottlenecks, thereby reducing waste and increasing operational efficiency. Externally, the application of data-driven design directly benefits customers. By leveraging data to understand customer usage patterns and preferences, companies can develop solutions that are highly tailored to actual user needs. Additionally, the continuous feedback loop from customer data allows for ongoing refinement of products and services.

This reflects in the case study presented, while illustrative, did not incorporate direct applications of AI or sophisticated data science techniques, which limits the depth of data interaction and learning that could be demonstrated. Future case studies should integrate these technologies to provide a more comprehensive understanding of their impact on DDD. As DDD increasingly integrates AI, the need for specific regulatory frameworks becomes paramount. These frameworks should guide companies not only in implementing DDD effectively but also in managing the lifecycle processes and key events critical to successful transformation. Although extensive research is performed in this paper, it represents just a foundational glimpse into the expansive and rapidly evolving realm of DDD. As technology, particularly in IT and AI, advances at a rapid pace, the results and frameworks presented here may soon require updates to remain relevant and effective. This continuous evolution underscores the transient nature of our findings and suggests that a periodic review could be instrumental in keeping the data-driven methodologies current.

Currently, our research has predominantly focused on the early stages of product development, with minimal exploration into the production and end-of-life phases. A targeted search for applications in Industry 4.0, as well as for strategies related to recycling, reusing, and remanufacturing (the R strategies), could significantly enrich the findings in these later phases. While we identified 40 use cases, only 12 use-cases are presented in detail. A thorough analysis of all 40 cases should be conducted to strengthen the results, thereby enhance the robustness of the findings. To expand our understanding, engaging with communities could provide a broader range of use cases and insights. In addition, our study was generalized across a standard lifecycle model, yet product-specific lifecycle adaptations could provide deeper insights tailored to specific industries or products. Each dimension explored within our study must reflect the broader range of possible scenarios and not just those outlined in generic terms. The question of whether our generic approach can be universally applied across all data types, or should be adjusted to cater to specific phases remains open. This necessitates further investigation into how generic standards can be customized to meet the unique data- and phase-specific needs of different projects.

In conclusion, the implementation of Data-Driven Design within business processes is intricate and multifaceted. It requires not only a robust theoretical framework but also practical applications that evolve with technological advances. The insights gained from this study provide an initial roadmap for organizations interested in harnessing DDD. However, concrete, actionable strategies must be developed as part of an ongoing dialogue among data scientists, industry specialists, and regulatory bodies to ensure that DDD can fulfill its potential in a rapidly changing technological landscape.

References

Bickel, S., Schleich, B., Wartzack, S., 2022. A New Projection Based Method for the Classification of Mechanical Components Using Convolutional Neural Networks. Proceedings of the Design Society 2, 1501–1510.

Bleisinger, O., Malek, C., Holbach, S., 2022. Machine Learning Based Simulation for Design Space Exploration. Proceedings of the Design Society 2, 1521–1530.

Briard, T., Jean, C., Aoussat, A., Véron, P., Cardinal, J.L., Wartzack, S., 2021. Data-driven design challenges in the early stages of the product development process. Proceedings of the Design Society 1, 851–860.

Chen, L., Wang, P., Shi, F., Han, J., Childs, P.R.N., 2018. A computational approach for combinational creativity in design. In: DS 92: Proceedings of the DESIGN 2018 15th International Design Conference. Presented at the DESIGN 2018 - 15th International Design Conference, pp. 1815–1824.

Chowdhury, S., Haftor, D., Pashkevich, N., 2018. Smart Product-Service Systems (Smart PSS) in Industrial Firms: A Literature Review. 10th CIRP Conference on Industrial Product-Service Systems 73, 26-31.

Dausch, V., Roth, D., Bohr, S., Kreimeyer, M., 2023. Challenges for the implementation of digital transformation in brownfield production systems, in Stuttgarter Symposium für Produktentwicklung SSP 2023: Conference Proceedings, pp. 163 – 174.

Deutsches Institut für Normung e. V., 2019. DIN SPEC 33453:2019-09, Entwicklung digitaler Dienstleistungssysteme (Development of digital service systems), Beuth Verlag GmbH.

Eickhoff, T., Forte, S., Göbel, J.C., 2022. Approach for Developing Digital Twins of Smart Products Based on Linked Lifecycle Information. Proceedings of the Design Society 2, 1559–1568.

Gadepally, V., Goodwin, J., Kepner, J., Reuther, A., Reynolds, H., Samsi, S., Su, J. and Martinez, D., 2019. AI Enabling Technologies: A Survey, arXiv preprint, arXiv:1905.03592

Ganz, W., Friedrich, M., Hornung, T., Schneider, B., Tombeil, A.S., 2021. Arbeiten mit Künstlicher Intelligenz (Working with artificial intelligence). Wilhelm, B., Riedel, O., Fraunhofer IAO, Stuttgart, Germany.

Hilbig, K., Nowka, M., Redeker, J., Watschke, H., Friesen, V., Duden, A., Vietor, T., 2022. Data-Driven Design Support for Additively Manufactured Heating Elements. Proceedings of the Design Society 2, 1391–1400.

Huikkola, T., Kohtamäki, M., Rabetino, R., Makkonen, H., Holtkamp, P., 2022. Unfolding the simple heuristics of smart solution development, Journal of Service Management, Vol. 33 No. 1., 121-142, Emerald Publishing Limited.

International Organisation for Standardisation (IOS), 2022. Informationstechnik - Künstliche Intelligenz - Konzepte und Terminologie der Künstlichen Intelligenz, Beuth Verlag, ISO/IEC 22989:2022.

International Organisation for Standardisation (IOS), 2023. Information technology — Artificial intelligence — Data life cycle framework, ISO copyright office, ISO/IEC 8183:2023(E).

Jiang, S., Sarica, S., Song, B., Hu, J., Luo, J., 2022. Patent Data for Engineering Design: A Review. Proceedings of the Design Society 2, 723–732.

Johnson, J., Hurst, A., Safayeni, F., 2023. Managing data-driven design: A survey of the literature and future directions. Proceedings of the Design Society 3, 2525–2534.

Kim, H.H.M., Liu, Y., Wang, H.C.L., Wang, Y., 2017. Special Issue: Data-Driven Design (D3), Mechanical Design, Vol. 139 (11).
Kirchherr, J., Reike, D., Hekkert, M., 2017. Conceptualizing the circular economy: An analysis of 114 definitions, Resources, Conservation and Recycling, Vol. 127, pp. 221-232.
Langley, D.J., 2022. Digital Product-Service Systems: The Role of Data in the Transition to Servitization Business Models, Sustainability, Vol. 14 (3),
Lee B., Ahmed-Kristensen S., 2023. Four patterns of data-driven design activities in new product development, Proceedings of the Design Society, Vol. 3, pp. 1925-1934.
Liu, Z., Ming, X., Song, W., Qiu, S., Qu, Y., 2018. A perspective on value co-creation-oriented framework for smart product-service system. 10th CIRP Conference on Industrial Product-Service Systems 73, 155-160.
Meyer, M., Wiederkehr, I., Koldewey, C., Dumitrescu, R., 2022. Planning the Analysis of Use Phase Data in Product Planning. Proceedings of the Design Society 2, 753–762.
Mozgova, I., Yanchevskyi, I., Lachmayer, R., 2018. Prediction of the residual life of a component under intensive random dynamic loading within the scope of the technical inheritance, in: DS 92: Proceedings of the DESIGN 2018 15th International Design Conference, 1643–1650.
Müller, B., Roth, D., Kreimeyer, M., 2023. Barriers to the use of artificial intelligence in the product development – a survey of dimensions involved, Proceedings of the Design Society, Vol. 3, pp. 757-766,
North, K., Kumta, G., 2018. Knowledge Management – Value Creation Through Organizational Learning, Springer, Cham, Switzerland.
Opazo-Baséz, M., Vendrell-Herrero, F., Bustinza, O.F., Vaillant, Y., Maric, J., 2023. Is digital transformation equally attractive to all manufacturers? Contextualizing the operational and customer benefits of smart manufacturing. In: International Journal of Physical, Distribution & Logistics, Management, Vol. 53 No. 4, 489-511.
Paliyenko, Y., Salinas, R., Roth, D., Kreimeyer, M., 2023. Vorgehen zur Modellierung des Wertschöpfungsnetzwerks smarter Produkt-Service-Systeme. 34. DfX-Symposium, 1-10.
Paliyenko, Y., Tüzün, G.J., Roth, D., Kreimeyer, M., 2022. Inquiry and Analysis of Challenges in the Development of Smart Product-Service Systems. Proceedings of the Design Society 2, 1935-1944.
Peruzzini, M., Wiesner, S., 2020. Systematic development ofproduct-service systems. Systems Engineering in Research and Industrial Practice: Foundations, Developments and Challenges. Springer International Publishing, pp. 265–296.
Qureshi, A.J., Gericke, K., Blessing, L., 2014. Stages in product lifecycle: Trans-disciplinary design context, in 24th CIRP Design Conference, pp. 224-229.
Tharma, R., Winter, R., Eigner, M., 2018. An approach for the implementation of the digital twin in the automotive wiring harness field, DS 92: Proceedings of the DESIGN 2018 15th International Design Conference, pp. 3023-3032.
Tüchsen, J., Pop, A.C., Koch, M., Schleich, B., Wartzack, S., 2018. Data-driven design selection and generation - an industrial case study on electric motors, in: DS 92: Proceedings of the DESIGN 2018 15th International Design Conference, 1709–1720.
Verein Deutscher Ingenieure 2021, VDI/VDE 2206:2021: Development of mechatronic and cyber-physical systems, Germany.
Weber, C., Wielang, M., Reimann, P., 2018. Konzepte zur Datenverarbeitung in Referenzarchitekturen für Industrie 4.0. Datenbank Spektrum 18, 39-50.
Zheng, P., Chen, C.H., Wang, Z., 2021. Smart Product-Service Systems. Elsevier, Amsterdam.