FOUR PATTERNS OF DATA-DRIVEN DESIGN ACTIVITIES IN NEW PRODUCT DEVELOPMENT

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ABSTRACT

In the midst of Industry 4.0 where digitalisation is stimulated through the Internet of Things (IoT), Big Data, and machine learning technologies, an increasing volume of valuable data has been acquired from sensors and interconnected devices. This data-driven paradigm can enable organisations to create new or improved products and services, build long-term customer relationships in a value co-creation manner, adapt to continuous business reconfiguration or address societal challenges such as sustainability. Scientific research addressing Data-driven design has increased steadily in the last few years. However, despite this, there is still a need for a comprehensive understanding of data-driven design processes. Thus, through a systematic literature review, we review the data-driven design activities observed in the new product and service development and types of data utilised in New Product Development (NPD) process. This paper contributes to design research and through reviewing the current landscape of Data-driven design identifies ten data-driven design activities and four-dimensional aspects in NPD process.

Keywords: Big data, New product development, Design practice, Data-driven design

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1 INTRODUCTION

In Industry 4.0, the cyber-physical systems, a mixture of physical and digital components, are fast-growing, generating a vast amount of data worldwide. Products are transformed into smart products to systems that can communicate with one another (Porter and Heppelmann, 2014), ultimately making decisions with minimum human input (Lee, 2021). Digitalisation brings new opportunities to integrate data to inform the design of new products and services, called data-driven design. Data-Driven Design (DDD) implies that the data being used assists the development of products and services. Despite a lack of a unified definition in literature, it has been widely adopted in various ways during the new product development (NPD) process. This includes understanding the type of data, how this can inform the designs of products, customise for user segments, support design decisions, and embed reliability into the systems. Notwithstanding a growing interest in data-driven design research in the NPD process, few works discuss a comprehensive understanding of data-driven design, reflecting the nascent field. For practitioners and researchers alike, understanding the types of data used in the data-driven design process and how data and analytics can support designers when developing new products and services would support the creation of suitable methods and processes. Although there are a few review papers on data-driven design, they are limited in certain NPD stages (Hou and Jiao, 2020), apart from Cantamessa et al.'s study, which proposes a comprehensive framework and challenges of digitalisation (2020). Therefore, we undertake a systematic literature review to comprehend the data-driven design activities observed in the new product and service development and the types of data utilised in NPD process. The paper describes the methodology of systematic literature review in Section 2, followed by the types of data-driven design activities and data sources employed in the NPD process (Section 3). Finally, conclusions are drawn in Section 4.

2 METHODOLOGY

For systematic literature review, we follow a structured approach to reviewing the relevant literature following certain steps, including planning the review, selecting and reviewing the papers, synthesising the results, and reporting the findings (Tranfield et al., 2003). The systematic literature review process started with a database search. We selected five electronic databases, including ACM Digital Library, Web of Science, Scopus, ProQuest, and IEEE Library, which offer comprehensive coverage of the topics under study. Our search strategy revolved around the term “Data-Driven Design”, “Data-Enabled Design”, “Data-Led Design” in the title and author keyword. While using snowballing as a search approach for systematic literature review, thirty-four studies were added that include papers using different terminologies of DDD, such as “Data-Informed Design” and “Design Analytics”. With the focus on one of the attributes of IoT, cyber-physical systems and smart PSS, which is to enable continuous development, we particularly investigated design activities employing usage phase data. Based on a systematic literature review, the paper aims to address the following questions: "How is sensor collected data and analytics utilised for product and service development and delivery?

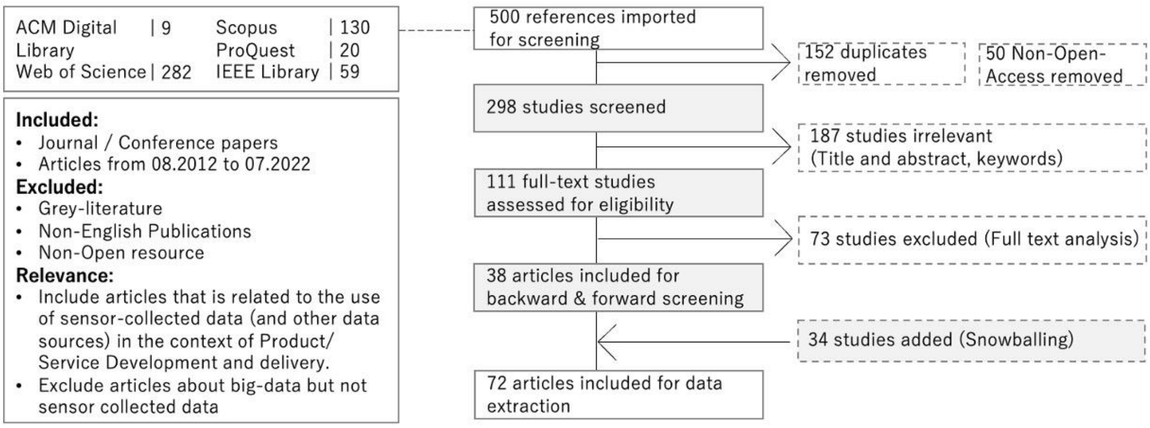

Figure 1. The review methodology

We included studies that employed any type of research design. We restricted the source type to English full-text peer-reviewed papers, such as journal articles and conference proceedings. This included papers

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in magazine articles that have been peer-reviewed. Grey literature and non-open resources were excluded. A search of the studies was conducted in July 2022 and limited to papers published between 2012 and 2022. A total amount of 500 documents have been found in the five electronic databases. After discarding duplicates and non-open access papers, a final set of 298 papers was considered for analysis. These papers have been assessed in two ways. First, the analysis of titles, abstracts and keywords led to a set of 111 papers. Then, the reading of the entire manuscripts was conducted to a final amount of 38 papers. The selection was based on the relevance of the research question. Specifically, we selected only those papers contributing to the use of sensor-collected data (and other data sources) and data analytics in the context of product and service development and delivery. Last, 34 more articles were added to the list through the snowballing method. Applying the criteria, a set of 72 articles were selected for data analysis. The entire process of selection and examination of the papers was conducted by the authors. Figure 1 shows the research strategy used in the systematic literature review.

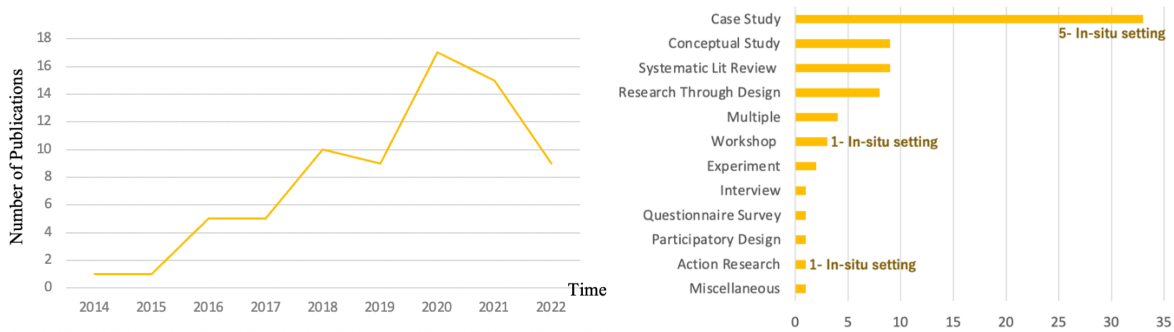

Figure 2. Numbers of publications, and research types and settings

Figure 2 depicts the number of publications over time and research types and settings. There has been a steady increase in publications from 2014 until 2022. Various types of research have been conducted, but case study methodology was the most applied to data-driven design research, followed by conceptual study, and systematic literature review. In general, most research conducted was mostly theoretical. Indeed, only ten percent of the research, three case studies, one workshop, and one action research, was performed on-site. Through the thematic analysis, we were able to identify DDD activities along with the future research agenda, which will be presented in the next section.

3 FINDINGS AND DISCUSSIONS

Findings indicate that usage data is utilised for all sub-phases of the NPD process in a value creation manner. A generic NPD process is applied to map which DDD activities and data sources are involved in each phase of the development process. The Launch phase is not considered and thus omitted, as there is no DDD activities involved. However, the 'in-service' phase is added, reflecting the attribute of cyber-physical systems continuous data-driven design processes (Lee et al., 2022). In the same vein, although building business strategy and ecosystem are more related to the pre-NPD phase, these activities are mapped alongside with NPD process. Also, although product portfolio planning happens in the planning phase, the papers are mapped in the 'In service' phase as the activities only happen with the data collected in the phase. The systematic literature review informed ten data-driven design activities, which are indicated in the colour legend and the type of data sources employed in the different development cycles (Figure 3). Each colour block indicates the number of papers that studied the topic and dealt with the type of data sources for DDD.

Some papers cover more than two types of DDD activities and do not explicitly mention the type of data source; thus, the sum number of papers for 'Type of DDD activities' and 'Type of data sources' do not match. Overall, it shows a clear predominance of studies integrating data science in the phase of ‘concept development’ and ‘in service’. Among ten data-driven design activities, validating/supporting design decisions is evenly distributed across the phases. Some activities depend on the phase, such as user behaviour change or assess/predict/improve the system performance. In terms of data sources employed in the process, utilising only sensor(s) collected data and integrating sensor(s) collected data with other data sources is fifty-fifty in proportion. As concept development and in-service are the two phases that involve data-driven activities the most, data sources are utilised the most in the two phases.

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Further details on type of data driven design activities, type of data sources utilised in NPD process, and the research agenda will be described below.

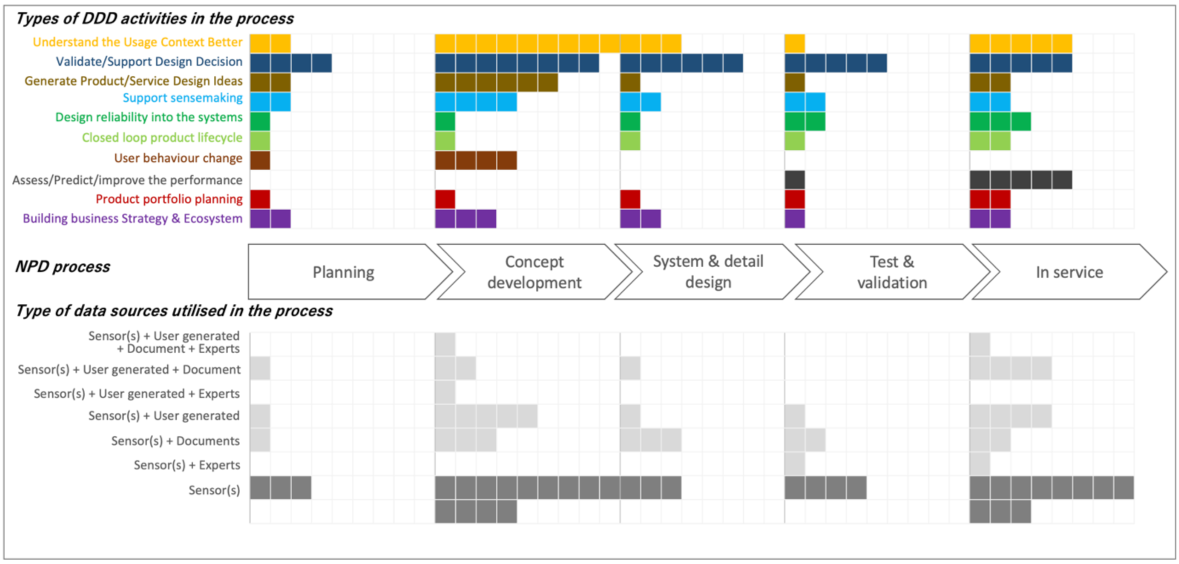

Figure 3. Type of data driven design activities and data sources in the NPD process

3.1 Type of data driven design activities in the NPD process

3.1.1 Understand the usage context better

Researchers consider data-driven design can improve existing approaches to understanding user context better for a couple of reasons, i.e., existing methods (observation, empathic design and interview) are not suitable to capture the actual usage context (van den Heuvel et al., 2022), latent customer needs and intrinsic product requirements (Lakoju et al., 2021), and often subjective and time-consuming (Engel and Ebel, 2019; Zheng et al., 2019). The ultimate aim of understanding the usage context better is to ensure the success of customised solution (product-service) design (Zheng et al., 2019). The majority of the studies focus on demonstrating how data and analytics can better understand the usage context in concept development and in-service phases and thus develop customised products and services. For example, researchers developed and deployed the sensor-embedded baby bottle, the 'data canvas' communication system to facilitate a continuous dialogue between the Health Care Professionals and parents, and the data dashboard to enable remote data collection and design intervention (Bogers et al., 2016: 2018; van den Heuvel *et al*., 2020).

Based on a data-driven design approach, designers can understand the user better and thus develop customised products and services. During this process, identifying essential and highly relevant data to inform customisation is critical. In this regard, Tan et al. (2020) propose a process of identifying the specific data required for customisation in order to move from a bespoke process to one that maximises patient comfort through a case study of orthoses fabrication. Stavrakos et al. (2016; 2016) developed an approach that uses anthropometric data from 200 head scans to inform the design variants needed in order to maximise comfort within the context of headset designs. The research led to a process that is now embedded within the company, and here data is collected independently from the product or product development process but then developed into a process that can be used early on to predict likely comfort without extensive prototyping and testing, and also to define the number of variants. Thus, in this example, the data collection is not from the product but from potential users informing the design of the products. On the other hand, Lakoju et al. (2021) and Zhang et al. (2017) propose formulas for collecting and processing valuable product usage data and improving user satisfaction. There is limited research on encouraging user engagement in data collection, which would affect the development of personalised products and services at the end (Dooley, 2021; Zheng et al., 2019: 2020). Each researcher's approach is distinctive; for instance, Zheng et al. (2019, 2020) propose a cloud-based data-driven cyber-physical approach, and computational algorithms reward people who share data. Moreover, Dooley (2021) discusses active and passive public participation methods in sharing data in the public sector.

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3.1.2 Validate and support design decisions

Along with 'understand the usage context better', 'validate and support design decisions' draws researchers' interest the most in data-driven design activities. Researchers investigate data-driven design for the validation of and support for design decisions for various reasons, including a lack of research on assessment models for early decision-making (Bertoni, Alessandro et al., 2017), the limitation of traditional product optimisation method (Zhang et al., 2019), the design uncertainties in complex system engineering (Du and Zhu, 2018) and the shortcomings of the current engineering practices in designing smart PSS (Machchhar and Bertoni, 2021). Accordingly, the studies on this DDD activities are classified into three sub-streams: how data and analytics can validate design hypotheses, reduce design variables through obtaining optimal values of design parameters, and empower a proactive closed loop of intelligent design decisions. Kushiro et al. (2014) and Bertoni et al. (2017) propose the phases of elaborating and validating requirements with data mining algorithms as decision support.

In order to reduce design variables, researchers' approaches are all different. Zhang et al. (2019), Du and Zhu (2018) and Yang and Xiao (2021) suggest a decision tree or a structural equation model with computational algorithms calculate and determine function requirement and design provability. Similarly, Zheng et al. (2019) propose a design structure matrix and algorithms for design change recommendation. Singh and Wilcox (2021) discuss statistical methods to quantify and optimise different types and sequences of decisions, whereas De longueville et al. (2021) propose a flow diagram of digital thread in the context of aircraft design. Finally, How and Jiao (2020) and Machchhar and Bertoni (2021) discuss the framework for closed loop of intelligent design.

3.1.3 Generate product and service design ideas

Data-driven generating product and service design ideas happens the most in the concept development phase through two different approaches; one is a conceptual model of the analytic approach to generate service ideas, and the other is service ideation tools for an intuitive approach. The analytic approach is discussed as there is a lack of concept generation methods from data (Kim et al., 2016), effective design approach for smart PSS service innovation (Zheng et al., 2018) and accordingly, the conceptual frameworks of informatics-based idea generation are proposed (Kim et al., 2016; Lim et al., 2018; Zheng et al., 2018). On the other hand, tools to encourage an intuitive approach are proposed due to the designers' challenges working with data (Lim et al., 2021) or difficulties applying the existing ideation tools for IoT development (de Roeck et al., 2019). Both ways of generating product and service design ideas can be complemented.

3.1.4 Build business strategy and ecosystem

Data-driven design activities of building business strategy and ecosystem are observed across different NPD phases. Most studies address how to scale up the smart PSS into a system of systems and data handling strategy. The evolution of the smart product, from non-connected (product) to one-to-one connected (smart product), multiple to one connected (product system) and ecosystem (system of systems) has been discussed by several scholars (Bogers et al., 2018; Porter and Heppelmann, 2014; Zheng et al., 2019). Watanabe et al. (2020) and Cantamessa et al. (2020) propose conceptual frameworks that help understand the ecosystem of connected products with a focus on the inter-relational and interdependent nature of IoT systems. In contrast, Bogers et al. (2018) explore the usage patterns of different personal health devices through an in-situ case study. Similarly, Noortman et al. (2022) introduce recommendations on how to scale up the data infrastructure and data handling processes in the clinical context, which can conflict with the explorative character of the data-enabled design. Wilberg et al. (2017) propose a data strategy development process for data-driven design.

3.1.5 Support sense-making

Several researchers highlight that data-driven design may support sensemaking in the concept development phase. The challenges of requirement elicitation include the cognitive load and potential mental bias of designers, limited data sharing between the departments within organisations, challenges of identifying stakeholders' requirements, the lack of deep understanding of the end users with the large scale and heterogeneous data and integrating domain knowledge into a common knowledge repository to support an integrated solution. To solve these issues, data management frameworks and methods for requirement elicitations are proposed, such as graph-based requirement elicitations (Hollauer et al., 2018;

Wang et al., 2019, 2021) and an ontology-based framework (Maleki et al., 2018). Ghosh et al. (2017) propose a customisable cyber-empathic design framework through which designers may integrate user-product interaction data with information obtained from traditional methods like surveys. It will assist them in mapping product features and attributes to consumer perceptions, ultimately reducing designers' cognitive load and potential mental bias. From a comprehensive point of view, Carlos Quiñones-Gómez (2021) explains how qualitative and quantitative data are incorporated into the design process and transformed into knowledge as design materials.

3.1.6 Embed reliability into the systems

While the cyber-physical systems are being delivered to the users, a large quantity of data and the system should be managed securely and reliably. However, developing reliable systems is challenging and draws various researchers' interest. Through the review, a couple of papers argue that product reliability can be improved through data and analytics. For example, Geiger and Sarakakis's (2016) conceptual paper argues that product reliability can be increased by requiring different data at different stages of the NPD process. Van Eck et al. (2019) develop a usability test scenario planning tool to embed reliability in the test and validation phase. The authors believe that test scenarios created manually are often limited and biased, reliant on the engineers' knowledge. Thus, using the tool's analytics to generate the test scenarios would overcome this. A secure and trustworthy data collection and utilisation method have been considered critical in reliable system development. Love et al. (2020) introduce the conceptual toolbox of a 'design plumber' through which a good quantity of data can be collected and managed in good quality. The system's reliability can be even more critical when used for medical purposes. Zhou et al. (2021) propose computational algorithms that monitor and detect anomalies in patients' bodies.

3.1.7 Serve product lifecycle better

With the product information, researchers argue that closed-loop product lifecycle management can be achieved. However, there are only a few studies on the emergent role of product usage data and the lack of interaction and iteration between big data analysis and various activities in the entire product lifecycle. Tao et al. (2018) introduce new models and methods for product design, manufacturing, and service driven by digital twins. Specifically, virtual factors and physical factors with data to be considered in each phase of conceptual design, detailed design and virtual verification are comprehensively explained as digital twin-based product design. Holler et al. (2016) describe the rationales, opportunities, conditions, and obstacles in enabling closed-loop Product Lifecycle Management (PLM).

3.1.8 Product portfolio planning

Two studies on DDD for product portfolio planning are identified, which are conducted by the same scholars (Meyer et al., 2021: 2022). The scholars argue that even if product planning and data analytics are two established and independent research areas and together, they span the new research areas, research on this topic is absent. Therefore, they explore the concepts, advantages, and challenges of utilising usage data in product planning through a systematic literature review and interview. According to Meyer et al. (2021), usage data-driven product planning consists of six main concepts: capturing of user-generated data, product operating data and environmental data; data feedback into product planning; data analysis with data mining and machine learning techniques; fact-based decision making; improvement of existing and future products; and reinforcing loop of inverse and forward design.

3.1.9 User behaviour change

Six studies are identified dealing with data-driven design for user behaviour change. Most of the studies utilise a specific approach to investigate user behaviour change, called 'data-enabled design', which is "a situated design practice of using data as a creative material for designing intelligent ecosystems". The studies highlight the need for a better understanding of everyday behaviour that how people interact with cyber-physical systems in a specific context. For instance, medication adherence (van den Heuvel et al., 2020), post-surgery lifestyle changes (Jansen et al., 2020; Lovei et al., 2020; Versteegden et al., 2022), and active lifestyle (Marti et al., 2016). Contrary, Montecchi and Becanttini (2021) propose a modelling framework to identify relevant data to collect for inferring user behaviour and inform the design of solutions capable of triggering sustainable behaviour.

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3.1.10 Assess, predict, and improve the system performance

The last research areas identified concerning data-driven design activities is 'assess, predict and improve the system performance'. Operational data collected in the text and validation and in-service phase can enhance the health of the product, which will then increase the product reliability (Geiger and Sarakakis, 2016; Shin et al., 2015). As such, an integrated design improvement approach consisting of data modelling and analysis techniques are proposed by a couple of researchers (Ma et al., 2017; Riesener et al., 2019; Shin et al., 2015). Taking another step forward, Khoshkangini et al. (2020) introduce the conceptual view of two machine learning pipelines for predicting individual components' failure/claims. From a comprehensive point of view, Orlovska et al. (2020) and Lukačević et al. (2022) discuss the benefits and challenges of using operational data in the system evaluation through case study methodology.

In summarising the literature on data-driven design, the DDD activities can be classified into four dimensions: a data-driven design for exploration, verification, proliferation, and trustworthiness (Table 1). Exploratory DDD, the primary role of data and analytics in the design process, is to understand the usage context better, generate product and service design ideas, and change user behaviours. Verificative DDD activities include supporting sensemaking and validating design decisions. DDD enables scaling up the existing systems through product portfolio planning, better-serving product lifecycle, and building business strategy and ecosystem. Data and analytics also contribute to the trust building of the system through the assessment, prediction and improvement of the system performance and embedding of design reliability into the systems.

Table 1. Four patterns of data-driven design activities

Exploration	Understand the usage context better; Generate product and service design ideas; Change user behaviour.
Verification	Support sensemaking; Validate and support design decision
Proliferation	Build business strategy & ecosystem; Product portfolio planning; Closed loop product lifecycle
Trustworthiness	Design reliability into the systems; Assess, predict, and improve the system performance

3.2 Types of data sources employed in NPD process

Each data source can be explained further in detail. Sensor collected data can be divided into three subcategories which are product and space usage (e.g. log data, pressure, timestamp, accelerometers, GPS, temperature, and sound), product performance (e.g. CPU utilisation, battery capacity, RAM, and Storage), and environment (e.g. weather). User-generated data include ratings and comments on products and services, video recordings, individual daily reports, and manual inputs of product use. Types of documents vary, including supply-chain data, point of sales data, requirement specification document, use scenario, crash simulation data, service provider data (maintenance cost), and marketer/designer generated data from observation and interview. In terms of types of data studied in DDD papers, sensor-generated data hold a dominant position, followed by 'sensor and user-generated data', 'sensor-generated data with documents' and 'sensor, user-generated data with document'.

Although integrating domain knowledge with big data is argued critical in improving detection accuracy, timeliness, and transparency (Zhou et al., 2021), suggesting new innovative ideas (Briard et al., 2021; Kim et al., 2016), and supporting sense-making (Maleki et al., 2018), only a few papers utilise data from domain experts with other data sources. Research papers that solely use sensor(s) data have a fifty-fifty chance of using data from one or multiple sensors. When using one single sensor-collected data, they are either product usage or performance data to understand users in an objective manner, improve product lifecycle, or assess the system performances. It is likely to use multiple data sources when DDD is undertaken to support sensemaking, enable co-development, and understand usage context better. Findings also indicate that use phase data is harnessed predominantly in the concept development and in-service stage, which contradicts the contentions used at the operations phase the most (Shin et al., 2009: 2014).

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4 CONCLUSION

The paper has presented the results of a systematic literature review investigating data-driven design activities and data sources involved in the NPD process. The systematic literature review identifies seventy-two scientific contributions to data-driven design activities in different product and service development stages. The analysis focuses on different data sources and data-driven activities identified to develop smart systems. The results indicate that currently, data-driven design activities involve four different data sources: sensor-collected, user-generated, expert-generated, and internal/external documents. These data sources were utilised in various combinations in different NPD phases. Also, the analysis results showed the types of data-driven design activities: 1. to understand the usage context better; 2. Generate product/service design ideas; 3. change user behaviours; 4. support sensemaking; 5. validate design decisions; 6. build business strategy and ecosystem; 7. plan product portfolio; 8. improve product lifecycle; 9. embed design reliability into the systems; and 10. assess/predict/improve the product performance. This paper contributes by identifying ten data-driven design activities that can be clustered into four aspects of data-driven design: a data-driven design for exploration, verification, proliferation, and trustworthiness. The four aspects of DDD will support understanding the types of design activities through which the practitioners can use data in the product development process. The research presented in part of a more comprehensive research effort that examines the state-of-the-art in DDD across new product and service development processes. The four-dimensional aspects of DDD still need to be further structured and positioned within the design and engineering design knowledge. Therefore, this paper's findings provide the basis for developing novel frameworks of data-driven design.

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