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D³IKIT: data-driven design innovation kit

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Abstract

The utilization of data in design is a crucial aspect of shaping the product and service development. Despite the lack of extensive research on this subject, this study aims to bridge the gap by introducing the 'D³IKIT', a data-driven design process and toolkit. Through workshops, this process and toolkit offer a practical method for creating innovative product and service concepts using data and machine learning. Developed and tested with the participation of 42 individuals, the 'D³IKIT' provides valuable insights for both practitioners and academics.

Keywords: data-driven design, internet of things (IoT), data-driven innovation, service design

1. Introduction

Industry 4.0 presents an opportunity for a shift towards more interconnected products and services, giving rise to intricate systems of systems. This shift demands the creation of new business and design processes and introduces fresh possibilities for harnessing data to create value (Gann et al., 2014; Papalambros, 2015; Porter and Heppelmann, 2014). Data-driven design is the use of methods, approaches, and processes that leverage data to support the development of products and services (Lee and Ahmed-Kristensen, 2023). With the continuous growth of data and its significance throughout the entire product lifecycle (Tao et al., 2018), companies are confronted with the challenge of how to extract meaningful value from it (Speed et al., 2019; Lee, 2022). The effective utilization of the data for value creation are recognized as pivotal technological drivers for companies to sustain competitiveness and drive innovation opportunities (Chattopadhyay et al., 2017; Lee et al., 2018; Lee et al., 2022b). The potential of using data in the design and development of new products and services is increasingly acknowledged by practitioners and researchers (Kim et al., 2017; Lee et al., 2019). For instance, the design research community is increasingly interested in exploring how product and interaction designers can interact with sensor data and integrate it into design processes. In other words, there is a focus on understanding how data can serve as a creative "design material." (Dove et al., 2017).
Nevertheless, only limited research seeks to explain how data is utilized in the design process (Bogers et al., 2016). There are a few studies explored the data-driven design process for designing new product service concepts (Quiñones-Gómez, 2021; Diamond et al., 2017; Kim et al., 2016; Van Kollenburg and Bogers, 2019; Zheng et al., 2018; Lee et al., 2022a). However, the majority of proposed data-driven design processes are conceptual, posing challenges for both practitioners in applying these approaches to their work and for academics to understand the validity of these approaches. Therefore, this study aims to develop a data-driven design process to design new product and service concepts through a series of workshops with industry, thus conducted in a real-world context. Two workshops were conducted with 42 practitioners and academics in total and 'D³IKIT' was developed and tested to generate new ideas from data and machine learning. The process includes developing novel design tools and processes to facilitate the generation of new product service concept design, specifically for using data to generate value for the companies. The structure of this paper is as follows. The paper describes

literature review of data-driven design concepts and existing data-driven design process (Section 2), followed by the methodology of data-driven design approach in Section 3 and the findings and discussions about the D³IKIT (Section 4). Finally, conclusions are drawn in Section 5.

2. Literature review

2.1. The concepts of Data-x design

The term Data-Driven Design was first introduced by Domazet et al. in 1995. Although it has been extensively explored in the literature, there isn't a universally agreed-upon definition. According to Lee and Ahmed-Kristensen (2023) review of the field and related concepts, it implies the use of methods, approaches, and processes that leverage data to support the development of products and services. Data-driven design stands out as one of the most frequently referenced concepts in the literature within the realm of related data-x design concepts, which encompass data-enabled design (Bogers et al., 2016), data-informed design , data-aware design, data-centric design (King et al., 2017), and data analytics. To summarise, "Data-driven design" serves as an overarching term, and the different concepts within the data-x design domain do not have mutually exclusive relationships (Lee and Ahmed-Kristensen, 2023). However, these approaches have diversified. For example, "data-informed design" primarily serves the purpose of supporting decision-making, while "data-driven design" encompasses this role and extends beyond it. In this context, "data-driven design," "data-aware design," and "data-enabled design" exhibit a more comprehensive level of collaboration and problem-solving compared to "data-informed design," "data-centric design," and "design analytics," which are more centred on providing design solutions by supporting decision-making in the design process. The term DDD is used broadly to describe various aspects within the New Product Development (NPD) process: the extensive use of Big data, the balanced integration of Big and Thick data, as well as the utilization of machine learning. Consequently, DDD can be defined as "a design approach that leverages big data or data science algorithms in conjunction with thick data for innovation in products and services."

Through an extensive analysis of the available literature, Lee and Ahmed-Kristensen (2023) have gained insights into the utilization of data and machine learning in new product and service development. In their study, they identified seven distinct data-driven design activities and examined the types of data sources employed within the new product service development process. Seven data-driven design activities include: planning, discovering, defining, generating, customising, maintaining and validating (Table 1). These data-driven design activities as an analysis tool, we explore what would companies like to use data for in their business context.

Table 1. Seven data-driven design activities and definitions (Lee and Ahmed-Kristensen, 2023)

Types of data-driven design activities	Definitions
Planning	Shape organisations' aspirations and goals; Set the strategic level of design; and plan product families and portfolio.
Discovering	Discover the design problems, use issues and thus understand the context better and change user behaviours
Defining	Define the feature specifications or the challenges in a different way from the insights gathered from the discovering phase
Generating	Create product and service concept ideas
Customising	Develop customised or optimised products and services
Maintaining	Support system maintenance through assessing or predicting the system performance
Validating	Support design reliability and effective decision making; and reduce uncertainty, complexity and risk.

2.2. Data-driven design process

Acknowledging the lack of studies on the design of service concepts starting from data, Kim et al (2016) propose a data-driven approach to designing new service concepts that integrates insights from the literature related to big data and service concept design. The suggested method encompasses five key stages: a) Gathering accessible data and consolidating it for analysis; b) Creating an analysis model to streamline the data analysis process; c) Examining the data to gain insights into customer behaviours and contexts; d) Formulating service concepts based on the knowledge derived from data analysis; and e) Crafting novel service ideas and concepts. Another study compares data-driven design and user centred design process (Diamond et al., 2017). Bogers and Van Kollenburg (2019) propose data-enabled design, which consists of two steps: contextual step in which design researchers gain contextualised understanding of the design space by utilising a combination of quantitative sensor data and qualitative user insights and informed step, in which design researchers design while the prototype(s) remain in the field. From a more comprehensive perspective, Lee et al (2022a) introduce a conceptual model of the IoT development process, which highlights continuous cycles of data enabled design. Feng et al. (2020) propose data-driven product design research framework through reviewing the product design process from a data-driven perspective. It consists of basic process of product design, classification of data-driven design methods, data modelling, and design knowledge base. Quiñones-Gómez (2021) present the data-driven design model process. Figure 1 shows the selected data-driven design processes from literature.

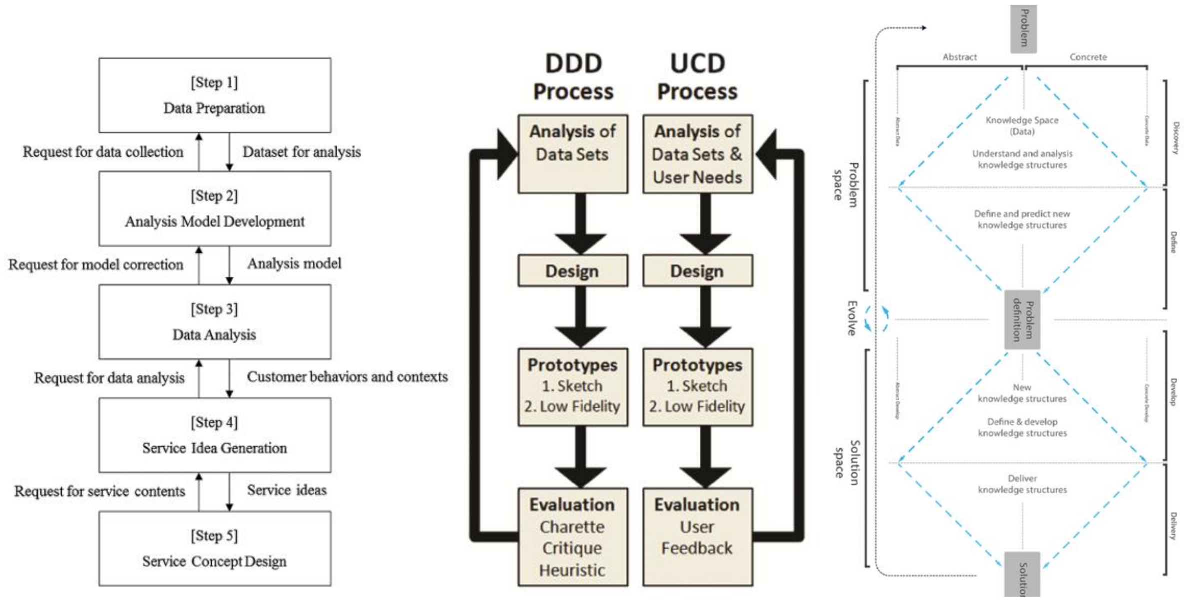

Figure 1. Selected data-driven design processes from literature (from left, Kim et al., 2016; Diamond et al., 2017; Quiñones-Gómez, 2021)

However, proposed design processes are either conceptual or based on specific context, which makes it difficult for the practitioners to apply the approach in their practice. Thus, we develop and test data-driven design process with toolkit, adapted from the Double Diamond Design Process, a representative of design processes. The section below will describe the detailed methodology of developing the data-driven design process.

3. Methodology

The data-driven design process and toolkit were designed and tested through workshops. The primary objectives of the workshop were, firstly, to understand how companies would like to utilize their data among the seven data-driven design activities, and secondly, to develop and validate the data-driven design process and toolkit. Accordingly, the workshop addressed the research questions: 1. What data-driven design activities would companies like to undertake to generate value; and 2. What are the data-driven design process and tools in the early phases of the product service design process? The objectives were first to comprehend the current opportunities of data-driven design within the product service development process and then to present the data-driven design process and tools, called "D³IKIT". Two workshops were held in person and same structure was adopted across both, consisting of three parts,

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namely understanding data-driven design, sharing data context/challenges and deciding the idea, and generating the data-driven innovation concept (Figure 2). Workshop lasted for 3.5 hours including three parts. The first one hour was dedicated to introducing the concept of data-driven design and the seven data-driven design activities with the framework. Then there was a problem definition point for both the first and second workshops. The first workshop was driven by the goal of achieving net zero, and the second workshop was driven by the mission that each company has faced. The next 1.5 hours were dedicated to sharing challenges and opportunities around potential data and making a problem statement, and the last hour was used to develop the selected idea more in detail to make it concrete.

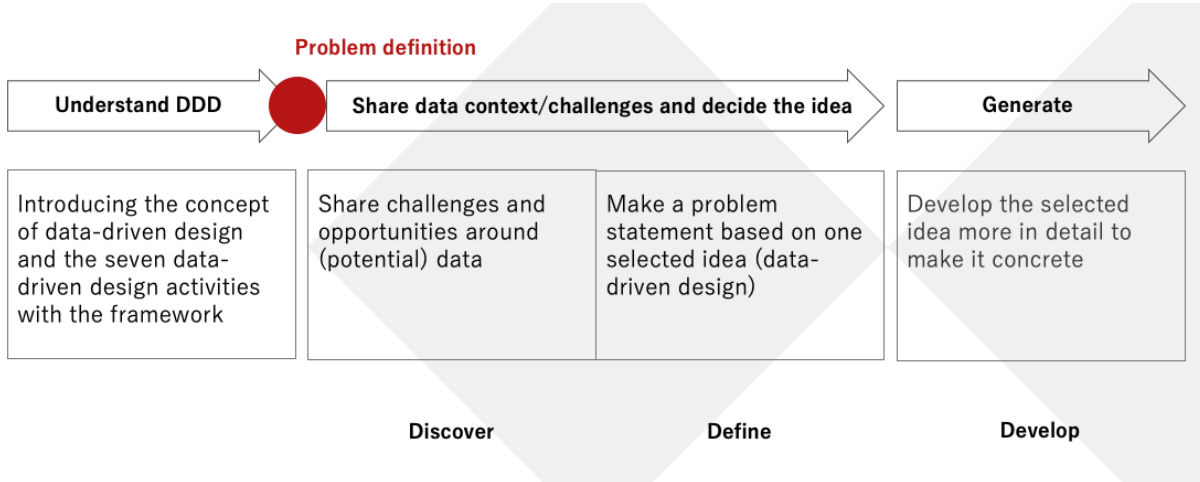

Figure 2. Workshop flow as data-driven design process

Two workshops were facilitated between May and June 2023. In the first workshop, thirty-three participants were involved, including thirty practitioners from the Foundation industry and three academics. They worked across different companies and sectors of the Foundation industry, including cement, plastics, construction, chemicals, glass, and metals, as outline in the Table below. In recognition of the global and national significance of sustainability and Net-Zero, the first workshop with the Foundation industry had a strong emphasis on these topics with the support of digital technologies. The participants' roles were varied, such as CTO, principal technologist, CEO, business development manager, cloud developer, lead resource energy analyst, and senior research scientist. In the second workshop, nine participants were involved, including four practitioners and five academics. The companies were from across industry and sectors, with participants representing a variety of roles (see Table 2).

Table 2. Summary of the workshop participants

Workshop	Participants	Industry/ Academia	Type of organisations	Role within organisations
1st Workshop Sector specific	33	Industry (30)	AI company; Concrete supply chain management; Industrial software; Construction material manufacturer; Material passport company; Waste company; Innovation consultancy	CTO; Principal technologist; CEO; Business development manager; cloud developer; lead resource energy analyst; senior research scientist
		Academia (3)	Business School; Engineering	Lecturer; PhD candidate
2nd Workshop Cross-sector	9	Industry (4)	Computer integrated systems design company; Digital agency; Software consultancy ; Sustainable urban development company	Marketing strategist; infrastructure asset manager; brand manager
		Academia (5)	Management School; Engineering School	Senior lecturer; lecturer; post-doctoral research fellow

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The data collected through the data-driven innovation canvas and the problem statement template were thematically analysed. The data were transcribed and summarised, prior to being coded into the seven data-driven design activities (Lee and Ahmed-Kristensen, 2023). The workshop flow was described to identify the structured data-driven design process and the tools. In the next section, the workshop outcomes will be discussed based on the data-driven design framework.

4. Findings and discussions

The workshop participants developed data-driven innovation concepts based on real world case studies. As a result of the workshops, the authors captured, analysed, and summarised the key elements of the real-world cases' data-driven innovation concepts (Table 3). Moreover, several tools and a process for data-driven innovation, including the data exploration template, problem statement template, and data-driven innovation canvas, were developed and tested to support the generation of data-driven innovation concepts. This section is structured by describing the process and tools along with the concepts generated, addressing the two research questions.

4.1. Which data-driven design activities would companies like to undertake to generate value?

Two workshops were driven by the goal of achieving net-zero (workshop 1) or the mission set by the companies (workshop 2), and problem statements were developed around these and then used to establish the mission (data-driven design activities). Therefore, they initiated the data-driven design process by exploring data challenges and framing their business challenges. The workshop participants worked in groups of three to six, generating eight problem statements along with eight data-driven innovation concepts for analysis. Companies posed various types of problem statements, with selected examples such as 'How might we develop a product passport for broken glass?', 'How might we generate data for AI for sustainability faster and cheaper?', and 'How might we improve salesperson's productivity to better connect with clients?' Based on the defined problem statement, the participants generated data-driven innovation concepts on the template, consisting of key elements (Figure 3). In this section, the critical elements on the data-driven innovation template are described and analysed, including mission (data-driven design activities), value proposition, key enablers, key data, key barriers, negative impacts, and benefits.

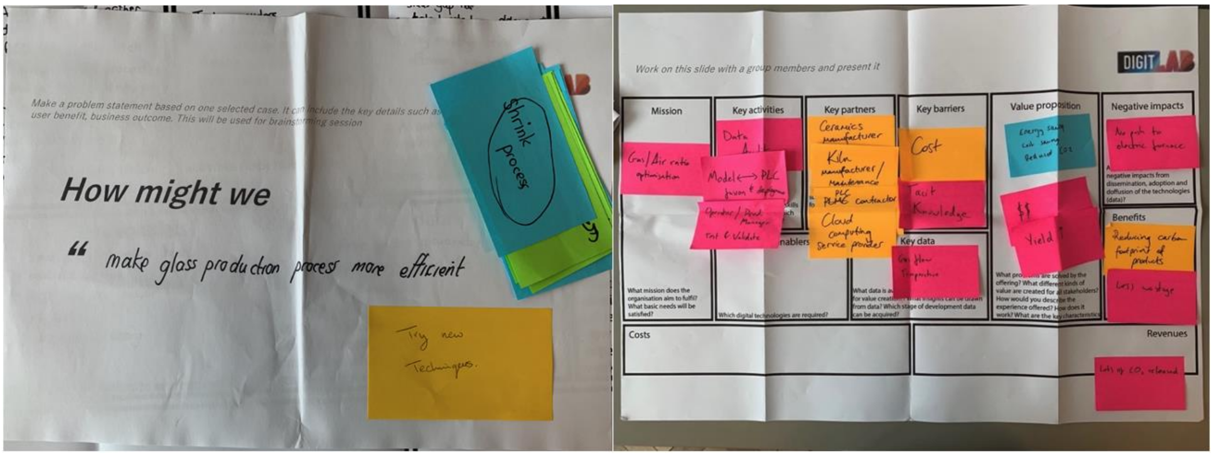

Figure 3. Problem statement and data-driven innovation template filled out by workshop participants

Types of data-driven design activities, value proposition, key enablers and data, and key barriers and negative impacts were captured, summarised, and analysed to better comprehend data-driven innovation concepts (table 3).

The types of Data-driven design activities: The workshop participants developed eight data-driven innovation concepts, which can be categorised into production (n=3), validating (n=2), generating (n=1), planning (n=1), and maintaining (n=1) within the data-driven design activities. Production was not

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included as an activity within the framework but was around the optimising of this process (for cost/ energy efficiency). Consequently, these would be categorised under customising (which includes optimising) within the framework and are around production due to the nature of the Foundation industries. In terms of data-driven innovation concepts for production, practitioners wanted to improve energy and cost efficiency in glass, ceramic, and timber production process using AI and data to optimise this process. Two groups described that generating synthetic data and democratising data would help to validate their design decisions. For other data-driven innovation concepts, developing a product passport for broken glass (maintaining), connecting better with clients (planning), and designing a system for a recovery of value from residual waste (generating) were addressed.

Table 3. Eight data-driven innovation concepts categorised into data-driven design activities

Types of data-driven design activities	No. of concepts developed	Value proposition	Key enablers and data	Key barriers and negative impacts
Customising (Production)	3	Improve the cost-efficiency of a small timber doorset manufacturer; Optimise processes to reduce energy use in ceramics manufacture; Make glass production process more efficient	IoT Tech for capturing data; Data on Gas flow and temperature; Data on Furnace process parameters (batch values, temperature, speed); Data dashboard; Data driven design; Job tracking tool; Machine learning for efficiency monitoring; Digital twin	Digital skills gap; Additional training; Tacit knowledge; Unemployment; Cost
Validating	2	Democratise data value and improve transparency, reliability and explainability of data-driven decision making; Generate data for AI for sustainability faster and cheaper	Testbed data; End user data; Consumers individual data; Machine learning; Numerical simulation i.e., finite element analysis	Data silos; Material robustness simulation; Resistance to change; Rebound effect; Financial demand
Generating	1	Design a system for recovery of value from residual waste on a regional scale	AI mechanized recognition and robotic recovery; Switch operator	Data privacy; Energy of Process; Cost
Planning	1	Improve salesperson's productivity to better connect with clients	Database on sales (customer order history, cost, time, price); Data analytics; Machine learning	Data privacy; Data availability; Data ethics; Limit future sales product options
Maintaining	1	Develop Product passport for broken glass	Molecule marker creator /identifier; Global marker database; Data on elemental composition and CO2 footprint	Destroy other supply chains

Value proposition: The value proposed by the majority of the companies through the use of data and machine learning was closely linked to resource efficiency and the reduction of waste and pollution. Other values included ethical decision-making, increased transparency, worker satisfaction, and ease in management. This can be explained by the fact that two-thirds of the companies were from the Foundation industry.

Key enablers and data: To optimise the production process, improve a system, democratise data value, participants believe the key enabler is to adopt machine learning algorithms. Other technologies suggested to achieve product passport for broken glass and efficient glass production process were

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digital twin, IoT tech for sensor, global maker database, and molecule maker creator. A wide range of data type was mentioned in accordance with the business context of the participants, for example user profile data, sales data, testbed data, material data, road surface data, and gas flow data, etc.

Key barriers and negative impacts: As expected, the key barriers to overcome for data-driven innovation were primarily around data privacy, availability, and skill gaps. There were also general barriers such as cost and technical issues. Companies listed various negative impacts, including an increase in financial demand or the use of materials when developing data to support efficient decision-making, unemployment to improve the production process, data ethics for planning future sales, and the destruction of existing supply chains for product passports.

Through the workshops, we identified that companies were keen on using data or machine learning to improve efficiency in the production phase or validate their decisions, thereby reducing business risks across new product service development phases. Companies prioritised the use of ML and big data in various areas, including optimising production for cost and energy reduction or supporting decision-making activities. They also aimed to bring impact to the business, system, practice, and process by better connecting with clients, generating a system for the recovery of value, democratising and generating data for efficient decision-making, and improving the maintenance of broken glass. Regardless of the potential barriers and negative impacts of data-driven innovation, practitioners described it as bringing benefits to the environment, society, as well as the companies. This includes saving costs, increasing social inclusivity, and reducing waste, energy, and carbon consumption.

4.2. D^3IKIT: Data-Driven Design Innovation KIT

Through the workshop process, we structured the data-driven design process based on a Double Diamond Design Process, a representative of design processes. D^3IKIT consists of data-driven design process coupled with the four tools: the data exploration template, problem statement template, data-driven innovation canvas, and data-driven design evaluation framework. The data-driven design process, coupled with these four tools, is illustrated in Figure 4. The intended users of this toolkit are designers and practitioners seeking to generate value from data in the creation of product service concepts.

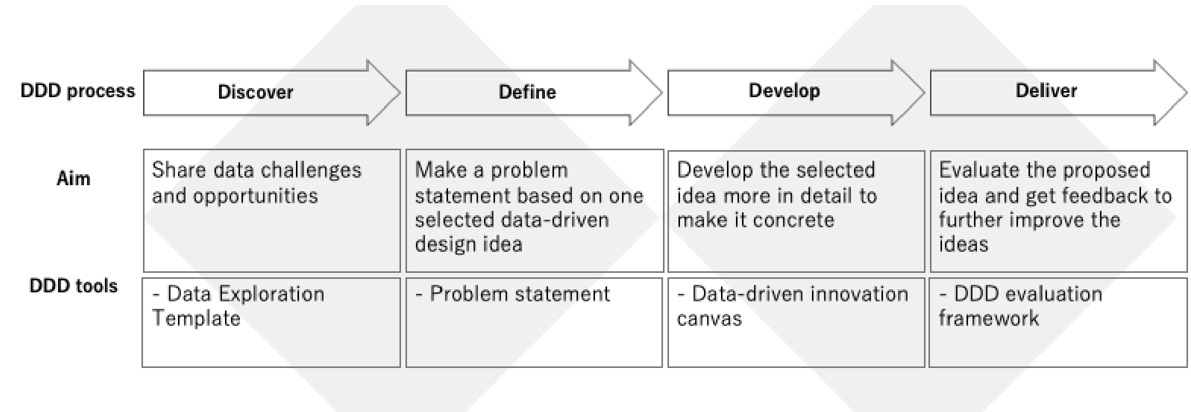

Figure 4. D^3IKIT: Data-Driven Design Innovation KIT

In the first part, the workshop introduced the theme and objectives, cantering around the concept of data-driven design and the seven associated activities within the framework. The primary goal of this session was to establish a shared understanding of data-driven design. Since the first workshop exclusively engaged with the Foundation industry, the focus on utilizing data or machine learning was specifically aimed at enhancing sustainability. In the second workshop, participants initiated the data-driven design process by addressing their own business challenges. The second part of the workshop aimed to uncover the participants' data contexts and challenges, exploring both opportunities and obstacles related to data-driven innovation. To identify potential projects, participants were tasked with formulating a problem statement based on a selected idea. In the third phase, participants delve deeper into the selected idea, refining it to a more concrete form. Both the second and third parts of the workshop were interactive sessions utilizing the provided D³IKIT. Participants were required to employ these tools in conjunction with following the data-driven design process. For instance, in the second part, they were given a data-exploration template and problem statement template and in the third part, a data-driven innovation canvas was provided as a tool, adapted from the business model canvas (Figure 5).

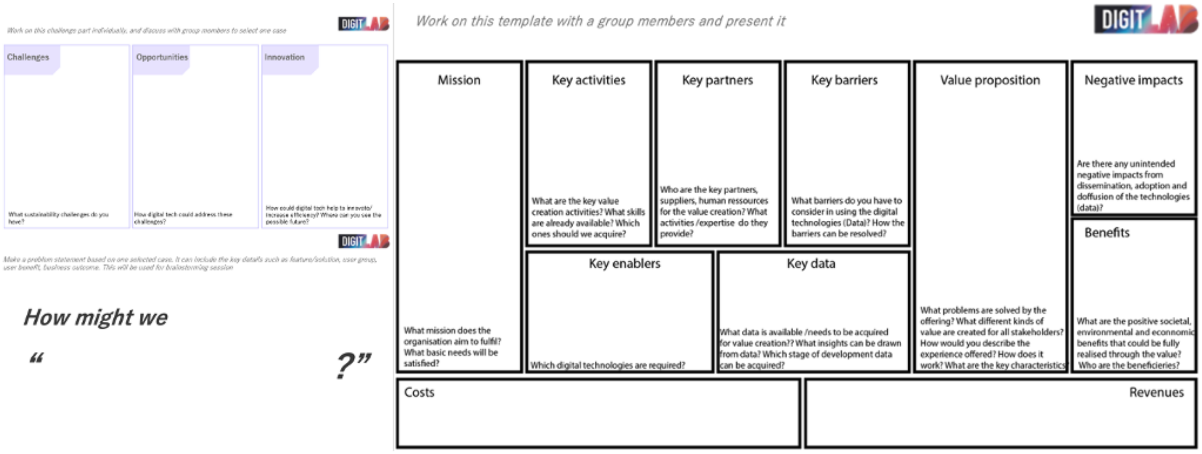

Figure 5. Data exploration and problem statement templates (left), and data-driven innovation canvas (right)

1. Data Exploration Template: This template aims to assist practitioners in comprehending the challenges, opportunities, and enablers for data-driven design. To guide participants through a comprehensive exploration of their data, a set of questions is provided, including: "What data challenges do you have?" "How could digital technologies address these challenges?" and "Where can you envision possible future developments?" By utilizing this template, participants will be well-prepared to formulate the problem statement for their data-driven design project and brainstorm ideas.
2. Problem statement template: The aim of this template is to help practitioners gain deeper insights into the concept of data-driven innovation by focusing on a specific challenge. By creating a problem statement based on a selected challenge, which may include key details such as features/solutions, user groups, user benefits, and business outcomes, participants can explore how data can generate new value.
3. Data-driven Innovation Canvas: This canvas aims to provide practitioners with a clear overview of the aspects of data that need consideration when conceptualizing data-driven design concepts. Developed from the Business Model Canvas (Osterwalder and Pigneur, 2010) and enriched by a comprehensive review of existing innovation canvas tools (Kronsbein and Mueller, 2019; Kühne and Böhmann, 2020; Mathis, 2015), it includes data elements and questions to enable workshop participants to explore ideas around data. Examples of these questions include: 'What are the associated data, and how could they be utilized to realize value?' 'What critical barriers do you have to consider in data practice?' 'What challenges do stakeholders face that could be solved, and how could your data address them?' 'What could be unintended negative impacts?' and 'What could be the positive societal, environmental, and economic benefits?' The canvas is intended to guide practitioners on which aspects of data to gather for generating value; it also helps them map, manage, and realize the value from the data they (can) have in an integrative way.

'D³IKIT', a data-driven design process and toolkit is distinctive from existing data-driven design processes in three ways. Firstly, unlike the processes proposed by Kim et al (2016) and Diamond et al. (2017), our 'D³IKIT' process begins with exploring data relates to the business goals, challenges and value creation. Secondly, the process differs from Quiñones-Gómez (2021)'s data-driven design model process as it was developed and evaluated based on real-world case studies in the context of new product service development. Lastly, this 'D³IKIT' is novel as it combines both the process and toolkit.

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5. Conclusions

This paper aims to develop 'D³IKIT', a data-driven design process and toolkit, which was tested and evaluated in industry. 'D³IKIT' enables practitioners and researchers to generate data-driven innovation concept ideas. Two workshops were conducted with over 30 practitioners and 10 academics across sector, enabling the testing and development of the ideas. Through the data-driven design workshops, companies were mainly interested in the use of data to optimise the production process (described as customising) focusing upon a net zero or validating their decisions among the seven data-driven design activities (Lee and Ahmed-Kristensen, 2023). From the mission statements generated , the businesses aspirations were beyond their organizations, for example including communication with the public and considering the traceability of products through their lifetime. This paper contributes with the D³IKIT, including the data-driven innovation canvas, data-stakeholder map, and data-driven design ideation template alongside data-driven design process developed by the authors. Through the workshops, the data-driven design process and tools were validated by forty-two practitioners. The process and tools are designed to stimulate discussions within organizations involving diverse stakeholders concerning the data resources and challenges within their own business context, in addition to concrete ideas.

Our research provides these contributions. First, we enhance the understanding of how companies use data or machine learning for their product service development which would provide the foundation for academic research around data-driven innovation. As there is a lack of how data or machine learning are utilised in real-world context, we show the eight cases of data-driven innovation. Second, by proposing the D³IKIT which has been evaluated, we enable practitioners to realize the potential value from the data within various business contexts. Although existing studies propose a data-driven design process, they are conceptual and lack pragmatic guidance for practitioners to adopt the approach in practice. Thus, the current research addresses this limitation. On the other hand, our study has some limitations. First, we only collected eight data-driven innovation concepts as these are developed in teams, which is a limited number for gaining meaningful insights, but will be extended upon in our current and future activities leading to further refinement. Secondly, only a couple of data-driven design tools are introduced with a high-level data-driven design process, indicating that the process and the tools can be enriched by conducting more workshops. We also aim to further develop the data-driven design process in more detail and intricacy through our ongoing activities, making it comprehensive and designed for practical use by designers. Thus, this will be our future research agenda.

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