MANAGING DATA-DRIVEN DESIGN: A SURVEY OF THE LITERATURE AND FUTURE DIRECTIONS

Johnson, Julie;
Hurst, Ada;
Safayeni, Frank

University of Waterloo

ABSTRACT

Data-driven design is expected to change design processes and organizations in significant ways. What actions should design managers take to ensure the best possible outcomes in this new data-driven design environment? This paper employs an interdisciplinary literature survey to distill key impacts that data-driven design may have on designers, design teams, organizations and product users. Findings reveal that designers may need a broader set of skills to be successful. For data-driven design to be most effective, design managers will be challenged with many integration tasks, including the integration of AI-based tools into design teams, the closer integration of interdisciplinary teams, the integration of qualitative design thinking methods with new data-driven design paradigms, and the integration of data and algorithms into traditional human-centred design practice, in an effort to overcome cognitive limitations and augment human skill. This paper identifies gaps in the literature at the intersection of data-driven design and design management, design thinking, and systems thinking.

Keywords: data-driven design, AI-driven design, Design management, Artificial intelligence, Design practice

Contact:
Johnson, Julie Irene
University of Waterloo
Canada
julie.johnson@uwaterloo.ca

Cite this article: Johnson, J., Hurst, A., Safayeni, F. (2023) 'Managing Data-Driven Design: A Survey of the Literature and Future Directions', in *Proceedings of the International Conference on Engineering Design (ICED23),* Bordeaux, France, 24-28 July 2023. DOI:10.1017/pds.2023.253

1 INTRODUCTION

What will design practice look like in the future? This question is critical because it drives many wide-ranging activities today. For example, how should we be educating and training our engineers and designers? What design processes should we be implementing in our organizations?

Data-driven design is described as a "true paradigm shift" (Cantamessa et al., 2020) that will profoundly change design practice. AI is predicted to reshape how organizations are structured and how product design and innovation are managed (Verganti et al., 2020; Haefner et al., 2021). New trends and tools in product development, including shorter product lifecycles and AI-based tools, require data and alter established product development processes (Bickel et al., 2019). With recent advances in AI, there may be many new opportunities including more customized designs (Cantamessa et al., 2020) and new business models (Bstieler et al., 2018). However, there may also be many potential pitfalls, e.g., over automation (Levy et al., 2021; Norman, 2007). The broader research question is then:

> *What actions should design managers take to ensure the best possible outcomes for designers, organizations, and product users in this new data-driven design environment?*

The literature on data-driven design can appear quite daunting; it is an interdisciplinary area disseminated in a multitude of disciplinary research outlets, represented by diverse and inconsistent terminology. This paper is one of the first to discuss data-driven design from the perspective of design management. A comprehensive literature survey of more than 200 books and papers from a variety of disciplines, including design, cognitive science, organizational theory, design management, human computer interaction (HCI), philosophy, etc. has been employed to distil some of the fundamental concepts and perspectives to inform approaches to the research question and practical implications for design managers (and perhaps even design educators). The results may be surprising, because they imply different training and management directions than may be currently taken.

This paper is structured as follows. Section 2 reports on some of the methodological challenges of synthesizing the literature on data-driven design, providing an overview of definitions and general characteristics of the literature. Section 3 provides a synthesis on the potential impacts of data-driven design on designers, organizations, and users. Building on this foundation, in Section 4, we offer some implications for design management, while Section 5 describes conclusions and future work.

2 METHODOLOGICAL CHALLENGE TO SURVEYING THE LITERATURE ON DATA-DRIVEN DESIGN

2.1 General approach, challenges, and considerations

The first author has more than 20 years of experience in new product development, both as an engineering designer and as a manager. As such, the approach to the literature review is very broad and informed by this experience. To understand data-driven design, it is first important to understand the theories of design practice, e.g., Schon (1983), Simon (1973), Cross (2011), and Bucciarelli (1994). Similarly, to understand the management of data-driven design, an appreciation for organizational theory is important, e.g., Mintzberg (1990), Ackoff (1979). The approach to the literature survey is one of seeking answers framed by the complexity of real design practice, recognizing that design is just as much an outcome of culture and organizational processes as it is of technology and market forces (Bucciarelli, 1994), and that managers manage "messes" (Ackoff, 1979). A broad survey can be revealing because similar concepts are often found in different disciplines (e.g., management is arguably a design activity itself). The literature survey deployed here touches on a wide range of topics, to see data-driven design through different lenses, e.g., improved design *tools*, improved design *inputs*, and possible design *task distributions* between AI and humans. In addition to design and management, review domains and topics included artificial intelligence (e.g., Mitchell, 2019), HCI, cognitive science, abductive logic, motivation (e.g., Fischer et al., 2019), philosophy (e.g., Thagard, 2021), and sensemaking (e.g., Weick, 1993). The intention is not to be exhaustive but to provide a synthesis of ideas reflecting the complexity of the design environment into which data and AI are being introduced.

A search for "data-driven design" on SCOPUS (accessed Nov. 26, 2022) resulted in 821 publications. A review of the keywords and abstracts showed that the term "data-driven design" is being used in a wide variety of fields, including mechanical engineering, controls, computing, design, civil engineering, landscape architecture, human factors, etc. Simply reviewing these abstracts in detail appears to require subject matter expertise from many fields. As such, the literature may be inaccessible to the typical

https://doi.org/10.1017/pds.2023.253 Published online by Cambridge University Press

design researcher. Other keywords and combinations were searched including "AI-driven design"; "data-driven" and "design" and "innovation"; "data-driven engineering"; "data-enabled design"; "design analytics"; "new product development" and "design" and "data analytics"; and "artificial intelligence" and "design" and "creativity". Many publications which are arguably about data-driven design are not classified as such, e.g., Bstieler et al., 2018 (AI, innovation); Jarrahi, 2018 (AI, decision-making); Ma and Kim, 2016 (data-driven product family design); McCaffrey and Spector, 2018 (human machine collaboration, innovation); Verganti et al., 2020 ("AI-empowered design"); Wilberg et al., 2018 (data strategy, connected products); Zhang et al., 2021 (AI, design). In addition, some papers are very high-level, e.g., Bstieler et al. (2018), Cantamessa et al. (2020) or "overly positive", with little discussion of return-on-investment, sustainability concerns or IP concerns. Finally, many case studies are only focused on data-centric companies, e.g., Airbnb, Netflix (Daugherty and Wilson, 2018; Verganti et al., 2020), with Tesla commonly presented as a rare example of data-driven design on a non-purely digital product (Cantamessa et al., 2020; Montagna and Cantamessa, 2019; Porter and Heppelmann, 2015).

2.2 Defining "data-driven design"

The number of papers on "data-driven design" has increased significantly since 2016 (Bertoni, 2020), yet it is difficult to find a common definition of the term. Trauer et al. (2020, p. 6) define data-driven engineering as "*a framework for product development in which the goal-oriented collection and use of sufficiently connected product lifecycle data guides and drives decisions and applications in the product development process*". Here, the emphasis is on data collected directly from the product, or "use phase" data (Wilberg et al., 2018). Others consider a broader definition of data. Bertoni (2020) found that the "data" in most papers on data-driven design comes from natural language processing of online reviews and social media. Ma and Kim (2016) refer to "customer preference data" - historical transaction data as an input to data-driven design. In this paper, "data" will be defined more broadly, as in Cantamessa et al. (2020). "Demand-side" data includes data from potential and actual customers, use phase data, data scraped from online reviews and forums, data collected from customer discussions, ethnographic observations, etc., and from market research activities (e.g., surveys). "Supply-side" data includes data generated by the design firm, e.g., collected from production systems, supply chain systems, etc., and inputs and outputs from previous designs (e.g., specifications, test results). A big picture view of data-driven design is provided in Figure 1.

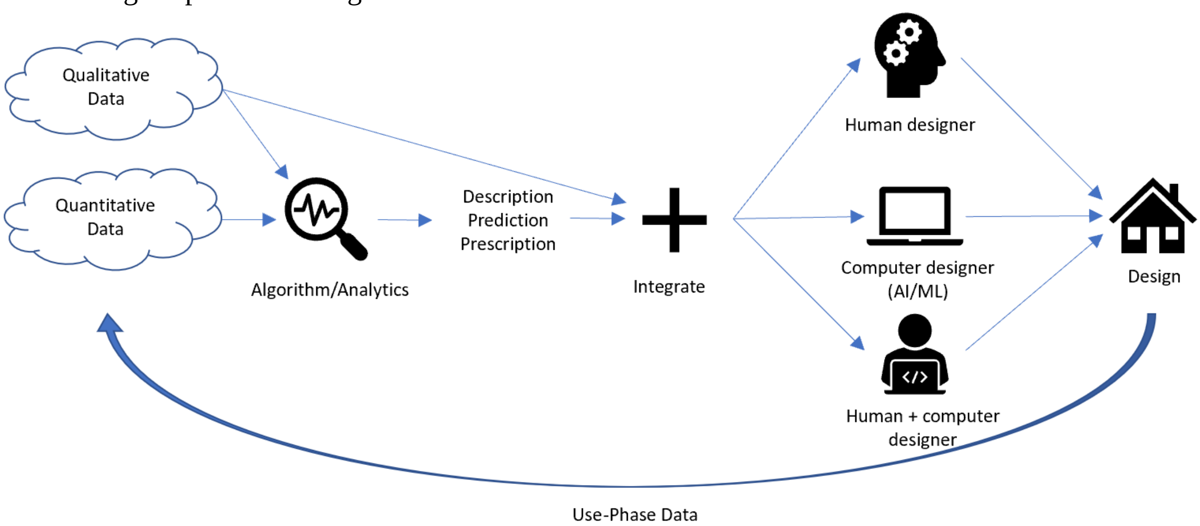

Figure 1: Data processing in data-driven design

It is also important to consider what is done with this data and who/what makes the decisions. There seems to be no clear consensus regarding what exactly "data-driven" means. The definition by Trauer et al. (2020) focuses on using the data to make design decisions. Some authors refer to "data-driven" as meaning decisions are made automatically by machines (Pryszlak, 2019; Verganti et al., 2020). Some authors differentiate between "data-inspired", "data-informed" and "data-driven" (Aishah, 2020; Stewart, 2019) where data-driven decisions are made by machines, data-informed decisions are made by humans guided by data, and data-inspired refers to explorations inspired by data. There is also reference to "data-augmented" (Werder et al., 2020), "data-enabled" (Bogers et al., 2016; Trauer et al., 2020) and "data-led" (Pryszlak, 2019), all of which generally refer to human-made decisions guided by data. In the current analysis, it is assumed that at least some of the data is analysed by either descriptive or predictive analytics, where predictive analytics can include statistical techniques, artificial intelligence and/or machine learning. Data integration is a major issue. For example, Norman (2013) highlights the trade-off between the "big data" collected via market research activities which is typically presented in "objective" numerical form and the "deep insights" collected from a relatively small number of people that are typically in the form of "subjective" observations. It is assumed that design decisions can either be made by a human designer, a machine or by a human-machine combination.

3 DATA-DRIVEN DESIGN: IMPACTS AND PERSPECTIVES

On a system scale, data-driven design will have impacts for designers, for the teams and organizations they work in, and for product users. Design managers will need to consider all of these impacts. The following sections highlight impacts and perspectives for each of these groups.

3.1 Designers

Researchers predict that data-driven design will have a significant impact on the role of designers. Some predict the need for more generalist designers with systems thinking skills who can coordinate the inputs from multi-disciplinary teams (Agostini and Filippini, 2019; Marion and Fixson, 2021; Norman, 2007; Pereira Pessôa and Jauregui Becker, 2020). Similarly, Verganti et al. (2020) argue that as some aspects of problem solving are automated, design becomes closer to leadership. Other literature predicts the needs for new fields such as "design analytics", which is responsible for turning data into useful design insights (Cantamessa et al., 2020). Many authors agree that designers will need to have better data analytics skills in the future (Bertoni, 2018; Pereira Pessôa and Jauregui Becker, 2020; Yang, 2018). In contrast to the need for more design generalists, some researchers call for designers who are very highly specialized and only temporarily assigned to design teams (Marion and Fixson, 2021; Yoo et al., 2012). As AI becomes more commonly used to provide preliminary designs, the role of some designers may change from that of solution provider to "solution selector" (Marion and Fixson, 2021).

Part of design research focuses on finding methodologies, processes and tools that can aid designers. Yet, many design methodologies are not actually used in industry, possibly because they are too complicated or are not field-proven (Birkhofer, 2011). So, in the context of data-driven design, which methodologies and tools would designers want to use? According to Jarrahi (2018), designers may be interested in using data-driven support when dealing with complexity, specifically in situations where there are many design-related inputs to be collected and analysed. Data can improve decision making, e.g., through access to high-volume, high-variety, high-velocity data, and aid with novel concept generation, e.g., by using use phase data to understand real use cases (Wilberg et al., 2017).

As AI-enabled design tools become more prevalent, Xin et al. (2018) highlight the importance of designing the systems used for data-driven design in such a way that designers' needs are considered. Norman (2007) highlights the issue of over automation, where the automation is so effective that humans no longer need to pay attention. Data-driven design, if implemented in a non-ideal fashion, may impact the performance of high performing design teams (Zhang et al., 2021) by causing teams to trust AI when they should not. There is a need for effective human-in-the-loop systems that allow for the efficient design of machine learning iterations (Xin et al., 2018). When people are out of the loop, it can be very difficult for them to intervene in the case of problems. Norman (2007) points out the importance of using care when automating to ensure that humans can retain their skills. For data-driven design to be successful, effective human-algorithm collaboration will be critical.

3.2 Design in the context of organizations

Design processes and design outputs must meet the needs of businesses. Business strategy revolves around value proposition and design outputs are a critical part of that value proposition. As designs become "smart", entire business models can change, for example, through ever-evolving designs that are sold as services rather than products. Relationships with customers also change (Cantamessa et al., 2020; Porter and Heppelmann, 2015). For example, customer interactions may change from one-time purchases to ongoing support. Issues of customer data privacy and security also move to the forefront.

Organizations are interested in reducing costs and risks associated with new product development. Wilberg et al. (2017) predicts that data-driven design will reduce the cost and risk of new product development by reducing information processing costs, improving decision making and enabling the

https://doi.org/10.1017/pds.2023.253 Published online by Cambridge University Press

exploration of new opportunities. Unfortunately, frameworks for incorporating data-driven design into the new product development process are still immature (Bertoni, 2018). Further, it is not yet clear which data analysis techniques (e.g., descriptive, predictive, or prescriptive) are most effective at each stage of the new product development process (Cantamessa et al., 2020).

To achieve advantage, businesses may prefer radical innovations rather than incremental innovations as a means of capturing a greater portion of the market. However, radical innovations often take decades before they are commercially successful (Norman, 2013). It is important to understand whether data-driven design can drive radical versus incremental innovations in a business' particular industry. There is some evidence that data-driven design may be best suited to evolutionary (incremental innovations/optimizations), rather than revolutionary design since revolutionary design may rely more on insights rather than on quantitative data (Wu et al., 2020). Nevertheless, there are a number of researchers who are investigating ways to use data to improve creativity (Carmona Marques, 2021; Chen et al., 2019; Luo et al., 2021; McCaffrey, 2018).

Design is often studied as an individual activity, ignoring the business and organizational environment in which it occurs. However, the majority of design occurs in teams and organizations. Organizations are typically focused on improving performance, which involves reducing errors and increasing insights/innovation (Klein, 2013). Unfortunately, processes intended to reduce errors and increase predictability can have a negative impact on insights and innovation (Gilson et al., 2014; Klein, 2013). As a result, organizational decisions and contexts can make the design environment more challenging. Garbuio and Lin (2021) argue that design frames are shaped not only by the experience and memory of design teams, but also by the strategic vision of organizational leadership. Data-driven design has the potential to impact this strategic vision.

Much of the recent literature points to the many significant organizational and process changes that will arise as a result of data-driven design (Haefner et al., 2021; Wilberg et al., 2017). In manufacturing firms, the nature of the work in core functions, from product development to after-sale service, is being redefined, with increased required coordination among them (Porter and Heppelmann, 2015). Many researchers predict that design teams will need to become more multi-disciplinary, with closer relationships between design, marketing, IT and other departments (Cantamessa et al., 2020; Porter and Heppelmann, 2015). Yoo et al. (2012) describe distributed design teams that are "heterogeneous" and temporary in response to the need for the integration of specialized knowledge. Marion and Fixson (2021) also highlight the temporary involvement of team members. Bucciarelli (1994) describes the design process as a social process of reaching consensus amongst participants. It is not evident how the social processes of temporarily formed teams would impact design outcomes.

3.3 User perspectives

Norman (2013) reminds us that customers and end users are not necessarily the same person and that designers must fully understand the needs of both. Often, the needs of the customer are quite different from the needs of the user, adding to the complexity of the design problem. Much of the recent research on data-driven design appears to focus on business-to-consumer case studies (Cantamessa et al., 2020; Verganti et al., 2020). The amount and type of data available to businesses directly serving consumers may be different than the data that is available to businesses which serve other businesses. This may mean that different data-driven design approaches are needed for companies that sell to consumers versus other businesses. For example, businesses which sell to consumers may be able to mine more online reviews, meaning that the process of need finding may be different.

Fundamentally, products are designed to meet the needs of users. However, users often aren't aware of their needs (Norman, 2013). As such, evaluating the quality of a design from a user perspective requires value-based judgement (Lawson and Dorst, 2009). Sensors could be used to help understand user needs. However, sensors measure different things than people do. Human perception is not the same as physical sensing (Norman, 2007). Correct interpretation of the data is critical.

Data-driven design may benefit users by enabling the provision of highly customized products (Cantamessa et al., 2020), e.g., by using data to understand and satisfy individual needs. However, the cost may be a loss of privacy. Algorithms and model assumptions are often not as ideal, transparent, or impartial as people assume (O'Neil, 2016). Similarly, Ackoff (1979, p. 99) points out that "*it is not feasible to measure, let alone include in a model, every relevant aspect of the styles of the decision makers and all others who hold a stake in a decision*". This means that product users might not be best served by data-driven design. There are important trade-offs to be considered by product users.

https://doi.org/10.1017/pds.2023.253 Published online by Cambridge University Press

4 IMPLICATIONS FOR DESIGN MANAGEMENT

The preceding sections detail the many factors, stakeholders, and perspectives that design management must consider in adopting data-driven design practices. Unfortunately, like data-driven design, design management is a vague concept in the literature - it is an emerging discipline that is not well defined or understood (Libânio and Amaral, 2014; Shigemoto, 2020) and research is relatively scarce with minimal empirical support (Chiva and Alegre, 2009). When combined with data-driven design, there is little guidance in the literature for design managers. According to Verganti (2011, p. 387), the challenge is "*being first in finding the right application of technological opportunities*". This is exactly the situation facing managers and organizations today as they attempt to incorporate big data and AI into their design processes. While there is recognition of the importance of design management - that good design is the result of a well-managed process (Carneiro et al., 2021, p. 198), there is debate about what that managed process should entail. "*The need for that process to deliver exceptional products is often overlooked*" (Moultrie et al., 2007, p. 362).

According to Dumas and Mintzberg (2010, p. 37) "*design cannot be managed like other activities*". Design management requires understanding the business context of the design (Hands, 2018; Carneiro et al., 2021), ensuring integration of creative, technical, strategic and market considerations (Chiva-Gomez, 2004, Shigemoto, 2020; Tvedt and Dyb, 2019), collaboration between interdisciplinary teams (Moultrie et al., 2007), and prioritizing the user perspective (Ozkan, 2021; Chiva-Gomez, 2004; Tuncer Manzakoglu and Dimli Oraklibel, 2021). With this overview, the following ideas attempt to answer the question of what actions design managers should take to ensure the best outcomes for *designers*, *organizations*, and *product users* in this new data-driven design environment.

Augmenting the skill of designers: Promote the integration of data-driven design into the designer's way of working. There is very little in the data-driven design literature that references the foundational theories of design practice, which seems to be an important oversight. If AI is to aid the design process, it should be integrated in such a way that it considers how humans actually design. One example is the use of AI to aid with information processing, especially as designers contend with increasingly complex situations with multitudes of inputs to be analysed (Jarrahi, 2018). Another example are 'primary generators', on which designers typically rely as initial design ideas (Lawson and Dorst, 2009). Algorithms can be used to search large spaces for primary generators as demonstrated by Fu et al. (2013), who used algorithms to search for "near" and "far" analogies in patent data. A possible action for design managers is to ensure that designers have training in AI so that they can understand its capabilities and limitations in design situations.

Augmenting the skill of designers: Promote data-driven design to help designers overcome cognitive limitations, e.g., limited expertise, limited memory, fixation, bias, and bounded rationality. Data-driven design can be used to augment human intelligence in the design process. Human designers may exhibit a number of biases (Chattopadhyay et al., 2020) and/or have limited expertise. AI-based systems can provide potentially valuable inputs to the designers, e.g., suggested software design improvements (Brown, 2021). However, such tools need to be used with caution. There is evidence that certain use of AI in design recommendation systems can negatively impact competence (Levy et al., 2021; Zhang et al., 2021). Further, certain AI recommendation systems have been shown to result in humans ceding agency to the AI (Levy et al., 2021). A possible action is to increase designers' awareness of their own cognitive limitations in designing and identify areas where AI could assist.

Augmenting the skill of designers: Designing/adopting smart tools for designers - HCI considerations will be key. Some designers may find themselves creating AI-based design tools for other designers. Similarly, design managers may have to choose which AI-based design tools are used by their design teams. As highlighted earlier, many practices and tools that have been created to improve design are not actually used in practice. To aid AI-based tool adoption, it will be important to consider human needs for relatedness, autonomy, and competency (Fischer et al., 2019) in the design and deployment of these tools. The effective design of these tools may be critical to successful deployment of data-driven design. Performance improvements expected by utilizing AI in design can only be achieved if the designers actually trust and are willing to work with the AI (Nandy and Goucher-Lambert, 2022). A possible action is to ensure that designers have adequate training in HCI, so that they can create/recognize design tools that will augment human design skill.

Improving design outputs for users: Integrate data-driven design with qualitative approaches like design thinking. There seems to be very little literature linking design thinking to data-driven design.

https://doi.org/10.1017/pds.2023.253 Published online by Cambridge University Press

Design thinking is popular set of principles and tools focused on user-centric design (Micheli et al., 2019). Common tools include ethnographic methods, journey maps, prototypes, field experiments, etc. At first glance, design thinking's more qualitative approaches may seem orthogonal to data-driven design. However, digital and AI innovation are expected to change human-centred approaches (Calabretta and Kleinsmann, 2017). Data may help designers better implement user-centric design approaches (Gorkovenko et al., 2020). For example, Ghosh et al. (2017) describe a case study in which shoes fitted with sensors are used to help understand wearers' perceptions of product features. A possible action is to foster an appreciation for qualitative data and how it should be combined with quantitative data to make design decisions. A challenge in organizational settings may be to find the right balance/weighting between qualitative and quantitative data.

Improving design outputs and design organizations: Take a systems thinking approach to data-driven design, considering benefits and costs/risks for all stakeholders. The intersection of data-driven design and systems thinking (Arnold and Wade, 2015) is another area where there seems to be a gap in the literature. Algorithm inherent biases (O'Neal, 2016) - a significant cause for caution in using AI in design - may not be evident until you “zoom out” and look at system-wide, long-term implications. Further, designers must carefully consider where AI-based tools are introduced into the design flow and predict where in the system they might have unintended impacts on designers, organizations, and designs.

Augmenting the skill of designers and improving design outputs: Keep a human in the loop for sensemaking/abductive logic. Abductive logic is considered to be an important part of design (Dorst, 2011; Martin, 2009, p. 26). It is what we use to hypothesize creative solutions to design challenges based on available data and prior experience. Computers are not currently able to understand causality or analogy, nor can they use these to generate creative abductive hypotheses (Thagard, 2021, p. 205). Thus, if the innovation process is fully automated as some anticipate (Cantamessa et al., 2020), a critical part of the design process will be omitted. For designers to devise creative solutions, it is important that they understand the people and contexts that they are designing for. As such, a possible action is to ensure that designers have meaningful exposure to the social sciences and that there is intentional integration of that knowledge base in design education and practice.

5 CONCLUSIONS AND FUTURE WORK

This paper was motivated by a need to synthesize the literature on data-driven design into practical insights that are of relevance to design management. If this paper starts a dialogue between researchers in these interdisciplinary fields, the objective will have been met.

If we consider the main tasks of design managers and the various ideas offered on data-driven design, an overall theme that emerges is that design management will require an even greater emphasis on integration/collaboration. This will include:

- integration of new smart tools and data into design teams, with the goal of augmented human intelligence
- increased integration between the interdisciplinary teams that collaborate on designs
- integration of qualitative human-centred/design thinking methods with new data-driven paradigms
- integration of data and algorithms with traditional design approaches, to overcome human cognitive limitations.

Further, it becomes apparent that we need to train designers to be good at what computers won't be able to do for the foreseeable future. This includes sensemaking and abductive logic. In other words, we need to train designers to understand the people and situations they are designing for. Such competencies are often not high priorities in STEM education or in technical hiring criteria.

Future work involves confirming these ideas in an empirical setting and attempting to disentangle the implications of these ideas. We can examine the extent to which these practices are happening or not and look for connections to design performance. Similarly, future research could investigate whether instilling the competences identified in this paper in student designers leads to better outcomes in practice. This paper identifies a number of gaps in the literature, particularly at the intersection of data-driven design with design management, design thinking and systems thinking. Further research in all these areas would be helpful to practicing design managers.

REFERENCES

Ackoff, R.L. (1979), “The future of operational research is past”, *Journal of the Operational Research Society*, Vol. 30 No. 2, pp. 93–104. https://doi.org/10.1057/jors.1979.22.

Agostini, L. and Filippini, R. (2019), “Organizational and managerial challenges in the path toward Industry 4.0”, *European Journal of Innovation Management*, Vol. 22 No. 3, pp. 406–421. https://doi.org/10.1108/EJIM-02-2018-0030.

Aishah, N. (2020), “Know what you are talking about: The difference between Data-Informed, Data-Driven and Data-Inspired in a nutshell.”, available at: https://medium.com/sapera/data-informed-data-driven-data-inspired-whats-the-difference-b02464a99641 (accessed 31 October 2021).

Arnold, R.D. and Wade, J.P. (2015), “A definition of systems thinking: A systems approach”, *Procedia Computer Science*, Vol. 44, pp. 669–678. https://doi.org/10.1016/j.procs.2015.03.050.

Bertoni, A. (2018), “Role and challenges of data-driven design in the product innovation process”, *IFAC-PapersOnLine*, Vol. 51, pp. 1107–1112. https://doi.org/10.1016/j.ifacol.2018.08.455.

Bertoni, A. (2020), “Data-driven design in concept development: Systematic review and missed opportunities”, *Proceedings of the Design Society: DESIGN Conference*, Vol. 1, pp. 101–110. https://doi.org/10.1017/dsd.2020.4.

Bickel, S., Spruegel, T.C., Schleich, B. and Wartzack, S. (2019), “How do digital engineering and included AI based assistance tools change the product development process and the involved engineers”, *Proceedings of the International Conference on Engineering Design, ICED*, pp. 2567–2576. https://doi.org/10.1017/dsi.2019.263.

Birkhofer, H. (2011), *The Future of Design Methodology* 1st Ed, Springer London, https://doi.org/10.1007/978-0-85729-615-3.

Bogers, S., Frens, J., van Kollenburg, J., Deckers, E. and Hummels, C. (2016), “Connected baby bottle: A design case study towards a framework for data-enabled design”, *Proceedings of the 2016 ACM Conference on Designing Interactive Systems*, pp. 301–311. https://doi.org/10.1145/2901790.2901855.

Brown, C. (2021), *Digital Nudges for Encouraging Developer Behaviors*, North Carolina State University.

Bstieler, L., Gruen, T., Akdeniz, B., Brick, D., Du, S., Guo, L., Khanlari, M., et al. (2018), “Emerging research themes in innovation and New Product Development: Insights from the 2017 PDMA-UNH Doctoral Consortium”, *Journal of Product Innovation Management*, Vol. 35 No. 3, pp. 300–307. https://doi.org/10.1111/jpim.12447.

Bucciarelli, L. (1994). *Designing Engineers*. The MIT Press.

Calabretta, G. and Kleinsmann, M. (2017), “Technology-driven evolution of design practices: envisioning the role of design in the digital era”, *Journal of Marketing Management*, Vol. 33 No. 3–4, pp. 292–304. https://doi.org/10.1080/0267257X.2017.1284436.

Cantamessa, M., Montagna, F., Altavilla, S. and Casagrande-Seretti, A. (2020), “Data-driven design: the new challenges of digitalization on product design and development”, *Design Science*, Vol. 6 No. e27, pp. 1–33. https://doi.org/10.1017/dsj.2020.25.

Carmona Marques, P. (2021), “A model for fostering creativity in the product development process”, *International Journal of Design Creativity and Innovation*, Vol. 9 No. 2, pp. 103–118. https://doi.org/10.1080/21650349.2021.1888807.

Carneiro, V., Barata da Rocha, A., Rangel, B., and Alves, J. L. (2021). Design Management and the SME Product Development Process: A Bibliometric Analysis and Review. *She Ji*, 7(2), 197–222. https://doi.org/10.1016/j.sheji.2021.03.001.

Chattopadhyay, S., Nelson, N., Au, A., Morales, N., Sanchez, C., Pandita, R. and Sarma, A. (2020), “A tale from the trenches: cognitive biases and software development”, 2020 *IEEE/ACM 42nd International Conference on Software Engineering (ICSE)*, pp. 654–665. https://doi.org/10.1145/3377811.3380330.

Chen, L., Wang, P., Dong, H., Shi, F., Han, J., Guo, Y., Childs, P.R.N., et al. (2019), “An artificial intelligence based data-driven approach for design ideation”, *Journal of Visual Communication and Image Representation*, Vol. 61, pp. 10–22. https://doi.org/10.1016/j.jvcir.2019.02.009.

Chiva-Gomez, R. (2004). Repercussions of complex adaptive systems on product design management. *Technovation*, 24(9), 707–711. https://doi.org/10.1016/S0166-4972(02)00155-4.

Chiva, R., and Alegre, J. (2009). Investment in design and firm performance: The mediating role of design management. *Journal of Product Innovation Management*, 26(4), 424–440. https://doi.org/10.1111/j.1540-5885.2009.00669.x.

Cross, N. (2011), *Design Thinking: Understanding How Designers Think and Work*, Bloomsbury Academic, an imprint of Bloomsbury Publishing Plc.

Daugherty, P.R. and Wilson, J.H. (2018), *Human + Machine: Reimagining Work in the Age of AI*, Harvard Business Review Press.

Dorst, K. (2011). The core of ‘design thinking’ and its application. *Design Studies*, 32(6), 521–532. https://doi.org/10.1016/j.destud.2011.07.006.

Dumas, A. and Mintzberg, H. (1989), “Managing design designing management”, *Design Management Journal*, Vol. 1 No. 1, pp. 37–43. https://doi.org/10.1111/j.1948-7169.1989.tb00519.x.
Fischer, C., Malycha, C.P. and Schafmann, E. (2019), “The influence of intrinsic motivation and synergistic extrinsic motivators on creativity and innovation”, *Frontiers in Psychology*, Vol. 10 No. 137, pp. 1–15. https://doi.org/10.3389/fpsyg.2019.00137.
Fu, K., Chan, J., Cagan, J., Kotovsky, K., Schunn, C. and Wood, K. (2013), “The meaning of near and far: The impact of structuring design databases and the effect of distance of analogy on design output”, *Journal of Mechanical Design*, Vol. 135 No. 2, pp. 1–12. https://doi.org/10.1115/1.4023158.
Garbuio, M. and Lin, N. (2021), “Innovative idea generation in problem finding: Abductive reasoning, cognitive impediments, and the promise of artificial intelligence”, *Journal of Product Innovation Management*, Vol. 38, pp. 701–725. https://doi.org/10.1111/jpim.12602.
Ghosh, D., Olewnik, A., Lewis, K., Kim, J. and Lakshmanan, A. (2017), “Cyber-Empathic Design: A data-driven framework for product design”, *Journal of Mechanical Design*, Vol. 139 No. 9, pp. 1–12. https://doi.org/10.1115/1.4036780.
Gilson, L.L., Mathieu, J.E., Shalley, C.E., Ruddy, T.M. (2014), “Creativity and standardization : Complementary or conflicting drivers of team effectiveness?”, *Academy of Management*, Vol. 48 No. 3, pp. 521–531. https://doi.org/10.5465/amj.2005.17407916.
Gorkovenko, K., Burnett, D.J., Thorp, J.K., Richards, D. and Murray-Rust, D. (2020), “Exploring the future of data-driven product design”, *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pp. 1–14. https://doi.org/10.1145/3313831.3376560.
Haefner, N., Wincent, J., Parida, V. and Gassmann, O. (2021), “Artificial intelligence and innovation management: A review, framework, and research agenda”, *Technological Forecasting and Social Change*, Vol. 162, pp. 1–10. https://doi.org/10.1016/j.techfore.2020.120392.
Hands, D. (2018), *Design Management: The Essential Handbook*, Kogan Page Limited.
Jarrahi, M.H. (2018), “Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making”, *Business Horizons*, Vol. 61 No. 4, pp. 577–586. https://doi.org/10.1016/j.bushor.2018.03.007.
Klein, G. (2013), *Seeing What Others Don’t: The Remarkable Ways We Gain Insights*, PublicAffairs.
Lawson, B. and Dorst, K. (2009), *Design Expertise*, Architectural Press.
Levy, A., Agrawal, M., Satyanarayan, A. and Sontag, D. (2021), “Assessing the impact of automated suggestions on decision making: Domain experts mediate model errors but take less initiative”, *Conference on Human Factors in Computing Systems - Proceedings*, pp. 1–13. https://doi.org/10.1145/3411764.3445522.
Libânio, C. S., and Amaral, F. G. (2014). Design Professionals Involved in Design Management: Roles and Interactions in Different Scenarios: A Systematic Review. In *ICoRD’13. Lecture Notes in Mechanical Engineering*. Springer India. https://doi.org/10.1007/978-81-322-1050-4_69.
Luo, J., Sarica, S. and Wood, K.L. (2021), “Guiding data-driven design ideation by knowledge distance”, *Knowledge-Based Systems*, Vol. 218, pp. 1–15. https://doi.org/10.1016/j.knosys.2021.106873.
Ma, J. and Kim, H.M. (2016), “Product family architecture design with predictive, data-driven product family design method”, *Research in Engineering Design*, Vol. 27 No. 1, pp. 5–21. https://doi.org/10.1007/s00163-015-0201-4.
Marion, T.J. and Fixson, S.K. (2021), “The transformation of the innovation process: How digital tools are changing work, collaboration, and organizations in New Product Development”, *Journal of Product Innovation Management*, Vol. 38 No. 1, pp. 192–215. https://doi.org/10.1111/jpim.12547.
Martin, R. (2009), *The Design of Business*, Harvard Business Press.
McCaffrey, T. (2018), “Human-AI Synergy in Creativity and Innovation”, *Artificial Intelligence: Emerging Trends and Application*, IntechOpen, pp. 143–160.
McCaffrey, T. and Spector, L. (2018), “An approach to human-machine collaboration in innovation”, *Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AIEDAM*, Vol. 32 No. 1, pp. 1–15. https://doi.org/10.1017/S0890060416000524.
Micheli, P., Wilner, S.J.S., Bhatti, S.H., Mura, M. and Beverland, M.B. (2019), “Doing design thinking: Conceptual review, synthesis, and research agenda”, *Journal of Product Innovation Management*, Vol. 36 No. 2, pp. 124–148. https://doi.org/10.1111/jpim.12466.
Mintzberg, H. (1990). The Manager’s Job: Folklore and Fact. *Harvard Business Review*, 68(2), 163–176.
Mitchell, M. (2019). *Artificial Intelligence: A Guide for Thinking Humans*. Farrar, Strauss and Giroux.
Montagna, F. and Cantamessa, M. (2019), “Unpacking the innovation toolbox for design research and practice”, *Design Science*, Vol. 5, pp. 1–30. https://doi.org/10.1017/dsj.2019.3.
Moultrie, James, Clarkson, P. J., and Probert, D. (2007). Development of a design audit tool for SMEs. *Journal of Product Innovation Management*, 24(4), 335–368. https://doi.org/10.1111/j.1540-5885.2007.00255.x.
Nandy, A. and Goucher-Lambert, K. (2022), “How does machine advice influence design choice? The effect of error on design decision making”, *Proceedings of Design, Computing and Cognition Conference*, pp. 1–20.
Norman, D.A. (2007), *The Design of Future Things*, Basic Books.
Norman, D.A. (2013), *The Design of Everyday Things (Revised and Expanded Edition)*, Basic Books.

O'Neil, C. (2016), *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*, Broadway Books.

Ozkan, G. (2021). Design Management as an Effective User-Centric Management Tool for Organizations. *Design Management Review*, 32(3), 46–54. https://doi.org/10.1111/drev.12271.

Pereira Pessôa, M.V. and Jauregui Becker, J.M. (2020), "Smart design engineering: a literature review of the impact of the 4th industrial revolution on product design and development", *Research in Engineering Design*, Springer London, Vol. 31 No. 2, pp. 175–195. https://doi.org/10.1007/s00163-020-00330-z.

Porter, M.E. and Heppelmann, J.E. (2015), "How smart, connected products are transforming companies", *Harvard Business Review*, Vol. 148, pp. 148–162.

Pryszlak, J. (2019), "The key differences between data-driven and data-led", *Forbes*, available at: https://www.forbes.com/sites/jakepryszlak/2019/03/08/the-key-differences-between-data-driven-and-data-led/?sh=39c6e14234d9 (accessed 30 October 2021).

Schon, D. A. (1983). *The Reflective Practitioner: How Professionals Think in Action*. Basic Books.

Shigemoto, Y. (2020). Designing Emotional Product Design: When Design Management Combines Engineering and Marketing. In *Advances in Intelligent Systems and Computing* (Vol. 952). Springer International Publishing. https://doi.org/10.1007/978-3-030-20441-9_4.

Simon, Herbert A. (1973). The structure of ill structured problems. *Artificial Intelligence*, 4(3–4), 181–201. https://doi.org/10.1016/0004-3702(73)90011-8.

Stewart, S. (2019), "Are You Data-driven, Data-informed or Data-inspired?", available at: https://amplitude.com/blog/data-driven-data-informed-data-inspired (accessed 30 October 2021).

Thagard, P. (2021), *Bots and Beasts: What Makes Machines, Animals, and People Smart?*, The MIT Press.

Trauer, J., Schweigert-Recksiek, S., Okamoto, L.O., Spreitzer, K., Mörtl, M. and Zimmermann, M. (2020), "Data-driven engineering definitions and insights from an industrial case study for a new approach in technical product development", *Proceedings of the NordDesign 2020 Conference, NordDesign* 2020, pp. 1–12. https://doi.org/10.35199/NORDDESIGN2020.46.

Tuncer Manzakoglu, B., and Dimli Oraklibel, R. (2021). A Design Management and Design Thinking Approach for Developing Smart Product Service System Design: Projects from Online Industrial Design Studio. *Journal of Design Studio*, 3(1), 107–116. https://doi.org/10.46474/jds.933488.

Tvedt, I. M., and Dyb, K. A. (2019). The soft factors in design management: A hidden success factor? *Emerald Reach Proceedings Series*, 2, 111–117. https://doi.org/10.1108/S2516-285320190000002032.

Verganti, R. (2011). Radical design and technology epiphanies: A new focus for research on design management. *Journal of Product Innovation Management*, 28(3), 384–388. https://doi.org/10.1111/j.1540-5885.

Verganti, R., Vendraminelli, L. and Iansiti, M. (2020), "Innovation and design in the age of Artificial Intelligence", *Journal of Product Innovation Management*, Vol. 37 No. 3, pp. 212–227. https://doi.org/10.1111/jpim.12523

Weick, K. E. (1993). The Collapse of Sensemaking in Organizations: The Mann Gulch Disaster. *Administrative Science Quarterly*, 38(4), 628–652. https://doi.org/10.2307/2393339.

Werder, K., Seidel, S., Recker, J., Berente, N., Gibbs, J., Abboud, N. and Benzeghadi, Y. (2020), "Data-driven, data-informed, data-augmented: How Ubisoft's Ghost Recon Wildlands live unit uses data for continuous product innovation", *California Management Review*, Vol. 62 No. 3, pp. 86–102. https://doi.org/10.1177/0008125620915290.

Wilberg, J., Fahrmeier, L., Hollauer, C. and Omer, M. (2018), "Deriving a use phase data strategy for connected products: A process model", *Proceedings of the DESIGN 2018 15th International Design Conference*, pp. 1441–1452. https://doi.org/10.21278/idc.2018.0213.

Wilberg, J., Triep, I., Hollauer, C. and Omer, M. (2017), "Big Data in Product Development: Need for a data strategy", *PICMET 2017 - Portland International Conference on Management of Engineering and Technology: Technology Management for the Interconnected World, Proceedings*, pp. 1–10. https://doi.org/10.23919/PICMET.2017.8125460.

Wu, L., Hitt, L. and Lou, B. (2020), "Data analytics, innovation, and firm productivity", *Management Science*, Vol. 66 No. 5, pp. 2017–2039. https://doi.org/10.1287/mnsc.2018.3281.

Xin, D.D., Ma, L.L., Liu, J.J., Macke, S.S., Song, S.S. and Parameswaran, A.A. (2018), "Accelerating human-in-the-loop machine learning: Challenges and opportunities", *Proceedings of the 2nd Workshop on Data Management for End-To-End Machine Learning, DEEM 2018 - In Conjunction with the 2018 ACM SIGMOD/PODS Conference*, pp. 1–4. https://doi.org/10.1145/3209889.3209897.

Yang, Q. (2018), "Machine learning as a UX design material: How can we imagine beyond automation, recommenders, and reminders?", *AAAI Spring Symposium - Technical Report*, pp. 467–472.

Yoo, Y., Boland, R.J., Lyytinen, K. and Majchrzak, A. (2012), "Organizing for innovation in the digitized world", *Organization Science*, Vol. 23 No. 5, pp. 1398–1408. https://doi.org/10.1287/orsc.1120.0771.

Zhang, G., Raina, A., Cagan, J. and McComb, C. (2021), "A cautionary tale about the impact of AI on human design teams", *Design Studies*, Vol. 72 No. 100990, pp. 1–23. https://doi.org/10.1016/j.destud.2021.100990.