Data-driven innovation: challenges and insights of engineering design

Design Science

Data-driven innovation: challenges and insights of engineering design

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Abstract

The value-creation opportunities enabled by the ubiquitous availability of data indisputably lead to the necessity of restructuring innovation processes. Moreover, the variety of stakeholders potentially involved in innovation processes and the apparent heterogeneity of scenarios and contexts imply much less established practices and routines and not yet constituted reference frameworks to lead the transition to data-driven product innovation. In this context, the paper attempts, from the analysis of the data-driven innovation processes of 36 Italian companies, to recognise the emerging innovation opportunities offered by the rich network of the resulting data flows. However, these opportunities also imply new tasks, which in turn raise further concerns. Building on data-driven design literature and on industrial practices in the field of innovation management, the authors discuss the role that research achievements in the field of engineering design can play in addressing such concerns.

Keywords: data-driven design, digitalisation, digital design paradigm, innovation process, digital innovation

1. Introduction

The set of technological advances brought about by digitalisation have enabled radical changes in products that have become 'smart', in processes that have abandoned their physical nature to become 'digital', and in services that are consequently enabled by such smart products and digital processes (Cantamessa *et al.* 2020; Verhoef *et al.* 2021). These changes are often accompanied by disruption in business models, industries and value chains, whereby 'servitisation' has become a pervasive phenomenon and 'digital' corporations have now risen to the top of the market capitalisation league tables.

Since digital technology has led to changes in many industries throughout the world, it is reasonable to presume that innovation processes, design and product development have consequently been affected.

Digitalisation, in particular, has been having consequences on designers, both individually and when they are part of a team, thus leading to changes in design processes (Porter & Heppelmann 2014; Bstieler *et al.* 2018; Cantamessa *et al.* 2020; Jiao *et al.* 2022). Moreover, digitalisation has induced a shift in the use of digital product data and also extended the types of data that can be used. Data, in fact, can be derived from both customers/users ('*demand-side data*') and the production/distribution chain ('*supply-side data*') (Cantamessa *et al.* 2020), or they can be

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specifically related to the features, performances or operating processes of a product, or to all such aspects throughout the product lifecycle (Wellsandt *et al.* 2015). Data may also be generated by different sources ('sensor-collected, user-generated, expert-generated and internal/external documents'; Lee & Ahmed-Kristensen 2023) and acquired through various channels (Zero-, First-, Second-, Third-party data; Khatibloo *et al.* 2017). Among others, a value chain perspective is deemed appropriate to reveal the organisational and operational consequences of digitalisation (Cantamessa *et al.* 2020), especially since a distinction into demand-side and supply-side is useful in analysing technological paradigm transitions like the digital one. 'Any technological paradigm (in fact) ideally is fostered by supply and demand-side elements' (Dosi 1982; Cantamessa *et al.* 2020).

The ubiquity of data has correspondingly been enabling advancements in data analytics, which, in turn, aid design decision-making processes (Van Horn *et al.* 2012), allow product innovation opportunities, but also imply challenges and operational changes in product development. However, these process changes have not yet been accompanied by any theoretically-framed or structured support, although proposals of practices to guide product design processes within data-driven innovation environments are emerging (e.g., Cao *et al.* 2021; Liu *et al.* 2022).

Therefore, the aim of this paper has been to determine what data flows characterise data-driven innovation processes. *The objective has been to validate, at least partially, the challenges and concerns resulting from the literature, which can be associated with the data flows and can be discussed in light of the engineering design resources currently available to designers.* The paper considers the definition of 'challenge', according to the Oxford dictionary, as a 'new or demanding task' that could test the current abilities and skills of designers, and 'concern' as an issue brought about by digitalisation that causes 'shared solicitous regard, anxiety or worry' in designers.

The paper builds upon the relational model of Cantamessa *et al.* (2020) and its following extensions –specifically Kim 2022 – which depict the new paradigm of data-driven design, and attempts to overcome their limitations. It does so through the analysis of 36 case studies of data-driven innovation processes, by considering a greater number of involved actors and discussing engineering design practices in light of the challenges and concerns that have emerged. As such, the paper can be seen as an extension of the works of Cantamessa *et al.* (2020) and Kim (2022), with the goal of validating and complementing those models.

The ultimate objective of the concluding discourse about engineering design practices is to identify relevant topics emerging from this knowledge domain that can support data-driven innovation and, at the same time, anticipate directions of further development for engineering design research.

The paper is structured as follows: first, the Literature Review outlines the challenges and concerns that arise from the usage of data by distinguishing the data type and roles; this section is followed by the identification of the gap in the literature and a reflection on the original contribution of the paper. The Methodology section then presents and briefly describes the analysed companies. Finally, the Results and Discussion are illustrated and followed by possible Implications and Conclusions.

2. Literature review

The 'Digitalisation' of product and process data has been characterising the evolution of product development processes for more than four decades. Since early digitalisation processes, product/process information migrated to digital models, which allowed product information to be conveniently generated and stored, and then to shift to 'virtual product models'. However, such a 'fast forward', which involved the substitution of hand drawings with CAD models, the integration of simulations and experimental data through Product Data Management (PDM) tools and the transition to Product Lifecycle Management (PLM) systems, has led to the progressive broadening of product digital data, from the micro-perspective of an individual designer to the multiple dimensions of enterprise operations and product life stages (Terzi *et al.* 2010).

Although product development was able to boast well-established practices of using digital data or integration processes with external data, digitisation was beginning to completely change the environment in which product development took place and, consequently, the role data could play as digital-based antecedents of innovation (Agostini *et al.* 2020; Luo 2023). Hence, the purposes of and the roles that data can play in aiding design and development activities are overviewed hereafter, together with a discussion about how data forces design and development to integrate with other business processes to enable innovation.

2.1. Customers' or users' data as sources of needs, preferences and behaviour

Amazon's story highlights the power that digital data processes provide with respect to traditional ones (Moore & Tambini 2018). Walmart was gathering more than 2.5 petabytes of data every hour from its customers' transactions already a decade ago (McAfee *et al.* 2012), and General Electric has become the leading manufacturing industry in managing customers' data and designing service offerings (Davenport & Dyché 2013).

Customers' data are mainly collected by recording the purchasing behaviour of customers through the observation of individual choices (Lesser *et al.* 2000), by investigating customers' preferences (e.g., Stone & Choi 2013; Jin *et al.* 2016; Ng & Law 2020) and sometimes by analysing customers' complaints and claims (e.g., Park & Lee 2011). It is apparent that these elements can guide product development in defining and choosing design alternatives (e.g., Park & Lee 2011; Gangurde & Akarte 2013), even if they change over time and, therefore, need to be continuously tracked. In this sense, customers' reviews (e.g., Tucker & Kim 2011) or social media mining (e.g., Jeong *et al.* 2019; Choi *et al.* 2020) are more able to address such dynamic capturing requirements.

Users' data are gathered in parallel from people who use products and services or from users' stakeholders (Cantamessa *et al.* 2012, 2016). In the same way as Facebook or LinkedIn collect data to suggest new personal contacts, Netflix continuously adapts its content offer according to individual daily choices of fruition. Nowadays, this usually occurs in digital services, but it is increasingly happening for products since designers integrate users' data with product ones (Ferguson *et al.* 2015) or because smart products are able to provide data about users or their usage during use (Wang *et al.* 2019). Smart speakers, such as Alexa,

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pick up conversations, and Tesla collects more data than most car companies, that is, data that spans from a vehicle's location and a car's settings to short video clips from the car's external cameras.

Users' data also allow the users' profiles (users' psychological and social characteristics, physical and sensory characteristics, demographics, ISO 20282-1 section 7, 2006), behaviour, needs and preferences to be detected, and this leads to the product features that are explicitly linked to the users' experiences being recognised (Timoshenko & Hauser 2019). Again, users' data are sometimes gathered from the field, even though perhaps with more design-oriented purposes (e.g., Lewis & van Horn 2013; Lee *et al.* 2017): about the users' profiles (Yang *et al.* 2019), about the most essential requirements (e.g., Li *et al.* 2013; Jiao & Yang 2019) or about the affordance elements (Hou *et al.* 2019). Sometimes, they are collected from sensor data or product usage logs to detect the users' profiles, behaviour or real-time interactions (e.g., Klein *et al.* 2019; Voet *et al.* 2019). Social media help identify the users' needs or preferences (Wellsandt *et al.* 2015), and identify those stakeholders that could affect the modes of product use (Rathore *et al.* 2018) or the lead users (Tuarob & Tucker 2014).

It is well known that demand-side data allows companies not only to have a real, and not simply estimated, understanding of mission profiles but also to continuously adapt to market stimuli. This adaptation might consist of newly added functions, identified through the analysis of data generated by already launched products, or real-time adjustment of the offering to address the evolving customers' needs or self-customised products (Porter & Heppelmann 2014).

However, this speed of adaptation is far from being taken for granted and represents a challenge that still has to be solved for designers (Challenge 1, in the following, CH1). Moreover, it calls for new analysis methods and leads to operational, managerial and organisational changes in design and development processes.

2.1.1. Contextual data and the role of complementary goods in determining environmental, economic and socio-cultural conditions

Not only are users a source of information, but also the usage context can be referred to. The usage context of a product represents 'all aspects that describe the context of product use that vary under different use conditions and that affect product performance and consumers' preferences for the product attributes' (He *et al.* 2012). The context of use is embodied by environmental or external/boundary conditions, including both physical and social aspects, the main usage goal(s) and other related equipment (ISO 20282-1 2006).

While marketing studies on environmental factors that influence adoption/purchasing are more traditional (Kotler 2000), those on the determination of usage are novel and are strictly due to the possibility of collecting real-time data from smart/digital systems (Sestino & De Mauro 2021). Wang *et al.* (2019), for instance, investigated various contextual data (e.g., raining or not, wind speed, etc.; ISO 20282-1 section 6.3, 2006) associated with the use conditions of smart bicycles (e.g., riding time), while Martí Bigorra and Isaksson (2017) associated environmental conditions with the car owners' driving styles.

Producers also relate such working context/external conditions with other data about products to derive insights into the performances/behaviour of products in relation to their main goal(s) (ISO 20282-1 section 6.1, 2006;

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Von Stietencron *et al.* 2017; Bertoni *et al.* 2017). Martí Bigorra and Isaksson (2017), for instance, included other factors that they considered beneficial for technical design analysis in their study, such as the precondition of a car before starting, which they associated with engine braking, smooth operation, etc.

Apart from working on environmental/external conditions, the influence that socio-cultural settings could have on the form and usage of a product, as an immaterial factor of a user's behavioural experience and interpersonal interaction (ISO 20282-1 section 6.4, 2006), has been investigated for decades (Ram & Jung 1990). New means for gathering data can support this practice. Hou *et al.* (2019), for instance, adopted online reviews to detect in what conditions customers use/interact/perceive products and how these affect product affordances.

Finally, complementary assets also play an important role in determining contextual data (ISO 20282-1 section 6.2, 2006), especially when an architecture design assumes more strategic implications since they are enablers of adoption and affect the technological paradigms (Montagna & Cantamessa 2019; Burton & Galvin 2020). These data often include the interaction of the system with complementary components, especially when such an interaction occurs through the real-time exchange of functional data.

Again, real-time data need to be collected, albeit about all the implications the product has for the outside. In order to ensure these data become readily usable for the definition of functional changes or design parameters, the procedures of design and development processes need to change (CH2).

2.1.2. Product usage and operational data used to analyse product performance

Product data have traditionally been investigated to analyse a system's performance, monitor failures and optimise efficiency. The emerging difference is that the analysis of data can be conducted in real-time, on data collected either directly from embedded sensors (for instance, spin rate and load weight, which allow a washing machine's bearing load to be calculated during washings; Klein *et al.* 2019), or from data that are 'around' the product, in order to provide insights into such a product. Tesla represents an emblematic case: the company was able to adapt the functional parameters of the suspensions of their cars without the car owners having to go to a maintenance station to do so (Muller 2019). Suspension damping can, in fact, be adjusted in real time on the basis of the driving preferences, specific driving locations or the encountered road conditions. Similarly, smart irrigation systems (e.g., *Irriga-Smart*; *Swamp*, Togneri *et al.* 2019) plan different irrigation operations according to the data received from weather stations or on the basis of different culture development needs and soil characteristics.

Field data from customers (e.g., Akinluyi *et al.* 2014; Joung *et al.* 2019), customers' services (e.g., Bandaru *et al.* 2015) and warranties (e.g., Bueno & Borsato 2014; Moudoub *et al.* 2018) are just a few examples of other usage data that can be used to aid designers in envisioning the failures, reliability and performance degradation of products, as well as in monitoring failure modes and detecting failure patterns. Similarly, reviews and social media data can help in the investigation of those product features that are debated more among people when they are commenting on their experience and the reasons why a certain product performs better/worse than others (e.g., Zhang *et al.* 2018; Kim & Noh 2019).

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The previously cited typologies of data can be used to investigate specific product features or components, especially when failure modes can be explicitly associated with failure-prone elements (Tseng *et al.* 2016; Ma *et al.* 2017; Pal *et al.* 2019). In other cases, they can allow comparative analysis to be conducted among performance indicators (Ma & Kim 2016; Mikulec *et al.* 2017) or provide indications on product industrialisation (Alkahtani *et al.* 2019).

Users' and usage data can also be considered to investigate the performance and functional improvements of a product, as well as how usage affects a product's lifecycle. This can lead to suggestions for design changes (e.g., Shin *et al.* 2015b) or even for conceiving product family design variants (e.g., Sotos *et al.* 2014). Again, in this case, data can be derived from embedded sensors (e.g., Klein *et al.* 2019; Voet *et al.* 2019), usage field data (e.g., Shin *et al.* 2015a) and warranty data (e.g., Dai *et al.* 2017).

In turn, the real-time collection of operational data could lead to immediate functional adjustments of the design parameters, but this challenge (CH3), although more advanced in designer practice, still partially needs to be addressed, especially considering its generalisation to all industrial sectors.

2.2. Supply-side data used to identify production/distribution requirements and industrialisation alternatives

Companies also collect valuable data from their manufacturing environments, such as production machinery, supply chain management systems, etc. (Ghobakhloo 2019), often using systemic approaches (Mahmood & Montagna 2013). In these cases, data are often analysed by focusing on cost and efficiency issues (Jenab *et al.* 2019) or by addressing sustainability (Li *et al.* 2021). However, they sometimes lead to broader benefits when this information is fed early to product development (Schuh *et al.* 2016; Tao *et al.* 2018). For instance, Tesla Model 3 proved to be particularly critical during the assembly phase, since many of its weld points and rivets were not suitable for heavy production automation (Welch 2018). Data obtained from the manufacturing sector stimulated the definition of alternative product architectures in view of the consequences in the assembly phase.

Maintenance processes or the prototyping and testing phases of development processes are obviously valuable sources of information. These data are used more traditionally (e.g., Product re-engineering) and are easier to imagine, in part due to the PLM systems usually implemented in companies which are accustomed to exploiting data from maintenance, e.g., from MRO (Maintenance, Repair and Operations) reports. Again, what is different is the immediate use of data. Field data on maintenance, for instance, can be used to determine changes in design parameters (e.g., material, functional constraints, Abramovici *et al.* 2017) or used more widely on entire components (Soleimani *et al.* 2014) with the purpose of reducing the probability of failure.

Similarly, data pertaining to logistics and the supply chain can affect the design of a product (Manohar & Ishii 2008): supply chain metrics, in fact, which were originally aimed at measuring the performance for customers, have a huge impact on the social and environmental sustainability aspects of the product itself, but also

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affect the material procurement and transportation constraints that define specific functional and shape requirements.

Supply-side data represent the traditionally most applied application, although real-time collection poses the same concerns as the other data analysis sources and with respect to the operational/managerial/organisational changes induced for design and product development (CH4).

2.3. New sources of data call for design analytics to support design decisions

Apart from the increased computational capabilities of companies, the ubiquity of data has enabled the creation and advancement of a new field, which is known as design analytics (Van Horn *et al.* 2012). Design Analytics embodies a set of practices and tools that support the transformation of design-related data to make them suitable for aiding design decision-making processes (Cotter 2014; Chiarello *et al.* 2021).

In general, data mining techniques (cluster analysis, conjoint analysis, etc.), optimisation algorithms, neural networks and machine learning are relatively well-established and widely applied to design problems (e.g. Liao 2010; Elgendy & Elragal 2016; Tan *et al.* 2019). The former are mainly used to suggest requirements from data patterns or to determine the optimal settings of design attributes; the latter are instead primarily applied for leveraging decisions on previous design cases or to provide designers with relevant insights into the reasons behind the generated predictions. Machine learning (mainly classified as supervised and unsupervised algorithms) is used for both descriptive and predictive purposes (for a review, see Kotsiantis *et al.* 2007; Leskovec *et al.* 2020).

There are many application contexts of such tools/techniques along with the different phases of product development. Cluster analysis, for instance, has been employed for descriptive purposes during the planning phase for product positioning purposes (Tao *et al.* 2018) and within requirement elicitation (Zhang *et al.* 2017). Conjoint analysis has instead been used to define customers' preferences and suggest the possible functions and performances of a new design solution (Song & Kusiak 2009). Finally, the multiple response surfaces methodology (Jun & Suh 2008), ordinal logistical regression (Demirtas *et al.* 2009) and genetic algorithms (Hsiao & Tsai 2005) have been used, for instance, to determine the optimal settings of design attributes to maximise customers' satisfaction. Case-based reasoning, data-driven design-by-analogy and neural network approaches have been used extensively during idea generation, either to leverage decisions of previous design cases (e.g., Hu *et al.* 2017) and analogical reasoning (Jiang *et al.* 2021) or to simulate design alternatives concerning specific performance parameters (e.g., Dering & Tucker 2017). Optimisation tools have mainly been employed for predictive purposes during the design phase of the details. In this case, the aim is to foresee the impact of a design change at the subsystem level on the overall performance of a system (e.g., Yao *et al.* 2017) or of design optimisation (Quintana-Amate *et al.* 2015). Finally, data-driven computational tools can support problem-exploration practices (Obieke *et al.* 2021) and information retrieval (Shi *et al.* 2017; Han *et al.* 2021) along the whole design process.

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However, the choice of using data to aid design decisions introduces certain technical, operational and managerial concerns and consequences, all of which will be discussed in the following.

2.4. The resulting concerns (CN) induced by data-driven design in product development

The aforementioned technical concerns specifically refer to data analysis techniques, the operational concerns refer to the purpose of using data, while the managerial/organisational concerns refer to the interactions of design teams during the innovation and development processes inside a company.

Technical concerns arise *since data analysis tools are contextual to the phase of product development in which they should be applied* (Concern 1, in the following, CN1) (Van Horn *et al.* 2012; Bstieler *et al.* 2018; Altavilla & Montagna 2019). Algorithms are specific to the context and application for which they were developed and cannot be applied independently for any purpose. Moreover, *the ability of algorithms to automate the learning process has experienced a lack of implementation during the different design and development phases* (CN2) (Fisher *et al.* 2014).

Three operational concerns emerge from the operational point of view. First, the modalities of the identification of the customer segments whose needs have to be addressed should be entirely changed for two reasons. On the one hand, customisation/personalisation leads to each customer being considered as a 'segment-of-one' (Canhoto *et al.* 2013), whose needs are different from the 'standard' ones (Chen *et al.* 2012; Ma & Kim 2016); on the other hand, companies are increasingly turning towards continuous/real-time interactions with customers and designers and therefore must keep abreast with the evolving needs not only of those who have already adopted such interactions but also of those who will adopt them (Roblek *et al.* 2016).

Therefore, the traditional separation between ex-ante product development and ex-post product use no longer exists, and *companies experience almost simultaneous elicitation and satisfaction of the customers' needs together with the validation of the corresponding product/service performance for each product development iteration* (CN3) (Montagna & Cantamessa 2019).

Moreover, since new needs are collected after commercial deployment and because of digital technology re-programmability, the possibility of derivative innovations emerges (Yoo *et al.* 2012). More in general, *designers discover implications that were not anticipated during the initial design process* (CN4) (Gawer 2010), new features that were initially not conceived and therefore *new functions and behaviour to be designed* (Van Horn & Lewis 2015; Bstieler *et al.* 2018; Wang *et al.* 2018). This transformation calls for the integration of information from different domains, such as marketing, design, manufacturing and after-sales services (Schuh *et al.* 2008; Li *et al.* 2019), and new competencies in data analysis (De Mauro *et al.* 2018). Furthermore, *the capability of managing such diversity in extensive volumes of data* (Li *et al.* 2015; Trunzer *et al.* 2019) *has become essential* (CN5) since virtual prototyping, digitalisation or simply collection from diverse data sources generate various data formats, *as has the requirement of making the use of such data volume effective* (Zhan *et al.* 2018).

Apart from operational processes, all these elements also have managerial consequences on the interactions that design teams have externally and on other

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functions and departments of the firm (e.g., Bstieler *et al.* 2018; Agostini *et al.* 2020), as well as on the product development process itself (Cantamessa *et al.* 2020).

First, it becomes impossible – but also irrelevant – *to develop a reliable and complete set of product/service specifications* (CN6) (Gunasekaran *et al.* 2019). Designers have to design an initial product version, which is then used as a basis for further product improvements/extensions. Subsequent iterations lead to iterative validation steps, and it is possible to wonder who should be in charge of deciding on these iterations, that is, designers, marketing people or data analysts (Song 2017). This, in turn, can lead to a reissuing (but also an amplification) of the problems posed by concurrent engineering practices (Krishnan *et al.* 1997), as well as reflections on the applicability of Agile principles (Ahmed-Kristensen & Daalhuizen 2015). Moreover, without a given or fixed set of specifications, producers cannot draft any legal documents, and certification processes should be revised coherently (Magnusson & Lakemond 2017; Song 2017).

Second, design modularity and platforms become key enablers (Porter & Heppelmann 2014; Rossit *et al.* 2019) since they enable customisation/personalisation (Mourtzis & Doukas 2014) and combinatorial innovations (Yoo *et al.* 2012; Marion *et al.* 2015). However, they have their counterpart and entail costs. *Companies are, in fact, faced with the issue of understanding the trade-off between cost, production constraints, openness and flexibility of the product architecture* (Ripperda & Krause 2017), *which has strategic and managerial consequences, such as significant economies of scale and a lower development cost* (CN7) (Simpson *et al.* 1999).

Moreover, apart from deciding what product components should be shared and what should not, companies have to choose what layers of the platform they will permit other firms to extend (Yoo *et al.* 2012) and, therefore, *they have to decide on a vertical integration at the organisational level* (CN8) (Cantamessa and Montagna, 2016; Cantamessa *et al.* 2020).

Third, 'form' decouples from 'function' (Zittrain 2006), and *'digital affordance' for features and functionalities of a digital product* (Oxman 2006; Yoo *et al.* 2012; Colombo *et al.* 2022) *might overturn the traditional approach to design, which was based on a relatively rigid mapping between functions, behaviour, and structure* (CN9). Product development managers have to control a process in which new structural (immaterial/digital) features and their related behaviour are added, even after the product has been designed, produced and delivered, thus introducing new functions or changing previously existing ones (i.e., derivative innovations). This situation may represent a means of encouraging and supporting *unpredictability in innovation processes* (CN10) (Austin *et al.* 2012), which implies *understanding how to control and support creativity and serendipity behaviour in such frequently changing processes* (Andriani & Cattani 2016).

A final shift occurs in design information and knowledge management. In the distant past, digitisation processes helped explicate design knowledge through modelling (CAD systems and simulations), thus making what had previously been done through intuition and experience (e.g., storing design choices and verification activities through validated parameters and variable values) codifiable. Instead, the progressive transition to design automation is currently having the opposite effect, that is, of attributing an active role in design processes to support systems. *Design support systems can incorporate the knowledge that had previously belonged to an individual or to the design team (CN11)*, that is, moving it from individuals to capital and changing process rules and organisation equilibria.

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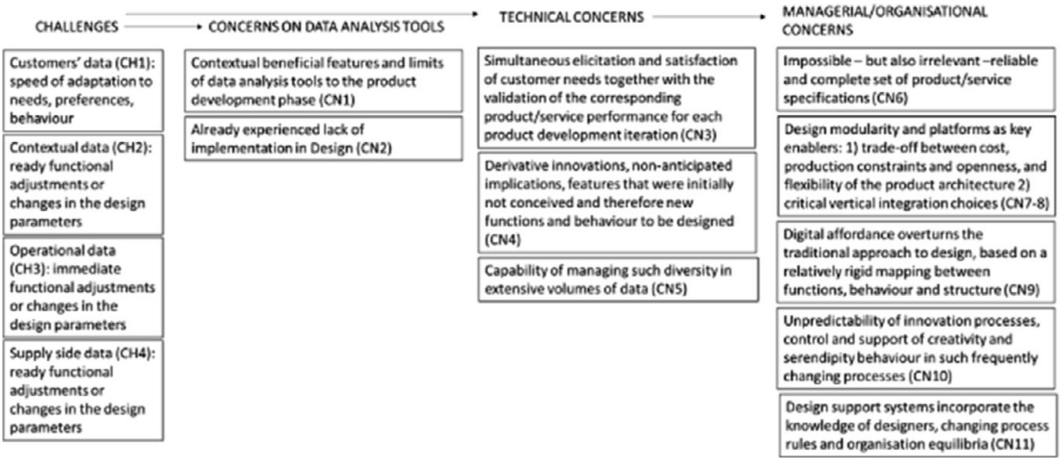

Figure 1. The challenges and emerging concerns according to the literature.

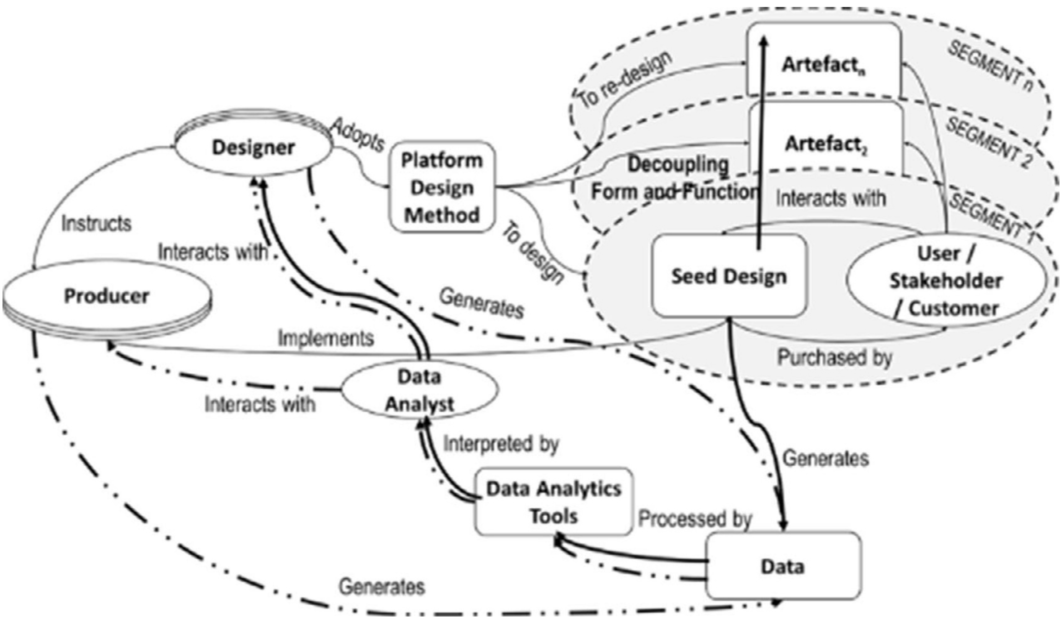

Figure 2. The new paradigm of the data-driven design context (as presented in Cantamessa *et al.* 2020).

2.5. Gap in the literature and original contribution of the paper

The previous discussion describes the opportunities, challenges and concerns about the use of data, as well as the operational and managerial changes in design and development (summarised in Figure 1), and it highlights an increasing relevance of design analytics in design, which has led to a new data-driven design paradigm (Cantamessa *et al.* 2020, in Figure 2).

The paradigm shown in Figure 2 represents a first overview of the shift that has been occurring in the data-driven design context; however, this overview fails to

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investigate the challenges and technical/operational concerns posed by the literature (the ones shown in Figure 1) in great detail and to characterise the innovative processes. In fact, it neither details the sources of the data flows and the involved stakeholders nor defines the emerging processes and practices. Indeed, only customers and producers are represented as stakeholders, without other players, such as complementors or policy-makers, who are typically decisive in innovation processes, being considered. At the same time, again with reference to the latter point, the model in Figure 2 does not represent a guideline for product design processes within data-driven innovation environments, as other emerging early proposals do (e.g., Cao *et al.* 2021; Liu *et al.* 2022).

Thus, the paper investigates data-driven innovation processes on the basis of 36 case studies and elaborates on their characterising data flows. The large number of analysed companies and the rich amount of data collected allow for the validation, at least partially, of the opportunities, challenges and concerns that emerge from the literature. Specifically, it reflects on the actors involved in the processes and their roles, the data and information exchanged, as well as the tools and methods adopted. This enables to build a relational diagram upon the data-driven paradigm of Cantamessa *et al.* (2020), incorporating also the extension of Kim (2022) about experience-centred data, so as to validate and complement that conceptual model. On the basis of the obtained results, considerations about the current engineering design practices that can contribute to addressing the emerged challenges are discussed.

Since the studies in the literature on emerging engineering practices (Cao *et al.* 2021; Liu *et al.* 2022) are still somewhat scant and not equally structured, the contribution of this paper, that is, of clearly and rigorously framing the resources for designers in such a data-driven environment, might constitute a definitive and original step forward. Moreover, it does so on the basis of the elements of complexity that emerged from the literature investigation and the validation of numerous case studies from different industries. This approach, albeit consolidated in adjacent fields such as the domain of innovation management, represents an element of novelty in the Design research.

3. Methodology

The present paper has analysed 36 Italian companies that have invested in Industry 4.0 technologies, using a qualitative multiple case study method, and investigated their resulting data-driven innovation processes. The selection criterion was aimed at representing the composition of Italian industry in terms of the most relevant sectors. Overall, 90% of the selected companies operate in the manufacturing sector, which represents the most important Italian industrial activity. Moreover, among these companies, 30% represent the metal and mechanical sector, 13% operate in the fashion industry and 9% operate in the furniture sector, while 6% operate in the food industry. These sectors are among the most relevant manufacturing sectors in Italy, according to the number of companies (Cappelli *et al.* 2024).

Although most companies in Italy are ‘micro’ enterprises (Istat, 2021), the companies considered in the sample are larger in size (i.e., medium-large companies). Such companies were included since they either represent leaders in digitalisation initiatives or are business units of multinational companies (hence,

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Table 1. Companies selected for the study

Operating sector	#	Offering and business activity	Corporate governance	Number of employees	Digitalisation initiative
Automotive industry	1	Design and production of complex interior components for the automotive sector	Listed	51–100	Support for development/ design
	2	Provision of solutions for race-car drivers	Listed	251–1000	Support for development/ design
	3	Development and production of gearboxes	Family business	1000+	Production process transformation
	4	Engineering and production of two-wheeled vehicles and compact commercial vehicles	Business unit of a multinational company	1000+	Service development
Biomedical sector	5	Production of prostheses and software solutions to support doctors	Controlled by a private equity fund	1000+	Support for development/ design
Chemical industry	6	Production of oils and lubricants for sheet metal cutting	Family business	10–50	Production process transformation
	7	Production of pharmaceuticals	Family business	101–250	Service development
	8	Production of chemicals for the rubber industry	Listed	101–250	Production process transformation
Consumer electronics sector	9	Production of digital cameras, projectors, imaging technologies, printers, multifunctional copiers and document management solutions	Business unit of a multinational company	251–1000	Service development
Fashion industry	10	Tailoring services of fabrics for the designing of personalised products	Business unit of a multinational company	10–50	Support for development/ design
	11	Creation of sportswear and sport-inspired leisure apparel	Listed	51–100	Service development
	12	Design and production of warp-knitted seamless apparel	Listed	51–100	Support for development/ design
	13	Design and engineering of international luxury brands in the apparel sector	Listed	101–250	Support for development/ design
	14	Screen printing and laser engraving for leather and synthetic decoration	Ltd company	0–9	Production process transformation

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Table 1. Continued

Operating sector	#	Offering and business activity	Corporate governance	Number of employees	Digitalisation initiative
Food sector	15	Production of dried fruit	Family business	101–250	Production process transformation
	16	Production of pasta	Listed	251–1000	Production process transformation
Furniture sector	17	Design and production of furniture elements	Ltd company	10–50	Production process transformation
	18	Production of furnishing elements in bent glass	Ltd company	51–100	Production process transformation
	19	Building, architecture, interior design and furnishing using flat glass	Ltd company	10–50	Production process transformation
Health care industry	20	Production of personal care and cleaning products	Business unit of a multinational company	1000+	Service development
	21	Operational services in the healthcare environment	Cooperative	1000+	Production process transformation
Logistic sector	22	Design, production and installation of automated warehouses	Family business	51–100	Service development
	23	Production of warehouse vehicles	Listed	251–1000	Production process transformation
	24	Design and production of automated material distribution and handling systems	Ltd company	10–50	Support for development/ design
Mechanical sector	25	Design and prototyping of mechanical components	Family business	10–50	Support for development/ design
	26	Development and production of machinery for the rubber industry	Family business	10–50	Support for development/ design
	27	Design, manufacturing and assembling of automatic spray guns	Ltd company	10–50	Production process transformation
	28	Design and production of mechanical components	Family business	101–250	Support for development/ design
	29	Provision of solutions for mechanical components	Family business	251–1000	Production process transformation
	30	Production of components for household appliances	Business unit of a multinational company	1000+	Production process transformation

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Table 1. Continued

Operating sector	#	Offering and business activity	Corporate governance	Number of employees	Digitalisation initiative
	31	Manufacture of complete final assembly plants for the automotive, aviation and aerospace industries	Business unit of a multinational company	51–100	Production process transformation
	32	Manufacture of elevators and handling systems	Listed	1000+	Service development
Metal industry	33	Production of semi-finished aluminium profiles	Family business	51–100	Production process transformation
	34	Hot and warm steel forging	Family business	101–250	Production process transformation
	35	Continuous process production of special steels	Business unit of a multinational company	1000+	Production process transformation
Shipbuilding industry	36	Construction of fast ferries	Listed	251–1000	Production process transformation

akin to an Small Medium Enterprise). In the latter case, the official registered number of all the corporation employees had to be considered.

Table 1 presents the sample and the different sectors in which the companies operate, together with a brief description of their offerings and other characteristics of their business model. The last column shows the scope of their digitalisation initiatives according to the adopted grouping approach explained below.

Data were collected through desk research in the field, and companies were chosen based on the documented digitalisation initiatives. Some of the case studies have been generated as a part of a project conducted with the Turin Chamber of Commerce between 2020 and 2022. The objective of such a project was to investigate the impact of design on strategic decisions and business model conversion choices (Bruno 2024).

The remaining case studies were selected from a number of contributions that describe the digitalisation processes of companies. Some were chosen from studies on the role of capabilities in digital transformation (e.g., Ardolino *et al.* 2018; Matarazzo *et al.* 2021; Mazali *et al.* 2023), others were taken from papers aimed at presenting efficient applications of digital tools and data analytics (e.g., Datar *et al.* 2020; Giallanza *et al.* 2020) and still others from contributions that examined digital trends in a given sector (e.g., Trino 2020). Such documentations recognised the exploitation of digital opportunities by analysing companies' management of innovation, strategies and business models. Changes in value creation processes, along with the relationships and transformation of roles, collaboration with stakeholders and the generation of new information and knowledge, were described. Therefore, from the readings, it was possible to extract the activities involved in the technological change resulting from those investments, which, according to their objective, led to the distinction of three prevalent groups, namely service development, production process transformation and support to

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Table 2. Characteristics of the groups and their initiatives

GROUP	Companies	Investment targets	Data-driven design activities	Data type
1 (Service development)	4; 7; 9; 11; 20; 22; 32	AI, AR, IoT, sensors, data analytics and data sharing, cloud platform	Understand the usage context better; User behaviour change; Assess/Predict/ Improve the performance; Build business strategy and ecosystem; Product portfolio planning;	Customers' data Contextual data Product usage and operational data (Section 2.1)
2 (Production processes transformation)	3; 6; 8; 14; 15; 16; 17; 18; 19; 21; 23; 27; 29; 30; 31; 33; 34; 35; 36	Remote Control Sensors, IoT, AI, AR and VR, MES, PLC, ERP, data analytics	Validate/support design decision; Design reliability into the system; Serve product lifecycle better; Assess/ Predict/Improve the performance	Supply-side data (Section 2.2)
3 (Support for development/ design)	1; 2; 5; 10; 12; 13; 24; 25; 26; 28	CAD 3D, AI, digital models for development and engineering, CFIST technology	Validate/support design decision; Generate product/service design ideas; User behaviour change	Design-related data (Section 2.4) Real-time feedback from consumers/ clients

development/design (the groups and their characteristics are later presented in Table 2, adopting the labelling of group 1, group 2 and group 3, respectively). Seven companies in the sample belong to the first group, 19 to the second group and 10 to the third.

Reflecting on the data flows and information gathered and exchanged in the processes, a relational diagram was built and overlaid upon the data-driven paradigm (Cantamessa *et al.* 2020, Figure 2). That activity was used to validate the already represented relationships and complement them with those that had emerged. Finally, the raised opportunities, challenges and concerns were examined against the findings from the literature review and framed according to the scope of the initiative (Table 3 in Section 4).

4. Results and discussion

4.1. Companies' digitalisation initiatives and the emerging data flows

Group 1 identifies the companies in the sample that have mainly invested in Artificial Intelligence (AI), Augmented Reality (AR) and Internet of Things (IoT) technologies to target specific customer segments or provide personalised services, coherently with section 2.1 of the literature review and with Wang *et al.* (2019),

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Table 3. Data flow types and the related opportunities and concerns

Data flow		Literature review		
GROUP	Data type	Consolidated opportunities	Identified concerns	Opportunities that have emerged
1 (Service development)	User data Usage context data (environmental and cultural conditions and the role of complementary assets)	Identifying the consumers' needs, preferences and behaviour Continuously adapting to market needs Understanding the performance, reliability, failure modes and patterns of the products	CH1, CH2, CH3, CN4, CN6, CN7, CN8, CN9, CN10	Alternative uses afforded by the product can lead to the introduction of new features and functionalities
	Product performance and operational data	Developing condition monitoring and preventive and predictive maintenance (Design for maintenance)		Reducing production costs
2 (Production process transformation)	Data from production machines Data from the prototyping and testing phases	Suggesting product architectures and design alternatives Satisfying stricter quality requirements	CH1, CH3, CH4, CN1, CN2, CN5, CN6, CN11	Improving plant efficiency Reducing the number of supervisory operators Reducing the environmental impact
	Updated information from suppliers and retailers Real-time data for the forecasting of the demand	Setting up a single integrated information system Reducing production costs and increasing efficiency	CH4, CN5	Obtaining higher-quality and more complex products Obtaining greater traceability and visibility along the supply chain Synchronising the information flows
3 (Support for development/ design)	Digital model data (CAD 3D, digital twins, Virtual Realty) Real-time feedback from consumers/clients	Determining the optimal settings of design attributes Simulating design alternatives Coordinating the design team	CH1, CH3, CN3, CN11, CN10	Designing personalised recommendations and receiving real-time feedback from consumers
	Codified tacit and procedural knowledge of an experiential nature		CN3, CN11	Integrating knowledge of the production processes in design teams and in algorithms for digital twins

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who had identified such a trend, especially about user and usage data (demand-side data). Moreover, thanks to their capacity to perform data analysis, these companies have been able to offer complementary or additional services (sometimes also very far from their original focus) to position themselves in different markets. This is the case of Company 9, which operates in the consumer electronics sector (Ardolino *et al.* 2018). By provisioning their printing machines with IoT sensors, they have managed to combine the sales of printers with a subscription for the automatic replenishment of consumables. Consequently, data on machine status and usage (e.g., the number of printed copies) have been used to generate automatic invoices and to schedule maintenance interventions and toner supplies.

Apart from demand-side data exploitation, some of the companies in the sample have also invested in digitalisation for production assets and automation (i.e., group 2) in view of increasing their production efficiency, integration and quality. The target technologies in group 2 mainly included IoT, Manufacturing Execution System (MES) or Programmable Logic Controller (PLC). Coherently with the literature, elements of non-quality tend to become less frequent or at least measurable and predictable, thanks to these technologies (Tao *et al.* 2018). For example, Company 36, which is a leading fast ferry operator, applied the principles of Industry 4.0 to a shipyard to collect accurate real-time data, especially during real-life condition tests (Giallanza *et al.* 2020). During thruster test runs, digital technologies, such as the IoT, cloud computing and big data analytics, allow specific control parameters (rotation speed, rated power, applied torque, etc.) to be monitored and real-time values (plus the maximum values) of the temperature, pressure and strain to be collected.

At the same time, industrialisation alternatives can be conceived as advanced technologies that enable the production of enhanced-performance products (Soleimani *et al.* 2014; Abramovici *et al.* 2017) or the minimisation of the environmental impact of production processes (Mayyas *et al.* 2012). For instance, Company 19 operates in the glass furniture sector and, thanks to investment in PLC and automation in their cutting and grinding lines, has been able to process large sheets of float glass up to 19 mm thick. Data from digital models are sent directly to digital printing machines, which are able to reproduce any graphical element and decoration using ceramic inks. Company 18 pursued digitalisation initiatives or even created 'ad hoc' technologies within the production environment in order to control the success of specific processes (e.g., glass bending process) and, at the same time, integrate environmental practices (e.g., reprocessing activities concerning waste and garbage) (Barbaritano & Savelli 2020).

Finally, digitalisation initiatives cannot exclude investments in CAD 3D and in AR for the development of a 'digital twin' and support in product development (i.e., group 3). Again, coherently with the literature in Section 2.4, these technologies support designers in the exploration of alternatives and their decision-making processes, and they assist the creative process by reducing designers' discretion (Chiarello *et al.* 2021). The development activities frequently take place in co-design mode with the customer/client, which is frequently the main goal of the investment. Companies 10 and 13, both of which operate in the fashion industry, are examples of this approach (Trino 2020; Mazali *et al.*, 2023). In Company 10, the user, supported by systems that gather data directly from customers (e.g., body scanner 3D), can personalise each tailoring detail through a 3D configurator. The output can be visualised in real-time through the 3D model

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so that immediate feedback can be obtained. Similarly, Company 13 has included 3D technologies in product development phases, thereby increasing the interactions between model makers and stylists, as well as enabling users to be involved in choosing the design solution. Coordination takes place remotely and almost in real-time.

Company 5 is a similar case, but in a different sector. Working on the production of prostheses and software solutions to aid doctors, they model a patient's skeleton, digitally reproduce the prostheses, detect any possible fitting problems and intervene in the fine-tuning (Mazali *et al.* 2023). When they employ additive manufacturing techniques, they send digital models directly to the production machines.

Table 2 shows the differences between the digital initiatives of the companies, grouped according to the objective of the activities in their innovation processes (i.e., group 1, group 2 and group3). The table highlights the technology investment targets and maps the data-driven design activities (as suggested in Lee & Ahmed-Kristensen 2023) affected by the initiatives. The last column reports the type of data exploitable thanks to the new technologies, with reference to the literature section where they are presented.

The data flows emerging from the case studies have been overlaid on the data-driven design paradigm (Cantamessa *et al.* 2020) and presented in Figure 3, distinguishing the initiatives from which they originate (i.e., group 1, group 2 and group 3). Such a representation emphasises how the observed data flows validate and complement the paradigm.

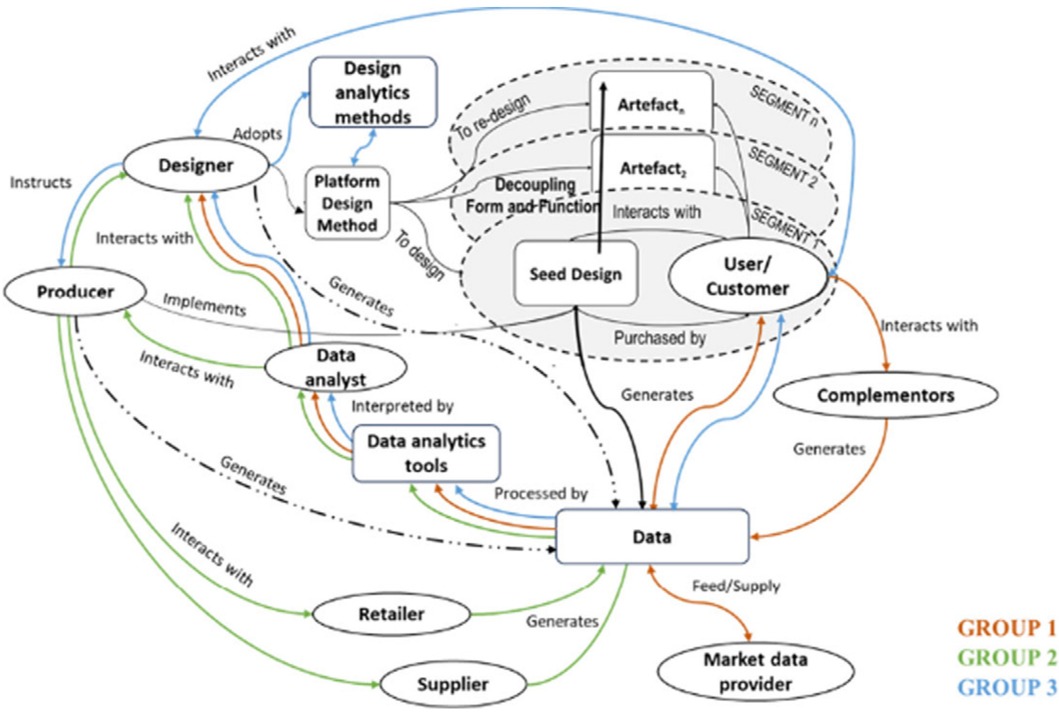

Figure 3. Extended data-driven design paradigm with the new data flows identified in the present study.

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Indeed, the role of both demand and supply flow of information is confirmed to be relevant and to involve designers and producers together with the novel figure of the data analyst. Moreover, the role of tools and methods in guiding designers' analysis activity is broadened, recognising the relevance not only pertaining to data analytics and platform design but also including design analytics methods.

Thanks to the case studies, new actors have been confirmed to be decisive in data-driven innovation activities, thus deserving consideration and, specifically, to be added to the paradigm. As a matter of fact, in light of a demand-side data evolution, actors like complementors and market data providers have demonstrated to be crucial in collecting data about the artefact usage and surrounding context, especially in those initiatives aimed at providing additional and personalised services to customers (i.e., group 1). Data provided directly by users, consumers and customers are also added here, with consideration of the extension of Kim (2022) with zero-party data, reflected in the dual-directional arrow between data and user.

The digitalisation of production assets and automation (i.e., group 2) instead revealed the contributions of external suppliers and final retailers in the exchange of data and information, often aimed at creating an integrated information system and generating new design alternatives. Finally, apart from confirming the direct observation of customers' interaction with the artefacts, and thus the continuous acquisition of data, the paradigm in Figure 3 also adds a potential direct relationship between the designer and consumers through real-time feedback exchanged during co-design activities (i.e., group 3).

4.2. Challenges and concerns emerged from the literature and from the study

The analysis of the companies' initiatives in digitalisation highlights the differences in the mode of action of the companies, which depend on their strategic intent, the scope and technological target of the initiative and the related application. Examining the companies was also useful in confirming the changes, concerns and challenges identified in the literature.

The digitalisation initiatives in group 1 have enabled companies to collect information on the users and their usage to develop tailored solutions and offer additional services. Data about the users' profiles, behaviour, needs and preferences, as well as environmental/external conditions, are gathered in real time, and the gathered information is used to create new design parameters and make functional adjustments. Thanks to this information, features that were not anticipated and new functions emerge (CN4, CN6, CN9, CN10). However, it is neither trivial nor automatic to change design procedures in order to ensure that these data become readily usable and to keep up with continuously evolving market stimuli (CH1, CH2, CH3). Such solutions in fact often involve trade-offs between costs, production constraints and flexibility of the product architecture, with certain consequences at the organisational level (CN7, CN8). Company 9 is a clear example of this. On the one hand, the connected machines have guaranteed consumers the possibility of automatically replenishing consumables as soon as the printers detect that the ink or toner is running out. On the other hand, this has raised issues in terms of security, doubts about complexity and costs due to the necessary hardware and software modifications. In order to address these problems and to maximise the potential of the obtained data and the benefits of large-scale projects, the company decided to develop a new platform as a layer of the 'technology stack' (Porter & Heppelmann 2014), in order to build and support new technology infrastructures.

The companies in group 2 are characterised by initiatives of digitalisation and automatisation in their manufacturing environment. Such companies have the aim of receiving data directly from the production machines and integrating their supply chain with an updated exchange of information. These interventions enable greater efficiency and higher quality, and also offer novel industrialisation alternatives (CH4). In the same way as in group 1, but this time with a broader scope, the changes that had to be introduced were far from being straightforward (CH1, CH3). Different domains, such as design and manufacturing and after-sales services are affected, as they are called upon to cooperate by integrating different competencies and to make what was previously done by intuition codifiable (CN5, CN11). All of this contributes to the development of an innovative environment that supports the interactive engineering of the company, where the design and development phases are performed in parallel rather than in series (CN6), in order to reduce production times and costs.

Company 36 is an emblematic case, as the complete digital transformation of manufacturing has not only involved the production and management of the shipyard but also the product design and engineering techniques. Experimental data are directly transmitted to the technical office so that engineers can analyse the data in real time and perform an interactive design to improve the performance of the entire system or of any critical components. The digitalisation initiatives in Companies 16 and 19 are linked to the production of higher quality and more complex products: data integration helps Company 16 to choose higher quality wheat for the production of pasta, while the automation of the machines allows Company 19 to process thicker glass sheets, realise engravings, etc. Conversely, Company 18 was able to reinvent glass by transforming the production process, thanks to the technological advancements and a continuous interaction between material and process engineers, designers and marketers. Such an innovative material is composed of recycled scraps from sheets of glass, resulting in random combinations of colours, which improves the creative features of the final products and fully embraces the principles of circular economy.

Finally, the companies in group 3 have pursued digitalisation initiatives in product development and (co)design activities with the users. The customers/users contribute to the creation of an artefact, validate its characteristics and performance and give real-time feedback (CN3). Again, in this case, challenges associated with the speed of adaptation and with immediate functional adjustments and changes in the design parameters have emerged (CH1, CH3, CN10). Moreover, the use of digital tools to support the design process considerably decreases the discretion of the designers (CN11).

In Companies 10 and 13, both of which work in the fashion industry, the users are actively involved in the design process. In Company 10, thanks to a 3D configurator, the users autonomously edit and simultaneously visualise their preferences, while a 3D body scanner enables immediate functional and design adaptations to be made; the users of Company 13 can intervene remotely in the exploration of the different design alternatives and eventually highlight errors or more suitable options. Instead, in Company 5, digital models enable different simulations to be run (e.g., to move a screw) and mechanical tests to be performed without destroying expensive samples. In all these cases, the experience and intuition of designers are incorporated into the support systems/tools, which have begun to play an active role in the process.

The aforementioned results have been summarised and structured in Table 3, specifically highlighting the changes, concerns and challenges that have manifested within the case studies, to which the engineering design domain can contribute. Indeed, for each group, the type of data that characterises the flow of information exchanged and gathered in the process involved in digitalisation initiatives is explicated. Then, the opportunities and concerns arising from such data flows are presented and divided depending on whether they are 'consolidated' or newly emerging from the case studies. The former are examined in light of the state of the art and presented in the 'Literature review' column, while the latter are summarised in the final column.

Information that is more relevant for design and development processes has been distinguished from information that has other purposes, with the latter highlighted in grey, even though all the information is relevant to the innovation strategies of the companies.

5. The potential role of engineering design

Most of the evidence emerged from the study validates the literature discussion proposed in Section 2. However, some of these elements are still not established in the literature and concern the possibility of

1) Designing personalised recommendations and real-time feedback from the customers/users;
2) Recognising alternative uses afforded by the product for the introduction of new features and functionalities;
3) Integrating knowledge about the production processes in algorithms for digital models to complement the designers' background, knowledge and expertise.

However, these elements of opportunity in data-driven environments present some unresolved problems related to the real-time data collection itself. Indeed, although innovation approaches are based on profound market research and are aimed at achieving an improved personalisation of customer experience, the adaptation of operational and management practices to arrive at the systematic use of real-time data still needs to be completed, and this involves an increasing variety of tasks and roles, as well as the definition of new practices and processes. However, some consolidated engineering design practices can help address the challenges arising from the new elements of complexity in such a data-driven environment and contribute to their resolution.

First, it is essential to radically enhance the changeability and adaptability of processes and products to ensure flexibility and deal with critical aspects rapidly. Moreover, exploiting supply-side data enables increasingly demanding requirements, in terms of quality, time and costs, to be dealt with. Practices such as *Design for Manufacturing, Assembly or Logistics*, etc. are aimed at reducing the lead times, total production costs and/or the total cost of ownership throughout the entire lifecycle, in view of ease of manufacturing, a simplified assembly of parts and reduced issues of transportation and maintenance (Emmatty & Sarmah 2012).

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Robust design instead focuses on making the functions of a product more consistent with variations in the downstream processes and environmental changes. *Design for Mass Personalisation* approaches enable the user to tailor a seed design according to their own preferences, even beyond the range of configurations initially conceived by the manufacturer (Ozdemir *et al.* 2022). Personalisation usually concerns aesthetic features, but it could also pertain to adjustments of product functionalities and ergonomics.

So far, personalisation has been introduced as the result of the explicit demands of consumers. However, *Machine Learning* algorithms, applied to the data collected in smart products, may be increasingly used to support the recognition of human preferences, even those that the users are not aware of, thus offering new personalisation opportunities. The comprehensive, special issue edited by Panchal *et al.* (2019) provides a rich overview of machine learning applications in engineering design, which can also be used to elicit users' preferences. Nevertheless, some gaps still exist in translating the observed behaviour into proposals for new product functions. For example, in the context of this study, Company 4 produces two-wheeled vehicles and has started to offer 'sharing services' to exploit real-time data about the density and timing of scooter movements to target specific customer segments, such as residents of the same building, and to develop tailored solutions (Ardolino, 2018).

The recognition of unexpected alternative uses could enable ex-post updates of the software of a product to match the new functionalities that are offered. In this perspective, *Affordance-based Design* (Maier and Fadel, 2009) provides the cognitive elements necessary to frame the development of smart products that can be easily upgraded to offer new functions and unexpected user experiences (Pucillo & Cascini 2014). For instance, the smart toothbrush made by Company 20, which produces personal care and cleaning products, could be used to help adult users monitor the hygiene habits of elderly people as a proxy for their wellness and care (Datar *et al.* 2020).

Overall, functional expansion is emerging as a pervasive phenomenon that increasingly involves consumer products, and the design theory allows such dynamics to be represented beyond the optimisation perspective of econometric models (Le Masson *et al.* 2019). Qualitative transformations of products are also being mapped through patterns derived from the empirical observations of the evolution of technical systems, as proposed in *TRIZ models* (Cascini 2012). In this context, the systematic comparison of successful and unsuccessful products with their predecessors (Borgianni *et al.* 2013; Casagrande-Seretti *et al.* 2019) allows the expected market appraisal of the alternative product profiles that have to be designed to be assessed in advance, thereby partially addressing the phenomenon of derivative innovations.

Furthermore, *User-centred Design* has analysed the similarities and differences in the concept of user value in different domains, such as anthropology, sociology, philosophy, business and economics, thus producing a comprehensive categorisation to distinguish between utility, social significance and emotional and spiritual dimensions of user value (Boztepe 2007).

The *Agile* approach, applied to design and development, also goes in this direction, thanks to its iterative process, as it does not force a designer to start working on high-fidelity prototypes straight away, but instead fosters interactions

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to constantly validate the users' needs, translate them into design attributes and improve the product (Da Silva *et al.* 2011).

This kind of data exploitation obviously raises serious ethical concerns about what the new balance between machines and human beings should be, and it might infringe on privacy and security regulations. These concerns are well known in the design of assistive technology. Participatory multidisciplinary approaches have already been successfully adopted in this field, and they could inspire reference models to incorporate ethical and social issues in the development of smart products (*Participatory Design*; Oishi *et al.* 2010; Udoewa 2022).

Finally, analogous considerations can be made for design practices aimed at integrating production process knowledge. Production process parameters can be taken into account in *Design Optimisation* models through both simulation and empirical approaches (Zhao *et al.* 2007).

Table 4. Concerns from the literature, opportunities recognised in the case studies and engineering design topics that might have a role in addressing them

Concerns indicated in the literature	Consolidated engineering design topics	Emerging topics in engineering design
Contextual beneficial features and limits of data analysis tools in product development (CN1)	Machine Learning for Engineering Design (Panchal *et al.* 2019)	Combination of customer evaluation with context information to customise offer (Kim & Hong 2019)
Lack of implementation of data analysis tools in design (CN2)	Machine Learning for Engineering Design (Panchal *et al.* 2019)	
Simultaneous elicitation and satisfaction of the customers' needs, and validation of the corresponding product/ service performance for each product development iteration (CN3)	Platform Design (Simpson *et al.* 1999) Agile approach (Da Silva *et al.* 2011)	Design for mass personalisation: (Ozdemir *et al.* 2022) Use of Large Language Models (LLMs) to support the elicitation and evaluation of customer preferences (Chiarello *et al.* 2024; Song *et al.* 2024)
Derivative innovations, not anticipated implications, new functions, behaviour and structures to be designed (CN4)	Affordance theory and models (Maier and Fadel, 2009; Pucillo & Cascini 2014; Colombo *et al.* 2022) Functional expansion (Le Masson *et al.* 2019) Technology paradigm assessment models (Borgianni *et al.* 2013; Casagrande *et al.*, 2019) Patterns of evolution of technical systems (Cascini 2012)	

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Table 4. Continued

Concerns indicated in the literature	Consolidated engineering design topics	Emerging topics in engineering design
Ability to manage such diversity in extensive volumes of data (CN5)	Robust Design (Park *et al.* 2006); Inverse Design (Hou & Jiao 2020) Design for Manufacturing, Assembly or Logistics (Emmatty & Sarmah 2012) Design optimisation and/or DDOM (Zhao *et al.*, 2007)	Design for sustainability, Eco-design (Pigosso *et al.* 2015; Ceschin & Gaziulusoy 2016)
Impossible – but also irrelevant – to develop reliable and complete set of product/service specifications (CN6)	Participatory design, Design ethics (Oishi *et al.* 2010)	Large participatory design involving communities (Udoewa 2022)
Trade-off between cost, production constraints and openness and flexibility of the product architecture 2) critical vertical integration choices (CN7–8)	Product platform and product family design (Simpson *et al.* 1999)	
Digital affordance overturns the traditional approach to design, which is based on a relatively rigid mapping of functions, behaviour and structures (CN9)		Affordance theory and models for digital artefacts (Colombo *et al.* 2022)
Unpredictability of innovation processes, control and support of creativity and serendipity behaviour in such frequently changing processes (CN10)	Technology paradigm assessment models (Borgianni *et al.* 2013; Casagrande *et al.*, 2019) Patterns of evolution of technical systems (Cascini 2012)	
Design support systems incorporate the knowledge of designers, changing process rules and organisation equilibria (CN11)		
Opportunities that have emerged from the case studies		
Design of personalised recommendations and real-time feedback to change the use behaviour (Table 3, Group 3)		Persuasive Design (Crilly 2011)

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Table 4. Continued

Concerns indicated in the literature	Consolidated engineering design topics	Emerging topics in engineering design
Alternative uses afforded by the product can guide manufacturers towards the introduction of new features and functionalities (Table 3, Group 1)	Affordance theory and models (Maier & Fadel, 2009; Pucillo & Cascini 2014; Colombo *et al.* 2022) Functional expansion (Le Masson *et al.* 2019) User value (Boztepe 2007); User-centred Design, PSS design (Vasantha *et al.* 2012; Machchhar *et al.* 2022); Interaction design and gamification (Sailer *et al.*, 2017)	
Integration of knowledge about production processes in algorithms for digital models, in order to complement the background, knowledge and expertise of designers (Table 3, Group 3)	Product Data Management (PDM); Product Lifecycle Management (PLM)	
Reducing the environmental impact (Table 3, Group 2)	Lean manufacturing in Industry 4.0, cyber-physical production system, big data-driven and smart communications, artificial intelligence for sustainability, the circular economy in a digital environment (Tseng *et al.* 2021)	
Obtaining higher-quality and more complex products (Table 3, Group 2)	Data-driven product quality prediction models (Ren *et al.* 2020)	

Table 4 presents the concerns that have emerged from the literature (Section 2, CN1-CN11) and the opportunities recognised from the analysis of the case studies (Table 3), relating them to the extant engineering design literature. In the second and third columns, indeed, the authors suggest some engineering design practices, either consolidated or emerging, that appear relevant to address those identified concerns and opportunities. Even though only in a preliminary state, this attempt at mapping concerns and engineering design resources is meant to offer insights into future directions of design research.

6. Conclusions

Exploiting digitalisation and data-driven innovation raises new concerns that have not yet been addressed for the current innovation and development processes or practices.

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The paper offers a structured overview of the use of data in innovation processes, distinguishing between the studies available in the literature on customer and user data, data related to the context (environmental conditions, sociocultural conditions, complementary goods), usage and operational data, as well as supply-side data. All these types of data can play a role in the design of smart products and digital services and allow the technical, operational and managerial changes necessary to lead such a data-driven transformation to be depicted. Starting from a careful literature review, this paper provides an original structured classification of challenges and concerns emerging in the field of data-driven innovation processes. These have been analysed and discussed against the information related to digitalisation initiatives that occurred in 36 Italian manufacturing companies from several industrial sectors. In doing so, the paper also proposes an updated version of the data-driven design paradigm presented by Cantamessa *et al.* 2020, incorporating the extension of Kim (2022). The analysis of the 36 Italian companies confirms the validity of the revised model by mapping the data flows and information gathered and exchanged in the innovation processes.

Among the others, it emerged that new operational and design tasks are becoming increasingly necessary, but the current industrial practice has no reference processes to address such tasks, and the literature does not offer adequate responses. Moreover, although design teams and processes are largely involved in the digital transition, the role design research and its literature can play in enabling data-driven innovation and overcoming emerging concerns is still unclear. The paper has attempted to provide a methodologically rigorous map of data flow types and the related opportunities and concerns. The latter ones offer the opportunity to suggest some consolidated engineering design literature resources that can provide useful support in building a new methodological reference framework for data-driven innovation.

On the practical side, the classification of the analysed companies into three groups (i.e., service development group, production process transformation group and support for development/design group), the elicitation of their investment targets and the data-driven design activities described in the reports of those digitalisation initiatives offer an overview of what is already ongoing in some advanced companies, hence worthy of consideration for replicability. Furthermore, strategically relevant data flow types in the groups of companies recognised in this study have been connected with innovation opportunities and might attract the attention of further stakeholders in the exploitation of product and process data. Ultimately, the collection of the proposed cases and new ones in a repository built on the main types of companies and data flows identified in this paper can provide practical guidance in industrial practice. Nevertheless, how to properly structure a repository with this intent requires further elaboration and preliminary testing; as such, it is not part of this study.

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