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Design Science

Data-driven design: the new challenges of digitalization on product design and development

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Abstract

Digitalization and the momentous role being assumed by data are commonly viewed as pervasive phenomena whose impact is felt in all aspects of society and the economy. Design activity is by no means immune from this trend, and the relationship between digitalization and design is decades old. However, what is the current impact of this 'data revolution' on design? How will the design activity change? What are the resulting research questions of interest to academics? What are the main challenges for firms and for educational institutions having to cope with this change? The paper provides a comprehensive conceptual framework, based on recent literature and anecdotal evidence from the industry. It identifies three main streams: namely the consequences on designers, the consequences on design processes and the role of methods for data analytics. In turn, these three streams lead to implications at individual, organizational and managerial level, and several questions arise worthy of defining future research agendas. Moreover, the paper introduces relational diagrams depicting the interactions between the objects and the actors involved in the design process and suggests that what is occurring is by no means a simple evolution but a paradigmatic shift in the way artefacts are designed.

Key words: data-driven design, digitalisation, digital design paradigm

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1. Introduction

'Digital is changing the world' has become a mantra in academic, industrial and policy-making circles. Digital technology has indeed brought changes and disruption to many industries worldwide, and 'digital' corporations have now climbed to the top of the league tables, as far as market capitalization is concerned.

So, if 'digital' is impacting the world, it is reasonably obvious that design is being affected too. This change is probably still in its infancy. In fact, the transformation brought by 'digital' product representations since the 1970–1980s (as can be found first in computer-aided design (CAD) and then in Product Lifecycle Management (PLM) systems) is likely to be nothing more than a preliminary step of a much deeper and broader transformation, which is still ongoing.

However, declaring that 'digital has changed, is changing and will change the world of design' risks to be rhetoric and to not help in addressing any problem. Such statements do not address what working on 'digital design' really means, either as practitioners, academics or policy-makers.

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This paper aims to provide a conceptual framework of the current and emerging challenges brought by digitalization on design and to highlight key research questions that still ought to be addressed. We believe that these research questions could lead to a better understanding of a new paradigm and to develop sound and industrially relevant tools and methods.

From a methodological point of view, the research has followed a top-down approach. In particular, three main contributions (Porter & Heppelmann 2014; Iansiti & Lakhani 2014; Bstieler *et al.* 2018) have inspired the main arguments of the paper and provided the insights to structure it. In order to broaden the vision and address the topic of digitalization in design, an extensive and interdisciplinary literature review of around 100 papers in the fields of *Management* (Management Science, Organization Science and Decision Sciences), *Innovation Management* (e.g., *Journal of Product Innovation Management*, *R&D Management* and *Technovation*), *Operations Management* (e.g., *Production Engineering*; *International Journal of Production Research*, *ASME Journal of Manufacturing Science and Engineering*, *The International Journal of Advanced Manufacturing Technology*) and *Engineering Design* (*Journal of Engineering Design*, *Research in Engineering Design*, *Design Studies*, *Design Science*, *ASME Journal of Mechanical Design*; *Computers in Industry*, *AIEDAM*) has been conducted. Some papers from the *Information Technology* and the *Data Science Domains* (e.g., *Advanced Engineering Informatics*, *IEEE Transactions on Knowledge and Data Engineering*, *IEEE Big Data*, *International Journal of Business Research and Information Technology*) were specifically included in order to allow more in-depth insights on enabling technologies.

This survey of literature has led to identifying three main streams of research for engineering design, each of which bears consequences at different levels (the detailed documentation linking each paper to each stream and consequence will not be reported in the paper but is available on request):

(i) **Stream 1**: literature shows that digitalization affects designers both at the individual level and as part of a team, and, specifically, the ways by which they work (*operative (OP) consequences*) and interact with other units in their firms (*organizational (ORG) consequences*). Furthermore, this impact appears to be different when looking at *supply-side data* (i.e., the data that come from the production value chain) and *demand-side data* (i.e., data coming from customers);

(ii) **Stream 2**: literature shows that digitalization has consequences on *the development process* itself since digital and agile environments both enable and force design routines and processes to change. This has not only *OP* and *ORG* consequences but also *managerial consequences* since these new processes have to be set up and governed;

(iii) **Stream 3**: part of the literature works on new tools that can support data-driven design processes. In the design context, this trend means investigating the field of *analytics for design*, whose consequences are mainly *operative*.

The following Table 1 summarizes these three streams of research, their impact at different levels and the section of the paper where they will be discussed. In particular, the three different levels represent the distinct consequences of implementing technology, that are operational, managerial or strategic and organizational (Cantamessa *et al.* 2012).

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Table 1. The high-level relationship between the consequences of digitalization and the main streams of research on design

	Operational consequence	Managerial consequence	Organizational consequence	Section
Stream 1: Consequences for designers working alone and in teams				
Demand-side data	√		√	3.1
Supply-side data	√		√	3.2
Stream 2: Consequences on development and design processes	√	√	√	4
Stream 3: Analytics for design or design analytics	√			5

These *OP*, *ORG* and *managerial* consequences lead designers to operate in a world of growing complexity. To convey this complexity in clear terms, we will adopt a relational model, as first developed in Cantamessa (2011) (see Figure 1), and adapt it to the emerging scenario.

The model, depicted in Figure 1 includes the main design paradigm elements in the 1990s. Designers were considered here either working alone or in a team and following a 'customer-driven' product development approach They were called to capture somehow insights about the interaction between artefacts and humans (which, depending on the role, could be users, external stakeholders or customers); based on these insights, they would aim at designing better products, at the same time, providing adequate information to the firms which would produce such artefacts. The concept of the artefact was at those times progressing beyond material 'products' and becoming broader, by also encompassing service components and business models. However, the approach to design was still strongly rooted in the tradition of designing physical goods.

The following discussion will adopt this relational model as a way to 'track the changes in the design context' (Cantamessa 2011) from the baseline situation to the emergent impact of digitalization. Compared to other macrolevel process models proposed by the literature (for a survey, see Wynn & Clarkson 2018), this representation allows to go beyond a description of the design process and shows the context in which it occurs, the actors involved and their mutual relationship. In the model, the differences brought by the emergence of 'digital' in designers' activities and relations will be discussed and highlighted, looking at the supply-side and demand-side elements that have emerged (or are emerging) in recent years.

The paper is structured as follows. Section 2 will provide a concise framework description of the most relevant 'digital' technologies and of the way with which they are shaping industrial sectors in general. Then, Sections 3–5 will provide a detailed description of the three aforementioned streams of research and the associated research questions. The final section will attempt to draw a few conclusions on this emerging paradigm of design in the digital era.

The dissertation will develop mainly around durable goods industries. Durable goods indeed are among the most impacted by digital transformation. Contrary to disposable or soft goods, they allow a higher possibility of retrieving data and

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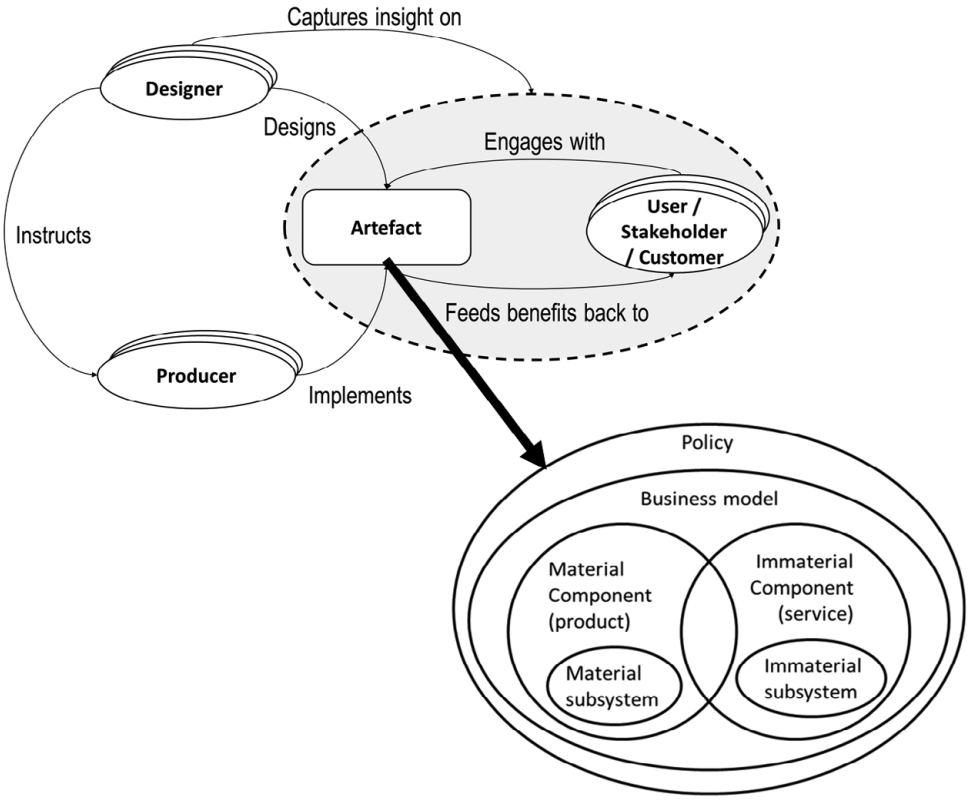


Figure 1. The relational model developed in Cantamessa (2011).

information directly from the field (something of that more complex systems, such as aeroplanes or power plants were already doing since a long time).

Examples from industry are generally provided throughout the paper to exemplify conceptual statements; however, a single case study has been predominantly chosen in order to have a common thread in the discussion. The case study is somewhat freely inspired by news and events reported from Tesla, the well-known battery-electric car producer. Tesla, in fact, easily lends itself as a poster example of transformations occurring in the design and innovation contexts following the emergence of 'digital' technologies. In fact, cars are the archetype of durable goods, and Tesla represents an emblem as it collects many data from everyday use and returns them to the user in the form of updates. Readers should be aware that the approach taken is not inductive since we are not using the Tesla case study as a source from which to derive the conceptual model. On the contrary, the conceptual model is built by elaborating results taken from literature, and news from Tesla are simply used as exemplifications of aspects of the model.

2. The enabling technologies of digital contexts are shaping a different world

The word 'digital' implies the computerization of previously 'analogue' products and processes. The computerization has indeed been occurring since the 1970s

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when computers progressively emerged and diffused. Computers have become both a new 'digital' product category and an enabler of a first 'information revolution'. In the context of design, product information was traditionally relegated to 'passive' paper-based visualizations (i.e., a drawing could only be looked at but could not automatically lead to calculations or simulations) that were unrelated to each other (i.e., the drawings of an assembly and its constituent parts could not interoperate with one another). Thanks to that early wave of digitalization, product information migrated to digital models. This has allowed tremendous progress not only in terms of more convenience in generating and archiving product information but also because digital product information became a real 'virtual product model'. For instance, digital models incorporated the structure and the history of the product and could support simulation under multiple perspectives (e.g., stress–strain analysis carried out with finite element methods, process analysis carried out with computer-aided manufacturing).

Nowadays, when using the word 'digital', the above-mentioned advances are further advanced by the following – and highly complementary – enabling fields of technology:

(i) *Internet protocols and always faster and cheaper connectivity.* In its many waves of innovation, the Internet started connecting people to contents through the World Wide Web; it then allowed unprecedented forms of communication and socialization among people through social networks. Nowadays, the Internet of Things (IoT) technology is leading to a continual connection and flow of data between people and objects and between objects and other objects;
(ii) *Augmented* and *virtual reality,* which allows richer representations of objects and environments, merging the real with the virtual, and vice-versa;
(iii) powerful and cheap IT equipment (processors, bandwidth and storage) which have enabled the virtualization of physical servers, leading to *cloud computing* and the possibility of storing *Big Data*;
(iv) *Data mining* can exploit the value hidden in massive amounts of heterogeneous data, by identifying patterns and behaviours in phenomena and occurring within systems, without requiring ex-ante theorizations;
(v) *Machine learning* allows the development of new forms of automation and decision-making, based on the re-elaboration and 'digestion' of large amounts of data.

These technological streams enable radical changes in products and services and beyond. Digitalization is, in fact, a paradigmatic change, in which not only the technological shift occurs but *behavioural/social* shifts in society can be observed, often accompanied by disruption into *business models* in industries and value chains. Table 2 describes the immediate effect brought by each technology, the ensuing impact on products and services and the consequences on both the side of demand (consumers and society in general) and supply (producers).

3. Stream 1: the OP and ORG consequences for designers

As shown in Table 1, the first stream looks at the impact of 'digital' on designers and their work, which, on the one side, includes the activities they have to carry out

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Table 2. Enabling technologies and their impacts

Technologies	Data availability	Technological shift	Societal/Behavioural shift	Challenges for business
Internet, Social Networks and *Internet of Things (IoT)*	Products are becoming 'smart' (i.e., they incorporate sensors, computing power and communication capabilities; (Cronin 2010).	'Smart objects' generate, communicate and use data, consequently adapting their behaviour. Smart objects allow digitalization of processes and services (Grüninger *et al.* 2010).	People and objects are involved in pervasive digital processes, through which they are continuously connected and engaged with one another (Porter & Heppelmann 2015).	Learning how to design smart products with the right feature sets. (Zawadzki & Żywicki 2016). Defining protocols/ processes to allow useful interaction between objects and people. (Rijsdijk & Hultink 2009). Defining proper data collection strategies from smart objects. (Porter & Heppelmann 2014). Defining value-creating product-service bundles. (Valencia *et al.* 2015).
Augmented and *Virtual Realities*	Reality can be supplemented by additional information, while virtual objects and worlds can be represented digitally in an immersive way (Lu *et al.* 1999).	Virtual representations can be used to substitute or to enhance reality to support humans in their actions (Guo *et al.* 2018).	People seamlessly engage with virtual or augmented representations (Füller & Matzler 2007).	Understanding value-creating uses of augmented and virtual reality (Dodgson *et al.* 2006). Developing 'digital twins' to support business operations (Tao *et al.* 2018).

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Table 2. Continued

Technologies	Data availability	Technological shift	Societal/Behavioural shift	Challenges for business
Cloud and Edge Computing	Data storage and processing capabilities are available at little cost and seamlessly connected to the world via reliable networks (Goranson 2003).	Computing power and storage can be allocated as desired (i.e., centralized versus decentralized). Massive amounts of data can be gathered, stored and processed (Big Data) (Bharadwaj & Noble 2017).	Humans generate and store (often unconsciously) a high quantity of data, based on the activities they perform, along with the smart products they use (Brown *et al.* 2011).	Defining data collection and processing strategies and architectures that can provide value and lead to higher competitiveness (Wu *et al.* 2019).
Data Mining	Information patterns are discovered in Big Data (McAfee *et al.* 2012).	A huge amount of data can be analysed and lead to the discovery of unexpected knowledge, generally without requiring ex-ante theorization and domain expertise. Significant increase in the value of data (Golchha 2015; Marjani *et al.* 2017).	Human decision-making, both for consumers and producers, is empowered by the insight generated by data mining techniques (Wu *et al.* 2019).	Achieving and exploiting economies of scale arising from data (Wu *et al.* 2019). Identifying meaningful patterns and extracting relevant knowledge from Big Data (Brown *et al.* 2011).
Machine Learning	Patterns in data enable the generation of sophisticated forms of automatic behaviour (Fisher *et al.* 2014).	It becomes possible to develop algorithms allowing automatic decisions or behaviours without having to provide explicit instructions (Leskovec *et al.* 2020).	Human decision-making is not simply aided by information but actively supported (or even substituted) by autonomous systems (Seidel *et al.* 2018).	Developing functional and value-creating autonomous systems (Jordan & Mitchell 2015).

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and the tools they can use (OP) and, on the other side, the way they operate within organizations (ORG).

Central to this discussion is the role of data. These are here classified for the analysis purposes into demand-side and supply-side since any technological paradigm ideally is fostered by supply and demand-side elements (Dosi 1982). In particular, data can derive both from the field ('demand-side data') and the side of the production/distribution value chain ('supply-side data'). Both demand-side (D) and supply-side (S) data have OP and ORG consequences. To track these consequences throughout the paper, we will associate a 'code' to each consequence/challenge, by combining these labels (i.e., D-OPi represents the *i*-th operational consequence due to demand-side data).

3.1. Demand-side data

Demand-side data are gathered from customers. They are mainly collected by recording customer purchasing behaviour, through the observation of individual choices (Lesser *et al.* 2000) as well as from stakeholders (Cantamessa *et al.* 2016) and, nowadays and increasingly in the future, from the actual use of smart products or digital services (Kagermann 2015; Bharadwaj & Noble 2017; Li *et al.* 2019) or even from the sheer presence of smart products in the environment (e.g., a smart speaker picking up conversations). Walmart, for instance, gathers more than 2.5 petabytes of data every hour from its customer transactions (McAfee *et al.* 2012), and Facebook or LinkedIn collect data to suggest new personal contacts (Davenport *et al.* 2012). GE has become the manufacturing industry leader in managing customer product data, to the point where it is becoming the most known developers of service offerings based on Big Data (Davenport & Dyché 2013). Tesla, similarly, collects more data than most car companies and varies from vehicle's location, car's settings and short video clips from the car's external cameras (Muller 2019).

Basically, the idea is that demand-side data will allow companies to understand user needs fully. Not only companies will be able to have a real, and not simply estimated, understanding of mission profiles, but they will also be able to adapt continuously, based on market stimuli. This adaptation might consist of newly added functions identified through the analysis of data generated by product already launched (Lewis & Van Horn 2013), up to a real-time adjustment of the offering to address the evolving customer needs (Brown *et al.* 2011) and self-customized products (Porter & Heppelmann 2014). The simultaneous adaptation is to be intended as the possibility by designers to continuously update product design and consequently product itself and have operational and organizational consequences for designers:

The first operational change regards *the identification of the customer segments whose needs must be addressed* (Canhoto *et al.* 2013; Roblek *et al.* 2016) (D-OP1).

In a context of mature product and services, a firm usually segments the market statically, using dimensions such as demographics, usage patterns, and so on, while products are still to be diffused, firms are used to distinguishing between the segments proposed by Rogers (i.e., from innovators to laggards, Rogers 1962). As a result, designers are used to derive the priorities of each customer segment at each step (Canada 2010), and any interaction with customers took place when a new segment had to be addressed.

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Nowadays, two changes are occurring through data gathered directly from product: (1) customization, or even personalization, is leading to consider each customer as a 'segment-of-one' and as a 'new need every time' (Canhoto *et al.* 2013); (2) companies are truly increasingly turning towards continuous and real-time interactions with customers so that designers must keep abreast with the evolving needs not only of those who have already adopted but also of those who will adopt (Roblek *et al.* 2016). In the first case, beyond the possibilities of approaching closer to each customer, it is possible to reach customers that belong also to the tails of the sales distribution curves. Those customers have needs that are different from the 'standard' ones, and fitting in niche markets (Chen *et al.* 2012; Ma & Kim 2016) can provide new needs to be addressed. In the second case, the continuous collection of upcoming needs from products already in the field both when they are 'sold' and – even more – when they are 'provided as a service', implies the redesign of products, simultaneously considering the upcoming customers who have not adopted yet and have to be acquired, as well as the existing customers, who must be kept loyal.

Tesla Model S is an example of how even the hardware of the car has been designed to offer the maximum flexibility to the changing customers' needs, starting from a control panel that allows changes in the interface and functionalities. Those needs are the ones that emerge from the feedbacks of customers but are also deduced by the uses that car owners make of their vehicles (Lyyra & Koskinen 2016).

The second change concerns the *almost simultaneous elicitation and satisfaction of customer needs together with the validation of the corresponding product/service performance in each product development iteration* (Montagna & Cantamessa 2019) (D-OP2).

Traditionally, the management of customer requirements involves an iterative procedure to elicit requirements by users, interpret them and, finally, define product specifications (Jiao & Chen 2006). After that, in the postlaunch reinnovation phase, customer satisfaction is usually assessed to redesign the product (Rothwell & Gardiner 1985). Nowadays, in agile contexts, companies continuously gather data from users after the commercial deployment of the product and use them as a basis for continuous technical improvement (Ülkü *et al.* 2012). In more and more industries, starting from digitalized services, product-development iteration simultaneously incorporates the elicitation and satisfaction of customer needs and the validation of corresponding performance (Montagna & Cantamessa 2019). Hence, testing and validation no longer follow the conception of the product but coexist in a continuous circle. Although today it is not possible to find this continuous circle of elicitation, satisfaction and validation in every sector, this is the direction that can be hypothesized.

For instance, as if it were producing a 'mobile phone on wheels', Tesla Motors exploit its data collection system connected to Tesla HQ in order to understand software bugs and errors and to release updates which can improve car performances (Walker 2015). In 2013, for instance, three Tesla Model S vehicles caught fire because of suspension problems (Bullis 2014) and – instead of starting a very costly vehicle recall process – Tesla simply sent out an over-the-air (OTA) update to change the suspension settings, giving the car more clearance at high speeds.

A third operational change is linked to the possibility of *having derivative innovations* (Yoo *et al.* 2012) or more generally, the chance *that designers discover implications which were not anticipated by the initial design* (Gawer 2010) (D-OP3).

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Basically, the ability to collect new needs determines new features that were not conceived initially and therefore new functions and behaviours to be designed (Van Horn & Lewis 2015; Bstieler *et al.* 2018; Wang *et al.* 2018). This phenomenon is already known for socio-technical systems that usually evolve over time (Geels & Kemp 2007). The diffusion of Facebook in developing countries, for instance, involved several technical problems, since it was not originally designed to be supported by poor communication infrastructures. A new set of requirements and solutions was required to be developed since the access to the Internet, and the quality of the connections entailed for a 'softer' version of the standard application (Wyche *et al.* 2014).

The ability to identify unanticipated implications can also avert or limit negative consequences in case of product defects or technological immaturity. For instance, significant diffusion of autonomous vehicles may entail significant negative impacts and externalities, and continuous and detailed observation of products operating in the field may allow firms to manage them in a timely and appropriate way.

Finally, a fourth change may involve *the automation of the innovation process or at least parts of it* (Bstieler *et al.* 2018) (D-OP4).

Since the 1990s, a variety of efforts have been made to automate portions of the design process, for instance in idea generation (e.g., Wang *et al.* 1995; Seidel *et al.* 2018). Marketing departments, among business functions, have intrinsically been spending generalized efforts in updating data collection processes from the field, and digitalization has fostered such an approach. The presence of such large amounts of data, simultaneously to the computational capability and pervasive use of computers in design (Anderson *et al.* 2018), is making nowadays the efforts for design automation closer to fruition. In particular, some attempts in the SW domain exist (Clarke 2018). Recently, Elon Musk has affirmed that 'computers will be able to do anything a human can by 2030–2040' (Lant 2017). However, these possibilities are still to be explored because while some examples exist in design optimization or prototyping, it is yet to be understood whether the early, more creative and less routinary design phases may be automated and to what extent (Kwon *et al.* 2018).

All these elements have consequences not only on operational processes but also on the interactions that design teams have with the other functions and departments of the firm.

A fifth change, therefore, concerns the *integration of IT, marketing and NPD functions* (Bstieler *et al.* 2018) (D-ORG1). Various authors have shown that marketers and designers need to cooperate closely (Cooper & Kleinschmidt 1986; Moore Geoffrey 1995; McQuarrie 2014), and that information technology (IT) should be integrated into the organization at various levels (Ward & Zhou 2006; Barczak *et al.* 2008). This collaboration between marketing, the IT department and the design function is nowadays even more crucial (Bstieler *et al.* 2018) if one wishes to share, structure and interpret continuously updated data throughout the product development process (Urbinati *et al.* 2018). The novelty is that this collaboration rests on the ability to analyse vast and rich amounts of continuously gathered data, which very probably will require the constant support of the new professional role of data analysts (refer to Figure 1). This ongoing collaboration makes thus necessary to define and formalize the roles and competencies that designers, marketers and data analysts should have with one another.

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Finally, the sixth change leads to *reshaping the relationships between customers and manufacturers* (Nedelcu *et al.* 2013; Espejo & Dominici 2017) (D-ORG2). Indeed, supplying goods to previously targeted consumers has become outdated (Dominici 2009); consumers do not just passively buy products, they increasingly participate in the process of value creation, even by unconsciously transmitting data on their usage (Espejo & Dominici 2017), at least for maintenance planning (Tao *et al.* 2018). Tesla, again, has created digital twins of its products to monitor their real-time use. Each car is equipped so to communicate constantly with its virtual twin located on a Tesla server, to detect product failures or suggest timely maintenance interventions (Schleich *et al.* 2017).

In other cases, product failures and degradation patterns (e.g., material ageing mechanisms) are not only useful for preventive and predictive maintenance but also for the definition of other product mission profiles (Aggarwal & Abdelzaher 2013). Customers, therefore, become producer–consumers or 'prosumers' (Nedelcu *et al.* 2013). The relationship between customers and manufacturers therefore changes, and the ownership of this process is to be understood, whether it should be managed by marketing, design teams or even automated outright.

In light of what has just been described, the corresponding demand-side evolution of the baseline model is represented in Figure 2. The main shift is represented by the presence of data that are not only systematically, but also continuously, generated, collected and analysed. These data are collected by direct, continuous and real-time observation of interactions between customers in different market segments and the artefact (Figure 2b). This is clearly different from the traditional methods for customer observation and elicitation of customer needs typical of the previous paradigm, depicted in Figure 2a. Data become a focal element in the new design paradigm, leading to the new figure of the data analyst. Data analysts work closely with designers and other business functions, such as the marketing department, eventually allowing a tight integration between them. Data analysts and designers are intended here both as working alone and in teams, both in the sense of the work they carry out and of the competencies they must possess.

These operational and organizational consequences give rise to some key research questions to be answered as shown in Table 3.

3.2. Supply-side data

In addition to demand-side data, companies collect reams of useful data from their production systems and operating environments. Data can be generated from a multitude of sources, such as production machinery, supply chain management systems and monitoring systems (Noor 2013; Ma *et al.* 2017; Ghobakhloo 2020), also using systemic approaches (Alfieri et al. 2012). The massive data generation and their systematic collection have been even more stressed with the revolution in production systems brought by Industry 4.0 actions.

Data from these sources are often collected and analysed with a focus on opportunities for reducing cost and increasing efficiency. Smart manufacturing, for instance, is often conceived as an environment in which a new wave of electronic sensors, microprocessors and other components allows a high degree of automation (Noor 2013) and provides real-time warnings about potential problems or opportunities for cost reduction (Jenab *et al.* 2019).

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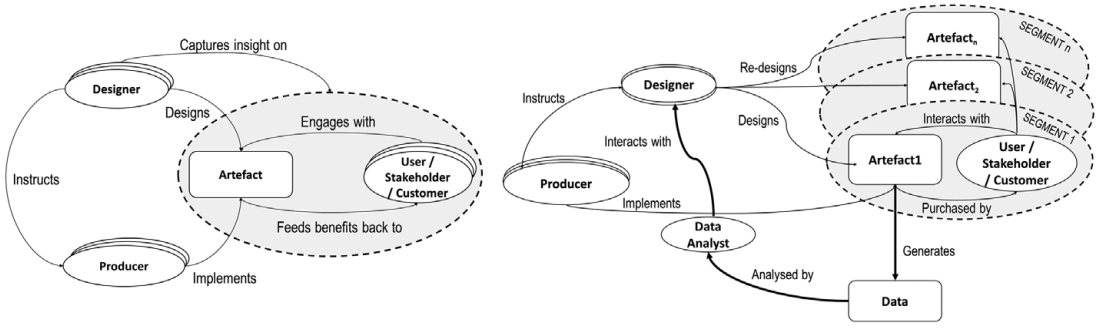


Figure 2. The shift from the old (a) paradigm to the new demand-side one (b).

Table 3. Operational and organizational consequences of demand-side data availability

Operational consequence	Derived research questions
Customization and personalization are leading to consider each customer as a 'segment-of-one' (Canhoto *et al.* 2013). Continuous (and real-time) interaction with the different customer segments that progressively appear along the diffusion curve (Roblek *et al.* 2016) (D-OP1)	What are the new theoretical models describing the diffusion of innovative products and services? What features should these models have in order to study diffusion?
Each iteration in development simultaneously incorporates satisfaction of needs and validation of performance (Montagna & Cantamessa 2019) (D-OP2)	How can companies operatively manage the data they continuously gather from users as a basis for continuous technical improvement?
Innovative uses lead to derivative innovations or to the need of managing unanticipated consequences (Gawer 2010; Yoo *et al.* 2012) (D-OP3)	How should companies look at innovative uses or unanticipated impacts of their products and introduce derivative innovations?
Possible automation of the innovation process or at least parts of it (Bstieler *et al.* 2018) (D-OP4)	Will AI algorithms lead to the automation of agile product and service development? What AI algorithms could lead to this automation?
Organizational consequence	**Derived research questions**
Integration of IT, marketing and NPD departments (Bstieler *et al.* 2018) (D-ORG1)	What new digital skills and competencies should be developed, allocated and integrated within companies? How should marketers and designers operatively interact with data analysts to envision innovation opportunities?
Change in the negotiating power between customers and manufacturers (Nedelcu *et al.* 2013; Espejo & Dominici 2017) (D-ORG2)	How will the agile approach alter the producer–customer relationship, which was up to now based on close relationships and structured flow of information on customer needs to be delivered to product and service designers? In this context, what will be the impact of AI algorithms?

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However, the effects of digitization of production processes can lead even to broader benefits, especially if this information is fed early in the development process (Schuh *et al.* 2016). Tesla Model 3, for instance, turned out to be particularly critical during the assembly phase, due to its many weld points and rivets that were not suitable for heavy production automation (Welch 2018). Data from manufacturing, in that case, provided information useful for industrialization, suggesting product architecture alternatives in view of the consequences on assembling.

The first operational challenge posed by supply-side data concerns *the need of having integrated information coming from different domains, such as design, manufacturing and after-sales services* (Schuh *et al.* 2008) (S-OP1).

These data traditionally are collected by companies through their ERP, MES and PLM systems. However, these systems are rarely integrated, and this prevents firms from having a unified view of this data and a rigorous approach to data collection (Asmae *et al.* 2017; Lanz & Tuokko 2017; Singh, Misra & Chan 2020). Especially in SMEs, interoperability and data exchange issues among system architectures still provide consistency matters (Telukdarie & Sishi 2018). For instance, product architectures and production bills of material are scantly put in relation (Altavilla & Montagna 2019; Behera *et al.* 2019), current systems often fail in tracking data changes (Li *et al.* 2015) and the granularity level and detail of the information are often not shared among systems to ensure satisfactory interoperability (Cheung *et al.* 2010).

In order to disentangle this situation, firms will have to proceed to define common conceptual models and shared procedures and frameworks for data collection (Sajadfar & Ma 2015). It is no coincidence that Tesla has chosen to develop a customized ERP in-house; a highly vertically integrated environment, in fact, cannot be cut by the standard solutions provided for the automotive sector. The common use of a single system not only has avoided the need for custom adaptations to other standard systems but also has provided the common views of the data, required to ensure interoperability (Clark 2013; Alghalith 2018). In particular, unified feature-based representations of products, which contemporaneously relate to functional geometry and manufacturability, can be generated and can be used to manipulate and evaluate part designs, according to part family information, multiple period production plans and market demand fluctuations (Lee & Saitou 2011).

Scattered data represent a problem not only within the firm but also by firms operating in the value chain; data must be bundled and unbundled according to the necessity of the analysis carried on at each product lifecycle stage (Altavilla & Montagna 2019). The challenge for companies again lies in developing such kind of common frameworks, and while some companies are still struggling to embrace the culture of PLM, the information system designed by Tesla again is able to face the challenge. Tesla system connects not only with standard PLM tools (specifically, in 2010, Tesla has also adopted Dassault System Catia V5 and Enovia V6 solutions) but also includes its world-class e-commerce system (Clark 2013; Alghalith 2018).

Once collected, the supply-side data come from diverse data sources and in highly various formats. Therefore, such digital contexts stress the operational requirement of *managing such diversity in extensive volumes of data* (Li *et al.* 2015; Trunzer *et al.* 2019) (S-OP2).

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Other data sources of data which require appropriate management include virtual reality, which has been employed since many years by designers to better visualize structure testing and verify assembly and maintenance processes (Sivanathan *et al.* 2017), as well as rapid prototyping, which has demonstrated its effectiveness in the context of product design activities (Schuh *et al.* 2016). These systems have nowadays begun to impose further requirements for data collection (Seth *et al.* 2011) and the need to avoid lack of convergence between the physical and the digital domains (Tao *et al.* 2018). The risk of inconsistency is inflated if the datum does not derive only from testing or verifying activities, which remain 'local' to the product development process, but it is constantly generated – and in large quantity – by digital twins (e.g., from robotic systems during production or in digital format from maintenance crews) (Mejía-Gutiérrez & Carvajal-Arango 2017). Tesla has defined specific partnerships (e.g., with PTC) to ensure data consistency on its product models (Schleich *et al.* 2017), and the attention of Tesla to data consistency of its platforms is easily proved by the number of positions opened for database engineers worldwide in each of its business areas.

Finally, even if one were able to guarantee interoperability between the systems, coherence and defragmentation of the data, regardless of the source and the format, *the effective use of all these data* still remains, also in a digital context, a significant operational problem for designers (Zhan *et al.* 2018) (S-OP3), because of a number of reasons.

First, companies already own a large amount of data which could be used to support decisions (Wu *et al.* 2013) but do not always even know what data are already available in their database and what data they are producing (Altavilla *et al.* 2017; Arnarsson *et al.* 2018). Second, designers often still do not know how to make the best use of these data (Arnarsson *et al.* 2018). Third, the magnitude of the phenomenon could force the use of AI algorithms but the potential of these algorithms is still not clear, especially when it comes to embedding the necessary knowledge from different technical domains (Dougherty & Dunne 2012).

At the moment, apart from design optimization and prototyping, it is not clear if AI algorithms will be able to interpret performance and functional patterns correctly and what type of contribution they can provide to designers. For instance, doubts have been raised with respect to their ability to generate feasible technical alternatives either on their own or by interpreting the intentions expressed by designers (Noor 2017). This adds – this type from supply-side data – to the previously mentioned problem of *design automation* (Bstieler *et al.* 2018; Seidel *et al.* 2018) (S-OP4).

Concerning the organizational consequences, the main effect that can be identified relates to the *procrastination of collaboration between Development, IT and the other operational departments* (Agostini & Filippini 2019) (S-ORG1).

The data integration requirements force, today more than ever, functional integration among other operational departments, such as production, maintenance, logistics, etc. (Liao *et al.* 2010). If Industry 4.0 actions have equipped production plants and operative processes with sensors and devices able to collect real-time data on process execution and companies are willing to use them not only to solve efficiency issues but also to feed design processes, the analysis of such a massive quantity of data and the interpretation of the evidences will require full functional integration, cross-domain knowledge and new competencies and skills (Agostini & Filippini 2019). Also, in this case, Tesla can provide an indication. Tesla initially did not hire expert engineers from the automotive field to avoid

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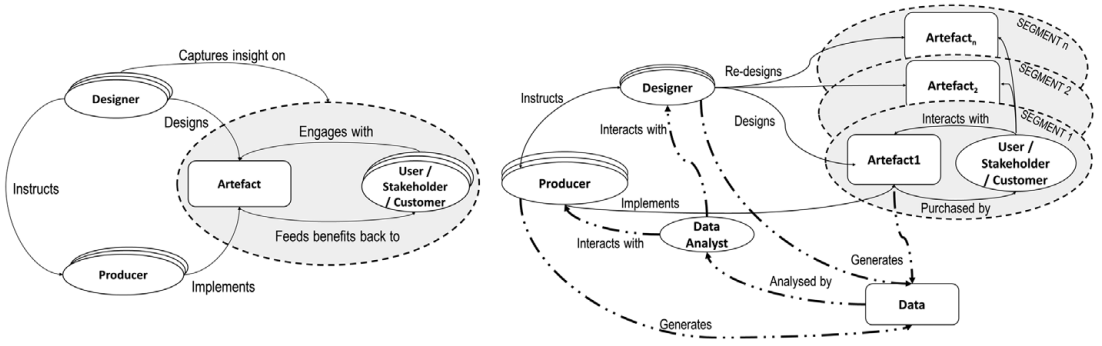


Figure 3. The shift from the old (a) paradigm to the new supply-side one (b).

fixation on traditional architectures and competence biases. However, it is possible that some erroneous design choices could have been prevented with proper specific knowledge (Welch 2018). To what extent can a firm do without specific and sector knowledge? So, given that designers with prior industry experience are likely to be involved, they will be required to enrich their competencies on other technical domains, to stress collaborations with colleagues from other specialist technical domains, as well as to develop digital skills to be able to interpret the evidences arising from data analyses. Moreover, they will have to be supported by data analysts that, at their turn, have to acquire the main principles of engineering design, as well as some fundamental knowledge from the specific technical field. It is difficult to conceive such a transformation of competencies in the short term. Moreover, one should wonder who – in organizational terms – should 'own' (i.e., be responsible for) such data-driven processes between designers, production engineers, industrialization teams or data analysts.

Figure 3b, therefore, depicts a further step into the new design paradigm, compared to the baseline model (Figure 3a). It includes the role of the supply flow of information, which is especially relevant to the producer and the designer (represented with the long dash-dot line). The centrality of the data becomes dominant. IT systems must be adequate to accommodate real-time information from the multiple systems associated with the various operating processes. The continuous and massive flow of data must be integrated and made reliable in order to be used effectively by the data science methods and tools and the results delivered to support design activities. Designers, producers and data analysts will have to work together, mutually integrating their knowledge and competences. Moreover, the producers, operate together in a group with assemblers and distributors (and coherently are represented as joined in the figure), surpassing the idea of a linear supply chain.

The research questions linked to the changes described above are summarized in Table 4.

4. Stream 2: the specific consequences on development and design processes

Digitalization and its enabling technologies additionally have impacts on product development (NPD), as process itself. First, because the product development process

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Table 4. Operational and organizational consequences of supply-side data availability

Operational consequence	Derived research questions
The information must be integrated from different domain perspectives, such as design, manufacturing and after-sales services (Schuh *et al.* 2008) (S-OP1).	What is the right level of granularity and detail of the information to ensure satisfactory interoperability among systems? What are the possible conceptual models, procedures and frameworks for data collection?
Extensive volumes, formats and sources of data lead to problems of inconsistency and lack of convergence between physical and digital domains (Li *et al.* 2015; Trunzer *et al.* 2019) (S-OP2) Interoperability between systems, coherence and defragmentation of the data regardless of the source and the format is still one of the major barriers (Zhan *et al.* 2018) (S-OP3)	What is the common and integrated set of parameters and variables that must be observed to ensure consistency and convergence? What is the right level of observation width to avoid data overwhelming and to generate the right information for innovation opportunities?
Possible *automation* of the *design* process (Bstieler *et al.* 2018; Seidel *et al.* 2018) (S-OP4)	Will AI algorithms lead to the automation of some of the activities in the design process? Which processes are ready for more automation? Will designers be able to express their rationale in a way that AI algorithms will be able to design autonomously? How much can AI algorithms integrate or even replace technical knowledge?
Organizational consequence	Derived research questions
The massive availability of data, now more than ever, will require full functional integration, cross-domain knowledge and new competencies and skills (Liao *et al.* 2017) Collaboration between IT, production and R&D departments will have to be made effective by integrating IT systems from different departments (Liao *et al.* 2010) (S-ORG1)	What new digital skills and competencies should be developed and integrated within companies? How should designers and production experts operatively interact with data scientists to envision new functional opportunities? What skills (digital and not) should designers and production experts develop? And dually, which specific and technical expertise will the data analyst have to develop? What will their roles be? Who has the ownership and the responsibility of such data-driven processes?

is changing in its nature. The traditional separation between ex-ante product development and ex-post product use does not exist anymore (Montagna & Cantamessa 2019). Second, because digital technologies themselves and new business models (i.e., the ones described in Section 2 and listed in Table 5) impose new guidelines for design (i.e., design pilots as named by Hermann 2016): Interoperability, virtualization, decentralization, real-time capability, service orientation and modularity.

These new design pilots lead again to operative (NPD-OP) and organizational (NPD-ORG) changes. Additionally, a further consequence emerges in relation to the management of the process (NPD-MAN). These consequences are described in columns 2–4 in Table 6.

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Table 5. The new design pilots imposed by technologies and business models

		Design pilots (Hermann, Pentek & Otto 2016)
Digital technologies	Internet protocols and connectivity	Interoperability
	Virtual realities	Virtualization
	Cloud computing and Big Data	Decentralization
	Data mining	Real-time capability
	Machine learning	Real-time capability
New business models	Servitization	Service orientation
	Mass customization	Modularity

From an operative and process point of view, since companies will continuously adapt their value proposition, changing in some cases their business model (Trimi & Berbegal-Mirabent 2012), *it becomes impossible – but also irrelevant – to develop a reliable and complete set of product/service specifications* (Gunasekaran *et al.* 2019) (NPD-OP1). Designers will have to design *an initial version of the product* (i.e., 'seed design'), similarly to the concept of 'minimum viable product', *as a basis for further product improvements and extensions* (NPD-MAN1). The subsequent iterations raise the need for iterative validation steps, and one may wonder to whom *the responsibility and authority in deciding on these iterations* should be assigned, whether to designers, marketing people or data analysts (Song 2017) (NPD-ORG1). In a way, this leads to a reissue (but also an amplification) of *the problems in project management already posed by concurrent engineering practices* (Krishnan *et al.* 1997) (NPD-MAN2). Activities and teams, in fact, must be managed in concurrency with an increasingly frequent exchange of information between the demand and supply-side information. Flexibility opportunities are constrained by project technical uncertainty and by the sensitivity of downstream activities, while coordination complexity is inflated for highly complex projects or when multiple parallel projects are ongoing. Attempts in this regard have been made, by integrating the Stage-Gate approach to agile principles (Ahmed-Kristensen & Daalhuizen 2015): in particular, stage-gate modalities are used to handle high-level requirements and project progress, while the agile elements are adopted to drive development, to support teams in validation and to find more conveniently design failures (Ahmed-Kristensen & Faria 2018). Finally, new contractual and administrative problems could arise. Indeed, without a given and fixed set of specifications, producers *cannot draft a legal document describing their product* but they have to keep changing and updating it, and *certification processes are all to be reviewed coherently* (Magnusson & Lakemond 2017; Song 2017) (NPD-MAN3).

In order to support the development of continuously improved products and services, *design modularity and platforms become key enablers*, and it is not by chance that digital technologies are facilitating their renewed use in design (Porter & Heppelmann 2014; Rossit *et al.* 2019) (NPD-OP2). Modularity and design platforms, now more than ever, in fact, are becoming fundamental given the

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multiplicity of needs led by product customization and personalization that are stressed and enabled by digitalization (Mourtzis & Doukas 2014). The development of combinatorial innovations is instead activated, thanks to these operative design practices (Yoo *et al.* 2012; Marion *et al.* 2015) (NPD-OP3). Tesla again confirms this tendency: an end-to-end workflow system (the 3DX system), heavily based on platform design, supported the ramp-up for the Model 3 and Tesla Energy in 2016.

Platform design has its counterpart and entails costs. Companies face the issue of understanding *the trade-off between cost, production constraints and openness and flexibility of the product architecture* (Krause *et al.* 2017) (NPD_OP4) that has strategic and managerial consequences, such as significant economies of scale and lower development cost (Simpson *et al.* 1999) (NPD_MAN4). Moreover, besides deciding which product components should be shared and which not, companies have to choose which layers of the platform they will permit other firms to extend (Yoo *et al.* 2012) and therefore they have to decide on vertical integration at the organization level (Cantamessa & Montagna 2016) (NPD-ORG2).

Moreover, digitalization generates further complexity in designing and integrating digital technologies in the product (Jung & Stolterman 2011). This is the problem of facing 'design affordance' for features and functionalities of a digital product (i.e., the problem of digital affordance seen in Oxman 2006; Yoo *et al.* 2012), which revolutionizes the traditional approach to design, based on a relatively rigid mapping between functions, behaviours and structure (Gero & Kannengiesser 2004).

Traditionally, the function of a product was a driver for its structural and shape characteristics. The function and the component trees were coupled entirely between themselves and with respect to system behaviours so that once the set of functions was defined, this was linked to the set of the behaviours and components (that were traditionally HW by nature). *The presence of digital components and the reprogrammability of digital technologies, in particular, enable instead the addition of new behaviours (not properly functions) after the product has been designed, produced and sold.* This implies that an SW platform but consequently also the structure and the physical parts, must be ex-ante enabled, so to accept ex-post behaviours. It may even happen that new components, specifically SW, but not necessarily, can be ex-post added to enable behaviours, inducing new physical features (i.e., forms) that were previously unimagined. The binding of form, behaviour and function is procrastinated, and facing digital affordance requires designers to *decouple* 'form' *from* 'function' (Autio *et al.* 2018) (NPD-OP5). Product development managers have to control a process in which new features and behaviours are added even after the product has been designed, produced and already is in operation. An example of this is the aforementioned software update system of Tesla that has been used by the company over the years to address problems and enhance performances of the vehicles ex-post when the product was already on the market. For instance, in 2013, Tesla sent out an OTA update to change the suspension settings, giving the car more clearance at high speeds (Bullis 2014).

This situation may represent a means to encourage and support *unpredictability in innovation processes* (Austin *et al.* 2012) (NPD-MAN5), and it is necessary to *understand how to control and support creativity and serendipity behaviours* in such frequently changing processes (Andriani & Cattani 2016) (NPD-ORG3).

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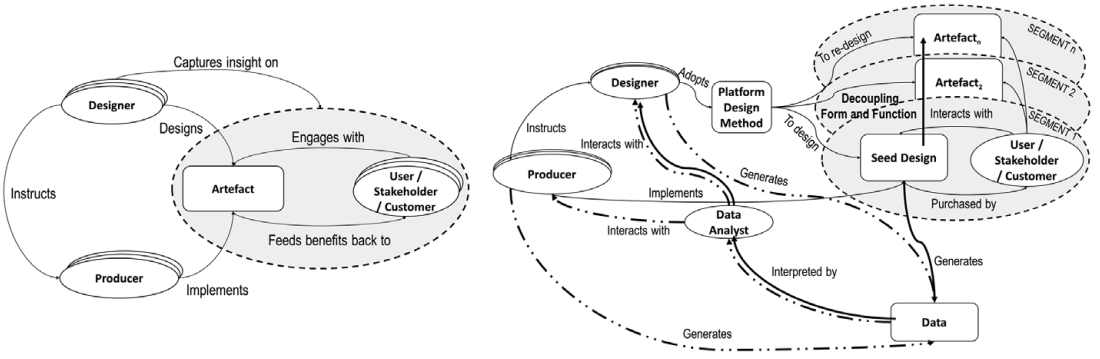


Figure 4. The shift from the old (a) paradigm to the new one (b) considering the specific consequences on development and design processes.

The last effect regards a further shift in design information and knowledge management. Years ago, product information was relegated to 'passive' visualizations and representations (i.e., a drawing on paper, which could be observed, but not operated upon with calculations or simulations), unrelated to each other. Then, digitization processes (CAD systems and simulations) through modelling helped explicate design knowledge-making codifiable what was previously done by intuition and experience (by storing design choices and verification activities through validated parameters and variable values). Paradoxically nowadays instead, the progressive transition to design automation is having the opposite effect, reporting tacitly the knowledge that a designer can afford the luxury of not having anymore, thus attributing to systems an active role in design processes. The implications of such a shift have not a secondary effect since the knowledge of individuals and the one incorporated into the organization are different. It is a matter of the individual, the team in which he works and the relationship of his/her competences within the knowledge base of the organization. If support systems automatically act for the designer and learn, they incorporate that knowledge that was previously of the individual or the design team; that knowledge, therefore, passes from the individual or team to knowledge base of the organization. Through automation, knowledge passes from its explicit to tacit form, changing the process rules and organization equilibria again since *it moves from individuals to capital* (NPD-ORG4).

Figure 4 adds to the baseline the specific effects of the new design pilots. Differently from the old paradigm, designers do not design the complete set of an artefact specification but start from a 'seed design', which will be iteratively improved and extended in a continuous platform-driven development process, where the design of form, behaviour and function may be procrastinated.

As a result of these changes, it is possible again to express further research questions in the last column of Table 6.

5. Stream 3: analytics for design or design analytics

The last research stream focusses on a new field, which is known as design analytics (Van Horn *et al.* 2013) and regards the processes and tools supporting the transformation of design-related data to suit design decision-making processes. Design analytics, in particular, is the process of inspecting, cleaning, transforming

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Table 6. Operational, organizational and managerial consequences on development and design processes

Specific shift	Operational consequence	Managerial consequence	Organizational consequence	Derived research questions
Product development is a never-ending story of experimentation and adaptation	It becomes irrelevant to develop a reliable and complete set of product/service specifications for the seed design (Gunasekaran *et al.* 2019) (NPD-OP1)	Agile management 'minimum viable products' (MVP) are the basis for further product improvements (NPD-MAN1) Concurrent Engineering issues (Krishnan *et al.* 1997) (NPD-MAN2) Set of product specifications is always changing. Issues in drafting permanent legal documents and renewing the certification processes (Song 2017) (NPD-MAN3)	Iterative validation steps managed either by the designer or the data analyst (Song 2017) (NPD-ORG1)	When products and services are developed in an agile context, how can the responsibility of the design decisions among the actors involved be managed? Moreover, how do firms manage legal issues (contractual obligations/terms of service), regulatory issues and certifications with respect to relevant authorities?
Product platforms and platform design become necessary	Product platform enables the possibility of improving product and services (Porter & Heppelmann 2014; Rossit *et al.* 2019) (NPD-OP2) Platforms become the main enabler of modularity and customization/personalization allowing combinatorial innovations (Yoo *et al.* 2012; Mourtzis & Doukas 2014; Marion *et al.* 2015) (NPD-OP3) Trade-off between production constraints and architecture flexibility (Krause *et al.* 2017) (NPD-OP4)	Platform design leads to lower development costs concerning a wider variety or more frequent product versions (Simpson *et al.* 1999) (NPD_MAN4)	Integration choices, deciding on which layers of the platform, should be externally extended (Yoo *et al.* 2012) (NPD-ORG2)	Which operational and organizational trade-offs that naturally arise by using design platforms will become the most relevant to be managed?

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Table 6. Continued

Specific shift	Operational consequence	Managerial consequence	Organizational consequence	Derived research questions
Digital representations, models and systems are incorporated into an artefact	Expand physical materiality by 'entangling' it with software-based digital functions. Form and function are decoupled (Autio *et al.* 2018) (NPD-OP5)	Decupling form and functions will support *unpredictability in innovation processes* (Austin *et al.* 2012) (NPD-MAN5)	Need to support creativity and serendipity behaviours (Andriani & Cattani 2016) (NPD-ORG3)	To what extent are design processes changing because of this shift? How can designers take into account both the physical and digital affordances of products/services?
Information and knowledge management must change			The transition from representation to model, from tacit to explicit and nowadays (through automation) from explicit to tacit changes again the process rules and organization equilibria. *Knowledge change is a relevant form and move from individuals to capital* (NPD-ORG4)	

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and modelling data to extract knowledge, which could be valuable to generate and evaluate new design solutions (King *et al.* 2013).

In general, data mining techniques (cluster analysis, conjoint analysis, etc.) and AI tools (e.g., neural networks and genetic algorithms, etc.) are rather well-established and widely applied to design problems (Tao *et al.* 2018; Tan *et al.* 2019). Among the AI tools, machine learning algorithms (mainly classified in supervized and unsupervized algorithms) are, instead, at their first attempts (for a review, Kotsiantis *et al.* 2007; Leskovec *et al.* 2020). They are used both with descriptive and predictive purposes, and there are many examples of application along with the different phases of product development.

Cluster analysis, for instance, has been employed with a descriptive purpose both during the planning phase, to distinguish between potential and target customer from a large dataset (Tao *et al.* 2018), and during requirement elicitation (Zhang *et al.* 2017; Shimomura *et al.* 2018). Conjoint analysis has been used, instead, in defining customer preferences and suggesting the possible functions and performances of a new design solution (Song & Kusiak 2009).

Prescriptive and predictive analytics often make use of AI techniques. Multiple response surfaces methodology (Jun & Suh 2008), ordinal logistical regression (Demirtas *et al.* 2009) and genetic algorithms (Hsiao & Tsai 2005; Kim & Cho 2005) have been attempted for instance to determine the optimal settings of the design attributes that achieve maximum customer satisfaction. Case-based and neural network approaches have been used extensively during idea generation, either for leveraging decisions on previous design cases (Hu *et al.* 2017) or for simulating design alternatives concerning specific performance parameters (Dering & Tucker 2017; As *et al.* 2018; Babutzka *et al.* 2019). Optimization tools have been employed mainly with predictive purposes during the detail design phase. The aim, in this case, is to foresee the impact of a design change at the subsystem level into the overall system performances (e.g., Yao *et al.* 2017) or design optimization (Quintana-Amate *et al.* 2015).

The use of design analytics techniques within the product development process also leads to operational consequences (DA-OP).

At first, each of these techniques, whether descriptive, prescriptive or predictive, has intrinsic characteristics that define the type and amount of input data it requires, as well as a propensity to generate outputs that may be more or less reliable and qualitative. *The choice of the technique to adopt is contextual to the phase of the product development* in which it should be applied (Van Horn *et al.* 2013; Altavilla & Montagna 2019) (DA-OP1). Therefore, it is not clear yet how and which techniques should be used in the different stages of the design and development process.

Second, the *majority of analytics* employed *are still descriptive*, while *predictive and prescriptive analytics represent the next and more insightful challenges* (Bstieler *et al.* 2018) (DA-OP2). At the moment, the main benefit is provided by the latter in identifying optimal improvements to solutions, while a wider exploration of a solution space remains to be fully dealt with.

A final operational aspect concerns the ability of algorithms to automate the learning process based on a large amount of data obtained in input and *to acquire autonomy for future data analysis processes* (Tan *et al.* 2019) (DA-OP3). Nowadays, this characteristic is provided mostly by machine learning algorithms (Fisher *et al.* 2014) that go beyond data mining, and AI approaches; however, these

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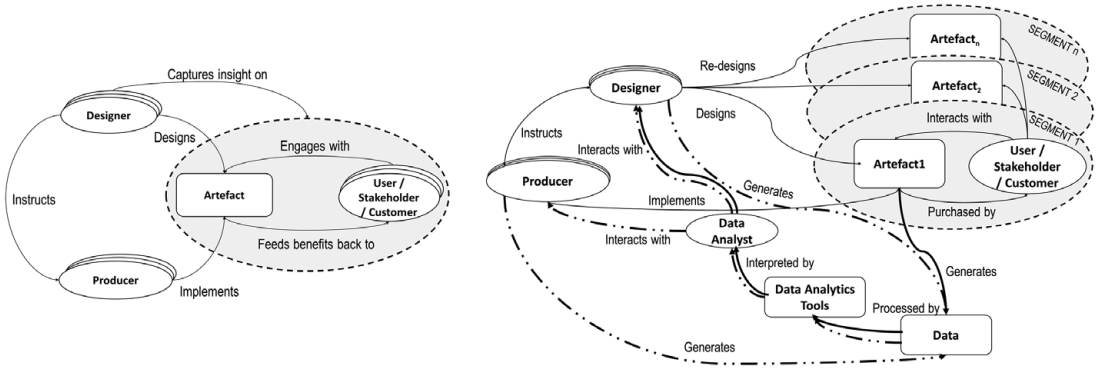


Figure 5. The shift from the old (a) paradigm to the new one (b) considering the data analytics.

approaches have still experienced a lack of implementation during the different design and development phases.

Also, in this last stream, Figure 5 depicts the change brought to the new design paradigm by the use of data analytics. Data analysis tools were already employed during the design process, even in the old paradigm. In particular, data mining and AI algorithms were part of those sets of tools used by designers to tackle a wide variety of design problems. Differently from the latter paradigm, the new one (depicted in Figure 5b) employs a new set of tools, and in particular, machine learning ones, that are increasingly pushed towards autonomy in learning from data and taking over part of the design process activities. This autonomy, together with the need for predictive and prescriptive analysis, and more accurate data analysis tools, is pushing them to become a separate element in the new design paradigm.

Finally, Table 7 summarizes the operational consequences and research questions related to this stream of research.

6. The complete data-driven design paradigm

Based on the previous discussion, it is possible to describe the resulting data-driven design paradigm, as in Figure 6, in which one can realize an increasing relevance of tools and methods, and especially the ones pertaining to platform design and design analytics. These take on an ever more central role in guiding the designers' interpretation and analysis activity and, therefore, in supporting design decisions. In other words, design methods are no longer to be seen as relatively weak supplements to a process that was mainly driven by human cognition and social interaction but have the potential to become dominant determinants of the outcomes of the design process. Moreover, their effectiveness will heavily rely on the existence of an appropriate IT infrastructure and organizational context.

The choice and appropriateness of the data analysis methods employed, as well as the methodologically rigorous use of platforms, are therefore likely to affect the quality of the solutions generated heavily.

Therefore, the choice of the methods to be used cannot be left to the designers' inclinations; it will depend instead on the strategic choices that firms will make in dealing with IT investment and in the way they will interpret the new role of data

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Table 7. Operational consequences on the use of data analytics tools for the design and development process

Operational consequence	Derived research questions
The choice of the type of different technique to be used depends on the phase of the design and development process in which it is applied (Van Horn *et al.* 2013; Altavilla & Montagna 2019) (DA-OP1)	What are the relevant analytics tools that are appropriate for each design activity and hence are they applicable in the different phases of the design and development process?
Predictive and prescriptive techniques represent the most insightful set of tools that can help the development team in better exploiting the advantages of data analysis (Bstieler *et al.* 2018) (DA-OP2)	How can prescriptive and predictive techniques be better integrated into the design and development process?
The new frontier of design analytics tool requires the autonomy of the algorithm in learning from the process and provide insights on data (Tan *et al.* 2019) (DA-OP3)	How much will the algorithm be able to learn from the process and obtain more and more autonomy? Is the autonomy related merely to their ability to recognize similarities? Or there are already capable of translating general goals into specific objective functions? Are they nowadays effectively autonomous, or they will continue to will simply provide a structure and analysis to the data, which will still be interpreted by the designers? Is this dependent on the level of structuring the design problem (structured, partially structured, unstructured problems)?

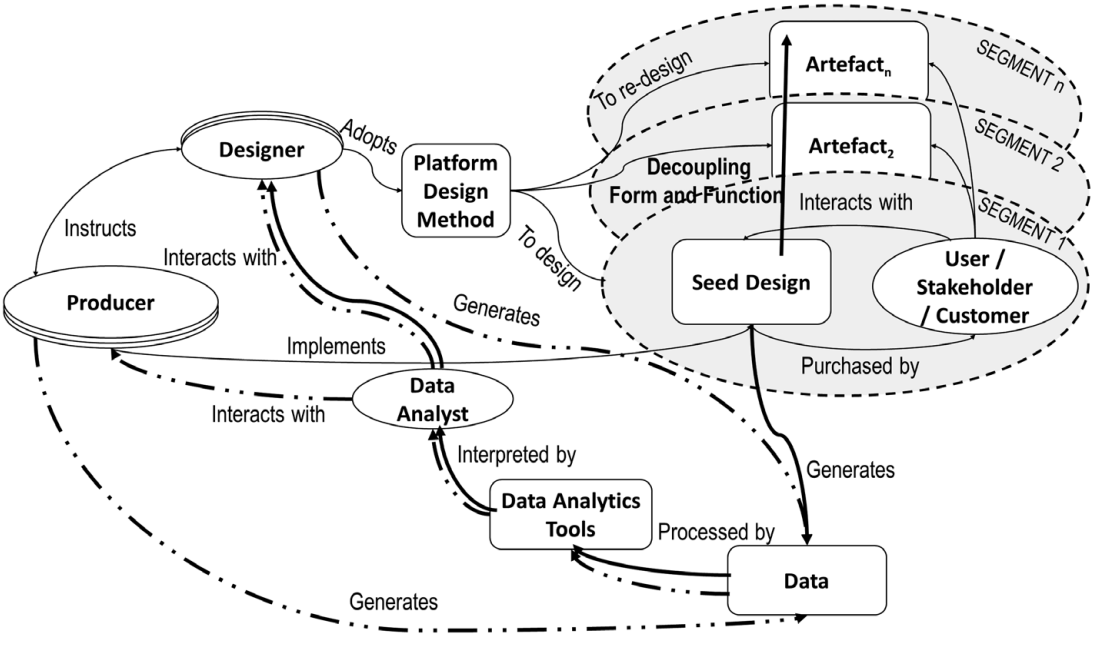


Figure 6. The new paradigm of the data-driven design context.

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analysis in the design process, that is, whether to internalize or outsource it; whether to create separate data analysis functions interacting at arm's length with other functions (including design) or to 'embed' data analysts within each function. The degree with which designers will be trained in data analysis (i.e., fully proficiency versus being able to perform simple tasks and interacting with specialists when needed versus being minimally trained to interact with specialists versus no training at all) will constitute a relevant issue. In some way, this is a similar problem to what firms had to tackle when first dealing with Design for X (DFX) methodologies in the 1990s, that is, the amount of competence and responsibility to be assigned to designers on complementary technical domains. The strategic issue at this point becomes evident.

These new design support methods, tools and systems, moreover, undermine the relationship between tacit knowledge, traditionally placed into individuals and the explicit knowledge, conventionally considered as an asset of organizations and incorporated into capital, which also provides a very interesting area of research, which however goes beyond the scope of this paper.

The number of new elements, as well as the complexity emerging from the relational diagram in Figure 6, suggests that this is by no means an incremental change but represents a true paradigm shift. This raises many research questions for academics, with the added difficulty of finding robust empirical foundations, given the recency of the phenomenon. Finding answers to these research questions is of obvious relevance for firms as well, since they risk having to enter this new paradigm by relying on intuition and (potentially costly) trial and error. Finally, there are very significant implications on education, due to the impact on the curricula of future engineers and designers.

7. Conclusions

The paper has attempted to provide a structured and rational discussion on the ways with which digitalization and the 'data revolution' are impacting the world of design. Based on the recent literature and preliminary anecdotal evidence, the paper has started by identifying five main technological areas with which digitalization is leading to change in both artefacts and design processes.

This description led to the proposal of a conceptual framework, organized around three main streams, and namely the consequences on designers, the consequences on design processes and the role of methods for data analytics. Given that these three streams have implications at individual, organizational and managerial level, the impact on design can be represented at the intersections between streams and levels. For each such intersection, the authors have then proposed a list of preliminary research questions, which might be used for defining future research agendas in the field.

Moreover, a conceptual framework has been proposed to describe the changing relationships between the objects and the actors involved in the design process. The resulting relational diagrams show a picture of significantly increasing complexity, which suggests that what is happening is not a simple evolution of current design theory and practice but a real paradigmatic shift in the way with which both 'new' and 'old' artefacts are designed. This has significant consequences for researchers involved in studying the phenomenon and/or developing design support methods and tools, for practitioners, involved in managing this deep change within firms

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and for educators, who must understand what new skills and competencies are to be given to students. As it happens in most paradigmatic shifts, the emergence of data-driven design has clear interdisciplinary implications, and it is noteworthy that researchers from adjacent fields, such as Verganti *et al.* (2020), have just recently started working on this topic as well. It is, therefore, possible that the further explorations in the new landscape of data-driven design may lead to contaminations and changes in the current boundaries between disciplines.

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