Big data ecosystem in Re-distributed Manufacturing (RdM) past and future

RECODE Network

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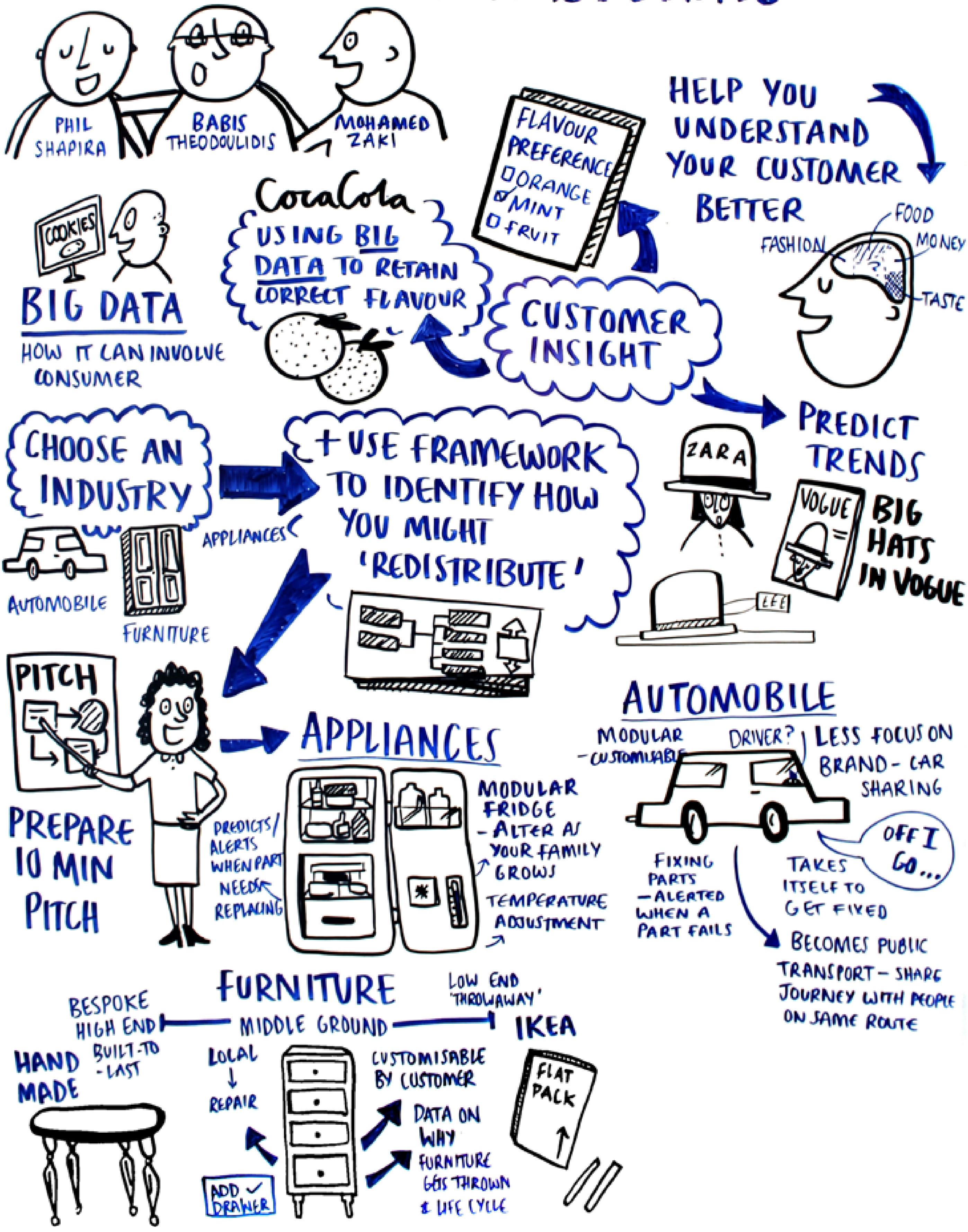
RECODE-NETWORK

THE ROLE OF BIG DATA IN THE FUTURE OF MANUFACTURING



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About Us

RECODE Network

The EPSRC-ESRC funded Network in Consumer Goods, Big Data and Re-Distributed Manufacturing (RECODE) has been created to develop an active and engaged community to identify, test and evaluate a multi-disciplinary vision and research agenda associated with the application of big data in the transition towards a Re-distributed Manufacturing model for consumer goods.

The exponential growth of available and potentially valuable data, often referred to as big data, is already facilitating transformational change across sectors and holds enormous potential to address many of the key challenges being faced by the manufacturing industry including increased scarcity of resources, diverse global markets and a trend towards mass customisation. The consumer goods industry, has remained largely unchanged and is characterised by mass manufacture through multi-national corporations and globally dispersed supply chains. The role of Re-distributed Manufacturing in this sector is often overlooked, yet there is great potential, when combined with timely advances in big data, to re-define the consumer goods industry by changing the economics and organisation of manufacturing, particularly with regard to location and scale.

The RECODE Network conducted five feasibility studies led by the academic core partners, steering group partners, and new partners who joined through the RECODE Sandpit on 02-03 March 2016. A multidisciplinary team comprised of internationally renowned experts from University of Cambridge and University of Manchester and practicing industry leaders in the fields of manufacture, big data and consumer goods, were involved in the delivery of this feasibility study.

RECODE has developed novel methods and undertaken innovative events to engage communities of academics, international experts, user groups, government and industrial organisations to define and scope a shared multi-disciplinary vision and research agenda. To find out more, visit our website: **http://www.recode-network.com**

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Introduction

Several scholars and industrialists predict that manufacturing operations will become more geographically distributed in the future, which is driven by an increasing need for mass customisation and more sustainable production. The future is not going to be about stretched-out global supply chains connected to a web of distant giant factories. It's about small, nimble manufacturing operations (Koten 2013). This more local and smaller scale production trend will continue because it is driven by rising oil and transportation costs as well as new regulations for emissions and ongoing developments in the area of manufacturing processes (Livesey 2012).

Additional drivers towards a more distributed concept include sustainability, mass customisation, a democratization of design, market and customer proximity, well-aimed use of resources and regionalism (Matt et al. 2015). The sustainability aspect is based on the assumption that a decentralized network of mini-factories is likely to reduce emissions through a reduction of transport. The trend towards mass customisation can be identified through an increasing number of individual product variants and configurations. Additionally, mass customisation is becoming a more and more viable model for a broad range of different industries (Jiang et al. 2006). This requires flexible manufacturing systems that are able to produce small quantities, which is likely to happen in a distributed way (Matt et al. 2015).

This transformation is supported by technological advancements like additive manufacturing, autonomous robots, Internet-of-Things, big data etc. Recent reports and studies emphasize the crucial importance of technologies as enablers for distributed manufacturing. In this context information and communication technology, sensors, cloud computing, autonomous robotics, additive manufacturing, Internet-of-Things and big data get mentioned by several authors (EEF 2015; Foresight 2013, Russmann 2015, Manyika 2011). For this reason, structures, processes and products are changing and become more differentiated and distributed (Spath et al. 2013). As a result of these new supporting technologies and developments in the area of distributed manufacturing the EPSRC coined the term "Re-distributed Manufacturing" as technology, systems and strategies that change the economics and organisations of manufacturing, particularly with regard to location and scale" (Pearson et al. 2013). This feasibility study was initiated to investigate the big data impact on Re-distributed Manufacturing in the consumer goods industry. To scope this feasibility study, the concept of redistributed manufacturing was investigated as a phenomenon of geographical redistribution. This is described by a localized model of production in the previous definition of Re-distributed Manufacturing (RECODE 2013). Additionally, the study focus lies on manufacturing businesses and not peer-to-peer production (e.g. desktop fabrication with 3D printers), which has already received a lot of attention in recent literature (Kohtala 2014).

Therefore, a two-fold research design was used: 1) manufacturing configurations and their underlying drivers were analysed, 2) big data applications that could influence these configurations were researched. This was done by utilising a conceptual framework built from an extensive literature review and a qualitative research approach based on the analysis of 24 cases, which were generated from primary and secondary data.

The analysis of the study revealed that the existing manufacturing configurations and manufacturing processes were mostly found to be capable of providing products identified through market segmentation. However, related to big data applications, an increasing resolution of customer insights could allow insights to be extended to the level of the individual customer, which promotes mass customisation. A strong link between mass customisation and distributed manufacturing was identified in the literature and some cases, whereas manufacturing configurations, in general, were found to be still driven by the incentive to produce high volumes and cut costs. This explains the diverse standpoints regarding mass customisation and distributed manufacturing that emerged in the case analysis. These standpoints were highly related to decisions on a product level and pointed out that some specific industries like footwear and cosmetics are interesting in this context. Therefore, a coexistence of manufacturing concepts is likely and further research on an individual product level needs to investigate the feasibility and value of distributed manufacturing.

This report firstly introduces an extensive literature review in the following section. The review is followed by a conceptual framework and a section describing the study design. The last section illustrates the findings of the analysis and includes a discussion and conclusion.

What we know: The past

The review combines the areas of Re-distributed Manufacturing, big data and manufacturing configuration which incorporates distributed manufacturing and operations strategy. The first section deals with literature regarding Re-distributed Manufacturing. By defining the term Re-distributed Manufacturing, two main areas for investigation were identified: big data and a localised model of production. The second section describes literature regarding localised production. This literature is derived from distributed manufacturing and operations strategy research. The big data concept is introduced in the third section. Finally, these aforementioned literature streams are combined in a conceptual framework.

Re-distributed Manufacturing

This section elaborates on the concept of Re-distributed Manufacturing, which the EPSRC coined as *"technology, systems and strategies that change the economics and organisation of manufacturing, particularly with regard to location and scale."* (EPSRC 2014; Pearson et al. 2013). An additional definition illustrates Re-distributed Manufacturing as *"a connected, localised and inclusive model of production and consumption that is driven by the exponential growth and embedded value of big data."* (RECODE 2013). These definitions show that there are several dimensions of redistribution (connected, localised and inclusive) and that the value of big data influences all of these dimensions.

The inclusive dimension, which is described as *"an inclusive model of production and consumption"* can be interpreted as a functional redistribution. This dimension is comparable to concepts of co-creation or co-production. Co-production refers to a *"participation in the creation of the core offering itself"*, while co-creation represents a concept, which includes the idea that value can only be created with and determined by the user in the consumption process or through use" (Vargo and Lusch 2008). Value co-creation can occur with or without co-production. However, both of these concepts illustrate that the consumer is part of the value creation process. The term redistribution" in this context means a higher involvement of the consumer in the process of design or production.

Another dimension of Re-distributed Manufacturing is described by the localized model of production. This emphasizes a change in the location and geographical configuration of production facilities with a particular focus on production scale and distance from production to customer. The redistributed concept in this context implies a shift to smaller scale and more localised production (Pearson et al. 2013). This feasibility study focuses in particular on Re-distributed Manufacturing as a model of localised production.

Manufacturing configuration

The manufacturing configuration describes the second part of the two-sided literature review. The term manufacturing configuration, in the context of this study, incorporates literature streams around distributed manufacturing, facility strategy as well as literature, concerned with competitive priorities and advantages to understand the evolution towards distributed manufacturing.

Prior to the last half of the 19th century, manufacturing was dominated by handicraft, one-at-a-time production on an as-needed basis as well as rural dispersion rather than concentration (Pred 1966). The craft production was characterized by a highly skilled workforce, extremely decentralized organizations, the use of general purpose machines, a very low production volume as well as production to the individual's specific needs and wants (Womack et al. 1990).

In the early 20th century, manufacturing businesses developed mostly as concentrated, urban phenomena which were based on significant labour and resource needs (power, water and materials) as well as proximity to major transportation systems (DeVor et al. 2012). However, the efficiencies of high-volume production on special-purpose machines came with the expense of flexibility (Piore and Sabel 1984).

In the mid-20th century, the markets were focused on growth, which was facilitated by the fact that the demand was previously higher than the supply. To sustain this growth, companies had to become international and tap into new markets. A side effect of this was an increasing international competition, based on price. This motivated a geographic shift of complete industries to low-cost countries like China (Bolwijn and Kumpe 1990; Young 1986).

Entering the last two decades of the 20th century the problem that mass production could no longer secure a workable match between the production and consumption of goods emerged (Doll and Vonderembse 1991; Piore and Sabel 1984). Combined with the empowerment of the individual, this would radically change the landscape of manufacturing (DeVor et al. 2012).

The concept of mass production and economies-of-scale can still be successful in various traditional industries today (Jiang et al. 2006). However, numerous scholars (Kotha 1995; Vallas 1999) discussed the slowly emerging transformation from mass production to mass customisation as well as a shift from high-scale mass production in a centralised factory toward small-batch customized production of high quality goods in more distributed facilities.

Distributed manufacturing

When defining the term distributed manufacturing, the important characteristic is the geographical dispersion of its components. It describes a transformation away from conventional mass production, long and linear supply chains, economies-of-scale and centralising tendencies (Kohtala 2014). Investigating the term of distributed production several research streams were identified. One major literature stream is concerned with the collaboration and organization aspect of distributed production systems. This includes simulations as well as web-agent and cloud-based manufacturing systems, which are driven by developments in the area of information and computer technologies (Saad et al. 2003; Valilai and Houshmand 2013; Wu et al. 2014).

Another stream investigates distributed manufacturing in the context of alternative business models and opportunities for more socially beneficial and responsive production and consumption. In this context the notion of distributed economies promotes small-scale, flexible networks of local socio-economic actors using local resources according to local needs (Johansson et al. 2005).

It was also found that there is no consensus regarding the size of facilities when talking about distributed production. This literature stream (see Table 1) investigates distributed manufacturing as a phenomenon on a factory level, whereas another stream researches it in the context of smaller production units (desktop-level manufacturing). Research on distributed manufacturing on a desktop-level emerged recently which is caused by advancements in manufacturing technologies, especially 3D printing. In this context DeVor et al. (2012) highlight three use cases: manufacturing at the point-of-sale, manufacturing at the mall and personal manufacturing. A literature review done by Kohtala (2014) summarizes similar concepts with more focus on the consumer as a producer which brings desktop manufacturing closer to the theme of peer-to-peer production.

In the theme of personal fabrication, a producer makes his own artefacts (e.g. in a maker-space). This producer has full control over the design and production. The scale of facilities, volumes and equipment is usually very small (Kohtala 2014). Matt et al. (2015) described the evolution of distributed manufacturing models. They highlight among other concepts non-location-bound factories and production laboratories which are comparable to the theme of desktop manufacturing. Another key characteristic of distributed manufacturing on a desktop-level is the blurring between production and consumption. Consumption may be instead referred to as “prosumption” and a customer may be a prosumer” (Toffler 1981), who also produces and not only consumes.

The second literature stream is described by distributed manufacturing on a factory-level. Here especially the themes of digital manufacturing (Industry 4.0), mass customisation and the ability to serve regional markets were highlighted. A decentralized configuration of smaller production facilities was directly linked with an automated, flexible, digital and smart production (Kohtala 2014; Matt et al. 2015; Spath et al. 2013). Butala et al. (2013) argue that companies need to be flexible to stay competitive in today’s global markets. To ensure flexible production and reduce time-to-market, companies should utilize geographically distributed manufacturing systems, wherein local resources are used for product development and production. The transformation towards small, flexible and scalable production units was often related to the need to full individual customer needs just-in-time. In this context, the term mass customisation emerged as a common theme. Bruccoleri et al. (2005) state that distributed production aims for more customer orientation as well as mass customisation.

The term mass customisation was first coined by Stan Davis (1989) as *“companies try to reach the same large segment of customers in the mass market but by treating them individually like a customised market”.* This definition got modified over time by several scholars. Pine (1993) emphasizes that a large variety of products with prices comparable to standard products are the main characteristics of mass customisation. Du et al. (2001) illustrate the concept of mass customisation with a more general definition as *“the technologies and systems to deliver goods and services that meet individual customers’ needs with near mass production efficiency”.*

	Factory-level	Desktop-level
MacCormack [1994]	Smaller, lower-scale plants serving demand in regional markets.	
Bruccoleri et al. [2005]	Distributed production aims for flexibility, agility and greater customer orientation as well as mass customisation.	
Kühnle [2010]	Simultaneous manufacturing presence in several regions to handle volatile market demands.	
Spath et al. [2013]	Industry 4.0; automated, flexible and decentralised production for small-batch series.	
Matt [2013]	Reconfigurable manufacturing systems for mass customisation operating in distributed facilities.	
Matt et al. [2015]	Flexible and reconfigurable factory, changeable and smart factory.	Non-location bound factories, manufacturing in production laboratories.
Kohtala [2014]	Digital manufacturing (bespoke fabrication, mass customisation).	Peer-to-peer production (mass fabrication, personal fabrication).
DeVor et al. [2012]		Manufacturing at the point-of-use, manufacturing at the mall, personal manufacturing.

Table 1 Different levels of distributed and decentralized manufacturing

Facility and capacity strategy

Facility strategy is a part of the operations strategy which is defined as *"the total pattern of decisions that shape the capabilities of any type of operation and their contribution to overall strategy, through the reconciliation of market requirements with operations resources"* (Slack and Lewis 2002). The facility strategy includes fundamental decisions, which have a huge impact on the firm's competitive abilities. Decisions regarding capacity strategy include the capacity levels, the number of sites, the size of sites as well as the site location (Slack and Lewis 2002).

Typical ways, described in the literature, to assess facility decisions are based on assessment criteria or mathematical approaches (Chen et al. 2014). Either way, the economic performance respectively cost minimization and profit maximization has been the driver in most cases (Drezner and Hamacher 2002; Melo et al. (2009). In the context of facility strategy and cost reduction, the term economies-of-scale needs to be explained. Economies-of-scale are the cost advantages that businesses can leverage due to size, output or scale of their operations. This is due to the phenomenon that the cost per unit of output generally decreases with an increasing scale since the fixed costs are distributed over more units of output. Important dimensions that influence facility strategy can be summarized by the competitive priorities that are explained in the next section.

Competitive priorities and advantages

The competitive priorities get mentioned by several scholars in the context of manufacturing strategies. Sometimes they are also referred to as market requirements (Slack and Lewis 2002; Thun 2008). The competitive priorities were originally developed for the use in the Boston University Manufacturing Futures Survey (Miller and Vollman 1984). They investigate a firm's competitiveness based on the dimensions of cost, quality, delivery and flexibility. These measures were used in several studies where they showed good reliability (Boyer 1998; Boyer and Lewis 2002; Schmenner and Swink 1998; Ward et al. 1998).

A focus on the cost dimension of facility locations results in reducing transportation, inventory, labour and process costs or increasing productivity. If the focus lies on quality, the workforce and the suppliers as well as offering consistent high performance and quality products get more important. Focusing on delivery requires shorter times-to-market and lead-times as well as closeness to the customer which potentially also changes the production processes and skills. However, a business that is based on flexibility is also likely to be close to the customer and employ special production technologies. Flexibility can include abilities like making rapid design changes, adjusting capacity quickly, making rapid volume changes and offering a large number of product features and a high degree of product variety (Boyer and Pagell 2000; MacCormack 1994). Competitive advantage is considered as an additional factor that influence facility strategy Porter (2008). According to Porter, a firm can gain a competitive advantage by following one of the three generic strategies: lowest cost, differentiation or focus.

Value creation in big data

To identify the impact that big data can have on manufacturing businesses, especially manufacturing configurations, possible methods of value creation need to be investigated. This approach is aligned with the definition of Re-distributed Manufacturing which highlights that *"a transformation is driven by the [...] value of big data."* (RECODE 2013). To bring different types of value creation into one taxonomy, big data applications are handled similarly to business model concepts. This approach was used by Hartmann et al. (2014) to describe so-called data-driven business models. In the context of this study, selected sections of the data-driven business model concept like data sources, key activities and offerings will be discussed to identify different types of value creation.

The amount of data sources is expanding rapidly by several phenomena. One phenomenon in this context is the widespread diffusion and adoption of social media platforms and mobile devices. In 2011, already 4 billion mobile-phone users were identified worldwide and the number is increasing (Fosso Wamba et al. 2015). Another phenomenon responsible for the growth is the Internet-of-Things (e.g. RFID technology). RFID-enabled item tagging is expected to generate a huge amount of data across the value chain of all industries (Ngai et al. 2012). The number of RFID tags rose from 1.3 billion in 2005 to about 30 billion in 2013, which also represents the increasing speed in data generation (Fosso Wamba et al. 2015).

Focusing on different types of data sources, Manyika (2011) identifies sensors, devices embedded into the internet, smart meters, RFID as well as transactional databases, collaborative product development databases (CAD, CAM, digital manufacturing), social media, customer feedback and point-of-sales data. Choudhary et al. (2009) mention database management systems and data warehouses (product/process design, assembly, materials planning, quality control, scheduling, maintenance, fault detection) as possible data sources.

There are several studies highlighting the benefits of big data (Fosso Wamba et al. 2015) but a taxonomy for various data sources is missing. For the purpose of this feasibility study, the terms of internal and external data are used. Hartmann et al. (2014) used a similar approach to investigate data-driven business models. Internal data relates to data, focusing on the manufacturing and business side, whereas external data focuses on the consumer side and the environment.

The different types of data activities include concept description (characterization and discrimination), association, classification, clustering and prediction. This taxonomy is used by Choudhary et al. (2009) to analyse data mining in the manufacturing context. Hartmann et al. (2014), on the other hand, define the following key activities: data generation, data acquisition, processing, aggregation, analytics (descriptive, predictive, prescriptive), visualization and distribution. Whereas this taxonomy is suitable to analyse data-driven business models in the context of big data startups, it needs to be adjusted for the established consumer goods industry.

Tapadinhas (2014) introduces an “analytics continuum”, which describes that different types of analytics like descriptive, diagnostic, predictive and prescriptive involve a different amount of human input until decisions or actions can be made. Descriptive analytics describe what happened and need an intense human input until a decision can be made. Diagnostic analytics describe why it happened. Predictive analytics state, what will happen and need less human input. Prescriptive analytics tell you, what you should do, which could also lead to automated decisions. Choudhary et al. (2009) identify several data users of big data applications in the manufacturing context: quality control, job shop scheduling, fault diagnostics, manufacturing process, manufacturing system, maintenance, condition based monitoring, design, supply chain, decision support and customer relations management.

	Internal (business environment)	External (consumer environment)
Data source	Internet-of-Things, Industry 4.0, sensors, smart meters, RFID, business apps (ERP).	Internet-of-Things, social media, mobile devices, public web, point-of-sales.
Data type	Product/process design, assembly, materials planning, quality control, scheduling, maintenance, fault detection.	Usage data, point-of-sales data, customer feedback, social media data.

Table 2 Various data sources and data types in the big data environment (noninclusive list; Choudhary et al. 2009; Fosso Wamba et al. 2015; Manyika 2011)

Conceptual framework

This framework was developed out of the aforementioned literature review. The aim of the framework is to provide a basis for the impact of big data ecosystem in Re-distributed Manufacturing. The framework incorporates two sides: the big data side and the side regarding the manufacturing configuration. The conceptual framework is illustrated in Figure 1.

The big data side is shown in the bottom part of the framework. It is derived from the considerations regarding value creation in big data. Comparable to business models the framework incorporates key resources (data sources), key activities (data activities) and a customer (data users). The data sources are divided into internal data sources that are focused on the manufacturing side and external sources that are focused on the consumer respectively the environment. The data activities include different types of analytics, and the data user is part of the value chain. This also describes that the focus lies on internal data users and not for example data monetization.

The upper part of the framework is concerned with the manufacturing configuration.

To analyse the manufacturing configuration, different literature streams were combined. The first one is competitive advantage, which divides companies into ones competing over price respectively differentiation. The next part highlights the competitive priorities. These are used to illustrate manufacturing decisions in a simple and powerful way. The last part incorporates the facility strategy. This part represents the degree of distribution, the closeness from production to the customer and the production scale. If there is a transformation towards distributed manufacturing, the facility strategy will illustrate it.

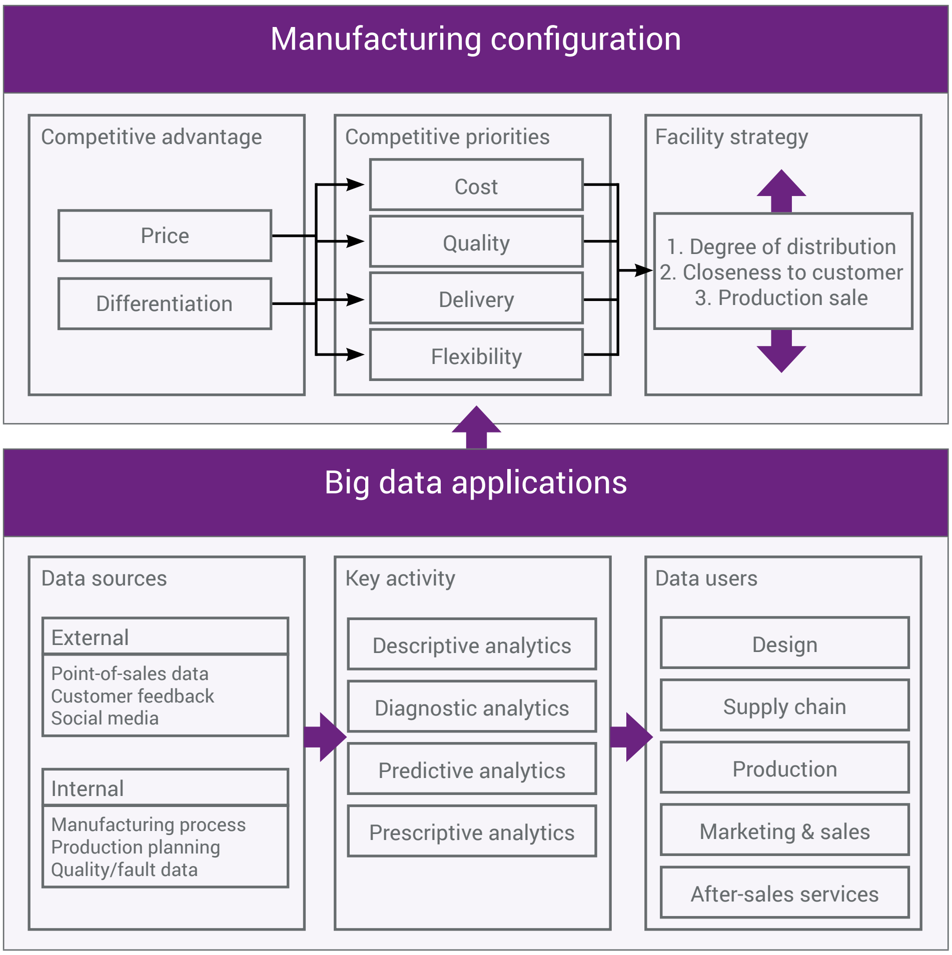

Figure 1 Conceptual framework to investigate the impact of big data on the manufacturing configuration respectively redistributed manufacturing

Methodology: Case studies

This feasibility study used an exploratory and descriptive approach. Multiple-case studies were undertaken in order to effectively investigate the impact of a specific concept (Re-distributed Manufacturing) through a whole industry sector (consumer goods), to uncover findings that were reliable and generalisable. Stebbins (2001) states that to understand any phenomenon, it is necessary to start looking at it in broad, non-specialized terms. Multiple cases enhance the reliability of the findings and minimise the observer bias (Voss et al. 2002). The embedded approach is suitable because there are different units of analysis within the cases (manufacturing configuration and big data application). The downside of a multiple-case approach is that more resources are needed and it is likely to provide less depth per case (Voss et al. 2002).

The feasibility study explored a broad context by stating to investigate the consumer goods sector. Following Yin (2013) and a similar study conducted by DuBois et al. (1993), industries and case studies were chosen according to specific criteria. Similar to the study from DuBois et al. (1993) the industries were chosen to provide a distinct contrast in terms of the characteristics of the products manufactured, major type of market served, product life cycles, and technological intensity. With this approach, the following five industries were selected: food products, soft drinks, personal products, clothing and consumer electronics (taxonomy by the Financial Times).

To screen for appropriate case studies, a criterion-based sampling approach was used (Miles and Huberman 1994). In total 100 cases (20 cases per industry) were generated from secondary data and screened for their manufacturing configuration and big data applications. Similar to studies from Kujawa (1983) and Pettigrew et al. (1988) cases were selected to represent extreme situations and polar opposites which make relationships more obvious. Voss et al. (2002) argue that a diverse snapshot facilitates examination. The case choices were based on conceptual grounds and not on representative grounds (Miles and Huberman 1994). The number of cases per industry is based on findings from Eisenhardt (1989) who states that a number between 4 and 10 works well. Therefore, the resulting sample of cases includes 4 to 6 cases per industry. Considering all of the abovementioned, a final sample of 24 cases was created, which is illustrated in Table 3.

Case	Products	Rev. [USD]	Interviewees
Case F1	Snacks (Crisps & Chips)	<50mn	Business Development
Case F2	Dairy, Biscuits & Confectionery	35bn	Supply Chain Manager EU
Case F3	Snacks & Soft Drinks	66bn	Process Supervisor
Case F4	Food & Soft Drinks	94bn	Development Project Manager
Case F5	Mineral Water	440mn	Process Controller
Case F6	Fresh Food & Soft Drinks	1.2bn	Member of Executive Board
Case F7	Food, Soft Drinks & Personal Care	48bn	Research Engineer, R&D Director
Coca-Cola	Soft Drinks	47bn	
Red Bull	Soft Drinks	6bn	
Danone	Water & Dairy Products	21bn	
Case P1	Personal Care (from standard to exclusive)	25bn	General Manager, Supply Planning Expert
Case P2	Premium Cosmetics	27bn	Supply Chain Planner
Procter & Gamble	Personal Care	83bn	
Nivea	Personal Care	7bn	
Case C1	Clothes	<100bn	Director
Case C2	Clothes	<200mn	Pattern Designer
Case C3	Premium Clothes	3bn	Model Maker Assistant
Case C4	Sportswear	16bn	Director Operations
Zara	Clothes	13bn	
Metersbonwe	Clothes	1.6bn	
Case E1	Consumer Electronics	25bn	Director Product
Case E2	Consumer Electronics	24bn	Manufacturing Director
Motorola	Consumer Electronics	9bn	
Apple	Consumer Electronics	183bn	

Table 3 Summary of the cases from the selected industries (food products, soft drinks, personal products, clothing and consumer electronics). By request of the interviewees, the cases with primary data were anonymised

The case studies analyse the current manufacturing configuration in different consumer goods industries, and by which criteria the configuration is motivated. Furthermore, the big data analytics used currently and in the future, and how this could affect the manufacturing configuration. This research used interviews (see Table 3) and secondary data as data sources. To collect primary data more than 80 people were contacted which resulted in a total of 17 interviews. The interviews were designed in a standardized way with open-ended questions (Turner 2010). The questions covered the topics of manufacturing configuration and big data applications according to the conceptual framework as well as the likely evolution of these two areas. The interviews were recorded and transcribed to enable further software-based analysis. Secondary data was derived from several sources including the Passport database (from Euromonitor International), news articles, company websites and annual reports.

Analysis and findings

This section presents the findings of the case study analysis in two sections. The first section provides an industry-specific analysis that focuses on the manufacturing configuration and big data applications of cases in the same industry. This section is used to give a snapshot of the current situation in several consumer goods industries. The second section illustrates a cross-industry analysis that reveals common propositions related to big data and distributed manufacturing as well as their likely evolution.

Industry-specific analysis

The industry-specific analysis is divided into the sections fast moving consumer goods, clothing and consumer electronics. This classification is motivated by similar manufacturing configurations within these groups.

Fast moving consumer goods: Manufacturing configuration (price)

This section consists of cases from the food, soft drink and personal care industry, which mainly compete over price. Through the analysis, it was found that the manufacturing configuration firstly depends on the product itself.

"The manufacturing configuration highly depends on sourcing strategies on a product level. There is not one single model because it is a highly dynamic environment. Markets and customers change dramatically – [R&D Director, Case F].

However, it was possible to identify a common understanding of how the manufacturing configuration in this case group is determined. In most of the cases, decisions about manufacturing configuration were mainly based on the cost dimension, especially on lowering the landed cost. This meant for most cases to operate the lowest number of facilities possible:

"Having 15 countries it makes no sense to have 15 factories. We will have the lowest number of factories possible to give us the lowest landed cost across Europe. Then we can leverage scale..." – [Supply Chain Manager EU, Case F2].

"We have many fixed assets on the ground so we need to maximize the operational efficiency. Volume and throughput through these assets are 'key'." – [R&D Director, Case F7].

This shows the importance of cost as a main competitive priority and driver for manufacturing decisions. The ability to operate fewer facilities allows investments in state-of-the-art equipment and efficient processes. Additionally, high production volumes were mentioned as essential in almost every case to cut down production costs. The dimensions of quality, delivery and flexibility were mostly described as company standards but with less influence on a manufacturing configuration.

Investigating the existing degree of distribution and facility strategy, it was found that in all cases the scope of a factory varied between country and continent level. For example, in Case F2 80% of the production for dairy products is distributed to five factories in Europe which shows a distribution on a country and continent level. Another example is Case F1 where snack products are produced with a country scope, which is driven by the idea to lower transportation costs.

Fast moving consumer goods: Manufacturing configuration (differentiation)

In Case P1 and Case P2, the investigated products include premium cosmetics. In these cases, a premium product brand justifies the production location and a bigger scope for one factory.

"The production location is a key element of the brand identity and valued by the customers." – [Supply Chain Planner, Case P2].

"The manufacturing configuration is depending on the channel-to-market and the exclusivity of the product. [...] But for our luxury products: They are produced only in one factory in France." – [General Manager, Case P1].

The previous cases illustrate a tendency towards centralisation. However, Red Bull, which is also classified as competing over differentiation, recently distributed their production configuration. In previous years Red Bull only produced centralized in Austria. They stated that the centralised production brings benefits like a guarantee for the same quality worldwide, very efficient production facilities and the ability to reduce the carbon footprint. However, recently they opened another factory in Brazil which is mainly driven by cost considerations. These cases show that redistribution is unlikely for some premium products, but there is an increasing cost pressure which can challenge a centralised model of production.

Fast moving consumer goods: Big data applications

Within the FMCG cases, an intense use of big data applications was identified. The applications focused especially on external data sources with the aim to better engage with the customer and to understand customer preferences, which made the design and marketing departments the main data users.

"People recognize that big data is necessary. [...] certainly big data is used as a way to better understand market dynamics." – [R&D Director, Case F7].

An example to illustrate the power of big data in the context of market insights is provided by Danone. Danone uses analytics to compare a variety of sales data which also includes data from competitors. By analysing the data, they were able to identify increasing sales of one specific Greek yoghurt in the US. These insights enabled the company to produce and deliver the right products for the right shopper. With predictive analytics, Danone increased its forecast accuracy from 70% to 98%. This is enabled by data from a two-year history of purchases which includes seasonalities as well as additional data from trends and promotions combined with sophisticated algorithms to project forward. As illustrated in the previous case, the ability to understand the customer can often be directly related to the ability to forecast demand:

"You cannot be left in a situation where shelf space is empty and consumers cannot buy your product. How you are able to respond to that will be key in a quite volatile and changing world. [...] Big data could be one answer." – [R&D Director, Case F7].

Focusing more on the manufacturing side, another case of intense big data use is provided by Coca-Cola. They developed an algorithm called "Black Book" which ensures that the consumer gets orange juice with a consistent taste 12 months a year, even though the main growing season of oranges only lasts three months. The algorithm helps to get the right mix of ingredients based on an analysis of up to 1 quintillion decision variables and diverse data inputs like orange sweetness, consumer preference as well as weather patterns. Through all the cases of multinational companies in this group, an intense use of big data was identified. Especially, applications with customer-focused data (external data) were in place. Companies that mainly compete over price try to differentiate themselves from the competitors by using big data to understand the customer and engage with him.

Clothing: Manufacturing configuration (cost savings and shorter time-to-market)

For the investigated cases, it was found that the manufacturing configuration within a case is always a mix between sourcing from local suppliers and sourcing from factories in Asia. Within the cases, this mix varied extremely:

"In our production more than 90% of the items are sourced globally [which means from Asia]. The rest is produced in Turkey or North Africa." – [Director Operations, Case C4].

"80% of the production is done in Europe. We operate for example an own factory in Turkey." – [Model Maker Assistant, Case C3].

This was different several years ago, when many clothing brands, motivated by the incentive to cut costs, transferred their production to low-cost countries like China or Bangladesh. Despite advancements in process technology in the past, the clothing industry is still an industry that is heavily dependent on labour and non-automated processes as well as mass production.

"Volume is 'king' in the fashion industry because 'economies-of-scale' are a big factor in sewing operations." – [Director, Case C1].

However, there is a trend for European brands to shift a part from their production from Asian low-cost countries to low-cost countries in Europe. This is motivated by cost savings, shorter time-to-market, local expertise and closeness between design and production:

"In the realm of fashion the near-shoring trend is definitely motivated by costs benefits. [...] Another benefit is, of course, a shorter time-to-market." [Director, Case C1].

"It is important to have a short distance between production and design. This improves quality and flexibility..." – [Pattern Designer, Case C2].

"Products that you need to get with a short time-to-market as a replenishment or for quick reactions to trends are sourced locally. [...] Also the product expertise of a producer can influence the sourcing decision." – [Director Operations, Case C4].

The ability to have a shorter time-to-market can normally only be utilized with smaller batches, which do not describe the main part of the business for most fashion companies. However, in the case of Zara the focus lies on fast small quantity batch production, which is sourced from Spain, Portugal and Morocco. This costs more, but it shortens the supply chain and enables Zara to react quickly. The Zara case shows that a quick response to the market is possible, but this is not only due to the closeness to the market. The internal structures are important as well. They need to be streamlined for the so-called "fast-fashion" model. In Case C4, they imitate this model with another manufacturing configuration. They use their 10% of local production capacity to quickly bring "fresh" looks into the stores. These new looks get more marketing attention which makes the whole retail store seem fresh whereas most of the products are standard and still sourced from Asia.

The investigation of manufacturing configurations showed a diverse mix of sourcing models. It was found that some of the manufacturing moved closer to the customer, which was motivated mainly by cost savings and secondarily by a shorter time-to-market. Additionally, it is important to mention that processes are less automated and highly depend on labour.

Clothing industry: Big data application

There were diverse standpoints about big data applications identified in the fashion industry. Whereas some cases based on secondary data highlighted the intense usage of big data, other cases that were based on primary data showed another picture:

"The fashion industry is in general not one of the most modern industries. Partly firms work with very old [computer] systems. Many of these systems are house made and developed in the 80s and 90s. [...] The finding that something needs to be done is there. [...] But many of the back-end systems need to be updated or exchanged first." – [Director, Case C1].

"We work less with big data and social media to generate trends for the production. [...] Some trends are generated from employee feedback in stores." – [Director Operations, Case C4].

It was identified that having access to the point-of-sales data is crucial. This data is used either way to still enable sourcing from Asia through better forecasting or to produce more local and react faster to trends.

"[A sportswear producer] opened their own retail stores to get more feedback from the market. The feedback was not used to shorten production cycles, but to improve forecasting. This enabled them again to order clothes from Asia." – [Director, Case C1].

Zara uses their point-of-sales data differently by focusing on speedy small quantity batch production with a market-responsive supply chain. For this, they intensively utilize their information systems which are fed by point-of-sales data and social media data to get the newest trends. Zara owns most of their supply chain which also includes the retail stores. This brings the advantage of having direct access to customer-related data. Metersbonwe tried to copy this model, but they faced the problem that 74% of their stores were franchises, which made the acquisition of point-of-sales data more difficult and brought them critical inventory issues. Similar to the Zara case, big data applications are used to find ways to the customer, which could include targeted marketing campaigns, new product development or better customer engagement:

"[Fashion companies] are using big data to generate targeted marketing campaigns and targeted offers. [...] In the area of marketing as well as for the purpose of segmentation and classification of customers' big data is important. Because the competition over price is at the limit big data is used to find other ways to the customer. [...] I see big data mostly used in the context of customer engagement." – [Director, Case C1].

The investigations showed the importance of point-of-sales data in the fashion industry. Additionally, it was highlighted that the adoption of big data applications in this industry is controversial. Whereas some companies like Zara use big data to forecast the newest trends and engage with their customers, there are also companies that still employ decade old computer systems. However, it was observed for the investigated cases that an intense use of big data for the purpose of new product designs can be related to a local production whereas the decision for a more local manufacturing is often driven by other factors like costs.

Consumer electronics: Manufacturing configuration (price)

For the observed cases in the consumer electronics industry, it was found that most of the production is still centralised. Like in previous industries economies of- scale and high volumes are an important factor in manufacturing decisions.

"For the most part [the production] is centralised. [...] The centralized model is used to employ economies-of-scale and to have high volumes, which gets the price down. [...] Mainly the cost factor is determining how the strategy is looking like." – [Director Product, Case E1].

Looking at centralised production models, the location itself is always important. For example, Apple invested 100 million USD in Texas to build a production line for a premium computer. They were able to produce locally because they compete over differentiation and sell their product for a premium price. In another case that is provided by Motorola, the strategy to produce in the US was not successful. In May 2013, Motorola opened a smartphone production in Texas with volumes of 100.000 phones a week. They produced a phone which was focused on personalisation rather than high-end specifications. The focus on personalisation motivated the decision to produce in the US, despite the fact that production is more expensive. However, after less than two years the production was moved from the US to China and Brazil because of weak sales and high manufacturing costs. In this industry, the production seems more static compared to previous industries. Manufacturing decisions are based on cost savings which promote a centralised and high-volume production model.

Consumer electronics: Big data application

In contrast to previously described big data applications, a new use case emerged in the consumer electronics industry. Here the product itself can become a data source which was not the case in the previously described industries. This enables better customer insights:

"We are still striving to use big data for customer insights. [...] We are analysing how the consumer uses our products. In the analysis, we can see for example regional differences in the use. [...] In the long term a big data application could be to offer the consumer exactly the product they need, based on their usage data. So we can tell them: According to our knowledge you may be happier with this product." – [Director Product, Case E1].

Like previously described, better insights can lead to new offerings or even customised products. However, other big data applications are similar to the previously discussed industries. The concept is used in marketing, supply chain planning or directly in the manufacturing:

"We have people in supply chain employing big data. I don't necessarily think that this is a big data problem. [...] We also use big data in marketing, which also includes analysing social media data". – [Director Product, Case E1].

"Use cases are to find root causes and to do preventive maintenance. [...] It is improving the quality and cost dimension of manufacturing." – [Manufacturing Director, Case E2].

The analysis of the consumer electronics industry revealed interesting possibilities for big data applications. The products can be used as direct data sources which bring the manufacturers high-quality user data and insights for more customized products.

Discussion

This section brings the findings from the multiple-case analysis together with existing literature. The industry specific analysis revealed a tendency to operate as few factories as possible. This enables the ability to utilize state-of-the-art technology and produce high volumes, which will cut costs through economies-of-scale. This finding is aligned with previous studies that underline the economic factor in facility decisions (Chen et al. 2014; Drezner and Hamacher 2002; Melo et al. 2009). Big data applications can be supporting functions in a shift towards distributed manufacturing. Decisions regarding facility strategy were identified to mostly depend on the cost dimension.

Industries such as fast moving consumer goods and some fashion businesses, which are competing over price, showed an intense use of big data analytics. Mostly customer-focused data (previously defined as external data) was used, and big data was seen as a new way to reach and engage with customers. The combination of data sources, speed through real-time insights as well as market segmentation for new products. The ability to segment the market could have an impact on manufacturing configurations, especially when the resolution of customer insights increases even more, which would promote mass customised products. However, these industries face challenges like cost and skill barriers for adopting big data analytics, getting access to data, as well as choosing right combinations of data sources to get valuable insights.

The theme of mass customisation reveals diverse standpoints in the analysis, ranging from "customisation is the future" to "customisation is not the big business", whereas literature states that mass customisation is becoming a more viable model for a broad range of different industries (Gilmore and Pine 1997; Jiang et al. 2006). Especially in literature the concept of distributed manufacturing is often directly related to mass customisation (Kohtala 2014; Matt et al. 2015). However, there is no consensus in the case analysis about if the existing production networks can be leveraged for mass customisation or a more distributed network will emerge. Next to the concern if existing production facilities can be leveraged, the question if mass customisation is required and desired is important. The Motorola case shows that a production close to the customer to offer customised smartphones is reasonable. However, there was no market demand for the product. This could be the same for several consumer goods industries.

These findings illustrate that the concept of distributed manufacturing in the end depends on decisions on an individual product or business case level. For example, footwear and cosmetics were mentioned as interesting in this context. These examples could relate to practices like desktop manufacturing and in-store production. However, there was no similar trend for most of the other consumer goods identified, which are still likely to be produced in huge facilities with high volumes and the aim to cut costs.

Conclusion

This feasibility study using an exploratory and descriptive approach to investigate the impact of big data ecosystem on Re-distributed Manufacturing in the consumer goods industry. The study explored case studies concerned with the manufacturing configuration on a facility level and drivers behind facility strategy. The second theme relates to big data and the impact it can have on the manufacturing configuration. To analyse these themes a conceptual framework was developed from an extensive literature review. The investigated industries included packaged food, soft drinks, personal products, clothing and consumer electronics. A multiple-case analysis showed that big data applications will act as a supporting function in Re-distributed Manufacturing.

In this context, it was identified that the existing manufacturing configurations can be leveraged in most cases for products that are identified through big data analytics and market segmentation. This means that no changes in the manufacturing configuration are likely. However, the increasing resolution of customer insights, which is driven by advancements in big data applications could allow insights on the level of an individual customer, not only a market segment. This opens opportunities for mass customised products. A strong link between mass customisation and distributed manufacturing was identified in the literature and some cases. Mass customisation would implicate changes on a facility layer which is still driven by the incentive to produce high volumes and cut costs. This explains the diverse standpoints regarding the value and feasibility of mass customisation that emerged in the analysis and that were highly related to decisions on a product level. Some products were mentioned as interesting in this context but not all consumer goods, which will lead to a coexistence of manufacturing configurations.

Possible future scenarios include manufacturing at the point-of-use, manufacturing at the mall and personal manufacturing. But this needs to be investigated on a product level. Here it is hard to predict how far consumer goods are suitable for desktop or in-store production and how much customisation, which would promote a distributed production, is actually needed and desired by the consumer.

Opportunities for future RECODE research agenda

While this exploratory study investigates the connection between big data applications and a redistribution of manufacturing in the consumer goods industry, there are many other drivers for a distributed model which seem to be not fully understood and provide significant opportunities for future research. For example, the sustainability of distributed production is highlighted in several studies (Rauch et al. 2015), whereas other studies depict a more challenging view (Kohtala 2014). In this context, future research should not confuse benefits of digital manufacturing with distributed manufacturing and investigate especially the benefits and challenges of a distributed production.

Additionally, further research is needed to understand the possibilities of desktop manufacturing in the context of consumer goods. New concepts like manufacturing at the point-of-use or in the store offer various opportunities (DeVor et al. 2012). Regarding the research design, further research should include an in-depth investigation of one representative case study which illustrates distributed manufacturing (e.g. in-store production of footwear).

The current study was of an exploratory nature and looked into several industries, whereas future research should investigate the methods of value capture and different business models, as well as the challenges and barriers of distributed production for one individual case. This could provide additional understanding for the concept of Re-distributed Manufacturing.


vapour present tries to precipitate out as
frost. If this is not addressed, clogging
of the pre-cooler matrix would occur in
a matter of seconds, stopping air flow.
The frost control system has been an
incredibly difficult technology to master,
but the engineers at Reaction Engines
have achieved this breakthrough. The
technology itself remains a closely
other than aerospace. One of the most
exciting prospects is in the water
desalination field, where initial studies
have concluded that the heat exchangers
could enable a 25% efficiency increase
or higher.
Reaction Engines' technology
development is being supported by the
UK Government through the provision
of expertise in areas such as regulation
a possibility.

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