Data-driven Operations Management: Organizational Implications of the Digital Transformation in Industrial Practice

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Abstract

The ongoing digital transformation on industry has so far mostly been studied from the perspective of cyber-physical systems solutions as drivers of change. In this paper, we turn the focus to the changes in data management resulting from the introduction of new digital technologies in industry. So far, data processing activities in operations management have usually been organized according to the existing business structures inside and in-between companies. With increasing importance of Big Data in the context of the digital transformation, the opposite will be the case: business structures will evolve based on the potential to develop value streams offered on the basis of new data processing solutions. Based on a review of the extant literature, we identify the general different fields of action for operations management related to data processing. In particular, we explore the impact of Big Data on industrial operations and its organizational implications.

Keywords: big data, operations, industry 4.0

Final draft of the manuscript. The version of record has been published and is available in Production Planning & Control, Volume 28 (2017) Issue 16; pp.1332-1343, http://www.tandfonline.com/10.1080/09537287.2017.1375148

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1 Introduction

The diffusion of digital technologies has quickly progressed over the past ten years. Data processing applications have permeated practically every field of human activity and reach nowadays far beyond their traditional fields of application into the private lives of their users (Yoo et al. 2012; Fritzsche 2016). By virtue of their ubiquitous presence, digital technologies allow previously unfeasible solution designs which are expected to disrupt existing business structures and create new fields of economic growth (e.g. Lee 2008; Porter and Heppelmann 2014). In the context of industry, this dynamic is frequently addressed as a forth revolution after (1) the introduction of machine-based labour in the 18th century, (2) the moving conveyor belts and job breakdowns of the early 20th century, and (3) the automatization of production in the late 20th century (Lasi et al. 2014; Kagermann et al. 2013). To remain competitive despite all disruptions, companies have to ensure that their business operations are highly flexible and adaptable to economic and technical change (Westkämper 2011).

The digital transformation of industry does not progress with the same speed in all fields of application. Numerous efforts to collect and exploit digital data were undertaken long before the turn of the millennium. Logistics and procurement, for example, have built huge data warehouses and information networks in the 1990ies to gain better insight and control about inventories, production volumes, and shipping processes in huge data warehouses (Stadtler 2015). This enabled companies to engage in new forms of Supply Chain Management (SCM) and Enterprise Resource Planning (ERP), with an enormous impact on the organization of industrial operations and the overall structure of business activity in manufacturing (Gunasekaran and Ngai 2004; Oberniedermaier and Sell-Jander 2002). The achieved performance finds a significant association in the degree of ERP systems integration and restructuring of organisation (Jungbae Roh and Hong 2015). Today, the volume, range and speed of data collection have exponentially grown. A simple extrapolation of the experiences with ERP and SCM allows a first estimation of the future impact of digital technology on industry and society, supporting the view that the ongoing transformation has the potential to dwarf everything that happened in the 20th century, in terms of technological as well as socio-economic change (Lee 2008).

The future impact of the digital transformation, however, cannot be adequately predicted by simple quantitative extrapolations from previous experience with information technology. There are also qualitative differences to consider, caused on the one hand by the further development of systems architectures and hardware elements, and on the other hand by the characteristics of the subject matter (Brettel et al. 2014). Data warehouses and systems applications of the late 20th century were for the most part built as centralized solutions in accordance with the existing structures of operations managements (Mertens and Griese 2002). Current approaches rather favour decentralized technical designs of distributed programming with a high level of autonomy (Bauernhansl et al. 2014). Furthermore, they explore possibilities to capture new value streams in vertical integrations of business activities across institutional boundaries (Kagermann et al. 2013). Collaborative supply networks for customized production are necessary to address the growing demand for individualized products (Fornasiero et al. 2016). Such value streams are not reflected by the existing organizational structures of industrial activity. In order to gain operative control over these value streams, companies have to introduce radically new managerial concepts which reflect the potential of digital technologies to develop new business opportunities. In this respect, information technology and operations management can be said to have switched roles: the possibilities of data processing take precedence over the organizational structures of industrial activity (Yoo et. al 2010).

Research on digital technologies has already provided a lot of insight into the potential of new solution designs in numerous fields of industrial application (Chen et al. 2016; Oks et al. 2016). So far, however, the organizational implications of these designs for operations management have only been sporadically addressed. An overall picture is still missing. This can be explained by the large variety of operative constraints across the different fields of application. We propose that there is nevertheless one perspective on digital technologies which allows us to draw general conclusions for operations management. This perspective turns the attention to the treatment of data in the different fields of application. What they all have in common is that they produce large volumes of data high velocity and variety. Such data, which are usually described as Big Data, cannot be stored and processed in the same way as data in conventional data warehouses (Bendre and Thool 2016). They need to be treated in a different way. In this paper, we review the extant literature on digital technologies to extract recurring patterns of big data management and analytics. We use our findings to create a structured overview of the challenges of digital technologies for operations management and the consequences which have to be drawn out of it in terms of organizational change.

The paper is divided in 5 chapters. Chapter 1 introduces to topic and motivation. Chapter 2 explains the background of Industry 4.0 and the capabilities of Big Data solutions. Chapter 3 describes the method used to extract data processing requirements from current research publications. Chapter 4 presents and explains results. Chapter 5 closes with discussion of requirements and matching with capabilities of Big Data solutions.

2 Background

2.1 The digital Transformation of Industry

In its literal sense, digitization means the encoding of data in digital formats. Data which has previously not been available for digital data processing thus becomes available. Digitization in industry started with data of high granularity with a low update frequency. Today, an increasing number of data is created by permanently operating sensors which measure highly specific attributes of physical processes with as similarly specific functional domain (Lee, 2008). The connection of the data with other digitally encoded data allows the creation of new structures to manage and control these objects. It makes them programmable, addressable, sensible, communicable, memorable, traceable, and associable (Yoo 2010). Through the association of physical processes with computational events, physical objects and their formal, symbolic representation can be addressed together. As a consequence, systems can be created which, according Geisberger and Broy (2012), "use sensors to capture data about what is going on in the physical world, interpret these data and make them available to network-based services, whilst also using actuators to directly affect processes in the physical world and control the behavior of devices, objects and services. These systems are known as Cyber-Physical Systems (CPS)".

In the course of the ongoing digital transformation of industry, products and production systems like machines, warehouses and operating resources are enhanced to such Cyber-Physical Systems (CPS) and connected to global production networks (Kagermann et al. 2013). The entities are commonly considered to possess a certain, local intelligence which enable them to execute autonomous decision procedures, communicate with each other, interpret available data, and trigger actions. In exchange with others, such entities can also form regulatory cycles with abilities of self-control and self-optimization (Lee, 2008). Intelligent products can be clearly identified, located at all times, know their history, status and alternative ways to completion. Intelligent production systems are connected to company's business processes, IT-systems and to the entire value chain in the production network. This enables real-time control and optimization of the value chain, starting with an order to the final delivery of the product (Kagermann et al. 2013). The convergence of the physical world and the digital world with CPS enables the new paradigm of autonomous and decentralized production (Brettel et al. 2014; Monostori 2014).

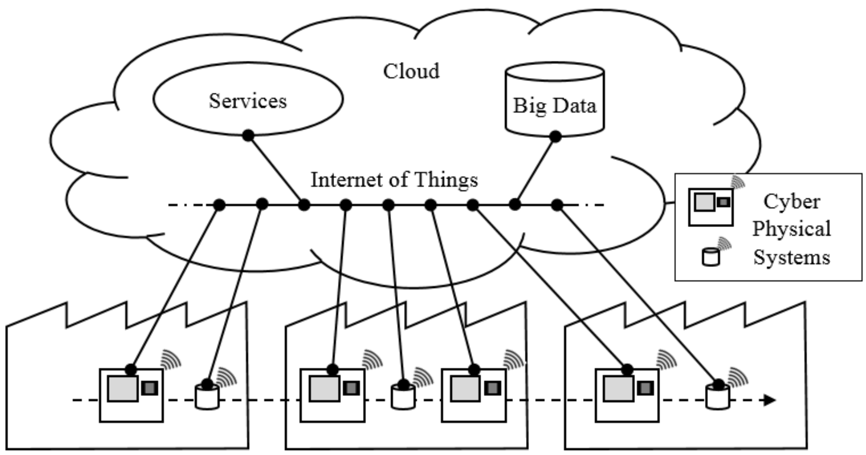

Figure 1. Solution-components of Industry 4.0

In order to highlight the revolutionary potential of the digital transformation of industry, it has become popular to address it by the term "Industry 4.0", which was first publically introduced at a German industry fair in 2010. The current discourse on Industry 4.0 names a wide manifold of concepts and solution-components (Figure 1). This includes, but is not limited to (1) CPS as intelligent entities in production (Sztipanovits et al. 2013), (2) Internet of Things as communication platform for CPS (Madisetti and Bahga 2014), (3) Cloud solutions for decentralized services (Verl et al. 2013) and (4) Big Data solutions for high-performance processing of large data amounts in production (Kagermann et al. 2013; Lee et al. 2013). The diversity of Industry 4.0 solution designs is mainly driven by the almost endless variety of purposes for which CPS can be applied. This includes self-organization in manufacturing and logistics, self-maintenance and repair, improved safety and robustness, real-time control, and more (Monostori 2014). Further diversity is caused by the specific requirements of the different subject matter in manufacturing, energy, mobility, health, and private consumption (Rehm et al. 2015). In terms of data management, on the other hand, the solutions which are discussed show many similarities which allow us to draw general conclusions about the implications of the digital transformation of industry for operations management.

2.2 Big Data Applications

The exponentially increasing amount of data used by digital technology has further consequences for application design. Previous information systems architectures considered data as a passive resource which could originated somewhere and was then extracted, transformed and related to other data according to a predefined data model. During the last years, the attention has shifted instead to more dynamic forms of data processing without reference to any predefined structural model. Data are increasingly considered as so-called Big Data. Drawing on early discussions among practitioners and consultants, Big Data are commonly characterized by the 3 V's: large volume, variety and velocity (Chen et al. 2014). Big data require further processing after collection in order to determine their relevance and interrelatedness, using algorithmic techniques such as association rule learning, cluster analysis, ensemble or machine learning, natural language processing, pattern recognition, spatial analysis and many more (Chen et al. 2016; de Mauro et al. 2015). The significance of the data for application consequently does not only depend on their origin, but also on the design of the methods used for their further treatment. For this reason, various authors have added further terms to the 3V's, such as value for application and veracity (Dijks 2012; Schroeck 2012). The design of the information systems used for processing the data can thus not be considered as independent from the exploitation of the data in business contexts (see also Fritzsche 2009). This turns Big Data into an important topic for the organization of operations management activities.

In comparison to CPS, research on Big Data is more closely connected to operative systems than prototypes and pilot applications. This makes it possible to discuss Big Data in reference to different software solutions rather than general application scenarios. Apache Hadoop is one of the most wellknown Big Data software solution, however, there is a great variety of others solutions e. g. Redis, SimpleDB, CouchDB, MongoDB, Terrastore, HBase or Cassandra (Cattell 2011). A common technical criterion to determine the scope of Big Data is the usage of NoSQL data bases. Several taxonomies have been proposed to classify the different NoSQL data bases (Cattell 2011; Pokorny 2013). Pokorny (2013) for instance uses the criteria of the data model and identified three kind of models: Column-oriented (e. g.

Cassandra), key-value (e. g. SimpleDB) and document-based (e.g. Mongo DB). Another criterion is related to principles of data processing (Agrawal et al. 2011). The first principle is batch processing and distributed computing of data (Gupta et al. 2012). Large and complex data is split into small subsets and then processed concurrently. A common algorithm is MapReduce which is tuned for a specific use cases. A representative software solution for this principle is Hadoop HDFS with MapReduce (White 2012). The second principle is to store data in a semi-structured data model which is adapted to the specific access pattern of a use case (Kaur and Rani, 2013). This enables real-time queries and random access on data without time-consuming operations and data joins. The software solutions Cassandra (Hewitt 2010), SimpleDB (Chaganti and Helms 2010) or MongoDB (Chodorow 2013) are representatives of this principle.

Both classification criteria (data model, principles of processing) are important characteristics when selecting a proper solution design for a specific use case. Table 1 compares four different designs regarding general capabilities and characteristics. Each design is a representative for the classification described above. A final selection of an appropriate Big Data software solution depends on use case, existing infrastructure and application scenario.

Table 1. Capabilities and characteristics of representative Big Data software solutions

BIG DATA SOFTWARE SOLUTIONS				
Capabilities /Characteristics	Hadoop HDFS & MapReduce	Cassandra	MongoDB	SimpleDB
Data model	File system	Column	Document	Key-Value
Batch processing / distributed computing	Yes	No	No	No
Real-time queries	No	Yes	Yes	Yes
Random access	No	Yes	Yes	Yes
Horizontal scaling	Yes	Yes	Yes	Yes
Strength	Data processing	Write	Read	Full Indexing
Architecture type	Master-Slave	Peer-to-Peer	Master-Slave	Web Service / Cloud Computing
CAP theorem	Consistency, Partition Tolerance	Availability, Partition Tolerance	Consistency, Partition Tolerance	Availability, Partition Tolerance

3 Research Design

Our research interest in this paper is directed at the implications of the digital transformation of industry for operations management. We propose that such implications can be derived from the study of Big Data management in the context of new digital technologies. For this reason, we review the extant literature in the field to identify common patterns in the treatment of Big Data which need to be considered from an operations management perspective. Our findings are then used to draft an overall picture of the data-oriented operations in industry which can serve as a basis for a re-organisation of operations management.

A widely accepted method in IS research to make valid interference from text can be found in the scientific technique of content analysis (Myers 1997). Content analysis uses clear rules and systematic procedures for analysis and interpretation of text (Klenke 2008; Krippendorff 2004; Mayring 2000). Compliance of rules and procedures delivers rigorous and replicable results (Krippendorff 2004). Core of the content analysis is a category scheme, achieving the objectives of analysis. Categories can be developed by deduction from theory or by induction using the analysed material (Mayring 2000). As relevant theory in the field of new digital technologies is widespread in various scientific disciplines (including production, logistic, IT, AI, mathematics, and more), this study uses an inductive category development approach based on scientific publications in related to the digital transformation of industry. This allows a grounded interpretation of material without pre-assumptions.

The process of content analysis:

The analysis of requirements of new digital technologies in industry regarding data processing was conducted using the process of content analysis according to Mayring (2000, 2008). Our object of analysis was the vision, objectives and concepts expressed in extant scientific literature in the field. The analysis was conducted with the objective to create a structured compilation of explicit and implicit requirements for data processing in the Industry 4.0 concept. More specifically, the analysis was guided by the following two research questions: (1) What are the requirements regarding the data that need to be processed? (2) What are the requirements regarding the processing of the data?

The search was conducted on journal papers, conference papers and white papers from the following scientific sources: general databases (ScienceDirect, IEEE Explore, Google Scholar), German journal data bases (ZWF, WT, IM). Publications were filtered using the keywords ‘industry 4.0’, ‘cyber physical system’, ‘internet of things’, ‘autonomy’, ‘decentralized’, ‘self-control’ in combination with the keyword ‘production’, ‘manufacturing’ or ‘logistic’. The filter was applied on title, abstract and keywords of publications in the period 2005 to 2015. The search resulted in 117 publications.

After selection of the material, rules for the process of category development were defined. Therefore, unit of analysis, selection criteria and level of abstraction were specified. The unit of analysis defines rules for the amount of text which is the basis for interpretation. As requirements are mostly described in implicit form, we choose ‘phrase’ as minimum and ‘section’ as maximum unit of analysis. This allows understanding and interpretation of requirements in the individual context of the paper, expressed in short statements as well as larger arguments. The selection criteria defines decision rules whether a unit of analysis contributes to the research question and objectives of analysis. In case of data processing, we analysed requirements regarding (1) Data: types, structure, format and sources and (2) Processing of data: operations, performance and conditions. The level of abstraction defines the rules to build a category for a unit of analysis which fulfils the selection criteria. In case of data processing requirements of industry 4.0, the rule is to choose the level of abstract in a way that categories for requirements are not specific to any approach or solution, but are applicable to the context of the digital transformation of industry in general.

As a next step, one researcher reviewed parts of the material applying the defined rules. The review was conducted using the software MAXQDA. The categories derived in this first loop were built closely from material. After only a few new categories occurred, a revision of rules and category scheme was conducted. Categories were merged to related aspects to receive distinct categories. Each content of the 27 resulting categories was then checked for reliability and its fit in the category, by means of a category description. Based on the resulting categories and codes the final examination of the material was conducted. A summative check of reliability was performed upon the coding of a second researcher. Therefore, the second researcher was instructed in object, objectives, research question and rules and then analyzed parts of the material. Mayring (2008) proposes a reliability of at least 70% for acceptable results of a content analysis. The summative reliability was calculated according to Holsti (1969) and proves the reliability of this analysis. Table 2 shows the aggregated reliabilities for each main category.

Table 2. Number of codings and summative reliability by main category

Category	C10	C20	C30	C40	C50	C60	C70	Total
Codings of Coder 1	27	34	23	73	27	29	20	233
Codings of Coder 2	25	30	28	81	30	27	18	239
Matching Codings	22	26	19	54	24	22	15	182
Summative Reliability	85%	81%	75%	70%	84%	79%	79%	77%

4 Findings

The result of our analysis is a structured compilation of requirements regarding data processing. It provides a comprehensive view on the content types that need to be processed and on the processing of that data in a digitalized environment. This result could only be produced by the accumulation of the findings, as the vast majority of the publications only addressed certain aspects or solution-components, without describing general requirements or structures for requirements. Table 3 shows the resulting category scheme with 6 main categories and 27 subcategories describing object, subject and conditions of data processing. According to our two research questions, it is grouped in requirements for data and for processing of data.

The first main category ‘Data Model’ (C10) shows requirements for characteristics of data, structure and sources to integrate in the context of the digital transformation of industry. The subcategory ‘Unify semantics’ contains requirements for a unified description of information and meanings in production. The unification of interfaces between entities in production are content of the next subcategory ‘Unify interfaces’. Together, semantics and interfaces address communication and data exchange among CPS in a comprehensive production network which various systems and objects. The second main category 'Data Integration' (C20) refers to different perspectives of data integration within an enterprise and beyond. The first subcategory 'Integrate life cycle' contains requirements to integrate life cycle data of CPS in engineering and operation processes. The next subcategory 'Integrate horizontally' focuses on requirements to integrate data along the value chain in an entire production network. The third subcategory 'Integrate vertically' contains requirements to integrate data from the automation pyramid (enterprise-, control-, device- and sensor-level). The third main category 'Data content' (C30) shows requirements for necessary data to be processed. Necessary data comprises authorization, specification, capabilities, production data, business data, condition data, sensor data, order data and knowledge.

The fourth main category 'Decision processing' (C40) refers to requirements for autonomous, de-centralized self-control and self-optimization performed in CPS networks. The first subcategory 'Monitor conditions' includes requirements for a permanent monitoring of conditions and health of production processes and equipment. Requirements for triggering decision-making depending on current situation are dedicated to subcategory 'Ad-hoc reaction'. The subcategory 'Admit autonomy' contains requirements for autonomy and freedom in decision processes in CPS networks. The next subcategory 'Optimize network' focuses on requirements for overall system goals and optimization when local decisions are made by CPS. Requirements for utilization of comprehensive models of the current production are part of the subcategory 'Utilize models'. The fifth main category 'Knowledge processing' (C50) refers to requirements for processing of actual and past data to generate knowledge and additional value for decision-making. The subcategory 'Generate models' contains requirements to derive models and rules from knowledge, generated from historical data in production. Requirements to adapt knowledge, models and data depending on application context are part of the sub-category 'Adapt knowledge'. The next subcategory 'Transform know-how' contains requirements to transform expert knowledge and experience in information models. The sixth main category 'Real-time processing' (C60) focuses on requirements for processing performance. Requirements to access entities and data in real-time are part of the subcategory 'Real-time data access'. The next subcategory 'Real-time communication' contains requirements for real-time communication and data exchange among CPS and within a network. Real-time requirements for operative production control are part of the sub-category 'Real-time control'. The last main category 'Safety and protection' contains requirements for IT-security within overarching value networks. The subcategory 'Network safety' refers to requirements to identify entities as prerequisite for communication and data exchange. The last subcategory 'Data safety' focuses on roles and rights for all entities to control data access and communication.

Table 3. Resulting Categories for data processing requirements of Industry 4.0.

DATA REQUIREMENTS		
Main category	**Subcategory**	**Requirement Description**
Data model (C10)	Unify semantics (C11)	Unify information models an meanings
	Unify interfaces (C12)	Unify interfaces and communication
Data integration (C20)	Integrate life cycle (C21)	Integrate data along the life cycle of CPS
	Integrate horizontally (C22)	Integrate data along the value chain and network
	Integrate vertically (C23)	Integrate data of automation pyramid
Data content (C30)	Include authorization (C31)	Include identification and access rights of CPS
	Include specification (C32)	Include technical specification of CPS
	Include capabilities (C33)	Include capabilities and properties of CPS
	Include production data (C34)	Include work plan and instruction of CPS
	Include business data (C35)	Include business data and parameters of CPS
	Include condition data (C36)	Include condition and status data form CPS
	Include sensor data (C37)	Include sensor an actor data from production
	Include order data (C38)	Include customer data and conditions of delivery
	Include knowledge (C39)	Include knowledge from analytics
PROCESSING REQUIREMENTS		
Main category	**Subcategory**	**Requirement Description**
Decision processing (C40)	Monitor conditions (C41)	Monitor conditions of actual production processes
	Ad-hoc reaction (C42)	Control processes depending on situation
	Admit autonomy (C43)	Admit autonomy in decision-making of CPS
	Optimize network (C44)	Optimize network in local decision-making
	Utilize models (C45)	Utilize comprehensive models of real production
Knowledge processing (C50)	Generate models (C51)	Generate models and rules from knowledge
	Adapt knowledge (C52)	Adapt knowledge to conditions of decision
	Transform know-how (C53)	Transform know-how and expert knowledge
Real-time processing (C60)	Real-time data access (C61)	Access data and CPS in real-time
	Real-time communication (C62)	Communication und data exchange in real-time
	Real-time control (C63)	Control and coordination of processes in real-time
Safety and protection (C70)	Network safety (C71)	Protect network against unauthorized access
	Data safety (C72)	Protect data against unauthorized access

5 Discussion

5.1 Data processing Requirements of new digital Technologies

Our findings suggest that the digital transformation of industry shifts the attention in the search for improvements of efficiency and effectiveness from physical production processes to the management of data involved in it.

Such improvements require a comprehensive integration of data (C20) and standardized semantics and interfaces (C10) to enable efficient communication and data exchange (Atmosudiro et al. 2014; Klocke et al. 2013). Activities for data integration include the horizontal, vertical and life cycle perspective (Brettel et al. 2014; Vogel-Heuser et al. 2009). Regarding the data content (C30), results show a wide range of data, covering the whole life cycle of a cyber-physical system in Industry 4.0. Besides specification (C32), the description of capabilities (C33) of cyber-physical systems is required to enable self-aware entities and self-organizing operational processes (Denkena et al. 2013; Höme et al. 2015; Letmathe et al. 2013). Furthermore, business data (C35) is required for monetary evaluations in operational decision-making (Fleischer et al. 2013; Lanza et al. 2013; Rekersbrink et al. 2007). This requirement was already part of the CIM-concept and finds it´s revival in Industry 4.0 (Mertens 2014). The comprehensive usage of knowledge (C39) from historical data in form of models and rules is another characteristic of Industry 4.0 (Auerbach et al. 2013; Frazzon et al. 2013).

Efficient processing of comprehensive data is another requirement of Industry 4.0. Entities like machines perform continuous monitoring of their own conditions and of their environment (C41) to detect critical deviations or situations (Herkommer and Hieble 2014; Lee et al. 2014) and to perform ad-hoc reactions (C42) upon critical situations (Grundstein et al. 2013; Overmeyer et al. 2013). Decision processes target the optimization of overall value chains or rather overall production networks (C44) (Rekersbrink et al. 2007), even when decisions are made by autonomous, decentralized entities (C43) (Blunck and Windt 2013; Rehder and Schatz 2014). Further enhancement of decision process in Industry 4.0 require the usage of a wide range of extracted and formalized knowledge (C50) generated from historical data (Auerbach et al. 2013; Lee et al. 2014). This knowledge can be used to determine parameters or predictions for decision processes. Sensors in the operative production deliver data in cycles of milliseconds (C37) (Bauernhansl et al. 2014). As a result, there is a huge and continuously growing amount of historical data which need to be processed. The requirement for real time processing (C60) addresses the access of entities and their data within the network (C61) (Plorin et al. 2013; Reinhart, Engelhardt, and Geiger 2013) as well as communication and data exchange among entities (C62) (Jatzkowski and Kleinjohann 2014; Scheifele et al. 2014) and real-time control (C63) (Sztipanovits et al. 2013). All interaction and communication among entities require processes for identification and application of rules and roles for data protection and security (C70) (Holtewert et al. 2013; Franke, Merhof, and Fischer 2010).

5.2 Implications for Operations Management

Figure 2 gives an overview of the new dynamics of data management which have to be considered by operations research in a digitalized industrial scenario. They can be organized in four different domains: a) adapted decision processes, b) extended repertoire of data, c) expanded data management, and d) big data treatment.

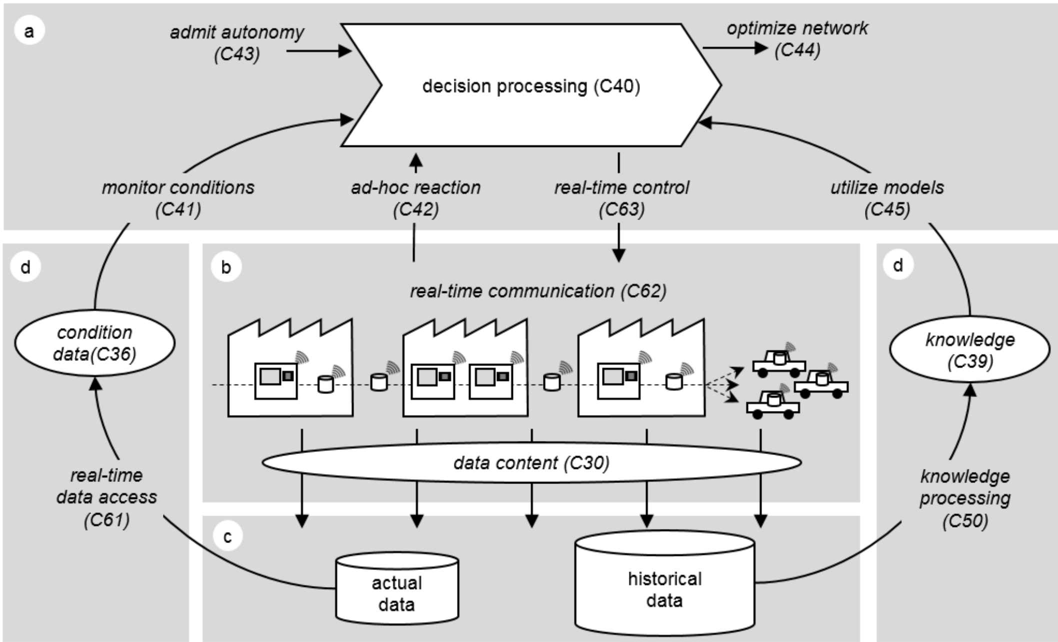

Figure 2. Levers of data-driven decision-making in operations

a) Adapted decision processes

Because of the changing quality of the data that are processed, operations management needs to revise the logic in which decisions are made. Data give direct insight into the actual state of resources and the progress of value creation processes in the industrial environment (C41). Operations management can react to events on the shop floor and elsewhere in the value creation network without any significant delays (C42). This allows close feedback-loops between decision making and monitoring of its consequences. Decision procedures can optimally be adapted to the present conditions in the value creation network (C63). Decisions can be based on comprehensive models developed from historical data and make use of knowledge about recurring patterns (C45). Furthermore, the decision processes can be distributed across different agents without constant references to a central controlling entity (C43) and situative assessments during the decision processes can reflect the overall requirements of the whole network in a better way (C44).

b) Extended repertoire of data

A lot of the data relevant in digital environments are already taken into consideration by existing approaches to operations management, such as quality data, material characteristics, product structures etc. in specifications of CPS (C32) as well as manufacturing data like work plans, bills of material etc. (C34); the same applies for status information (C36) regarding logistics and manufacturing in MES and ERP systems (see Sendler 2009; Loos 1999; Mertens and Griese 2002). At the same time, however, new kinds of data become relevant as well. This includes authorization data (C31) as well as machine capabilities (C33). Furthermore, sensorial data which were previously only sporadically retrieved are now available ubiquitously (C37). This creates a comprehensive view of the whole value creation network in large detail (Atmosudiro et al. 2014; Koch et al. 2014). At the same time, a lot of practical knowledge which was so far only accessible as implicit knowledge of engineers, technicians and workers can now be made available in information systems (C39).

c) Expanded data management

The extended repertoire of data goes along with new requirements for data management. Data structures have to be expanded, adapted in related in new ways to give an appropriate account of the actual operations (C31, C33, C39). Furthermore, data which have so far often been kept in separate databases related to specific applications (e.g. CAD, ERP) now need to be accessible via an individual information model, containing all life cycle of entity. This creates further requirements for coordinated updates and consistency checks. Relying on specific interfaces and exchange protocols creates huge risks of deviating information. Therefore, other, more comprehensive solutions need to be introduced (see e.g. Vogel-Heuser et al. 2009). In sum, this can be described as a vertical as well as horizontal integration across whole value creation networks (Anderl et al. 2014; Kagermann et al. 2013), as a comprehensive digital image (or “digital shadow”) of the industrial operations (VDI/VDE 2015). The creation of such an image can be accomplished on the basis of a systematically developed general information model (Höme et al. 2015). Such a model has to consider all specific types of data that are involved (C31-C37).

d) Big data treatment

Last but not least, the specific characteristics of Big Data need to be taken into account. In order to cope with the high volume, velocity and variety of the data, operations management has to adopt new strategies for data treatment which go beyond the systematic routines of loading, transforming and presenting data for further usage in conventional data warehouses. We see three issues requiring high performance processing of large data volumes and appropriate Big Data approaches:

(1) *Instantiation and lifecycle approach of Entities*: Life cycle integration (C21) of entities (e. g. machines) require the instantiation of an object in the information model. All data (C30), active data as well as historical data, have to be stored to be accessible for data processing (e. g. Data Mining). The anticipated growth of objects and of containing data (e. g. sensor data) are drivers for Big Data.

(2) Knowledge processing of historical data: Data basis for generating knowledge (C50), are historical data from operational processes (e. g. sensor data, good movement, manufacturing processes). Data mining methods are used to recognize pattern, relations and trends in historical data, to derive rules and models (C51) which can be applied to improve and optimize operational processes (C45). To recognize relations and pattern within historical data requires massive parallel processing of Big Data.

(3) *Real-time access on entities in the network*: Real-time decision-making and control are major requirements for a timely response on operations dynamics (e. g. machine failure, delivery delay) (C60). Actual operation data from the value chain (C41) is required to achieve overall system goals and optimization (C44). This involves random access on data of all entities within an overall network, in real-time (C61).

Comparing these three issues with the capabilities of Big Data solutions (Table 1) leads to the finding, that two unique Big Data approaches are necessary. The issues form two general Big Data use cases with fundamental differences regarding access and processing patterns and underlying data. The first general use case *Knowledge Processing* handles time consuming data analytics, mining and prognosis on large amounts of passive data (C50). Real-time queries and random access on data are not crucial in this case. This requires Big Data solutions that support batch processing and distributed computing e.g. Hadoop HDFS with MapReduce. The second general use case *Entity Access* performs ad-hoc queries on entity data from the overall network for operative decision-making (C40, C60). This requires Big Data solutions that support real time queries and random access. Depending on infrastructure and application scenario Cassandra, MongoDB or SimpleDB could be a relevant software solution. Both use cases have a general character and require individual adaption to the context of application.

6 Conclusion

The digital transformation of industry is under way, but it is still far from being finished. Its revolutionary potential, as it is addressed by terms like “Industry 4.0” has not yet fully materialized. As a consequence, the extant literature can only roughly anticipate the future impact of digital technologies, based on general conceptual considerations and first practical experience with prototypes and pilot projects. A literature review like the one performed in this paper reflects all the limitations of its source material. It is constrained by the current state of discussion in the field, and there is good reason to believe that a lot of new insights will be gained very soon which will allow us to draw a much better picture of the digital transformation in the future.

It is also necessary to keep in mind that the nomenclature in research is also still in its early stages. The selection of papers based on specific search terms can therefore easily lead to the exclusion of contributions which are highly relevant to the subject matter, but use a different terminology. This must be considered as a general problem of emerging fields of research where discourse has not yet progressed far enough to establish a stable vocabulary. We are confident, however, that the consideration of seminal papers like Lee (2008) or Kagermann et al. (2013) in the choice of the keywords has allowed us to reduce oversights of relevant literature to a minimum. Comparisons to other reviews in the field such as Monostori (2014) or Oks et al. (2017) also show that other authors operate with the same vocabulary as we do, which further reassures the robustness of our approach.

Additional limitations are caused by the method of content analysis itself. The method uses a set of rules to analyse text passages. In case of data processing requirements, the context of a statement or of an argument is highly relevant for understanding and interpretation. That´s why we choose 'phrase' as minimum and 'section' as maximum unit of analysis. However further reaching interpretations of a paper, are not covered by our analysis and might result in additional categories for data processing requirements in the Industry 4.0 concept. Furthermore, our calculation of reliability neglects effects of aggregation and category number (c.f. Holsti 1969). Sources in other languages than German and English have been omitted in disregard of the numerous excellent publications in the field of engineering in French, Chinese and other idioms.

Nevertheless, we believe that our research provides important insights for academia and industry. To our knowledge, we are the first who have studied the implications of the digital transformation for operations management from a data processing perspective. This perspective has allowed us to identify a general dynamic in all the various fields of application of new digital technologies. New ways of processing large volumes of data with a high velocity and variety in the context of Big Data go hand in hand with the introduction of cyber-physical systems in industry. With Big Data, data treatment becomes an integral part of the different activities necessary to arrange and control industrial activity, and as such a major success factor for operations management. Based on our literature review, we were able to identify four domains in which Big Data will affect operations management in the future. Since these four domains span across the conventional organizational boundaries in industry, restructuring efforts are necessary in order to ensure that the revolutionary potential of the digital transformation can be exploited. Companies which successfully undertake these efforts can be expected to gain a huge competitive advantage.

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