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The Data-Driven Process Improvement Cycle: Using Digitalization for Continuous Improvement

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Abstract: Industry 4.0 is the first industrial revolution to be announced a priori, and there is thus a significant ambiguity surrounding the term and what it actually entails. This paper aims to clearly define digitalization, a key enabler of Industry 4.0, and illustrate how it can be used for improvement through proposing an improvement cycle and an associated digitalization typology. These tools can be used by organizations to guide improvement processes, focusing on the new possibilities introduced by the enormous amounts of data currently available. The usage of the tools is illustrated by presenting four scenarios from Kanban control, where each scenario is mapped according to their digitalization level.

Keywords: digitalization; digitization; Industry 4.0; improvement cycle; lean manufacturing

1. INTRODUCTION

In contrast with the three previous industrial revolutions, Industry 4.0 is the first to be announced a priori (Drath and Horch, 2014). Although a great opportunity to shape and optimise the solutions before they are fully released, the lack of empirical data makes the research highly theoretical and there are plenty of disagreements and differences in the literature regarding what Industry 4.0 is and what it consists of (Buer et al., 2018). Different perspectives in various studies have resulted in more than 100 different Industry 4.0 definitions in literature (Moeuf et al., 2017). New definitions of Industry 4.0 are proposed regularly, and large differences between these can be found both in semantics and in content. In general, definitions can change slightly over time. The need to propose new definitions and not conform partially or entirely to existing definitions leads to the assumption that there is still not a common opinion about Industry 4.0.

On the other hand, it might be too early to establish a definition of Industry 4.0. Although we can find pilot Industry 4.0 projects, some claim that we need to wait years, maybe even decades, before we will see “real” smart factories as envisioned by Industry 4.0 (Almada-Lobo, 2016, Bonekamp and Sure, 2015). Some ambiguity in concepts may also be valuable as it allows practitioners the flexibility to adapt the concept to fit a specific situation (Osigweh, 1989). Given the rapid speed in which Industry 4.0 is evolving, it can be argued that to define it now is pointless since it will merely be an image of a moving target, i.e. only valid at a certain point in time.

Nonetheless, this ambiguity in definitions makes it harder to align research in the area, as well as it makes it more complicated for practitioners to understand what Industry 4.0 entails and how to achieve this transition. The lack of a clear and agreed-upon definition will lead to empirical testing of an inexact and imprecise concept, and consequently, results from empirical testing make marginal contributions and prevent academic progress (Meredith, 1993, Shah and Ward, 2007). It is important for researchers within the field of Industry 4.0 to attack this ambiguity issue early and standardise the definition, converge the scope and synthesise the objectives of Industry 4.0. Hermann et al. (2016) emphasizes the current ambiguity surrounding the Industry 4.0 term and proposes four design principles guiding practitioners and scientists on how to approach Industry 4.0.

Pfohl et al. (2017) point out digitalization of processes and products as a key enabler of Industry 4.0. Others mention full digitalization as one of the core elements of Industry 4.0, enabling intelligent planning and control of production processes and networks (Erol et al., 2016). However, as with Industry 4.0, there is significant ambiguity in research regarding what digitalization entails, which steps that needs to be undertaken to get there, and how to measure the progress towards getting there.

To measure and evaluate processes within organizations, maturity models have been a popular tool among academics for numerous years, and are typically based on a pre-defined best-in-class description, with pre-described stages on the path towards reaching the top level (De Bruin et al., 2005, Wendler, 2012). Although a maturity model can be a useful tool in contexts where an end goal and best-in-class is clearly defined, it is problematic to use a maturity model in an emerging field because of the obvious ambiguity in what being best-in-class actually entails. Therefore, to develop a maturity model for digitalization is, in the best case, a qualified guess, heavily based on the researcher’s perception of the ideal state.

This paper proposes to break the road towards improving processes through digitalization into five clearly defined steps, forming an improvement cycle. Employing this view avoids the possible bias issues mentioned above and provides a clear roadmap for moving towards a higher degree of digitalization of processes. This paper will introduce the proposed improvement cycle together with a digitalization typology to classify the different steps in the cycle. Following this, the usage of the cycle is demonstrated and the possible usage areas of this cycle are discussed.

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2. THEORETICAL BACKGROUND

2.1 Clarifying Digitization, Digitalization, and Digital Transformation

Following the predictions of Moore's law, hardware is now available with such processing power at such an affordable price that it enables the ubiquitous computing prophesied by Mark Weiser (1991). This aspect is one of the triggers for the trend of an increased level of ICT integration, popularly known as the "fourth industrial revolution". This is leading to a steep increase of research papers talking about terms as digitization, digitalization, and digital transformation. Some are using these terms interchangeably, while others claim there is a significant difference between the terms. This ambiguity confuses the reader, uncertain whether the author is seeing the terms as interchangeable or not. This paper aims to present definitions for these three concepts, central in the recent technological advances influencing all areas of business.

Schumacher et al. (2016) highlight some of the current confusion regarding the terms digitization and digitalization. Through a review of the literature, they argue that while digitization is about the conversion of analog signals into digital signals together with its storage and transfer, digitalization describes the effects, impacts, and consequences triggered by the availability of digital information. They thus consider digitalization and digital transformation as equivalent (Schumacher et al., 2016), while other authors do not distinguish between digitization and digitalization (e.g. Kagermann, 2015, Leyh et al., 2016). Khan (2016) presents some of the disagreements in the literature regarding the clarification of digitization, digitalization, and digital transformation. We propose that there is a need to further distinguish these three terms. Precisely defining these terms supports the construct validity of research in this field. Based on the literature findings, we suggest these definitions:

- **Digitization:** The conversion from an analog format into a digital format.
- **Digitalization:** The use of digital data and technology to automate data handling and optimize processes.
- **Digital transformation:** Creating new business opportunities through the use of digital data and technology.

Fig. 1 further depicts the relationships between these three terms.

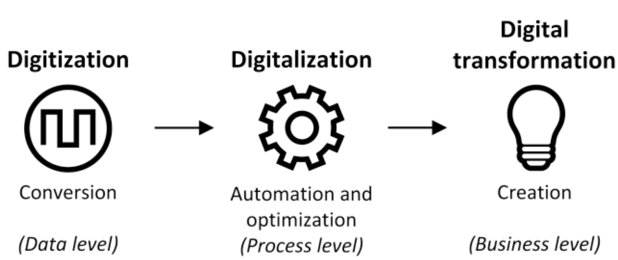

Fig. 1. Digitization, digitalization, and digital transformation (Adapted from Maltaverne (2017))

A number of maturity models for digitalization and Industry 4.0 have been proposed the last few years. Examples include the System Integration Maturity Model Industry 4.0 (SIMMI 4.0) (Leyh et al., 2017) and the IoT Technological Maturity Assessment Scorecard by Jæger and Halse (2017). Both of these are to be used on an overall business level, and lacks proper empirical evidence of what characterizes best-in-class organizations. It is a significant gap between the high-level assessments in these models and the actual digitalization efforts that is needed to reach it. This paper proposes to measure specific processes in relation to how they use digitalization to improve their processes, through the use of an intuitive improvement cycle.

2.2 Improvement Cycles

Continuous improvement is essential for every organization aiming to stay competitive (Bicheno and Holweg, 2009). Improvement cycles gives a disciplined and structured framework for continuous improvement. Improvement cycles can be compared to control loops in industrial control systems, which continuously gather information to control processes towards a specific objective.

A number of improvement cycles have been proposed throughout the years: PDCA (Plan – Do – Check – Act), DMAIC (Define – Measure – Analyze – Improve – Control), IDEA (Investigate – Design – Execute – Adjust), 8D (Bicheno and Holweg, 2009), and RADAR (Sokovic et al., 2010) are some of the prominent examples.

Improvement cycles can be used as an overarching and standardized method to pursue improvement in organizations. Although seemingly simple, they are powerful tools and PDCA is considered a foundation of the Toyota Production System (Bicheno and Holweg, 2009).

3. RESEARCH METHOD

The research presented in this paper has used a conceptual research approach as presented by Meredith (1993). The work is motivated by existing literature and known challenges related to the recent trends of digitalization and Industry 4.0. The common features and opportunities presented by existing research have been adapted into an improvement cycle perspective through the use of philosophical conceptualization (Meredith, 1993).

4. THE DATA-DRIVEN PROCESS IMPROVEMENT CYCLE EXPLAINED

The competitiveness of today's business environments is constantly increasing, and the ability to continuously improve is a key success factor. As part of their quest to stay competitive, organizations have invested considerable sums into developing their digital infrastructure. ICT solutions can enable both cost savings and new business opportunities. As a "by-product" of these solutions, large amounts of unstructured data are created, which are often not used further for improvement purposes (Gantz and Reinsel, 2011). These unused data are typically known as “idle data” (Schmidt et al., 2015). Having large amounts of “idle data” has been indicated as an important part of implementing Industry 4.0 (Schmidt et al., 2015). Increased computing power has facilitated the possibilities of using big data analysis to discover patterns and improvement possibilities from datasets in which a human not necessarily would have found a pattern. This is the basis of every data-driven model. However, even if big data analysis is proven applicable in some cases, implementation is still scarce. This section introduces the data-driven process improvement cycle and relates it to the emerging trend of digitalization. This section introduces the five steps of the improvement cycle (Section 4.1), as well as the possible different states for each step (Section 4.2).

4.1 The Five Steps

Step 1: Collection of data

You always need data to support your decision making. In general, data can be collected sporadic, periodic, or continuous. The data may appear in a physical or digital format, and may be collected with or without human intervention. Data can be obtained in different ways e.g. through measuring, counting, reading, or similar. The collected data give you information about today’s situation and the current status of the key variables. It is thus assumed that you know what these key variables are and that sensors or other means of obtaining the data are organized for this purpose. This step obtains the data input and transforms it into shareable data.

Step 2: Sharing

After the data is collected, it needs to be shared with the right actors that will process this data further. Data can be shared in different ways; ranging from paper-based documents between people to digital transmission between a machine and a cloud-based server. The basics of data sharing are the one-to-one exchanges of data between a sender and receiver. The technology advances in the recent years increased the possibilities of sharing data. Increased connectivity and data sharing velocity have led to a higher availability of data (Gantz and Reinsel, 2011, McAfee and Brynjolfsson, 2012). The sharing step describes in which way the data is exchanged between the different actors.

Step 3: Analysis

The analysis step is concerned with the process of data inspection, cleaning, transforming, and modelling in order to discover useful information. Data inspection is the first quality control whether data can be read in the first place or not. Data cleaning checks the data for errors in terms of completeness. It detects and removes errors and inconsistencies from the data to improve the data quality (Rahm and Do, 2000). The data transformation part is an approach to find a deterministic mathematical function for each point in a dataset. Finally, data modelling analyzes data objects and their relationships to other data objects. It starts with the development of a conceptual model specifying how data relates to each other and is then transferred to a mathematical model (Rahm and Do, 2000).

Step 4: Optimization

The optimization step is an adjustment process of changing a specified set of parameters to find an optimal or near-optimal solution without violating any restrictions (Rothlauf, 2011). The basis for the optimization process is the mathematical model established in Step 3. As the computer power has increased exponentially over the years, it is now possible to use more advanced optimization algorithms. With increased computational effort, the solution quality increases. Nevertheless, it is favorable for achieving fast results and response to use models that need low computational effort. The results of the optimization step are the basis for taking an improvement decision, which in the next step have to be integrated back into the system.

Step 5: Feedback

Analyzing the collected data and discovering improvement possibilities is of no use if not fed back into the process. The results and information from the optimization step have to be transformed, shared, and implemented in order to ensure feedback to the process.

The data-driven process improvement cycle is illustrated in Fig. 2.

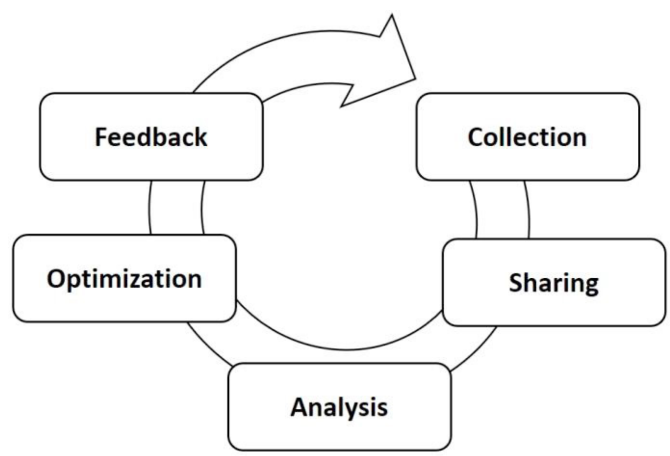

Fig. 2. The data-driven process improvement cycle

4.2 The Digitalization Typology

While industry traditionally has emphasized automating physical processes, the fourth industrial revolution focuses on automating informational processes and integrating these with physical processes through the use of cyber-physical systems (CPS) (Kagermann, 2015). CPS are “automated systems that enable connection of the operations of the physical reality with computing and communication infrastructures” (Jazdi, 2014, p. 1). Relating to the increasing degree of digitalized processes, every step in the improvement cycle can be mapped according to two dimensions: *data format* and *data handling*. The dimensions are summarized as a 2x2 matrix in Table 1.

Data format: Data is typically appearing in either digital or non-digital format. The obvious advantages of handling data in digital format are among other the increased flexibility, speed, and accessibility, together with reduced variable cost (Smith, 1999). On the other hand, a non-digital format also has some advantages, such as the ease of use and no proneness to system crashes.

Data handling: The cycle also differentiates on whether the step is undertaken manually or automatically. In manual operations, humans have a role in completing and ensuring the step is completed. If the step is fully automated and autonomous, no human intervention is required.

The two dimensions are illustrated in Table 1. Each of the steps in the improvement cycle can find themselves in one of these four states. State 1 represents traditional paper-based situations, characterized by a large proportion of manual data handling. State 2 might be effective but is inherently inflexible. State 3 has digitized the data flow, with the obvious benefits this entails, for instance related to cost, time, and flexibility. However, human intervention is still needed. State 4 represents a situation where the data is digital and handled automatically, which is a step towards enabling self-optimizing processes.

Table 1. Digitalization typology

		Data format	
		Non-digital	**Digital**
Data handling	**Automated**	State 2: "Determined"	State 4: "Digitalized"
	Manual	State 1: "Dated"	State 3: "Digitized"

Digitalization

4.3 Example – The Case of Kanban

This section will use the case of the well-known lean manufacturing tool Kanban as an example of how a management process can be mapped using the methods described in this paper. Kanban is used as a signal in pull production, signaling a workstation that they should supply materials to another workstation downstream in the process. We present four different Kanban-scenarios, each forming a separate level based on their digitalization maturity. This section briefly introduces each of the levels.

Level 1: Traditional physical card-based Kanban

The Kanban system traditionally relies heavily on physical cards. Although these cards are intuitive and easy to understand, there are some issues and limitations with it. The ability to handle a large number of variants, the lack of flexibility, and the risk of losing the actual cards are among the challenges faced in traditional Kanban systems (Thoben et al., 2014). Relating it to the data-driven process improvement cycle, all five steps are thus executed both manually and the data is in a physical format. For most of the time, only the first two steps are undertaken, by collecting the data about materials that need replenishment, and then sharing this to the preceding workstation. Typically, this data is rarely used to complete the improvement cycle by analyzing the frequency of the Kanban signals and optimizing the number of Kanban cards and bin sizes.

Level 2: e-Kanban

An electronic Kanban system, known as e-Kanban, is able to meet and handle some of the challenges typically associated with physical Kanban cards (Drickhamer, 2005, Thoben et al., 2014). Transmitting the Kanban signal electronically also makes it significantly more applicable for interplant deliveries. However, even if the system now is digital, the process of transmitting Kanbans is still manual. Typically, a human worker still has to manually inspect for when material replenishment is needed (collection) and then sending the Kanban, normally through scanning a barcode or entering it manually into the computer system (sharing). Analyzing and optimizing is also normally done manually.

Level 3: Autonomous Kanban

Being able to automate the replenishment decision and the transmission of the Kanban signal will practically automate the Kanban loop (Hofmann and Rüsch, 2017). An industrial example of an autonomous Kanban system is the iBin system delivered by Würth presented in Kolberg et al. (2017). This bin automatically records the material level and sends it to the inventory control system. Based on this, orders are sent automatically to suppliers when needed (Kolberg et al., 2017). However, even if the Kanban loop is autonomous, it does not mean it is continuously improved automatically. The number of cards and bin sizes are still fixed, which might result in material shortages, or in the opposite case, materials might spend an excessive amount of time in intermediate inventories, halting endeavours to decrease throughput time.

Level 4: Self-optimizing Kanban

Building on the autonomous Kanban system, a self-optimizing Kanban process is not only able to run the Kanban loop autonomously, but also use the collected data to analyze and prioritize improvements. A self-optimizing Kanban system autonomously adjusts the bin size as well as the number of cards in circulation according to predefined performance objectives, such as cost, throughput time, or similar.

Table 2. Comparison of the Kanban scenarios (see Table 1 for explanation of the different states)

	Collection	**Sharing**	**Analysis**	**Optimization**	**Feedback**
Level 1: Traditional Kanban	State 1	State 1	State 1	State 1	State 1
Level 2: e-Kanban	State 3	State 3	State 3	State 3	State 3
Level 3: Autonomous Kanban	State 4	State 4	State 3	State 3	State 3
Level 4: Self-optimizing Kanban	State 4	State 4	State 4	State 4	State 4

5. DISCUSSION

We propose that organizations will reap the most benefit from digitalization when all five steps in the presented improvement cycle are both digital and automatic (State 4). Processes might be partly or fully digitized, but as long as the cycle is not completed automatically, the full potential of digitalization is not realized. Organizations can use the data-driven process improvement cycle as a part of their digital transformation. The data-driven process improvement cycle has relevance for both practitioners and scholars. This section outlines some of its possible usage areas.

Mapping and measurement of digitalization levels

As previously mentioned, there exists no established model on how the digitalization degree of a process can be measured. The data-driven process improvement cycle presents a simple approach to illustrate and measure an organization's efforts towards digitalizing their processes. The method highlights the importance of not digitizing and digitalizing just for the sake of it, but to focus these efforts towards actually improving processes. The data-driven process improvement cycle highlights that the digitalization efforts should be directed towards the five steps essential in any continuous improvement regime.

Guide to prioritizing improvements

Similar to maturity models, a process mapped according to the data-driven process improvement cycle clearly points out areas of improvements, in this case areas for increased levels of digitalization. It thus creates a process-specific roadmap towards digitalization. Similar to PDCA, it is used for individual processes, and organizations will find it beneficiary to develop an overall business framework to coordinate the individual improvement projects. It is also important to recognize the steps required to implementing new technologies, such as strategic planning, justification, training, and installation in addition to the actual implementation (Chan et al., 2001). The method presented in this paper is by itself not guiding how the digitalization transition should occur, merely pointing out the potential digitalization areas. This method may be used as part of a more overarching methodology for implementation of new technology, such as the APROS (Automation Project Selection) method (Alfnes et al., 2016).

Plan for improvement

An organization typically starts with an optimization goal in mind, such as increased productivity or reduced cost. The data-driven process improvement cycle provides an intuitive interface on how a system for continuous improvement of a specific variable can be designed. In these cases, the cycle should be gone through in the reverse direction, starting with specifying the optimization goals. Then an analysis process should be designed, specifying which data that should be collected in order to facilitate improvements. The lasts steps are to plan how data can be supplied and collected, respectively. This way of thinking could especially be useful for SMEs, whose limited financial resources forces organizations to pragmatically evaluate which data to collect. It is thus a "pull" way of thinking, asking for specific data, rather than "push", where you try to find improvement opportunities from whatever data supplied.

6. CONCLUSIONS

This paper introduced the data-driven process improvement cycle, a method for mapping and guiding digitalization efforts. It further highlights some of the differences in the literature regarding the definitions related to Industry 4.0 and presents some of the issues that this ambiguity might lead to. Furthermore, a clear distinction is made between digitization, digitalization, and digital transformation, which is useful to ensure construct validity in future research efforts within this domain.

The proposed improvement cycle differentiates itself from earlier improvement cycles in that it highlights the necessary steps for data-driven improvement efforts. It is universal in the way that it does not limit itself to specific digital technologies, but instead focuses on the functionality of the employed solutions regarding the data format and the degree of automated data handling. The presented examples from Kanban control illustrates how the tool can be used in practical situations.

The digitalization typology presented together with the improvement cycle can also be applied in other contexts, to classify the digitalization degree of process steps. The "plan for improvement" usage of the cycle also presents a novel and intuitive method for organizations to guide their digitalization efforts.

Future research efforts should focus on testing the model in empirical settings.

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