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# Enabling Smart Production: The Role of Data Value Chain

✉Natalie Agerskans<sup>[0000-0002-6842-0648]</sup> Jessica Bruch<sup>[0000-0002-5963-2470]</sup>, Koteswar Chirumalla<sup>[0000-0002-7512-4425]</sup> and Mohammad Ashjaei<sup>[0000-0003-3469-1834]</sup>

Mälardalen University, Hamngatan 15, Eskilstuna SE 631 05, Sweden  
natalie.agerskans@mdu.se

**Abstract.** To stay competitive, manufacturing companies are developing towards Smart Production which requires the use of digital technologies. However, there is a lack of guidance supporting manufacturing companies in selecting and integrating a combination of suitable digital technologies, which is required for Smart Production. To address this gap, the purpose of this paper is twofold: (i) to identify the main challenges of selecting and integrating digital technologies for Smart Production, and (ii) to propose a holistic concept to support manufacturing companies in mitigating identified challenges in order to select and integrate a combination of digital technologies for Smart Production. This is accomplished by using a qualitative-based multiple case study design. This paper identifies current challenges related to selection and integration of digital technologies. To overcome these challenges and achieve Smart production, the concept of data value chain was proposed, i.e., a holistic approach to systematically map and improve data flows within the production system.

**Keywords:** Digital Technology, Smart Manufacturing, Industry 4.0

## 1 Introduction

To stay competitive in the fourth industrial revolution and boost sustainability, manufacturing companies are developing towards Smart Production [1]. Smart Production is a system that generates and collects data across the entire product lifecycle and converts this data into valuable insights that are applied to optimize production processes in a smarter way [2]. Consequently, to enable Smart Production, manufacturing companies need to address aspects related to data management, i.e., the entire process from generating data at its source of origin until data is applied in to add value [3]. This requires using a combination of different cutting-edge digital technologies such as Industrial Internet of Things (IIoT), 5G, and Artificial Intelligence (AI) to fulfill the data management tasks [4]. However, the main obstacles in accelerating Smart Production are selecting and integrating suitable digital technologies for data management in each specific production system [5]. This can be explained by the highly complex nature of advanced digital technologies [6] and the overwhelming number of continuously evolving digital technologies available on the market. Many digital technologies have several useful characteristics allowing applicability in different ways [4]. This makes it a

complex task to understand what digital technologies to select and how these should be integrated in an optimal way. Further, the complex nature of a production system makes integration of new technology a challenging task. If changes are made in one part of the production system, it will affect its subsystems as well as its processes [7].

A number of studies examining Smart Production has been conducted. However, the majority of these studies focus on integrating one digital technology alone while Smart Production requires integration of several synergizing digital technologies [1, 4]. Therefore, more studies are needed to investigate how several digital technologies should be combined in an optimal way and how this problem can be approached by having a holistic perspective [1]. Further, Silva et al. [5] conducted a systematic literature review to identify recent publications on selection and integration of digital technologies. Their study confirms the findings from Müller et al. [8] which showed that Smart Production has mainly been looked at academically, but there has been limited attention on how manufacturing companies can select and integrate digital technologies. Silva et al. [5] concludes that previous studies on the topic is insufficient and more research is needed.

Considering the above motivations, there is a research gap on holistic approaches related to selection and integration of synergizing digital technologies for Smart Production. However, in order to propose such an approach and ensure all relevant aspects are considered, it is first considered necessary to identify current challenges that manufacturing companies are facing related to this topic. Therefore, the purpose of this paper is twofold: (i) to identify the main challenges of selecting and integrating digital technologies for Smart Production, and (ii) to propose a holistic concept which can be used to support manufacturing companies in mitigating the identified challenges in order to select and integrate a combination of digital technologies for Smart Production.

The outline of this paper is as follows: Section 2 presents a literature review, while Section 3 presents the research methodology. The case study findings and discussions are described in Sections 4 and 5, respectively. Finally, Section 6 concludes the paper indicating some future work.

## **2 Literature Review on Smart Production**

### **2.1 Digital Technologies**

Although the term digital technology is frequently mentioned in previous research related to Smart Production, it is hard to find a clear definition for the term [9]. However, previous research on digital technologies and Smart Production [1, 3, 4] mainly deal with the general idea of software and hardware technologies applied for automated data management, including data collection and storage, in a digital context with the purpose of optimizing processes and increase value creating activities. There are many advanced digital technologies available on the market which can be linked to Smart Production. Focusing on the technologies that facilitate the data management, each technology is developed with a specific purpose, i.e., customized to solve a dedicated issue in the data management for Smart Production [4]. Tao et al., [3] identified the following critical phases for data management in Smart Production:

1. *Data sources and collection.* Refers to the points of origin where data is generated and the method of data collection. The technologies within this phase include sensors and data acquisition devices.
2. *Data communication.* Refers to the transmission of data from their sources to the places where they will be stored, processed, and visualized. Various technologies based on wireless and wired communication are within this category, e.g., WiFi.
3. *Data processing and storage.* Refers to the operations conducted to extract information from data and the place where collected data is stored. Typical technology examples include databases and data analytics tools.
4. *Data visualization and usage.* Refers to the techniques used to present data to end-users and the context in which data is applied to fulfill a purpose. IoT platforms are common technologies that serve this purpose.

## 2.2 Challenges of Selecting and Integrating Digital Technologies

Previous research has identified many digital technologies that can be connected to a Smart Production context. For instance, Klingenberg et al., [4] conducted a systematic literature review on digital technologies related to Industry 4.0 and identified more than 60 digital technologies. At the same time, since Industry 4.0 and Smart Production are new phenomenon, some digital technologies are still evolving [4]. However, companies often lack internal knowledge related to what benefits would come from integrating different digital technologies in production [6], making it challenging to select suitable digital technologies. Further, there is a lack of guidance on how to select a combination of different digital technologies that matches the existing production system elements. Instead, a common approach is to select and integrate one digital technology at the time without having a holistic perspective on the entire flow of data [4]. For instance, using smart sensors to collect large volumes of data without having a plan for how this data should be used to support production processes [10]. This can result in an extended time required until a full-fledged integration of technologies. In the worst case, selection of inappropriate digital technologies can lead to unprofitable investments [4].

Further, digital technologies will allow manufacturing companies to replace many manual work tasks with automated processes. Thus, the role and responsibilities of humans working at the shop floor will drastically change, which calls for new skills and competences, combining traditional production engineering with IT engineering [6]. Other challenges relate to the establishment of new interconnections between different actors [6, 11]. New actors will be introduced, and existing actors will play new roles. This comes with several challenges involving lack of existing IT infrastructure for data exchange, lack of IT and analytical capabilities, and new ways of collaborating using data as a resource [4, 10, 11].

## 3 Research Methodology

This study adopts a case study design [12] based on two reasons. First, case studies are appropriate for exploring novel subjects requiring increased theoretical insight. Second,

case studies rely on empirically rich data including the context and experience of participants. This was considered essential for increasing the practical relevance of findings. A multiple case study involving companies from different industries and of different sizes was chosen to cover different contextual aspects that may contribute to the results. This was considered important to ensure results applicable for different types of companies in the manufacturing industry. The data was collected using semi-structured interviews and workshops with four manufacturing companies, two large companies and two Small Medium sized Enterprises (SMEs). An overview of the four companies and the collected data is presented in Table 1. The empirical data was analyzed using thematic analysis which is a systematic approach for capturing patterns in qualitative datasets. The data analysis included an iterative comparison of the empirical data and literature by following six concurrent activities: (i) data familiarization, (ii) generation of codes, (iii) searching for themes, (iv) reviewing themes, (v) defining and naming themes, and (vi) writing the paper [13]. In step (iv), empirical data was analyzed and sorted using the four categories identified in literature: data sources and collection, data communication, data processing and storage, and data visualization and usage. The concept of data value chain was developed based on an iterative analysis and cycles between empirical data and related literature following a case study approach. During the process, design science guidelines [14] were followed to identify priority areas of intervention and related solutions.

**Table 1.** Overview of studied companies and collected data

	<b>Company A</b>	<b>Company B</b>	<b>Company C</b>	<b>Company D</b>
Type of products	Heavy vehicles	Railway	Investment casted components	Electronics
Company size	Large	Large	SME	SME
<b>Data collected:</b>				
Interviews (No.)	6	3	2	23
Workshops (No.)	-	-	1	8

## 4 Challenges of Selecting and Integrating Digital Technologies

The empirical analysis showed that manufacturing companies are currently facing several challenges related to selection and integration of digital technologies for Smart Production. The identified challenges were classified in different themes which in turn were sorted into the following categories: (i) data sources and collection, (ii) data communication, (iii) data processing and storage, (iv) data visualization and usage, and (v) general challenges. These overall categories of challenges along with their reported examples are presented in Table 2. An overview of the identified themes of challenges is presented in this section, while a detailed analysis and presentation of the collected challenges are remained for the future work.

**Data sources and collection** included challenges related to generating data from its source of origin where three main themes of them include the following. The first theme is *manual work processes and reporting*. Operators were manually reporting data in the system which led to mistakes due to the human factors. Generating data from manual

work processes was also challenging since there was no clear way how to generate this data automatically. The second theme is related to the *collection of operators data* which considers the challenges of privacy aspects when having the human operator as an object to collect from the data. The third theme is *automatic data generation and collection*, where ensuring that the collected data reflected the reality.

The second category is the **data communication** that covers themes related to transmitting the data from their sources to the places where they will be stored, processed, and visualized. The first theme considered the challenges of enabling data exchange between systems and equipment, known as *interoperability*. *Data accessibility* during the system failure and achieving *structured data communication*, such as attaching time labels on data, were two other themes of data communication challenges category.

The third category is **data processing and storage** which includes themes related to the operations conducted to extract information from data and the place where collected data is stored. The first theme, *pre-processing* considers the operations conducted to prepare data for analysis. This was especially considered a challenge for data which had only been used for manual analysis purposes and thus required categorization and cleaning. *Manual data analysis*, the second theme, was usually time consuming and

**Table 2.** Overview of categories and exemplary quotations

<p><b>Data sources and collection</b></p> <p>“... how to make the data that really reflects the reality, there is no errors due to forgotten reporting or not working system integration or stuff like that.” (Process and IT Engineer, Company A)</p> <p>“So it is difficult to find a way to, combined with the other technological aids we have, collect data and send it further so the administrative part is eliminated” (Production and Logistics Developer, Company B)</p>
<p><b>Data communication</b></p> <p>“... it was the first time it happened that the network was down, the WiFi, and we could not produce, because it is not quality assured according to the process...” (Head of Production Planning, Company B)</p> <p>“So I see this is as the biggest challenge actually, to get all of the systems connected ” (Process and IT Engineer, Company A)</p>
<p><b>Data processing and storage</b></p> <p>“...we are collecting a lot of data. And actually, we are not so great with correlating that data with some other features which we can also collect” (Process Engineer and IT Engineer, Company A)</p> <p>“... we speak different languages in different domains. And how do we manage to break the language or communication barriers?” (Production Preparation Process Director, Company A)</p>
<p><b>Data visualization and usage</b></p> <p>“Let’s say that we have processed 100 products and there have been 50 quality faults (...) but I cannot tell if it these faults are on one or several products...” (Operator, Company D)</p> <p>“So, I can, at any given time, see what the status is and even call operators and say “Hey, you need to stop”, or whatever. But I also have a lot of other stuff to do...” (Production Manager, Company C)</p>
<p><b>General challenges</b></p> <p>“... I think it's easy to get lost in cool solutions and technologies that may not be value-creating...” (Production and Logistics Developer, Company B)</p> <p>“Some roles, some jobs will have to change, or some jobs will disappear, but people will have to do something else or new type of jobs – so this is probably one of the main threats when you discuss with people” (Head of IT, Company A)</p>

required good data analysis skills by operators, which was in many situations not considered a good way of analyzing data. However, ensuring automatic *data analysis quality* is a complex task since the quality of the data analysis relies on the quality of the collected data. Some commonly mentioned problems were data inconsistency, data inaccuracy, and incompleteness, which all contributed to lacking quality of the data analysis. As a result, the generated data could not be used. *Data security* was the third theme within this category. The mentioned challenges were mainly regarding the data storage and giving access authorization to different roles to prevent the data being misused.

**Visualization and usage of data** is the fourth category which refers to themes related to the data content and techniques used to present data to end-users and the production context in which data is used. The theme *data visualization quality* considered aspects related to how data was presented to the end-user. Several companies mentioned that useful data was available to end-users, however the data was not actually used. The main reason for this was that the data was not presented in a format that was supported by the end-users in their work tasks. Another challenge was related to the *work processes*, i.e., the application area where the data should be applied to generate value. Developing current routines into work processes suitable for Smart Production was considered demanding as well as identifying digital technologies that were user-friendly for operators.

The last category is **general challenges** which covers themes that could be related to all four previous mentioned categories, yet not directly connected. The theme *usefulness and development of technologies* is considered as a challenge related to identifying how different systems can be utilized and developed in the best possible way for specific production systems. *Resources* was another theme which included challenges such as lack of skills and competence, culture, and time constrains for involvement of people to work in Smart Production projects. The theme *defining a business case* refers to the challenges to ensure the right digital technologies are selected and invested in.

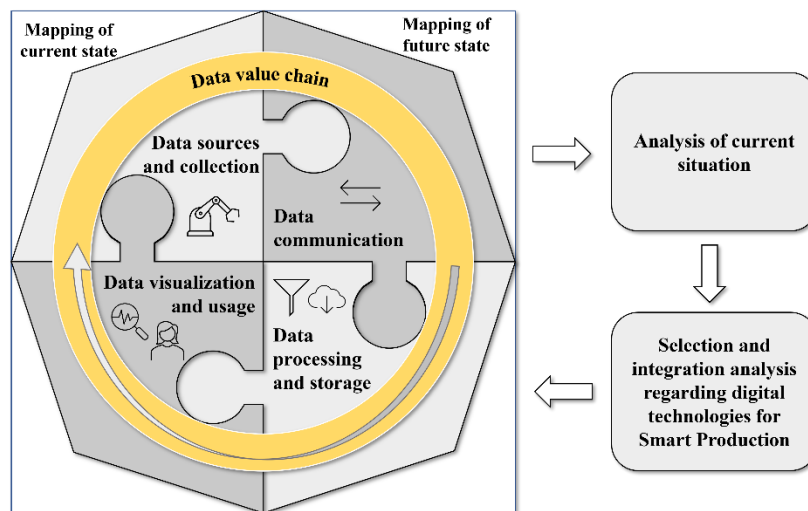
## 5 The Concept of Data Value Chain for Smart Production

Previous chapter presented themes of challenges related to data management within the production system. The empirical findings show that not addressing these themes of challenges can hinder manufacturing companies from achieving the desired benefits, i.e., generating value in a production context. It is therefore clear that manufacturing companies must have a holistic perspective on how to manage their entire data flow within the production system in order to convert data collected into valuable information which is applied to yield positive impacts on production.

The theoretical and empirical findings show that the concept of data value chain can be used to describe the data flow within a production system as a series of steps that are required to generate value and useful insights from the data. The data value chain can be used to describe the complete data lifecycle from a technical point of view, which includes data sources and collection, data communication, data processing and storage, and data visualization and usage. The empirical findings show that all these phases must be managed in a way that require minimum or no effort from humans. Therefore, having both efficient and effective data value chains is a key enabler for Smart Production.



Since the empirical findings show that all challenges of selecting and integrating digital technologies for Smart Production are somehow related to the data value chain, we propose the concept of data value chain as an approach to facilitate the selection and integration of digital technologies in order to move from current situation to Smart Production. The concept can be used in three steps. First, the current data flow within the production system is mapped based on the phases of the data value chain. This gives an overview of the data available, technologies, systems, and other resources used for data management, which is essential when defining compatibility requirements for new digital technology investments. Second, the mapped current situation is being analyzed by listing challenges, for example missing data, problems in current technological infrastructure, and lacking work processes. Third, by analyzing the challenges, suitable actions can be identified to mitigate the challenges. This can, for instance, involve the need for new investments or improvements regarding the integration of existing digital technology. The proposed improvements are finally mapped as a desired future data value chain, where Smart Production is the goal, to give a holistic overview before actions are taken. The data value chain concept and its pillars are shown in Figure 1 that provides a set of knowledge to analyze the current situation that in turn will assist to select and integrate a set of digital technologies for desired Smart Production. Notice that the process is iterative which helps to update the data value chain challenges.



**Figure 1.** The pillars of the data value chain concept and how the concept can be applied

## 6 Concluding Remarks

This study contributes to the ongoing discussion of selecting and integrating digital technologies to enable Smart Production [1, 5] by identifying current challenges and proposing a practical, holistic concept to overcome these challenges. More specifically, 15 themes of challenges were identified related to selection and integration of digital technologies. These themes showed that a key enabler for Smart Production is having both efficient and effective data management within the production system, where the

entire flow from data generation to data usage must be considered. In this study, both large and SME manufacturing companies from different industries were selected to show that the discussed categories of challenges are applicable for different manufacturing companies. Further, the overall concept of data value chain was presented, i.e., a holistic approach which can be used to map the data flow within a production system to support engineers and managers involved in Smart Production projects when selecting and integrating a combination of digital technologies for Smart Production.

Planned future research includes a more detailed analysis of the presented themes of challenges related to Smart Production and extending the presented data value chain concept by developing a framework including application guidelines and validation of findings. Moreover, the research involves a more detailed analysis of how different digital technologies should be selected and combined to achieve Smart Production.

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