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Digital Technologies for Enabling Smart Production

Examining the Aspects of Selection and Integration

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DIGITAL TECHNOLOGIES FOR ENABLING SMART PRODUCTION

EXAMINING THE ASPECTS OF SELECTION AND INTEGRATION

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Abstract

With the development towards Industry 5.0, manufacturing companies are developing towards smart production. In smart production, data is used as a resource to interconnect different elements in the production system to learn and adapt to changing production conditions. Common objectives include human-centricity, resource-efficiency, and sustainable production. To enable these desired benefits of smart production, there is a need to use digital technologies to create and manage the entire flow of data. To enable smart production, it is essential to deploy digital technologies in a way so that collected raw data is converted into useful data that can be applied by equipment or humans to generate value or reduce waste in production. This requires consideration to the data flow within the production system, i.e., the entire process of converting raw data into useful data which includes data management aspects such as the collection, analysis, and visualization of data. To enable a good data flow, there is a need to combine several digital technologies. However, many manufacturing companies are facing challenges when selecting suitable digital technologies for their specific production system. Common challenges are related to the overwhelming number of advanced digital technologies available on the market, and the complexity of production system and digital technologies. This makes it a complex task to understand what digital technologies to select and the recourses and actions needed to integrate them in the production system.

Against this background, the purpose of this licentiate thesis is to examine the selection and integration of digital technologies to enable smart production within manufacturing companies. More specifically, this licentiate thesis examines the challenges and critical factors of selecting and integrating digital technologies for smart production. This was accomplished by performing a qualitative-based multiple case study involving manufacturing companies within different industries and of different sizes. The findings show that identified challenges and critical factors are related to the different phases of the data value chain: data sources and collection, data communication, data processing and storage, and data visualisation and usage. General challenges and critical factors that were related to all phases of the data value chain were also identified. Moreover, the challenges and critical factors were related to people, process, and technology aspects. This shows that there is a need for holistic perspective on the entire data value chain and different production system elements when digital technologies are selected and integrated. Furthermore, there is a need to define a structured process for the selection and integration of digital technologies, where both management and operational level are involved.

Sammanfattning

Med utvecklingen mot Industri 5.0 utvecklas tillverkningsföretag mot smart produktion. I smart produktion används data som en resurs för att koppla samman olika element i produktionssystemet i syfte att lära sig om och anpassa sig efter förändrade produktionsförhållanden. Vanliga mål för smart produktion inkluderar resurseffektivitet, och en hållbar produktion anpassad utifrån människan. För att åstadkomma dessa önskade fördelar, behöver tillverkningsföretag använda digitala teknologier för att skapa och hantera hela dataflödet. För att möjliggöra smart produktion är det viktigt att implementera digitala teknologier på ett sätt så att insamlad rådata omvandlas till användbar data som kan tillämpas av maskiner eller människor för att skapa värde eller minska slöseri i produktionen. Detta kräver hänsyn till dataflödet inom produktionssystemet, det vill säga hela processen att omvandla rådata till användbar data som inkluderar datahanteringsaspekter som exempelvis insamling, analys och visualisering av data. För att möjliggöra ett bra dataflöde krävs det att flera digitala teknologier kombineras. Många tillverkningsföretag står dock inför flera utmaningar när de ska välja lämpliga digitala teknologier för sitt specifika produktionssystem. Vanliga utmaningar är relaterade till det överväldigande antalet avancerade digitala teknologier som finns på marknaden, samt komplexiteten hos produktionssystem och digitala teknologier. Detta gör det till en komplex uppgift att förstå vilka digitala tekniker som ska väljas och vilka resurser och åtgärder som behövs för att integrera dem i produktionssystemet.

Mot denna bakgrund är syftet med denna licentiatuppsats att undersöka hur tillverkningsföretag ska välja och integrera digitala teknologier för att uppnå smart produktion. Mer specifikt så undersöker denna licentiatuppsats vilka utmaningar och kritiska faktorer som finns för att välja och integrera digitala teknologier för att uppnå smart produktion. Detta uppnåddes genom en kvalitativ multipel fallstudie med tillverkningsföretag inom olika branscher och av olika storlekar. Resultaten visar att identifierade utmaningar och kritiska faktorer är relaterade till de olika faserna av datavärdekedjan: datakällor och insamling, datakommunikation, databearbetning och lagring samt datavisualisering och användning. Generella utmaningar och kritiska faktorer som var relaterade till alla faser av datavärdekedjan identifierades också. Dessutom var utmaningarna och kritiska faktorerna relaterade till människa, process och tekniska aspekter. Detta visar att det finns ett behov av helhetsperspektiv på hela datavärdekedjan och olika element i produktionssystemet när digitala teknologier väljs och integreras. Dessutom finns det ett behov av att definiera en strukturerad process för val och integration av digital teknik, där både ledning och operativ nivå är involverade.

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Natalie Agerskans
Västerås, October 2023

List of Papers

This thesis is based on the following papers, which are referred to in the text by their Roman numerals.

I. Agerskans, N., Bruch, J., Chirumalla, K., Ashjaei, M. (2022) Enabling Smart Production: The Role of Data Value Chain. *Advances in Production Management Systems. Smart Manufacturing and Logistics Systems: Turning Ideas into Action*. Cham: Springer Nature Switzerland, pp. 477-485, https://doi.org/10.1007/978-3-031-16411-8_55

II. Agerskans, N., Ashjaei, M., Bruch, J., Chirumalla, K. A Framework to Support the Selection and Integration of Digital Technologies for Smart Production. Under review in International Journal of Production Research.

III. Agerskans, N., Ashjaei, M., Bruch, J., Chirumalla, K. (2023) Critical Factors for Selecting and Integrating Digital Technologies to Enable Smart Production: A Data Value Chain Perspective. *Advances in Production Management Systems. Production Management Systems for Responsible Manufacturing, Service, and Logistics Futures.* Cham: Springer Nature Switzerland, pp 311–325, https://doi.org/10.1007/978-3-031-43662-8_23

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My contribution: Jessica Bruch, Mohammad Ashjaei, and Koteshwar Chirumalla helped identify and formulate the research problem. I planned the research, collected and analysed data, and wrote and revised the manuscript after receiving feedback from Jessica Bruch, Mohammad Ashjaei, and Koteshwar Chirumalla.

Contents

1. Introduction

This chapter describes the importance of the research areas, selecting and integrating digital technologies to enable smart production in manufacturing companies. This is followed by a problem formulation containing the motivation for this research. Then the purpose, research questions, and scope are presented. The chapter ends with an outline of this thesis.

1.1 Background

The manufacturing industry is currently facing a new era where technological and social systems work in harmony to produce products (Tóth et al., 2023). This revolution is commonly referred to as Industry 5.0 and is driven by the unique opportunities of using novel digital technologies to manage a key resource, which is data, to support decision making and enable a resilient, human centric, sustainable, and competitive production (Maddikunta et al., 2022). Digital technologies include software and hardware technologies that enable a digitalized and automated handling of data to optimize processes and increase value creating activities (Berger et al., 2018; Ghobakhloo, 2020a). Some examples of digital technologies include Cloud Computing, Industrial Internet of Things, Artificial Intelligence, Augmented Reality, and Simulation (Klingenberg et al., 2019; Xu et al., 2018; Zheng et al., 2020).

Digital technologies can be deployed to interconnect all available resources and devices within the production system which allows manufacturing companies to generate data to learn more about their production processes (Schuh et al., 2020). The desired benefits include timely and data-based decisions, proactive ways of working, safe and ergonomic work conditions, and a resource efficient production (Zizic et al., 2022). For instance, production equipment can communicate with each other, humans, automated processes, and other resources to enable transparency of the current situation and predictions about future scenarios (Asad et al., 2023; Czeczot et al., 2023). This allows appropriate actions and decisions to be taken in real time or even before a problem occurs (Schuh et al., 2020). The desired outcome of utilizing digital technologies in the production system is what is defined as smart production in this licentiate thesis.

To enable smart production, it is essential to deploy digital technologies in a way so that raw data is converted into data that can be applied by equipment or humans to generate value or reduce waste in production (Shahin et al., 2020). This requires consideration to the data flow within the production system, i.e., the entire process of converting raw data into useful data which includes data management aspects such as the collection, analysis, and visualization of data (Aydin, 2023; Curry, 2016). To enable a good data flow, there is a need to combine several digital technologies. This is important since they have different functions and capabilities and one digital technology can therefore not fulfil all data management aspects (Klingenberg et al., 2019). Thus, smart production is not about having a single digital technology in place; instead, there is a need to use of a set of interconnected digital technologies that, when combined in a synergising way, complement each other, and bring the most benefits from data to achieve production in a smarter way (Choi et al. 2022).

This requires a purpose-oriented selection and integration of digital technologies for smart production (Silva et al., 2022). Technology selection is the process of investigating what technologies should invest in to improve the current situation and reach defined objectives (Reza Hamzeh et al., 2018; Karsak & Ahiska, 2005). This includes comparing different technologies on the market, performing an evaluation based on needs, and defining a business case (Lamb & Gregory, 1997; Sjödin et al., 2018). Technology integration is the process of installing the technology in the factory and linking the technology within other elements in the production system such as people, process, information systems and other technologies (Ortega et al., 2022; Tortorella et al., 2021). This requires consideration to aspects, such as communication interfaces, culture, education, and work processes (Ghobakhloo, 2018; Sjödin et al., 2018). Consequently, technology integration in this licentiate thesis does not only consider technological aspects. Instead, technology integration is seen as the entire process from installation to the point where technology and production system elements are combined and used to their fully intended potential.

Considering this background, essential for manufacturing companies to enable smart production is to carefully select and integrate a combination of digital technologies.

1.2 Problem Formulations

Despite the benefits of deploying digital technologies, many manufacturing companies are facing challenges when selecting and integrating a combination of digital technologies (Hamzeh & Xu, 2019; Santos et al., 2023; Silva et al., 2022). Rather than taking a holistic approach to the entire data flow within a system, a common practice is to select and integrate digital technologies one at a time (Choi et al., 2022). However, having a limited perspective of the data flow comes with several risks to achieve the smart production. One risk is lacking compatibility with other technologies and systems, known as interoperability (Chen et al., 2008). Another risk is that the data is not accessible in the right time or format, which can hinder suitable decisions and actions to be taken when needed (Schuh et al., 2020). Because of potential risks, the selection of unsuitable digital technologies can result in unprofitable investments where a lot of resources have been dedicated, but targeted benefits were not achieved (Sjödin et al., 2018).

Problems in selecting and integrating digital technologies often arise due to the overwhelming number of digital technologies available on the market (Chiarello et al., 2018). For instance, Klingenberg et al. (2019) identified more than 60 types of digital technologies related to smart production and more are continuously and rapidly developing (Liu et al., 2021; Waters et al., 2022). Moreover, these digital technologies can be applied in different ways and in various still evolving production contexts. Some examples include planning, internal logistics, equipment maintenance, and quality control (Tao et al., 2018). All these options and possibilities creates an uncertainty of what benefits can be achieved in specific production systems and the adaptions needed to existing resources (Sjödin et al., 2018).

Furthermore, since new digital technologies are fast developing, they may also obsolete much faster compared to traditional technologies such as production equipment or will with time be used in new ways (Liu et al., 2021; Waters et al., 2022). This should therefore be considered when selecting new digital technologies. However, the selection of digital technologies is often conducted in a non-structured way, with the selection most often being based on the experience and intuition of decision-makers (Bertoncel et al., 2018; Santos et al., 2023) — sometimes without consideration of the company's strategies (Santos et al., 2023). This situation makes it hard to avoid mistakes while the search for better guidelines is justifiable. Thus, authors Müller et al. (2018) and Silva et al. (2022) have previously called for empirical research to facilitate manufacturing companies in the critical task of selecting and integrating digital technologies. The current organisational structure and ways of working are not suitable for selecting and integrating a combination of digital technologies for the entire data flow in a structured way (Bertoncel et al., 2018; Santos et al., 2023).

1.3 Purpose and Research Questions

Based on this above background and problem formulation, the **purpose** of this **licentiate thesis** is to examine the selection and integration of digital technologies to enable smart production within manufacturing companies. To meet this purpose, three research questions have been formulated:

Research question 1: What are key challenges of selecting and integrating digital technologies to enable smart production?

Research question 2: What are critical factors to consider when selecting and integrating digital technologies to enable smart production?

Research question 3: How to support the selection and integration of digital technologies to enable smart production?

1.4 Scope of the Licentiate Thesis

This licentiate thesis looks to examine the selection and integration of digital technologies to enable smart production within manufacturing companies. The concepts of selection and integration of digital technologies and smart production delimit this thesis.

In this licentiate thesis, production is the application area in which digital technologies should add value. Examples of application areas include production planning, process optimization and control, production logistics, equipment maintenance, and quality control. Thus, data engineering tasks, product design, external partners, and the development process of digital technologies are not included in the scope. Smart production covers the benefits that should be achieved in the application areas, meaning that digital technologies should be deployed to manage data in order to enable desired smart production benefits.

This licentiate thesis also focuses on the data flows required to enable smart production. These data flows can be outside of the production system as data can, for instance, be collected from other departments in the organization or other partners in the supply chain. Moreover, this licentiate thesis is conducted in the belief that selecting and integrating digital technologies to enable smart production requires consideration to different elements in the production system. This means that different aspects that are found relevant to the selection and integration of digital technologies are included in the research. This can include collaboration with stakeholders in other departments than production and external partners.

Furthermore, this research considers both Small and Medium sized Enterprises[1] (SMEs) and large manufacturing companies within different industries. This was considered important to increase the relevance of findings for different types of manufacturing companies.

1.5 Outline of the thesis

The remainder of this thesis is organised as follows. Chapter 2 presents the theoretical background used in this thesis. Chapter 3 includes its research methodology. Chapter 4 summarizes the appended papers. Chapter 5 presents the results of this work by analysing and synthesizing the findings related to the three research questions. Finally, Chapter 6 discusses the findings and concludes this thesis. The three papers underlying this thesis are appended to this work.

[1] To qualify as a Small Medium Enterprise (SME), three criteria must be fulfilled. First, a SME must be considered an enterprise meaning that a SME must be engaged in an economic activity regardless of its legal form. Second, a SME must employ less than 250 people. Third, a SME must have either an annual balance sheet total not exceeding EUR 43 million or an annual turnover not exceeding EUR 50 million (European Commission, 2015).

2. Theoretical Framework

This chapter presents the theoretical framework. The chapter presents the complexity of smart production followed by an overview of the selection and integration of digital technologies for smart production.

2.1 Smart Production

The terms manufacturing and production are often used as synonyms. However, in this licentiate thesis these terms are distinguished as argued for in the past (Bellgran & Säfsten, 2010; Bruch, 2012; Rösiö, 2012). Production here concerns the system required to *transform raw materials into finished products or parts of products*, compared to manufacturing which concerns the system needed to *put products on the market* (CIRP, 1990). However, manufacturing is seen as hierarchical superior production, where manufacturing involves a series of interrelated operations and activities including production and additional functions such as product design, shipping, and sales (Bellgran & Säfsten, 2010).

As described in the introduction, smart production involves technological and social systems that work in harmony to produce products in an Industry 5.0 context (Tóth et al., 2023). However, there is no clear definition of how a smart production system should look like. In this research, smart production involves a desired state that manufacturing companies aim to achieve in Industry 5.0, where commonly mentioned objectives include resilience, human centricity, sustainability, and competitive production (Maddikunta et al., 2022). Accordingly, smart production is about process innovation — namely, *'the implementation of a new or significantly improved production or delivery method. This includes significant changes in techniques, equipment and/or software'* (OECD & Communities, p. 49). Changes in production do not occur in a vacuum; they require a holistic approach. Production can be seen as a system involving a combination of many different elements, such as technology, people, and processes (Bellgran & Säfsten, 2010).

2.1.1 Technology Aspects

Smart production requires using technologies with capabilities of managing digitalized and real-time data, i.e., digital technologies (Berger et al., 2018; Ghobakhloo, 2020a; Parhi et al., 2022). Digital technologies include software and hardware technologies related to Industry 5.0 that enable the digitalised and automated handling of data to optimise processes and increase value-creating activities (Ghobakhloo, 2020a). These include a wide variety of simpler to extremely complex digital technologies, where each digital technology constitutes different capabilities (Klingenberg et al., 2019) and relies on a particular set of integration factors (Ghobakhloo, 2020a). Moreover, digital technologies must be integrated with existing elements in the production system to collect relevant data and transform this data into valuable insights to support actions and decisions in production (Manimuthu et al., 2022; Tripathi et al., 2022). However, it is not enough to only have digital technologies installed in the production; it is how they are integrated within the production system to manage the key resource, which is the data, that will determine what benefits will be achieved (Cioffi et al., 2020; Klingenberg et al., 2019; Schuh et al., 2020). Therefore, smart production requires having a holistic perspective on the entire data value chain, which can be described as a series of steps required to generate value from data. The data value chain includes the following phases (Tao et al., 2018):

- *Data sources and collection*. The data sources refer to the points of origin where data are generated, and data collection is the method used for data acquisition (AlSuwaidan, 2021). Examples of data sources include products, production equipment, and production processes (Tao et al., 2018). Production equipment with built-in data collection capabilities, sensors, and Radio Frequency Identification (RFID) (AlSuwaidan, 2021; de Jesus Pacheco et al., 2023; Manimuthu et al., 2022), are examples of digital technologies that can be used for data collection.
- *Data communication.* Data communication refers to the transmission of data from their sources to the places where they will be stored, processed, and visualised. Various digital technologies based on wireless and wired communication fall within this category, including WiFi, Ethernet, and 5G (Ghobakhloo, 2020a; Rao et al., 2021). The Industrial Internet of Things (IIoT) platforms are also commonly used for connecting different data sources via the internet (Arnold et al., 2021; Parhi et al., 2022).
- *Data processing and storage.* Data processing refers to the operations conducted to extract information from data, such as by using Artificial Intelligence (AI) and Big Data Analytics (Cioffi et al., 2020; Maddikunta et al., 2022; Manimuthu et al., 2022). Data storage, as the name suggests, is the place where data are stored for analysis or until

used. Typical digital technology examples include databases and cloud storage (O'Donovan et al., 2019).

- *Data visualisation and usage.* Data visualisation and storage are the techniques used to present data to end-users and the context in which data are applied to fulfil a purpose. For example, relevant data can be visualised in the form of charts, diagrams, or figures using tablets, monitors, Augmented Reality, or Virtual Reality on the shop floor (Burova et al., 2022; Simões et al., 2018; Tao et al., 2018). IIoT platforms are also common technologies that serve this purpose (Arnold et al., 2021).

Previous research has analysed the roles and opportunities of digital technologies from different perspectives. However, different authors have clustered digital technologies in different ways and provided varying definitions for the same digital technology or no definition at all (Klingenberg et al., 2019). This may lead to confusion due to the lack of consistency in what is meant by different terms of digital technologies as well as their capabilities and application areas (Sjödin et al., 2018).

2.1.2 People Aspects

The fundamental element in a manufacturing company is the people (Hozdić & Makovec, 2023). The changes toward smart production have therefore a significant impact on people working within the organization (Ciffolilli & Muscio, 2018). Whether they are operators who will be the end users of digital technologies on the shop floor, or managers leading a smart production project, they are all affected by the process of developing towards smart production (Saniuk et al., 2020; Sjödin et al., 2018; Zizic et al., 2022). It is, therefore, helpful if important stakeholders are flexible in adapting to new ways of working with digital technologies and new ways of learning and sharing data (Lepore et al., 2022). As stated by Bellgran & Säfsten (2010, p. 149): *'How, what, and in what way people think affects of course the final result, and not least – the way to get there'*. However, a production development project can overlook the human aspects of change and instead focus on the technical aspects (Bellgran & Säfsten, 2010). This can hinder digital technologies from being used to their full potential or in worst case not used at all (Heidemann Lassen & Waehrens, 2021). Examples of important human aspects to consider include active participation of key stakeholders in problem-solving activities and developing capabilities to explore opportunities for using new digital technologies (Tortorella et al., 2020).

Smart production focuses on human centricity by improving the quality of people's working conditions and workplaces (Maddikunta et al., 2022). This includes improving ergonomics, such as eliminating heavy lifting and repetitive movements (Scalona et al., 2023). Furthermore, smart production offers opportunities for operators to collaborate with connected production equipment in an environment that provides safe work (Zizic et al., 2022). The work should, dependent on the need, be supported by data-based assistance via user-friendly human-computer interfaces to support timely decisions and actions (Schuh et al., 2020). This can involve real-time information from different processes in production (Tao et al., 2018).

2.1.3 Process Aspects

Another important element that should be considered in the development towards smart production, is the processes. As pointed out by Sharma et al. (2014): *'despite the hopes of many, insights do not emerge automatically out of mechanically applying analytical tools to data. Rather, insights emerge out of an active process of engagement between analysts and business managers using the data and analytic tools to uncover new knowledge'* (p. 435). Consequently, there is a need to consider the processes and ways of working applied in development project to enable smart production (Ghobakhloo, 2020a; Schneider, 2018; Sjödin et al., 2018).

Moreover, many work processes within the organization are likely to change. Today, organizational processes are characterized by decentralization, where decision-making processes are delegated by top managers to lower-level managers or sometimes to shop floor workers (Molino et al., 2020). The objective with decentralization is to shorten the decision-making process by those who have the most information and ability to react in real-time. However, to enable this way of working, data presented to decision makers must provide useful information presented in a user-friendly way when needed to enable fast decisions and actions (Klingenberg et al., 2019; Schuh et al., 2020).

2.1.4 Combining People, Process, and Technology Aspects

The elements in a production system are interrelated in an organised but complex way (Bellgran & Säfsten, 2010). Therefore, making changes in one part of the system affects sub-processes and other parts of the system (Gopalakrishnan et al., 1999). This highlights the complex nature of production and implies that the transformation towards smart production requires consideration of many parameters as well as their relationship to each other (Zizic et al., 2022). Smart production should, therefore, be designed for specific production systems, with consideration to context, organizational structures, and company size (Klingenberg et al., 2019; Müller et al., 2018). Thus, retrofitting of existing production systems is required (Sjödin et al., 2018). In this context, manufacturing companies should avoid isolated smart production solutions as they can lead to challenges related to synchronization and coordination with existing production equipment and processes (Müller et al., 2018).

Considering the above, it is important to have a holistic perspective of the current situation and how digital technologies can be applied to achieve the best results in terms of people, processes, and technologies (Zizic et al., 2022). However, existing research focuses more on either people aspects (Hozdić & Makovec, 2023; Nahavandi, 2019; Romero & Stahre, 2021), process-related aspects (Abraham et al., 2019; Raptis et al., 2019; Schneider, 2018), or technical aspects (Estrada-Jimenez et al., 2023; Phuyal et al., 2020; Zeid et al., 2019). Those studies that have a holistic perspective are at a more general level (for example, Sjödin et al., 2018 and Zizic et al., 2022) and does not consider how people, process, and technology aspect should be combined to enable smart production.

2.2 Selection and Integration of Digital Technologies

Generally, technology selection involves making critical decisions related to the profitability and growth of an organization in an increasingly competitive industry (Karsak & Ahiska, 2005). This includes collecting information from different sources about alternative technologies and evaluating them against each other based on pre-defined criteria (Lamb & Gregory, 1997). Examples of criteria include cost, risk, organizational fit, and people acceptance (R Hamzeh et al., 2018). The selection of digital technologies, however, often unfolds in a non-structured manner, relying on the intuition and experience of decision-makers, occasionally disconnected from the organization's performance measurement system or manufacturing strategy (Bertoncel et al., 2018; Santos et al., 2023). Despite this, recognizing the complexity of this decision-making process, scholars emphasize the need for a well-defined methodology in the selection of digital technologies (Chu et al., 2019; Santos et al., 2023; Silva et al., 2022).

Technology integration refers to the process of installing the technology in the factory and linking the technology with other elements in the production system (Ortega et al., 2022; Tortorella et al., 2021). This requires a holistic perspective of aspects related to people, processes, and technology to enable the collection of relevant data and the transformation of such data into valuable insights to support actions and decisions in production (Manimuthu et al., 2022). Considering this, it is not the digital technologies themselves that will make production smarter, but rather how they are integrated to manage the key resource, which is the data (Klingenberg et al., 2019).

The selection and integration of new digital technologies to enable smart production requires a high investment in people, processes, and technology at both the corporate level and supply chain level in order to generate the desired deep and positive impact on business processes (Ghobakhloo, 2018; Kache & Seuring, 2017; Zizic et al., 2022). For this reason, decisions related to the selection and integration of digital technologies are strategic decisions that must be aligned with the business strategy (Schneider, 2018). However, the combination of the variety and complexity of evolving digital technologies, lacking the internal understanding of digital technologies, and high financial investments may lead to unprofitable investments if inappropriate digital technologies are selected (Klingenberg et al., 2019; Sjödin et al., 2018). Therefore, a key challenge for companies is to define a certain business case when selecting digital technologies (Ghobakhloo, 2020a; Kazemargi & Spagnoletti, 2020; Sjödin et al., 2018).

Silva et al. (2022) conducted a systematic literature review about selection and integration of digital technologies for smart production and concluded that this subject has received more attention in recent years, but the amount of attention does not compare to the focus of use of these technologies. As this is a complex process, consideration to multiple factors is needed (R Hamzeh et al., 2018). Moreover, previous academic studies do not consider the how a combination of digital technologies should be selected and integrated to generate value as a system (Klingenberg et al., 2019; Tao et al., 2018).

3 Research Methodology

This chapter presents the research methodology used for this licentiate thesis. The chapter includes a description of the research approach, research process, research design, description of cases and data collection, and data analysis. Finally, the chapter ends with a reflection on the quality of this licentiate thesis.

3.1 Research Approach

In this licentiate thesis, a case study approach to fulfil its purpose (Yin, 2018). When undertaking a case study approach, it is important to explain the rationale for the research. Three reasons justify this choice.

The first reason for selecting a case study was related to the research context and the type of research questions formulated for this licentiate thesis. This research involves exploratory "what" and "how" questions, which both are suitable for investigation by using a case study approach (Yin, 2018). Furthermore, case studies are suitable when exploring areas where the current knowledge is limited and, thus, require building new insights into the theory based on empirical data (Ketokivi & Choi, 2014; Yin, 2018). Moreover, the context of this research is a contemporary phenomenon that needs to be examined in a real-life context (Yin, 2018).

The second reason was the need to collect empirically rich data to facilitate the practical relevance of findings (Barratt et al., 2011). This was relevant due to the lack of empirical research within the area of selection and integration of digital technologies for smart production (Müller et al., 2018; Silva et al., 2022). Since the case study approach naturally includes data collection related to the context and experiences of practitioners, the case study approach is very useful for bringing together academic relevance with practical scenarios (Fisher, 2007). Moreover, case studies are in-depth studies focusing on one or several objects of study in regard to several variables (Karlsson, 2016). Applying the case study approach can, therefore, enable an in-dept and detailed understanding of the studied phenomenon (Karlsson, 2016; Säfsten & Gustavsson, 2020; Voss et al., 2002).

The third reason for selecting a case study approach was related to its suitability to study the same case at different points in time (Karlsson, 2016; Yin, 2018). This was considered relevant since this research considers both the selection and the integration of digital technologies, which usually occur in different phases. To only study these two processes for one given point in time would, therefore, not give a detailed picture of both the selection and the integration of digital technologies.

3.2 Research Process

This research process involved interaction between existing academic literature and manufacturing practice, meaning that the research process was influenced by rising or dissolving opportunities at manufacturing companies (Karlsson, 2016). For this reason, it was considered essential to follow a clear research process involving different steps to help avoid failed research results (Yin, 2018). This research applied the research process steps suggested by Säfsten and Gustavsson (2020), which are visualized in Figure 1. The steps of the research process include defining the problem area, formulating purpose and research questions, conducting a literature review, designing the case studies, executing the case studies, summarising empirical results, analysing and synthesising data, and discussing the results and drawing conclusions. As explained by Karlsson (2016), a research process has iterative steps and back-loops. For this reason, these steps were not followed linearly. Instead, the research process was characterized by reflection and questioning arising from empirical findings.

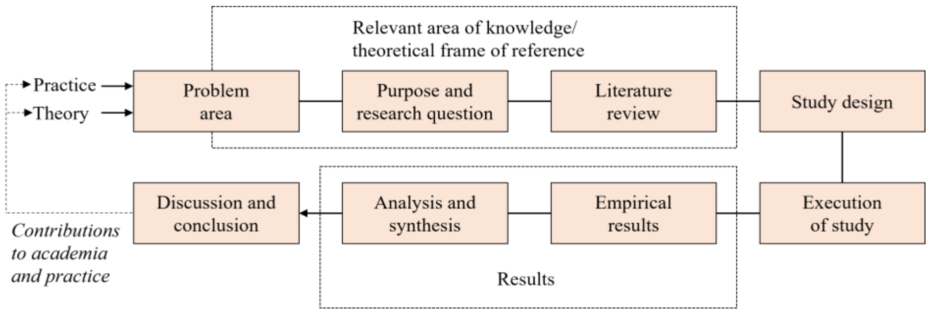

Figure 1: The research process adopted for this research (Säfsten & Gustavsson, 2020)

To fulfil the purpose of this thesis and answer the research questions, this thesis includes three papers and each paper contains an independent purpose. The relation between these papers and the thesis research questions is presented in

Table 1.

Table 1: Overview of appended papers and their relation to thesis research questions and case studies

Title of paper	Paper purpose	Thesis research question 1	2	3
Paper 1 - Enabling Smart Production: The role of data value chain	To identify main challenges to achieve Smart Production and how manufacturing companies can mitigate these challenges in order to select and integrate suitable digital technologies to enable data management for Smart Production	x		
Paper 2 - A Framework to Support the Selection and Integration of Digital Technologies for Smart Production	To support manufacturing companies in systematically selecting and integrating digital technologies for efficiently benefiting data value chains for Smart Production.	x		x
Paper 3 - Critical Factors for Selecting and Integrating Digital Technologies to enable Smart Production: A Data Value Chain Perspective	To identify and analyze the critical factors of selecting and integrating digital technologies for efficiently benefiting data value chains for Smart Production.		x	x

3.3 Research Design

The research design is a plan that guides the researcher in how to go from research purpose and research questions to answering research questions and drawing conclusions (Yin, 2018).

3.3.1 Number of Cases

This research is conducted in the belief that the selection and integration of digital technologies for smart production are influenced by contextual factors. This means that instead of there being one better way of selecting and integrating digital technologies, there is a need for manufacturing companies to adapt the selecting and integration based on the specific situation of the smart production project. For this reason, it was considered relevant to study multiple cases to include different smart production contexts. This contributed to minimizing risks that often come with single case study research, such as misjudging a single event and limited generalizability of results (Voss et al., 2002; Yin, 2018).

3.3.2 Unit of Analysis

The unit of analysis refers to the main focus of inquiry within case study research (Yin, 2018). The purpose of this licentiate thesis is to investigate the selection and integration of digital technologies for smart production within manufacturing companies. For this reason, the unit of analysis in the proposed research is the selection and integration of digital technologies within the context of smart production projects. The unit of analysis and context is visualized in Figure 2.

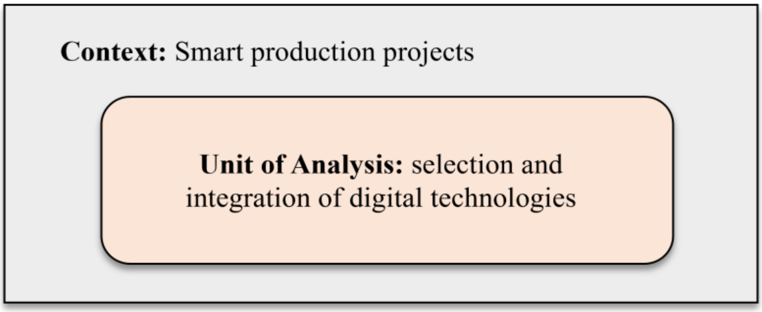

Figure 2: Unit of analysis for this licentiate thesis

3.3.3 Case Selection

The selection of cases for this research was conducted based on theoretical logic of sampling (Eisenhardt, 1989), meaning that cases were selected based on criteria identified in theory (Säfsten & Gustavsson, 2020). In this research, four criteria for the selection of cases were defined: (1) manufacturing companies in different industries and of different sizes, (2) internal production system, (3) use of Lean philosophy, and (4) relevant smart production projects.

(1) To cover a variation of smart production context for selecting and integrating digital technologies, it was considered important to study cases with manufacturing companies within different industries and of different sizes. Therefore, both large companies and Small Medium Enterprises (SME) should be included. This allowed the collection of

different perspectives and ways of working, which provided a richer and more detailed understanding of the investigated phenomenon.

(2) To collect data related to the selection and integration of digital technologies, selected cases needed to have projects where there was a need to select and integrate digital technologies.

(3) To facilitate an easier collection of data and a better understanding of the studied phenomenon, the selected cases had to be manufacturing companies with in-house production. This allowed conducting observation on the shop floor and made it easier to get in touch with relevant people to collect data from.

(4) To select and integrate digital technologies for smart production, it was considered relevant for manufacturing companies to first have a good understanding of and to actively work with their value flows, processes, and challenges within the production system. The selected cases, therefore, had to practice Lean philosophy in production.

3.4 Description of Cases and Data Collection

The research presented in this licentiate thesis is based on four cases conducted at four different companies. In Table 2, an overview of the cases is presented.

Table 2: Overview of the selected cases and manufacturing companies

	Case A	**Case B**	**Case C**	**Case D**
Type of products	Heavy vehicles	Railway	Casted components	Electronics
Company size	Large	Large	SME	SME
Approx. number of employees	2100	350	60	50
Longitudinal case (L) or reference case (R)	L	R	R	L
Presented in paper	1, 2, 3	1, 2, 3	1, 2, 3	1, 2, 3

Figure 3 presents the timeline of when data from the different cases were collected and when the papers were published. As can be seen in Figure 3, a continuous review of academic literature was conducted during the research process. The findings from the literature review were used to provide an understanding of scientific literature related to the selection and integration of digital technologies for smart production. The literature review was also used to design the case study and analyse empirical data. Figure 3 also shows that the data collection related to Case D started before I started my PhD studies.

During 2019 I did my master thesis at Case D as a part of a research project. After my master thesis, the collaboration with Case D continued when I started working as a research engineer in January 2020 and when I became a PhD student in September 2020. Cases A, B, and C were all initiated and conducted during my PhD studies.

As can be seen in Figure 3, Case A and Case D were conducted during a longer period compared to Case B and Case C. Naturally, more data was collected from Case A and Case D, enabling more in-depth studies. These two cases are, therefore, seen as longitudinal cases where the main data has been collected. Case B and Case C are seen as reference cases to complement data collected from Case A and D. The remaining sections present the different cases and data collection techniques used within each case.

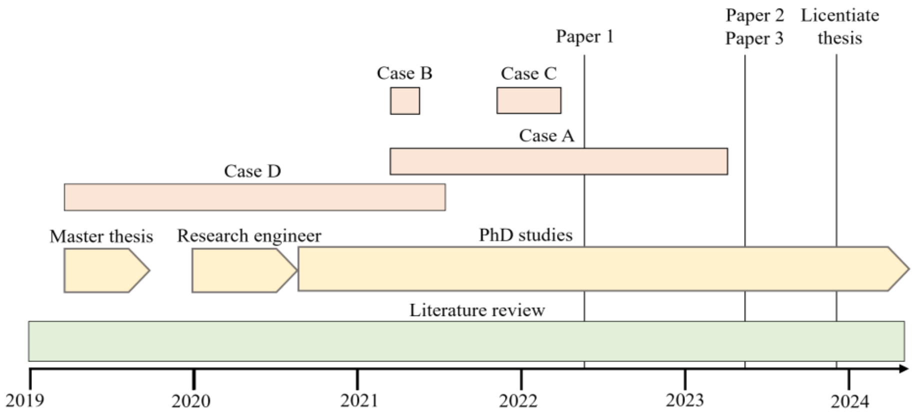

Figure 3: Timeline of cases and paper publications

3.4.1 Case A – Longitudinal Case

Case A was conducted at a large manufacturing company within the heavy vehicle industry. Data was collected between May 2021 and May 2023. The objective of Case C was to investigate how digital technologies could be selected and integrated for improved Overall Equipment Effectiveness (OEE) in a smart production context. Empirical data was collected by conducting interviews, participant observations, and document collection. An overview of the empirical data collected is presented in Table 3Table 3: Summery of data collected for Case A.

Semi-structured interviews were conducted via online video meetings while the respondents shared their screens to show documents related to the case. First, general questions were asked related to the background and current position of respondents. Afterward, topics related to current and desired future practices, data, methods, and technologies were discussed. Handwritten notes were made during the interviews and after each interview. The online meeting was recorded, and the interview was afterwards transcribed.

Various meetings were held to discuss different aspects related to Case A. These meetings mostly included project meetings with internal competencies working in the project and meetings with digital technology providers to discuss aspects related to digital technology integration. During these meetings, notes were taken, which allowed the collection of data related to the case and feedback on findings.

Table 3: Summery of data collected for Case A

Technique	No.	Duration (min)	Description
Online interviews	11	30-80	Selection and integration of digital technolo gies, Smart Production Participants: Head of manufacturing engineering and research, System and process developer, Head of IT, Smart production team leader
Workshops	2	90-120	Analysis of current state and desired future state in smart production Participants: Head of manufacturing engineering and research, System and process developer, Head of IT, Smart production team leader
Shop floor observations	4	30-60	Information related to production and routines
Informal conversations	10	5-15	Information related to the case and feedback
Various meetings	19	10-60	Project meetings, meetings with software provider
Documents	7		Information about the company, data available, data, data sources available, software applications, digital technologies

Observations were conducted on the shop floor to understand the production processes, terminology, and practices. During these observations, questions were asked to the employees to ensure a correct understanding of the observed events. Moreover, documents such as company presentations were collected to get a general understanding of how the companies operate. This was useful to complement data collected during interviews.

3.4.2 Case B – Reference Case

Case B was a retrospective case study at a large manufacturing company within the railway industry. The objective of case B was to investigate how the company has selected and integrated digital technologies for process improvement and production logistics, which was a part of a smart production project. An overview of the empirical data collected can be found in Table 4. Data was collected between May 2021 and August 2021.

The data was primarily collected through semi-structured interviews via online video meetings. The interviews started with general questions related to the background and current position of respondents. Then, questions were asked related to the selection and integration of digital technologies for Case B. To illustrate the studied situation with figures, the respondents shared their screens to show documents related to Case B. Handwritten notes were made during the interviews and after each interview. The online meeting was recorded, and the interview was afterwards transcribed.

The interviews were video and audio recorded and afterwards transcribed. Supplementary data was collected by documents such as presentations related to the company and studied case.

Table 4: Summery of the data collected for Case B

Technique	**No.**	**Duration (min)**	**Description**
Online interview	3	47-66	Analysis of current state and desired future state in smart production Participants: Production manager, Production engineer
Informal conversations	2	5-10 min	Information related to the case and feedback
Documents	3		Information about the case company and case C

3.4.3 Case C – Reference Case

Case C was a real-time case study carried out at an SME that manufactures casted components. The objective of Case C was to investigate how digital technologies could be selected and integrated for improved efficiency in process control and product traceability in a smart production context. Empirical data was collected by conducting interviews, participant observations, and document collection. An overview of the empirical data collected can be found in Table 5. Data collection started in December 2021 and finished in April 2022.

Semi-structured interviews were conducted face-to-face and via online video meetings. During the first interview with a respondent, questions were asked related to background and current position. Afterwards, topics related to current and desired future practices, data, methods, and technologies were discussed. Handwritten notes were made during the interviews and after each interview, the interview was transcribed.

Participant observations were conducted on the shop floor to understand the production processes, terminology, and practices. During these observations, questions were asked to the employees to ensure a correct understanding of the observed events. Moreover, documents such as company presentations were collected to get a general understanding of how the companies operate. This was useful to complement data collected during interviews.

Table 5: Summery of the data collected for Case C

Technique	**No.**	**Duration (min)**	**Description**
Face-to-face interviews	2	60-100	Selection and integration of digital technolo gies, Smart Production Participants: Production engineer, Production planner
Online interview	1	109	Analysis of current state and desired future state in smart production Participants: Production manager
Shop floor observations	1	60	Information related to production and routines
Informal conversations	5	5-15	Information related to the case and feedback
Documents	3		Information about the case company and case C

3.4.4 Case D – Longitudinal Case

Case D was a real-time case study carried out at a SME within the electronics industry. The objective of Case D was to investigate how digital technologies could be selected and integrated for improved quality control in a smart production context. Empirical data was collected by conducting interviews, workshops, participant observations, and document collection. An overview of the empirical data collected can be found in Table 6. Data collection started in April 2019 and finished in June 2021. During the period April 2019 to July 2019, I was doing my master thesis and was present at the company 2-5 days per week, allowing a richer collection of data. Data collection after this period was conducted during visits.

Semi-structured interviews were conducted face-to-face. Respondents were initially asked to describe their background and work tasks. Afterwards, topics related to current and desired future practices, data, methods, and technologies were discussed. Handwritten notes were made during the interviews. After each interview, the interview was transcribed into a word document.

Observations were conducted on a daily basis during the time I was present at the company. The observations were conducted on the shop floor to understand the production processes, terminology, practices, and current production status. During these observations, questions were asked to the employees to ensure a correct understanding of the observed events. Informal conversations with the employees were seen as opportunities for participant observations since these conversations allowed for discussions, feedback and opinions related to the case study.

Various meetings were held to discuss different aspects related to Case D. For instance, weekly meetings, software applications, data quality problems, long-term objectives, data quality requirements, and future steps for the company to take. These meetings allowed the collection of data related to the case and feedback on findings. The weekly meetings were related to the overall company performance, overall company information, ongoing projects, overall production performance, and issues related to production. This gave an overall understanding of how the company operates. The participants attending these meetings were either employees at the company only or competence from external parties such as suppliers and researchers. During all various meetings, notes were taken.

Secondary data were collected from the company in the form of documents. In Case D, documents were used for verifying data and complementing data collected during interviews by studying more specific and detailed data. To ensure a correct understanding of the documents collected, each document was first explained by a person familiar with the document.

Table 6: Summery of the data collection for case D

Case	**No.**	**Duration (min)**	**Description**
Face-to-face interviews	23	10-130	General description of work tasks, current work practices, data available, data gaps, current challenges, expectations of Smart Production, enablers for Smart Production Respondents: 6 operators, 2 Production engineers, Production manager, CEO
Workshops	5		Challenges, desired future state, case definition Respondents: 6 operators, 2 Production engineers, Production manager, production planner, sales manager, quality manager, CEO, 2 suppliers
Shop floor observations	Daily*	10-120	Information related to production and routines
Informal conversations	Daily*	5-20	Information about the case and feedback
Various meetings	38	10-90	Discussion on results, potential improvements, information about software applications and databases, long-term objectives, information about the overall case company performance
Documents	36		Information about the company, data available, data, data sources available, software applications, digital technologies.

*During the period I was present at the company on a regular basis

3.5 Data Analysis

A literature review was conducted in parallel to designing the research and collecting and documenting the empirical data. The empirical data were analysed using a thematic data analysis which is a systematic approach for capturing patterns in qualitative datasets (Braun & Clarke, 2006). The data analysis included an iterative comparison of the empirical data and literature by following six concurrent activities (Braun et al., 2019). The data analysis process in visualized in Figure 4. The first activity involved data familiarisation by reading transcriptions to get an overall understanding of the data. The second activity was the generation of codes by reading the transcriptions again while highlighting interesting quotes from each interview and assigning codes that describe each highlighted quote. This activity resulted in first-order categories of codes. The identified quotes were then transferred into a spreadsheet. The third activity involved searching for themes by identifying patterns among the challenges in the spreadsheet. The fourth activity involved reviewing themes by looking into the relationships among themes and by reading literature and theoretical framing to identify the final third-order dimension.

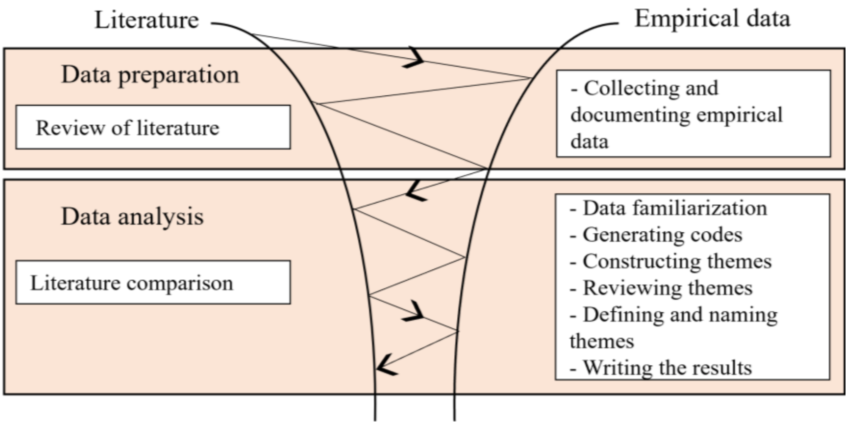

Figure 4: The iterative data analysis process in this thesis was based on the steps by Braun et al. (2019)

One example of coding from the first to the second and third is provided in Table 7. The empirical data were analysed and sorted based on categories identified in the literature: data sources and collection, data communication, data processing and storage, and data visualisation and usage. The fifth activity involved a detailed analysis of each theme by identifying second-order themes. Relationships between themes were further analysed. Finally, the sixth activity involved writing the results.

Table 7: Example of coding from direct quotes

Direct quotes	First-order category	Second-order themes	Third-order dimension
"... He said "Oh, this is very bad, something really wrong happened, this is catastrophic, the whole production will be wrong with this". And since I'm familiar with the issues, I went to production and said "Hey, did you miss typed 76 instead of 86?" – and that was the case." **Production Manager, Company C**	Human factor affects data collection	Manual work processes and reporting	Data sources and collection
"The big limitation is exactly what I mentioned earlier that we have to generate the data somewhere and it will be a manual data generation. So that is the big difficulty that we have, finding a way to do it so that it is not noticeable that we are generating data manually. As an example, we log a lot when we start up a product and end a product and it is done in paper form and a protocol that is then entered into a computer. And there are processes like that to generate data, but it's still an administrative process, that someone sits and fills in a form even if you've done it on a computer. So, there is a difficulty in finding a way to still, with the other technical aids we have, collect data and go to the next step in such a way as to eliminate the administrative part of the whole thing" **Production Engineer, Company B**	Generating data from manual work processes		

3.6 Quality of Research

Since this research is based on a case study design, the quality of research has been judged based on four criteria: construct validity, internal validity, external validity, and reliability (Yin, 2018).

Construct validity measures the extent to which correct operational measures have been established for the concepts being studied. However, since case study research often includes subjective judgments, establishing construct validity is often problematic (Yin, 2018). The use of multiple sources to collect data from, also called data triangulation, increases the construct validity of the research (Voss et al., 2002; Yin, 2018). As described in section 3.4 (see Tables 3-6), multiple sources of evidence were used in all four cases. In the longitudinal cases, Case A and D, rich data was collected from multiple sources of evidence. Case D especially included viewpoints from many respondents within the organization. Even though Case B and Case C mainly applied semi-structured interviews to collect data, company document collection was also applied. Moreover, in Case B and Case C, the interviews were conducted with two and three respondents, respectively, which minimized the risk of unanswered questions.

Internal validity concerns whether a research study provides a basis for answering the research questions of a research study or whether alternative explanations of the results do exist (Leedy & Ormrod, 2005). Thus, internal validity is about establishing causal relationships (Yin, 2018). In this study, internal validity was strengthened by using several real-time case studies. This was helpful in identifying cause-and-effect relationships, which strengthened the internal validity. Furthermore, a frame of reference was used to develop codes for interpreting empirical data. Matching with patterns presented in previous academic studies on smart production, therefore, helped strengthen the internal validity. Moreover, after each conducted observation, reflections, and notes were written as soon as possible to remember important aspects observed.

External validity shows whether and how findings from a case study can be generalized (Yin, 2018). To strengthen the external validity in this research, each paper had a multiple case study design to strengthen replication logic. However, even though four cases were studied, only the two longitudinal cases A and D were in-depth case studies that involved a more extensive data collection during a longer period. Naturally, this allowed a deeper understanding of cases A and D compared to the two reference cases B and C. It can therefore be argued that the generalizability and depth of this research are limited, which are common general limitations of case study research. However, the ambition of cases B and C was to get a general understanding of these companies' challenges and critical factors of selecting and integrating digital technologies for smart production, which these cases served. This allowed strengthening the results from case studies A and D by comparing and complementing them to the results from cases B and C. Furthermore, empirical findings from all cases were extrapolated in relation to similar results presented in previous academic studies within the topic.

Reliability refers to whether a conducted study can be replicated by another researcher and obtain similar results (Yin, 2018). The key enabler for reliability is to thoroughly document all activities and procedures in the research study. A case study protocol was used for each case to document how each study was conducted. A case study database was also used to document how each study was documented. The data analysis process is presented in each paper, including use of techniques such as coding. This licentiate thesis also including several real-time studies, facilitates establishing a chain of evidence to strengthen reliability (Karlsson, 2016).

4 Summary of Appended Papers

This chapter presents a summary of the three papers included in this thesis. For each paper, the title, purpose, methodology, findings, implications, and contribution to licentiate thesis are presented.

4.1 Paper I

Title: Enabling Smart Production: The Role of Data Value Chain

Research Gap: The main obstacles in accelerating smart production are selecting and integrating suitable digital technologies for data flows in each specific production system. However, most previous studies focus on integrating one digital technology alone, while smart production requires the integration of several synergizing digital technologies.

Purpose: Paper I was 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 to select and integrate a combination of digital technologies for Smart Production.

Methodology: A multiple case study at four manufacturing companies of varying sizes was chosen to cover different contextual aspects that may contribute to the results.

Findings: The findings showed that the 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 findings of this paper included 15 themes of challenges, which were categorized based on the data value chain: (i) data sources and collection, (ii) data communication, (iii) data processing and storage, (iv) data visualization and usage, and (v) general challenges. These themes showed that it is important to have both efficient and effective data management within the production system, where the entire flow from data generation to data usage must be considered. Moreover, the concept of data value chain as a method was proposed, i.e., a holistic approach that 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.

Implications: This paper shows that selecting and integrating digital technologies are complex but critical tasks as they determine how and if smart production will be achieved. Furthermore, the paper contributes to a common understanding among academia and practitioners of what obstacles to tackle when selecting and integrating a combination of digital technologies.

Contribution to the Licentiate Thesis: This paper contributes to answering thesis research question 1 by identifying themes of challenges related to the selection and integration of digital technologies. Furthermore, identified challenges were related to people, process, and technology aspects, which supports the argument that a socio-technical perspective is needed.

4.2 Paper II

Title: A Framework to Support the Selection and Integration of Digital Technologies for Smart Production

Research Gap: There is a lack of research on how manufacturing companies can select and integrate digital technologies in a systematic way, as these decisions are often based on the experience and intuition of decision-makers.

Purpose: To support manufacturing companies in systematically selecting and integrating digital technologies for efficiently benefiting data value chains for Smart Production. To fulfil this purpose, two research questions were answered in this paper:

(1) What are the challenges of selecting and integrating digital technologies for Smart Production?
(2) How can manufacturing companies select and integrate a combination of digital technologies in a systematic way to enable Smart Production?

Methodology: A multiple case study at four manufacturing companies of varying sizes was chosen to cover different contextual aspects that may contribute to the results.

Findings: The results included a more detailed analysis of the 15 challenges identified in Paper I by providing a third level of subcategorization. Furthermore, a holistic technology selection and integration framework was proposed. The framework was composed of four technology clusters (TC): TC1 – Data application, TC2 – Data communication, TC3 – Data storage, and TC4 – Data processing. Each cluster represents a set of technologies with dedicated functions associated with the cluster definition, and all clusters must be considered. As new digital technologies are continuously being developed, the findings show that the clusters must be as abstract as possible and technology-agnostic to ensure that they encompass existing, developing, and potential future technologies.

Implications: The in-depth analysis of the challenges in this paper contributes to a deeper understanding of the obstacles manufacturing companies face when selecting and integrating digital technologies, which is required in order to find suitable solutions. The proposed framework is one step in the right direction towards overcoming the challenges as it shows how to systematically select, combine, and integrate relevant digital technologies for a specific application area in smart production.

Contribution to the Licentiate Thesis: This paper contributes to answering thesis research questions 1 and 3. The contribution to research question 1 includes a more detailed analysis of the previously identified challenges. The paper contributes to answering research question 3 by presenting the technology selection and integration framework.

4.3 Paper III

Title: Critical Factors for Selecting and Integrating Digital Technologies to Enable Smart Production: A Data Value Chain Perspective

Research Gap: There is a lack of research on how to address the challenges of selecting and integrating digital technologies in order to build data value chains for smart production.

Purpose: To identify and analyse the critical factors of selecting and integrating digital technologies for efficiently benefiting data value chains for smart production.

Methodology: A multiple case study at four manufacturing companies of varying sizes was chosen to cover different contextual aspects that may contribute to the results. Moreover, the critical factors were based on the data value chain concept, which was identified in paper I.

Findings: This paper extended the work presented in paper I by using the proposed framework to map two cases to identify current problems and define a desired future state with a full-fledged data value chain. The findings of this paper were categorized based on the data value chain: (i) data sources and collection, (ii) data communication, (iii) data processing and storage, (iv) data visualization and usage, and (v) general critical factors. Furthermore, 13 themes of critical factors were identified related to the different data value chain categories. The findings showed that there is a need to clearly define the requirements of what should be achieved in each phase of the data vale chain.

Implications: This paper provides a structure for managers, shop floor workers, and IT competencies to work together in cross-functional teams when selecting and integrating digital technologies to enable data value chains for smart production. Furthermore, the paper contributes with hands-on guidelines on what should be considered when selecting and integrating digital technologies.

Contribution to the licentiate thesis: This paper contributes to answering thesis research question 2 by identifying themes of critical factors related to the selection and integration of digital technologies. The critical factors were related to people, process, and technology aspects and can, therefore be applied to overcome the previously identified challenges. These findings also support manufacturing companies in the selection and integration of digital technologies, which is related to research question 3.

5 Synthesis and Discussion of the Results

The purpose of this licentiate thesis is to examine the selection and integration of digital technologies to enable smart production within manufacturing companies. This chapter fulfils this purpose by synthesizing and discussing the empirical findings. Answers to the research questions are also provided.

This licentiate thesis identifies challenges, critical factors, and examines how the selection and integration of digital technologies in manufacturing companies can be supported. An overview of the research questions and their relation to the appended papers are presented in Table 8.

Table 8: The research questions and their relation to the appended papers

Thesis Research Question		**Paper** I	**Paper** II	**Paper** III
1)	What are key challenges of selecting and integrating digital technologies to enable smart production?	x	x	
2)	What are critical factors to consider when selecting and integrating digital technologies to enable smart production?			x
3)	How to support the selection and integration of digital technologies to enable smart production?		x	x

Figure 5 shows a general overview of the results from the empirical analysis conducted for this thesis. Moving from left to right, Figure 5 visualises the different phases of the data value chain, which are based on Tao et al. (2018): data sources and collection, data communication, data processing and storage, and data visualisation and usage. There is also a general category with aspects that are related to all phases of the data value chain. In the middle, an overview of identified challenges is presented. The right part of Figure 5 shows and overview of the critical factors. Furthermore, it is visualised how the aspects of people, process, and technology are related to identified challenges and critical factors, respectively. The following sections will describe these findings in more detail.

Phase of the data value chain	Challenges	People	Process	Technology	Critical factors	People	Process	Technology
Data sources and collection	- Manual work processes and reporting	x	x	x	- Define data collection requirements	x	x	x
	- Data generation and collection		x		- Consider the people	x	x	
	- Operator data	x		x	- Evaluate limitations and constraints			x
Data communication	- Interoperability		x	x	- Define data communication requirements			x
	- Data accessibility	x	x	x	- Enable interoperability		x	x
	- Structured data communication		x	x	- Define routines for disturbances	x	x	
Data processing and storage	- Data security			x				
	- Manual data analysis	x	x		- Define data storage requirements		x	x
	- Data analysis quality		x	x	- Define data processing requirements	x	x	x
	- Pre-processing		x	x				
Data visualisation and usage	- Data visualisation quality	x		x	- Define data visualisation requirements	x	x	
	- Work processes	x	x		- Define data usage requirements	x	x	x
General challenges/ critical factors	- Usefulness and development of systems			x	- Develop a data driven organisation	x	x	
	- Resources	x	x		- Work processes in smart production projects		x	
	- Defining a business case	x	x		- Identify areas for smart production		x	x

Figure 5: Identified challenges and critical factors of selecting and integrating digital technologies and their relationships to people, process, and technology

5.1 Key Challenges of Selecting and Integrating Digital Technologies

Research question 1 in this thesis is: *What are key challenges of selecting and integrating digital technologies to enable smart production?* This research question addresses the challenges manufacturing companies may face when trying to select suitable digital technologies and integrate them in a resource-efficient way to achieve desired effects in production, i.e., smart production. The following text synthesises and discusses the results of research question 1.

This thesis extends the current understanding of the challenges related to the selection and integration of digital technologies. Previous literature discusses these challenges at a general level (Phuyal et al., 2020; Raj et al., 2020; Sjödin et al., 2018), in one or a few application areas of production or specific digital technologies (Bueno et al., 2020; de Jesus Pacheco et al., 2023; Laskurain-Iturbe et al., 2023), or focusing just on one or two phases of the data value chain (Cioffi et al., 2020). Moreover, existing research focuses on either people challenges aspects (Hozdić & Makovec, 2023; Nahavandi, 2019; Romero & Stahre, 2021), process challenges (Abraham et al., 2019; Raptis et al., 2019; Schneider, 2018), or technical challenges (Estrada-Jimenez et al., 2023; Phuyal et al., 2020; Zeid et al., 2019), but not their combination. Accordingly, this thesis provides a new, holistic perspective on challenges encountered when selecting and integrating digital technologies. The findings of this thesis provide a detailed understanding of the specific sources of the challenges, i.e., people, process, and technology, in relation to each phase of the entire data value chain. These findings extend those of previous scholars, who have so far failed to provide a detailed account of their specific origins. In doing so, the thesis also helps to respond to criticism of prior research, which often fails to delineate between different sources of challenges in relation to the data value chain.

The findings show that the 15 challenges presented in paper I and further analysed in paper II, are all related to people, processes, and/or technology. This is in line with previous research e.g. Fattouh et al. (2023), Chirumalla (2021), and Sjödin et al. (2018). Figure 5 shows each identified challenge and whether they at the studied case companies were described as related to people, processes, and/or technology. For example, the table shows that the first challenge, which is manual work processes and reporting, is related to all aspects of people, process, and technology. This challenge is influenced by human factors, which is related to people, and difficulties in generating data from manual work processes, hence the connection to process. The connection to technology comes from the fact that it is difficult to find technical solutions which do not have a negative impact on people and the work process. If the work process were to remain manual in the future, the companies would have difficulty finding technical solutions where neither the human factor would have a negative impact nor the new work processes would be longer through, for example, extra work steps for the operators. This is a typical example showing the relationships between people, process, and technology and their impact on an identified challenge.

Figure 5 also shows that 8 challenges have a connection to people, 11 are related to process, and 10 are connected to technology. This does not necessarily mean that process aspects are more important than people aspects, but rather that more of the challenges are influenced by the processes. This is in line with for example Klingenberg et al. (2019) and Schuh et al. (2020). Even though process-related challenges when generating value from data are not new (Sharma et al., 2014), the research in this thesis shows that these challenges are still faced by many manufacturing companies. Further, as a side effect, this research also shows that these process-related challenges are causing additional issues related to people and technologies, as shown in Figure 5. Accordingly, this thesis is an important step to provide a comprehensive understanding of the challenges to be able to find suitable coping mechanisms ahead.

It can also be seen in Figure 5 that data communication and data processing and storage only have one challenge each that is connected to humans, while the other phases have two. The same phases, however, have more challenges that are linked to process and technology, which shows that these phases are affected more by work processes and technology and less by people. This can be compared to visualisation and usage challenges, which are more related to people than to processes and technology.

As can be seen in Figure 5, there are a total 15 challenges, and each phase of the data value chain has challenges that are linked to people, process, and technology. This shows the complexity, not only within each phase of the data value chain but also when looking at the entire data value chain. As highlighted in the theoretical framework, if changes are made in one part of the production system it affects sub-processes and other parts of the system (Gopalakrishnan et al., 1999). Adding new elements such as digital technologies to a production system, therefore requires a thorough analysis to avoid a negative outcome of the system as a whole.

This research can be helpful for managers involved in smart production projects to have an initial understanding of what potential challenges may be faced when selecting and integrating digital technologies. This can help managers prepare and adapt the project accordingly.

5.2 Critical Factors of Selecting and Integrating Digital Technologies

Research question 2 in this thesis is: *What are critical factors to consider when selecting and integrating digital technologies to enable smart production?* This research question considers critical factors that can help manufacturing companies overcome the identified challenges related to research question 1. The following text summarizes and discusses the results of research question 2.

The 13 critical factors presented in paper III are in line with the challenges related to people, processes, and/or technology and the different phases of the data value chain. Figure 5 visualises the relations between each identified critical factor and the three categories of people, process, and technology. For example, you can see that the first critical factor, "define data collection requirements" is linked to three categories. Since domain experts are the people who have the best understanding of the work process, they can provide valuable input on what data needs to be collected from different parts of the work process. This shows the connection to both people and processes. Furthermore, technical aspects need to be considered when defining the requirements of digital technologies for data collection. This is a typical example that shows how people, process, and technical aspects are related to each other in identified critical factors.

In Figure 5, 8 critical factors have a connection to people, 11 are related to process, and 8 are connected to technology. Each phase of the data value chain, as well as the general critical factors, has critical factors that are linked to all three categories. This shows that in each phase, you need to have a holistic perspective on how people, processes, and technology are affected in the process of choosing and integrating digital technologies for smart production. Furthermore, it can be seen that data communication and data processing and storage, like the challenges in Figure 5, have more connections to processes and technology than to people. This supports the argument that these parts of the data value chain should be more automated and less influenced by human aspects (Cavanillas et al., 2016; Schuh et al., 2020; Tao et al., 2018). Moreover, the empirical findings show that data collection, data processing, and data visualization and usage are phases of the data value chain that should be given extra attention since they are highly dependent on each other. This means that for instance, by collecting good and complete data, many problems in data processing and data usage can be avoided due to lacking data quality (Cai & Zhu, 2015; Cattaneo et al., 2022; Schuh et al., 2020).

Something that differs from the challenges are the general critical factors where there are more connections to process, which shows that the general critical factors focus is more on work processes. The need for more focus on process aspects confirms the findings from research question 1 which shows that many challenges related to processes still needs to be addressed (Klingenberg et al., 2019; Sharma et al., 2014; Zizic et al., 2022).

As been pointed out by Silva et al. (2022) and Müller et al. (2018), the selection and integration of digital technologies have been looked at more academically, highlighting the need for guidelines to practitioners. The critical factors identified can be used to provide managers with more hands-on guidelines on what to consider when selecting and integrating digital technologies. By considering these critical factors, challenges withing the same phase of the data value chain (see Figure 5) can be addressed. However, the due to the complexity of a production system and challenges related to the selection and integration of digital technologies, there is a need to have a holistic picture of the entire data value chain as well as people, processes, and technologies.

5.3 How the Selection and Integration of Digital Technologies Can Be Supported

Research question 3 in this thesis is: *How to support the selection and integration of digital technologies to enable smart production?* This research question addresses the support needed to select and integrate digital technologies in a resource-efficient way. The following text summarizes and discusses the results of research question 3.

As can be seen in Figure 5, manufacturing companies are facing diverse challenges when selecting and integrating digital technologies, and all identified challenges are associated with the different phases of the data value chain. As the data value chain can be used to describe the data flow within a system in order to generate value and useful insights, it means that a lacking data value chain can have a significant effect on the value and useful insights generated for decision-making and action (Klingenberg et al., 2019; Schuh et al., 2020). To support in tackling these challenges, manufacturing companies can use the proposed technology selection and integration framework that is visualised in paper II Figure 2. This figure shows the relationships between the four proposed technology clusters (TCs). As the TCs are somehow dependent on each other, it highlights the need for having all TCs in place without problems affecting the data value chain. This supports the findings of previous research emphasizing the need for having a holistic perspective on different technologies needed to achieve smart production (Klingenberg et al., 2019; Silva et al., 2022; Tao et al., 2018).

Paper III illustrates how the framework can be used by following three steps: 1) mapping current technologies and methods, 2) mapping current challenges, and 3) defining future state. Following these steps can help manufacturing companies get an overview of what technologies and methods are currently used for the different TCs, but also to get an understanding of problems related to people, processes, and technology that need to be addressed. Having an understanding of the problems and required capabilities that need to be addressed will help define what measures to take in order to achieve the desired future state (Klingenberg et al., 2019; Schuh et al., 2020). Furthermore, the critical factors presented in Figure 5 can support this activity, where aspects related to people, process, and technology should be considered.

To further support manufacturing companies in selecting and integrating digital technologies, there is a need to build further on how to use the proposed framework and the identified critical factors combined to achieve full-fledged data value chains. This should involve a structured process specifying how and in what order the different critical factors should be addressed and how they are related to the identified challenges and proposed technology selection and integration framework. Having a structured process with well-defined activities and decision points can help managers in planning and executing smart production projects where digital technologies are selected and integrated (Ghobakhloo, 2020a; R Hamzeh et al., 2018; Santos et al., 2023; Silva et al., 2022). However, having a structured process in place will not be enough. There is a need to first have a clearly defined smart production strategy that is in line with the company's business goals. Furthermore, there is a need to consider available resources, such as financial resources available for the project and human resources, such as the right competence from both production and IT. Thus, the selection and integration of digital technologies to build data value chains require the involvement of both operational level, who will have the active role in smart production projects, and management level which has to set the direction of the project and support with resources. This has been visualized in Figure 6. As the figure shows, to support the selection and integration of digital technologies, both people involved at the management level and operational level need to align their preferences, expectations, needs, and activities in smart production projects. As explained earlier, this should be done considering the aspects of people, process, and technology in an integrated way so it is possible to enable an efficient and effective data value chain in smart production projects.

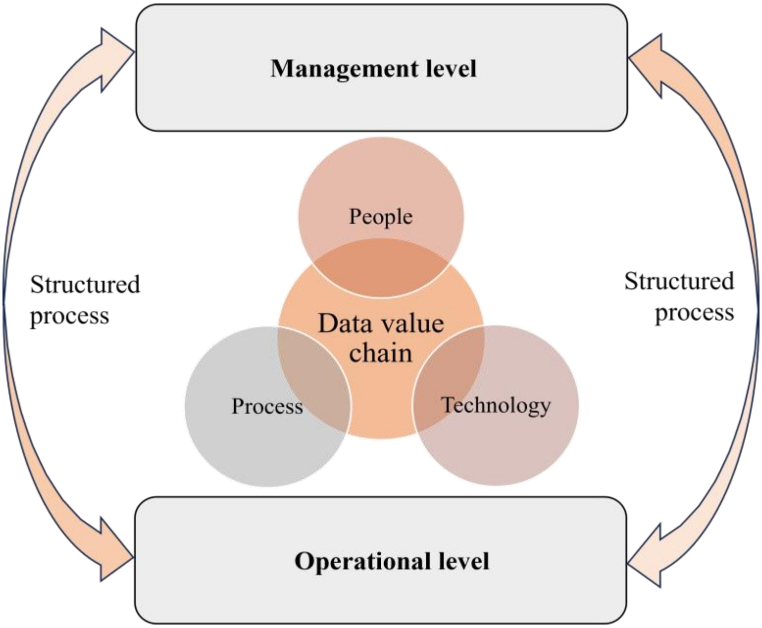

Figure 6: A proposal of way of working in smart production projects considering both management and operational levels when selecting and integrating digital technologies

6 Final Remarks

This final chapter presents the conclusions of this licentiate thesis. Academic and industrial contributions are outlined. The fulfilment of the purpose and answers to the research questions are provided, followed by limitations and future research.

6.1 Conclusions

The purpose of this licentiate thesis is to examine the selection and integration of digital technologies to enable smart production within manufacturing companies. To fulfil the purpose of this licentiate thesis, three research questions were formulated. These questions were answered based on an analysis of four studied cases in combination with previous research on the selection and integration of digital technologies and smart production. The answer to each research question will be presented below.

Research Question 1 - What are key challenges of selecting and integrating digital technologies to enable smart production?

Paper I addressed the challenges of selection and integration of digital technologies and identified 15 themes of challenges. The findings show that these themes of challenges are all linked to the different phases of the data value chain. By identifying the challenges of selection and integration of digital technologies, paper I contributed to answering research question 1 but also guided the further analysis of the challenges, which is presented in paper II.

The analysis of this licentiate thesis shows that the identified themes of challenges are related to either people, process, and/or technology aspects. Furthermore, each phase of the data value chain has identified themes of challenges that are related to all aspects of people, processes, and technology. This means that key challenges of selecting and integrating digital technologies are connected to the entire data value chain and related to aspects of people, processes, and technology. Moreover, a challenge itself is to have a holistic perspective in finding a system solution where all challenges related to the entire data value chain are addressed.

Research Question 2 - What are critical factors to consider when selecting and integrating digital technologies to enable smart production?

Paper III addressed the critical factors of selecting and integrating digital technologies and identified 13 themes of critical factors. To ensure the relevance of critical factors, they were during the analysis phase designed to address the already identified challenges. For this reason, the themes of critical factors are also linked to the different phases of the data value chain. The findings show that addressing the phases of data collection, data processing, and data visualization and usage is extra important as they are highly dependent on each other. Extra focus should, therefore, be on having a clear connection between these phases. Furthermore, this research question has been answered with more hand-on guidelines showing practitioners what actions should be taken.

The analysis of this licentiate thesis shows that in order to address the identified challenges in research question 2, consideration must be taken to people, process, and technology in each phase of the data value chain. A critical factor is, therefore, to define requirements for each phase of the data value chain where people, process, and technology aspects are addressed. Moreover, a holistic perspective is needed on the entire data value chain to select and integrate a set of synergising digital technologies that complement existing elements in the production system.

Research Question 3 - How to support the selection and integration of digital technologies to enable smart production?

Paper II and paper III are contributing to answering research question 3 by analysing how the selection and integration of digital technologies can be supported. Paper II further analysed the themes of challenges presented in paper I, which resulted in a deeper understanding of the challenges of selecting and integrating digital technologies. Understanding the challenges before initiating a smart production project can help managers prepare and plan for the project.

Paper III presented a practical approach on how to support manufacturing companies in selecting and integrating digital technologies. This included identifying hands-on critical factors that manufacturing companies can use to address the themes of challenges related to the data value chain. Paper III also presented a practical approach involving three main steps that manufacturing companies can take when evaluating the current situation and future situation. It can be concluded that four technology clusters need to be considered to fulfil different functions of the data value chain, but there is not a specific set of technologies that needs to be used. Hence, both simpler to very complex digital technologies can be relevant depending on the production system. Moreover, defining a structured process for selecting and integrating digital technologies in combination with a clear smart production strategy and involvement of the right resources can support manufacturing in selecting and integrating digital technologies.

6.2 Limitations and Future Research

This licentiate thesis examines the selection and integration of digital technologies to enable smart production within manufacturing companies. During this research process, several future research directions have been identified.

The validation of the findings is the next step. This research has been conducted by studying two main cases within the manufacturing industry. Analysing generalization was conducted by studying two reference cases from two different manufacturing companies and relying on theory. However, it is important to also confirm the findings by including additional cases from other manufacturing companies that fit the selection and sampling criteria. This includes studying more types of manufacturing companies and application areas. Highly relevant application areas for smart production include those related to sustainable production (Ghobakhloo, 2020b), for example Twin Transition where digitalization and sustainability strategies are combined (Muench et al., 2022). Focusing on different manufacturing companies and application areas also opens for further research on how different contextual factors can influence the selection and integration of digital technologies. This is relevant since the context of a research study is very important, as the chosen case may limit the results. This is due to cultural, economic, and organizational influences that will vary between organizations and countries (Müller et al., 2018).

The results of this licentiate thesis have also pointed out data collection, data processing, and data visualization and usage as phases of the data value chain that should be given extra attention since they are highly dependent on each other which adds to the complexity. Another direction for further research could therefore be to focus on more in depth on these phases of the data value chain. This can involve studying cases where challenges are faced in these specific phases.

This licentiate thesis has provided an initial understanding of how the selection and integration of digital technologies can be supported. In doing so, this research confirms the studies by (Klingenberg et al., 2019; Santos et al., 2023), showing that there is a need to develop a structured process for selecting and integrating a combination of digital technologies. Relevant for future research would be to investigate if and how existing technology selection and integration frameworks can be applied for such a process. When developing a process for selection and integration of digital technologies, it should also be investigated how identified challenges should be addressed and how critical factors can be applied. This should also include ways of working in the selection and integration process, such as roles and competence needed and how different departments and external partners (for instance, suppliers, technology providers and system integrators) should collaborate.

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