

Advancing the Development Process of Digital Twins for Production Systems

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Abstract

Manufacturing companies are increasingly making substantial investments towards digital twins to enable the continuous optimization of their production processes. To maximize the value of these investments, a structured development process can facilitate faster development, enhance resource planning, and reduce overall costs while simultaneously increasing the probability of successful digital twin developments for production systems.

Existing literature principally addresses specific steps and challenges within the development process, leaving a need for deeper holistic exploration into how digital twins can be developed in industrial manufacturing settings. This gap represents a significant challenge for manufacturing companies, as the incorrect execution of this process could result in a considerable loss of valuable time and resources.

The purpose of this thesis is to explore the development process of digital twins for production systems. This thesis studies the development process of digital twins within a global manufacturing by adopting real-time longitudinal case study methodology. By focusing on the development process aspects, this licentiate thesis seeks to generate new insights that will be useful to those responsible for or involved in the digital twin development process.

This thesis provides three main contributions. Firstly, it identifies key requirements when developing digital twins for production systems, highlighting the need to focus on not only technical requirements, but also requirements related to people and processes. Secondly, based on physical, virtual, and process complexity, it identifies the sources of complexity when developing digital twins for production systems. Thirdly, it provides insights into the development activities within digital twin development processes, offering significant guidelines for researchers and practitioners.

This thesis presents a framework that offers a practical contribution to support practitioners in the process of developing digital twins for production systems. It outlines a structured approach to assist practitioners in mitigating the complexities of digital twin development process. The approach outlines key stages and considerations to facilitate the holistic perspective of the process, providing a practical tool for manufacturing companies to enhance their efforts and increase the potential for success in digital twin developments for production systems.

I am incredibly grateful for this opportunity to explore new technologies and expand my knowledge. This experience has changed my approach to problem-solving. This journey has deepened my commitment to bridging the worlds of academia and industry, which need each other to keep up with growing complex innovations.

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*Adrian Sanchez de Ocaña
Lund, October 2024*

List of Papers

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

I. Sanchez de Ocaña, A., Bruch, J., & Aslanidou, I. (2023, September).

Model Simplification: Addressing Digital Twin Challenges and Requirements in Manufacturing.

In *IFIP International Conference on Advances in Production Management Systems* (pp. 287-301). Cham: Springer Nature Switzerland.

- **Work Distribution:**

Adrian Sanchez de Ocaña initiated the paper and is the main author. I conducted the literature review and case study.

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IV. Schmidt, B., Sanchez de Ocaña, A., Grahn, G., Karlsson, I., & Ng, A. H. C. (2022, May). *Augmented Reality Approach for a User Interface in a Robotic Production System*. In *SPS2022: Proceedings of the 10th Swedish Production Symposium (Vol. 21, p. 240)*. IOS Press. Wang, W., Bandaru, S., & Sánchez De Ocaña Torroba, A. (2019). *Improved human-robot collaboration through simulation-based optimization*. In *Advances in Manufacturing Technology XXXIII (Vol. 9, pp. 153-158)*. IOS Press.

V. Wang, W., Bandaru, S., & Sanchez de Ocaña, A. (2019). *Improved Human-Robot Collaboration through Simulation-Based Optimization*. In *Advances in Manufacturing Technology XXXIII (Vol. 9, pp. 153-158)*. IOS Press.

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1. Introduction

This chapter presents the background to this research, focusing on the digital twin development process for production systems. This is followed by the problem statement containing the motivation for the research needed in this field, the research purpose, and the research questions that guided the research process. This chapter ends with an explanation of the research's scope and the thesis outline.

1.1 Background

There has been a long-standing interest in smart production for academia and industry (Kusiak, 2018). As production processes have become more complex, mechanized, and computerized, new information technologies have emerged to support these advancements. Smart production refers to completely integrated and cooperative production systems that react instantly to changing conditions and demands in the plant, supply chain, and consumer needs (Lu et al., 2016). It is equally crucial to comprehend the evolution of human interactions and processes, as these elements are indispensable for optimally exploiting the potential of technology development in smart production (El Maraghy et al., 2021).

One of the key progresses in this area is the rise of simulation modelling to support smart production (Brettel et al., 2014; Mourtzis, 2020; Stavropoulos & Mourtzis, 2022). The process of developing and testing a computerized mathematical model is known as simulation modelling (Chung, 2003). New methods for simulation modelling have been developed in the last years as an evolution of other traditional simulation methods. Mourtzis (2020) presented different advanced simulation methods and tools, such as advanced augmented and virtual reality tools supported by the internet of things (IoT), hybrid simulation, digital twins, and forecasting (Mourtzis, 2020). Among these, digital twins stand out due to their unique capability to closely mirror production systems (Uhlmann et al., 2017).

Digital twins, as coined by NASA (Glaessgen & Stargel, 2012; Shafto et al., 2012), offer the possibility of simulating real-world physical objects. They have been the subject of considerable research interest, with numerous researchers adopting this term. Since the term's initial appearance in 2015, the number of publications has demonstrated a consistent upward trajectory (Tao et al., 2022). However, researchers and companies do not have a standard definition (Barricelli et al., 2019; Jones et al., 2020; Kritzinger et al., 2018; Semeraro, Lezoche, Panetto, et al., 2021). In the smart production context of this thesis, a digital twin is defined as:

A virtual representation of elements of the production system that can be used with various simulation and analytics techniques. It is distinguished by the synchronization between the virtual and physical systems, using near real-time data and virtual models from sensors, systems, and connected smart equipment. The digital twin supports lifecycle management by possibly enabling continuous monitoring, optimization, and predictions, facilitating the evolution of the physical system through its lifecycle over time (Barricelli et al., 2019; Jones et al., 2020; Negri et al., 2017; Tao et al., 2022).

Numerous advantages are associated with digital twins for production systems. Specifically, digital twins can provide a geometrical representation of a physical object in terms of physics and dimensions (Söderberg et al., 2017). By generating synthetic data, digital twins enable the automatic creation of virtual images for the training of deep learning models (Alexopoulos et al., 2020). The utilisation of digital twins enables companies to adopt a more comprehensive and nuanced approach to decision-making, comprising the analysis of the present situation, the diagnosis of previous challenges, and the forecasting of future changes (Chaplin et al., 2020). In order for manufacturing companies to make well-informed judgements with regard to production, a data-driven approach to decision-making is made possible by the digital twin. Data-driven approaches use data analysis rather than intuition to inform decisions (Provost & Fawcett, 2013). Digital twins, when coupled with the digital representation of facilities, surroundings, and people, may be utilised to teach shop-floor users (Attaran & Celik, 2023). Furthermore, through digital twins, it is possible to digitise knowledge, which can be documented, transferred to models to provide a common understanding in the company (Bayer et al., 2014; Qi et al., 2021). In addition, through the utilisation of simulation tools and virtual reality tools, digital twins can facilitate stakeholders' and operators' deeper comprehension of complex physical designs and processes

(Bayer et al., 2014). Similarly, digital twins enable the connection of the whole production system, providing further visibility and transparency to operations (He & Bai, 2021a).

Most research explores the definition of digital twins, their benefits, and how they should operate when implemented in production systems (Attaran & Celik, 2023; Barricelli et al., 2019). However, there is a notable lack of studies focusing on the development process of digital twins for production systems, particularly the steps and challenges involved in making digital twins functional and applicable to their intended purpose (dos Santos et al., 2022; Onggo et al., 2018; Tao et al., 2022).

With the goal of advancing, development refers to the deliberate effort to cultivate skills, expand knowledge, and produce physical or software artefacts (Halman et al., 2006).

Furthermore, a process is defined as a measured, organized collection of activities intended to provide a particular result. (Davenport, 1993).

The development process of a digital twin refers to the structured phases and activities required to realize a digital twin from concept to implementation. This typically includes the design, modelling, and implementation phases, as outlined by Glatt et al. (2021) and Segovia and Garcia-Alfaro (2022).

Using a process is a form of applying a structured approach, which is critical when developing digital twins for production systems, as it provides a clear roadmap that deals with and helps manage the inherent complexity of these systems (Jia et al., 2022, 2023; Thamhain, 2014). The rationale for using a defined process is based on the understanding that technological projects, including those pertaining to digital twins, are frequently susceptible to economic and technical risks (Thamhain, 2014). Furthermore, digital twins are complex due to the involvement of highly skilled personnel from various parts of the organization, the need to integrate multiple disciplines and departments, collaborations with software providers, and the incorporation of real-time data and advanced simulations (Kober et al., 2024; Thamhain, 2014). A structured approach ensures that each phase of the development process is planned and executed methodically, reducing the risk of inefficiencies and errors that could lead to wasted resources and delays (Sjödin et al., 2018). Furthermore, following a well-defined process allows for better communication and alignment among stakeholders, ensuring that the value is created by developing and applying a technology (Sjödin et al., 2018; Thamhain, 2014). Therefore,

understanding and researching the development process is crucial for realizing the value of digital twins for production systems.

1.2 Problem Statement

Developing digital twins presents two key challenges: defining the requirements for (1) the digital twin's system and for (2) the development process (Hassani et al., 2022; Li et al., 2021). A lack of clear requirements for the digital twin itself often leads to conflicting stakeholder expectations, especially when multiple viewpoints on its use exist (Fuller et al., 2020; Tan et al., 2021). For example, stakeholders may have differing expectations regarding the level of detail the digital twin should replicate, leading to conflicting requirements and expectations. If a highly detailed digital twin is pursued, it might require more data and computational power; consequently, this requirement will affect the development process. This approach has also resulted in communication issues throughout the process (Kober et al., 2024).

Furthermore, although technology requirements placed on digital twin systems, such as real-time data integration, scalability, stable data acquisition, interoperability, and autonomous connectivity, have been the subject of previous research (Durão et al., 2018a; Kober et al., 2022; Shao & Helu, 2020), the lack of attention directed towards people and process requirements such as developing intuitive human-machine interactions for non-technical users and designing workflows for effective digital twin integration has become evident (Liu et al., 2022). These requirements can involve procedures for the development of a digital twin and for people involved in and related to the development process. The ambiguity in requirements when developing digital twins is further compounded by several sources of complexity inherent to both the physical production system and the virtual environment (Atkinson & Kühne, 2021; Caldarelli et al., 2023; Jia et al., 2022, 2023).

Despite the growing interest in digital twins, successful development processes remain rare due to the numerous sources of complexity in meeting digital twins' requirements (Atkinson & Kühne, 2021; Caldarelli et al., 2023; Savolainen & Knudsen, 2021). This complexity of the digital twin development process is a distinguishing factor, as fulfilling the various requirements to develop a continuous replica of the production system necessitates the collaboration of numerous stakeholders and systems (Atkinson & Kühne, 2021). Accordingly, it is reasonable to suggest that these development processes require a considerable amount of time and resources. Although the complexities

of digital twin development processes are evident, the underlying reasons for this complexity have yet to be investigated. Furthermore, the concept of complexity has been explored in other fields (Caldarelli et al., 2023), but its relevance to digital twin development process in production systems has yet to be studied (Atkinson & Kühne, 2021). These complexities not only make the development of digital twins for production systems more difficult due to the various requirements involved, but they also blur the clarity of the process, which remains poorly understood (dos Santos et al., 2022).

There is a notable lack of clear guidance for the development process of digital twins for production systems, despite considerable academic interest in digital twins (dos Santos et al., 2022; Onggo et al., 2018; Tao et al., 2022). The processes, steps, and phases of digital twin development are often unclear, leading to confusion in appointing teams, establishing milestones, and defining the necessary activities (dos Santos et al., 2022; Fuller et al., 2020; Zheng et al., 2022). This gap in the literature highlights the need for development frameworks that address both the requirements and complexities of the development process of digital twins for production systems.

1.3 Purpose and Research Questions

Previous research has contributed to an increased understanding of digital twin benefits for production development. As the previous subsection emphasized the ambiguity and lack of clear requirements which hinder success within digital twin development processes, the purpose of this thesis is to explore the development process of digital twins for production systems. This knowledge may be vital for achieving digital twins that support decision-making at manufacturing companies.

The following research questions (RQs) are formulated:

- **RQ1:** What key requirements must be considered when developing digital twins for production systems?
- **RQ2:** What are the sources of complexity when developing digital twins for production systems?
- **RQ3:** How can the development process of digital twins for production systems be supported?

1.4 Scope

This research project originated from an academic gap in the exploration of this phenomenon and the industrial need to acquire expertise and knowledge for the further development of digital twins as well as strategically develop this area. The initial scope of the research was to investigate how digital twins can be developed, what benefits they might bring to the industry to improve their operations in production, and where they are most suitable to be applied. Following a research clarification study from both stakeholders in the industry and the existing literature, the purpose of the study was refined to focus exclusively on the development process of digital twins in the production system. Consequently, the RQs are exploratory, combining “what” and “how” questions. This research can be considered applied research.

This thesis studies the development process of digital twins for production systems in an industrial production setting, with a focus on technology, people, and process. The aim is not to further improve technology, but to explore the development process, applying existing technological knowledge related to data and models. It considers both the technology and managerial aspects of the process. The case study is conducted at Alfa Laval, where discrete-event simulation (DES) is utilised as the primary method for modelling the digital twin of the production system. DES, which models system behaviour as a sequence of discrete events over time, is a well-established technique in the manufacturing domain (Banks, 2005).

The development process of the digital twin for production system is analysed through three distinct perspectives that guide the exploration:

1. **Technology, People, and Process Framework:** The first study adopts this framework to highlight how technology, humans, and the process influence the requirements when developing digital twins.
2. **Physical, Virtual, and Process Complexity:** The second study explores the sources of complexity in the digital twin development process using a physical, virtual, and process complexity lens.
3. **Process Perspective:** The third study adopts this perspective, proposing a framework that supports the systematic development of digital twins. This holistic process view emphasizes the sequence of activities for development from concept to implementation.

This thesis focuses on the development process of the digital twin for production systems, specifically from a developer’s perspective. It does not address the user’s perspective or challenges related to the post-implementation phase. Collaboration with third-party software providers is an integral part of the

development process of digital twins for production systems. This collaboration ensures the know-how to meet technical and managerial requirements in the digital twin's development process.

The application area for the digital twin is the factory production system, focusing on production development scenarios for production management, flow leaders, and planning teams.

1.5 Outline of the Thesis

The remainder of this thesis is organized as follows: the Frame of Reference chapter outlines the current state of research, followed by the Research Methodology chapter, which details the chosen research method, process, and design. Next, the Summary of Appended Papers chapter provides brief summaries of the included papers. This chapter is followed by an analysis of the RQs. Finally, the Discussion, Contributions, and Future Work chapter presents the main findings, contributions, and potential directions for future research.

2. Frame of Reference

This chapter serves as the frame of reference for the thesis and provides the theoretical foundation for the research. It begins with an overview of the production system theory, followed by an introduction to digital twins, including their main components and various implementations. The chapter then outlines the process of developing digital twins and the associated requirements. Lastly, the concepts of complexity and simplification in modelling are explored. Taken together, this chapter forms the core theoretical framework applied throughout the thesis.

2.1 Production Systems

A production system is a group of personnel, tools, and processes arranged to carry out an organization's production activities (Groover, 2016). It can be divided into two main components: facilities and production support systems.

The facilities include the physical factory where different production assets, such as equipment, are located. The production support systems are the processes the business employs to control production and address the logistical and technical issues that arise while placing material orders, moving work through the plant, and ensuring that goods satisfy quality requirements (Groover, 2016).

Production support systems are separated into four major components: business functions, product design, production planning, and production control (Bellgran & Säfsten, 2010). Business functions communicate with customers. Product design integrates client expectations with company objectives (Petersen et al., 2005). Production planning then determines how the product design will be manufactured while considering the material needs, process, schedule, and capacity. Finally, production control manages and guarantees that the production plans are carried out (Bellgran & Säfsten, 2010).

In systems theory, a production system can be understood as a complex, adaptive system composed of interdependent components, such as machinery, data flows, human operators, and organizational processes, that continuously interact to achieve shared objectives (McCarthy et al., 2000). Systems theory emphasizes the importance of understanding not just individual components, but also the interrelationships and feedback loops that define the system's overall behaviour (Efthymiou et al., 2012; Linnéusson, 2018).

Digital twins serve as a virtual embodiment of these systems, capturing the dynamic interplay between physical components and their digital representations (Bianconi et al., 2020; Duan et al., 2023; Loaiza & Cloutier, 2022). The digital twin's capacity to simulate and monitor complex interactions aligns with the systems theory principle that small changes in one part of the system can propagate and lead to significant impacts elsewhere, enabling more holistic and integrated decision-making (Duan et al., 2023; Gejo-García et al., 2022; Jinzhi et al., 2022).

Digital twins are useful in production planning because they allow for the collection of data from shop-floor systems, such as production equipment, manufacturing execution systems (MES), and enterprise resource planning (ERP) systems, in order to analyse the current state of the production system as well as any variations in demand from customers, inventory, and resources (Agostino et al., 2020). This insight may then be used to allow demand-driven, on-time delivery, resource optimization (i.e., material, labour, and equipment), cycle time reduction, and inventory-cost reduction (Shao & Helu, 2020). In addition, a constantly operating digital twin is a critical enabler for production re-planning in the event of a breakdown. Any production system procedure, such as robotic manipulation or transport shuttle movement, might result in a physical failure (Novák et al., 2020).

2.2 Digital Twins for Production Systems

2.2.1 Digital Twin Components

Digital twins have five major components: virtual models, physical entities, connections, purpose, and data (Qi et al., 2021). Virtual models can include simulation models of different kinds, such as DES models, continuous simulation models, geometrical models, and analytics models (Agalianos et al.,

2020; Huang et al., 2021). These models represent the geometries of the system, their behaviour, and the different states when they are in operation.

The physical entity is the unit or system scope to be represented in the virtual world and be mirrored through models. These can entail from a single machine to a production line to a complete factory. Defining the use of the virtual representation of these, for example, mirrored machined or production lines would be the purpose. Purpose refers to the use of this particular digital twin. Digital twins can have different goals and areas of application. For example, they can enable the design of a new production system environment (Kombaya Touckia et al., 2022). They can be used to optimize running production in terms of scheduling (Negri et al., 2021). They can assist with monitoring energy and achieving greater energy efficiency (Vatankhah Barenji et al., 2021).

Data refer to the availability of data collected from the physical entity and fed into the models. These data allow us to understand their behaviour and the current condition of the machine or system and enables prediction. The last component is the connections that connect the physical environment, the data collected, and the virtual models. It may include multiple data acquisition systems such as sensors, MES, and IoT and connections to other enterprise systems and models in which relevant data are stored (Minerva et al., 2020; Negri et al., 2020). Figure 1 summarizes the main components of a digital twin, highlighting the connection between these components that are closely related to each other.

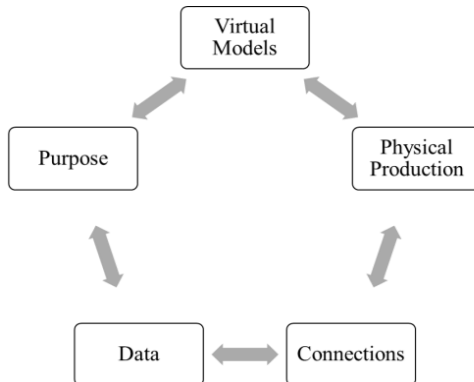


Figure 1: Digital twin components (Qi et al., 2021)

2.2.2 Development of Digital Twins

Numerous literature reviews have further examined the development of digital twins (Liu et al., 2022; Melesse et al., 2021; Semeraro, Lezoche, Dassisti, et al., 2021; Tao et al., 2022). The literature reviews show a wide variety of digital twin developments due to the failure to use standards (Liu et al., 2022; Tao et al., 2022). In most cases, digital twin developments are not generic and are based on the actual application, requirements, and issues of the particular scenario (Tao et al., 2022). They are often addressing technical problems that are not integrated within the organization.

The majority of the models developed are unidirectional models that provide information from a physical production system to a person (Liu et al., 2022). It is uncommon for models to be bidirectional. In other words, a person cannot make decisions in the model and have them executed automatically in the physical system.

Most digital twins use more than one form of the model to describe the physical system. One of the fundamental components of a digital twin is the virtual model. Within the digital twin, quite a few model constructions are possible. Tao classified the models of the digital twin into four different kinds: the geometrical model, physical model, behavioural model, and rule model (Tao et al., 2022). Likewise, Liu et al. (2022) categorized the constructed models into geometrical, analytical, state-based, kinematics, dynamics, finite element model, and computer-aided design. Thus, most studies represent the physical system using more than one model type (Liu et al., 2022).

The software used to create and run virtual models is heterogeneous. The simulation software utilised in digital twin research is quite broad, is tailored to each study, and includes both simulation-based solutions and data analytics-based solutions. Some of the IoT and simulation software pointed out are Siemens product lifecycle management (PLM) software, Matlab, Dassault Systems 3D, PTC ThingWorx, Microsoft Azure, IBM Watson, Twin Thread, and Visual Components (Liu et al., 2022; Semeraro, Lezoche, Dassisti, et al., 2021; Tao et al., 2022). Moreover, most digital twin developments have been conducted at the unit level rather than the system level (Tao et al., 2022). Solutions that allow scalability and the combination of different digital twins into larger systems are currently lacking (Liu et al., 2022).

2.2.3 Process of Developing Digital Twins

The process of developing digital twins can be divided into three phases: design, modelling, and implementation (Segovia & Garcia-Alfaro, 2022). In the design phase, objectives, functional requirements, process plans, and system architecture are established. The modelling phase focuses on selecting, developing, and validating models as well as integrating them with other models (Biller & Biller, 2023). Finally, the implementation phase ensures the synchronization of the digital twin with the physical system, providing a common interface and addressing the security aspects of connections with other systems or extraction data from the factory.

Complex digital twin designs include multiple components, including material properties, spatial geometry, internal divisions, interfaces, models, and how the system should be integrated as a whole. (Angjeliu et al., 2020). This phase outlines the steps involved in the process as well as the connections between the various parts that make them possible. In addition, it determines which system attributes and functionalities will be included in the digital twin. The data from both the physical and virtual shop floors are integrated into a unified model using techniques such as filters and neural networks, thereby ensuring that the data are transparent and coherent for analytical purposes (Raffaelli et al., 2021).

The development of a more detailed and accurate digital twin is a more costly process (Kober et al., 2023). To model a larger system, a series of smaller digital twins are combined, verified, and adjusted to align with a holistic perspective that represents the characteristics of the real system (Tao et al., 2022).

The integration of various data sources, models, and interfaces, as well as their security, is necessary during the digital twin implementation phase (Segovia & Garcia-Alfaro, 2022). It is crucial to minimise delays in the transfer of data (Kober et al., 2022) to ensure that the digital twin can quickly simulate. Two key aspects of implementing digital twins are to transform simulation models by utilising real-time production data and including automated updates (Overbeck et al., 2023).

2.2.4 Digital Twin Requirements

Previous studies emphasize real-time data, integration with other systems, and a high level of accuracy as requirements for digital twin implementation (Durão et al., 2018a; Ferko et al., 2022). Real-time data facilitate immediate insights and feedback and the ability to address continuous and dynamic changes within the production system while integration ensures that the data are shared among multiple systems (e.g., MES, ERP and PLM systems) and the digital twin models (Uhlemann et al., 2017). Accuracy consists of providing a virtual representation that reflects the real-world system as closely as possible, including behavioural and geometrical aspects, reducing errors in predictions and optimizations (Maier et al., 2017; Robinson, 2022).

Achieving a digital twin for complex systems, such as production systems, may require combining multiple digital twin models. These models can simulate different parts and aspects of the production system. For example, digital twins can represent individual machines, tooling processes, production lines, or even larger systems like supply chains. This multi-model integration enables a more holistic approach for a decision, but also increases the complexity of the digital twin. Therefore, digital twins still require a focus on factors such as maintainability, performance, and compatibility (Jia et al., 2023). Maintaining a digital twin over time requires that it can be easily updated and scaled, while performance relates to the ability of the twin to run simulations quickly, enabling prompt decisions to address any problems (Durão et al., 2018a; Shao & Helu, 2020). Compatibility, on the other hand, allows models to work across various digital twin platforms and software vendors (Lu et al., 2020; O’Connell et al., 2023). Often, certain trade-offs occur between digital twin requirements, like reducing computation time (do Amaral et al., 2022; Yang et al., 2023). The ability to speed up simulations occurs at the expense of accuracy, particularly in fast-moving production systems, where real-time adjustments are needed to prevent costly downtimes or delays (do Amaral et al., 2022; Robinson, 2022).

Another critical requirement for the development of digital twins for production systems is adaptivity (Erkoyuncu et al., 2020), which allows for adjusting predictions depending on changing conditions in the production system and the data extracted from the supporting systems, such as MES. Unlike simulation models that are static, adaptive digital twins provide a dynamic representation based on the data and learning of intelligent algorithms, which allows for ongoing process optimization (Akata et al., 2020; Biller & Biller, 2023; Erkoyuncu et al., 2020; Qiao et al., 2021). This capability enables

companies to adapt operations not just in terms of the design of the production system, but also continuously, responding to everything from machine wear and tear to shifting demand patterns (Qi et al., 2018; Roy et al., 2020). The adaptability of digital twins creates more value in environments where variability and uncertainty are constant factors (Negri et al., 2021). However, despite this promising potential of adaptive digital twins, more research is needed (Alnowaiser & Ahmed, 2022).

Making the digital twins not only adaptable but also fully traceable is another requirement, meaning that changes and updates to the models can be tracked and understood by users and developers (Durão et al., 2018b; Lu et al., 2020). Developing a digital twin that can continue learning over the lifecycle is another key requirement (Biller & Biller, 2023). Lifecycle learning would enable a digital twin to evolve alongside the physical system it mirrors. This learning capability requires the integration of advanced artificial intelligence techniques, particularly in machine learning algorithms (Biller & Biller, 2023; Chaplin et al., 2020; He & Bai, 2021b). These algorithms should be able to learn from small-scale changes, such as changing the sequence according to which a task is performed, to large-scale changes that, for example, require a redesign of the factory layout. The prediction results should change promptly to reflect these changes. Further research into these areas is necessary to achieve fast, real-time results in production systems, where conditions can change unpredictably (Andronie et al., 2021).

In conclusion, digital twin requirements have been addressed by different researchers, mainly from a technology perspective, focusing on the properties of models and algorithms to accurately represent the production system. However, less is known about people's requirements for the development of digital twins and how these requirements are enabled throughout the process. Moreover, significant effort remains related to identifying and integrating the people and process requirements necessary for successfully developing digital twins, such as user training, collaborative workflows, and effective communication strategies, before they can fully reach their potential.

2.2.5 Complexity and Simplification in Modelling of Digital Twins

Managing complexity is an important activity of the digital twin development process. There are two types of complexity: structural and dynamic complexity (Brady & Davies, 2014). Structural complexity refers to integrating parts and subsystems into a larger system along with their interaction to fulfil a purpose (Balcázar et al., 2012; Shenhar et al., 2007). Dynamic complexity involves how a system evolves over time, requiring adaptation and learning from changes (Edmondson, 2012). Predicting the causal reaction to changes in the production system is difficult as even a small change can completely alter the behaviour of such a system. Therefore, dynamic complexity is often overlooked when evaluating how production systems and their virtual models will evolve in the future (Brady & Davies, 2014).

Previous research has found a link between complexity in models and factors like the level of detail or understanding of the model (Golay et al., 1989; Webster et al., 1984). Unclear modelling goals, poor system modelling, and limited understanding of the real system can all be causes of complexity (Chwif et al., 2000). Larger and more complex virtual models have been developed over time (Henriksen, 2008).

Although no agreed-upon metrics for model complexity exist, some proposed indicators are the number of processes, operations, resources, products, and interactions among elements (Ahmed et al., 2016). One suggested method for measuring complexity divides it into structural complexity (number of objects, connections, and properties) and software complexity (code length, cyclomatic complexity, and computational difficulty) (Popovics & Monostori, 2016). Similarly, Arora and Barak (2009) proposed the utilisation of running time to measure model complexity in computer science. Measuring complexity is performed to identify the resources and the time of the development process of such a model. To optimize return on investment, models should have just enough detail to explain the physical system and enable a decision (Nutaro & Zeigler, 2018). To avoid complexity, models could start out as a simple model and gradually add detail (van der Zee, 2017).

Model simplification reduces complexity by using rules and strategies, making models easier to create and faster to run (Frantz, 1995). Simplification can involve adjusting model boundaries to reduce inputs, aggregating data to reduce components, or using a meta-model (a simplified version of the actual model) like a mathematical formula or algorithm (Lidberg et al., 2021).

2.3 Research Framework

The general research framework of this thesis depicted in Figure 2, which illustrates how the development process of digital twins in production system companies is studied. Three different scope levels are explored: corporation, factory, and specific factory area. As shown in the elements of the right part of the figure, this thesis explores the requirements, complexities, and activities involved in the development process of the different contexts. The manner in which this research framework is realized in disparate papers and studies will be elucidated in greater detail in the chapter that follows, which is devoted to methodology.

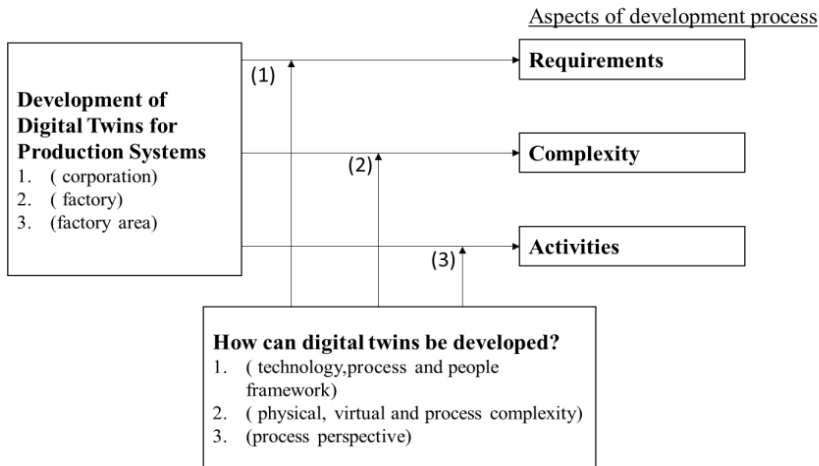


Figure 2: General research model

3. Research Methodology

This chapter outlines the research methodology, starting with the research approach and the context of the industrial Ph.D. at Alfa Laval. It then covers the research design, followed by the research process descriptions of the three studies conducted. The chapter explains the methods of data collection and analysis as well as the unit of analysis and addresses research quality by discussing validity and reliability.

3.1 Research Approach

The research approach selected for this thesis was a collaborative research approach. This approach was chosen because it effectively bridges the gap between academic exploration and industrial application. As highlighted by Anderson (2001), academic research increasingly occurs in conjunction with industrial practitioners, addressing industry-related challenges to enhance the practical relevance of applied research. By fostering collaboration, this approach allowed for a deeper understanding of how organizational structures impact system outcomes (Anderson et al., 2001; Berglund et al., 2020; Ellström, 2007; Pasmore et al., 2008; Svensson et al., 2007).

The industry and academia have different interests. Academia adopts a more explorative approach whereas the industry focuses on exploiting the research's resources (Hillerbrand & Werker, 2019). By adopting a collaborative research approach, a suitable balance between these two interests was achieved. Selecting this approach led to the creation of high engagement from academia and industry. Throughout the research process, close collaboration with practitioners facilitated the development of a shared understanding of the study's objectives and outcomes (Ellström, 2007). This strategy allowed for creating knowledge through collaboration between scholars and practitioners (Svensson et al., 2007).

This research was conducted as part of my industrial Ph.D. program, during which 20% of the time was contributed to the Automation and Digitalization department at Alfa Laval's Global Operations Development. This role

provided me with direct access to personnel, information, challenges, and opportunities for applied study, significantly enhancing both the academic and practical dimensions of my thesis. The dissemination and implementation of research work and outcomes within the company are conceivable, adding value to the thesis.

In addition, the research was affiliated with Mälardalen University's Indtech research school, which focuses on implementing Industry 4.0 and applied AI in production systems. This collaboration included partnerships with 12 leading industrial companies, research institutes, technology centres, and support organizations, further strengthening the research's relevance and impact.

3.2 Selection of Research Method

The research method utilised for this study was a case study, which has several interpretations (Merriam, 1998; Stake, 1995). Stake defined a case study as the investigation of the particularity and complexity of a single case in order to comprehend its activity in the context of significant circumstances (Stake, 1995). In this research, the case study method was chosen to explore and gain insights into the RQs about the development process.

The case study method was chosen based on its strengths in addressing the research. Firstly, the case study method allows for the examination of multiple perspectives, uncovering different viewpoints, highlighting key stakeholders, and analysing how they interact (Simons, 2009). This approach is particularly useful for explaining not only what happened, but also why it happened. Secondly, the case study method facilitated a deeper investigation into the dynamics and processes of development. By carefully documenting, analysing, and evaluating events as they unfolded, the case studies helped identify crucial elements for successful development and examine the patterns and relationships between them (Simons, 2009). Accordingly the case study method proved valuable in gaining practical insights relevant to the RQs.

3.3 Research Design

The plan that directs the researcher from the research purpose and questions to the answers and conclusions is known as the research design (Yin, 2009). This thesis employs a single longitudinal, real-time case study design, although a preliminary research clarification was conducted using a retrospective approach.

3.3.1 Real-Time vs. Retrospective Case Studies

This research uses a longitudinal real-time case study, meaning that the cases are investigated as they occur. Collecting data in the present context allowed for the observation of the process of developing digital twins for production systems as it unfolded, providing insights into challenges, decisions, and interactions. The benefits that this approach provided to the thesis are:

- **Timeliness:** The findings reflected the current state of digital twin development in industry, making the research relevant to practitioners that want to implement these systems (Säfsten & Gustavsson, 2020; Simons, 2009).
- **Dynamic Insights:** Observing the case in real time provides opportunities to capture cause and effect as well as the interactions and the response to those interactions, which is usually lost in retrospective cases (Säfsten & Gustavsson, 2020).
- **Stakeholder Engagement:** The research enabled an in-depth exploration of stakeholders' perspectives, thereby enhancing the quality of the research (Baskarada, 2014; Säfsten & Gustavsson, 2020; Simons, 2009; Yin, 2009).

3.3.2 Case Study Selection and Criteria

The following criteria were used to guide the selection of case studies:

- The chosen case studies focused on discrete production system, a sector that has received relatively little attention in previous research.
- Selected factories exhibited a proactive culture towards integrating new technologies into their operations — a critical factor in successful technology implementation (Murphie & Potts, 2017; Park et al., 2004).
- Preference was given to areas with minimal reliance on external factors or interconnected processes, thereby helping to reduce complexity.

- Factories with an existing MES which aids in data collection were prioritized, as MES has been identified as a key enabler in the development process of digital twins (Negri et al., 2020).
- The availability of software for digital twin development was also considered.

The selection of the cases for this study was driven by the need for an initial understanding of the status of digital twin development processes within Alfa Laval's global organization in order to understand digital twin developments in the discrete manufacturing industry. Alfa Laval is present in more than 30 different factories, allowing for a broader perspective in the research than focusing on a single factory or line supports, thereby providing an entire view of various digital twin development processes across the organization. This study clarified which problems research should focus on.

The Eskilstuna factory was chosen due to its recent implementation of a MES, which enhanced its capacity to collect operational data. This factory's current interest in leveraging operational data with digital twins, coupled with its business need for improved lead time predictions, made it an ideal candidate for this research. In selecting the specific area within the Eskilstuna factory for detailed analysis, criteria were established to ensure a manageable complexity level. The chosen area was characterized by its relative simplicity compared to other parts of the shop floor, being less dependent on crossflows from various production areas. This isolation allowed for a more focused modelling effort, enabling the application of digital twin principles at a small scale.

3.3.3 Unit of Analysis

A unit of analysis is the main subject or entity the researcher intends to analyse in the study (Yin, 2009). This thesis has an overarching unit of analysis that encapsulates the unit of analysis presented in the different studies. The unit of analysis for this licentiate thesis is digital twin development processes for production systems. The unit of analysis and context are illustrated in Figure 3.

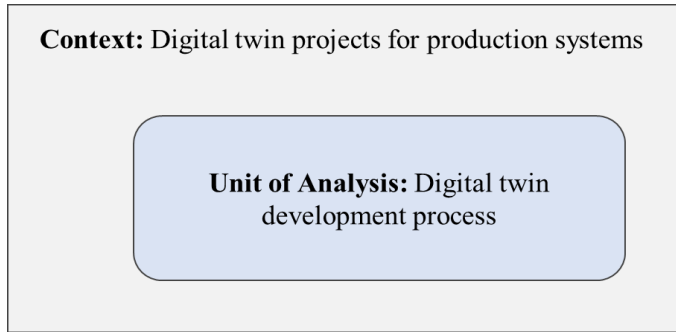


Figure 3: Unit of analysis and context for licentiate thesis

3.4 Research Process

A research process is a methodical collection of evidence secured by phases that can assist in evaluating the evidence to form scientifically valuable conclusions (Johnson & Gill, 2010). In this study, the research process followed the steps proposed by Säfsten. The classical research process usually follows a unidirectional process encompassing problem formulation, study design, data collection, and data analysis (Säfsten & Gustavsson, 2020). However, when the problem area is more extensive and less researched, it becomes highly iterative, bidirectional, and flexible, as in the current research, in which the research design was constantly iterated based on empirical findings. The research process started by reviewing relevant literature to formulate the problem and defining the RQ, then designing the study and selecting the appropriate methods and techniques, collecting the data and ensuring the data's quality and validity, and finally analysing the data and deriving the findings and conclusions.

Figure 4 details the elements of the research process and presents an overview of the entire research process for the licentiate thesis, from motivation to the different outcomes and papers presented in the previous timeline.

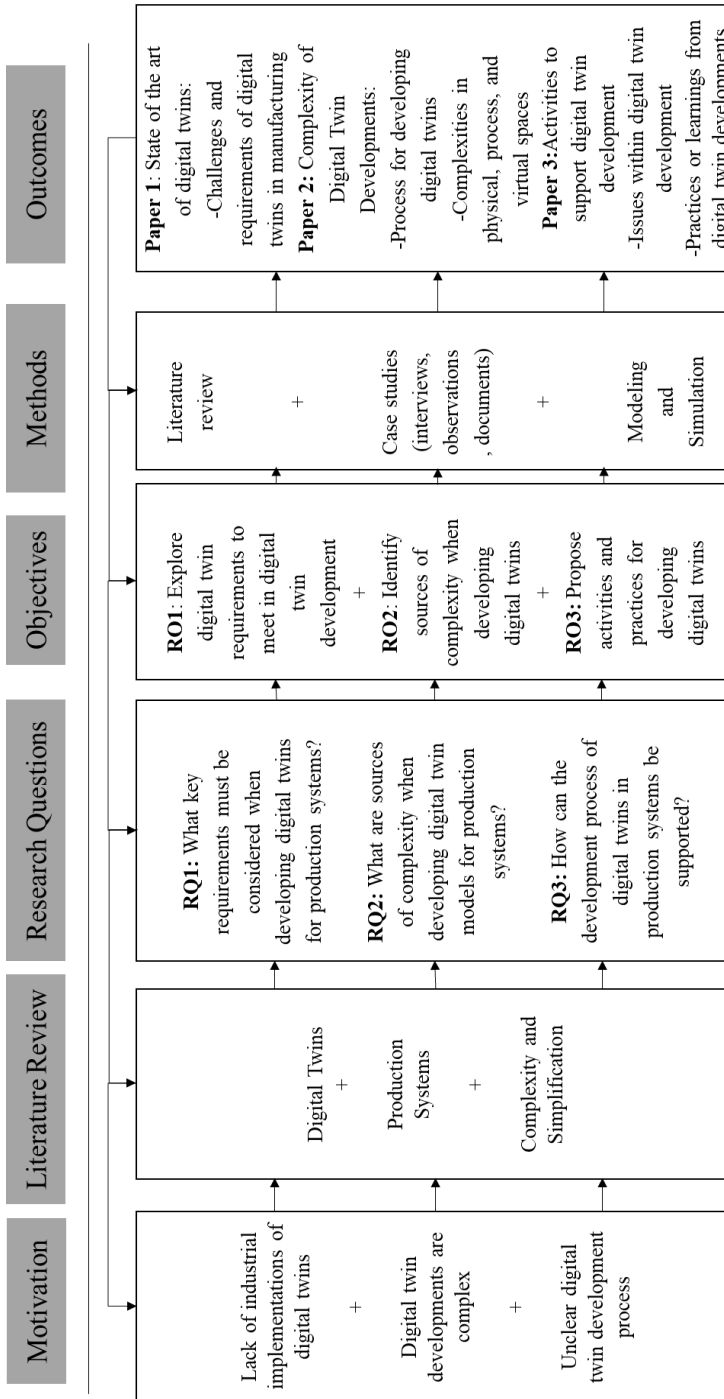


Figure 4: Research process

The Ph.D. journey began in April 2022, with the research proposal being submitted both internally and to Advance Production Management System conference in September 2023, where the first paper was also presented. The second paper was submitted to the Swedish Production Symposium and presented in April 2024. The third paper is currently undergoing revision with the International Journal of Production Research. Having successfully passed the initial screening process, the manuscript has been provided with feedback to facilitate its improvement.

3.5 Description of Studies

This thesis includes two studies and three articles, each with its own goal, to fulfil the objective of this thesis and answer the RQs. The relationship between these publications and the thesis RQs is presented in Table 1, which also provides an overview of the research methods.

Table 1: Overview of case study design

	Study A	Study B
<i>Study aim</i>	<ul style="list-style-type: none"> • Research clarification • Explore challenges and requirements for digital twins 	<ul style="list-style-type: none"> • Identify sources of complexity when developing digital twins • Propose activities and practises for developing digital twins
<i>Research method</i>	Single retrospective case study	Single longitudinal real-time case study
<i>Relation to RQ</i>	RQ1, RQ3	RQ1, RQ2, RQ3
<i>Data Collection</i>	Interviews, observations, documents, factory visits	Practical digital twin development, meetings, observations, documents, factory visits
<i>Outcomes</i>	Paper 1: State of the art of digital twins <ul style="list-style-type: none"> • Challenges of digital twins for production systems • Requirements of digital twins for production systems 	Paper 2: Complexity of digital twin developments <ul style="list-style-type: none"> • Process for developing digital twins • Complexities in physical, process, and virtual spaces Paper 3: Digital twin development process <ul style="list-style-type: none"> • Activities to develop digital twins • Development Issues • Lessons learned for developing digital twins

3.5.1 Paper 1: Research Clarification Study A

Case Study A elaborates on global operation development within Alfa Laval. It provides an overview of the current status of Alfa Laval's implementation for digital twins and current production development practices for digital transformation. The case study involves multiple data collection activities, such as semi-structured interviews, factory visits, roadmap documents, and project meetings. The data collected shed light on the vision for digital twins in production, challenges, requirements, and opportunities associated with this technology.

The aim of the study for this case study is to analyse the state of the art of digital twins within the global organization of Alfa Laval, as the case study aims to get an overview of the current status of digital twin implementation and production development practices across 30 different factories — specifically, the challenges that digital twin developments are facing and the requirements that are associated with digital twins in the global organization. This first case study is based on data collected between May 2022 and March 2023. The collected data consisted of semi-structured interviews, field notes, company records, and continuous dialogues. The respondents were selected based on their engagement in the ongoing work and represented different hierarchical levels to get diverse perspectives on digital twin challenges and requirements. Furthermore, meetings were held every six weeks, focusing on joint learning and the dissemination of research results. The project meetings reflected in Table 2 are specific to digital twins. In addition to the formal meetings, data were collected at several additional meetings as part of the automation and digitalisation team in production development. The template used for the semi-structured interviews is attached in Appendix 1.

All participants allowed the recording of the interviews. The empirical data were analysed using a thematic analysis, a systematic approach for dividing qualitative data into themes. The following steps were followed: transcribing the interviews, coding the data, identifying themes, analysing themes, and reporting findings (Braun & Clarke, 2006).

The summary of data collected is reflected in Table 2.

Table 2: Data collected for Paper 1

<i>Methods</i>	<i>No.</i>	<i>Duration (minutes)</i>	<i>Types of data collected</i>
<i>Semi-structured interviews</i>	9	40–60 minutes	Participant background: digitalisation and digital twins. Respondents: Automation and simulation specialists, PLM managers, production and technology development managers, and digitalisation managers
<i>Participant observation</i>			
<i>Project meetings</i>	34	60	Presentations, project status, future work
<i>Joint learning and dissemination</i>	6	60	Research feedback and result discussion
<i>Factory visits at different sites</i>	5	180	Current site status in digitalisation
<i>Informal discussions</i>		Continual	Opinions and project activities
<i>Documents</i>			Production system guidelines, lean digital factory, and simulation documents

3.5.2 Paper 2: Real-Time Single Longitudinal Case Study B

Case Study B elaborates on the Eskilstuna (Sweden) factory inside the high-speed separation business unit at Alfa Laval. This factory frequently acts as a pilot for digitalisation systems. This case study involves examining the factory as a whole to get an overview of the factory's particularities and feasibility of developing a digital twin. A discrete event-based digital twin model is started for the whole factory. The case study also involves further examining the operational data available in the factory — specifically, MES data and how data from the MES could support a digital twin of the production system.

The aim of this case study is to analyse the digital twin development process at the factory level to examine the factory as a whole, its particularities, and the feasibility of developing a digital twin for it. The case study also focuses on the operational data available in the factory and how it could support a digital twin of the production system. More specifically, it analyses the complexity of developing digital twins by examining the factory, data availability, the development process of digital twins, and an initial simulation model.

Data were collected from September 2022 to October 2023. To collect relevant data, the MES and its production data were analysed, and several meetings were held with the manufacturing execution team and production development team inside the factory related to development processes in data-driven solutions, with a focus on enhanced data collection. A data-mapping and system-mapping project was completed, followed by several meetings with software suppliers of digital twins, to elaborate on the DES model and disseminate the information. A factory visit was also held in addition to a discussion of production system processes and idiosyncrasies, a discussion with production managers on more relevant factory objectives, a presentation of

digital twin concepts, and the creation of digital twin interfaces and connectors.

Table 3: Data collected for Paper 2

<i>Methods</i>	<i>No.</i>	<i>Duration (minutes)</i>	<i>Types of data collected</i>
<i>Production Data</i>			Production data were extracted from the shop-floor system (e.g., MES, including team size, processing times, setup times, shifts, routes, etc.)
<i>Simulation Model</i>			A DES model was created with the data extracted that enabled the prediction of the delivery on time.
<i>Participant Observations</i>			
<i>Project meetings</i>	35	60	Presentations, project status, future work
<i>Joint learning and dissemination</i>	7	60	Research feedback and result discussion
<i>Factory visits</i>	3	180	Current site status in digitalisation
<i>Informal discussions</i>		Continual	Opinions and project activities
<i>Documents</i>			Production system guidelines, lean digital factory, and simulation documents

3.5.3 Paper 3: Real-Time Single Longitudinal Case Study B

The continuation of Case Study B takes place in one particular area of the Eskilstuna (Sweden) factory inside the high-speed separation business unit at Alfa Laval. This particular area is producing small components. The area is composed of 19 stations and has two main flows that most products follow. It is composed of a team of 12 operators and a team manager.

The study analyses the digital twin development process in an area that produces small components in Eskilstuna. The case study applies a data-driven modelling method to analyse the practical development of the digital twin for this area — specifically, the activities regarding the development of a digital twin.

Data were collected from September 2022 to February 2024. The data collected for Paper 2 were used and further expanded by visiting the factory with a focus on this particular area and meeting the team manager. Meetings with the local IT organization of Eskilstuna were held, and several shop-floor status board meetings were attended at different levels, including at the team level, where the team manager communicates with the operators, and at the factory level, where the different areas communicate with each other. Several meetings were held with the software supplier to troubleshoot the digital twin solution and extend the knowledge in its deployment. In addition, the area in the digital twin model was further examined and analysed while including more detailed information. Lastly, the advancements in the development process of

the digital twin were further discussed with the simulation and analytics team inside global operations.

Table 4: Data collected for Paper 3

<i>Methods</i>	<i>No.</i>	<i>Duration (minutes)</i>	<i>Description of data collected</i>
<i>Production Data</i>			Production data were extracted from the shop-floor system, such as MES, including team size, processing times, setup times, shifts, routes, etc.
<i>Digital Twin</i>			A digital twin was created with the data extracted that enabled the prediction of the delivery of products on time.
<i>Observations</i>			Insider field notes
<i>Project Meetings</i>	47	60	Presentations, project progress, future activities
<i>Software Supplier Meetings</i>	21	60	Meetings with digital twin software supplier to develop and troubleshoot solution
<i>Semi-structured Interviews</i>	9	40–60 minutes	Respondents: Automation and simulation specialists, PLM managers, production and technology development managers, and digitalisation managers
<i>Joint Learning and Dissemination</i>	7	60	The researchers presented and discussed research results with practitioners
<i>Factory Visits</i>	4	180	Current site status in digitalisation
<i>Informal Discussions</i>		Continual	Opinions and project activities
<i>Documents</i>			Production system guidelines, MES documents, simulation software supplier documents, lean digital factory, and simulation documents

3.6 Data Analysis

To analyse data for this licentiate thesis, the research employed iterative and flexible approaches across two empirical studies to fulfil the thesis’s aims and RQs. Initially, a comprehensive literature review informed the design of both studies, with adjustments made as the research progressed.

For RQ1, the data were first analysed using a thematic analysis, allowing patterns and themes to emerge directly from the data without a predefined framework or categories. Therefore, the theoretical lens of people, process, and technology was not applied or used from the beginning, but applied later as recurring patterns became apparent that this framework could be used. By doing so and allowing the data to guide the analysis, a flexible analysis was achieved to explore insights from participants’ experience and perspectives.

In contrast, the analysis for RQ2 was guided by establishing a theoretical framework, and the physical, virtual, and process complexities were assigned as high order themes to classify the data. Similarly, for RQ3, the high-level phases of design, modelling, and implementation were used from digital twin

development process literature (Glatt et al., 2021; Segovia & Garcia-Alfaro, 2022). The qualitative data analysis was conducted using the systematic method outlined by Miles et al. (2014), which emphasizes structured processes such as data reduction and data display. This deductive approach allowed for the validation and refinement of these theoretical categories based on empirical findings, ensuring that the research was grounded in both theory and practice.

Due to the large volume of data collected in RQ2 and RQ3, data reduction was important for managing the analysis. This reduction was achieved by coding the data and abstracting redundant information, focusing on identifying core concepts relevant to the RQs. Miles et al.'s (2014) framework, with its emphasis on progressive data simplification, was particularly suited to handling the extensive data from RQ2.

The data in RQ1, RQ2, and RQ3 were visually organized using post-it notes and Excel files to facilitate interpretation, helping to identify patterns and relationships within the large dataset. Conclusions for both studies were based on evidence and logical reasoning. These conclusions were tested and validated by practitioners, ensuring a shared perception of digital twin phenomena.



Figure 5: Qualitative data analysis process from Miles et al. (2014)

Further description of the analysed data is provided in Table 5, in which dimensions adopted in the different studies are connected to the RQs and their categories briefly described.

Table 5: Description of dimensions, themes, and categories in analysed data

Research Questions	Dimensions	Categories
<i>RQ1: What key requirements must be considered when developing digital twins for production systems?</i>	Digital Twin Challenges	<ul style="list-style-type: none"> • Technical challenges and solutions for data acquisition, model development, and integration • Process transformation for model-driven decision making • People skills and attitudes for data and model utilisation and collaboration
	Digital Twin Requirements	<ul style="list-style-type: none"> • Technical requirements and trade-offs for data analytics and simulation • People's needs and preferences for data analytics and simulation • Lifecycle management and improvement for data analytics and simulation
<i>RQ2: What are the sources of complexity when developing digital twins for production systems?</i>	Sources of Complexity in Digital Twin Developments	<ul style="list-style-type: none"> • Physical, virtual, and process complexity of digital twins • Human complexity and uncertainty in digital twin development and utilisation • Data and model complexity and diversity in digital twin integration and evaluation
<i>RQ3: How can the development process of digital twins for production systems be supported?</i>	Digital Twin Development Process	<ul style="list-style-type: none"> • Activities to support digital twin development • Design, modelling, and implementation phases • Issues within digital twin development • Practices or learnings from digital twin developments

3.7 Research Quality

3.7.1 Construct Validity

Construct validity assesses the extent to which proper operational measurements for the concepts under consideration have been created (Yin, 2009). During the data-gathering process, construct validity must be evaluated. As such, construct validity refers to how well research explores what it promises to investigate — namely, how well a process leads to an accurate observation of reality (Denzin & Lincoln, 2011; Gibbert et al., 2008). The utilisation of numerous sources of evidence supports construct validity (Denzin & Lincoln, 2011; Yin, 2009). Data from semi-structured interviews, simulation models, field notes (e.g., workshops, meetings, and casual talks), and corporate records were collected and compared to account for this. Construct validity was reinforced in two ways: initially, via an analysis of early data given to project

participants and other academics who offered input for each study at conferences or during journal submissions, especially meetings with my supervisors, and, second, by tracking projects as they were carried out rather than retroactively, making it easier to construct a chain of evidence (Gibbert et al., 2008).

Validity was constructed within the company by discussions with the smart manufacturing program manager (every 4 weeks), global production development managers (every 6 weeks), technology managers (every 6 weeks), PLM manager, simulation and analytics managers (every 3 weeks), and digitalisation teams (weekly). All industrial Ph.D. meetings with the stakeholders were continuous. As a result, being part of the company in which Studies 1, 2, and 3 were conducted allowed me to get a more detailed and accurate observation of the reality commonly discussed with practitioners. It also allowed for observer reality over time, which strengthens the constructed validity (Leonard-Barton, 1990).

3.7.2 Internal Validity

Internal validity, also referred to as logical validity, refers to the causal linkages between variables and outcomes (Cook et al., 1979; Yin, 2009). To ensure internal validity, this research was performed on site and followed real-time cases to enable the better understanding of the chain of events. A frame of reference was utilised to create codes for understanding the empirical data. Matching the patterns revealed in prior academic research on digital twins helped increase the internal validity. As the studies were in-depth single case studies, they presented a better opportunity to establish cause-and-effect relationships than multiple case studies, in which it is more difficult to determine a clear cause and effect (Leonard-Barton, 1990).

3.7.3 External Validity

External validity or generalizability is based on the intuitive idea that theories must be proven to account for occurrences not just in the context in which they are researched, but also in other contexts (Calder et al., 1983; McGrath & Brinberg, 1983). In this research, analytical generalization was performed. Analytical generalization differs from statistical generalization in that it relates to generalization from empirical facts to theory rather than population generalization (Yin, 2009). This research follows a nested approach. Rather than performing and evaluating many case studies of various companies, researchers may undertake multiple case studies within the same organization, which is considered a nested approach (Yin, 1994). Consequently,

generalization can be improved by performing multiple case studies within the same organization. In addition, the description and justification of sampling within the case studies have been introduced in previous chapters to help the reader appreciate these choices and be better able to apply similar general criteria to other companies.

3.7.4 Reliability

Reliability refers to the lack of error, which allows later researchers to achieve similar conclusions if they repeat the study following the same procedures (Denzin & Lincoln, 2011; Yin, 2009). Detailed documentation of all actions and procedures in the research is a critical facilitator for transparency. Each case used a case study protocol to detail how each study was carried out. In addition, a case study database was employed to track how each research was documented. The case study database included interview recordings and documents as well as versions of simulation models and manuscripts versions. Each publication describes the data analysis method, including the use of tools such as coding. This licentiate thesis, which also includes multiple real-time experiments, aids in the establishment of the chain of evidence (Karlsson, 2010). In Study 1, the interview guide was used for all interviews, and all respondents got the same information about the study, ensuring that the same rules and procedures were followed throughout the study.

3.8 Ethical Considerations and Responsibilities in Industrial Research

This thesis follows the ethical guidelines of both Mälardalen University and Alfa Laval as well as the recommendations of the Swedish Research Council in God forskningssed (2017). The ethical principles of honesty, transparency, and accountability guided the research process and the reporting of results. This research was funded by Alfa Laval and the Swedish Knowledge Foundation, but the researcher maintained full autonomy and integrity. The researcher also acknowledged the contributions of other researchers and practitioners involved in the development process.

The research topic of digital twins for production systems, has various ethical implications for different stakeholders and users. The stakeholders include the industrial partner Alfa Laval, the academic supervisors and the research school Indtech, the users of digital twin simulations, the customers of Alfa Laval's products, and society at large. The research aims to balance the interests and values of these entities. The research also considers the potential

ethical dilemmas and challenges associated with digital twins, such as privacy, and welfare associated with data monitoring in the digital twin models and the production shop floor.

The research methods used in this thesis are experiments and application studies on industrial systems using simulation. Therefore, no human subjects or personal data are involved in the research, and no ethical vetting is required. However, the research data and models are owned by Alfa Laval and subject to non-disclosure agreements, which limits the transparency and replicability of the research. The simulation model is created in proprietary software, which could be improved by using open-source software.

4. Summary of Publications

This chapter summarizes the papers included in this thesis, focusing on the findings of each paper.

4.1 Paper 1

The first paper studies the challenges and requirements of digital twins based on a longitudinal case study in Alfa Laval. The paper utilises interviews, observations, and company records to capture the state of the art of digital twins in this case study. The data are analysed using a thematic analysis and categorized using the people, process, and technical framework. The findings provide numerous viewpoints on the difficulties that prevent the company from adopting digital twin models.

The identified technical challenges include obtaining real-time data, integrating diverse data sources, and ensuring comprehensive model integration. Process challenges involve aligning various departments, managing change, and maintaining models effectively. People-related challenges arise from the novelty of the technology, the need for new competencies, and efforts to ensure usability for individuals who are not technical experts. Addressing these challenges requires strategic alignment, continuous maintenance, and effective communication to maximize the benefits of digital twin models in production systems. Several requirements are identified as well. Technical requirements include real-time data collection, processing, and simulation insights, with an emphasis on accuracy, real-time synchronization, and data integration. Participants highlight the ever-changing and dynamic nature of digital twin models, emphasizing the importance of continuous updates and validation against real-time data to ensure high accuracy. Process requirements place a need on adaptability, reusability, maintainability, and model revision handling to enable systematic simulation across multiple production stages. Finally, people requirements emphasize the importance of developing accessible, explainable, and interpretable models that decision-makers can understand and effectively use, bridging the gap between digital representations and real-world decision-making processes.

The research underscores the need to consider requirements related to technology as well as people and processes when developing digital twin models. It is imperative to consider the requirements from the perspective of the

individuals involved. A comprehensive understanding of the digital twin concept, along with the processes involved in its development and enhancement, is essential for all stakeholders. Moreover, decision-makers must be able to utilise and rely on these models and forecasts. The models must be straightforward to use and interpret.

Table 6: Requirements for digital twin development

<i>Themes</i>	<i>Requirements</i>	<i>Related Challenges</i>
<i>Technical</i>	Synchronization	Data acquisition, unclear fidelity needs
	Computational efficiency	Complexity
	Near real time	Data transfer IT/OT, data acquisition, unclear synchronization needs
	Integration	Data silos, interdepartmental development, data transfer IT/OT
	Scalability	Incompatibility
	Accuracy	Data acquisition, uncertainty, data transfer IT/OT, unclear fidelity needs
<i>People</i>	Granularity	Data acquisition, data transfer IT/OT
	Accessible for operational decision-maker	New way of working
	Explainability	Trust, complex to use, value understanding, low knowledge
	Interpretability	Trust, complex to use, value understanding, low knowledge
<i>Process</i>	Role-based views	Collaboration, interdepartmental development
	Adaptability	Effort to maintain, governance
	Reusability	Model lifecycle supporting systems
	Maintainability	Effort to maintain, governance
	Revision handling	Model lifecycle supporting systems

4.2 Paper 2

The second paper studies the sources of complexity in the development of digital twins based on a case study of one of the factories at Alfa Laval. The paper utilises simulations, observations, and company documents to collect data on the main sources of complexity that cause challenges in the development of digital twins for production systems. The data are analysed using a qualitative analysis based on data reduction.

The findings are organized around three main sources of complexity when developing digital twins for production systems: the physical system, the virtual entity, and the process of developing the digital twin. The results show that sources of complexity in the physical production system include a high level of interrelatedness of resources, a high reliance on human intervention, and a high rate of evolution/variation. The high level of interrelatedness increases the size of the model to include more entities while the human intervention in data collection originates less data quality and more

unpredictability of the production process. Moreover, a production system that suffers many changes will have a high dynamic complexity.

The findings indicate that sources of complexity in the virtual environment include multipurpose and multiscale high realism and fidelity as well as tacit and non-measured knowledge in models. The inclusion of multiple purposes and objectives requires the balance and trade-offs between objectives when developing the digital twin model. In addition, high fidelity requires more details to be included in the model in order to achieve accuracy resulting in complex digital twin models.

Finally, the paper examines the sources of complexity in developing digital twins for production systems, highlighting challenges such as the ambiguous and manual nature of the development process, the diverse systems and data structures that hinder integration, and the lack of methods for evaluating and refining models against real-world systems. There is no common or structured process to guide the development of digital twins, and there is a scarcity of methods to evaluate and refine the model with the “real” system.

Table 7: Sources of complexity in digital twin developments for production systems

<i>Themes</i>	<i>Sources of Complexity</i>
<i>Physical</i>	<ul style="list-style-type: none"> • High level of interrelatedness of resources • High reliance on human intervention • High rate of evolution/variation
<i>Virtual</i>	<ul style="list-style-type: none"> • Multipurpose and multiscale models • High realism and fidelity • Tacit and non-measured knowledge in models
<i>Process</i>	<ul style="list-style-type: none"> • Ambiguous and non-automated development process • Heterogenous system and data structures impede integration • Deficiency of methods to evaluate and refine model with “real” system

4.3 Paper 3

The third paper studies the development process of digital twins for production systems based on a longitudinal case study in an specific area of one of Alfa Laval’s factories. It utilises simulations, observations, and company documents to collect data of the development process and its main activities using a three-phase high-level framework of design, modelling, and implementation. The data are analysed using a thematic analysis. The findings are organized according to three main themes: development activities, issues, and learnings. In total, 17 development activities are identified, grouped into design, modelling, and implementation categories. In addition, the study identifies 15 development issues and 16 lessons learned that manufacturing companies can apply to succeed in digital twin developments. Key development activities in the design phase include defining objectives, requirements, and use cases; evaluating manufacturing processes and data infrastructure; and

selecting digital twin architecture, data structure, and project detail levels. Modelling activities involve data collection, model construction (behavioural, visual, or physical), tool selection, model validation, and experiment design. Implementation focuses on interface development, data integration, usability testing, model tuning, and the establishment of security measures. Practical implications emphasize redesigning data collection for digital twin compatibility, enhancing stakeholder collaboration, and standardizing data attributes.

To further the understanding of the technical solution in this publication, Figure 6 shows the connection between physical and virtual spaces, the main data captured come from the MES systems which can incorporate IoT sensors. Data from the factory are exported to a production data lake outside of IT, where they are reorganized and structured in an adequate format for the digital twin application to use. The digital twin solution comprises three main elements: a simulation server, factory database, and a user interface server.

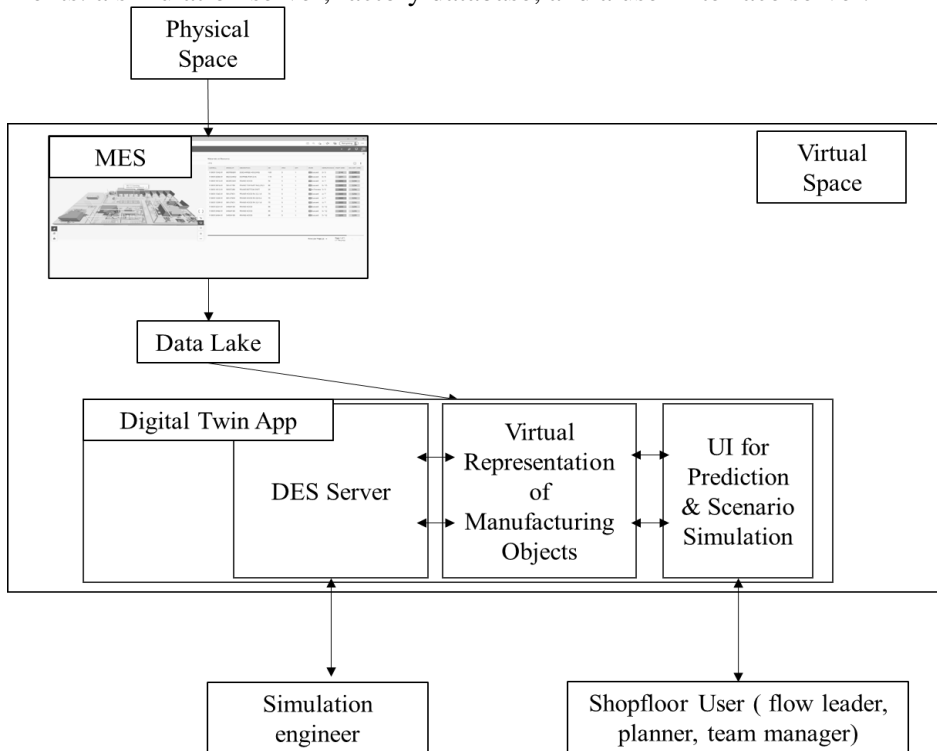


Figure 6: Describing physical and virtual spaces

Figure 7 shows the interaction between these data servers and simulation user servers. Timely production data are loaded onto the digital twin application that will transfer the data to the simulation server and the corresponding digital twin model — in this case, the DES model. This transfer of data is triggered by the app user, who clicks the load data buttons or starts the simulation of a

new scenario. Then the data are configured on the model, the model is run, and relevant key performance indicators (KPIs) are extracted from the model to the user interface (UI) to enable resource interpretation.

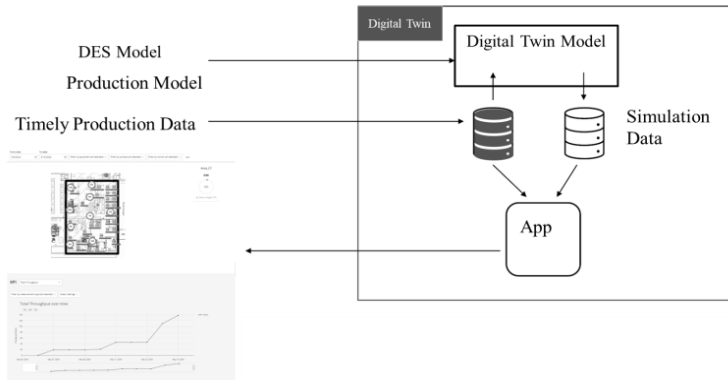


Figure 7: Digital twin application

Figure 8 presents an example of a comparison of two simulated scenarios in the digital twin tool to illustrate how results are visualized. In this particular case, the user has decided to change the number of workers in the factory (i.e., workforce), affecting overall equipment effectiveness (OEE), worker productivity, and throughput.

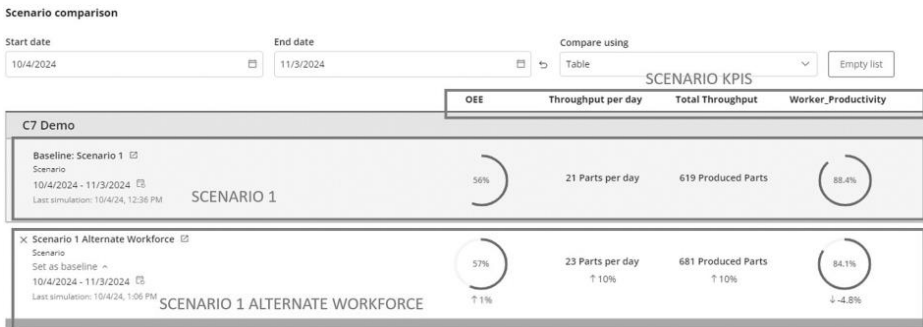


Figure 8: Scenario Comparison on digital twin tool

5. Analysis

This chapter addresses the research questions by examining the requirements, sources of complexity, and development process of digital twins. It begins with an exploration of the key requirements for digital twin development. Next, it identifies and explains various sources of complexity in digital twin development. The chapter then details the development process, providing a step-by-step overview of how digital twins are developed. Finally, it integrates these insights, offering an overarching view of the interplay among requirements, complexity, and development processes in digital twins.

5.1 Requirements of Digital Twin Developments

- *RQ1: What key requirements must be considered when developing digital twins for production systems?*

The development process of digital twins for production systems demands a thorough understanding of various critical requirements across various phases, from design to implementation. Requirements not only enable the digital twin to function correctly, but also to fulfil their goal and meet stakeholders' and organizations' expectations. In line with previous research (Agrawal et al., 2022), the findings point to the importance of having a holistic perspective when identifying critical requirements (i.e., it is not sufficient to focus only on technical requirements; there is a need to include process and people requirements as well).

1. Technical requirements:

The findings of Paper 1 underscore the significance of accuracy and synchronization as pivotal technical requirements for digital twin development, a conclusion that corroborates prior research (Durão, Haag et al., 2018). It is essential to achieve precise near-real-time synchronization between physical systems and their digital counterparts (Barricelli, Casiraghi et al., 2019). Without accurate data and models, predictions made by digital twins become unreliable and practically ineffective.

One contribution of this research, as illustrated in Paper 3, is that using a digital twin application may allow the factory to motivate the improvement and correction of its master data. Data and model synchronization is required to ensure that changes in the physical system are promptly reflected in the virtual environment and that there is no divergence from reality. The digital twin developed in Paper 3 demonstrates the importance of automatic synchronization and updates in models and data. Human data entry by a modeller should only be considered for significant changes to the physical system.

Although real-time updates are frequently emphasized in the literature (e.g., Durão et al., 2018a; Ruppert & Abonyi, 2020; T. Uhlemann et al., 2017), it may not always be necessary for data to be updated in real time. The findings presented in Paper 3 indicate that, in many instances, the delivery of data in a timely manner may be sufficient, provided that it aligns with the operational requirements of the digital twin. This perspective broadens our understanding of the synchronization requirements, suggesting that the frequency of data updates should be context specific rather than universally in real time.

2. Process requirements:

In the context of developing digital twins for production systems, several key process requirements have been identified in Paper 1, including adaptability, reusability, maintainability, and revision handling. These requirements underscore the importance of developing novel approaches to working practices and highlight the need for structured change management processes. For example, as illustrated in Paper 3, the role of the modeller has expanded to encompass a broader scope of responsibilities, including data management, model development, system integration, and data transfer, in addition to the modelling tasks typically undertaken in traditional simulation development processes. Change management facilitates the transition that shop-floor teams must undertake to rely on outputs from the digital twin system when making decisions.

In order for a digital twin to be maintainable over time, it is essential for relevant governance structures to be in place. Governance is of equal importance in defining the responsibilities for managing digital twins, clarifying the accountability of data and models, and establishing procedures for use, updates, and revisions. For instance, it is necessary to determine who is responsible for ensuring that the data quality is continuously good and who is responsible for updating the model in the event of significant changes in the production system. It is essential to maintain up-to-date data and models to ensure accuracy (Ferko et al., 2022).

The papers identify collaboration across teams as a further key requirement. Developing digital twins entails the utilisation of different technical models, data, systems, and managerial skills. Digital twin development processes are characterised by multidisciplinary collaboration (Kober et al., 2024). For example, clear and effective communication between data

collectors and data consumers is essential in order to ensure that the data requirements for the appropriate modelling of the digital twin are met (see Paper 3).

3. People requirements:

For accepting the digital twin implementation by the shop floor, scalability, explainability, and accessibility are critical requirements identified in Paper 1. The most crucial requirements are scalability, or the potential for scalability from a small-scale use case that can be replicated in other parts of the factory or even other factories, and reusability. The capacity for scalability serves to augment the impact of the digital twin.

From the standpoint of people requirements, accessibility on the shop floor has been inadequately addressed. To illustrate, the prevailing view is that digital twins are the domain of digital twin developers and data scientist. This research, however, offers insights that should be incorporated by team managers, production planners, and flow leaders, not only by simulation and data engineers. It is also essential to provide an explanation of the methodology used to generate the predictions in order to fulfil people requirements. The findings indicate that, if the process of prediction generation is not transparent, the reliability of the digital twin will be called upon and not accepted by the operational teams.

A people-centric approach to the development of digital twins for production systems is one in which individuals are empowered to determine which KPIs they wish to view and which scenarios they wish to test, based on their requirements. However, it has become evident that the perspectives of maintenance engineers, team managers, production planners, and those involved in new product introduction differ significantly. Consequently, there is no digital twin applicable in all contexts. For individuals to perceive the value of a digital twin, they must be able to discern its immediate applicability to their daily tasks and how this can be integrated into their existing processes. For instance, integrating a digital twin into daily planning tasks is likely to facilitate greater acceptance. This is connected to the question of how much the solution should be tailored to suit the specific requirements of the situation.

In the process of developing digital twins, the requirement for reducing computation time and accelerating simulations has been identified (Singh, Weeber, et al., 2021, do Amaral, Montevechi et al., 2022). However, this is not always the case. It is important to consider the decisions that the individual must make and the time required to make them. Indeed, the speed of the model is dependent on the requirement for a rapid decision. To further explain this, the planning of the subsequent month may not be a matter of great urgency. However, in the event of a machine malfunction on the shop floor, a prompt decision-making process may be required.

In order to satisfy the accessibility and explainability requirements identified by this research, it is essential to provide individuals with the necessary training and skills to utilise digital tools effectively. Furthermore, it is crucial to determine which individuals should have access to the digital twin and whether these individuals are capable of interpreting the results without the requirement for specialized training or role-specific views. In addition, the models should be explainable in a manner that facilitates comprehension and interpretation, enabling stakeholders to derive actionable insights and make informed decisions based on the simulation outcomes.

The findings contribute to the literature on digital twin requirements by providing contextual insights into what these requirements imply when viewed through technology, process, and people dimensions. Whereas previous research (Durão et al., 2018a; Kober et al., 2022; Shao & Helu, 2020) primarily emphasizes technical requirements, this study broadens the scope by examining the need for process and people-related requirements, such as explainability and accessibility, which are critical yet underexplored.

5.2 Sources of Complexity in Digital Twin Developments

- *RQ2: What are the sources of complexity when developing digital twins for production systems?*

The complexity inherent in digital twin development presents sources that stem from physical, virtual, and process complexity, which must be considered from the early design stages through implementation. Based on both our data and the literature (Atkinson & Kühne, 2021; Robinson, 2022), it becomes evident that complexity originates from multiple sources — primarily, from the physical entity being modelled, the virtual entity itself, and the development process. Understanding these sources is essential to managing and mitigating the challenges of the development process of digital twins.

1. Complexity from physical system:

Developing a digital twin introduces complexities that can arise from various sources inherent in the physical system being replicated. The first of these is the availability of accurate data collected from the physical production system, which must be sufficient to feed into the digital twin (Friederich et al., 2022b). The absence of data collection systems and the presence of poor quality data will increase the complexity of such a development.

One potential source of complexity is the inclusion of a physical scope that is too expansive and exhibits a high level of interrelatedness for the digital

twin. For example, the scope may range from a single machine to an entire factory, and it is essential to consider all relevant indicators of complexity. A method of elucidating these elements of complexity is through the examination of the number of relationships and interactions within a system, as discussed in Paper 2. It can be posited that the greater the number of interactions and elements within a production system, the higher the level of complexity. To illustrate this, it is often more straightforward to model a system that follows a linear flow and has a consistent throughput than one that involves multiple machines and crossflows.

One significant source of complexity can be attributed to human factors, both within the production system (Gubanova, 2021) and in the processes of data extraction and reporting. The data indicate that automated systems are typically more accurate, thereby facilitating more precise modelling. As discussed in Paper 2, the modelling of manual systems is inherently more complex due to their inherent unpredictability. Similarly, data synchronization often relies on human input, which can introduce inconsistencies and errors, as found in Paper 2. This can occur, for example, in the documentation of incidents in production, such as the documentation of downtimes and reasons or rework and reasons (Bokrantz et al., 2018), which further contribute to the complexity of developing a digital twin.

2. Complexity from virtual system:

The virtual system has the potential to introduce a considerable degree of complexity into the development of a digital twin. Low modelling skills or unclear simulation objectives have been identified as potential causes of complexity (Chwif et al., 2000). This is a similar phenomenon to that observed in cases where multiple objectives are present, which can also contribute to overall complexity.

Increasing the requirement of objectives a model must fulfil adds to its overall complexity, consequently extending the time needed for development. In order to achieve this, a greater quantity of data is required, a greater number of KPIs must be validated, and a greater level of detail is necessary.

A further key indicator of complexity derived from critical technical requirements is the high degree of accuracy identified in Paper 1. Such accuracy will entail a greater investment of time in modelling to contain the full range of details observed within the digital twin model, thereby increasing the overall complexity. This finding support existing literature, which suggests that complexity applied to models indicates a relationship between the level of detail and the overall complexity (Robinson, 2022; Webster et al., 1984) or between the capacity to understand the model and complexity (Golay et al., 1989).

3. Complexity from process:

The process of developing digital twins introduces a unique set of complexities, particularly when the solution must be adapted to align with the specific requirements of the individuals and the production system. If the solution is to be highly tailored to the specific individual and factory in order to fulfil the people requirements identified in Paper 1, the complexity of development will increase, as more work will be required on low-code interfaces to adjust the different views and customize the KPIs that the specific individual wants to see as well as how often they want these KPIs loaded into the application from the model.

Another source of complexity is the technical requirement of system integration, which must be considered. As discussed in Paper 2, in order to feed data into the digital twin, numerous systems may need to be integrated. However, if the integration relies on a single system capable of aggregating all the necessary data for updating the digital twin, it significantly reduces the complexity of development.

Furthermore, the process of developing digital twins has emerged as a source of complexity due to the lack of clarity surrounding it. For instance, the manufacturing industry is still in the process of determining the best approach to its development, as evidenced by this research, which led to the study of the process, as discussed in Paper 3. It is evident that close cooperation with software suppliers is required, which indicates that the process is still in its early stages of development and is highly complex. Paper 3 also identified the necessary steps for a manufacturing company to tackle complexity.

This research contributes significantly to the theoretical understanding of digital twin development, addressing complexities that have not been explored in prior studies. In addition, it has significant implications for the managerial and modelling aspects of digital twin development. Manufacturers can readily assess the complexity of their production systems and identify potential complexities in developing a digital twin. This allows them to select an appropriate level of complexity when developing digital twins for production systems and to develop strategies to address identified complexities in collaboration with software suppliers.

5.3 Digital Twin Development Process

- *RQ3: How can the development process of digital twins for production systems be supported?*

Developing a digital twin requires a systematic approach that addresses the goals, core activities, and expected results across each phase of the development process lifecycle: design, modelling, and implementation. By breaking down the process into these distinct phases, manufacturing companies can better manage the complexity inherent in the development of digital twins.

1. Design phase:

During the design phase, the complexity of the physical system directly impacts how the digital twin will be structured. Complex systems often involve multiple data sources and types (e.g., sensors, manual inputs, and historical data). In this phase, a comprehensive assessment of the development process's complexity is essential, considering the three identified dimensions: physical system, virtual system, and process. The cost-benefit analysis will be contingent upon the number of complexities present in the digital twin development process, as identified in Paper 2. It can be reasonably deduced that greater complexity will result in more expenditures of effort and costs.

Individuals' requirements further dictate design specifications. Different individuals may require varying levels of detail and different interfaces to interact effectively with the digital twin. It is essential to consider individuals' skill levels and training capabilities when designing a digital twin.

The design phase encompasses the definition of development process objectives; the specification of requirements pertaining to technology, process, and personnel; the delineation of use cases; and the assessment of production system and data acquisition infrastructure (Segovia & Garcia-Alfaro, 2022; Shao & Helu, 2020). The result of this phase is a documented development process specification that outlines the digital twin architecture and data structure as well as a cost-benefit analysis and feasibility study.

2. Modelling phase:

In the modelling phase, the established requirements serve as a foundation for the selection of appropriate modelling techniques and tools. A promising approach for the selection of tools and modelling techniques is to consider a type

of model or technique already utilised in the company, potentially as a static model. The incorporation of dynamic capabilities into existing models is a valuable strategy to also reduce the complexity of development.

During the modelling phase, production data are collected and prepared, and a digital twin model is developed to accurately capture the behaviour of the shop floor and its visual and physical aspects, as identified in the technical requirements. As demonstrated in Paper 2, the degree of accuracy required for the digital twin will inevitably lead to a corresponding increase in the complexity of the development process. Moreover, digital twin systems must be updated and initially created from production data logs (Friederich et al., 2022b; Overbeck et al., 2023), thereby fulfilling the technical requirement of synchronization when data logs are updated continuously. Following this phase, an offline digital twin model is produced, which can then be employed for experiment design and analysis, thereby fulfilling the technical requirement of data analysis at this stage.

3. Implementation phase:

Finally, the implementation phase requires developing a production interface; integrating data sources, models, and interfaces; and testing and verifying the digital twin application's usability and functionality (Biller & Biller, 2023; Segovia & Garcia-Alfaro, 2022). The implementation of a user interface during this phase allows the realization of the people's requirements, particularly those pertaining to individual needs as outlined in Paper 1. As stakeholders engage with the system, the feedback collected during this phase can inform adjustments to the digital twin's design and functionality. When individuals perceive that their input is valued and leads to tangible improvements, they are more likely to engage with the digital twin actively and contribute to its success. Ultimately, the output of this phase is a connected shop-floor digital twin application that can be used for near real-time monitoring and optimization of the shop floor. Process requirements to ensure that the digital twin system adapts and is maintained should be introduced, such as real-time production data and automated updates (Overbeck et al., 2023).

The findings contribute to the literature on digital twin development by clearly specifying a stepwise approach to digital twins for production systems. Providing a list of activities based on industrial insights can allow us to clarify the digital twin development process and make better choices through the development process of digital twins. Paper 3 also identifies best practices or learning that can support managers and organizations aiming to develop digital twins for data-driven decision-making. It is important to note that each phase has development trade-offs among requirements, such as choosing the right fidelity level and considering the development process time and cost.

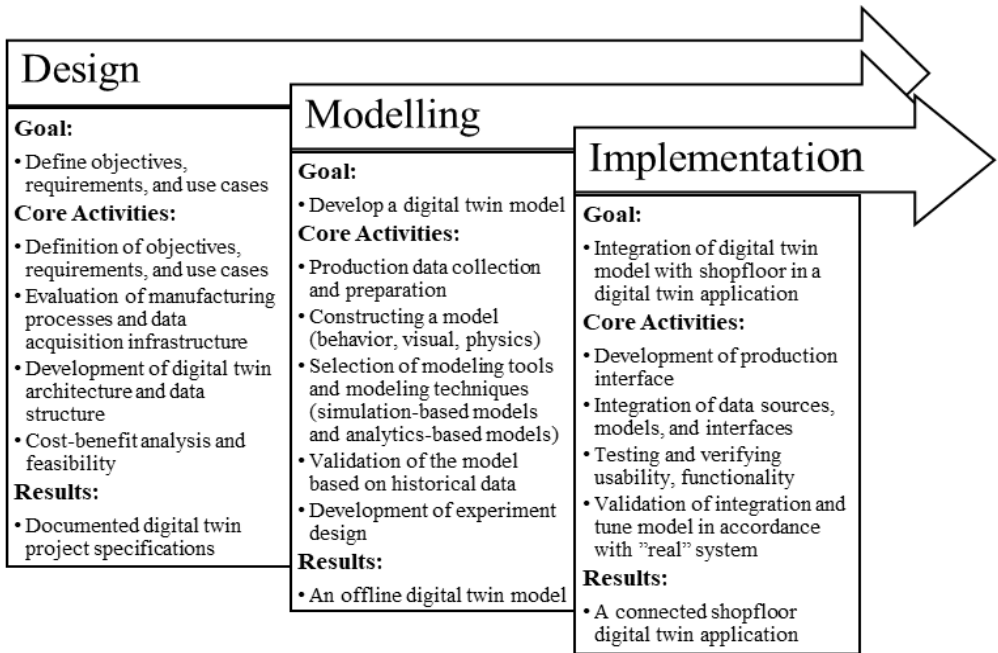


Figure 9: Activities for developing digital twins for production systems

A complete list of activities is provided in the reprint of Paper 3

5.4 Overview of Requirements, Complexity, and Development Process of Digital Twins

Figure 10 presents a framework for developing digital twins, illustrating the connections among the design, modelling, and implementation phases. It identifies the complexities that modellers and managers are likely to encounter throughout the digital twin development process.

The framework provides an overview of the principal activities in each phase of the development process, thereby facilitating understanding of both the required outcomes and the associated complexities. The framework integrates considerations of human, technological, and process factors, providing a comprehensive view of the entire development process from multiple perspectives. In contrast to many digital twin development methodologies that focus predominantly on the virtual space, this framework also emphasizes the importance of the physical space, highlighting how complexities in the physical domain can lead to challenges in the virtual domain.

It is essential to consider the interrelationship among people, processes, and people requirements across all phases of the digital twin development process, as these factors must be continuously taken into account throughout the entire process. The complexity of the physical system was placed on the design phase, as the evaluation of the production system infrastructure, processes, and the scope of physical systems are typically conducted during this phase for digital twins. The virtual complexity was placed on the modelling phase, as it primarily influences the modelling of the system. Finally, the process complexity was placed on the implementation phase, as this is when diverse system integration and the lack of methods to calibrate the physical system with the virtual system can occur. However, it is important to note that the physical, virtual, and process elements within a given system are not isolated, but rather interact and influence one another.

By methodically examining each dimension, this framework enables teams to identify and address potential challenges in digital twin development processes for production systems. It can be utilized as a checklist or roadmap throughout the design, modelling, and implementation phases, encompassing technical functionality, individual engagement, and long-term process alignment. This structured approach can enhance the effectiveness of the development process of digital twins for production systems.

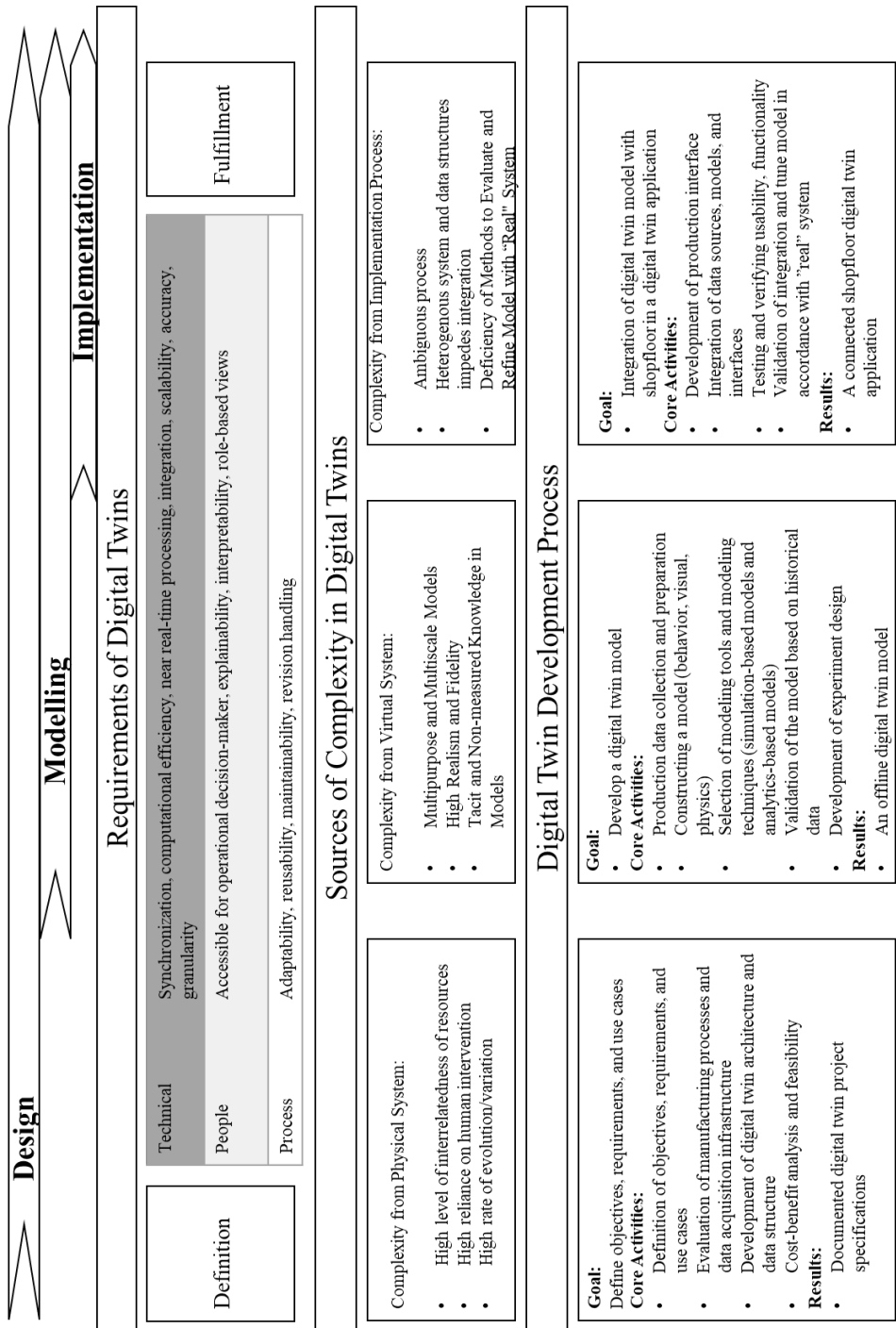


Figure 10: Framework to support digital twin development processes for production systems

6. Discussion and Conclusion

This final chapter presents the conclusions of this licentiate thesis. Academic and industrial contributions are outlined. It also describes avenues for future research.

In this licentiate thesis, a significant challenge was initially identified: the process of developing digital twins for production systems has received limited research attention thus far. To address this identified gap, this thesis has explored the development process of digital twins for production systems. To fulfil the purpose, the focus has been on requirements, sources of complexity, and the development process of digital twins. The framework highlights that the design, modelling, and implementation phases are frequently concurrent and overlap in digital twin projects. Furthermore, an analysis of the elements was presented, based on the findings of a longitudinal single real-time case study. The findings highlight that it is crucial to adopt a structured approach to the digital twin development process. This work serves as an initial attempt to provide guidance to both academic and industry practitioners on the development process of their digital twins. Therefore, a novel process framework for the development process of digital twins, comprising three discrete phases, has been proposed.

6.1 Discussion

Building on the insights explored in this thesis, a discussion emerges on the role of digital twins in industry. The insights from this research on the industry work indicate that digital twins are a personal concept that currently reflect the views of the individual seeking to achieve the digital twin. In addition, there is a lack of consensus on the enterprise level regarding the agreement on a digital twin concept. For example, an automation engineer may express a desire for a digital twin, as may a planning engineer, a mechanical engineer, or a design engineer. Each of these professionals may have different considerations and requirements for their digital twin, which may result in a disparate understanding of what constitutes an optimal digital twin.

This research process yielded significant insights, with one of the most pivotal being the realization that digital twins are not merely models. At the outset

of this research, a digital twin was conceived as a model within the context of computer simulation software. However, this research revealed that digital twins are a system comprising sensors, data collection systems, data lakes, models, simulation servers, and user interfaces, which collectively provide an output for users to make more informed decisions (Tao & Zhang, 2017). Indeed, when contemplating a digital twin of a production system, it becomes evident that a vast network of digital systems and software, including PLM, MES, maintenance systems, quality systems, and energy systems, collectively represent the entire production system. It can thus be argued that this digital footprint works together to enable and support the production system, which represents a potential model for digital twins as a whole. This finding contrasts with the alternative view of digital twins, in which a digital twin is created for each specific functionality and use, and the production systems are comprised of numerous smaller digital twins that communicate with each other. This latter view appears to be more prevalent in current research. This results in a loss of perspective, which in turn facilitates local optimizations of specific elements within the production system. However, it becomes challenging to identify and optimize the production system in its entirety when viewed through these multiple perspectives. Consequently, local optimizations that are suboptimal for the system are implemented without first searching for a global optimization of the production system (Lidberg, 2024).

The concept of digital twins has been identified as a pivotal element in the domain of smart production (Friederich et al., 2022; Leng et al., 2019; Lu et al., 2020; Moiceanu & Paraschiv, 2022; Novák et al., 2020; Raffaelli et al., 2021; Tao et al., 2019). It represents the pinnacle of smart production transformations, wherein sensors and systems are deployed and a comprehensive representation of manufacturing objects and their behaviour is created. This representation can then be visualized in dashboards, 3D, or extended reality technologies. Digital twins represent the central topic of this transformation, as the mere capture of data from sensors or visualization in extended reality technologies is of limited value if there is no organized virtual representation of the production system or its constituent elements. Therefore, it can be argued that the full potential of data, sensors, and visualization technologies is not realized in the absence of digital twins. This finding underscores the centrality of digital twins in the context of smart production. This centrality is reflected in the evolving definition of digital twins, which adapts to the rapid advancements in digital technologies.

The definition of a digital twin has evolved to encompass a broader range of capabilities, including real-time, lifecycle management, intelligence, and self-learning properties (Barricelli et al., 2019; Newrzella et al., 2022). This expansion in functionality has introduced new complexities in the practical realization of digital twins, which has undoubtedly proven challenging to achieve in the context of a larger physical production system. Nevertheless, such developments have been successfully achieved in warehouses, products,

and specific industry processes, particularly in the context of process industry and unit-level digital twins that focus on a single machine. In the context of a broader system, there is always a certain degree of data incompleteness, inconsistency, or quality issues. Furthermore, the lack of automation in the data extraction, cleaning, modelling, and learning processes from the physical environment represents a significant challenge for organizations seeking to develop digital twins, as numerous steps and elements must be accurately aligned. Consequently, any limitations in the definition of digital twins when humans are central in the systems and not all data are automatically collected should be addressed. To quickly reflect the real world, it must be a highly reliable, automated, and efficient system with no human intervention, but ultimately controlled by humans to facilitate informed decision-making in the production context. Given these complexities, one might question whether digital twins can truly achieve the level of seamless integration and accuracy required to be fully viable in large-scale, highly dynamic production systems.

It would be beneficial to ascertain whether it is feasible to create a fully visual, fully immersive replica of reality that is 100% accurate. The term "twin" in "digital twin" suggests a close, almost identical relationship between two entities. However, although the word "twin" evokes this notion of identity, digital twins are rarely, if ever, completely identical to their physical counterparts. The question thus arises as to whether this is indeed the case. The primary purpose of models is to effectively represent reality good enough to inform decision-making. Consequently, the mere act of enhancing the accuracy of virtual representations may result in the incurrence of additional costs and development time, which is contrary to the fundamental objective of modelling. Moreover, a fully predictable and 100% accurate system will only be feasible when sensors are installed in every machine and process and every stock level is controlled, with the inclusion of energy readers to account for this variable. Once this is achieved, production will become autonomous, with no human interference in the production systems. Imagine a production facility where autonomous guided vehicles (AGVs) drive seamlessly between workstations, coordinated with robotic arms that pick up and place items while intelligent conveyor systems dynamically transport products — all synchronized in a fully automated, self-orchestrating, and self-optimizing flow.

The realization of the perfect digital twin for larger production systems is not likely in the near future. Consequently, the key to the future of digital twins in production systems lies in simplification. In order for lines and plants to be continuously simulated and predicted in the near future, it is necessary to simplify the process. Simplification of the development process of digital twins is essential, including automated modelling, chat GPT-assisted modelling, and similar techniques (Freitag & Hildebrandt, 2016; Jackson et al., 2024; Reinhardt et al., 2019). In addition, the solution should be easily maintainable and not dependent on expert knowledge from a development point of view; for the

users of digital twins, the need to have a Ph.D. level of knowledge to develop and use a digital twin should not be required.

In conclusion, considerable progress has been made in order to make digital twins a reality in production systems. However, it will likely take many years to achieve a photorealistic and 100% accurate representation of the production system. In the meantime, it is necessary to make a number of trade-offs and compromises in order to make progress towards this goal of developing system-level digital twins for production systems.

6.2 Scientific Contributions

The scientific contributions of this licentiate thesis include identifying and categorizing challenges and requirements related to the development of digital twins, addressing RQ1. Structuring these findings into technical, process, and people dimensions provides multiple perspectives. Although previous studies have emphasized technical requirements (Durão et al., 2018a; Kober et al., 2022; Shao & Helu, 2020), this research highlights the overlooked people and process requirements rather than providing only technological requirements. Consequently, it offers a multifaceted perspective for researchers and practitioners in digital twin requirements.

Another significant contribution of this study is the exploration of sources of complexity in digital twin development, which has been overlooked in existing literature. Applying this theoretical frame of reference, which has been used in other fields (Atkinson & Kühne, 2021; Brady & Davies, 2014; Caldarelli et al., 2023), uncovers the origin or root of previously identified issues. It identifies sources of complexity involved in the development of digital twins in production systems that can be attributed to different factors, such as the physical environment being modelled, virtual models, and the process itself. It provides understanding on how complexity arises in different phases of a digital twin development process, as shown in Figure 10. The answers to RQ2 support researchers and practitioners in identifying, anticipating, and mitigating the complexity that they will encounter during the digital twin development process. Therefore, the thesis extends the surface-level challenges typically discussed in digital twin research (Attaran & Celik, 2023; Fuller et al., 2020; Kober et al., 2022; Mendonça et al., 2022). For instance, the physical production system can have a high number of manual processes and great variability, increasing the complexity. Moreover, the process itself can be a source of complexity due to unclear procedures and specifications and miscommunications related to terms and expectations.

This research process distinguishes itself from previous research by offering a holistic, structured process to digital twin development for production systems that covers the entire process rather than focusing on isolated phases

or activities. Prior studies have tended to focus on specific aspects of digital twin development process for production systems, such as model development or real-time data integration techniques (Friederich et al., 2022a; Ruppert & Abonyi, 2020; Tao et al., 2022), without providing a cohesive view of the entire development process. This thesis fills this critical gap by offering a process that considers the interconnections between different phases of development process, from initial design and formulation to final implementation, and emphasizes a coordinated approach that addresses both technical and non-technical challenges. The process also provides grounds for future researchers to systematically describe, organize, and advance digital twin development process in a more structured and coherent manner, facilitating further advancements in the field.

6.3 Industrial Contributions

The results of this research stem from collaborative efforts with industrial partners in exploring the development process of digital twins for production systems. Therefore, this research contributes to the transition to adaptive, resilient, and data-driven production systems and supports industry partners in leveraging digital twins. By developing digital twins, industries can optimize operations in real time and improve decision-making processes through data-driven insights. These models enable manufacturing companies to shift from a reactive to a proactive approach to production management, making quicker and more informed decisions.

The findings of this research are particularly relevant to industrial practice, identifying the requirements, complexities, and activities when developing a digital twin. This includes the collaborative nature of the project, which incorporates industry feedback to ensure that insights, methods, and models are both technically sound and practically applicable in industrial settings. Through this approach, companies can find new optimization opportunities in areas such as capacity planning, scheduling, and throughput.

The findings of this research argue that a key development process aspect is the democratization of simulation tools, enabling non-technical individuals (e.g., managers, production planners, and maintenance engineers) to directly interact with these models for decision-making purposes. This can contribute to a culture of continuous improvement, where simulating production becomes integral to daily operations. The findings of this research give credibility to the claim that the development of digital twins provides a competitive advantage for manufacturing companies transitioning to data-driven production systems.

Furthermore, the framework shown in Figure 10 makes a significant industrial contribution by systematically connecting the design, modelling, and

implementation phases, thereby offering a roadmap for addressing practical challenges in the development process of digital twins for production systems. The framework's managerial implications lie in its ability to guide managers through each development phase by highlighting critical human, technological, and process factors, thereby ensuring that decision-makers can proactively navigate potential complexities.

6.4 Limitations and Future Research

This licentiate thesis examines the development process of digital twins for production systems to facilitate data-driven decision-making within manufacturing companies. However, one major limitation of this research is its focus on a generalized development process of digital twins for production systems, which may not adequately address the specific choices and variations required for different contexts and applications. This limitation highlights the need for further research to evaluate these contextual factors

Based on the findings, this thesis also presents different directions for future research. As this thesis presents the findings of a single manufacturing case company, a logical next step is to validate these findings through a multiple-case study approach, allowing for a broader examination of their applicability across various contexts. The process of theoretical sampling involves identifying cases that either extend emergent theory or replicate prior cases (Eisenhardt, 1989) to identify a reference population of possible cases.

Furthermore, the maintainability and time to develop digital twins remain challenges today, as each digital twin is developed for a specific application, user, and set of goals and KPIs. One avenue for future research could investigate the standardization and simplification of data, interfaces, and models to maximize the development and use of digital twins within different application areas and contexts, thereby reducing development efforts and enabling scalability.

This thesis focuses on the developer's perspective for the development process of digital twins. The study can be further complemented with a user-centric approach, evaluating the development process from the perspective of users to complement developers' views.

Finally, future research can focus on applying multicriteria decision analysis (MCDA), which could help in evaluating development decisions within the digital twin development process. This approach can assist by prioritizing different activities and features based on factors such as user needs, resource availability, and technical feasibility.

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Appendix 1: Interview guidelines

The purpose of this interview is to get a deeper understanding of how Digital twins are currently used at Alfa Laval and to identify digital twin adoption opportunities.

How results will be used: After all interviews, we will summarize and present the results. The results will also be used to define my research scope. You as respondent will be kept anonymous when sharing the results of this study.

Any questions before we start?

Ask if it is okay to record the interview.

General questions:

1. What is your current job role? How many years have you had this job role?
2. How many years have you worked at Alfa Laval?
3. How many years of experience do you have related to digitalization in production?

Overall - Digital twin:

1. What does digital twin mean to you?
2. Do you know if Alfa Laval has a defined vision for the digital twin?
3. Can you explain?
4. According to you what are the main “constituents”/fundamentals of a digital twin?
5. Do you know if Alfa Laval has today “digital twins”?
6. In which areas do you apply digital twins?
7. Can you describe how Alfa Laval’s is working today with digital twins?
8. According to you, what are the current and potential opportunities of implementing digital twins?
9. What strengths can digital twins bring to Alfa Laval’s development?

10. Do you have an example from Alfa Laval in which a digital twin was successfully implemented?
11. According to you, what are the potential threats that can challenge the development towards using digital twins?
12. What are the current and potential weaknesses/limitations that Alfa Laval has to implement digital twins?
13. Can you share a real application example from Alfa Laval about how weaknesses/limitations challenged development/ use of digital twins?
14. How do you handle (or plan to handle) these weaknesses/ limitations?
15. What competencies do you think are required to work with digital twins?
16. Do you think we have the necessary competencies to work with digital twins? What is lacking?
17. Do you think a global or a local approach should be pursued for the implementation of digital twins?