STOCKHOLM SCHOOL OF ECONOMICS

MASTER THESIS

Artificial Intelligence in Manufacturing – Value Delivery

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Abstract

The manufacturing industry faces challenges resulting from technological development. Reports are claiming that incumbent firms push the development in various ways as a result of their market power. Artificial Intelligence (AI) is increasing in use, enabling new types of product and service offerings which allows and forces firms to innovate their business models but not least their operating models. In this abductive research study, employees from six manufacturing firms have been interviewed. By utilizing the Operational- & Business Model Alignment and the Nested Business Environment Framework, an answer to what the effects of AI-development are on value delivery in manufacturing firms has been achieved. Three categories have been identified where AI-development is currently happening in manufacturing firms: *Servitization, Supply-Chain & Support Functions,* and *Smart Manufacturing*. The three components of value delivery which are *scale, scope,* and *learning* were studied, and it was found that the effects on these following AI-development depend on the category and stage of transformation the category finds itself in. In identifying these effects it was found that the unconstrained growth associated with digital operating models incorporating AI is to a certain degree limited by the effects AI-development has on value delivery and consequently the operating model. This paper highlights the importance of understanding the transformation that value delivery undergoes as a consequence of AI-development. The findings aim to aid manufacturing firms in understanding this change process and what appropriate strategy to adopt in order to achieve the best possible long-term results for the business.

Title
Artificial Intelligence in Manufacturing - Value Delivery

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Table of Abbreviations

Notion	**Abbreviation**
Artificial Intelligence	AI
Battery Electric Vehicles	BEV
Digital Manufacturing	DM
Digital Twin	DT
Estimated Time of Arrival	ETA
Information Technology	IT
Intelligent Process Automation	IPA
Intelligent Document Processing	IDP
Machine Learning	ML
Robotic Desktop Automation	RDA
Robotic Process Automation	RPA
The Nested Business Environment Framework	The NEST Framework

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1 Introduction

1.1 Topic and Problematization

New realities emerge for companies as a result of digital technologies transforming most industries (Steiber et al., 2020). One industry affected is the manufacturing industry which is facing significant challenges when it comes to digital transformation and implementation of Artificial Intelligence (AI), and the consequences are still uncertain. The ongoing technological disruptiveness within manufacturing is one of the great challenges ahead. Interestingly, Coccia (2018) claims that industrial change is driven by incumbent firms as they possess the organizational structure and market power to support implementation. Evans (2017) made a distinction between, AI, robotics, networking, and advanced manufacturing, where AI-development is likely to be the backbone allowing for new products and services to be offered. Incumbents are trying to adapt their business models as a response to the rapid technological advancements permeating most of the business landscape (D'Ippolito, Petruzzelli, and Panniello, 2019). When it comes to manufacturing companies that have been more analog historically, this challenge can be an everyday struggle and it is important to deal with this appropriately as we are entering the age of Industry 4.0.

1.2 Previous Research and Research Gap

As Industry 4.0 emerges, AI will be one of the building blocks ensuring that the manufacturing industry can stay competitive. Zeba et al. (2021, p. 1) claim that, "Manufacturing is undergoing a transformation from intelligent manufacturing, which is knowledge-based, to smart manufacturing, which is knowledge-enabled and data-driven." Research on AI has increased since the term Industry 4.0 was introduced (Zeba et al., 2021). There is also a shift where manufacturing firms are forced to move from a mainly transactional and product-based business model approach, towards more relationship- and service-focus. Enholm et al. (2021) state that this service-trend and the increased demand for more individualized products and services, force companies to move towards more AI adoption.

Today, around 80% of large companies have adopted some form of AI in their business models which is an increase of 70% in the last five years (Makarius et al., 2020). Existing research on AI increases (Zeba et al., 2021). Most research focuses on various technologies built on AI rather than enablers for adoption (Kinkel, Baumgartner, and Cherubini, 2022). Benefits of AI-use range from making predictions, increasing efficiency and enabling better real-time optimization (Townson, 2021). AI is more than capable of making the same predictions as an employee in some cases and the advantage AI has over humans is that it has a pre-programmed decision-making procedure (Soelberg, 2017). Consequently, AI enables more consistent decision-making (Dick, 2019). In light of this, there are businesses that are well-positioned to take full benefit of such digitalized systems whereas others need to introduce new ways to create value for their customers (Iansiti and Lakhani, 2020).

The manufacturing industry is one of the industries that dominate digital transformation and business model innovation research. The research focus has mainly been to understand the impact of new disruptive technologies and to identify processes to transform. However, few studies have focused on how the process transformation takes place (Vaska et al., 2021). Thus, this paper will focus on transformation, the operational effects resulting from AI-use, and what this means for manufacturers' ability to deliver value moving forward. As a result, the research gap that this thesis aims to close relates to the operational effects of AI-development in manufacturing firms.

1.3 Thesis Purpose and Research Question

Manufacturers need to consider and implement AI into their roadmap for the future to stay competitive (Lee et al., 2020). To be competitive, manufacturers need to digitalize their business models, but not least their operating models. This has proven to be a struggle for many because of barriers related to their existing operating model and business model (Iansiti and Lakhani, 2020), but also due to a lack of digital vision (Sjödin, Parida, and Visnjic, 2022). Manufacturing firms that up to this point make a lot of profit from their analog business practices might be reluctant to install the changes needed as it might not evident how it will be value-adding short-term. Looking at how these changes impact the operating model is a way for manufacturers to make better strategic choices.

The operating model details the value delivery-strategy of a business. The value delivery for manufacturing firms is a prerequisite for sustained competitive advantage, and such value can arise from the engagement in digital servitization using AI-capabilities to enhance workflows and processes (Sjödin et al., 2021). The emergence of AI will thus influence manufacturers' ability to deliver value to customers. Therefore, the research question is as follows:

What are the effects of AI-development on value delivery in manufacturing firms?

Being aware of how to incorporate AI usage into the existing operating model is important for a long-lasting technological edge. The research findings of this thesis can hopefully bring great value for manufacturing firms, by showing how AI-development affects the operating model and to advise on what strategy to adopt for AI-projects.

1.4 Delimitations

This study concerns AI and manufacturing firms operating in Sweden. A manufacturing firm, also called an industrial organization, is one that develops and supplies products for its customers (Kärkkäinen, Piippo, and Tuominen, 2001). AI is defined as, "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Haenlein and Kaplan, 2019, p. 5). This thesis aims to get a better understanding of AI and the meaning behind AI-transformation strategies in practice in manufacturing firms, by interviewing various people employed in manufacturing firms operating in Sweden, that work with AI somehow within the organization.

2 Literature Review

The literature review follows a funnel approach based on the chosen research topic, namely AI in the manufacturing industry. Therefore, starting with the two main components: manufacturing firms and AI. Based on the literature, the main use for AI was identified as being automation. Next, connecting the identified areas of use to value delivery to map how AI as a competitive tool, is used in the manufacturing industry.

2.1 Manufacturing Firms

Digital technologies transform most companies and industries (Steiber et al., 2020). Hence, manufacturing companies' abilities to respond to these changes are vital, and this digital transformation has functioned as a catalyst forcing management to adopt new product processes to achieve a sustained competitive advantage (Cooper and Kleinschmidt, 1991). Zawislak, Fracasso, and Tello-Gamarra (2018) found that firms can be highly innovative without being technology intensive. Thus, the importance of having other innovative capabilities is outlined, such as technological, operational, managerial, and transactional capabilities (Zawislak, Fracasso, and Tello-Gamarra, 2018). Digitalization boosts new product success and company competitiveness in manufacturing firms (Salmen and Ryglova, 2022). Interestingly, technological change is suggested to come as a result of the existence of disruptive firms rather than disruptive technologies. Industrial change is said to be driven by incumbents as opposed to entrant firms since incumbents possess the market power and structure to better support path-breaking innovations across markets (Coccia, 2018).

At present, there is a movement where manufacturing firms move towards offering product-service-related bundles, heavily assisted by machines, as opposed to the product-focused logic that historically has been the dominating strategy (Chowdhury, Haftor, and Pashkevich, 2018). Martìn-Peña, Sànchez-Lòpez, and Garrido (2020) mean that this demonstrates the shift in the industry from merely producing and selling a single product to instead offering integrated solutions catering to each customer's specific needs. Wireless connectivity, smart components such as sensors and control systems and machine-embedded software have unleashed a new era of competition for manufacturers (Chowdhury, Haftor, and Pashkevich, 2018). Customers demand more personalized products and digitalization enables servitization (Martìn-Peña, Sànchez-Lòpez, and Garrido, 2020). Chowdhury, Haftor, and Pashkevich (2018) state that challenges stemming from the emergence of smart technologies force manufacturers to invent new solutions for their customers instead of relying on traditional products. Companies operating in a well-performing market tend to be successful despite their digitalization efforts and thus manufacturing firms need to give their digitalization strategy a lot of thought to obtain better results as they have many fields and aspects to cover (Salmen and Ryglova, 2022). With that said, the need to use technology has become an integral part of the demands put on firms, and to improve their technological capacity firms should invest in R&D activities (Islami, Mulolli, and Mustafa, 2018).

2.1.1 Section Summary

The emergence of wireless connectivity, smart components and advancements in software has led manufacturers to offer product-service-related bundles. In turn, forcing servitization in a industry where technology and AI play an integral part in providing these offerings. This shift has put pressure on manufacturers to adapt their strategies to be able to compete.

2.2 Artificial Intelligence

AI is said to influence, "every aspect of the human condition" (Johnson et al., 2018, p. 2668). Plenty of articles cover the topic and it is said to influence the future of many aspects of the business including autonomous vehicles and medical assistance devices (Hengstler, Enkel, and Duelli, 2016), robotic process automation (Pramod, 2022), production and manufacturing (Guerra-Zubiaga et al., 2021), cardiology (Johnson et al., 2018), medicine (Hamet and Tremblay, 2017), marketing (Kozinets and Gretzel, 2021), and employment (Haenlein and Kaplan, 2019). AI has been proven to have current and immediate potential, especially in manufacturing firms. Huang and Rust (2018) state that there are four types of AI referred to as being the following where the former precedes the latter: mechanical, analytical, intuitive and empathetic. This shows that AI's influence on the mechanical aspects, manufacturing processes and automation, is imminent. As AI still can be considered a novel technology, a strong business case for its use needs to be formulated and aligned with the existing strategy. Hence, an exact problem formulation is needed for adoption to occur (Enholm et al., 2021). The success of AI-implementation is dependent on three factors, namely high speed and infinitely scalable computing power infrastructure, rich data sets, Machine Learning (ML) and deep learning algorithms. These elements require management capabilities, expertise and infrastructure flexibility (Wamba-Taguimdje et al., 2020).

AI can be categorized into supervised learning, unsupervised learning, and reinforcement learning (Iansiti and Lakhani, 2020). This refers to the number of data points involved in the development of the tool as well as the level of human interaction required in the process. Enholm et al. (2021) state that AI-applications can be divided into automation (systems tasked to replace labor) and augmentation (applications aiding humans in making decisions). On a process-level there are effects stemming from AI-use such as process efficiency, insight generation and business process transformation while on a firm-level, the effects of AI used in operations can be categorized into operational performance, financial or accounting performance, market-based performance, and sustainability performance (Enholm et al., 2021). The application of AI seems to be, not surprisingly, industry specific since AI for industrial use is defined by Peres et al. (2020, p. 220122), as a, "systematic discipline focusing on the development, validation, deployment and maintenance of AI-solutions (in their varied forms) for industrial applications with sustainable performance." The term industrial AI refers to the particular goals of AI in the manufacturing industry where the use of AI encompasses many areas such as autonomous vehicles, batteries, robotics, renewable energy, steel, and semiconductors (Kim et al., 2022).

AI can help to meet new and tougher customer demands for more individualized products and services (Enholm et al., 2021). Thus, companies are forced to adapt and move towards more AI-adoption. The risks with using AI are a lack of appropriate AI-governance practices. As the research in this domain is in its early stages, firms must consider the negative and unintended consequences that can occur with AI-use (Enholm et al., 2021). When browsing available research the benefits of using AI become evident. However, skepticism exists as well. Some decades ago the worry was that just because a computer says something, it does not mean it is the right thing to do. Hence, humans should not be so ignorant when it comes to AI (Boden, 1984). As knowledge around AI becomes better over time, the concerns have shifted to be more solution-oriented. Technical limitations (explaining what the machine is doing, and interpreting its results), practical limitations (data availability and labeling), and limitations in use (algorithm transparency, biases in the data, and how it was collected), are mentioned (Chui, Manyika, and Schwartz, 2018). Other limitations that hinder the use of AI in manufacturing are the lack of interpretability and data shortages causing performance degradation (Kim et al., 2022). Chui, Manyika, and Schwartz (2018) discuss the issue of how to apply insights from models in one area to another, called transfer learning. AI has its challenges in terms of implementation, use, and interpretation of its result, but also moral, ethical, and legal concerns (Dignum, 2018).

2.2.1 Section Summary

Although the emergence of AI may present promising opportunities for the manufacturing industry, there are still impediments to overcome. In particular, aligning the existing company strategy with a business use-case that utilizes the technology, is needed for adoption to occur. Different taxonomies of AI have also been developed depending on the degree of human involvement needed in its utilization or depending on its use. AI enables automation, which is shown in many ways.

2.3 Automation

Although AI has already disrupted many industries, these are often tied to processes that are already digital by nature such as in finance or order-taking systems (Evans, 2017; Iansiti and Lakhani, 2020; Hyun et al., 2021). The outlook for automation is promising, some predictions say that up to 45 percent of work tasks can be automated and AI will play a crucial role in this transformation (Burström et al., 2021). More advancements are needed in the areas of robotics, manufacturing automation, and networking for industrial manufacturers to be able to leverage the opportunities that AI presents (Evans, 2017).

2.3.1 Robotics

Robotic Process Automation (RPA), Robotic Desktop Automation (RDA), and Intellectual Process Automation (IPA) are terms frequently used in literature to categorize different types of automation initiatives (Evans, 2017; Pramod, 2022; Hyun et al., 2021). The traditional perspective on robots as a physical object that works in an assembly-line has since Industry 4.0 been extended to include automation of cognitive functions (Pramod, 2022). The term robot also incorporates computer processes that can replace human cognitive functions that are often considered repetitive (Evans, 2017). Seasongood (2016) provides a taxonomy for categorizing these efforts. Namely, RPA is concerned with the automation of tasks that can be seen as non-client facing and more operational in character. Additionally, the term RDA incorporates automation of activities that traditionally have been regarded as more white collar in nature, such as consolidation of data and payment processing (Seasongood, 2016; Evans, 2017). Hyun et al. (2021) suggest a third level, the automation of human judgment through IPA. This level focuses on processes that are non-routine and require the application to recognize patterns instead of just following predetermined rules as in RPA and RDA (Hyun et al., 2021). As a consequence, IPA applications require RPA or RDA design that is combined with an AI to be able to make human-like decisions (Pramod, 2022).

2.3.2 Manufacturing Automation

Pramod (2022) argues that although manufacturing organizations have started to adapt to Industry 4.0, challenges still exist to complete this transition. These challenges are often tied to the integration of vertical and horizontal production systems as a consequence of lacking technological readiness (Pramod, 2022). This transition puts pressure on manufacturers to create more versatile factories and assembly-lines to configure and be updated, being able to produce a range of different products (Guerra-Zubiaga et al., 2021). To achieve this, manufacturers have started to utilize Digital Manufacturing (DM) to simulate the production processes, optimize flows and analyze bottlenecks in a Digital Twin (DT) of the factory (Pramod, 2022). AI also presents opportunities to make the manufacturing process more intuitive and controllable. The integration of AI into the manufacturing process allows for continuous optimizations of specified objectives such as completion time and lower costs (Lu, Xu, and Wang, 2020). However, few-large scale production projects are yet to be launched. Much due to the novelty of the technology and the high costs tied to full-scale implementation, resulting in many AI-projects in production remaining at a small scale or in a digital sandbox (Kerns, 2019). Another reason for the comparably slow adoption of AI in production is the vast architecture needed for its implementation in terms of collaborative intelligence. Intelligent factories will need to collect data from many different sources, and be able to communicate for better design decisions as well as timely and predictive responses (Nof and Silva, 2018).

2.3.3 Networking

Even though the emergence of AI has generated many opportunities for improvement in manufacturing firms, there are still many barriers to full-scale implementation in terms of data collection as well as communication between the physical and the digital world (Kerns, 2019). Manufacturing firms need to embed digital capabilities in their factories to be able to collect and process data. These components are crucial to enable the 4.0 industry and firms need to design their network of devices to synchronically collect the necessary data. This generates the obstacle of inter-connectivity of these devices where the network of devices need to be able to efficiently and securely communicate the data in real-time (Tran-Dang and Dong-Seong, 2021). On top of these challenges, firms need to consider the vulnerabilities of these systems in terms of data privacy and information overload (Nof and Silva, 2018; Tran-Dang and Dong-Seong, 2021).

2.3.4 Section Summary

Robotics, manufacturing automation, and networking are areas where AI-application in the manufacturing industry is beneficial. The state of manufacturing automation is explained by covering that digital twins of the factories have been developed where AI can be used. Networking encompasses how manufacturers can collect the necessary data to implement AI-tools. The link between the digital and physical world is quintessential in the emergence of smart factories where the use of smart devices and sensors enables data collection and communication. Thus, highlighting its importance when utilizing AI as a competitive tool.

2.4 AI as a Competitive Tool

Some areas where AI has proven to be able to automate processes are within budgeting and planning, inventory and replenishment, and improving real-time visibility of assets as well as making end-to-end supply-chains more efficient, which include the elimination of redundant processes (Wamba-Taguimdje et al., 2020). Indicating that AI is a must-have for manufacturing companies pursuing a sustained competitive advantage.

New players that fully utilize the potential of digital transformation in their operating model can change the rules of the game and challenge traditional companies. In a truly digital operating model, the cost of serving an additional customer is practically zero. Much due to there being little to no human involvement. The only cost in such a model is the cost of computation that is often carried out in the cloud at a marginal cost (Iansiti and Lakhani, 2020). This digital transformation does not come unrecognized by the traditional industry that is increasingly starting to rethink and adapt its operating models to become more digitized. This enables AI to drive a higher degree of automation, which potentially can result in relatively unconstrained growth as the bottleneck of human labor is removed (Iansiti and Lakhani, 2020). The emergence of digital companies has also enabled companies to innovate their business model by introducing new ways to create value for their customers through, for instance, better predictions of their needs. In contrast to the way incumbent firms in traditional industries capture and create value via the same source, novel companies that are inherently built on a digital foundation have found new ways to capture value through third parties by selling data (Iansiti and Lakhani, 2020). Thus, the need for business model innovation has emerged and incumbents need to evaluate their value- creation, delivery and capture (Burström et al., 2021).

2.4.1 Business Model

On top of the technological barriers to integrate AI, manufacturing firms need to consider the horizontal perspective of their business model. That is, to what extent they should acquire external services when implementing AI. The emergent need for business model innovation in manufacturing firms is not only dependent on the vertical capabilities but also on the external relationships of the firm and the horizontal integration of the value chain (Burström et al., 2021; Nagy et al., 2018). Burström et al. (2021) found that in such an implementation the boundary between what is external and internal becomes fuzzier. The implementation process becomes less linear as it requires a complex network of external suppliers of products and services making it crucial for incumbents to develop and manage networks.

Although AI offers a plethora of areas for implementation on the value creation side of the business model, firms must apply a market perspective and consider whether its development is tied to customer needs. Failing to do so could lead to unnecessary costs (Burström et al., 2021). AI-implementation in production can create higher value for customers in terms of fewer faulty products and increased run-time. It also offers the opportunity for firms to pursue a more servitized business model incorporating customization and demand prediction. Firms that fully leverage these opportunities can create a more customer-centric business model (Burström et al., 2021; Sjödin et al., 2021), and can then benefit from co-creating these solutions with the relevant stakeholders by applying a constant feedback loop to continuously improve the services (Sjödin et al., 2021).

"The use and development of new, unknown technologies is a risky activity and is currently expensive, although it promises considerable savings, thus increasing revenue for those who make the decision early" (Nagy et al., 2018, p. 7). It is not surprising that few incumbent manufacturers have yet to launch full-scale AI-projects considering the impending risks tied to adoption and organizational complexities. The emergence of AI brings with it the need for innovation which is evident in the business model in terms of new ways to create and capture value, but also in the way manufacturers operate to deliver value to their customers.

2.4.2 Operating Model

A firm's operating model concerns how value is delivered to the customer (Vaska et al., 2021). Value delivery comprises process- and activity-configuration (Burström et al., 2021), namely the organization of people, technology and software required to deliver the offering to the customer. These efforts often refer to a firm's ability to scale, achieve a sufficient scope and continuously adapt to changing circumstances through learning. These objectives should be closely interlinked with the goals set by the business model to achieve the desired performance (Iansiti and Lakhani, 2020). Such value delivery dimensions could for incumbents relate to the front-line and back-line service staff or technological support systems (Burström et al., 2021). The value a firm can create and capture is dependent on the efficiency of its operating model. A firm's operating model has traditionally been a bottleneck for the capacity to create and capture value (Iansiti and Lakhani, 2020). Integration along the supply-chain is thus a necessity for firms to deliver the most value possible to customers (Kahlen and Patel, 2011). Routinely being able to deliver value to the customer in a cost-efficient way is important (Biloshapka and Osiyevskyy, 2018).

Vaska et al. (2021) state that digital transformation has an impact on value creation, delivery and capture in most companies and industries. AI initiates opportunities for firms to radically create new operating models (Euchner, 2020). To configure a value delivery system where AI is involved, firms need to develop technology-based capabilities and employee competences. Due to the complexities of doing so, incumbent AI-use risk being limited and only experimental (Burström et al., 2021). AI has the operating benefits of being able to supervise product and process flows as well as maintenance processes (Burström et al., 2021; Sjödin et al., 2021) while enabling the development of digital systems for order-tracking and tracing as well as better integrated value-chain activities. AI-applications have not disrupted major parts of the manufacturing industry yet. Most incumbents perform small-scale AI-innovation projects to identify their competitive edge through the utilization of AI (Burström et al., 2021). Value delivery for manufacturers can refer to the engagement in digital servitization or using AI-capabilities to improve work processes, and there is a need to further understand how to best leverage AI in core business processes since AI is rarely fully implemented among industrial manufacturers. Operating models need to be better integrated with AI-use in organizations and one solution to this is to increase the scale, scope and learning opportunities of AI. Many firms fail to consider the value delivery dimension, but if considered, a firm will gain a competitive advantage (Sjödin et al., 2021).

2.4.3 Section Summary

AI offers many areas for implementation on the business model side. However, firms must consider whether its development is tied to a customer need. Value delivery, which is part of the operating model, comprises the activities needed to deliver on the promises set by the business model. These activities concern the firm's scale, scope and learning capabilities. AI will play a crucial role in transforming manufacturing firms' operating models along these dimensions.

2.5 Identified Gap in Literature

There is a lack of consolidation concerning AI-development and its effects on value delivery in manufacturing firms, from a processual perspective. The literature is missing a clear distinction and consolidation of what these parts are and what AI-development means for value delivery and operations in manufacturing firms over time. Thus, the gap this thesis aims to fill is related to the change process. Meaning, that a description of the effects on value delivery over time is needed as AI becomes an increasingly integral part of operations in manufacturing firms.

This thesis follows an abductive approach, see Methodological Approach and Method. Considering that the researcher cannot identify all existing literature since the collection of empirical data and theoretical conceptualization goes hand in hand. Hence, the need for theory arises (Dubois and Gadde, 2002). Thus, the two following frameworks are used to close the, by this thesis, identified gap in literature.

3 Theoretical Frameworks

Two frameworks will be used in this thesis. Firstly, The Operational- & Business Model Alignment by Iansiti and Lakhani (2020) to understand the components of value delivery and its relations. Secondly, the Nested Business Environment Framework (the NEST Framework) by Möller, Nenonen, and Storbacka (2020) to understand the occurring process of change resulting from AI-development.

3.1 The Operational- & Business Model Alignment

The Operational- & Business Model Alignment by Iansiti and Lakhani (2020) outlines the relationship between the business model and the operating model of a company and its various components. Starting with the business model, which is divided into two parts. The left part is concerned with value creation and value capture. Value creation is the value a business can bring to the customer. Value capture is concerned with how the company can create value for itself which in most cases concerns firm profit (Iansiti and Lakhani, 2020).

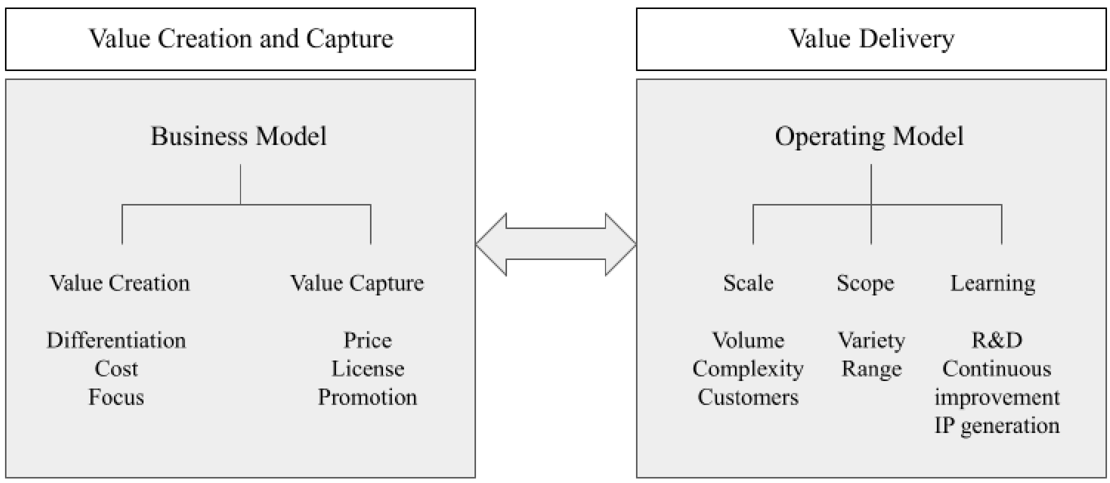

Figure 1: *The Operational- & Business Model Alignment (Iansiti and Lakhani, 2020)*

The operating model of a company often comprises a complex set of processes that ultimately has the goal of delivering the value promised by the business model. Its components range from the assembly line that produces the actual product to the capital investments required to house stock of ready-to-ship products. These activities come down to three overarching objectives to deliver the promises of the business model. These are, to *scale* production, work within a relevant *scope* and the ability to continuously improve and be flexible to changing circumstances through *learning*.

Scale is about complexity as well as developing and organizing activities that enable the company to serve more customers at the lowest possible cost. These activities often relate to efforts to either increase volume or lower costs through optimization of the production process. Second, the scope of the operating model comprises what activities are relevant to the company and hence the verticals that the company decides to pursue. It also incorporates activities that have synergistic effects across a subset of these verticals. Thus, it is about variety and range. Lastly, learning captures the activities of the operating model that enable the company to continuously improve but also its ability to be flexible and respond to threats and opportunities. This category concerns R&D, continuous improvement and IP generations and has proven to be essential for companies to remain viable and competitive (Iansiti and Lakhani, 2020).

The performance of a company is argued to be tied to its ability to align the business model with the operating model and how a firm allocates its resources to align them to the overarching strategy. This alignment is integral to the value of a business. In a digital operating model, the employees do design and manage the software-automated and algorithm-driven infrastructure that delivers the end-product or service. Whereas in a pre-digital operating model the employees deliver the product or service manually. The trajectory for growth is completely different. This shift alters how management needs to operate, and removes bottlenecks tied to the pre-digital operating model that would have restrained scale, scope and learning in the firm (Iansiti and Lakhani, 2020). To understand this process of change, the NEST Framework will be utilized.

3.2 The Nested Business Environment Framework

The Nested Business Environment Framework was constructed by Möller, Nenonen, and Storbacka (2020), and allows for an understanding of the environmental complexity faced by firms. The framework consists of three parts, see Figure 2: the Nested Layers, Conditioning Forces and the Transformation Phases and Microprocesses. Only parts of the NEST Framework are used in this study. That is, the nested layers (section 3.2.1) are not guiding the investigation nor the analysis. The framework assumes the business environment to be in constant change and this transformative state is essential for the decision to use this framework.

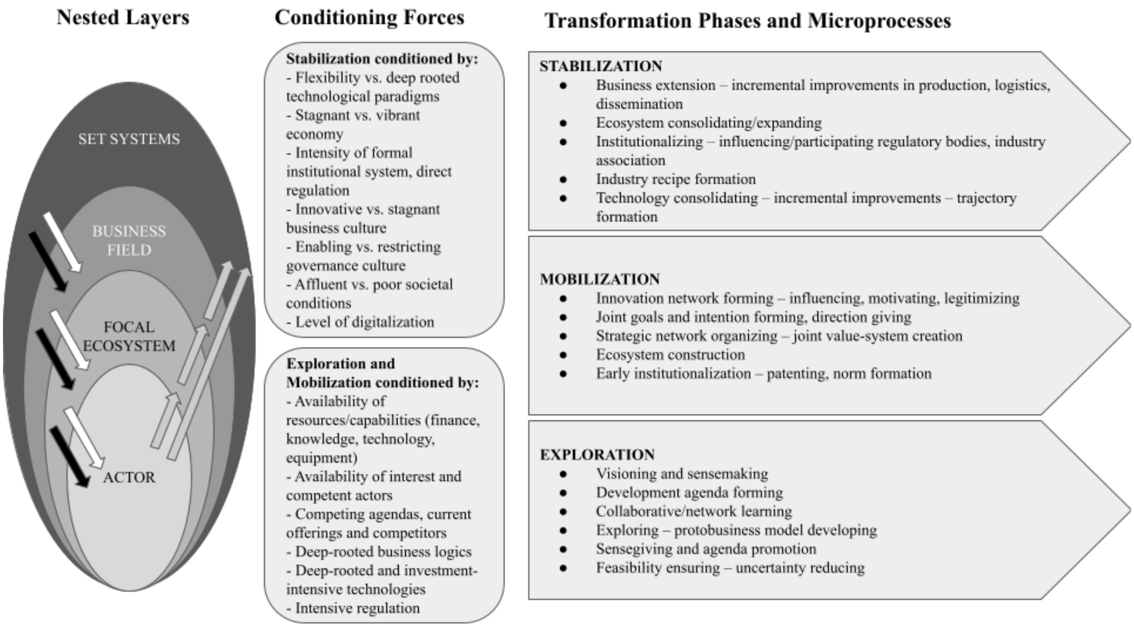

Figure 2: *The Nested Business Environment Framework (Möller, Nenonen, and Storbacka, 2020)*

3.2.1 Part I - The Nested Layers

The four interlinked nested layers which make up the business environment on a macro-level constitute the first part of the framework (Möller, Nenonen, and Storbacka, 2020). This part will not be the focal point as the transformative process is the main purpose of this thesis.

3.2.2 Part II - Conditioning Forces

Part three of the framework is the transformation phases, including the microprocesses, consisting of three main stages called *exploration*, *mobilization*, and *stabilization*. However, part two in the NEST Framework outlines a dichotomy of conditioning forces impacting the three stages of transformation in part three. Conditioning forces comprise activities that enable or constrict transformation. The distinction between a conditioning force and transformation is conceptual and hence the practical implication is to treat them as collective forces either supporting or limiting change processes (Möller, Nenonen, and Storbacka, 2020).

Exploration and mobilization are considered to be a mutual and interlocked process as the conditioning forces are the same for both process stages. A company does not perform exploratory actions in isolation from any mobilization efforts and as soon as mobilization takes place it does not mean that a company can not go back to explorative activities. The joint conditioning forces affecting the stages of exploration and mobilization are the availability of capabilities such as knowledge, finance and technology. Also the availability of resources such as equipment and competent actors. Competing agendas, offerings and competitors are limitations whereas business logic, and intensive regulations, in addition to investment-intensive technologies are factors either restricting or enabling companies to be in an explorative or mobilizing phase in the change process (Möller, Nenonen, and Storbacka, 2020).

The following stabilization phase is conditioned by the level of flexibility as well as how vibrant the economy or industry is that the company finds itself. Business complexity in terms of the level of incremental improvements, ecosystem expansion, and technology consolidation are also conditioning factors in addition to how much regulation exists, the governance culture as well as the level of digitalization (Möller, Nenonen, and Storbacka, 2020).

3.2.3 Part III - The Transformation Phases and Microprocesses

The transformation phases, including the microprocesses seen in Figure 2, consist of three main stages called exploration, mobilization, and stabilization. The dynamic character is prominent, especially when fast and critical events are occurring according to the framework. Examples of such events are the rise of the commercial internet, the introduction of web browsers, and company websites (Möller, Nenonen, and Storbacka, 2020). All are similar to the rise of AI, thus making this transformative framework applicable for this study.

3.2.3.1 Exploration

The first transformative phase is called exploration. The first part is about sense-making and constructing path-breaking business innovations and is thus heavily learning-oriented containing idea development and experimentation. The framework highlights that innovations, even the most radical ones, combine new with existent knowledge. In practice, it means that both new and existing elements of technology, business ideas and organizational ideas are combined in various ways in an attempt to be innovative. The second part is about prototyping, sensegiving and promoting business opportunities, setting the agenda and pitching the idea, and addressing potential risks and uncertainties. Competition between actors in the market is pushing further exploration efforts. An innovation-friendly environment is characterized by risk-taking, legal stability, and a contract- and trust-based social system (Möller, Nenonen, and Storbacka, 2020).

3.2.3.2 Mobilization

The second phase is called mobilization. It is about business opportunity promotion and gathering of the resources needed to install change. Mobilizing resources calls for knowledge-creation and developing an agenda, setting the roadmap for establishing long-term change. It involves selling the idea to partners and others needed for the project to happen as well as creating collaborative coalitions. In a change process, project management must enable specified goal construction, organization, and orchestration. In this stage, as opposed to the previous exploration phase, the process moves towards the materialization of the value system underlying the business offering, hence making it more concrete and feasible which can take years. The involvement of partners, the need for goal alignment, legitimizing the efforts and forming joint goals and direction are factors of importance that take time to establish. Mobilization entails constructing the right team, division of responsibility, mobilizing a strategic network, forming ecosystems, and agreeing on shared management principles involved in the process. In this stage of the process, the competition between coalitions targeting the same customers becomes evident. This serves as a constraining factor as the competition for resources, partners, intermediaries and end-customers can either develop a new prospering business field or destroy long-term profitability (Möller, Nenonen, and Storbacka, 2020).

3.2.3.3 Stabilization

The third phase is called stabilization. To establish business environment transformation, normative actor behavior needs to change long-term. Actor behavior needs to expand, consolidate and institutionalize the explored and mobilized business solutions and their infrastructural base. During the mobilization phase, the invention is scaled-up and disseminated. To expand adaptation, the already established ecosystems are needed as well as to incorporate new actors. It is about institutionalizing the constructed solution. Thus, in stabilization, further mobilization acts are needed. In the stabilization phase, actors need to safeguard the value system just constructed against incumbent competitors. Two ways to defend value systems are through incremental innovation and improvement in sub-systems. Hence, constant adaptation and transformation are needed. Such can be renewing roles, responsibilities and value-capture within the ecosystem. Stabilization is achieved when company-specific progress becomes an industry requirement or even a market requirement, meaning an interwoven part of successful business practices. In the stabilization phase the ecosystem that the business is part of expands and there is a consolidation of technology as well as influences on institutionalized regulations (Möller, Nenonen, and Storbacka, 2020).

3.3 Theory Discussion

The Operational- & Business Model Alignment by Iansiti and Lakhani (2020) allows for the study of the three individual parts of value delivery. The book by Iansiti and Lakhani (2020) has been cited frequently during the two years since its release. The book has been used and cited especially in innovation research. For instance, Culot et al. (2020) use the book in their study of the emergence of Industry 4.0, Koroteev and Tekic (2021) apply the book in their research of AI trends in the gas- and oil industry, and Tschang and Almirall (2021) in their paper that researches the implications of AI on employment. Although the book in which the model is presented has been cited frequently in innovation research, the model has yet to be used in a similar context as in this paper. Therefore lacking the empirical rigor as other models might provide, which can be explained by the model being no more than two years of age.

The NEST Framework was constructed in 2020. Understandably it has not been used and cited by many given its short lifespan but it was used as a theoretical lens by P. Guenther and M. Guenther (2022) to describe a firm's transformational business environment. Due to the high-tech nature of the innovation this paper looks into, utilizing a modern framework is an advantage as it is more likely to consider factors of relevance for today's modern age. This speaks to the advantage of using the NEST Framework. Ultimately, this paper aims to answer what the effects of AI-development are on value delivery. These effects are not set in time, but rather a constantly evolving process. A transformative process derived from the NEST Framework, where the authors Möller, Nenonen, and Storbacka (2020) claim that previous studies are too detail-oriented and hence the NEST Framework aims to provide more of a holistic approach. On the one hand, this is good for analyzing the transformational process and implications of AI-development in manufacturing firms. On the other hand, it falls short in terms of detailed explanatory power which might be considered an issue. The framework however does not focus or specialize in a specific business area but rather focuses on a general level, making its three transformation stages more easily applicable in various contexts. Thus applicable to the scope of this thesis. Complemented by the Operational- & Business Model Alignment by Iansiti and Lakhani (2020) which allows for a comprehensible understanding of the transformative effects initiated by AI-development on the components making up value delivery.

3.4 Summary of the Theoretical Frameworks Used

These two frameworks will be used to consider the transformation resulting from AI-development and its effects on value delivery in detail. The Operational- & Business Model Alignment by Iansiti and Lakhani (2020) depicts the relationship between the operating model, value delivery and its components scale, scope and learning. The NEST Framework by Möller, Nenonen, and Storbacka (2020) describes the transformation in three steps, exploration, mobilization and stabilization, and will help to determine in what stage AI-development is in. These three stages are influenced by conditioning forces either restraining or enabling the activities within each transformative stage.

4 Methodological Approach and Method

4.1 Research Approach

This thesis aims to uncover what effects AI-development has on value delivery by conducting interviews and thus this research study is explorative by nature. The following research approach was used as a consequence. This thesis is based on ontological constructivism where the social world is made real by the people constituting it. Supported by such an understanding of reality, this thesis assumes epistemological interpretivism to gain knowledge of that reality (Bell, Bryman, and Harley, 2019). This thesis aims to elicit and explain the perspectives of the interviewees to understand their social world and behavior. It is built on the assumption that the organization is socially constructed by the individuals constituting it (subjectivist), and the purpose of our research is to propose minor changes to improve how business is and could be conducted (regulatory) (Bell, Bryman, and Harley, 2019). Knowledge is deemed to be subjective as the reality presented is based on the combined views of the people taking part in the study, which fits as the described phenomena investigated is inherently made up of individual thoughts. As this thesis is guided by the condition that the social world is made up of and constituted by the people in it in combination with a desire to Verstehen (Bell, Bryman, and Harley, 2019), we argue that making interpretations of subjective knowledge allows us to answer the research question by the means of the respondents' combined Lebenswelt. Finally, a narrative literature review was conducted to map the chosen research area. According to Bell, Bryman, and Harley (2019), a narrative review is more suitable for qualitative research basing its strategy on epistemological interpretivism, making it appropriate to use in this study.

4.1.1 Abductive Methodology

This thesis is sprung out of abductive reasoning by continuously considering data and literature. The interviews were conducted and analyzed simultaneously. This was done to overcome the linear limitations that come with following either an inductive or a deductive approach. The abductive approach allowed for theory to be carefully selected in conjunction with data, to make certain that theory was well-grounded in data, and so the data could be explained by theory. The abductive approach allows for pragmatic research and back-and-forth engagement with empirical data and literature, enabling theoretical development (Bell, Bryman, and Harley, 2019). In addition, back-and-forth engagement between empirical observations and theory allows for a better understanding of the two (Dubois and Gadde, 2002). Dubois and Gadde (2002) say that an abductive approach is preferable for many reasons as a result of the continuous engagement between empirics and reality, claiming that theory cannot be understood without empirical data. As we did not know exactly what to uncover when gathering data, performing the literature review or searching for theory, the abductive reasoning and hermeneutic approach were useful and help to explain our process of thought.

The interviews were structured according to the Operational- & Business Model Alignment's division of value delivery into the three components, scale, scope and learning. See the Interview Guide in the appendix A.1. The answers to these questions allowed the identification of the categories that are presented in the Empirical Data section. As an abductive study successively modifies theory, in part because of unexpected empirical findings as well as theoretical insights, it is common to mix theoretical models and concepts (Dubois and Gadde, 2002). The data collected during the interviews indicated that there is a critical underlying change process and thus the need emerged for a framework describing transformation. The NEST Framework emerged during the interview phase as a useful framework to understand the operative change process caused by AI which is why both the NEST Framework and the Operational- & Business Model Alignment will be used in conjunction.

4.2 Interview Selection and Execution

The selected interview participants are presented in Table 1. This is a qualitative study containing 15 interviews with employees working in manufacturing firms operating in Sweden. The conditions were that the interviewees were employed by a manufacturing firm operating in Sweden and had any kind of work-relationship with AI at the time of the interview. The respondents needed to have an operative connection to AI for us to be able to provide a holistic view of the effects of AI-development on value delivery.

Choosing six different companies to interview was done to collect data from companies with various accomplishments within the industry, to hopefully find patterns for the manufacturing industry as a whole. The prerequisite that the people interviewed have some kind of affiliation with AI indicates that the firm is working with or considering AI-tools. The input stemming from the interviews might vary due to company affiliation but it is by no means less varying within the same company as people have different roles, various capabilities and thus different things to say on the subject. The scope of this thesis allows for such width in company affiliation and role responsibility and the research does rather benefit from this diversity within the chosen boundaries. The authors' personal networks have played part in the selection as well as referrals from previous interviewees to others within the same company. AI-development within the industry is a relatively novel phenomena and thus there are not too many people within these organizations to talk to. Also, as different companies have reached various levels in their development, this affects the availability of people to speak to between firms.

Ten interviews were recorded. Some interviews were not recorded for privacy reasons. Not recording the interview was a prerequisite for the interview to happen in some instances. The constant tradeoff between recording and the respondent feeling as if he/she could speak freely was continuously prevalent throughout the process of collecting data. Having some of both improves overall reliability as recordings increase the precision with which the data are presented, and a respondent feeling as if he/she can speak more freely might generate responses not disclosed otherwise. One of the authors was responsible for conducting the interview and the other focused on note-taking and asking clarifying questions when the interview was not recorded. That is to make sure that what was said by the respondent was put in writing without intentionally misconceiving it. The names of the respondents and organizations are anonymized for confidentiality reasons, as per Table 1.

Table 1: *List of Interviewees*

Title	Area	Company Type	Interview Medium	Duration (Minutes)
1. Project Leader	Logistics	Vehicle Manufacturer	Microsoft Teams	35
2. Data Scientist (1)	Digital Transformation	Component Manufacturer A	Microsoft Teams	40
3. Data Scientist (2)	R&D	Component Manufacturer B	Microsoft Teams	35
4. Senior Data Scientist	Central IT	Vehicle Manufacturer	Microsoft Teams	45
5. Product Manager	Data & Mobility Services	Vehicle Manufacturer	Microsoft Teams	45
6. Head of Artificial Intelligence	Central Coordination	Manufacturer & Materials Processor	Microsoft Teams	45
7. Lead Data Scientist	Operational Services	Vehicle Manufacturer	Microsoft Teams	45
8. Product Owner	IoT & Connectivity	Manufacturing & Services	Microsoft Teams	35
9. Senior Manager	Operating Model	Component Manufacturer A	Microsoft Teams	35
10. Head of Intelligent Automation	Center of Excellence	Manufacturer & Materials Processor	Microsoft Teams	45
11. Costs Specialist	Operating Model	Component Manufacturer A	In Person	30
12. Concept Innovation Manager	Data Analytics & AI	Manufacturing & Services	Microsoft Teams	45
13. Business Developer	Global Technology Team	Manufacturing & Services	Microsoft Teams	40
14. Head of SCM Digitalization	Corporate	Manufacturer & Materials Processor	Microsoft Teams	45
15. Production Engineer	Logistics	Materials Processor	Microsoft Teams	20

4.3 Data Collection Process and Sampling

The collected data comes from primary sources. The study follows a cross-sectional research design, focusing on the time when it is written, and the interviews were conducted according to a semi-structured interview approach. The semi-structured interview approach allowed us to keep an open mind and uncover factors that were not considered relevant to begin with. This approach is good for enabling concepts to emerge from the data (Bell, Bryman, and Harley, 2019). The Interview Guide in appendix A.1 is based on the Operational- & Business Model Alignment (Iansiti and Lakhani, 2020). It was created to understand the effects of AI-development on value delivery, and thus followed the structure of the components making up value delivery, namely scale, scope and learning as can be seen in Figure 1.

A purposive sampling approach was used, meaning that it is not random but rather a strategic form of sampling to serve the purpose of this study. It follows a generic purposive sampling process, based on the established criteria needed to answer the research question. The criteria are that the person in question must work in a manufacturing firm operating in Sweden while at the same time working with AI-operations in some way. The companies and employees have been carefully selected, as outlined in the Interview Selection and Execution 4.2. The research approach does not allow for any generalizability as the chosen sampling process is considered non-probability sampling. Achieving an adequate sample is important and can be more of a continuous process throughout the research study (Dubois and Gadde, 2002). As a sub-set, snowball sampling has been utilized as we have been making use of referrals from previous interviewees. One issue with this is that the sample will not be representative of the population but since a purposive sampling process was used this would not have been the case either way. The need for generalizable results is not as crucial in qualitative research as in quantitative research (Bell, Bryman, and Harley, 2019) and thus its downside is mitigated. The fit between snowball sampling and qualitative research is thus a better one. Bell, Bryman, and Harley (2019) state that the purpose of a qualitative study is to make theoretical observations rather than presenting generalizable results, which is why our chosen sampling approach fits the purpose of this thesis whereas the negative effects resulting from non-generalizability are minimal.

4.4 Empirical Data and Analysis

The data presented in the section Empirical Data are detailed as a retelling of the interviews from us as authors, complemented with referrals to what was said by the respondents' in the conducted interviews and with quotes. The following three areas of AI-development in manufacturing were found. See Table 2.

Table 2: *The Three Identified Categories*

AI-Development in Three Areas
Servitization
Supply-Chain & Support Functions
Smart Manufacturing

To make the data more presentable under each category, the following subcategories are used under each main category: *Use-Case Development*, *AI-Use* and *Organizational*

Challenges. These three subcategories were thematically derived from the interviews, grouping the data to better make sense of it. Finally, the overarching theme of *Centralization* is presented. Centralization is a common finding for all three categories and thus the data regarding centralization is presented separately to avoid repetition. The aim of the Empirical Data section is to present the data objectively, thus grouping the data based on themes derived from the respondents' statements. Next, the analysis section will use the two theoretical frameworks as lenses to analyze the data. Table 3 presents the structure of the Empirical Data section.

Table 3: *Structure of the Empirical Data*

Structure of the Empirical Data
Servitization Use-Case Development AI-Use Organizational Challenges
Supply-Chain & Support Functions Use-Case Development AI-Use Organizational Challenges
Smart Manufacturing Use-Case Development AI-Use Organizational Challenges
Centralization
Empirical Data Summary

The Analysis section follows the structure of the three transformation stages of the NEST Framework, namely exploration, mobilization and stabilization. Under each transformation stage the three components of value delivery, scale, scope and learning are discussed. First, each of the three areas where AI-development is currently happening, identified in the data, will be analyzed and placed in one of the three transformation stages from the NEST Framework. As this thesis looks at AI-development, the NEST Framework is useful since it depicts a process of transformation allowing us to circle in on various development-stages. Second, after having determined what stage of development Servitization, Supply-Chain & Support Functions, and Smart Manufacturing are currently at, an analysis will follow looking at what it means for value delivery. The Operational- & Business Model Alignment provides us with the components of value delivery and thus we are able to see the effects of AI-development in detail. To increase research reliability, an inter-coder consistency was established, meaning that the data were analyzed jointly by the two authors of this thesis.

4.5 Qualitative Research Criticism

The aim was to reach data saturation. When the respondents generated increasingly similar responses, the data was considered adequate to answer the research question. This thesis also strives to fulfill reliability. Among criticism towards qualitative research, Bell, Bryman, and Harley (2019) state that it can be considered too subjective and too significantly dependent on the researchers' personal relationships. Hence, critiquing the snowball sampling used in this thesis. However, such a sample serves its purpose for this thesis as the goal is to uncover the efforts of a few manufacturing firms' AI-development and thus referrals to colleagues within the same organization to interview are beneficial for this study given our constructionist approach to research. In addition, it is complicated to replicate a qualitative study and any generalizable conclusions can hardly be made given that this study is based on 15 interviews. Since the data is collected from a relatively small number of people in a certain local context where the researcher currently is located (Bell, Bryman, and Harley, 2019), generalizability is not achievable because the data are sensitive to the social context. However, Bell, Bryman, and Harley (2019) further explain that the purpose of a qualitative study is not to come up with any generalizable results but rather to make theoretical observations. The key is rather the quality of the assessment made from the collected qualitative data. Therefore, the chosen research approach for this thesis is arguably fitting given that making a quality assessment and followingly a theoretical contribution is the goal of this thesis.

Another issue is the lack of transparency resulting from a qualitative study. It is important to outline how the respondents were selected and the process from data to analyzing and making conclusions need to be clear to the reader (Bell, Bryman, and Harley, 2019). To mitigate this, we have provided a detailed elaboration of how the respondents were selected and the methodology-, empirical data- and analysis sections will assist in understanding the process from raw data to conclusions. Conducting qualitative research allows us to research a partly unobservable phenomenon (Bell, Bryman, and Harley, 2019), as the data collected in this study is unique given the constructionist epistemological nature of this study, and is thus an argument for why this research approach is suitable. Other data quality concerns have to do with the consistency and trustworthiness of the data which the extensive Methodological Approach and Method section aims to mitigate. Given the qualitative nature of this research study, the prevalence of response bias makes it more difficult to validate the accuracy and truth of the findings. One way to mitigate this issue of response bias is oftentimes by having unstructured interviews (Bell, Bryman, and Harley, 2019). This is why semi-structured interviewing was used to initiate the conversation and then allowed the respondents to share valuable insights based on their own experiences.

4.5.1 Non-Face-To-Face Interviewing

14 of 15 interviews were conducted online. When conducting non-face-to-face interviews via Microsoft Teams the ability of the researcher to build rapport with the interviewee and the ability to pick up on visual cues decreases (Bell, Bryman, and Harley, 2019). The recent developments with Covid-19 forcing online meetings to become standard practice in many cases, this issue is not as relevant as when Bell, Bryman, and Harley's book was released two years ago. Also, Bell, Bryman, and Harley (2019) state that offering the respondent to meet via online communication tools may increase the probability to get people to agree to be interviewed. Conducting the interview online was sometimes a prerequisite in this study, for example, because the interviewee was not stationed within proximity to Stockholm where the authors of this thesis are located. Conducting the interviews over Microsoft Teams made it easier to record with good audio quality and be able to take extensive notes to better capture what was said.

4.5.2 Translation

Ten interviews were held in Swedish and then translated into English for the purpose of this thesis. Scholars argue that translation is a cause for questionable results since vocabulary and its meaning might differ between two languages (Bell, Bryman, and Harley, 2019). Speaking one's second language might also be a cause for error. Although we as authors strive to minimize wrongful interpretations in the translation process, there is a risk that cultural influences such as our educational background interfere with the meanings in the translation process. This needs to be taken into consideration when interpreting the results of this thesis.

4.6 Ethical Considerations

This thesis follows a philosophical ethical approach called the deontological view. This view of research ethics says that you can never justify unethicality in research (Akranga and Makau, 2016). It is of utmost importance for the validity of this study that the collected data was interpreted correctly and presented as true to the heart as possible. To respect an interviewee's desire to remain anonymous is important to uphold research ethics and all the information disclosed about the respondents in Table 1, including whether the interview was recorded or not, was agreed upon beforehand. The primary focus was the respondent's privacy which in some cases enabled him/her to speak more freely.

5 Empirical Data

The data will be presented separately from theory before it will be analyzed in conjunction with theory in the Analysis section. The data is divided into three categories where AI-development is currently happening in manufacturing firms: Servitization, Supply-Chain & Support Functions and Smart Manufacturing. Followingly, split into three subcategories respectively: Use-Case Development, AI-Use and Organizational Challenges. Lastly, the common theme of Centralization is presented separately in section 5.4 since this was mentioned across the three categories. Table 4 describes the categories in more detail.

Table 4: *Description of the Identified Categories*

Category	Description
Servitization	Refers to the transition towards more service-based offerings resulting from AI-development.
Supply-Chain & Support Functions	Refers to the incorporation of AI in manufacturers' efforts to automate internal processes in supply-chain and support functions.
Smart Manufacturing	Refers to production where manufacturers have started to incorporate AI in manufacturing and assembly processes.
Centralization - (Servitization, Supply-Chain & Support Functions and Smart Manufacturing)	Common for all three categories above is the need to centralize AI-competence in the organization.
Subcategory	**Description**
Use-Case Development	The process of identifying a problem, prioritizing, and analyzing affected stakeholders in the areas where AI can be applied.
Areas of Use	Refers to the areas in which the respondents see value in AI-use.
Organizational Challenges	Refers to the organizational challenges emanating from AI-development.

5.1 Servitization

"How do you place a bet on two different things? To keep making money on what you already have without promising too much for the future, resulting in customers to stop purchasing what you have." – Concept Innovation Manager

5.1.1 Use-Case Development

The interviews depict a seemingly radical shift in how the introduction of AI can affect manufacturing firms' products. In particular, due to the transparency data collection introduces, resulting in a twofold change. One leads to more available data to internally push product innovation based on how the existing product is used. The other, presenting new service offerings. Both were elaborated upon by the Product Owner on the topic of use-cases in data collection, "It is more of an internal effectivization and can expand our service, to achieve a better service. The second part, where you are part of a flow of products, where the customer has an interest in getting processed data from us to optimize their flows and become more efficient in their work. That is where we have the opportunity to sell data to them." There is a need to make a distinction between the two effects, customer-driven innovation and internally driven innovation.

According to the Product Manager, the availability of data has triggered a shift in knowledge-power between stakeholders as the market has become more efficient, resulting in the manufacturers losing the knowledge advantage they previously had over their customers. As data from the use of the physical product has become publicly available between stakeholders, there can no longer be any inefficiencies to hide behind. This shift in knowledge-power has introduced a twofold conundrum, where the first is that the product has to satisfy the basic needs of the primary customer. The second is to supply the secondary customer with the data to ensure that the primary customer has delivered on its promise. This has led to a transition in innovation-focus, as explained by the Product Manager who said that they are currently in a phase where they are forced to become more service-driven and that it is mainly the customers who push this development. The customer wants the company to be part of their digital journey and take part in helping them to customize solutions tailored to their needs. Certified by Data Scientist (2) who questioned what the point is if just looking at the data and that it is all about customer value in the end as they strive to create customer value to help the company.

The Lead Data Scientist said that this effect can be seen from another perspective. Namely what influences the customer to demand this type of service, pointing to the fact that recent legislations within the European Union have enforced the change through the incentivization of more sustainable product alternatives, in this case Battery Electric Vehicles (BEV), where a more comprehensive data collection is necessary. BEV requires data on battery health, range prediction etcetera which in extension indirectly affect the need of customers as they demand more available insights of the physical product. Thereby presenting new service opportunities which imply that the need for a servitization of the industry is also driven by such environmental factors.

The availability of data has sparked innovative potential caused by internally-driven innovation. The Product Owner noted the following about servitization, “Previously, you started by collecting data and then applying AI on that with the hopes of achieving good stuff. I believe that we are now changing direction and taking the approach of considering what it is we want to achieve, and then the next step is to consider how we can use AI or ML. I think the development goes in that direction, to not be paralyzed by AI but rather focus on the benefits from it.” Although, further explained, “This is a trend within data treatment, however, that is not enough to make money. We have the technology, we have the algorithms. How do we make money?” The Concept Innovation Manager similarly mentioned, “I am often two, three, four steps away from the customer and I need to go through key account managers when I need to talk to a customer, which makes the process slow.” It seems as when the innovation is internally driven by available data and technological capabilities, the respondents testify to the fact that it is uncertain whether the customer wants it.

5.1.2 Areas of Use

The application of AI-solutions to the gathered data is still in an early phase. The main challenge is to develop the relevant use-cases for AI as explained by the Product Owner, “The challenge is to collect relevant data and be able to make correct conclusions based on that data. It is dull to use AI without being able to connect it to a use-case.” Further, given the early state of AI-applications development, the Product Manager noted that they envision making this development part of the core business in the long-run. As of now, much of the development is carried out in conjunction with external suppliers. It seems as if many of the interviewees see value in using AI from a business perspective. The Product Manager said that self-service is needed, expressing the need for a market platform where customers log in themselves. The Product Manager stated that they are still at an early stage in terms of AI-development and when it comes to the transformation towards being more service-driven. However, the Concept Innovation Manager described that, “We have been challenged by management whether data collection is something we want to focus on. Then the counter-question is whether the services can be achieved with the use of data. [...] You have to apply the thinking that those who see the value in it will also be willing to pay more for it over time.” The Business Developer discussed a possible remedy for this, “The first is often to start visualizing data, here it is possible to see what happens with the [product X] in terms of usage. [...] It is possible to do quite a lot without taking AI into play and you actually have to take the customer along this journey where you start off with the data visualization and then introduce more intelligent services before you head into AI-solutions and predictions and so on. [...] You need to try to get the customer to mature through the journey and realize what it implies." As such, in the development of AI-applications, the service needs to be developed in conjunction with the customer to allow for successive adaptation thereby increasing the likelihood of customer value creation.

Another challenge is that AI-solutions can cannibalize existing product and service offerings. The Product Owner described that, "We already have half our revenue coming from the sales of products and the other half from aftermarket services. Hence, already half of our income comes from recurring revenue and taking care of our customers." The Business Developer noted that predictive maintenance could lead to a loss in aftermarket services since AI-solutions will be able to predict when the product will break, and thus the need for replacement and repair services decreases. "It becomes a bit psychological because often the customer thinks that if we go to the site then there is someone who does something physical and then there is a cost for us who do it. Then they are willing to pay more for this service, but if there is someone who does something remote that the customer does not know and does not see what is happening, then there is an immediate feeling that this is something that you do not have to pay that much for. That it does not cost us much to deliver this because it's probably software and software is always free," said the Business Developer. It is not clear whether the perceived value of predictive maintenance outweighs the current service offering. Especially since it implies that the work is less obvious to the customer, resulting in less revenue through aftermarket services. As an example, predictive maintenance means cloud-based work instead of a technician physically traveling to the customer resulting in a generally lower willingness to pay for software-based services. For such services to become more profitable than current offerings, new revenue streams need to be reconsidered, which requires the involvement of new stakeholders, said the Business Developer.

5.1.3 Organizational Challenges

When it comes to new advanced technology as with AI, there is uncertainty around how this will be managed organizationally. The Lead Data Scientist mentioned that you need to start with data collection, cleansing, integration, and reporting before moving on to forecasting followed by ML and then deep learning, "An usual mistake within these types of organizations is to as fast as possible start to work with advanced analytics, resulting in that you hire data scientists who are expected to perform wonders with advanced analytics. Then, you are at the top of the pyramid but you don't have a solid foundation. You have to start from the bottom." When moving towards being more service-oriented you need to focus on building a customer-centric organization according to the Product Manager. This is something that larger manufacturing firms tend not to be suited for as they have historically been more product-focused. It becomes difficult to accommodate AI when an industry is used to doing things in a certain way together with the market. The Product Owner said, "It is a pretty big challenge for us because we have worked with traditional products before that may have a ten-year life-cycle and we know that when to produce another product we just give the old specifications to the engineer who knows how to do it since before, but this time with new components. To push development both for the technology and the market at the same time, is something we have not done for a very long time. It is a challenge. We have to be agile which is not that easy in an organization that is used to being waterfall-based." With the new technology, an organization has to be able to customize its services in terms of service design, user experience, user interface and customer demand according to the Product Manager. All of this requires new IT-systems and advanced tools but also an organization capable of adapting to specific customer requirements. The Product Manager also said that it is important to make the data available for whoever is going to utilize the services, which require an IT-infrastructure. Operationally, the employees need to embrace, push for and adapt to this change. The Concept Innovation Manager said that there is a big uncertainty in that employees tend to be stuck in how they always have done things which makes it difficult to change the way they think. "I would say that the most difficult part is to change people's behavior. People are shaped in the organization and have learned how to sell and they know how to get a reward. [...] It is difficult to sell something different." To accommodate the need for more advanced technology like AI, more people with tech backgrounds are hired to management positions in these manufacturing firms. As stated by the Concept Innovation Manager, "Many technology companies have senior managers with an educational tech background." The complication of servitization is that the more you need to customize what you sell, the more difficult it is to scale, compared to selling standardized products. The sales channels and how the internal reward systems are set up has to be rethought according to the Product Manager. When a complete corporate setup is optimized for selling products and all of a sudden the company has to be more service-based, it causes not only technical issues but evidently also organizational struggles.

5.2 Supply-Chain & Support Functions

"I'm going to put them [the projects] into two boxes. One is around production. [...] We are also looking into other projects within the corporate functions." - Head of Artificial Intelligence

5.2.1 Use-Case Development

AI is not only relevant in direct production scenarios but also for companies' various support functions as well as for projects in supply-chain. Data Scientist (1) claimed that in 90 percent of cases the solution is a fairly simple AI-program, not necessarily the most advanced and cool computer program. Utilizing AI-solutions allows for scale, meaning they can be transferable across divisions within the same organization. "We are building the basics but I think that the driving force is that we do something and then once we have something we can move forward, expand it, and scale it up in different areas. We are doing something for one division and then we can use the same model for other divisions' sales to predict that without doing everything again," said the Head of SCM Digitalization. Regular employees will be allowed to build local automation tools as well. According to the Head of Intelligent Automation who said, "We've started to consider the option for regular users, so-called citizen developers, to build local automations." This strategy allows for any employee to develop tools beneficial for their work processes can arguably be claimed to allow for the birth of a stream of automation processes within a company. When it comes to advanced technologies such as AI, the technology already exists in many circumstances. Sometimes it is more than enough with a simple programmable AI-solution. The Head of SCM Digitalization said, "It is a little bit too much at the moment that we have a tool, and we try to find the problem for it. It's a challenge to get these ideas directly from the business." Several respondents express that the difficult part is to find the business case for it. That is whether to start with available data or to ask what the business issue is, thus change the process to accommodate automation.

5.2.2 Areas of Use

The Product Manager explained that there is potential when it comes to the applications of AI and ML in predicting and automating processes in their supply-chain. The main challenge is currently making the data available, further noting that much of the supply-chain will be able to be integrated using AI which will increase the value of their service. Data Scientist (2) expressed that it is of importance to understand that AI can be of domain-specific use to help customers with quality issues and thus the company needs to understand what processes can be automated. The Head of SCM Digitalization discussed how they use AI accordingly, “We have a logistics track-and-trace project which we started a year ago. There we have built a track-and-trace setup for logistics to have real-time visibility and ETA-calculus at any given time on the delivery. That is kind of related to AI because of the ETA-calculus, and of course modeling based on the best information to estimate when the truck or asset will arrive to the customer. [...] On other projects we are estimating when the material should be ready from production. We start to estimate three weeks before the confirmed delivery time or dispatch time, we start to estimate when the delivery should be ready for dispatching and there we use AI. Then we have projects starting now with the sales forecasting or supply-chain forecasting so we need ideas to develop the tactical planning process with the AI-model. Then also on demand-sensing, utilizing existing data in the current situation to estimate what will happen in the coming weeks.” In addition, AI built into RPA allows for the use of more advanced technological tools. The Head of Intelligent Automation stated that, “Most suppliers of RPA have included AI in their current software.” Such tools are used to automate processes within support functions such as finance, Human Resources, IT, sales and purchasing. Intelligent Document Processing (IDP) is used with an AI-component in purchasing to streamline processes, and rating models for the credit departments are developed which take the current market situation into account as well as sales forecasting. The Head of SCM Digitalization said that there are, “Benefits to gain on forecasting if we can do it better. Sales forecasting is very much about time, how early you can make decisions.” Moreover, the Head of Intelligent Automation claimed that, “Instead of using people as duct tape between systems, we’ll use technology. This is where I’m seeing the great benefit of this. [...] The great advantages with RPA are not to save employee expenses but rather increased quality, being able to deliver information in greater frequencies whilst minimizing wrongdoing and increasing reliability.”

5.2.3 Organizational Challenges

The Head of SCM Digitalization said, “It is important that you have dedicated people working on these things. [...] An [unit within the organization] organization that serves many divisions and can utilize time and resources for this kind of development.” The Head of Intelligent Automation described that the IT-department is the biggest opponent to RPA since it is a threat to their existence. Another obstacle is that there are very few within the organization who possess the appropriate competence and thus more than often the firm has a central department in place that focuses and pushes these AI-initiatives and automation projects. There is a challenge in pushing and anchoring these initiatives throughout the organization. The Concept Innovation Manager said that, “Early-stage innovation should be anchored in the various divisions we have.” Data Scientist (2) referred to a combination of an overarching strategy and internal drive to implement AI-solutions. As the Head of SCM Digitalization stated, “We are working on developing these data scientist skills and resources. Lacking them in the start, typically people that get in might be young and quite inexperienced so it will take time to develop.” Also, the challenge of getting the users and managers to take the time to automate rather than drowning in operative work is a daily struggle. “When you combine RPA and AI [...] that’s when you can achieve these great changes in how to process information,” said the Head of Intelligent Automation. Then there are the issues related to ethics for example when using AI to screen resumes and trying to improve old systems. There seem to be benefits of starting from scratch. “In doing something new, you don’t need to carry on all the legacy challenges and misalignments [from an old system],” said the Head of SCM Digitalization. In sum, the respondents stated the process needs to be the core of automation rather than just looking at what can be automated with tools the company currently possesses.

5.3 Smart Manufacturing

The interviewees expressed several key challenges when it comes to the implementation of AI-solutions in production.

5.3.1 Use-case Development

The Project Leader compared them, a vehicle manufacturer, and companies like Spotify where more data is available, referring to that in manufacturing much of the data is not available from the start which makes it more difficult to derive use-cases directly from the data. The Senior Data Scientist stated that, “I have access to many data sources but I still only have access to about 30 of the total 250 available and it would be a security risk for both me and the whole company if I had access to more.” Even if the data shows optimization potential it might not be viable from an operational perspective. Especially since the required data need to be of consistent quality. The Data Scientist (1) explained that they have divided their strategy into two parts. One that aims to implement manufacturing tasks that, based on previous factories and experts, are known to be useful. While the second part is more exploratory and based on their overarching vision to become more data-driven. The primary goal here is to collect as much data as possible from the manufacturing process and develop useful applications for it afterward.

The Senior Manager further explained how AI can be used in the design of the factory. Most of the manufacturing processes can be derived from the end-product before the factory is built as product specification impacts process specification, which in turn impacts the design of the factory. This translates into how the factory needs to be designed to produce these components. AI can be used in the modeling of the factory to achieve an optimized design, resulting in a DT that can be used as a blueprint to build the actual physical factory and minimize the cost of equipment. The Cost Specialist explained that, on top of this, an operational blueprint that is developed in conjunction with the up-and-running factory can be used to continuously optimize processes and implement new measurements. Hence allowing for capturing of measurements from the operating factory and syncing of the blueprint to be updated with real-time data. Based on the data from the operating factory, AI could be used to further optimize the manufacturing processes as explained by the Cost Specialist.

Generally, the interviews dictate that AI-use in manufacturing is still in an early phase and the current focus lies mainly on developing the infrastructure. The Cost Specialist explained that they aim to build an infrastructure that paves the way for AI-applications in the future and hence the current goal is to collect as much data as possible from the whole production process. This trend was confirmed by the Project Leader who said that they still have yet to launch any full-scale projects. They are still in the experimentation phase where the main focus is to develop use-cases and see if these projects could be technically viable in the future.

5.3.2 Areas of Use

When it comes to the use of external services in AI-development the interviewees had different views, much depending on their operational strategies. The Senior Data Scientist said, “[The Company] has some guidelines on what should be deemed core and hence be developed in-house. AI is not necessarily core so we should buy more. We are however not that good at doing that.” On the contrary, when asked a similar question the Senior Manager pointed out that they do not want to rely on what their suppliers propose. They want to know the specifications themselves to be able to learn and improve down the line. This is what enables AI-use in the design of the factory. AI can be used in the modeling of the factory and thus in optimizing the capital expenditures of equipment. Even though much of the factory is supplied by external providers of machines, the actual implementation of the machines is developed in-house which is what enables the use of AI-solutions down the line. Although AI plays an important role when making scalable factories, it also introduces the problem of black-box solutions.

The Senior Manager further explained that, only because something works in a specific factory context, it does not necessarily imply that it will work in another as the context changes. A lot of work has to be put into making the factory model explainable. If this can be achieved the models could essentially be transferred between factories, making the factory design itself part of the core and thus part of how value is created.

There are still uncertainties to deal with as pointed out by the Senior Data Scientist, "...securing the right competence, achieving sufficient data quality and the necessary IT-infrastructure." Although the plan might be sound on paper, there is uncertainty tied to its implementation. To overcome this, the Senior Data Scientist emphasized the importance of working with simulation tools, safety margins and transparency, "To be completely honest, the toolbox is not entirely set yet. I can develop an algorithm and have the necessary data. The next step is putting this in production and in some IT-systems. That demands quite a lot of technical solutions and you have to be able to monitor it. Few have the complete toolbox in place that considers all the different possible variants that can arise."

5.3.3 Organizational Challenges

Given the early stage of the AI-development in production, a lot of work is needed to create an organization that fosters these solutions. The Project Leader took it so far as to point out that change management is their largest obstacle rather than actual system development. This is strengthened by the Production Engineer who stated that, "...we have a lot of older people working in the industry that can have a hard time seeing the benefits with or being able to learn how to use such a solution." One challenge stems from the nature of automation in production. That is how to transition the previously manual workforce to another division once these functions have been automated. It is evident that this development of AI-solutions in manufacturing requires close collaboration between a range of affected teams which requires cross-functional teamwork. The Project Leader emphasized the need for close collaboration with logistics, IT and production teams. IT tends to be a bottleneck as pointed out by the Senior Data Scientist. Further strengthened by the Head of Artificial Intelligence who said, "[The Company] is an old company and we have had a lot of legacy systems and you need to update them and then build something on top of it. This is costly. It is costly in the sense that the return of investment for a data project by itself is zero actually, because it is how we are going to use it later that will bring money." The Senior Data Scientist expressed, "A huge organizational challenge worth mentioning is that for companies like us that are not new, IT-native or cloud-native, but have IT-systems that are older than 10-20 years, results in a big portfolio to manage. To then add these new AI-applications, and try to make it work with the existing IT-landscape which has to work, but you cannot turn these old systems off because then something else stops working. This is a real challenge." This statement shows how these old IT-systems can sometimes prove to be inadequate for a given AI-solution. Some projects might be put on hold until the IT-systems are replaced by new and adequate ones, resulting in a need for tight collaboration with IT to ensure that projects are technically viable before trying to develop and implement them.

Another organizational challenge has to do with ensuring data quality. This was noted by the Data Scientist (1), "Ensuring the data quality is a difficult problem. Much due to the fact that we've grown fast. In the beginning, our strategy was to hand this responsibility to each product team who was oblivious [of the data quality] until the data was actually used. This made it difficult to backtrack where the problem emanated from. Today, each product team is responsible for the data they upload from the beginning and they have to flag if something is wrong." To that end, ensuring that the data is of the right quality directly influences the responsibilities in the organization. Many of the production-related projects tend to emanate from below with a need for further support from the top. The Senior Data Scientist said, "Organizationally it is a combination of push and pull, bottom-up and top-down. Everything we do is internally driven with an overarching vision to become more data driven." Further strengthened by the Production Engineer who said, "It is most definitely an internally driven process." The projects themselves are identified at a low level. For them to get developed and implemented there is a large need for support from top management.

5.4 Centralization

Common for all three categories, Servitization, Supply Chain & Support Functions, and Smart Manufacturing is that the respondents express the need for the competence to be centrally organized. Data Scientist (2) said that you should have a centrally governed organization to start with since the competence in regards to AI is scarce, and then you disseminate the knowledge throughout the organization.

The Senior Data Scientist mentioned a centralized entity, "If anyone, our group has that role [...] Yes, there is such a coordinating role and it works pretty well." It appears as if the governance is centrally coordinated while what is done operationally is bottom-driven. It is important to establish a connection between the central team focusing on the technical aspects and R&D, with the teams working closer to customers in the business areas, various divisions and support functions. These teams are the ones with better knowledge of the processes and what actually is needed in terms of improvements, which is something the central team has less of. There are challenges with centralization as mentioned by the Head of Artificial Intelligence, "For example, I'm heading a program but my resources are in a different team and have their own manager who has his own projects and resource needs. It's not ideal from an organization's point of view but there's no ideal organization because if you do it some other way around you'll have some other problems. But I need to align very closely to the Business Intelligence Team Manager on the resources I need and the projects I'm running and make sure they are in line with his resource-need." Judging by these statements, centralization is a crucial strategic step towards achieving success with AI-development. Centralization matters for the success of rolling out AI operatively in these manufacturing firms. Competence being scarce is an impediment and the need for operations to be carried out bottom-up with strategic support from top management appears to be essential. Table 7 in section A.2 summarizes additional statements made that support centralization.

5.5 Empirical Data Summary

Table 5: *Data Overview*

Empirical Data Summary			
Category	**Servitization**	**Supply-Chain & Support Functions**	**Smart Manufacturing**
Use-Case Development	Ensuring that use-cases allow value capture and monetization whilst still creating value for the customer.	Corporate automation saves time and improves precision. It is desirable to not just try to find a problem for the available AI-tools in the organization, but also to develop new ones for proper business cases.	Developing use-cases in conjunction with affected teams to ensure operational viability. Pursuing both exploitative and explorative applications.
Areas of Use	In close collaboration with the customer. Where areas of use are predictive maintenance and online self-service customer platforms.	Track-and-trace, logistics, process automation within support functions, demand-sensing, forecasting and IDP.	Modeling factory processes to optimize factory design. Continuously improving the production processes.
Organizational Challenges	Letting the projects emanate from below and being customer centric. Scaling sales as the product becomes more customized.	Ensuring data quality, anchoring initiatives in the organization and developing the necessary skills. Old IT-systems can prove to be inadequate for a given AI-solution.	Transitioning the previously manual workforce as processes are automated. Cross-functional teams and working close to the IT-department. Ensuring that teams are accountable for the data they upload.
Centralization	Centralization matters for Servitization, Supply-Chain & Support Functions and Smart Manufacturing. Having a core team responsible for AI-development to coordinate these efforts is a key strategic factor. AI-competence is scarce which requires a central unit. You need to make sure that the technically knowledgeable team and the business units work closely together for the technical team not to be too far away from the customer/market.		

6 Analysis

The NEST Framework (Möller, Nenonen, and Storbacka, 2020) details the change process currently happening due to AI-development and the Operational- & Business Model Alignment (Iansiti and Lakhani, 2020) depicts the components of value delivery. Figure 3 shows how the combination of these enables an answer to the research question.

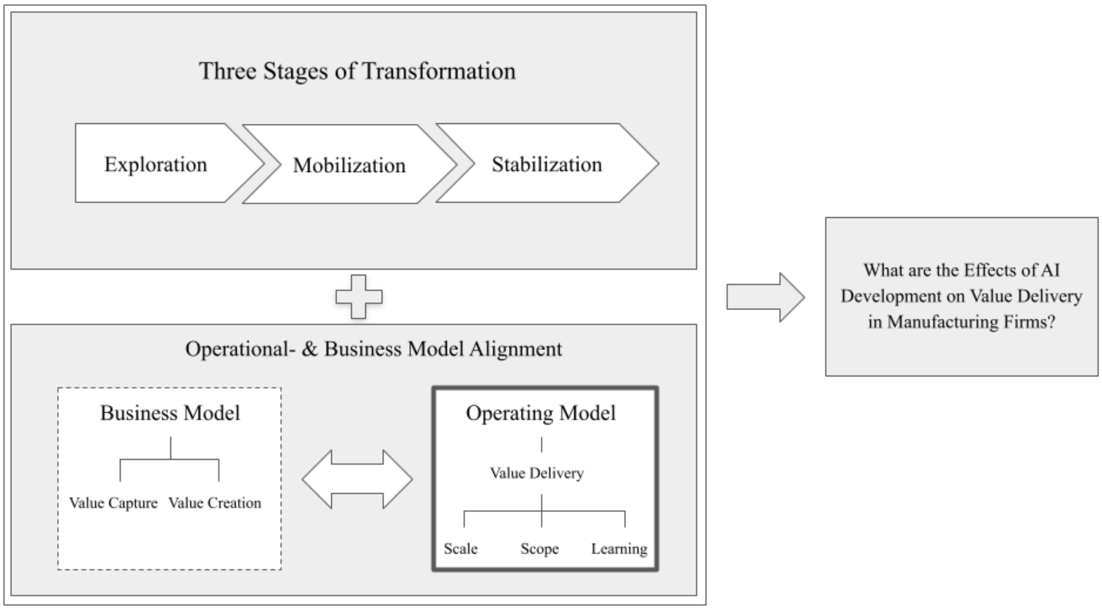

Figure 3: *Theory Conceptual Map*

The data assembled from the interviews will be analyzed following the structure of the transformational three-stage process in the NEST Framework, to identify in which phase Servitization, Supply Chain & Support Functions, and Smart Manufacturing are currently in terms of AI-development. Once the stage is identified, an analysis will follow to determine what it means for value delivery on a component level (scale, scope, and learning) for each of the three categories. See Table 6. Ultimately, to learn the effects of AI-development on value delivery in manufacturing firms.

Table 6: *Analysis Overview*

Structure of the Analysis
Exploration Value Delivery Scale Scope Learning
Mobilization Value Delivery Scale Scope Learning
Stabilization Value Delivery Scale Scope Learning

6.1 Exploration

Smart Manufacturing finds itself currently at this stage in the transformation process. Based on the interviews there is not yet any major implementation of AI-solutions in manufacturing. With that said, there are many areas that show potential and where the interviewees believe that AI-solutions will be impactful in making production processes more efficient. Most of the work can be considered experimentational and consists of gathering relevant data and ensuring data quality, building the DM and operational models and developing the necessary IT-infrastructure. The interviewees described these activities in an open-ended manner, meaning that the respondents did not elaborate on what the end solution would look like but rather focused on how these three operational processes need to be developed to foster future AI-implementation. This goes in line with the activities that characterize the exploration phase, in particular since the respondents to a large extent did not elaborate on specific resources that are needed. Pointing toward the fact that there are still challenges that need to be overcome to enable progression to the mobilization stage. The interviewees agreed on the fact that AI offers great opportunities for Smart Manufacturing both in terms of DM and modeling of a more efficient factory design, and in the development of IPA-applications to automate tasks in the up-and-running production. Interestingly, AI-development in itself was not considered a challenge but rather described the main hurdle as being the organization of people, data collection, and the IT-infrastructure needed for its implementation. This could to some degree be explained by the fact that none of the interviewees had reached the stage of implementing AI in production. Rather, the main focus lies in developing a viable operating model that fosters AI-implementation. Most indicated that there is often not a need for better or more advanced AI-applications than the ones that already are available in the case of Smart Manufacturing. Hence, these are regarded as solutions that can be applied to the specific use-case once the operating model is in place.

6.1.1 Scale

These initiatives have an impact on the possibility to scale production. Two primary applications of AI were identified. The first one is in the design of the factory where data from the product specifications and machine suppliers can be applied to AI-algorithms, to achieve an optimized factory design, resulting in a DT of the factory. This DT can reduce the waste in the building of the physical factory and hence lower the cost of equipment. Having a DT of the factory introduces the possibility to reproduce factories at a lower cost once an optimized design has been achieved. As the context for the factory changes, the DT might have to be tweaked to match the novel context. In comparison to building a new factory from scratch, having a blueprint through the DT makes scaling up to multiple factories more efficient. Having a DT based on models that incorporate AI-solutions can lower the complexities and in extension the costs related to building and designing factories. The second application is within the up-and-running production, where sensors can be used to collect data from manufacturing and assembly processes to develop use-cases for AI. The interviewees had so far identified two use-cases, either being related to the automatization of labor-intensive processes such as quality controls or in the optimization of processes that were already automated. For instance in critical manufacturing processes where physics models might fall short due to high complexity. AI can be used to replace these complexities by modeling with an AI-application based on the collected data from production instead, resulting in better product quality or a more efficient production process. In essence implying that the factory can produce more and less faulty products, thus affecting the scale dimension.

6.1.2 Scope

Although still in the exploratory stage, AI-development in Smart Manufacturing is already affecting the scope of operations. The interviewees saw value in developing AI-solutions for manufacturing in-house. Given its early stage most did not possess the full range of capabilities needed, hence external consultation were acquired. However, the goal is to possess the required toolbox down the line. The availability of resources is also something that is deemed a conditioning force for the exploratory phase, hence firms need to acquire the necessary resources for this to be an enabling instead of restricting factor and in turn allow for progression to the mobilization and stabilization phase.

The importance of working cross-functionally was highlighted to make AI-solutions operationally viable. Especially given the high degree of legacy that exists in IT-systems and the need for accountability for data quality, resulting in a need for development of the solutions in conjunction with a range of teams. The toolbox for what is needed is not yet determined which requires a high degree of organizational flexibility and being open to change in scope.

6.1.3 Learning

As for learning, the interviewees described AI-development in manufacturing as a bottom-up process. The use-cases are identified at a low level, close to production. Given the lack of knowledge on how to develop the necessary solutions, a central entity is needed for the dissemination of knowledge. A parallel can be made to the conditioning force of availability of interested and competent actors which can be assumed to increase as a result of the dissemination of knowledge throughout the organization. Again, concluding that cross-functionality between the central AI-team and production is essential for learning, where AI-solutions are applicable for use-case development. AI-development is also affecting the learning capabilities when it comes to the design of the factory. Meaning that it will be possible to learn from the up-and-running factory as more data becomes readily available, allowing for further improvements down the line. In sum, AI-development has a twofold effect on the learning dimension of the operating model. That is through the availability of data as well as enabling the organization to better adopt the technology. Thus, promoting future use-case development with the technology.

6.1.4 Exploration Conclusion

For Smart Manufacturing, the operating model is not fully developed yet. The effects on scale are mainly derived from optimizations in the manufacturing process, but also from lessening the complexities related to building new factories, which enables production of more products and factories at lower costs. The effects on scope are hard to foresee given the early stage of development, but there is a high need for cross-functionality between teams in making sure that the solutions that are pursued will be operationally viable in a given context. The latter also has an effect on learning since cross-functionality fosters the learning and development of competence related to AI-development in the affected teams, while the availability of data enhances the learning capabilities and makes it easier to develop AI-use-cases.

6.2 Mobilization

Servitization finds itself currently at this stage in the transformation process. Experimentation and visioning have been going on for a while, and now move towards selling the idea to partners, resource-gathering, and creating more knowledge around the topic in question, while developing the proper competence. Deep-rooted business logic such as the historical product focus is a restraining conditioning force in addition to the fact that many manufacturing firms are transactional as well as heavily invested in equipment and machinery. Lacking the required IT-infrastructure, is another conditioning force, to be able to customize solutions and provide continuous service after purchase. Servitization of this traditionally product-focused line of business has reached a state where more solutions are entering the market. IT-platforms for aftermarket services and customer self-service are onboarded. As of now this constitutes a major competitive advantage and not something that can be considered industry standard practice, while most realize that it is necessary. The data supports what the NEST Framework claims constitutes the mobilization phase, namely that now it is about gathering the resources needed and building the IT-infrastructure, as well as educating employees on how to sell, which requires a reconfiguration of internal reward systems accommodating that change. Manufacturers are re-shaping the organization to be more agile to have the capacity to customize their offerings as opposed to what was necessary with the traditional product-based strategy. A key component defining the mobilization stage is the materialization of the value system, which is shown by how manufacturers are working with making data available for customers and setting up an IT-infrastructure and platforms for customer self-service. Working towards creating these offerings in collaboration with the customer, allowing them to take part in the digital journey, looking at new hires and the increasing value of technical skills further up in the hierarchy show that Servitization finds itself in the mobilization stage.

6.2.1 Scale

When it comes to scale, AI-development adds to the risk of cannibalizing existing sales of products and services. Predictive maintenance is a major service offering resulting from AI-technology. The issue is that it can cannibalize current aftermarket services by decreasing the need for repairs. Questions arise regarding the need for new revenue streams and what stakeholders to involve to accommodate the shift from a product-centered organization. The product-centered organization where the life-cycle of a product previously might have been ten years, and having a waterfall-based structure, to now move towards being agile instead to accommodate customization requirements and high-tech aftermarket services including AI-solutions. This transition is tricky as manufacturers initially need to bet on two different strategies simultaneously, namely the cash cow that is the current sales of products versus future AI-based offerings. This is not beneficial for the ability to maximize scale. The reality of software-based services generally having a lower customer willingness to pay is part of the issue. The cognizance that with AI-solutions you can serve an additional customer at practically no extra cost fosters the need to include the customer on this journey as co-creators of these services in terms of service design, user experience and interface, to educate them on the value delivered by manufacturers. Servitization forces customization and the need to collaborate with the customer. Implying more human involvement and thus fewer benefits from scale. The mismatch in expectation and perception needs to be adhered to when delivering value. Employees need to learn how to sell and customers need to not only state their specific needs but adhere to and be educated on the underlying costs and efforts put in by manufacturers.

6.2.2 Scope

When it comes to scope, AI-development leads to increased transparency and data availability. The shift in knowledge-power has moved from being with the manufacturer to being somewhat more evenly distributed amongst stakeholders. AI-development pushes service-driven operations further and the scope shifts from being merely transactional to a joint digital journey. Customer value-creation can only be reached through this joint service construction, which is driven internally, by the customer as well as by environmental influences. When delivering value, data visualization and intelligent services need to be established before entering a stage where AI-tools are being used in conjunction with these services. The shift in knowledge-power amongst stakeholders and to consider internally-driven, customer-driven as well as environmentally driven innovation are important when setting the scope of the business following AI-development.

6.2.3 Learning

When it comes to learning, AI-development is a continuous learning-process enabling improvement of quality, control, and efficiency. There is an ongoing shift from starting by collecting data and then applying AI in the hopes of achieving some kind of result, to considering what the goal is and then taking the necessary steps to apply AI as a solution. Learning will increase as AI is made an increasingly larger part of the core business. Working from the ground-up, with data cleansing, integration, and reporting and then applying more advanced technology. There is a lot of learning to be done as manufacturers historically have been product-focused. This shift, which is intensified by AI-development, means that manufacturers need to adhere to the customer to an even larger extent, thus making customer-centricity and hiring people with a tech background to management roles important. It is important to establish the basics before starting with advanced analytics and hiring data scientists. When there is a setup in place, optimized for selling products, that suddenly moves towards more service-based AI-governed offerings, it causes not only technical issues but evidently also organizational struggles. AI-development impacts the learning process by taking things back to the basics, making manufacturers realize that they need to start from the ground up and reiterate their business operations. Looking at what needs to be done rather than allowing currently available tools to govern what business opportunities to go after.

6.2.4 Mobilization Conclusion

Servitization finds itself in the mobilization stage making AI-development impact value delivery in terms of the need for an alignment in expectation between manufacturers and their customers for scale, for scope the shift in knowledge-power requires the firm to include the customer in the service-driven operations, and starting from the ground up with the basics for learning. Performing these actions as part of the operations will allow for further mobilization efforts to take Servitization into the stabilization phase.

6.3 Stabilization

The category Supply-Chain & Support Functions finds itself currently at this stage in the transformation process. The final stage of the transformation process indicates that the process slowly moves towards a more stable state, meaning that the industry is getting used to the new existing reality. When behavior is changed normatively, expanded and consolidated towards being institutionalized then the change process becomes stabilized. Automation of supply-chain and support functions is up-and-running. The invention is somewhat scaled-up and consequently disseminated. External actors offering IPA-solutions are part of the established ecosystem. An important part of stabilization is to conduct further mobilization efforts. What encompasses much of AI-use in general, is that it can be of particular use in various functions and thus help to achieve better quality through automation. In terms of supply-chain- and support-function-initiatives there are many cases where there is an uncomplicated AI-program capable of achieving certain goals, assisting in making judgments or providing real-time data. Efforts in automation comprise having a central team of dedicated people working with the implementation but also initiatives such as aiming for regular employees to build local automations, putting ideas into practice as well as spreading existing solutions to other divisions inside the company. These further mobilization efforts in conjunction with renewing roles, hiring desired competence, and incremental improvements to streamline processes show that automation of Supply-Chain & Support Functions is in the stabilization phase. Tangible examples are track-and-trace projects and IDP. As automation finds itself in this stage rather than having completed it means that company-specific progress has yet to become standard practice in the market and is so far a competitive advantage rather than a requirement. An indication of Supply-Chain & Support Functions reaching this stage is that ethics are considered to a larger extent. For example when using AI to screen resumes in the human resource department, possibly impacts regulations which is a conditioning force for the stabilization phase. The relatively far-reaching use of AI in Supply-Chain & Support Functions places it in the stabilization stage where it is slowly progressing towards a constant state of yet more incremental improvements.

6.3.1 Scale

When it comes to scale, it is about internal adaptation and transferability across divisions, which is enabled by many AI-programs being fairly uncomplicated. AI-solutions allow for scale as sales predictions can be made across departments for example, but also as there is a desire to allow for local automations to be built by regular users. To scale the use, dedicated people working with this is considered a requirement, preferably organized as a central entity that can serve many at the same time. Even though automation efforts have come a long way, knowledge and expertise are scarce which is why a central entity is needed to anchor these initiatives throughout the organization. On top of this, to enable central coordination, there is a need for categorization of processes in the business units which calls for further recruitment of the necessary competence. An issue is that most people with the appropriate technical skills and education are at an early stage in their careers and are consequently inexperienced. Another challenge is to get current employees and managers to take the time for these projects. The technology already exists even though it might be provided by external suppliers which lower the toll on business units as they do not have to create the AI-tools themselves. Automation of these processes allows manufacturers to reduce inefficiencies and redundancies leading to reduced costs. In that sense, scale is and will continue to be achieved.

6.3.2 Scope

When it comes to scope, AI-development has led manufacturers to be able to deliver value to customers by making their internal processes even more efficient, thus cutting costs overall. RPA including AI-components, within finance, human resources, and sales departments indicate such efficiency. Automation in supply-chain, including Estimated Time of Arrival (ETA)-calculus with real-time visibility, allows customers to better predict what resources they need to accommodate. These logistics projects are of direct customer benefit whereas other projects such as demand-predicting and sales forecasting allow manufacturers to respond better to customers' desires and thus allocate their resources more efficiently. IDP in purchasing streamlines processes. In-house operations, financing and customer credit allowance benefit from credit rating models taking market conditions and sales forecasting into account. Being reliant on external providers of AI-tools is an uncertainty because the less knowledge the manufacturers have about the technicalities behind the product the less control they have. As manufacturers are first and foremost providers of manufactured goods, it can be argued whether incorporating much of this AI-development in-house makes sense. So far it has been better to develop a business understanding of what can be done and then browse the market for a solution, rather than trying to develop this advanced technology in-house. Value delivery within the automation of Supply-Chain & Support Functions has come a long way when it comes to AI-development. It seems as if much can be explained by the fact that this does not pertain to the core business but rather consists of several smaller and less complex processes which are thus easier to automate.

6.3.3 Learning

When it comes to learning, there is now a shift where the business dilemma or desired process to automate is identified before the search for the appropriate AI-tool as opposed to starting with the available tool and then trying to find something to do with it. These processes are not part of the core business which makes them less risky to experiment with, allowing for faster feedback loops compared to Servitization and Smart Manufacturing. When it comes to delivering value, learning serves as a building block that enables AI-development to be more reliable. Firms have also been forced to question the nature and existence of certain processes. Such learning pertains to the ethical dilemmas concerning data ownership rights as well. AI-development has initiated screening of existing processes, where new knowledge is created as a consequence of a desire to implement AI-tools in automation of Supply-Chain & Support Functions.

6.3.4 Stabilization Conclusion

Automation in Supply-Chain & Support Functions have come a long way. Its effects on value delivery relate to working with external AI-service providers focusing on making internal restructuring enabling scale, the AI-development does not pertain to the core business but rather consists of fewer complex processes which are easier to automate in terms of scope, and AI-development has increased learning as it has made manufacturers look over their internal processes and reassessing their existence.

7 Discussion

So far, the theoretical frameworks in conjunction with the identified empirical categories have been used to understand the effects of AI-development on the components of value delivery. This section aims to aggregate these components to view the effects on value delivery at large. The effects of AI-development on value delivery have a general impact on an organizational level. As most firms express how centralization is necessary to adopt and develop AI, this says something about the future of the structure of large manufacturing organizations. There will be a need for more specialized entities within the organization as they progress and become even more advanced in terms of technological development. Having a centralized unit mitigates the scarcity of specialist knowledge as fewer people can develop the competence and disseminate it throughout the organization, while business units working directly with clients function as a mediator between the central entity and the client.

Based on the empirical data and the analysis, it can be noted that AI has not disrupted the way manufacturers deliver value to their customers overnight. Rather, it is a process that undergoes many phases and has an effect on various areas of operations to different degrees. In some areas, AI-solutions are deemed to be such a competitive advantage that it is added to the firm's list of core activities and hence developed in-house. As a result, there is a need for a toolbox in terms of the organization of people, technology and software so that firms can act proactively to new challenges that emerge as they progress through the different phases. This thesis suggests that the three categories Servitization, Supply-Chain & Support Functions and Smart Manufacturing in which AI is used have come to different lengths in terms of progress, which is explained to some extent by the complexities associated with the respective categories of development. Some categories require more or different resources than others to progress through the stages, implying that the areas where AI is used demands different operating models depending on which stage they find themselves in. In particular, where AI-development is considered to be part of the core business and the long-term goal is to create an operating model that fosters these types of solutions. Although there are many factors impacting which phase of development the different areas are in, the nature of the AI use-case likely puts different demands on the operating model. That is since some use-cases might be considered more or less trivial compared to others and imply less risk. Considering the capital-intensive nature of production it is likely that the development of an AI-solution to automate a step in the manufacturing process implies more risk compared to one with the goal of sorting resumes in a recruitment process. Consequently demanding a more rigorous operating model that incorporates how to deal with the uncertainties related to the specific category. With this in mind, it is not surprising that some areas have progressed longer than others given that their operating model might differ and be subject to constraining factors that hinder further progression.

There is previous research focusing on digitalization in manufacturing, digital transformation as a catalyst for change and how manufacturers move towards offering more product-service related bundles (Chowdhury, Haftor, and Pashkevich, 2018; Martìn-Peña, Sànchez-Lòpez, and Garrido, 2020; Enholm et al., 2021). In addition, there are studies concerning various types of AI and how it influences mechanical aspects (Huang and Rust, 2018) as well as strategic decisions (Sjödin et al., 2021). Moreover, studies are covering how AI forces a digital shift resulting in innovation of operating models and business models. The emergence of digital operating models has forced traditional industries to adapt and in turn enable the use of AI to drive automation (Iansiti and Lakhani, 2020; Burström et al., 2021). AI has also been proven to be able to automate several processes applicable for manufacturing firms (Wamba-Taguimdje et al., 2020). The results of this paper verify this transformation to a large extent, especially when it comes to the need for new operating models as a result of AI-development. Manufacturers have started to dedicate teams with the sole purpose to push this transformation throughout operations. Although Peres et al. (2020) bring up that applications of AI are industry specific, this thesis contributes to existing research by pointing out the need for a distinction to be made between the categories where AI is used. Especially considering that these come with different implications, one of which is the alignment with the value creation and value capture as part of the business model. As shown in Figure 1, there is an established connection between the operating model and the business model. Although a digital operating model that incorporates AI-use in itself might imply a higher degree of scalability of operations, in some cases it also comes with implications for the business model. In particular, when it comes to servitization as this demands a new type of customer-centric operating model that most manufacturers do not have in place. The operating model for servitization includes work that is directed towards ensuring value creation for the customer. This could lead to less monetizable services compared to current offerings. In that sense, some work will also need to be directed towards working with new stakeholders to develop new revenue streams and long-term value capture. This introduces a new bottleneck as the solutions need to be developed and customized together with new stakeholders, thereby limiting scalability as the customer-facing side of the firm needs to take on new and more labor-intensive responsibilities. On the one hand, AI offers the opportunity for manufacturers to increase scalability through automation. On the other, introducing new types of bottlenecks that limits the scalability as new stakeholders are introduced. Questioning the, in literature, otherwise established notion of unconstrained growth associated with digital operating models that incorporate AI. This realization points to the need for a comprehensive stakeholder analysis when developing specific use-cases for AI, which could raise questions about whether it is something that is aligned with the current business model. If not, further consideration is needed to decide if the alternative business model is something worth pursuing. The lack of consolidation of the effects of AI-development on value delivery from a processual perspective constitutes the identified gap in literature that this thesis aims to fill. Even though AI has not disrupted the way manufacturers deliver value to their customers overnight, it undoubtedly is in the process of doing so.

8 Conclusion

8.1 Answer to the Research Question

What are the effects of AI-development on value delivery in manufacturing firms?

The effects of AI-development on value delivery depend on the category and the phase of transformation. The category Smart Manufacturing is in the exploration phase where the effects on scale span optimizations in the manufacturing process and lessening the complexities of building new factories. The effects on scope encompass the need for cross-functionality between teams to ensure operational viability, and the effects on learning comprise employee competence-building and data availability. The category Servitization is in the mobilization phase where the effects on scale span the need for an alignment of expectations between manufacturer and customer. The effects on scope encompass the shift in knowledge-power requiring manufacturers' to include the customer in its servitization efforts and the effects on learning comprise building new systems from scratch. The category Supply-chain & Support Functions is in the stabilization phase where the effects on scale span the work with external service providers. The effects on scope encompass less complex processes that are easier to automate, which do not pertain to the core business, and learning comprise the reevaluation of internal processes. AI-development leads to Servitization and the need for customer-centricity, Supply-Chain & Support Functions are efficient when conducted in close collaboration with external service providers and Smart Manufacturing demands rigorous operating models. In sum, the effects of AI-development on value delivery are impactful throughout. By identifying the effects of AI-development on value delivery, this thesis has shown that the infinite scalability associated with AI is to some degree limited by the addition of new components added to the operating model.

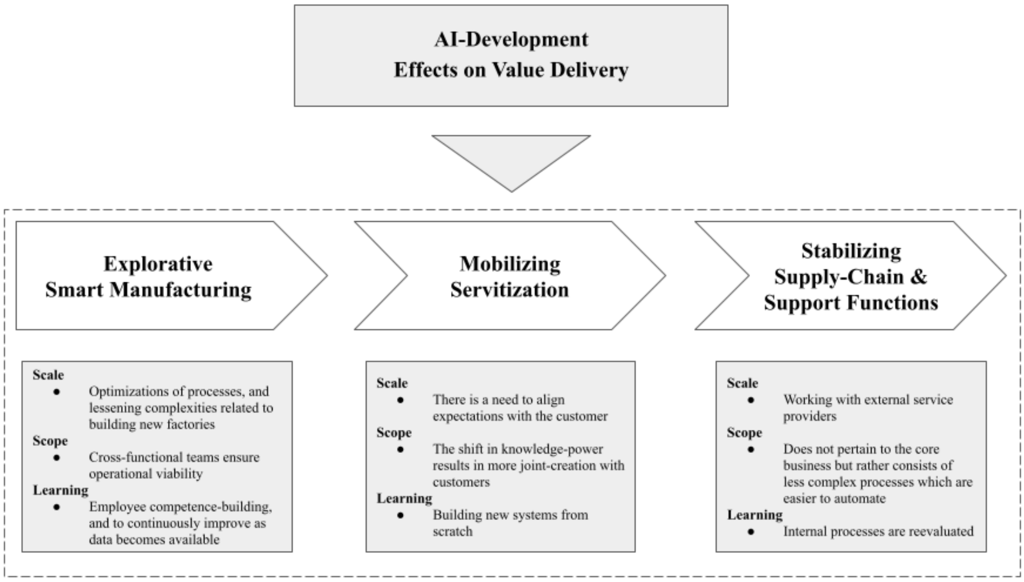

Figure 4: *Effects of AI-development on Value Delivery*

8.2 Contributions to Theory

This thesis contributes to theory by combining the three transformational stages in the NEST Framework with the Operational- & Business Model Alignment. Thereby demonstrating the transformative nature of the operating model resulting from AI-development. Combining the two frameworks accordingly shows how various stages of a change process impact the operating model in more detail while also helping to explain more long-term implications for the business model of a firm. Even though it should be noted that this thesis focuses on the operating model, the combination of theory as has been done in this thesis allows for further interesting areas of research which will be discussed in the Suggestions for Further Research 8.4. Resultantly, the theoretical contribution of this thesis adds explanatory value to the transformation taking place in the context of the operating model, and the resulting effects on value delivery.

8.3 Implications for Management

This thesis contributes to management by advising the manufacturing industry on how to make strategic decisions when it comes to AI-implementation. The results stemming from this thesis allows the industry to learn to anticipate the needs for the entire stage of development toward full-blown AI-use. Therefore, by identifying what stage of development firms find their AI-initiatives in, the appropriate activities and needs can be anticipated for the current and future transformative stages. This thesis can advise in how to make AI part of operations, to achieve a long-lasting technological advantage. The results of this thesis will thus provide value for firms when considering what strategy to adopt for AI-projects.

8.4 Suggestions for Further Research

The study of what effects AI-development has on value delivery in manufacturing firms calls for several interesting adjacent areas for future research. This thesis mainly encompasses the effects on the operating model, a study researching the effects on the business model while utilizing the same theoretical framework as presented in this thesis would therefore be of interest. It would also be relevant to utilize the results of this study to investigate the effects of AI-development on value delivery in other adjacent industries to the manufacturing industry, to compare the inter-industry effects. Also, to perform the same study with firms that do not operate in Sweden would be of interest to see if there are any influences from the Swedish market explaining the results of this thesis. This thesis cannot present any generalizable results given its qualitative nature, where the chosen purpose is instead to make theoretical observations. In addition, as the sample is not large enough to achieve generalizability, conducting a quantitative study to test for generalizability by increasing the sample would be of interest. An empirical study trying to quantify the impact that AI-development has on the components of value delivery would add nicely to this study, yielding yet more fruitful insights and implications on the topic.

8.5 Limitations

The results in this thesis need to be considered in the light of the specific research context and should not be confused as generalizable. The Theory Conceptual Map seen in Figure 3 illustrates the process used to answer the research question and cannot be considered a generalizable model. The effects of AI-development on value delivery shown in Figure 4 is an illustrative summary of the findings answering the research question and should not be considered a generalizable model. In addition, even though it is beneficial to gather data from multiple companies, the settings that the different companies find themselves in differ. The six companies in this study are all part of the manufacturing industry but they all run different businesses, producing and selling various offerings. The very nature of having different companies as part of the study means that they will all have varying levels of AI-development which will influence the interviewees, and thus have to be accounted for when interpreting the results of this thesis. Also, this study does not cover any data from interviews with company executives and members of the board of directors but rather focuses on the perspective of operative employees. Additional insights would likely have come from the addition of such interviews. Moreover, combining the two theoretical frameworks as done in this thesis comes with the risk of misinterpreting the original authors' intentions with their respective framework. Lastly, the results derived from the collected data in this thesis are not static in time when this thesis was written, and the expectation is that reality will look different in the future.

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A Appendix

A.1 Interview Guide

Introduction

- What project(s) are you working on at the moment, with regards to AI?
- How do you work on these projects?
    - Across departments?
    - Special unit?
- Any particular pain points/obstacles you have encountered in these projects?

Business Model

- How do you think AI could affect the business model?
- How would you present the advantages of such a project? What factors would you bring up?
- Given that the project you are working on turns out to be a reality, how will that affect your group? The company as a whole?

Scale

- Are these projects tied to customer needs or do they come from internal needs?
    - Is it efficiency-related or as a response to customer needs?
    - If customer-related, what are their needs and how will this solution help?
- How do you ensure that these solutions are scalable?
    - Most important factors?
    - Biggest obstacles?
- How do you make sure that the data you use are of the required quality?

Scope

- Have you encountered any organizational obstacles when implementing these solutions?

    - What about change management?
    - Different systems used in different departments etc?
    - Decentralized versus centralized?

- Do you work with outside consultants/services or mainly in-house development?
- Why outside counsel/in-house? Benefits/downsides with each.
- If so, what type of external services do you use?

Learning

- What have been the main uncertainties when working on these projects? Outcome related, implementation, adoption etc.
    - How do you deal with these uncertainties?
    - Anything that did not go as planned? How did you manage that?

At the End of the Interview

- Any potential ethical dilemmas with using AI-tools?
- Any other key issues we have missed that you find relevant?
- Is there anyone that comes to mind at your company, who would be interesting for us to talk to?

A.2 Tables

Table 7: *List of Statements Concerning Centralization*

Additional Statements Supporting Centralization:	
Respondent	Statement
Business Developer	“If you are to use AI-algorithms, then we face the issue of not having that many people within our organization capable of dealing with them. This is of course a knowledge gap, which we need to close somehow. I believe that it’s important to centralize knowledge when you face the reality that comes with new technology. You can’t disseminate it in the organization too early because then the knowledge becomes too diluted. It’s better to start building knowledge around the subject centrally, and then spread it to the rest of the organization. As with [the Concept Innovation Manager] who works in ‘group center’ [the central division dealing with development] and tries to establish a connection with the divisions. That’s the challenge, that many do not understand the technology, what it means and what it can do. Building competence around AI, data engineering and such is an area of competence in high demand everywhere.”
Concept Innovation Manager	“We have a department which is engaged in early innovation. [...] We should rather be measured on whether we manage to push out what we do to the divisions or not. We create and mediate a lot of knowledge which flows out in the organization. [...] We are not that many who posses the appropriate skills”
Data Scientist (2)	You should have a centrally controlled organization to start with since the competence with regards to AI is scarce, and then you spread it in the organization. We are encouraged to find market opportunities, and we work closely with product managers who know the customer well. We work with someone who knows the processes because building a product is not just a technical issue, there is a lot of management and leadership involved.
Head of Artificial Intelligence	“Pulling everything together. Different organizations in the company that should be involved because we have a scattered IT-landscape. These are resources that are scarce. […] We have a core team that is spread out, and I’m coordinating it. [...] Most of the time our projects have three pillars; data scientists, data experts, and business experts.”
Head of Intelligent Automation	“Working cross-functionally is a must in my view to succeed. [...] We have a team consisting of people from various geographic locations and different parts of the business who all work together in our team called Center of Excellence. This has been a key to success. Me and my virtual team are responsible for governance, methodology, quality, delivery, goal alignment, administration, maintenance and that we follow strategic decisions. […] Partly, you need support from the top. This must be anchored and supported by top management and then you need someone pushing for it to get done. [...] You need a central entity taking ownership to be able to scale.“
Lead Data Scientist	“What do new business processes require? A new way of organizing. Who in a company has the mandate to change the current organizational structure? [...] To succeed with digital transformation, we must work in a new way, we must develop a new operating model and the only ones who can do that is the top-management. […] We need to support our managers with information for them to make informed decisions. It is not possible to change the organizational structure bottom-up. It is impossible. It's a lot about educating the managers.”
Product Owner	“There is a central team within [company X] looking specifically at pre-development, AI and ML. The technology exists and there’s good enough algorithms to run AI, but the input to these algorithms is important. In the group where I work, we do have a central team working with AI and ML, but they can’t achieve real progress if they end up top far away from the market. [...] The need is created in the business areas and must be transformed into technical requests and requirements, which can then be brought up within this AI team for them to have a look at the technical aspects to achieve something that generates money in the end.”
Project Leader	The entire company needs to work together to combine all the ideas, since it differs how far the groups have come. Change management is perhaps more important than system development in these kinds of situations.