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Doctoral Thesis in Machine Design

Revising Business Model Innovation: Towards a Value Process Framework for AI-based Offerings

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Stockholm, Sweden 2022

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Abstract

Advances over the last few decades in digital technologies in general and artificial intelligence (AI) technology in particular have transformed many industries. There are many successful AI use cases in industry. However, the adoption rate of AI technology by incumbent traditional industrial manufacturing firms in their offerings remains far too low compared with the big claims made about the contribution of AI to the world economy. Incumbents' current view of AI as merely a technology resource with which to increase automation and efficiency is far too narrow and needs to be changed. Instead, AI can be a dynamic capability giving competitive advantage to incumbents if they explore AI's value implications in their business models (BMs). Furthermore, current value discussions both generally and within BMs are too individualistic, transactional, and operational and lack the process orientation required for a more comprehensive understanding of the value potential of AI, leading to business model innovation (BMI) for incumbents.

With the overall ambition to support AI incorporation into incumbents' offerings, this thesis proposes a process-based value framework for AI-driven BMs. For this purpose, this thesis research has produced five studies, including various methods, to understand the value processes within BMs in light of digitalization. Owing to the complex nature of the phenomenon under study, the methods used in the studies include quasi-experiments, case studies, semi-structured interviews, in-depth interviews, card sorting, longitudinal research, quantitative survey analysis, literature review, and literature mapping as required and relevant for the different studies.

The studies highlight that digital and AI technologies could potentially create new values (e.g., self-learning and intelligent offerings) for different stakeholders, provide new mechanisms for value delivery through digital servitization, and enable previously impossible value-capture techniques such as value-based dynamic pricing within BMs. It can be observed that value in digital BMI is constantly changing and hence needs to be focused on explicitly within BMs and introduced as a value-identification process. Furthermore, AI entails new value process relationships in which value creation and delivery are much more integrated, dynamic, and personalized per customer, highlighting the required emphasis on hyper-personalization.

This thesis analyzes the challenges and opportunities AI has provided within BMI in order to propose a modified value process framework for AI-enabled BMs, including value identification, value manifestation, and value capture, compared with the commonly proposed BM value processes of value creation, value delivery, and value capture. The proposed view consolidates value processes, including the individual, relational, and transactional values required by AI-based BMs, rather than just the transactional view of value covered through standard BM value processes, a view that highlights only the operational aspect of value within BMs.

Furthermore, this thesis discusses how the current approach to AI within BMI is more from a resource perspective and therefore cannot realize the full potential of AI technology. The thesis elaborates on how incumbents can utilize AI technology within BMI to create a competitive advantage by concentrating on the process view of value through the proposed new framework for handling highlighted opportunities and challenges. The new role of ecosystem stakeholders as innovation partners within BMI utilizing data/AI-driven capabilities and organizational value changes is discussed. Finally, this thesis highlights implications for BMI theory in terms of new value processes and implications for practice in terms of the BMI framework, concluding by presenting challenges and opportunities arising from the usage of AI within BMI by incumbents.

Keywords: Digitalization, Value, Artificial Intelligence, Business Model Innovation

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Working on an industrial Ph.D. thesis is not always straightforward, and I must admit to undergoing a few frustrating periods. During the research period, the world saw the worst pandemic of modern times (COVID19) and I changed companies and roles. From my current vantage point at the end of this journey, I give sincere thanks to my professional colleagues Johan Simonsson, Ulf Axelsson, Anton Kullh, and Clas Gunneberg for all their ideas, support, and encouragement.

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Girish Kumar Agarwal

Stockholm, Sweden
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List of appended studies/papers in this thesis:

<u>Paper A</u>

Edge AI Driven Technology Advancements Paving Way Towards New Capabilities
Agarwal, G. K., Magnusson, M., & Johanson, A. (2021). Edge AI driven technology advancements paving way towards new capabilities. *International Journal of Innovation and Technology Management, 18*(01), 2040005.

<u>Paper B1</u>

Perception of value delivered in digital servitization
Simonsson, J., & Agarwal, G. (2021). Perception of value delivered in digital servitization. *Industrial Marketing Management, 99*, 167–174.

<u>Paper B2</u>

Value capture in digital servitization
Agarwal, G. K., Simonsson, J., Magnusson, M., Hald, K. S., & Johanson, A. (2022). Value-capture in digital servitization. *Journal of Manufacturing Technology Management*. Advance online publication. Doi:10.1108/JMTM-05-2021-0168

<u>Paper C</u>

Value changes during service delivery
Agarwal, G. K., Swan, E., Axelsson, U., Magnusson, M., & Johanson, A. (2021). Value changes during service delivery. *Proceedings of the International Conference on Engineering, Technology and Innovation (ICE) 2021* (pp. 1–10). doi:10.1109/ICE/ITMC52061.2021.9570232

<u>Paper D</u>

Towards a value process framework for AI-enabled business models
Agarwal, G.K., Lu. L., Magnusson, M., & Johanson, A. Towards a value process framework for AI-enabled business models. Submitted to *International Journal of Technology Management*, under review.

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1. Introduction and background

1.1 Digitalization and AI

Digitalization is a process by which products and services shorten distances between people and things. It increases mobility. It makes network effects decisive. It allows the use of specific data to such an extent that it permits the satisfaction of the needs of individual customers—be they consumers or businesses. It opens up ample opportunities for innovation, investment, and the creation of new businesses and jobs (Rodrigues, 2020). Digital technology is also frequently referred to as general-purpose technology (GPT) (Bresnahan & Trajtenberg, 1995; Devereux & Vella, 2018), bringing about more substantial change than have many other technologies (Cockburn et al., 2018; Guderian, 2019) in the past. We are currently observing the emergence and combination of various digital technologies coming into industrial applications for supporting and transforming various business processes (Cockburn et al., 2018). On a closer look, it is apparent that digitalization should be considered an overarching concept comprising the usage and adoption of a broad range of technologies with different characteristics and innovation potentials. The technologies in question include robotics, additive manufacturing, mixed (augmented and virtual) reality, the Internet of things (IoT), "big data," and others (Lee & Lee, 2015). As digital technologies have now reached a level of maturity that collectively makes them applicable and adaptable in industry (Boer et al., 2021), the wealth of complementarities among them has led to an emerging new industrial revolution, "Industry 4.0," that is fundamentally challenging and disrupting the nature of doing business (Lasi et al., 2014). One digital technology now likely to move from being a hyped and much-debated topic to a critical component of industrial firms' business models is artificial intelligence (AI) (Keshavarzi & Van Den Hoek, 2019).

As IoT (Lee & Lee, 2015) enables connectivity and computing on end devices (Porter & Heppelmann, 2014), the possibility of capturing data at the source has emerged, and this, in turn, has fuelled the next chapter of technology development, largely focusing on advanced data analytics and AI (Boehm & Thomas, 2013). Due to its specific nature, AI technology evokes both dystopian (Fletcher, 2018) and overwhelmingly positive feelings among experts and laypersons (Chui et al., 2018). Today, a rapidly growing stream of research on AI primarily focuses on hardware technology for data storage and processing and on software algorithmic modeling techniques (Goodfellow et al., 2017), and we observe various companies starting to implement this technology. From being a technology primarily adopted in software and social-media–intense industries, AI is now entering strategy and operations in more traditional industry verticals, such as industrial manufacturers and consumer goods assembly.

As a technology entrepreneur and a practitioner in the industrial manufacturing industry in various technology roles over the last two decades, I have seen various technology phases such as the dot com, Internet, e-commerce, IoT, cloud, Industry 4.0, and AI phases. I recall that adopting every major new technology has been far from easy for industrial manufacturers, with AI being no exception. The adoption of AI in offerings from industrial manufacturing organizations remains low (Alsheibani et al., 2018). While the impact of AI on the world economy is well under discussion (Bughin et al., 2018), with potential contributions as high as USD 15.7 trillion by 2030, AI arguably brings about substantial opportunities and challenges for many industrial manufacturing companies (Stoica et al., 2017). The advantages of AI for industrial manufacturers are primarily concentrated in value creation through operational excellence rather than in other value areas with implications for customers and/or BMI users.

AI technology is typically thought to allow new production methods with a more limited or changed role for human workers. Such technologies do not replace today's production systems but are implemented in existing systems to reduce cost, limit risk, or take over work processes that are dull or dangerous for people (Lee et al., 2018). In this way, implementing new technologies is associated with process innovation carried out by the workers (Patel et al., 2018), which means doing the same thing but in a much better way and thereby increasing efficiency through data-driven automation and other techniques. There is a significant risk that this production view is far too narrow and should be complemented with technologies utilized for innovation, with the resulting consequences representing value for all stakeholders within the ecosystem (Chesbrough, 2007a). This thesis highlights that AI is commonly treated like any other technology, enabling new functionality or performance today. In this view, AI technology would not benefit adopting customers and users unless it can be used purposefully to create new value that is distributed to stakeholders with accepted or new business models (BMs).

While AI generates value through efficiency in current BM processes, as a next step, AI can also generate value within the BM by enabling new capabilities that were not possible before. Furthermore, AI technology can also support innovative BMs and BMI by enabling dynamic capabilities. This view of AI technology can generate value within products, services, innovation processes, and BMs, thereby enabling much broader and deeper adoption of AI within BMs. This value view of AI technology has been discussed (Haefner et al., 2021) but needs further elaboration. Through data-driven marketing, AI can contribute to stakeholder value by enabling the mass customization of services based on individual needs (Ma & Sun, 2020). AI can differentiate stakeholder value by incorporating data-driven technologies within strategy processes (Schilling, 2017). AI can also contribute to stakeholder value through generated effectiveness by prediction-based operational transformation (Dogru & Keskin, 2020). When combining AI's impact on industries from an efficiency and stakeholder value perspective with disruption from digitalization, technology disruption is observed to be driving BM disruption. Hence, there is a clear and urgent need for an improved understanding of AI's impact on designing innovative future services and value within BMs from both the product and process perspectives.

Many industrial manufacturing firms have a history of delivering value based on their offerings' functionality, quality, and price, relying primarily on traditional transaction-based BMs, including manufacturing and selling products using channel partners (Oliva & Kellenberg, 2003). However, emerging and rapidly maturing technologies, not least digital technologies, enable new opportunities to create, deliver, and capture value in much more intelligent ways using connectivity, IoT, cloud, and AI (Porter & Heppelman, 2014). Consequently, "firms will need to move up the value-added chain and embrace knowledge-intensive, high-skilled manufacturing to compete more on quality and less on price" (DTI, 2004, p. 12). Usage of AI can go far beyond both price and quality. It can help companies create differentiation to bring about internal and customer value (Chui & Ng, 2018). Hence, "manufacturing organizations must rethink their strategy and enter the debate on how more innovative practices might enable them to create higher value and ultimately to improve their competitive position" (Noke & Hughes, 2010, p. 132).

Focusing on AI's specific use in offerings within manufacturing companies gives rise to a shared view of how AI can be used. It has recently been indicated that AI may be fruitfully used to sustain competitive advantage by reducing costs, moving into new businesses, better understanding customers, and proactively responding to changing customer needs. However, AI will also bring about new competition, and it is at present very unclear which organizations will, in the end, be the ones reaping its benefits in terms of increased revenues or reduced costs (Lee & Lee, 2015). To understand the impact of value created, delivered, and captured for stakeholders, we first need to understand the gaps in current digital–physical product development knowledge (Hendler & Boer, 2019). Then we need to understand how the capabilities of digital technology in general and AI technology in particular influence both customer values and costs, thereby promoting effectiveness and efficiency through innovation within organizations (Granstrand & Sjölander, 1990; Hinings et al., 2018). Moreover, we shall also try to understand what values digital technology in general and AI in particular have for various business stakeholders (Güngör, 2020; Wheeler & Sillanpa, 1998).

1.2 AI and its impact on value

This section highlights how AI can also be viewed as a value impactor and not merely a resource. While AI technology, including data-driven approaches, enables transformation in industries, adopting these technologies is arguably highly dependent on the value they create and deliver for customers and other stakeholders. In English, "value" is defined as "how much something is worth in money or other goods for which it can be exchanged" (Brown, 2020). In a business sense, value as a concept can be vague and subjective, and hence rather tricky to define and agree on when used in assessing product and service offerings. While value as a concept is highly subjective (Cengiz & Kirkbir, 2007) and driven by customers' expectations of the product and service offerings, customers' expectations of organizational offerings have been changing rapidly and growing over the last few decades, and this has been observed across industries and segments. Perceiving value in business offerings is especially tricky as customers' expectations of intelligent and connected solutions are increasing, as is the value perceived in offerings, and the companies providing such offerings are constantly being transformed in the eyes of customers.

While a boom has been noticed in recent years in the research area of AI algorithms and techniques such as deep learning and neural networks, the use of AI technologies to alter, change, and improve BMs is highly dependent on the value they eventually create for customers. A value model can be defined as a data-driven representation of the worth of what a company is doing or could do for its customers. Numerous value models for customers and other BM stakeholders have been discussed in the research. Smith (1776) conceptualized value as both objective and subjective. Objective value, such as price and failure rate, is quantifiable and can be a basis for transaction. At the same time, subjective value can be more perception based, including feelings, motivation, and a sense of achievement. Even contemporary literature differentiates between value-in-use, i.e., subjective, and value-in-exchange, i.e., objective and transactional (Eggert et al., 2019). Anderson et al. (2007) stated that value in business markets can be quantified in monetary terms (Eggert et al., 2019), but highlighted that the conceptualization of value remains ambiguous, especially the value perceived by customers according to the perceived benefits accruing from the offering. VM (2020) introduced a value model that firms can use to emphasize their business opportunities while developing products to achieve unrivaled customer value and knowledge through deepened relationships with customers. Lindgreen et al. (2012) outlined three value processes within servitization, i.e., value analysis, value creation, and value delivery, to achieve customer value in the offering and further detail the activities needed in order to structure, bundle, and leverage the value creation for customers. Woodruff (1997) focused on the individual customer's value perspectives, proposing a customer value hierarchy model to classify different customer value concepts before proposing a customer value determination process that firms can use to transform customer value learnings into actions during their offering design. Multiple value frameworks are presented in the literature, such as that of Payne and Holt (2001), which addresses value from a relationship perspective to create, deliver, assess, and determine value through engagement with customers, employees, and external stakeholders, and that of Eggert et al. (2019), which addresses value from a transaction perspective, considering value-in-use and value-in-exchange in different business markets. However, these frameworks seldom include the value implications of AI technology, which need to be highlighted and better understood.

While value expectations relate to lower costs, better quality, and new functionalities (Fazio et al., 2016), the emphasis on customers' expectations is extending to encompass new BMs, which, on one hand, is impacting servitization (Vandermerwe & Rada, 1988) and, on the other, is creating more integrated services within business ecosystems (Gajen & Gossain, 1998; Jacobides et al., 2018). Data-driven digital technologies create new capabilities and generate new values for customers and other stakeholders within existing BMs. Furthermore, industrial manufacturing incumbents can use AI technology to create new innovative value offers by creating new BMs and adopting business model innovation (BMI) to maintain their relevance and position in the market (Christensen, 1997; Corea, 2017).

1.3 AI and business models

In essence, a BM should define how a company creates, delivers, and captures value (Teece, 2010). AI-driven capabilities generate new functionalities and features for business offerings utilizing AI as a resource. However, this may be an overly narrow view, and we need to consider the various effects of these resources. These capabilities can be used to reduce costs, increase speed to market, or improve quality, in what can be termed efficiency improvements by means of AI-driven capabilities. On the other hand, AI technology can also offer new or improved products and services by enabling customization based on individual prediction-based services in the manufacturing and supply chain, differentiation based on market-driven pattern analysis in marketing, or effectiveness based on intelligent services from advanced data analytics in sales, operations, and research and development (R&D). This highlights that AI capabilities impact the underlying value dynamics of the BM, namely, value creation, value delivery, and value capture.

AI capabilities (Verganti et al., 2020) have value implications in BMs with multiple customers and suppliers simultaneously. Technology provides capabilities that not only can identify the customers and users who are innovative but can start to treat them as entrepreneurs, crowdsourcing the recipe for business in the form of data and insights and using capabilities derived from customer engagement and interaction datasets to determine the next steps in BMI (Aversa et al., 2015a). AI also offers new business combinations called constellations for BMI (Aversa et al., 2020), which have implications for value. Exemplifying such constellations for BMI are services based on predictive maintenance, future prediction, trust-based solutions, and value-based pricing (Hinterhuber, 2004). In addition, by using new types of digital platforms (Cenamor et al., 2017) and by increasingly embedding connectivity and intelligence into products (Porter & Heppelmann, 2014), companies develop data-driven solutions in new innovative ways, for example, to understand customers, predict the behavior of products and services, and prevent failures (Goyal, 2019). AI technology gives the profound ability to analyze complex problems such as categorizing consumers or predicting user behavior based on processing millions of data points. AI can be not only a source of increased efficiency through automation but also a key to offering new or improved products and services. AI can transform the way companies perform their business (altering their BMs) and fundamentally enhance the value enabled by new BMs, as the value process dimensions of BMs (i.e., value creation, value delivery, and value capture) are changed.

Customer engagement approaches can be categorized in four ways, as highlighted in the "Business Model Zoo" (http://www.businessmodelzoo.com/): in the "product model," the company develops a product or standardized service for customers; in the "solution model," the company engages with a customer's problem to provide an integrated solution; in the "matchmaking model," the company links buyers and sellers in its online or physical marketplace; and in the "multi-sided model," the company provides different products or services to different customer groups such that the value proposition is multi-sided, meaning that one customer group gets additional benefits from the other group's transactions. AI technology can enable new and different BM configurations through additional capabilities to create and deliver value for customers (Aversa et al., 2015b). In the "product model" approach, a supplier creates the product (value creation) and sets the price (value capture); then the buyer consumes the product (value delivery) without much dialogue or transparent relations with the supplier (Lamming et al., 2005). The product model approach is being challenged in favor of a more "dyadic solution model" approach in which value is co-created, primarily enabled by IoT, sensors, connectivity, the Internet, the cloud, social media forums, and AI (Baden-Fuller & Haefliger, 2013), especially in industrial manufacturing firms. This includes using data to identify buyers' value aspects, which are introduced during value creation and delivery in the form of an end-to-end or value-added solution rather than the product itself. Even "matchmaking" and "multi-sided" BMs are well supported by AI. For example, in the matchmaking approach, no direct user value is provided; instead, the value is delivered by joining up two previously disconnected groups of customers, allowing them to trade an underlying good or service on a common platform, and creating "triadic" or "multiadic" BMs. These BMs often use AI-based platform capabilities, as in the case of Uber and Airbnb. Also, in multi-sided BMI, firms connect two customers in parallel, providing service and value to one (the actual user) and giving value to another group (the paying customer), often using advanced data analytics and AI, as in the case of Google (Christensen et al., 2016). The role of AI technology in value processes via digital platforms, including APIs and open-source software (Wnuk et al., 2014), adds value whereby people contribute to these open sources and tap into such communities to introduce different BMI cases (Clauss et al., 2019).

One might perceive BM as typically beginning with value creation, but what is sometimes not emphasized is “how” this value is identified and “why” this value is essential. A successful BM creates, delivers, and captures the value, but the basic assumption concerning what value to create in the first place is sometimes overlooked or not emphasized enough. The value-creation step within the BM value framework starts with the identified gap or requirements (identification) based on certain “value assumptions” made by the incumbent firms regarding their customers (Jokubauskienė & Vaitkienė, 2017). While these value assumptions may be valid and yield good insights into the value that firms should be looking to create and deliver, such that profitable capture can be arranged, it is not always the case that identified value assumptions hold concerning the potential assessed (Raian et al., 2011). Digitalization and AI technology enable objective decisions based on real-time advanced data analytics to connect products with services for new offerings and to connect these with different partners and customer processes to create new value networks through combined value identification. While AI plays a vital role in providing data and insights from different customer-value process perspectives, AI can also provide inputs for making sense of these insights into customers’ value identification, which is critical for BMI (Jacobides et al., 2018).

1.4 Problematization and aim of the thesis

Value research concentrates on the overall offering level and applies mostly a transactional or operational perspective. While some studies investigate the process aspects of value (Wikström, 1996), they seldom investigate the dimensions of value involved in the BM, let alone detailing the interactions and changes within the value dimensions during the end-to-end business modeling process. In AI-driven BMs, the value emerges and evolves as the service creation, delivery, and usage happen by capturing data and generating insights. This phenomenon of value dynamics through digitalization, emphasizing AI technology, impacts the company’s BMs in far more complex ways than does a causal chain that variance theory can explain. Different stakeholders have multiple events, activities, and choices that impact value dynamics and need to be considered from a process orientation (Langley, 1999). It is also observed that the temporal aspect of these value dynamics is an under-researched area that needs to be looked into concerning the phenomenon examined here. Hence, this thesis focuses on value as a process rather than a transaction and highlights the need for a framework that combines individual, transactional, and relational views of value together within BMs.

Commonly, value research takes an operational or transactional view of value; it highlights that by considering the process view (Langley, 1999), our understanding of value dynamics within AI-driven BMI can be addressed much more deeply. This is because value is perceived and dynamic and hence changes and transforms during the value creation, distribution, and capture steps of BMs (Michel et al., 2008). A process view of value is explicitly required within AI-driven BMs due to sequences of eclectic and temporal events taking place at multiple levels within BMs. Some scholars have applied the process view of value as well. For example, the entrepreneurial literature has touched on value identification under concepts such as effectuation theory and boundary objects (Boland & Tenkasi, 1995). Value is identified as the offered solutions proceed within the BM, providing tangible next steps for further solution development. Value creation and delivery have been investigated from several angles, such as customer engagement (Zhang et al., 2017), the impact of value on customer engagement and stickiness through social networks, customer relationships (Walter & Ritter, 2003), and value as driven by customer relationships through adaptations, trust, and commitment. As well, value creation and delivery have been investigated in several domains, considering, for example, how e-business (Amit & Zott, 2001) is impacting new value aspects such as convenience and how value co-creation (Oliveira et al., 2017) is driven within business-to-business settings (Walter et al., 2001) and sharing between buyers and suppliers. Value capture shows up in the innovation management and marketing literature, in which value (Chesbrough et al., 2018) is captured by open innovation (Munir et al., 2017) through companies' dependence on each other's capabilities, and in the BM literature on pricing (Hinterhuber, 2004), in which value-based price models are determined as per customer-perceived value. However, the work is commonly limited to one or two aspects of the value process without attempting to put forward an extensive end-to-end framework and without a focus on the value process when it comes to AI technology in particular.

Value research is often performed from an overall organization or offering perspective or from the perspective of one value-process aspect, such as delivery, creation, or capture. To understand more comprehensive value implications of AI technology for BMI, this research posits that a more comprehensive value framework is required when dealing with AI technology specifically within BMI. Some researchers have worked on a BM template for AI solutions. For example, based on a study with 14 cases, Metelskaia et al. (2018) presented a BM canvas that describes the building blocks of BMs for AI solutions specifically with reference to creating or analyzing AI solutions, consolidating existing AI practice cases and their impact on BMs. Looking deeper, one realizes that Metelskaia (2018) was referring to value in the same way as did Osterwalder and Pigneur (2010) and Osterwalder et al. (2005), i.e., just from a technology standpoint, again missing the value coverage within BMI.

Overall, this research aims to explore AI technology's influence on the value processes within BMs, thereby fostering insights into the impact of AI on both efficiency and more fundamental value changes in

BMs. The desired effect is to help industries successfully incorporate AI technology into BMI activities and the resulting offerings. This is achieved by proposing a tentative framework for value within AI-driven BMs. The scope is industrial manufacturing companies aspiring to increase digital servitization in the business-to-business (B2B) and business-to-consumer (B2C) segments. The research approach is to theoretically and empirically investigate how the phenomenon of digitalization, with a particular emphasis on AI technology, impacts value creation, delivery, and capture within a company's BMs and BMI efforts. This is achieved through a series of research studies highlighting the need to focus on different value processes within AI-driven BMs. Furthermore, the present findings and analysis help us work towards a value-process–oriented framework, to propose how value could be reflected in future AI-enabled BMI research and practice.

1.5 Outline of the thesis

This thesis includes five papers and an extended summary. We start with an exposition of prior theory concerning digitalization, value, and BMI, followed by the research questions addressed in this thesis. Then we outline the research setting of this thesis and the research methodologies used in all the appended papers, followed by summarizing the results of these papers. Next, we analyze the papers to highlight the need for updated value processes within AI-driven BMI and work towards a framework. Finally, we discuss the results as they answer our research questions before concluding the thesis by presenting its implications for theory and practice, highlighting the limitations of this thesis, and making some suggestions for future research.

2. A brief overview of digital technology development

Charles Babbage is credited with inventing the first mechanical computer, the Difference Engine, which eventually led to more complex electronic designs (Copeland, 2000). However, the actual development of computers can be considered to have started in the 1940s, and these computing machines became accessible to corporations in the 1960s with the advent of mainframe computers performing central processing and computations (Mahoney, 1988). Since then, technology advances and adoption have been critical for innovation in the industrial manufacturing industry. As technology advanced, computers became personal, and distributed processing and computational client–server architecture evolved. During this journey, several streams of hardware and software advances were worked on and made available, complementing each other to give impetus to industry digitalization.

As a continuation of technological advances, in the late 1990s and early 2000s, two hardware- and software-related digital advances with impacts on industry have emerged, namely, information and communication technologies (ICTs) and cloud. ICTs offering "capacities to acquire, store, process and transmit information" (Steinmueller, 2000, p. 361) have increasingly been incorporated into products to enable new innovative functionalities and features (Davies, 1996; Nightingale & Poll, 2000; Nightingale et al., 2003). Cloud, central storage, and processing solutions enable a group of different workloads to better access the required resources in an automated manner (Longbottom, 2017, pp. 13–22). The National Institute of Standards and Technology (NIST, 2011) defines a cloud system as "a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction."

During the early 2010s, the Internet of Things (IoT) concept started to be used more broadly. Even though we lack a standard definition and framework for this term, the International Telecommunication Union (ITU) now defines IoT as "a global infrastructure for the Information Society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies" (ITU, 2012). At its core, yet again, IoT digital technology enables innovation by combining hardware and software components and thereby providing new functionalities and BMs (Porter & Heppelmann, 2014). IoT can typically be envisioned to consist of three components: 1) things (also referred to as devices or sensors); 2) connectivity (enabling data communication); and 3) intelligence (usually cloud analytics to derive insights from data).

With ICT, IoT, and cloud as enablers, a data burst (Chui & Ng, 2018) occurred soon after 2010, and this was one of the leading contributors (together with computational and algorithmic capabilities) to the spring of AI, seen in the mid 2010s after a long AI winter. AI is the study dealing with the simulation of intelligent behavior or introducing the capability to imitate intelligent human behavior on machines. AI has its roots in the Turing test developed by Alan Turing in the 1950s to test machines' abilities to exhibit intelligence. John McCarthy coined the term "artificial intelligence" (AI) in 1955 (McCarthy et al., 2006) and made it a research stream during the Dartmouth Conference in 1956 with Marvin Minsky, Allen Newell, and Herbert A. Simon.

Today, AI is a set of technologies being exploited by almost all industries in different use cases (Chui et al., 2018), and its impact on the world economy is under discussion (Bughin et al., 2018). During the mid 2010s, with many advances in IoT sensors and actuators, greater processing power, cheaper storage, greater connectivity bandwidth, and network improvements, industry started concentrating more on advanced AI technologies such as Edge computing directly on IoT devices. Other technology concepts such as "Fog" and "Ubiquitous" are extended versions of, similar to, or related to Edge. As advances in technology and devices have enabled AI computing, intelligence derived through the extensive computational cloud and AI solutions can run directly on devices, enabling intelligent products. As IoT rolls out globally, 40–80 billion connected devices are predicted by 2025 (Carrie & Reinsel, 2019), representing five to ten connected devices per individual.

Still, it is common for industrial manufacturing use cases and research studies to focus on the immediate and obvious benefits of IoT-connected devices. Frequently, technology shifts start with a strong focus on technical aspects, with attention being concentrated on the use of technology as such and hence possibly overlooking the full potential value that could be imparted through the technology to all aspects of new digital BMs (Opresnik & Taisch, 2015). This thesis highlights that AI technology in manufacturing industries has often been seen as a physical technology resource to promote efficiency through automation, cost reduction, and quality improvements. This thesis identifies that AI technology contributes to and can exploit the value processes of BMs, namely, value creation, value delivery, and value capture, within organizational offerings, thereby providing capabilities driving new offerings, new ways of doing business, and competitive advantage. This thesis emphasizes that while AI technology can be used as a resource to generate efficiency and automation, this resource view of AI technology is somewhat limited and incomplete; AI technology can also generate competitive advantage by creating value within the BM.

3. Exposition of theory

Concerning the ambition underlying this research, namely, to explore value within digitally (AI in particular) driven BMs, it is not easy to understand the complex phenomenon of value dynamics in the setting of digital BMs as it includes many aspects: individual value perceptions that can constantly change over time; the value of relationships within organizations and with customers; and value in different BM transactions between stakeholders and others. To understand this complex phenomenon of value changes within digital BMs, mixed-use theory is applied, with this section drawing on three literature streams. First, we consider different concerns within BMI and how digital technologies are impacting and driving BMI. Then we look into the concept of value to understand various aspects and perspectives that research has examined regarding value as concerns customers and BMs. Finally, we consider current research discussions of AI technology's impact on BMs from the resource and capability perspectives.

3.1 Business model innovation

On a high level, a BM represents a conceptual model of a business (Teece, 2010) and can be described as the way companies commercialize their ideas (Chesbrough, 2010). The importance of good BMs cannot be underestimated (Magretta, 2002), and with a business model, the innovation approach also entails a need to challenge and innovate different components of the current BM (Hedman & Kalling, 2003). The BMI concept is commonly used in business journals, company annual reports, and academic articles, but the concept is young as a research topic, having been studied in a structured way only since the early 1990s. Today, there are many lively relevant research streams, and this section will introduce the topic, explain some of the critical elements of BMI, and cite examples of some successful BMI cases and activities (Chesbrough, 2007b). Chesbrough (2010, p. 1) even stated that "a mediocre technology pursued with a great BM may be more valuable than great technology exploited with a mediocre business model." An intelligent connected product "opens up a spectrum of new business models" (Porter & Heppelmann, 2014, p. 21). However, it is also known that it may not be new digital technologies that will pose significant challenges to success, but the "ability to articulate the value of digital technologies to the organization's future" (Kane et al., 2015, p. 4), and hence to create a BM that can capture the value generated (Teece, 2010). The reason is that, even though a BMI approach may offer great possibilities, many companies struggle to make a profit on their new business that is mainly related to services (Benedettini et al., 2015). Some companies even fail to profit from their servitization efforts, defined as a service paradox in the literature (Baines et al., 2017).

From a simple customer-oriented value perspective, BMs are frequently referred to as a means to create, deliver, and capture value (Teece, 2010). Multi-sided BMs (Aversa et al., 2020) differ from traditional models by bringing new dimensions to value creation, delivery, or capture. For example, these models include customers who might not always be the same as direct beneficiaries, incorporate the demand perspective into the BM, and highlight the implications for value-based capturing techniques. Amit and Zott (2010, p. 2) defined a BM as “the bundle of specific activities conducted to satisfy the perceived needs of the market, including the specifications of the parties that conduct these activities” This definition captures the essence of a BM: how to do business from a holistic perspective, emphasizing value creation for all relevant stakeholders. There is widespread consensus that BMs are systemic, transcending company boundaries (Amit & Zott, 2001), but also that they pose unprecedented innovation challenges (Itami & Nishino, 2010), especially when it comes to the strategic and tactical levels (Casadesus-Masanell & Ricart, 2010).

BMI as a concept has been coined and discussed over the last decade and can be regarded as the introduction of a new or modified BM for commercial value creation (Berglund & Sandström, 2013, p. 276). BMI is still a developing topic as the Industry 4.0 revolution reshapes the economic landscape, driving competitiveness and accelerating growth (Schwab, 2017). The open system nature of BMI can cause structural challenges for firms due to the resulting uncertainties and risks, often stemming from feedback loops (Berglund & Sandström, 2013). Consequently, systemic and holistic considerations need to be encouraged in this type of BMI (Amit & Zott, 2010). Both the BM and BMI literature streams address value as an overall concept covering value creation, delivery, and capture, but they seldom include in-depth explorations of these specific value aspects (Amit & Zott, 2012) or, especially, of their impacts due to AI. Research has worked towards a BMI typology (Taran et al., 2015), but AI technology adds value to products, services, and offerings through creating new capabilities, affecting business relationships by transforming the business offering (Hultman & Axelsson, 2007). The more profound change is that AI technology transforms the value processes at the core of the BM concept, a matter that has not been thoroughly investigated.

Apart from technology, another more recent aspect of new BMs is that the innovation process should focus on monetary revenues and “societal wealth improvements” (Thompson & MacMillan, 2010). This social view means that companies should focus less on strategy and purpose, as companies have a lot to gain from employee attention and financial goals (Geissdoerfer et al., 2016), a value also affected by AI and data technologies. Hybrid organizations combine welfare and commercial logic to address a more significant challenge than just firm performance (Spieth et al., 2019). Today’s customers (especially the new generation) seek good products and services provided by enterprises associated with social contributions and activities. Investors looking for the inclusion of social agendas in the articles of association of organizations that sometimes retain substantial wealth are looking and asking for social

BMs (Santos et al., 2015; Yunus et al., 2010) rather than economically driven ones. Technology and, specifically, AI are playing a vital role not only in advancing social causes but also in enabling innovation in BMs to create value for society in one of three ways: contributing to poverty eradication, increasing education, and reducing pollution; creating positive externalities such as reduced consumption; and reducing externalities, for example, by reducing waste and optimizing resource use. There can be many ways towards social innovation enabled by technology (Munoz & Cohen, 2017). For example, on the governance side, BMs such as cooperative societies have come into existence and, with articles of association at the institutional strategy level, have a social agenda. On the demand side, positive externalities are created and, for example, water ATMs give access to clean water to the masses where it is unavailable or people cannot afford it. On the supply side, BMs can address neglected and ruled-out resources in society, for example, as done by Auticon, an IT consulting company for employees affected by autism. There is increasing debate about whether and how companies can ever balance their economic and social commitments, especially when there is always a tussle between short- and long-term gains when it comes to everyday execution and the contribution of technology to the same (Faik et al., 2020).

3.1.1 BMI as a source of competitive advantage

Firms that desire to change an aspect of their current business operation can proactively work with BMI (Giesen et al., 2007). It has been proposed that continuous BMI could be an excellent way to outperform the competition and that a company's BMI may be a key focus area in itself (Mitchell & Coles, 2003). BMI has been described as the output of an innovation process that replaces and revises the BM currently in use (Foss & Saebi, 2016; Massa et al., 2017). BMI must happen before it is too late (Massa & Tucci, 2013), and to maintain a prosperous business, understanding when it is time to alter the BM is fundamental (Johnson et al., 2008). BMI may redefine existing offerings, for example, the value delivered to customers and how that value is appropriated, but is not in itself a process of identifying new products or services (Björkdahl, 2009). At the same time, digitalization has in recent years accelerated the opportunities to create new types of offerings in which products and services are combined in new ways (Witell & Löfren, 2013). Digitalization has enabled value creation that was not possible before. These complex digital offerings would, in many cases, also require BMI. Research on digital BMI has attracted significant interest in recent years and is concentrating on the transformation driven by digital technologies (Aagaard, 2018).

It is helpful to view BMs as models, as this is a powerful way to describe, classify, and understand structure and linkages (Baden-Fuller & Morgan, 2010) in BMI. A model can be broken into different model elements (Recker et al., 2009), and these elements can then be manipulated to increase BMI. The

BM concept can be seen as having a modular design, for example, consisting of the value creation, value delivery, and value capture elements proposed by Teece (2010). These elements can then be experimented with using different operators, for example: *splitting*—separating a BM element into two or more new model elements; *substituting*—replacing one BM element with another performing the same task; *augmenting*—establishing a new BM element or elements to account for a new layer in a multi-sided BM, in order to increase the value of the BM or its elements; *inverting*—leveraging a specific part of a BM to form a standalone element or standalone BM; *excluding*—removing a component to narrow the BM's function; and *porting*—moving a BM component (or an entire model) from one domain to another (Aversa et al., 2015b). These approaches facilitate a modular understanding of the BM concept and of how BM modeling can be approached. As the current way of doing business becomes obsolete, companies need to innovate and remodel their BMs through BMI, if not the entire model at once, then at least parts of how they create, deliver, and appropriate value (Zott et al., 2011).

Any new technology could be pursued with different BMs, each of which could bring success—as Chesbrough (2010, p. 355) has stated, "a mediocre technology pursued within a great BM may be more valuable than a great technology exploited via a mediocre BM." It has been argued that continuous BMI is an excellent way to refine the company's BM and outperform the competition, making innovation a critical focus area (Mitchell & Coles, 2003). BMI may redefine how existing offerings are delivered to customers and how value is appropriated, but it is not in itself a process for new product or service identification (Björkdahl, 2009); however, the latter could be challenged and advanced by AI, thereby blending new product development and BMI. Nevertheless, BMs should be innovated before it is too late (Massa & Tucci, 2013).

Almost all BMI output can be fitted into four different types of BMs. 1) In the *product model*, the company develops a product or standardized service to sell to its customers; the value proposition is transactional and provided as a product or standardized service. 2) In the *solution model*, the company engages with a customer and provides an integrated solution to the problem faced; the value proposition is a relational and tailored solution for each customer. 3) In the *matchmaking model*, the company links buyers and sellers in its online or physical marketplace; the value proposition is transactional in order to facilitate exchange. 4) In the *multi-sided model*, the company provides different products or services to different customer groups; the value proposition is multi-sided, with one customer group gaining additional benefits from another group's transactions (see http://www.businessmodelzoo.com/). Companies can operate several BMs simultaneously, making it essential to understand how different resources and capabilities can be reused in several models. Operating a BM portfolio can accelerate revenue growth, but a successful approach requires a focus on linkages and interrelations between different areas, such as the resources and capabilities of various BMs (Aversa et al., 2017), which will help outline the expected performance output.

There are many examples of companies that have successfully adopted BMI for their competitive advantage. One such company is Amazon, which runs a suite of BMs including a broad range of models, for example, Amazon Marketplace (online shopping), Amazon Webservices (cloud service platform), and Amazon Prime (Streaming) (Aversa et al., 2020). A well-known example of a missed opportunity for transformation is that of Kodak, which, even though it participated in the advent of digital photography, as one of its inventors, still failed to transform itself, partly because the new technology challenged its existing film-driven BM; once a "cash cow," selling and developing film was not quickly abandoned by Kodak (Gavetti et al., 2005). A successful example of BMI is provided by Nestlé, which began to sell coffee machines at low cost, so that it could subsequently sell the capsules needed to make coffee at high margins. This change in BM increased both profit margins and growth for Nestlé (Björkdahl & Holmén, 2013). Another well-known BMI was realized by Rolls Royce, which offered the "power by the hour" model under which a contract for maintenance at a fixed price was set based on engine availability (Smith, 2013). Another example is that of Atlas Copco, in whose BMI both products and services became revenue complements, overcoming the substituting effect of services versus products (Visnjic & Looy, 2013).

As shown in the above examples, technology often plays a vital role in applying different operators within BMs, enabling various BMI implementation archetypes. The following section looks further into BMI functionality, operators, and implementation.

3.1.2 BMI synergies, complementarities, and externalities

To move up and broaden the value coverage of BMI, one observes a logical movement from business strategy (how to compete) to corporate strategy (where to compete), which is also termed "BMI diversification" (Aversa et al., 2019). Examples include Amazon and Netflix, which started with one BM and then moved into others to achieve diversification at the corporate level. BM diversification can be described differently from BMI diversification (Kim & Min, 2015). BM diversification could relate to multiple unrelated business areas entered for risk mitigation purposes, whereas BMI diversification exploits synergies, complementarities, and network externalities arising with BMI (Snihur & Tarzijan, 2018). BMI diversification could also be described as when the customer engagement model is changed from the original model, which eventually means that the value proposition is also changed, which must result in a different BM, as otherwise it would merely cannibalize the old model (which might not always be the desired result). In multiple customer engagement models, the role of ecosystem partners becomes crucial within BMI for innovating value dimensions. Looking at the demand side, two complementary models emphasized by researchers are "one-stop-shop" models, such as malls, superstores, and gas stations with their add-on convenience stores, and "network-effect" models, which arise from multiple customer groups with affinity effects (Ye et al., 2012). For example, in a network-effect model, if one side of the platform has more customer groups, groups on the other side are attracted, which supports the platform's business. Hence, due to digital technologies, the network effect contributes both directly (supporting both sides of the platform) and indirectly (customer profile data yielding insights). This substantiates the role and importance of the ecosystem within BMI. Technology plays a vital role in providing data and insights and thereby enabling value within the BMI ecosystem.

The importance of digital technologies and value innovation in BMI diversification can be illustrated by the case of Formula One, whose core business was making fast cars and winning races. However, this was not sustainable as costs were much higher than the returns from winning races; hence, new ecosystem-based BMs were also adopted, such as sponsorship, selling knowledge to auto companies and other industries, technology sales within Formula One, and running driving training schools. After a qualitative factor analysis (QFA) to determine which configuration of the above BMs would work best for Formula one (Aversa et al., 2015a), a counter-observation was that selling technology and talent was the best Formula One BM. This could be because giving technology to peers enhances data collection: internal technology development and training drivers yield better insights into necessary car technology improvements, which eventually results in winning races. The two ways incumbent firms should react in order to add value by adding to the BM portfolio within the ecosystem are: in cases of complementary assets, firms must align the assets with the early addition of a new BM to the portfolio; in cases of conflicting assets, firms must create new, more autonomous BMs within the portfolio (Markides & Charitou, 2004).

The core of BMI diversification is to deliver fundamental value by offering new growth opportunities or adding to a current business, reducing the risk, or optimizing and enhancing performance. Diversification is usually achieved in one of three ways (Casadesus-Masanell & Ricart, 2011). First, *horizontal diversification* entails entering a new business area and introducing new products or services under a current or new brand, depending on the nature of the business. To cite an automotive industry example, in 1989 Nissan launched Infinity as a luxury brand with a new offering targeting a new segment of customers. Second, *vertical diversification* entails making changes in the business value stream such as partnering with suppliers or distributors. Netflix, for example, has gone from being only a distributor to venturing into production, thereby gaining ownership of a larger part of the whole value chain. Lastly, *geographical diversification* entails expanding into new markets where a selected offering is usually launched, under a current or new brand, for example, having specific content or tailored offerings in different countries via essentially the same service, as in the case of Netflix.

Diversifying BMs allows for value impact by adapting to ever-changing market trends and technology. To build momentum in the BMI diversification transformation, one can take advantage of or respond to societal shifts or trends (Giudici et al., 2018). For example, Netflix utilized the increased Internet use and bandwidth to add streaming as a service versus sending DVDs via mail, and Fuller's is a traditional beer brewing company that is now a leader in education and training in the brewing field, building on the DIY/microbrewing trend. Apple's AppStore has gone from initially being a supporting service for the new iPhone product line, to being a substantial part of the company's overall business. This illustrates how shifts in technology and customer behavior can be leveraged towards fundamental value aspects with the diversification of BMs. It also creates the opportunity to create a separate new venture, adding to the current business instead of making potentially significant changes to a current functioning business (Casadesus-Masanell & Tarzijan, 2012).

BMI diversification to create a BM portfolio will ultimately contribute to the firm's value through building competitive advantage, since this presents opportunities independent of one another in the company. The company's capability can benefit from testing new opportunities without interfering with current business or customers, and from catering to new customer groups that might be challenging to attract to a current business. BMI portfolio creation results in a complex group of offerings by incumbents and develops the traditional role of the ecosystem encompassing incumbent firms and their customers (Jacobides et al., 2018). The relationship is not just limited to a transaction-based model linking stakeholders, but entails deeper interaction with customers. Under these circumstances, the dependence of incumbents on their ecosystem partners is redefined, and the specific roles they play in value identification within the complex digital offerings of incumbents needs to be looked at in greater depth.

Having looked into BMI theory, this thesis notes that in technology-driven BMI, there is a need for further emphasis on value discussions, especially when it comes to applying the process view of value. Furthermore, digital BMI has been considered from a general digital technologies perspective and, given the specific nature of AI technology, there is a need to emphasize value discussions specifically within AI-driven BMI. The implementation of AI in BMI has been regarded as an enabler of previously impossible applications that may sometimes appear questionable, such as tracking one's heartbeat while reading an e-book and obtaining indications of an individual's personality, likes, etc. The questionable nature of such potential applications partly accounts for the less-than-expected adoption of AI technology within BMI by industrial firms. This section has examined the prior state of digital technology, value discussions, and BMI; the following section looks into technology's contribution to BMI.

3.1.3 Technology as a driver of BMI

Around two centuries ago when the "bespoke" model was prominent in business, with more user-specific and customized products and significantly less opportunity to reuse and standardize, economies like those of China and India contributed majorly to the world. However, when mass-production, standardization, and the Industrial Revolution peaked in the nineteenth century, the western world dominated the global economy. Strategy discussions and research from the 1970s until the first decade of the twenty-first century have largely concerned organizational structures, competition, resources, and capabilities. Discussion of BMs intensified only toward the end of the first decade of the twenty-first century. One might notice that, during the same period, the digitalization boom happened within the technology space (Nightingale & Poll, 2000), playing a significant role in the BMI debate by enabling new possibilities.

When we investigate the "BM zoo," it becomes apparent that the earlier "dyadic product" approach in which the supplier creates the product (value creation), sets the price (value capture), and then the buyer consumes the product (value delivery) without any dialog or transparency with the supplier is being phased out. More and more, "dyadic solution" approaches are being adopted, especially in industrial mass production, which is the scope of this thesis. In "dyadic solution" BMs, suppliers and buyers co-create value, primarily enabled by digital technologies such as IoT, sensors, connectivity, Internet, cloud, and social media forums (Porter & Heppelmann, 2014). The value is created through capturing buyer data and experiences and then using those data to identify buyers' value aspects, which are introduced during value creation and delivery in the form of end-to-end or value-added solutions rather than the product itself.

A key enabler of new BM services that has attracted considerable attention in the literature is the need for digital technologies to facilitate business transformation and new BMs (Ardolino et al., 2016; Belvedere et al., 2013; Boehm & Thomas, 2013; Hsu, 2007). Examples of such techologies are sensors, actuators, and connectivity devices embedded in products (Porter & Heppelmann, 2014), using a data-driven approach (Sorescu, 2017) and AI-based BMI solutions to understand the customer, predict and adjust product and service behavior, prevent failures, and create new types of enabling digital platforms (Cenamor et al., 2017). Product–service offerings relying entirely on ICTs are sometimes referred to as cyber–physical systems (Boehm & Thomas, 2013). These technologies enable new capabilities (Boehm & Thomas, 2013; Keshavarzi & Van Den Hoek, 2019), providing excellent value to customers via functionalities to implement transparency in business relationships (Eggert & Helm, 2003).

“Triadic” or “multiadic” BMs such as “matchmaking” and “multi-sided” BMs are closely tied to digital technology. For example, no direct user value is provided; instead, value is delivered by joining up two previously disconnected groups of customers, allowing them to trade an underlying good or service on a common platform. These platforms are often digital solutions, as in the case of Uber and Airbnb. Also, in multi-sided BMI, when firms connect two groups of customers in parallel, providing a service to one group (actual users) and giving value to another (paying customers), means are incorporated to prevent the two groups from connecting either by design, rule, or competitive technological advantage, as in the case of Google (Baden-Fuller & Haefliger, 2013). The role of a digital platform draws on both the individual and ecosystem perspectives, such as APIs and open-source software, which people contribute to and companies tap into in order to introduce various BMI cases.

Various digital technology-driven capabilities (Verganti et al., 2020) enable value creation by curating customer engagement and interaction data in order to understand users’ needs and value aspects and even to predict insights, enabling formerly impossible proactive measures through machine learning and data science. These digital capabilities also lead to BMI with simultaneous multiple customers and suppliers from different domains for the same business, providing multiple revenue streams (Larsson, 2017). These digital capabilities also enable a reduction in the cost of goods sold, as in the case of the computer processor company ARM (Aversa et al., 2017), where community sourcing and expert panel forums are used to gather future customer requirements, which are incorporated by the firm to sell to the same audience. This provides cost neutrality for microprocessors produced on the assembly line and builds competitive advantage by meeting customer expectations and understandings. As stated above, technology can identify the innovative customers and users and start treating them as entrepreneurs, crowdsourcing the business recipe using data and insights and using customer engagement and interaction datasets to determine the next steps in BMI.

Netflix started to leverage AI within its BMs to deliver value as early as 2010. It has continuously transformed the business landscape with the help of AI and big data in creating an automatic problem-solving loop by sharing the data across the organization. Its search engine, for instance, is powered by gathering accurate realtime customer data and model training to drive virtually every aspect of the business process, from user-centered personalization to picking the best candidates, from instantly importing user interaction data to the next iteration of analysis and even selecting the titles for production (Fink et al., 2020). AI is the primary driving force providing new values for Netflix products and the entire purchase, sale, and distribution strategy. At the same time, AI technology also provides capabilities to remove the limitations of information isolation, data transformation delay, and workforce analysis boundedness, thereby accelerating the transformation of the Netflix BM into a highly efficient and self-learning framework.

Another example is the hospitality industry, which is complicated by its customers' diversity of cultures, personal backgrounds, ages, travel purposes, and other factors. As an indication of cultural complexity, Booking.com provides 43 languages on its chatbot using AI natural language processing (NLP) solutions. The traditional operating model requires labor-intensive investments in people to be hired, trained, and coordinated to achieve people-centricity. AI technology has driven a significant transformation of the hospitality sector with companies like Airbnb consigning the operational onus to hosts, and broadening the options connected to everyone's needs based on perception engines driven by AI. Through collecting enormous amounts of user-interaction data, data scientists have developed extensive logging within the booking flow that allows them to collect insights into what guests see, how they react to different types of interfaces, how much time they spend on a listing page, how long it takes to make a booking request, and the exact time it takes them to decide to return to search (Dai, 2017).

Technology in BMs can be viewed from two perspectives, one being the individual, business unit, organization, or ecosystem perspective, and the other being the digitalizing of core aspects, enabling open platforms through technology and the new method challenges that technology is enabling (Haefliger, 2019). This matrix of the two perspectives highlights how technology can be mapped together with BMs and can be an excellent tool for discussing how companies can traverse different scenarios during BMI. On one hand, technology enables companies to build foundational digital infrastructures such as cloud storage, mobile frameworks, social media interfaces, local intelligence, connectivity, data storage, analytics capability, and data-driven decision-making, thereby enabling new capabilities. On the other hand, technology is being included in strategy work for customer needs identification, focusing on customer experiences, identifying gaps in current offerings, concentrating on individual behavioral aspects, looking into new values and possibilities, and extending current values.

As outlined in the above examples, technology enables BMI capabilities to contribute to fundamental BM value aspects. This thesis argues that technology's impact on fundamental value aspects within BMI is an under-researched area that merits further exploration (Kong et al., 2019; Meijer et al., 2019; Zeng et al., 2019). The subsequent theory section accordingly covers value concepts treated within different current research streams.

3.2 The concept of value in business

Research has long conceptualized value in various ways. It has been discussed as a combination of "objective," i.e., quantifiable, qualities, such as price and failure rate, that can be transacted upon, and "subjective," i.e., unquantifiable, perceived qualities, including feelings, motivation, and a sense of achievement (Smith, 1776). Value has been referred to as the economic benefit within trade exchange (Von Mises, 1920), and the development of the concept has continued with the value-in-use and value-in-exchange conceptualizations of Eggert et al. (2019). Value-in-use refers to the usage part of value, as shaped by the individual perception of value. Value-in-exchange refers to the transaction and relationship part of value, existing between the BM stakeholders. The concept of value has been considered an effect of individual perception (Lapierre, 2000) within the literature streams of marketing, innovation management, and BMs. Value has also caught the interest of practitioners from a behavioral perspective (Wilson & Jantrania, 1994). In business, the value concept has been applied to different fields. In accounting, value is the monetary worth of assets, business entities, goods sold, services rendered, liabilities, or obligations acquired (Treacy & Wiersema, 1995). In economics, value is the worth of all the benefits and rights arising from ownership, together with the utility or the power of a good or service to command other goods, services, or money via involuntary exchange (Hammer, 1996). In marketing, value is the extent to which a good or service is perceived by its customer to meet his or her needs or wants, and is measured by the customer's willingness to pay for it depending more on his or her perception of the worth of the product than on its intrinsic value (Heskett et al., 1994). The value concept has been discussed in more recent strategy literature, where all actor-perceived consequences are generated from resource deployment (Ritter & Lettl, 2017). Actors on the customer side determine value by means of their willingness to pay or the benefits they derive (Brandenburger & Stuart, 1996), while on the demand side, value is considered "the worth in monetary terms of the technical, economic, service, and social benefits a customer receives in exchange for the price it pays for a market offering" (Anderson et al., 2006, p. 24).

Khalifa (2004) analyzed customer value and concluded that while the management literature on value is generally clustered around three categories of value, i.e., shareholder value, stakeholder value, and customer value, the last is the source of almost all other values (Hammer, 1996; Heskett et al., 1994; Lemon et al., 2001; Treacy & Wiersema, 1995). Khalifa (2004) also outlined that customer value includes three complementary models: customer value in exchange, customer value build-up, and customer value dynamics. With the advent of servitization, while incumbents can be associated with the customer over the entire lifecycle of the product, versus the product-exchange transaction only (Vandenbosch & Dawar, 2002), they also have an opportunity to play with customer value dynamics during the service lifecycle while value accrues, as service progresses from selection, through installation, delivery, and usage. In addition, and at the same time, digital technologies enabling continuous insights into customer experiences throughout the service lifecycle (Slater & Narver, 2000) can be used for continuously transforming customer values. While research has looked into different value conceptualizations, such as objective and subjective value (Smith, 1776), and value-in-use and value-in-exchange (Eggert et al., 2019), the value concept remains ambiguous, especially value as perceived by customers evaluating the perceived cumulative benefits of an offering from the monetary and subjective perspectives.

Various customer need assessment models have been outlined in different literature streams, and Sheth et al. (1991) have identified multiple customer-value dimensions from these customer need models. Functional value (Fagerstrøm et al., 2010; Stigler, 1950) represents the "rational economic man's" perspective on customer value. Epistemic value (Brown, 2018; Hirschman, 1980; Teng, 2019) is value in terms of the customers' exploratory, novelty-seeking, and variety-seeking motives. Conditional value (Kummer et al., 2018; Park, 1976) addresses value as dependent on customer situations and circumstances. Emotional value (Holbrook, 1983; Khan & Mohsin, 2017) considers the value arising from aroused feelings or affective states, while social value (Ajitha & Shivakumar, 2017; Veblen, 1899) adds the value aspects of products and services visible to or shared with others, aspects that contribute to the overall perceived value of the offering to the customer. While the above outlines our understanding of value research, the inherent subjectivity and dynamism of value as a concept (Zeithaml, 1988) mean that value changes during the customer's usage of the offering. Hence, we need to better understand changes in and variations of perceived customer value throughout the lifecycle of the service—beginning with deciding to choose the service and continuing with signing the service contract, initiating the service, and usage. Digital technologies and especially AI can play a significant role in examining this longitudinal setup in which perceived value is a complex phenomenon and a product of: expectations, during the service decision and contract signing; perception, during service initiation; and satisfaction, during service usage (Bolton & Drew, 1991a, 1991b).

Research refers to value discussions within BMs from different viewpoints and in terms of different dimensions, being interested in the value of digital BMs. The next section accordingly highlights different value discussions within the BM to understand their viewpoints and coverage, before the impact of technology-specific value on the BM is considered in subsequent chapters.

3.2.1 Value constellations and business models

Multiple value-related concepts have been proposed and used to assess and realize the value of BMs. The value chain concept can be invoked, depending on which "value" is added through each activity to a company's products or services targeting customers (Porter, 1985). As global market competitiveness has increased, organizations have struggled to maintain their privileged positions, implying a need for innovation to create value for customers and sustain revenue growth (Peppard & Rylander, 2006). While the value chain logic explains the increment in value through BM offerings, it has been challenged by limitations such as value co-creation (Oliveira et al., 2017) and complemented by the value network concept, describing a combination of players co-creating value (Peppard & Rylander, 2006). The dynamic nature of value networks enables value analysis to include various stakeholders, instead of focusing solely on the company perspective. Multiple players perform functions simultaneously rather than sequentially in value networks, and value is jointly co-created with customers and other external stakeholders (Galvagno & Dalli, 2014)). Companies have created value within value networks by deliberately letting complementarities enter the market (Aversa et al., 2020), sometimes copying to create network externalities through augmentation (Blackburn, 2002), creating an expanded market to create value. As the network's scope and capacity increase, mutual adjustments are needed from multiple parties (Stabell & Fjeldstad, 1998), giving rise to concepts such as value ecosystems (Ritala et al., 2013), value stars, and value constellations (Normann & Ramirez, 1993), in which different stakeholders combine in different combinations to create value for customers and share value with one another.

The term "value" is understood in different ways in different academic fields. Randmaa et al. (2011) have proposed value-system models for products, services, and businesses, considering multidisciplinary viewpoints from the product–service system, strategic management, organization management, relationship marketing, value network, and other perspectives. Value-system models create unexploited opportunities for companies to create competitive advantages (Randmaa et al., 2011). Multiple frameworks have been developed by which to understand value analysis in business, measure capabilities, and enable innovation. Lindgreen et al. (2012) presented a framework for value orchestration based on value analysis, value creation, and value delivery, focusing on resource management through three types of activities for value orchestration: structuring, bundling, and leveraging resources. Woodruff (1997) proposed an extensive value model based on individual customers' value perspectives, establishing competitive advantage for the organization. Bolton and Drew (1991a) and Oh (1999) have exemplified frameworks for customer-value implications in terms of service quality steps and the customer satisfaction process, respectively.

Moreover, we also observe a stream of research proposing a holistic approach to organizations' value and offerings. For example, VM (2020) outlined an extensive value model of different value aspects within an organization, its offerings, and its relationships with different stakeholders. Looking at the cited value models and frameworks, it can be argued that the focus of these models and frameworks has been either operational or transactional, with value being created or realized when the offering changes hands among the various organizational internal stakeholders or among customers' and other external stakeholders. These models and frameworks seldom refer to value from the BM perspective, and their focus in the value discussion has not been from a technology perspective.

To understand the structure and linkages of value within BMs, we need to describe BMs as models that can be broken down into different modules, which can then be used to manipulate different business offerings (Baden-Fuller & Morgan, 2010). Baden-Fuller and Haefliger (2013) identified the following main modules within BMs: 1) customer identification, 2) customer engagement, 3) value delivery and linkages, and 4) monetization. Another approach to BM design that has become popular in companies is the framework developed by Osterwalder and Pigneur (2010), who outlined the "BM canvas," comprising: 1) customer segments, 2) value propositions of products, 3) channels of communication, distribution, and sales, 4) customer relationships, 5) revenue streams, 6) key resources, 7) key activities, 8) key partnerships, and 9) cost structure. The BM canvas can be an effective tool for documenting a BM and facilitating visual interactions between critical elements of the BM (Osterwalder et al., 2014). The BM concept can be consolidated and seen as having a modular design, for example, divided into the value creation, value delivery, and value capture processes proposed by Teece (2010). It is a straightforward generalization of the BM concept, with value creation representing the offerings, customer needs, and unique benefits (Teece, 2010), value delivery representing the capabilities, activities, and partners (Amit & Zott, 2010), and value capture representing the revenue, costs, and risks (Chesbrough, 2010).

The following quotation from Teece (2010) offers a good summary of the topic but also a starting point for an exposition of theory: "Whenever a business enterprise is established, it either explicitly or implicitly employs a particular BM that describes the design or architecture of the value creation, delivery, and capture mechanisms it employs" (p. 1). It would then be logical to claim that companies have always employed specific BMs, no matter how old they are or what they do. It may then come as a surprise that the different BM-related research streams are relatively young, emerging in the late 1990s (Kraemer et al., 1999; Hoerl, 1999; Afuah & Tucci, 2001; Alt & Zimmermann, 2001; Hedman & Kalling, 2003), but since then accelerating into a very active and lively research field (Zott et al., 2011). BMs and strategy may be connected in several ways. Strategy concerns the choices companies make about what to do and not to do (Gavetti & Rivkin, 2005), and there could be a need to protect the competitive advantages of a BM design through granular strategy work (Ritter & Lettl, 2017) that makes the design more difficult for competitors to imitate (Teece, 2010). Casadeus-Masanell and Ricart (2010) framed the relationship between the concepts in the following way: "a business model, we argue, is a reflection of the firm's realized strategy" (p. 195).

Another type of BM change is the move towards the product–service system (PSS) (Goedkoop et al., 1999; Haase et al., 2017), in which the BM is transformed from producing product-based transactional value to producing servitization-based relationship value. The technical aspects of PSS and its impact on PSS value have been discussed (Azarenko et al., 2009). Many have studied the relationship between PSS and BMs (Barquet et al., 2013; Ostaeyen et al., 2013; Reim et al., 2016). Some have investigated the value implications from an online business perspective (Raphael & Zott, 2001), others from the perspective of network design with BMs (Nenonen & Storbacka, 2010). Identifying the value "from a product or service" versus "of a product or service" is a complex matter of perspective. There are plenty of models and approaches for determining factors and measuring perceived value.

While there has been some work mapping technical capabilities onto values (Lee & Lee, 2015), the value implications of servitization, digitalization, and PSS have rarely been discussed. In servitization and PSS discussions, the focus has been on challenges, opportunities, and approaches regarding adoption to implement BMI, with little discussion from a value perspective. A typology has been proposed based on the functional hierarchy within PSS (Ostaeyen et al., 2011). We propose that the discussion of value when it comes to combining technology with BMs is an area that merits more attention, in order to adopt technology within BMs. Ultimately, ICT, IoT, and AI are just technologies unless we utilize them to deliver perceived value to stakeholders. AI is an extensive research area but entails a major concentration on modeling techniques. However, many problems arise when integrating AI into business models (Wuest et al., 2016), and little attention is paid to how AI technology-driven capabilities impact the value models of different stakeholders (Björkdahl, 2020). Hence, we need to understand how AI technology contributes to various value processes within BM. We also need to understand how AI technology transforms perceived value and how this technology enables new capabilities in products and services, providing new functionalities within existing BM designs. Finally, we also need to understand how AI enables insights into customer interactions with services in order to provide personalized solutions for better engagement. However, before we look into how value is impacted through digital business models, another observation about the dynamic nature of value within BMs needs to be discussed.

Having looked into BMI and various value theories, with their emphases on individual, operational, and transactional aspects, followed by a discussion of value in BMs, the following theory section highlights discussions of AI and value in BMs.

3.3 AI and value in business models

Researchers have defined AI in different ways (Wang, 2008). This thesis applies Russell and Norvig's (2016) understanding of AI as an assemblage of technological components that collect, process, and act on data in ways that simulate human intelligence. Canhoto and Clear (2020) build on this, stating that "like humans, AI solutions can apply rules, learn over time by acquiring new data and information (e.g., via machine learning—ML), and adapt to changes in their environment" (p. 184). Many intelligent products and services have recently emerged, and emerging technologies such as big data, cloud computing, blockchain, and IoT are becoming increasingly familiar. Today, almost every field, including healthcare, automobiles, finance, gaming, environmental monitoring, and agriculture, applies one or more of these technologies, changing how humans live, work, and amuse themselves (Soni et al., 2020). The advance of the economy through AI (Furman & Seamans, 2019) is enhancing the evolution of Industry 4.0 (Schwab, 2017), simultaneously inducing a notable transformation of businesses and even the overall economic system (WEF, 2016). The changes caused by intelligent technologies impel organizations to adopt strategic decision-making processes (Merendino et al., 2018) and reshape their value processes and business ecosystems. AI technology has also added value to customers by providing new features and capabilities in products and services (Verganti et al., 2020), such as predictive maintenance and anomaly detection.

Highly successful companies such as Amazon, Airbnb, and Uber have used digital technologies to transform themselves and their markets and BMs (Aversa et al., 2020). While traditional incumbent firms in the industrial manufacturing segment are adopting digital technologies to gain new capabilities (Mikalef & Gupta, 2021) and to transform themselves, they are facing multiple challenges (Simonsson & Magnusson, 2018). Digital innovation in industrial manufacturing and consumer goods assembling companies has commonly focused on productivity gains, product design, process improvements, and workforce flexibility based on ICT rather than on implementing digital technologies radically in the way Amazon, Airbnb, and Uber have done in order to gain new business capabilities (Fabiani et al., 2005; Pavitt, 2001). Although AI technology has been around since the 1950s, when Johan McCarthy et al. (2006) described the Dartmouth Summer Research Project on Artificial Intelligence, we have seen growing interest in the subject only in the last few years. This growth can be attributed to advances in other digital and hardware technologies such as computing power, storage, cloud, and connectivity. AI adoption in technology companies such as Google, Apple, and Microsoft comes as their products, services, and BMs revolve around digital technologies or are directly based on them. However, the adoption of AI technology is much slower in incumbent sectors such as industrial manufacturing, consumer goods, and medical services. The following section covers two aspects of the value contribution of AI, as a resource and as a capability.

3.3.1 AI: Resource-based and capability view

Technology is often described as a specific type of knowledge and can thus be regarded as a particular type of resource (see, e.g., Granstrand, 1998). This view of technology as a resource also offers us a key to analyzing its potential value for businesses more objectively. Using extant knowledge of the resource-based view (RBV) (Barney, 1991; Wernerfelt, 1984), it is possible to identify and analyze the potential value of technologies such as AI. The RBV has developed into one of the dominant streams of strategic management research, making it an influential theoretical framework for understanding how firms achieve competitive advantage (Barney, 1991; Wernerfelt, 1984). AI technology has also been addressed together with the RBV (Mikalef et al., 2019; Ristyawan, 2020). At the heart of the RBV, one finds various resources, which have been categorized in slightly different ways. One common way of distinguishing between different resources is to divide them into specific physical (e.g., specialized equipment and geographic location), human (e.g., expertise in chemistry), and organizational (e.g., superior sales force) assets that can be used to implement value-creating strategies (Nelson, 1991). A critical insight of the RBV is that resources, with some obvious exceptions, are rarely in themselves a source of competitive advantage (Peteraf, 1993). Since there are functioning markets for most, but not all, types of resources, which makes it difficult to have unique access to a specific resource, any advantage gained from this resource is hardly sustainable over time. Simply owning and controlling a resource is insufficient for gaining a sustainable competitive advantage. This is only the case for resources that yield direct rents from ownership and not through their use in transformation processes.

Penrose (1959) pointed out that differences in performance are instead largely determined by the way resources are used, not by the resources themselves, emphasizing the role of management in bundling resources to generate capabilities. From a strategic management perspective, capabilities are far more interesting to companies than are resources, because even if different companies build on the same resource base, their capabilities tend to be idiosyncratic, which explains sustained differences in economic performance (Grant, 1991). To evaluate the potential value of AI technology, the first step would be to identify and analyze the specific capabilities it can realize. To analyze the inherent value of technology as a resource, frameworks such as VRIN (VRIO) have attracted considerable attention in the RBV. The VRIN framework evaluates to what extent a resource or capability displays these four characteristics—valuable, rare, inimitable, and non-transferable—and to what extent it constitutes a potential source of competitive advantage (Grant, 1991).

In addition to the evaluation of an AI technology's unique individual capabilities, which primarily provide efficiency gains, we also see a need to consider how these capabilities can be combined with other existing and new capabilities to offer enhanced and substantially new offerings and to transform processes, products, services, and BMs. Again, via these individual or combined capabilities, AI contributes to value from both the product and process perspectives within existing BMs. This view of how capabilities and resources are managed and changed over time is a core feature of dynamic capabilities theory (Teece, 2007; Teece et al., 1997; Tiguint & Hossari, 2020), explaining how companies' resource bases and capabilities can be changed and enhanced over time by altering resource coordination, integration, deployment, and change (Brown & Eisenhardt, 1998; Eisenhardt & Martin, 2000). Although dynamic capabilities actually exist at a meta level and usually do not offer any competitive advantage in themselves, they are fundamental to continuously improving and changing their constituent resources and capabilities so that their strategic assets match changing industrial characteristics and needs (Amit & Schoemaker, 1993). In this process, dynamic capabilities can be used to build new resources and capabilities and to enhance existing resource and capability configurations (Eisenhardt & Martin, 2000).

It has been observed that AI technology causes value changes in two main ways: first, by inducing new functionalities and features as resources and, second, by enabling new configurations and constellations in customer offerings as dynamic capabilities. Implementing new functionalities and features can be associated with process innovation carried out by the workers (Patel et al., 2018), which means doing the same thing but in a much better way, thereby increasing efficiency through data-driven automation and other techniques. Enabling new configurations can generate value within products, services, innovation processes, and BMs. AI can contribute to stakeholder value by facilitating mass customization (Ma & Sun, 2020), strategy enablement (Schilling, 2017), and prediction-based operational transformation (Dogru & Keskin, 2020). Various capabilities are driven by AI to curate customer engagement and interaction data in order to understand the needs and value aspects that users expect and even to predict the insights needed for proactive measures through machine learning and data science—all of which was not possible before (Chiang, 2019; Kunz et al., 2017). While AI-driven capabilities generate new functionalities and features for business offerings utilizing AI as a resource, these capabilities impact the underlying value dynamics of the BM, which needs to be understood and addressed further in research. When combining the impact of AI on industries from the efficiency and stakeholder value perspectives with disruption from digitalization, technological disruption is observed to be driving BM disruption. Hence, this thesis emphasizes that AI has more fundamental implications for value than merely being a technology resource. Through a series of studies, this thesis highlights that AI technology has unique characteristics that make it stand out from other past technologies and can be used as a competitive advantage by firms (Valencia et al., 2019) rather than merely as a resource (Gupta et al., 2018; Wen et al., 2020).

Having looked into the two value aspects of AI (i.e., resources and capabilities), the following section highlights the impact of both these aspects on BMs before considering the need for a process view in this assessment.

3.3.2 AI-enabled value through changes to business models

Apart from efficiency gains and the value implications for existing BMs, AI can create business values in other ways. For example, online platform companies regard customer behavior data as an essential asset for promoting customer engagement in various ways. The data are usually processed using AI (including machine learning) to create personalized profiles, predict behaviors, and optimize recommendations. When a customer interacts on a software platform such as Spotify, every user activity is captured—such as search clicks, time spent keyboarding, music played, collections saved, likes, items forwarded to friends, third-party platform access, and new activities—for personal customer profiling to create preferences and behavior prediction solutions (Ramos & Blind, 2020). AI enables new product and service offerings and creates new capabilities that can transform current BMs and drive values, bringing innovation to existing BMs and enabling BMI. While the values arising from these capabilities can be captured in different situations and use cases in enterprises, AI technology also delivers better performance and opportunities from existing capabilities such as predictive and preventive maintenance, efficiency and control, productivity and reliability, and product performance (Verganti et al., 2020).

In some cases, customer data created by firms are a source of revenue: customer data profiles are sold or utilized by other companies for online marketing, personalized recommendations, and advertising (e.g., Spotify's commercial ads). The impact of data and AI-enabled insights and capabilities on BMs depends on the value AI can generate for different stakeholders (Wheeler & Sillanpa, 1998). Hence, before we can fully understand AI's impact on BMs, how AI impacts different value processes of BMs needs to be investigated.

Different technological advances have helped firms provide services by combining products and services, resolving customer pain points, increasing customer loyalty and retention, improving profit margins, addressing competition, as well as addressing reduced market demand by providing new innovative services and climbing the value chain (Barbieri et al., 2021). On one hand, sensors, actuators, and microprocessors are being embedded in products through ICT (Nightingale et al., 2003) and IoT (Porter & Heppelmann, 2014) technologies; on the other hand, connectivity, cloud, and computing technologies (Longbottom, 2017, pp. 13–22) are enabling connectivity, realtime data capturing, remote processing, and agile decision making through data insights for better customer value delivery.

Combining the power of big data with technologies like ICT and AI within BMs not only provides constant contact with customers to collect regular and updated data from every interaction with the service, but it also provides capabilities to predict future customer values and to anticipate and proactively offer those service configurations to customers (Chiang, 2019; Kunz et al., 2017). While servitization drastically increases the interaction of customers with the service provider, as compared with product-based BMs, AI technologies allow continuous integration, such that the service providers can constantly track the perceived customer value of the offerings, as well as continuous deployment to transform values as offerings continue, continuously changing the value. In addition, such transformation of value can be used to provide hyper-personalized, tailor-made services for specific individual customers (Goyal, 2019). In technology-driven BMs, value-added services seem to rely greatly on the operational excellence of the manufacturing and logistics process, whose performance can be enhanced by adopting ICTs and AI (Belvedere et al., 2013).

Today, data are captured and transformed at unprecedented speed and in unprecedented volume (Frizzo-Barker et al., 2016), producing datasets from various sources, such as interactions, behavior, observations, sensors, sales, marketing, and manufacturing. For instance, a new product launch can become very popular among potential consumers through social media platforms using AI engines. The production scale and sales strategy for a hot commodity can be determined quickly with instant network externality updates. AI techniques can create pulling impact via the network, with more data capture providing better insights and leading to customer lock-in. This happens in the case of mobile applications, which provide a wide variety of functionalities such as shopping, payments, entertainment, transportation, and banking, all at the same time due to network externalities.

Advanced combinations of products and services can be facilitated through digitalization, in what can be defined as “complex digital offerings.” A complex digital offering is an offering created using various digital technologies, such as IoT, connectivity, sensors, remote sensing, big data, and AI, to create, deliver, and capture value in totally different ways from existing or new stakeholders. New data may not resolve anything when equivocality is high and when the value for BMI is disruptive and assumes an unclear field. Also, if we focus on only one value dimension, we miss out on other dimensions and opportunities (Fazio et al., 2016); this can be addressed by first emphasizing value identification and then noticing, observing, and understanding the value transformation that happens in customers’ perceptions throughout the usage lifecycle of the product or service. This view can be facilitated and enabled by AI technology, by combining significant volumes of data and by mining patterns in ways that are not humanly possible. Big data and AI capabilities arguably address the challenges of information overload, data fatigue, and data sense-making (McKinsey Global Institute, 2016).

Having looked into BMs, the concept of value, and the implications of AI for BMs and value, this thesis emphasizes that AI technology has implications for the core value elements for customers and stakeholders within BMs, which need not depend on transactional or operational interactions as was the case in traditional BMs. We observed that, on one hand, we have value frameworks and models addressing customer value from various perspectives (i.e., individual, transactional, and relational) in industrial setups, and, on the other hand, we have value dynamics discussed within various BMI areas to create, deliver, and capture value on an ongoing basis. There is an observed lack of process orientation in value discussions (Wikström, 1996). A process view (Langley, 1999) of value is therefore needed, highlighting and deepening the value that AI-based BMs create through the iterative process of value creation, value delivery, and value capture. Process theory can be considered a rigorous and systematic description of the "generative mechanisms or set of mechanisms at work … and their resulting outcomes" (Cornelissen, 2017, p. 5), which we believe is required to understand the dynamics between value aspects of the BMs. This thesis argues that applying the value concept in a BM as a process could create an appropriate value for the business offering. Research has attempted to investigate BMI from a process perspective (Andreini et al., 2021), categorizing existing work as linear (Van de Ven & Poole, 1995), recursive (Cloutier & Langley, 2020), parallel (Cloutier & Langley, 2020), and conjunctive (Tsoukas, 2017), but further elaboration is required of the value aspects of BMs and BMI. Furthermore, AI-driven BMI unites the individual, transactional, and relational value viewpoints, which cannot be encompassed without the process view, and only through the current view of value creation, value delivery, and value capture within BMI (Teece, 2010).

For example, the value capture concept surfaces in the marketing (Chesbrough et al., 2018), innovation management, and BM pricing (Hinterhuber, 2004) literatures. However, these literatures approach value capture from an operational perspective when the sale, purchase, or transfer of services occurs, rather than from a process perspective, which is required when addressing value capture, due to the subjective and transformative nature of value (Zeithaml, 1988). Hence, we need to work towards a value process framework for AI-enabled BMs that encompasses all three value perspectives—individual, transactional, and relational—together with a process view. For this purpose, the next section will outline the research questions of this thesis.

3.4 Research questions

Having looked into current theories of BMI and value together with the impact of AI on BMI and value, a lack of process aspects in the discussion of value in digital BMs is observed. Furthermore, it is also observed that AI is improving efficiency, helping implement servitization-based BMs, and enabling new ways of creating and sharing value for customers around the existing BM value processes. On the other hand, AI is creating new value processes within BMs. We need to reconceive or modify our current conception of value processes in BMI to understand these new value processes. Hence, to accelerate the incorporation of AI within industrial manufacturers through a better understanding of value in digital BMI, the overall research objective of this thesis is to develop a process-driven value theory of AI-driven BMs by proposing a framework for value dynamics within digital BMs. To work towards the anticipated value theory, several propositions are put forward in this thesis, addressed in the various papers constituting this research. The two overarching research questions are outlined below:

RQ1: How does AI technology foster innovation in the BM processes of value creation, delivery, and capture in manufacturing firms?

RQ2: How does AI technology change the core value processes of BM and the relationships between them?

Apart from the above research questions, we highlight and discuss challenges and opportunities when using AI technology for BMI in incumbent manufacturing firms.

4. Research setting and methodology

To address the above research questions, four studies were performed, resulting in five papers. This section outlines the overall setting of this thesis research and presents the research design. The section continues by covering the methods used for data capture and analysis in all five studies. Finally, this section ends by outlining the reliability and validity of the constituent studies of this thesis based on their context and scope.

4.1 Research approach and background

The author of this industrial research has been the head of a global innovation unit—also referred to as the AI Lab—of a Nordic industrial manufacturing firm. The author is responsible for data-driven digitalization in this firm and was at the heart of the digitalization journey that the industry is undertaking, resulting in the present studies conducted in collaboration with different industry and academic partners. The thesis research was well anchored within the organization's general management team. It was co-supervised by one of the management group members (also an adjunct professor at KTH Royal Institute of Technology) responsible for the overall innovation agenda of the firm. One of the main reasons for the long-term success of Nordic industrial manufacturing firms has been their transformation capability: it is deeply embedded in their DNA, allowing them to learn and reinvent themselves at times of opportunity and threat. The firm to which the author belonged has been in operation for three centuries and changed industry segments over the years, from defense to sewing machines, home appliances, bicycles, and finally outdoor power equipment. This emphasizes how often the firm has transformed itself in the past. The firm is an industry leader in outdoor power tools for gardens, forestry, and construction. This thesis research was executed collaboratively and in partnership with other industrial companies, industrial networks, and academia, including KTH Royal Institute of Technology (KTH), Copenhagen Business School (CBS), and various programs of agencies such as VINNOVA (Swedish Agency for Innovation Systems), WASP (Wallenberg AI, Autonomous Systems and Software Program), and Combient. This research is based on collaboration between critical resources of the AI Lab, industry partners, startups, academia, and other research agencies to understand the impact of digital technologies in general and AI technology in particular on the value aspects of BMI.

The day-to-day responsibility of the author within the industrial manufacturing firm was to ensure the creation and adoption of AI-based solutions with the ambition of leading AI-based innovation within the firm and industry. The author could balance his roles in industry and in this research project as the concepts, approaches, and research questions of the thesis project were well aligned with the industry role.

The author was deeply involved in the planning, execution, assessment, and reporting of all the research studies (papers A–F). Due to this opportunistic setup and the role of the author, the studies undertaken as part of this research were scoped for practical relevance and closely observed for analysis. It was possible to guide the control variables accordingly and access relevant data points required for assessment and triangulation (Kihlander et al., 2011).

This research is phenomenon based (Von Krogh et al., 2012) rather than driven by any specific theory or method. Phenomenon-based research is defined by Von Krogh et al. (2012, p. 278) as addressing "regularities that are unexpected, that challenge existing knowledge (including the extant theory) and that are relevant to scientific discourse," and is appropriate in the early phases of research explorations when relevant theories are not yet fully developed. To understand the phenomenon of value dynamics within digital technology-driven BMI, case-study methodology (Yin, 2011), supplemented with several additional methods, was utilized during this thesis research to understand the phenomenon. As Dubois and Gadde (1999, p. 554) stated, it is a well-supported view that "the interaction between a phenomenon and its context is best understood through in-depth case studies." The research questions proposed for this thesis are exploratory, suggesting that the case study would be the preferred scheme (Kumar, 2019). Concerns regarding case-study research have been noted (Flyvbjerg, 2006), but have been clarified and dismissed by others such as Yin (2011). The usefulness of case-study methodology in phenomenon-based, explorative, and qualitative research, which is the scope of the thesis, motivated us to proceed. This thesis has applied an abductive approach (Dubois & Gadde, 1999) for discovering new things, systematically combining the results to develop our understanding of theory and empirical phenomena. The background and position of the author within the industry helped in properly selecting important and informative cases with which to answer the research questions. The author's position also facilitated access to individuals and information needed for the research cases, which is crucial for case-study research (Crowe et al., 2011)

The intention is to understand the phenomenon and propose an initial relevant theory without getting into the causality chain of the phenomenon. The sense-making regarding the perceived value delivered to customers by AI technology within BMs is argued to be a combined individualistic and societal phenomenon. At the same time, in the author's view, although constructs and relationships between AI-technology–enabled capabilities and customers' perceived value do exist within BMs, solely empirical data do not give complete insights or indicate dependencies. Hence, the research approach needs the support of observations backed by theory and qualitative assessment. In conceptualizing the phenomenon, this research focuses on companies active in the digital transformation that are, on one hand, incorporating new technologies into their products, services, and operations, and, on the other hand, trying to establish innovation procedures implemented via digital and AI technologies. Within the overall methodology of using case studies in the present research papers to understand the phenomenon, the methods used include quasi-experiments, case studies, semi-structured interviews, in-depth interviews, card sorting, longitudinal research, quantitative survey analysis, literature review, and literature mapping. The choice and usage of the methods were based on the scope and ambition of the research, which was to understand the complex setup of value dynamics within business models, especially in light of digital technologies such as AI (Von Krogh, 2018). This varied methodological coverage presented an excellent opportunity for the author to take advantage of his mixed role in industry and academia and intentionally strive to understand the phenomenon under study.

This research utilizes an abductive approach to systematically combine (Dubois & Gadde, 2002) observations in a series of studies, presented in the appended papers. To exploit AI in organizations, AI not only needs to be implemented in new BM opportunities as resources/capabilities, but also to be associated with the transformation of more fundamentally perceived values that it brings to all stakeholders within an ecosystem. Due to the complex nature of the research, rather than starting from a specific theory, a phenomenon-based approach with cases has been undertaken (Flyvbjerg, 2006). Owing to his unique role straddling academia and industry, the author had an excellent setup to explore the value dynamics of business model innovation in light of digitalization through real-life research cases in which actual paying and using customers were used as research subjects and the author was involved in action research (Avison et al., 1999) when conducting some of the studies summarized here.

While organizations are juggling different approaches to adoption of digital technologies at the same time, if we consider the components of the phenomenon of interest individually, the aspects that this research has addressed include: AI technology and the new capabilities that it enables concerning personalized experiences; and future BMs and how AI technology transforms the perceived value models of the ecosystem stakeholders. This research project mixed theoretical analysis and practical, real-life customer case-study analysis using quantitative and qualitative methods. Given that the constituent studies of the thesis use different methods, samples, and analytical techniques, we will cover these per study below.

This thesis research was consolidated from four different studies, which were developed into five individual papers demonstrating the relevance of this consolidation. The ambition is to answer the two research questions using the observations, assessments, and findings from the respective papers outlined in Figure 1.

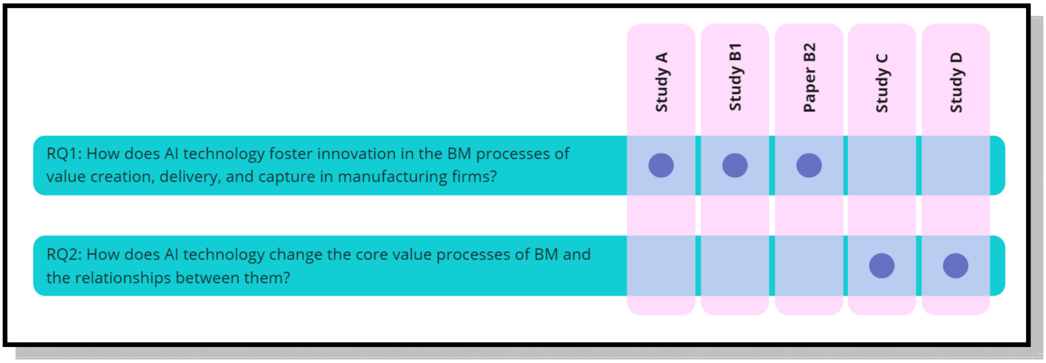

Figure 1: Research design.

4.2 Description of performed studies

This section covers the different methodologies adopted in the constituent studies of this thesis. We start with a consolidated description in Table 1 and then describe each study in detail.

Table 1: Research methods used in the appended papers.

Study	Primary data	Secondary data	Method	Assessment
A	Semi-structured interviews with two stakeholders per quasi-experiment: • Internal: product manager and R&D manager • Startup: technical lead and project manager Six interviews in total	Project documentation	Three quasi-experiments (industrial PoCs) and Qualitative (Gioia methodology)	153 first-order concepts 22 second-order themes Four aggregated dimensions Gioia et al. (2013) Resource-based view of Barney (1991) and Grant (1991)
B1	Internal surveys in two industrial manufacturers: • Product/category managers • R&D managers and engineers • Sales/marketing and after sales • Operations executives and personnel • Others 137 valid responses	Company documentation	Hypothetical case of B2B offering based on AI: dynamic pricing Quantitative assessment (regression)	Normality check: Shapiro-Wilk Homoscedasticity check: Levene's test Regression: statistical significance, model fit, collinearity, and coefficients (individual entrepreneurial orientation and functional affiliation)

B2	Internal surveys in two industrial manufacturers: • Product/category managers • R&D managers and engineers • Sales/marketing and after sales • Operations executives and personnel • Others 137 valid responses	Company documentation	Hypothetical case of B2B offering based on AI: dynamic pricing Quantitative assessment (regression)	Normality check: Shapiro-Wilk Homoscedasticity check: Levene's test Regression: statistical significance, model fit, collinearity, and coefficients (transparency)
C	Two-month campaign: external survey 97,933 total unique views 5959 clicked the campaign link and visited the landing page 145 chose and completed the survey Designing and offering cut-grass-as-a-service together with a partner for an entire season (longitudinal) 13 paying customers, with two rounds of in-depth interviews: • one at service initiation • second after two months into the service Card-sorting activity during the second interview	Service provider data and Product-connected IoT data	Quantitative (CFA) Qualitative Longitudinal	CFA: variance, covariance, and regression weights Normality check: Shapiro-Wilk Homoscedasticity check: Levene's test Regression: statistical significance, model fit, collinearity, and coefficients Qualitative: Yin (1994)
D	Scopus web search (392 papers) Literature mapping: VOS viewer (252 papers) Cluster analysis (154 keywords) Corpus analysis	Value theory assessment	Literature review	Scopus search (five years ending 31 March 2020): Value (6.38 M) AI (34 K) BM (29 K) Altogether: 392 papers Literature mapping: 252 high and medium relevant papers 154 keywords (occurrence more than three times) Cluster analysis: Businesses: three (operation, measurement, model) AI: ML, vision, data, another tech. Corpus: 184 papers (frequency and range) Value manifestation (F:210, R:65) Value capture (F:148, R:71) Value identification (F:0, R:0)

Study A: Edge AI-driven technology advances paving the way toward new capabilities

Data collection

Data collection was based on three concrete empirical quasi-experiments and on interviews at startups and a Swedish industrial manufacturing firm dealing in outdoor power equipment for professional and consumer use. This study explored functionalities enabled through AI and mapped them onto different capabilities that are key to delivering value and transformation for business stakeholder groups through the use of an analytical framework derived from the RBV (Barney, 1991; Wernerfelt, 1984) and dynamic capability theory (Teece, 2007; Teece et al., 1997). Each of the three quasi-experiments identified a use case, regarded as a hypothesis. These use cases were not disclosed in the paper as they were the intellectual property of the studied firms and disclosing them would pose a competitive disadvantage. Sensor data were captured during realtime product usage based on the hypothesis, followed by appropriate annotations and quality control. The dataset was then divided into training and test datasets, after which several machine-learning algorithms were applied on a training dataset to create models with the best performance on test data with the required accuracy. Finally, these models were optimized and deployed on the products to be field tested for robust performance. The experiments were followed by interviews with stakeholders within the project teams to identify and explore the enhanced and new functionalities enabled by the technology, together with related future opportunities. These interviews were conducted in two parts for every quasi-experiment: part one with the companies' internal project representatives, i.e., product manager and R&D manager; part two with the startup representatives included in the project, i.e., technical and project manager.

Data analysis

Experiment results and data captured from the interviews were analyzed together, leading to a validated set of observations. The list of features and functionalities was discussed, observed, and identified during the interviews with stakeholders, followed by the authors' consolidation. After all the above sequentially conducted interviews, a consolidated list of functionalities and features enabled by Edge AI was compiled, followed by their mapping onto capabilities, for which we turn to the VRIN (VRIO) framework (Barney, 1991; Grant, 1991), which has attracted considerable attention in the RBV. The coding and assessment process followed a recently proposed structured methodology for qualitative data analysis (Gioia et al., 2013). The first step was to carry out the first-order analysis by identifying terms and keywords used by the interviewees without distilling any categories. A total of 153 first-order concepts emerged from all the coding work done by all three authors. In step two, which was executed jointly by all the authors in multiple sittings, the concepts obtained from step one were combined to give category labels. An extensive exercise to refer to notes and audio recordings was undertaken to identify these second-order themes, so as not to lose the intention of the message conveyed by respondents. Consolidation of all category labels during step two generated a total of 22 second-order themes (which do not include the themes delivered by and related to other technologies and resources apart from Edge AI). Finally, in step three, the emergent second-order themes were further distilled into aggregate dimensions using interview data interpretation but also by mapping the obtained 22 themes onto the VRIN (VRIO) framework (Barney, 1991; Grant, 1991), in which the themes were classified based on valuable, rare, inimitable, and non-transferable properties of the opportunities presented by end-customer offerings. The themes from the third step were consolidated into four aggregated dimensions, which can also be classified as emerging capabilities enabled by Edge AI technology from all these quasi-experiments.

Study B1: Perception of value delivered in digital servitization

Data collection

The interest of this study was in understanding the role of the individual's entrepreneurial orientation in overall perceived value and what impact the organizational role of the individual has on the perceived value within AI-driven digital offerings (in the case of value-based pricing). The study conducted an empirical assessment with a much broader approach, in terms of multiple organizations and multiple roles within them, to understand whether the adoption of such offerings (e.g., value-based pricing) within the organization is a function of the roles of individuals within the organization or a function of the individuals themselves (through the entrepreneurial orientation exhibited by them individually). This paper applied a quantitative approach to a broad range of roles in two big industrial organizations with over 10,000 employees, and found that barriers to the perception and hence diffusion of value-based pricing in the companies were not limited to organizational units or roles, but actually included individual traits and attributes as well. To understand the total value perceived by different organizational stakeholders, a survey was designed with the hypothetical case of a value-based revenue model (Diderich, 2020). The survey presented a value-based pricing offer in which the value created and delivered could be made transparent to stakeholders with the help of digital technologies. Although the buyer is exposed to more introduced uncertainty, such as possible variance in price during the contract and uncertainty as to the duration of the contract itself, the digital-technology–based offering still provides much greater value due to its transparency. There were two variable components in the above cases: "Yr" (duration in years) and "Per" (maximum % increase or decrease per quarter). Three durations of the subscription agreement were used, namely, 2, 4, and 6 years, and three maximum percentage increase or decrease levels in subscription pricing per quarter were used, namely, 0%, 5%, and 20%. This gave rise to nine use cases presented to respondents from the two companies surveyed at random. The target audience was individuals working on digital offerings within the organization, and the target roles were:

product/category managers, R&D managers and engineers, sales/marketing and after sales, operations executives and personnel, and others. These stakeholders were a good proxy for customers' needs, requirements, and value perceptions, given their roles, experiences, and daily interactions. A total of 137 completed surveys were obtained, which were used for the analysis. To ensure that our understanding of the cases was coherent with the survey responses, it was decided to choose the respondents only from those organizational units of the two companies that were either creating or selling digital solutions and services.

Data analysis

The empirical results obtained from the survey were analyzed in multiple steps starting with the other variables used in the survey to determine whether or not they could be considered control variables for our assessment (Forza, 2002). The other variables were transparency and uncertainty regarding contract length (six years and four years, with two years as the base reference) and price variance (20% and 5%, with constant price as the base reference). An equation was formulated to determine whether or not the significance of entrepreneurial orientation remained valid with other variables.

Having determined the impact of the control variables, the relationship between overall entrepreneurial orientation and total perceived value was assessed in the next step by including entrepreneurial orientation from the previous step to determine whether there is any moderation or mediation between entrepreneurial orientation and the control variables. The linear regression equation was considered to assess the overall significance of the model, determine the model's overall fit (R^2), and understand the obtained regression coefficients to determine the effect and impact of the entrepreneurial score on the overall perceived value.

The aim of the next step of the study was to extend the linear regression model from the previous step by adding factors capturing the individual's role in the organization. "Roles" are categorical variables in our case with five different options. To determine their relationships with the total value and to understand which roles (i.e., categorical independent variables) contributed to the overall value, we had to create dummies for the five "Roles." To map this onto the regression model, an analysis of variance (ANOVA) was conducted between and within the categories of each variable under consideration. In our case, we allocated the dummies as below. The case of Role = "Other" was chosen to be the base scenario for the variable "Role" against which the regression coefficients for "Sales," "PM," "RD," and "Ops" would then be analyzed. An equation was formulated based on the roles respondents chose in the survey. After the regression was carried out, the overall statistical significance of the variance and model was examined, together with the analysis of the model's fit through R^2 values and collinearity in obtained coefficients before interpreting the coefficient values to understand the contribution of various roles to the overall value perception.

Then, as the last step, a linear regression equation was formulated for the total value perception regarding the four entrepreneurial aspects covered in the survey questions. All the independent variables (i.e., the risk-taking, proactiveness, autonomous, and innovation capabilities calculated as average scores provided by the respondents for all related questions in the survey) and the dependent variable (i.e., total perceived value calculated as the total value aspect question responses) were continuous. The assessment was checked for the overall significance of the model and overall fit of the model (R^2); finally, the obtained regression coefficients were examined to understand the effects of entrepreneurial properties (i.e., risk taking, proactiveness, autonomy, and innovation) on the overall perceived value.

Paper B2: Value capture in digital servitization

Data collection:
To understand the influence of uncertainty on overall perceived value, the same exploratory survey as in paper B was used to create additional datasets to understand how a value-capture strategy could work through the hypothetical case of value-based pricing (Diderich, 2020). Thanks to digital technology, the value created and delivered can be made transparent to stakeholders and provide increased value in the offering, even though buyers end up having more uncertainty introduced into the contracts of the fictive industrial cases introduced in paper B. Although the data were collected using the same survey, the relevant data elements analyzed in the two papers differed greatly and were presented separately, emphasizing the specific parts relevant to the study.

The sample of the final two Nordic industrial companies in which to recruit respondents and present the survey was based on the maturity exhibited by the companies not only in handling digital technologies but also in adopting these technologies in their BMs. The initial list of companies was motivated by the relationships of the researchers with various Nordic industrial companies, academic and business collaborations in past research projects, and the timelines of this research project. The target respondents were individuals working on digital offerings in the two organizations. Since the presented case was unique and specific, the respondents were chosen from organizational units in the two companies found relevant to the research, i.e., units either creating or already selling digital solutions and services, to ensure understanding of the case and coherent responses. As the study aimed to understand customer value from the case offers, internal organizational unit representation was valid. Some respondents (e.g., R&D and operations) had been or still were customers of the industry use case (assembly-line motor procurement) presented in the survey. Other respondents (e.g., product and sales managers) were a good proxy for customers' needs, requirements, and value perceptions given their roles, experiences, and daily interactions. In total, five sub-organization units were identified, and the survey was forwarded to all employees in those business units in both companies. Respondents were given two weeks to respond, which most did (for an overall response rate of over 90%). Conducting this survey across more than one company and multiple roles in each company ensured the cross-referencing and triangulation of value perceptions across organizations and roles. In total, 137 responses were captured and analyzed.

Data analysis:

We started the assessment by performing a two-way ANOVA at an overall uncertainty with the two parameters (i.e., variance in price percentage and duration of the service contract) in order to understand differences in the means and significance of the overall independent variables (i.e., year ["Yr"] and percentage ["Per"]) as well as their effect on the overall value perceived by respondents (Forza, 2002). The dataset's normality preceded this step, and homoscedasticity tests were followed by post hoc analysis.

After that, a regression analysis was conducted to understand which specific options (both "Yr" and "Per" are categorical variables in our case with three options each) within our independent variables influenced the contribution to overall value. Regression preceded the Cronbach's alpha assessment of all the value dimensions and related questions asked during the survey for the case. Since we use categorical independent variables, we were required to create dummies for both the "Yr" and "Per" variables to use them in the regression model. The case with a two-year contract and 0% price change in the quarterly subscription charge was chosen as the base scenario for "Yr" and "Per," respectively, against which the regression coefficients were analyzed. Based on the regression results, the overall statistical significance of the variance and model was examined together with the analysis of the R^2 values and collinearity of the obtained coefficients before interpreting the values.

Having identified the impact of uncertainty in terms of contract length and possible price variance on overall perceived value, the sensitivity to transparency within the buyer–supplier relationship was assessed to understand whether there is any mediating or moderating impact (Baron & Kenny, 1986). The two transparency questions in the survey captured the changes in the willingness of the respondents to subscribe to the service (one of the nine cases presented) if the negotiations every quarter (except in the fixed-price case) were based on actual service provider data or controlled by a neutral third party, respectively. Consequently, the final regression equation with transparency as an independent variable was analyzed.

Study C: Value changes during service delivery

Data collection:

This study was conducted in two phases. Phase I consisted of a survey within a business-to-customer (B2C) set-up conducted to understand the different value dimensions of customers' experience when evaluating digital-enabled service offerings and making a purchase decision. A survey, rather than interviews, was chosen to capture this data in order to sample a broader population; given the subjective nature of value, we wanted to expand on the initial value dimensions by means of quantitative assessments to enhance the observations' validity and reliability. It was conducted as an open survey offered through social media. To understand the influence of various value dimensions (Sheth et al., 1991) on perceived value, and thus their impact on purchase decisions, a marketing campaign was conducted on Facebook and Instagram targeting consumers in Scandinavia with a lawn-care offering called "cut-grass-as-a-service," for the maintenance of a green and healthy lawn. The campaign drove traffic to an open landing page where the offering was presented alongside one of four price-point variants: two yearly flat-rate options and two flexible seasonal-rate options. From the campaign landing page, we captured sign-ups of potential customers interested in the service corresponding to one of the four initially identified price points and driving traffic to the surveys. The survey was conducted on SurveyMonkey, and the traffic was routed to ensure equal distribution capture of all four price points. The campaign was active for two months and received 97,933 total unique views; 5959 people clicked the campaign link and visited the landing page, of whom 145 opted in and returned a completed survey.

Phase II was a longitudinal study involving multiple consumer segment customers studied throughout the digital service offering lifecycle for one season. Qualitative methods included direct interviews, indirect observations, and digital data assessment captured during the service offering to understand whether the value dimension of customers' perceived value changed during the service offering lifecycle. A longitudinal study was chosen for this phase, as we wanted to observe whether the values changed during the lifecycle of the service, for which it was crucial to keep the service and customer constant during the value change period to maintain the required validity and reliability of the observed results. To recruit customers for phase two, direct-sales activities were initiated in two regions of Scandinavia. The goal was to recruit approximately 15 private consumers with suitable gardens and lawn areas. More than one region was targeted to ensure triangulation and analyze whether geographical location played any part in the dynamics of value-perception transformation. Sales activities resulted in the recruiting of 15 paying pilot customers who were prepared to sign up for, run, and pay for "cut-grass-as-a-service." It was crucial to identify and recruit only those pilot customers prepared to pay for the service, as their view of delivered value could shift if they received the service for free. The service was to be initiated in May 2020 and continued through October 2020. This period also represented the entire grass-cutting season in the

Scandinavian climate region and was agreed on by all recruited pilot customers. The customers were aware of the project's pilot status and agreed to participate in multiple rounds of interviews during the six months following their anticipation and experience of the delivered service. Although we initially recruited 15 customers, we executed end-to-end service installation, execution, interview data collection, and analysis only for the 13 customers included in this study.

In addition to the interview data, there were two other datasets. The first of these came from the service provider, which was the partner in executing "cut-grass-as-a-service" at all customer locations (i.e., lawns). This dataset comprised dated recordings of all planned, executed, and unplanned activities per customer. The second dataset comprised the connected mower sensor data collected for the duration of the pilot per customer and stored at a central cloud location.

<u>Data analysis:</u>

In Phase I, the first step of the survey analysis was to understand and empirically determine whether the survey questions were correlated to one another and captured the exact value dimensions, or whether they were perceived as very different and probably failed to capture the anticipated value dimensions. This analysis was conducted using confirmatory factor analysis (CFA). Finally, the variance, covariance, and regression weights were calculated for the confirmatory factor analysis model laid out earlier, to understand whether different items within the same value dimension were or were not measuring the same thing. After verifying the assessment from an overall CFA-model perspective, we proceeded with regression analysis in order to understand what value dimensions played what roles in contributing to the total perceived value for the survey respondents when making the purchase decision. Total perceived value was formulated as linear regression equation 7, with total perceived value for the consumer being the dependent variable and the independent variables being the different value dimensions contributing to the overall perceived value, namely, epistemic, social, functional, emotional, and conditional values (Sheth et al., 1991). After the regression was carried out, the overall statistical significance of the variance and model were examined together with analyzing the R^2 values and collinearity of obtained coefficients before interpreting the values.

In Phase II, the first round of interviews was conducted when the service began and was based on a semi-structured interview format. The interview consisted of questions regarding the customers' profiles and yards, and about different value dimensions, such as functional, epistemic, conditional, emotional, and social values, relevant to and playing an essential role for customers. After several months of service, when pilot customers had experienced different aspects of the service and formed an opinion of it, the second round of interviews was conducted. This time, sessions were separated into two parts, a semi-structured interview followed by a card-sorting activity (Harloff, 2005) in which the pilot customer could design his/her offering. The customers were presented with multiple service elements, including their cost, and could choose what elements they would like included in the service and what elements would be optional.

In addition to the interviews, two other data sources included cross-references to confirm the value dimension per customer throughout the service lifecycle of the pilot period (Yin, 1994). Our partner's service provider received the first dataset in executing "cut-grass-as-a-service" at all the customer locations (i.e., lawns). This dataset included dated recordings of all planned, executed, and unplanned activities per customer. It was analyzed to understand the total number of activities required from the service provider's perspective, and to understand whether a particular customer required more or fewer unplanned activities and whether this affected their perception of service value and, if so, how. The second dataset was the connected mower sensory data collected for the duration of the pilot per customer and stored at a central cloud location. These data were periodically analyzed to reach out to the customers in case of any observed machine malfunction, prepare for customer interview sessions, and understand customer reasoning regarding value perceptions.

Study D: Towards a value process framework for AI-enabled BMs

<u>Data collection:</u>
To understand the correlation in existing research between the three concepts "AI" technology, "BMs," and "value," the first step was to conduct a literature search (Xiao & Watson, 2019) of papers published in the last five years. We chose the online library Scopus as the search platform, as it is the largest abstract and citation database of peer-reviewed literature. We used the search string "value" AND "business model" AND ("artificial intelligence" OR "AI") in searching all articles from 2015 to 2020 (as of 31 December 2020). A generic and broad term "value" was used as a search criterion so as not to miss much relevant literature; we wanted to start broad and then focus in on various value aspects during later steps of the assessment. When searching for the keywords separately on Scopus, the number of papers was unmanageable; for example, "artificial intelligence" yielded more than 34 thousand, "business model" more than 29 thousand, and "value" around 6.38 million results. This large number of identified studies was unsuitable for manual literature study, correlation identification, or gap assessment; however, when the search keywords were combined to include all the three aspects, the results shrank to 392 papers, all of which were reviewed in this study.

Data analysis:

We recorded the publication year and journal for each of the 392 papers for time-variant change analysis and trend analysis, respectively. After reading abstracts of all publications, each paper was classified by the degree of correlation with the three keywords used in the search string: “high related” if all three keywords were identified in the abstract, “medium related” if any two of the three keywords were identified in the abstract, and “low” or “not related” if one or no keyword was identified in the abstract. After identifying the literature articles in step one, a literature mapping exercise was conducted to understand the correlation, if any, between the AI, BM, and value streams. This was done using the VOSviewer software for constructing and visualizing bibliometric networks. After the above steps, a cluster analysis was conducted using the keywords obtained with VOSviewer. The modularity-based clustering in VOSviewer is a variant of the clustering algorithm developed by Clauset et al. (2004) to detect communities (clusters) in a network; the algorithm also considers modularity. This measure evaluates the quality of community (cluster) structures (Newman & Girvan, 2004).

All obtained clusters were listed and categorized separately in the business and technology domains. We followed the well-established BM canvas (Osterwalder & Pigneur, 2010) to classify all terms in the business domain. Each specific technology was classified into the relevant area of AI technology; for instance, data visualization, social media data analysis, data extraction, data features, data mining, and big data were all categorized as “data.” To discern value study trends and current value theoretical studies, we identified all clusters having to do with value; we then referred to the literature on corresponding value theories to understand other current value study trends and current value theoretical studies. Primary value-related theories were extracted from all cited articles in the cluster and, based on the assessment of this theory research, gaps were identified and three cyclic and iterative process dimensions of the value transformation framework were proposed.

Lastly, having identified the literature gaps and proposed a value process framework with updated value process dimensions, the next step was to further explore the usage of different value process dimensions in the reviewed literature to understand any over- or under-emphasis. To have a complete and detailed understanding of how existing studies analyze value process dimensions, we used the contents of all searched papers (containing the value factor) as the further target for Corpus analysis. All files were converted using the AntFileConverter from PDF and Word (.docx) files into plain text in the Corpus tool. Corpus analysis was conducted on AntConc, a corpus analysis toolkit for concordance and text analysis. All accessible and high- and medium-relevance papers from previous steps were downloaded from Scopus and converted to the plain text used in AntConc for term searches referring to the various value process dimensions per the proposed framework. Different combinations of terms containing the specific word (in our case, “value”) were analyzed for frequency (total number of times all terms are used) and range (how many papers contain the terms) when it comes to the proposed value process dimensions within the framework.

4.3 Validity and reliability

Reliability and validity describe desirable psychometric characteristics of the research (Andrade, 2018), and we address these from the internal, external, and concept validity perspectives before highlighting this research’s generalizability. Internal validity concerns whether the study’s design, conduct, and analysis address the research questions without bias. External validity concerns whether the study’s findings can be generalized to other contexts. Concept validity concerns the coverage and relevance of the theories used to assess the phenomenon of interest.

The internal validity of all the papers included in this research compilation should be considered strong within the research scope and context. The designs of all the papers, whether case study or survey, always included triangulation and cross-referenced multiple datasets to ensure that the assessment was not biased and provided an objective view of our research questions.

Reflecting on external validity, the research papers involved partners, companies, and respondents primarily within the Nordic region. Hence, the general applicability of the findings can be questioned from a regional scope perspective. Since the current study investigates major industrial manufacturers in the Nordic region only, the survey and interview data could have introduced bias concerning the authority and power asserted by these manufacturers over their suppliers, which should be considered when interpreting results. Additional surveys in different regions would be an exciting supplement to the studies conducted here. The number of cases assessed in the studies in this research is arguably insufficient to support the claims made. Surveys with 137 and 145 respondents, case studies with nine respondents, and a longitudinal study of 13 users cannot be entirely reliable when it comes to supporting the general claims. While more surveys should be conducted to capture the value perceptions of B2B and B2C customers, studying different cases for digital offerings should also be considered to generalize the findings of this research thesis. In some studies, the interviewees were not the actual customers who used the digital services and would directly understand their perceived value; instead, the ecosystem partners were used as a proxy, being closer to and sharing a daily relationship with the customers.

Similarly, study C involved one digital servitization concept end to end in one incumbent only. Study B investigated the customers’ perception of the value of digital offerings as assessed via the proxy of customers, i.e., the incumbent’s product and R&D managers. While these internal employees could be considered to have a good understanding of the end customers, as product and category managers work with them on a day-to-day basis, the sample could be considered biased and not entirely valid for end-user value perceptions. More focused studies including direct representatives of actual customers rather than proxies could further substantiate the claims made by the included papers.

The theoretical framework used to observe the phenomenon included digitalization, AI technology, value, and BM theories, providing excellent contextual validity to this research. This research tries to work towards a tentative theory by exploring rather than concluding. The phenomenon under study is somewhat complex and ever changing, so replicability is not one of the salient features of this research.

Since this research is primarily phenomenon driven and uses many theoretical concepts to cover the end-to-end phenomenon under consideration, many existing theories were used but were influenced by the use of these theories in industry. This being industrial Ph.D. research, the conceptual terminology in the research and generated output was adapted to appeal to an industry audience, giving this research moderate concept validity. The concepts examined within the phenomena are complex and subjective, so the reliability of the study would be rated as moderate.

With all this said, as the scope, reach, and situation of this research are relatively limited for multiple reasons (e.g., the scope of and access to resources for an industrial Ph.D.), there are clear limitations to the generalizability of this work. Although the assessments were conducted using qualitative and quantitative methods and rigorously following the chosen methods, digital technology, a general-purpose technology, can have numerous potential applications that merit further research. The theoretical findings of this thesis can be applied to the studied incumbent industrial manufacturing firms, which primarily worked in B2B setups in the past but are now becoming exposed to data and AI technologies and trying to adopt B2C and B2B2C models by embracing digital technology.

5. Summary of appended papers

As value is a complex subject, which concerns perception and is constantly changing and evolving, it needs to be studied from the perspective of creating new capabilities and of BM value dynamics. For this purpose, five studies were conducted to understand the value implications of BMs from the individual, transactional, and relationship perspectives. This section is the culmination of the overall analysis presented in this thesis. Before addressing the research questions and the results of every paper, Table 2 outlines the contributions made by the different authors of the respective studies and papers.

Table 2: Author contributions.

Study/Paper	Order of authors	Authors' contributions
A	Agarwal, Magnusson, Johanson	Agarwal ran all the quasi-experiments within the industrial manufacturing firm. Agarwal and Magnusson jointly created the interview guide. All the authors jointly conducted the interviews. Agarwal led the data analysis, which was then reviewed and verified by Magnusson. Agarwal led the paper writing with support from Magnusson and under the supervision of Johanson.
B (1)	Simonsson, Agarwal	Agarwal and Simonsson jointly planned the project and created the survey. Agarwal took the lead in analyzing the data and Simonsson in writing the paper. Simonsson and Agarwal made equal contributions to the paper. Both authors did equal work with equal contributions, so the sequence of authors is arbitrary.
B (2)	Agarwal, Simonsson, Magnusson, Hald, Johanson	Agarwal, Simonsson, and Johanson coordinated and planned the project with multiple industrial partners. Agarwal and Simonsson jointly created and reviewed the survey, which was then tested by Magnusson and Johanson. Agarwal led the data analysis, which was then reviewed and verified by Magnusson and Hald. Agarwal and Hald led the paper writing with support from Simonsson and Magnusson and under the supervision of Johanson.
C	Agarwal, Swan, Axelsson, Magnusson, Johanson	Agarwal and Swan coordinated and planned the project phases using a go-to-market strategy and coordinated with the service provider to set up the digital offering. Agarwal and Swan jointly created the interview guide and survey structure. Axelsson, Magnusson, and Johanson reviewed and tested the survey and interview guides. Swan collected the data through online surveys, whereas Agarwal and Swan conducted the longitudinal interviews and collected the card sorting data. Agarwal and Swan conducted the data analysis, which was then reviewed and verified by Axelsson, Magnusson, and Johanson. Paper writing was led by Agarwal and supported by all other authors.
D	Agarwal, Lu, Magnusson, Johanson	Agarwal planned the study. Agarwal and Lu conducted the literature review and mapping supported by Magnusson. Agarwal, Lu, and Magnusson conducted a detailed analysis with support from Johanson. Paper writing was led by Agarwal, supported by Lu and Magnusson, and reviewed by Johanson.

5.1 Paper A

Authors: Agarwal, Girish Kumar; Magnusson, Mats; and Johanson, Anders

Title: "Edge AI-driven technology advancements paving way towards new capabilities," IJITM 2020

With the objective of investigating AI technology as not merely a resource but rather a dynamic capability promoting an organization's competitive advantages, the following research questions were set for this study:

- RQ 1: What new capabilities does Edge AI technology enable for product and service offerings?
- RQ 2: In what way can Edge AI as a technology resource provide competitive advantage for organizations?

Results:

The study highlighted that AI technology could enable new dynamic capabilities for organizations, such as: “self-calibration,” relating to the incorporation of different types of intelligence into devices; “enhanced sensing,” relating to functionalities such as data- and software-driven virtual intelligence; “selective capture,” relating to the ability of devices to decide what to capture; and “reputation,” relating to customer perception of the value of devices. The findings indicated that technology, which has normally been treated as a mere resource from a strategic management perspective, is not interesting unless it is applied to create and exploit an inherent value. While the application and inclusion of technology in combination with BMs and other organizational concepts are important for the actual value delivery, empirical observations indicate that the view of technology as just a resource can be transformed with the advent of the latest digital technology advances. For example, although just a technology, Edge AI enables organizations to innovate and provide offerings that were not previously possible. Furthermore, these identified capabilities have the potential to be dynamic products with “selective-capture” and “self-calibration” learning capabilities, dynamically transforming the offering to constantly deliver value from the service. For example, by generating essential data and intelligence to be analyzed on the device itself, AI could be regarded as a dynamic capability in several ways. First, it can create data, a vital resource today. Second, it can improve and change product or service configurations based on realtime user interactions without being dependent on connectivity or other considerations, thereby enabling self-learning offerings based on customer needs. Moreover, by creating platforms that enable data-driven services, AI may play a key role in establishing network externalities and strengthening the achieved competitive advantage. Consequently, as Edge AI, like AI in general, makes it possible to create and use knowledge in new ways, this technology also has the potential to change how innovations are generated (Cockburn et al., 2018); in that sense, it is also a dynamic capability in itself.

In addition, a list of enhanced capabilities was also identified in this study using Edge AI technology: predictive and preventive maintenance, efficiency and control, productivity and reliability, and product performance. These capabilities were probably not created by Edge AI technology but were to significantly involve and enhance the existing capability enabled through other means within BMs.

5.2 Paper B1

Authors: Simonsson, Johan and Agarwal, Girish

Title: "Perception of value delivered in digital servitization"

With the objective of investigating the effect of AI-based capabilities on the value perceptions of customers regarding the value delivery of offerings within digital BMs, the following research questions were set for this study:

- RQ 1: Understand the enabling role of digital technologies in digital servitization innovation
- RQ 2: Understand the influence of IEO on the perception of value delivered within digital servitization

Results:

The output of the study indicated that, apart from transparency, none of the other control variables, such as contract duration and price variance, displayed any statistical significance regarding their contribution to the total perceived value of digital offerings. When incorporating an entrepreneurial orientation (Lee et al., 2011; Bolton, 2012; Bolton & Lane, 2012; Claes et al., 2005; Lumpkin et al., 2009; Speier & Frese, 1997) into the assessment, the overall model fit increases and the role of entrepreneurial orientation, and that of transparency, shows up as statistically significant, while the other control variables of contract duration and price variance remain statistically insignificant. This clearly indicated no mediation or moderation effect between the other variables and entrepreneurial orientation. Hence, all other variables can be treated as control variables to understand the impact of entrepreneurial orientation on total perceived value in digital offerings.

It was also observed that none of the roles turned out to be statistically significant, but at the same time, risk-taking ability and innovativeness were the only two aspects that exhibited statistical significance. In contrast, proactiveness and autonomy did not contribute to the total perceived value of the digital offering. This indicated that it is not the role of the individual, but rather the innovative and risk-taking capability, that determined the value perceived in the case of the studied digital offering.

This suggested that AI technology-based capabilities could be used to promote new values in BMs during the value-delivery stage of digital offerings and highlighted how and where these value aspects are targeted within BMI.

5.3 Paper B2

Authors: Agarwal, Girish Kumar; Simonsson, Johan; Magnusson, Mats; Hald, Kim Sundtoft; and Johanson, Anders

Title: "Value capture in digital servitization"

With the objective of investigating what the role of AI-based capabilities in the value-capture/value-appropriation of the BM within digital offerings, the following research questions were set for this study:

- RQ 1: How does contractual flexibility in the value-capture strategy influence the perceived customer value of digitalized service offerings in a manufacturing context?
- RQ 2: What role does transparency play in the relationship between customer uncertainty (in light of contractual flexibility) and the perceived customer value of digitalized service offerings in a manufacturing context?

Results:

A normality check using the Shapiro-Wilk test indicated that the data for the use case with no price variance deviated significantly from a normal distribution, but all the other cases had a statistically significant normal distribution. Levene's test for homoscedasticity yielded a statistically non-significant value, therefore not rejecting the null hypothesis. The overall difference in the means of the two uncertainty measures was statistically significant for "price-variance limit" but not for "contract length." The estimated marginal means plot indicated that the total value perceived by respondents generally increased with overall uncertainty in terms of greater contract lengths and price fluctuations. However, there might be a slight decrease in the rate of increase of total value of 5–20%, with a slight decrease in value reported over four years of 5–20%.

The effect of contract length and price-variance limit on total perceived value was statistically significant. It was also observed that the contract lengths of six and four years and the price-variance limits per quarter of 20% and 5% resulted in about a 20% greater contribution to total customer perceived value than in the base scenarios of a two-year contract length and a constant price, respectively. Furthermore, respondents' sensitivity to transparency in the overall perceived value of AI-driven digital offerings yielded a substantial increase in our model's explanatory power and in the significance level of the overall regression model. Adding average transparency also rendered all the earlier uncertainty-related independent variables (i.e., contract length and price variance) non-significant, illustrating the solid mediating effect of individuals' sensitivity to transparency on the overall value of uncertain digital offerings. The Cronbach's alpha for all survey questions regarding the various value dimensions was 0.924, highlighting the excellent reliability of the measure.

The findings of this study demonstrated that capabilities such as transparency provided by AI-based digital offerings can be used for previously impossible and completely different value-capture mechanisms, highlighted as a challenge by previous research (Hinterhuber, 2017).

5.4 Paper C

Authors: Agarwal, Girish Kumar; Swan, Erik; Axelsson, Ulf; Magnusson, Mats; and Johanson, Anders

Title: "Value changes during service delivery"

Having observed digital technologies and the AI enablement of capabilities for value creation, value delivery, and value capture within BMs, this study was conducted as a longitudinal study to understand what value implications digital and AI technology can have for value dynamics within BMI throughout the offering lifecycle. Hence, the following research questions were formulated:

- What different customer value dimensions are considered when consumers consider purchasing digitally enabled services?
- How does perceived value change during the use of the service?

<u>Results:</u>

Based on the CFA model, output did achieve a minimum. The absolute model fit index indicated that the model fit the data well. The factor loadings of observed variables onto latent variables all turned out to be statistically significant. The variances of all observed variables indicated that the model fit the data well and that the items used to measure the different value dimensions were valid. The dependent variable "total perceived value" was primarily implicated in the regression analysis by the "functional" and "conditional" values. Regarding each statistically significant value dimension's contribution to the total value, the "conditional" value dimension played a much more significant role than the "functional" value.

The data collected through interviews showed that the customers mostly perceived the "functional" value dimension(s) at an early stage (within one to three weeks of service delivery), combined with other value dimensions such as the "emotional" and "epistemic" ones. As the service delivery progressed, a change in some customers' value perceptions was observed. This change in perceived value was not only from one value dimension to another, but sometimes within the same value function, such as the price function of "functional" value losing its perceived relevance to customers, and the increased relevance of the "performance" function of "functional" value. It was also observed that while some values were considered unimportant during the initial stages, as the service progressed and dominant functional values were delivered, other value dimensions, such as "emotional" and "epistemic" ones, played more critical roles in the overall value perceived by the customer.

This result emphasized that value constantly changes in digital offerings as customers and offerings mature, and that capabilities provided by digital technologies such as AI can be used to deliver these value aspects to customers on an ongoing basis.

5.5 Paper D

Authors: Agarwal, Girish Kumar; Lu, Lu; Magnusson, Mats; and Johanson, Anders

Title: "Towards a value process framework for AI-enabled business models"

Having examined the above studies, there was a need to reconsider the value-creation, value-delivery, and value-capture dimensions within BMI against the specific background of AI-based digital technologies for a better understanding of the technology's capabilities and adoption in the industry and its offerings. However, it was crucial to understand the existing literature on value theories before working towards this framework. Hence, with the overall aim of exploring how AI technology affects value in BMs, this paper investigates existing value frameworks through a literature review and identifies the need to modify the existing value dimensions of BMs, i.e., value creation, value delivery, and value capture.

Results:

Based on the results of the keyword searches, the identified papers referred to far fewer value-related sub-categories than BM or AI sub-categories. Literature mapping of the keywords of the identified papers emphasized that AI technology-related discussions dominated, with some references to BMs, but that there was a significant lack of value discussions regarding AI technology and BM combined. While the cluster analysis highlighted four areas for AI and three for BMs, the same could not be achieved for value, as the references available in the identified papers were limited. Due to this limitation when it came to the cluster analysis of value, a separate value theory assessment was conducted to highlight that value theories can be categorized to cover the value view from an individual, transactional, or relationship perspective. This emphasized the lack of a process view within value discussions, specifically within AI technology-driven BMs, and gave insights into the other three value dimensions proposed for an AI-based BM framework. The dimensions are: "value identification," being motivated by the individual value view; "value manifestation," combining value creating and value delivery and motivated by the transactional value view; and finally "value capture," which includes current value appropriation and is motivated by the relationship value view. Based on the above value views underlying BMI, process-based value dimensions of AI-enabled BMI were analyzed and proposed as "value identification," "value manifestation,” and “value capture” rather than the traditional dimensions “value creation,” “value delivery,” and “value capture”. Finally, corpus analysis was performed on the papers under review concerning the new value framework dimensions, revealing that “value manifestation” was strongly emphasized, followed by “value capture,” and with no occurrences of “value identification.”

6. Analysis and discussion

This section analyzes the included papers and discusses their findings in light of the thesis's research questions.

The section starts by addressing RQ1—"How does AI technology foster innovation in the BM processes of value creation, delivery, and capture in manufacturing firms?"—utilizing the observations from papers A, B1, and B2; this is followed by outlining propositions for different value aspects impacted by AI within BMs.

Then, we analyze RQ2: "How does AI technology change the core value processes of BM and the relationships between them?" We consider how AI changes the BM's core value processes and their relationships, thereby giving rise to new processes; this is followed by outlining the propositions concluded from papers B2 and C regarding new value processes. The two new value processes analyzed are value manifestation, which emerges from value creation and delivery, and value identification, in which value keeps changing throughout the offering lifecycle within BMI.

Finally, RQ3: "What challenges and opportunities can be identified when using AI technology for BMI in manufacturing firms?" This is addressed in paper D, which concludes that there are value frameworks and models treating customer value from various perspectives (individual, transactional, and relationship) in industrial setups.

We conclude this section by analyzing all five papers (i.e., A, B1, B2, C, and D). The first four papers (i.e., A, B1, B2, and C) discuss value dynamics within BMI areas that continuously create, deliver, capture, and, ultimately, manifest value. Paper D highlights different values (i.e., individual, transactional, and relational) that need to be explored further to better adopt AI in BMs. A tentative framework incorporating the new process view of value in AI-based BMI offerings is proposed.

6.1 AI contribution to core BM value processes

This section is divided into three sub-sections consolidating the analysis from papers A, B1, and B2, to analyze how AI technology impacts value creation, delivery, and capture, respectively, through various capabilities as a resource and a value impactor within BM and BMI.

6.1.1 New value creation

It was noticed that AI could exploit resources such as the physical devices themselves, producing data used to introduce new and enhanced capabilities not possible before. It was also observed that it is essential to consider possible network externalities and to emphasize the role of data as a unique resource, as they can be utilized to create additional value with the help of AI-based analysis. To summarize, paper A shows that to understand the value that technology brings to business, the capability view provides a foundational theoretical framework for mapping, representing, and identifying the capabilities of enhanced and new functionalities offered by AI technology to deliver and transform value. However, this view primarily focuses on organizational and entrepreneurial resources, whereas the latest technological advances enable similar capability view on physical products and services. Hence, we use the RBV (Barney, 1991; Ristyawan, 2020; Wernerfelt, 1984) and dynamic capabilities theory (Teece, 2007; Teece et al., 1997; Tiguint & Hossari, 2020) to map and analyze the extended and newly enabled capabilities offered by AI technology.

As per the analysis, the identified aggregated dimensions were based on previously impossible AI-enabled capabilities within current customer offerings of industrial manufacturers and consumer goods assembly companies. The four identified dynamic capabilities were self-calibration, enhanced sensing, selective capture, and reputation. "Self-calibration" relates to incorporating different types of intelligence into devices over time, the self-gaining of experience by the device by prediction, enabling mass customization by learning as per usage, and creating different levels of "smartness" in different device segments. "Enhanced sensing" relates to functionalities such as data- and software-driven virtual intelligence, reduced time to scalability, ability to make decisions during realtime sensing, and increased intelligence as per device experience. "Selective capture" relates to the ability of devices to decide what to capture, when to capture it, and how much to capture, allowing for connectivity-agnostic and -compliant behavior. "Reputation" relates to customer perception of the value of utilizing AI by enabling functionalities such as intent capture by implementing integrity on the devices.

A particular challenge related to the implementation and use of these new capabilities will therefore likely be how to handle their disruptive features (Christensen, 1997; Christensen & Rosenbloom, 1995), which requires that they be managed differently from existing but improved capabilities, resulting in improved performance along established performance value dimensions (Christensen, 1997). As frequently highlighted in the RBV literature (see, e.g., Grant, 1991), capabilities are usually far more interesting than single resources as a source of competitive advantage, as the former are idiosyncratic and challenging to acquire. Bundles of resources constitute capabilities, and we have aggregated the identified functionalities and features closely related to single resources to identify capability blocks. Paper A highlights that AI technology can act as a dynamic capability to create new value within BMs, which was not possible before. Hence, a mere technology view of AI technology is inadequate for understanding its total potential usage within BMI.

As previously noted, much attention has been paid to organizational and management resources within RBV, as these provide companies with dynamic capabilities (Boccardelli & Magnusson, 2006). However, assessing new digital technologies such as AI suggests that physical products using such technologies are also becoming candidates for providing dynamic capabilities. These technologies can be a key to long-term competitive advantage by not only providing intelligence and intelligent machines but also by generating data and continuously adjusting the interrelationship between a firm's strategic assets and critical factors in its external environment (Amit & Schoemaker, 1993), and in that sense forming a dynamic and proactive capability. While bundling functionalities and features (enabled by AI) together as capabilities, we also noticed that they could be classifiable as technical (i.e., self-calibration, enhanced sensing, and selective capture) and organizational (i.e., reputation) ones. Although a capability is difficult to observe directly due to its composite and abstract nature, it is a construct that helps us understand the potential for creating and appropriating value. This also underscores the importance of not applying an overly narrow technological perspective to the benefits of new digital and AI technologies.

During the assessment, some of the AI capabilities were also mapped against existing capabilities within organizational processes, products, and services that companies already possess through other technology and organizational resources such as quality controls, productivity measures, and governance routines. In conclusion, AI also yielded a set of capabilities that we referred to as enhanced capabilities (rather than new capabilities); these were identified to substantiate existing capabilities within the companies rather than being enabled, as new capabilities were unavailable. The ones observed in paper A were predictive and preventive maintenance, efficiency and control, productivity and reliability, and product performance.

To conclude, a capability-based view of AI technology was applied in the three AI quasi-experiments conducted for paper A. We identified new capabilities enabled by AI technology that differed from traditional manufacturing capabilities and that could not be offered before. These capabilities were enabled through previous technology shifts combined with process and organizational excellence. Also, multiple enhanced capabilities were identified through AI technologies to generate products and services that match specific customer needs (Ulwick, 2006). For this view, the following propositions are formulated from to paper A's findings:

- *Proposition 1: AI introduces new dynamic capabilities for product and service development.*
- *Proposition 2: AI enhances existing dynamic capabilities for product and service development.*
- *Proposition 3: AI-enabled physical products can be used as dynamic capabilities within BMs.*

We propose that AI impacts value creation within BMs based on the above propositions. AI technology has commonly been treated as a resource with which to improve efficiency and automate business processes. While this view of AI technology as a resource is helpful for understanding BMs, it is not a complete view of the capabilities that AI technology can drive within BMs. The value process view of AI technology can advance our understanding of BMs from a strategic management perspective, thereby contributing to radical changes in them. Although just a technology, AI enables organizations to innovate and provide offerings that were not possible before. AI-enabled capabilities identified in this research have the potential to enable dynamic products with “selective-capture” and “self-calibration” capabilities to learn and transform the offering dynamically to constantly deliver value out of the service (Verganti et al., 2020). For example, by generating essential data and intelligence and analyzing it on the device itself, AI could continuously learn and change the product or service configurations based on realtime user and solution behavior without being dependent on connectivity, enabling intelligent, innovative, and self-learning offerings. Moreover, AI may play a key role in establishing network externalities by cross-referencing different domains’ data. Consequently, AI makes it possible to create and apply knowledge in new ways; this technology can also change how innovations are generated (Cockburn et al., 2018).

6.1.2 New value-delivery mechanisms

Today, many industrial companies are pursuing a servitization strategy (Vandermerwe & Rada, 1988) to provide more value for different stakeholders, including their customers. Along with new product–service offerings, existing BMs are used as bundles of products and services with a logic different from that of pure product offerings (Kindström, 2010) as they incorporate a substantial contribution from digital technologies such as AI (Soni et al., 2020). One key aspect of a BM is how the value is delivered (Teece, 2010), and the literature suggests several ways companies could approach it. Two less-explored value-delivery aspects are individual entrepreneurial orientation (Cosenz & Noto, 2017; George & Bock, 2011) and applicable functional affiliation, both of which influence overall perceived value. It is interesting to understand the enabling capacity provided by digital technologies and their impact on the perceived value of technology-driven digital offerings.

In paper B1, survey respondents were randomly presented with one out of nine variants of the same contract in which contract terms differed. Critical constructs of the case also included the fact that digital technologies would monitor the service and that price levels could, based on the information gathered, be renegotiated every quarter if agreed to by both parties. A finding was that digital technologies play a twofold role in the types of digital offerings exemplified by the survey case. One role is to facilitate the predictive maintenance and monitoring of the electric motor, including providing baseline data to the involved parties. The other role is to present these data to both the supplier and customer to create transparency, allowing both parties to share the same baseline information on which the recurring renegotiations of price can be conducted. Previous research has noted that lack of access to data and lack of trust are two key barriers to the adoption of value-based delivery (Töytäri et al., 2015). Scholars have also called for research on the “relationship between ex-ante value quantification and ex-post value verification” (Hinterhuber, 2017, p. 174). The analysis from paper B1 suggests that digital technologies that can monitor components on a production line and share different value-driving parameters with involved stakeholders can answer these calls and provide a foundation for proper dynamic delivery of the developed value aspects. Digital technologies further allow for realtime sharing of operational status, rather than monthly summaries or retrospect reports, which may also influence the adoption rate for such offerings.

Hinterhuber and Liozu (2017) further claims that value quantification is an essential research priority but that customers tend not to recognize value even when they see it. This challenge could be addressed by digital technologies, and the varying value could be regularly updated and presented to the customer. Iyer et al. (2015) concluded that “pricing is a decision that needs to be continuously examined and frequently adjusted,” and that “this calls for detailed information on the environment as well as information on the impacts of prices on the firm’s marginal profits. The inability to respond to such internal and external considerations fairly quickly may also contribute to pricing errors that affect the organization’s objectives and performance adversely” (p. 14). Here digital technologies may respond to the identified value delivery challenges. Estelami et al. (2016) proposed using extended warranties to satisfy customers suffering from product failures, but the present research suggests that fair dynamic delivery enabled by digital technologies could be an alternative approach.

Hinterhuber and Lizou (2017) have pointed out that it is the individuals in organizations, not the organizations themselves, who perform activities. It accordingly becomes essential to understand the link between individual actions and company value-delivery performance. Other authors have also noted that individuals matter (Hallberg, 2017; Töytäri et al., 2017). The findings of paper B1 strengthen our understanding of how these traits are distributed through a company. Paper B1 also revealed that an individual’s entrepreneurial orientation, innovativeness, and willingness to take risks all play a role. The diffusion of value-based delivery models is hence dependent on the individual entrepreneurial orientation, but functional affinity is not.

In summary, the findings of this paper show that individual entrepreneurial orientation influences the perceived value of digital offerings, but that functional affiliation does not appear to be statistically significant. These findings imply that the entrepreneurial orientation of individuals, rather than their role in the organization, determines the perceived value they foresee within digital offerings, which can be influenced through the application of capabilities provided by digital technologies such as AI for value delivery to customers. This emphasizes that value delivery in digital offerings is dependent not only on the features provided by the offering but also on the individual's innovation orientation and risk-taking ability. This analysis provides insight into the value aspects to be considered when incumbents create and assemble offerings. Hence, the following propositions are formulated based on paper B1, building towards a value theory of AI-led BMs:

- *Proposition 4: A perception of value shared among BM stakeholders can be supported by AI-enabled value quantification.*
- *Proposition 5: The transparency offered by AI-enabled value quantification improves the value perceived by BM stakeholders.*

We propose that AI affects value delivery within BMs based on the above propositions. Combining the power of current digital technologies such as ICT, big data, and AI within BMs provides a continuous touchpoint with customers by which to collect regular and updated data from all customer interactions within the digital service (Chiang, 2019; Kunz et al., 2017). While these techniques have been looked into to uncover customer value from various data sources such as the web (Linoff & Berry, 2002) and various industry domains (Huang et al., 2009), the same data and digital techniques provide opportunities to create transparency between the digital service provider and the customer when it comes to the actual value delivery. These data-driven and transparent AI services determine what and how value is created. For example, the service provider can be transparent in sharing the captured digital data with the service consumer to showcase not only the performance of the digital service but also how the new value was delivered using advanced prediction and anomaly detection analytics, creating opportunities for new value-delivery strategies (Töytäri et al., 2015).

6.1.3 New value-capture techniques

Digital servitization introduces new opportunities and challenges for traditional manufacturing suppliers and buyers who want to create more value by increasing the share of digital services within their offerings. Value capture in BM and AI applications is crucial for understanding customer needs more deeply. Paper B2 advances our understanding of value capture design in digital servitization; at the very least, embracing uncertainty in contract design may be an attractive approach if we exploit digital capabilities to generate transparency. Analyzing the results suggests that although the digital offering introduces more uncertainty (Reim et al., 2016) in terms of higher potential price fluctuations and longer contract commitments, it is perceived to deliver better value (Settanni et al., 2017; Smith et al., 2014; Teece, 2010) compared with less uncertain digital offerings with shorter contract durations and smaller price fluctuations. The above observations have implications for the traditional handling of value-capture design alternatives within servitization. Service contracts have primarily been designed to reduce uncertainty and risk (Durugbo, 2013; Grubic & Jennions, 2018). The conclusion is an exciting finding that total customer-perceived value increases despite varying contract terms, including longer durations and non-fixed prices, as firms and their customers usually agree on contract terms beforehand. Despite higher uncertainty, that customers are still willing to choose such offerings from suppliers implies that customers perceive digital technology-enabled services differently and need to be understood at greater depth to contribute to the service paradox (Gebauer et al., 2005; Szasz et al., 2017). Findings of paper B2 indicate that services' digital capabilities contribute to better value capture due to increased customer value. It was further found that functionalities such as transparency can be vital in organizational capabilities (Barney, 1991; Teece, 2007) to retain existing customers and even attract new ones. These observations suggest that this higher value opportunity is available to companies that can manage the digital capabilities of the product–service needed for advanced service offerings (Cenamor et al., 2017; Simonsson et al., 2020). This infrastructure can generate the necessary data insights needed to deliver on the promise to supply continual performance monitoring set out as a prerequisite for the contract. Access to baseline data is necessary for the parties to have a productive ongoing value discussion. Earlier research has presented fewer examples of servitization initiatives based on data and AI capabilities than did paper B2. The present case of an advanced AI-based servitized offering reflects a technologically turbulent industry, wherein more benefits are perceived despite the risks of adopting contracts based on financial results (Böhm et al., 2016).

Another observation from paper B2 suggests that one of the significant reasons for the considerable perceived value of uncertain digital offerings is individuals' sensitivity to the transparency enabled by digital technologies. The offering case in the survey states that: "every quarter, the contract allows you to renegotiate the subscription price based on the value delivered," which, while introducing more price uncertainty (Hald & Mouritsen, 2018; Lerch & Gotsch, 2015), still gives a transparent view of the services delivered and the value added, thereby reducing value uncertainty (Kreye, 2019). Arguably, this brings about an increased sense of control and commitment, thereby delivering greater value (Eggert & Helm, 2003). This alludes to new BMI designs (Cenamor et al., 2017; Corea, 2017) in which an increase in uncertainty (Durugbo & Erkoyuncu, 2016) increases value substantially by concentrating on digital technologies that create transparency. This suggests that even though there is "objective uncertainty," what influences customers' view of value in digital BM design (Ardolino et al., 2016) is the "perceived uncertainty." This means that the overall total value perceived in uncertain digital offerings is dependent on individuals' sensitivity to the perceived transparency (Hultman & Axelsson, 2007). Effectively, the mediating nature of transparency suggests that uncertainty (Hinterhuber, 2008b) does not play any significant role when put together with transparency (Lamming et al., 2005). On one hand, there is reluctance to adopt digital offerings and new BMs such as value-based revenue models (Hinterhuber, 2017); on the other hand, it is observed that digital technologies (specifically AI-based ones) can enable digital offering functionalities (Brynjolfsson & McAfee, 2017), contract designs (Durugbo & Erkoyuncu, 2016), and capabilities (Frank et al., 2019; Grubic & Jennions, 2018).

Paper B2 concludes by presenting several exciting findings concerning the capabilities that AI can enable within value-capture techniques in BMI. One finding concerns the value in value-based pricing, which requires that companies understand the full range of values provided, converting that range into a single fixed figure (Hinterhuber, 2017). Some critical barriers to the successful implementation of such an approach are access to essential data needed for value assessment and a lack of transparency between parties (Töytäri et al., 2015). However, through a value-based approach, flexibility in pricing provided transparency as a default parameter in the surveyed case relationship. Hence, although decision makers feel personally familiar and comfortable with value-based pricing, the digital technologies and BMs in different scenarios will likely impact the pace of adoption, moving towards more extended contracts with frequent renegotiations based on AI-supported maintenance techniques. The findings therefore have implications for the willingness to scale purchases of technology-enabled service offerings in the long term. The findings suggest that value increases when uncertainties concerning varying conditions are introduced into the contract. This positive side of uncertainty mechanisms may facilitate the understanding and the adoption of new service offerings. Hence, the following proposition is formulated based on paper B2:

- *Proposition 6: The AI-enabled quantification of value facilitates dynamic and outcome-based value-capture strategies*

Based on this proposition, we suggest that AI impacts one of the critical parts of a BM: the appropriation of value (Teece, 2010), which includes how a company is paid for the offered products or services. Setting a reasonable price for a product or service has been defined as revenue management in the literature (Dolgui & Proth, 2010), and the prices companies decide to charge for their offering portfolios of products or services therefore represent important decisions (Morris, 1987). The literature generally categorizes pricing as cost, competition, or value based (Hinterhuber, 2004). Interestingly, many scholars have identified value-based pricing as an exciting approach, although it is the least used and explored (Hinterhuber, 2004, 2008; Ingenbleek, 2014; Kienzler & Kowalkowski, 2017). Commonly, a value-based pricing approach first identifies the value delivered by the product or service to the customer over the lifecycle, then quantifies the value in terms of the pricing offer, and finally tags the product or service with the quantified value together with a unit of measurement such as a one-time price, leasing price, or subscription price. While the literature notes several barriers that companies face when adopting value-based pricing, i.e., value assessment and value communication, through data visibility and advanced predictions, AI builds the transparency needed to assess the inherent value of the offering (Töytäri et al., 2015). Quantifying the value is an essential aspect of value-based pricing, which AI can do initially and during service delivery. The shared access to baseline data becomes a foundation on which value-based pricing can be taken to the next level of dynamic pricing.

6.2 AI creating new value processes within BMI

Having observed that digital technologies such as AI successfully provide new capabilities targeting different value aspects of BMI, this sub-section formulates more value propositions concerning the interactions and relationships among value creation, delivery, and capture. Then, we utilize the analysis from paper C to highlight the value dynamics operating within digital- and AI-enabled BMI. The section emphasizes the importance of value manifestation, in which value creation and delivery merge, and of value identification, in which value keeps changing throughout the offering lifecycle within BMI. This matter has not been examined with the necessary rigor, which this thesis argues is essential for exploiting the full potential of AI-based digital technologies and their adoption in industry.

6.2.1 Value manifestation

Value manifestation is a combination of value creation and value delivery. In product-oriented BMs, the value proposition does not change over time, and the relationship with the customer is primarily transactional (Oliva & Kallenberg, 2003). In contrast, in servitization, value creation and value capture are constantly happening side by side, enhanced and impacted by AI-technology–driven capabilities, which are of interest in this research. In paper C, it is observed that servitization brings two significant changes. First, the service may continuously change based on added functionalities that redefine the value proposition (Agrawal et al., 1993), especially by merging value creation and value delivery in services, as they happen together. Second, the perceived value and the value types of the service will change over time due to developing customer perceptions, which is the case as incumbents explore new services and BMs (Aversa et al., 2020). This brings complexity to innovation leaders exploring new technology and BMs as they advertise potential value to launch BMs while simultaneously monitoring and responding to customer experiences and perceptions of value over the service lifecycle (Vandenbosch & Dawar, 2002). That is one reason for the importance of innovation leaders' iterative exploration of new technology, customer experiences, customer value perceptions, and BMs. A servitization strategy may bring direct financial benefits, relationships, and loyalty. Still, many industrial manufacturing companies are in an early stage of adopting servitization BMs, and customers are not usually involved in the value creation and delivery.

Hence, many companies are arguably still quite product centric (Tukker, 2004), offering services defined from a supply perspective.

Observations from paper C indicate that perceived value at the initial purchase point seems to be driven more by the "functional" (Fagerstrøm et al., 2010; Ferber, 1973; Stigler, 1950) and "conditional" (Kummer et al., 2018; Park, 1976) value dimensions than by the "emotional" (Holbrook, 1983; Khan & Mohsin, 2017, Kotler, 1974), "social" (Ajitha & Shivakumar, 2017; Veblen, 1899; Warner & Lunt, 1941), or "epistemic" (Brown, 2018; Hirschman 1980; Teng, 2019) ones. Therefore, customers making purchasing decisions regarding the digitally enabled service examined in paper D were most impacted by the service offering's functionality, such as its overall results, price, and saved time and labor, as well as by the conditions imposed by adopting the service, such as required changes to the yard. Further assessment indicated that the "conditional" value dimension played a more significant role than the "functional" dimension. This indicates that conditional dimensions resulting from the decision to buy or not to buy the service, in this case, were more important than the exact functionality or features included in the service. Service designers must accordingly consider customers' conditional impact brought about by the digitally enabled service offerings, at the customer segment level or individual level, i.e., hyper-personalization (Buganza et al., 2020; Goyal, 2019), to ensure higher perceived value and hence a purchase decision in the case of B2C customers.

In paper C, it is observed that while the actual service and consequently the value delivered was unchanged from the service providers' perspective, the perceived value for the customers (Lapierre, 2000) seemed to develop as they encountered new situations and experienced unexpected aspects of the service. These experiences and value perceptions are primarily shared among customers, but there are also individual stories. As the survey and interview data highlighted, most of the customers were driven by the functional values of the service, and a change in their value dimension between the first and second interviews was observed for many, but not all, customers. As the service was delivered, several anticipated values (Sheth et al., 1991) were confirmed by most customers, although this was not equally clear for some of them. Moreover, the interviews indicated a shift from the initial functional focus to emotional values in several cases, values that some customers increasingly perceived as the service delivery progressed. A possible explanation of the interview results is that the functional aspects may be less prominent in a particular use case once all functional tasks are taken care of satisfactorily. At this point, customers may shift their attention to other value aspects—for example, a feeling of relaxation at not having to put effort and thought into mowing the lawn—letting more emotional values take precedence.

From comparing the interview results reported in paper C, we observe that customers have idiosyncratic experiences of the service delivered. It is difficult to observe any clear explanatory patterns regarding changes in value perceptions. At least for the service studied in paper D, we conclude that change happens to a great extent on an individual level. The above indicates that while customer perceptions of value continue changing during the service lifecycle (Slater & Narver, 2000), firms can utilize digital technologies to collect various datasets (Chiang, 2019; Kunz et al., 2017) with which to understand and even predict customer value perceptions and adjust their offerings to promote better acceptance and adoption of services in general (Baines et al., 2017; Oliva & Kallenberg, 2003) and digital services in particular. These individual changes represent challenges and opportunities for the service provider regarding pre-sale, service configuration, delivery, and communication during delivery. This highlights a potential need for hyper-personalization (Buganza et al., 2020; Goyal, 2019) within servitization, as occurred when lighting damaged the equipment and support was alerted, followed by the replacement of the damaged components as part of the service, which was significantly enabled by the capabilities of digital technologies such as AI.

As perceived values are constantly changing, and this change is very individualistic as well, a service needs to be managed as constantly to deliver value from an overall perspective (Bolton & Drew, 1991a; Oh, 1999; Payne & Holt, 2001; Woodruff, 1997) throughout the service lifecycle. Managing expectations by capturing requirements, perceived values, and contexts is a key to adapting to changing customer expectations and, in the end, offering more valuable hyper-personalized services. Also, changes in value perceptions could be vital to retaining customer engagement over a more extended period (Slater & Narver, 2000), so that the perceived value should be developed to deflect customer churn. Digital capabilities to collect and process product, customer, or contextual data are essential to capture needs and visualize values and insights (Linoff & Berry, 2002). We have reached the “AlphaGO moment” for companies (Igami, 2020), when technology outperforms humans and AI-driven capabilities are fundamental not only to understanding customers, using data-driven technologies, but also to using them to actively scale, adapt, and change offering designs throughout the service lifecycle, sometimes even multiple times.

Paper C concludes that the value-manifestation aspect of BMI driven by digital technology in general and AI in particular has far more implications for value as value creation and value delivery come to be more integrated, which needs to be understood and addressed in depth. Paper C emphasizes that the value-manifestation aspect of value will be a key to adopting these technologies within BMI, since it takes care of the dynamic nature of value and needs to be explicitly addressed in more depth in BMI literature and practice. Hence, the following proposition is formulated concerning value manifestation according to paper C:

- *Proposition 7: AI facilitates the continuous identification, manifestation, and capture of changes in customer value via data capture and analysis, throughout the lifecycle of the product–service within the BM.*

Based on the above proposition, we propose that value creation and value delivery, together as the concept of value manifestation, can directly correspond to firm strategy. In creating value, value delivery should already be taken into consideration. During the value-creation process, forethought regarding value delivery will provide much better clarity and traceability of corresponding value targets, giving perspective on the firm's strategy execution (Afuah, 2004). Therefore, the value-manifestation dimension can be complex because it involves many organizational processes and units in traditional structures, such as product management, R&D, manufacturing, customer support, sales, marketing, and finance, all of which are necessary to make value creation and delivery a reality. The design and delivery of AI-driven offerings provide unique opportunities to redesign the process of value creation and delivery by means of data ingestion and insight capabilities that can be used for different metrics when monitoring the performance and transformation progress required during value manifestation. Examples include using NLP-based AI sentiment models to capture stakeholders' value perceptions during early prototyping, or using prediction and preventive anomaly AI models to reduce errors and increase quality (Kunz et al., 2017). This dimension could also include various channels and ways of creating and delivering value.

6.2.2 Value identification

Historically, the value-creation step within BMs starts with the identification of gaps or requirements based on certain "assumptions" made by incumbent firms (Jokubauskienė & Vaitkienė, 2017). While these assumptions are usually reasonably valid and give good insights into the value that firms should be looking to create and deliver so that profitable value capture can be arranged, it is not always the case that the identified value assumptions hold concerning the assessed potential. The BMI literature investigates ongoing value generation through innovation within the various BM journey stages of creation, sustaining, innovation, and efficiency (Christensen et al., 2016). The literature covers value creation by means of the value proposition and resources during the creation phase, value delivery by appending processes, and value capture by incorporating the profit formula over the product–service lifecycle; however, it does not highlight the need for and importance of value identification, as this thesis does, which is crucial for digital-technology–enabled capabilities.

Along with value creation, value identification can be an essential complement to the existing BM value dimension, as AI technology itself is not particularly interesting to companies and customers (except in cases driven specifically by innovation and newness); rather, it is the value that the technology can bring about that makes it interesting to both companies and users. A technology-driven solution should target, deliver, and be measured against identified value aspects, using an approach of constantly reviewing and updating these identified and targeted aspects as the offering matures (Teece, 2010). This is more relevant and important with AI-driven solutions, as the data captured throughout the offering process enables both regular and in-depth analysis (using technologies such as ML and DL) of customer interaction, offering usage, and value delivered. We can then use these data to predict insights in the interest of future preparations and improvements in areas such as safety, personalization, and realtime performance, and hence constantly indicate a greater number of various value aspects that customers expect from the offerings and how they can be enabled in the existing solution (Dai, 2017). When incorporating technology in the firm's strategy, value identification can diagnose what technology could bring to the business aim, identify the overall value objective the technology can create, and then divide it into sub-aims. Nowadays, technology enables the pre-measurement of value; for instance, through simulation, A/B testing, and modeling, firms can predict the value before making a strategy to adopt a new technology. Different measurements or predictions can precisely simulate the test results and identify the potential value of meeting or not meeting certain needs (Ramos & Blind, 2020). Hence, value identification could serve as the basis and take the lead in directing the steps between other value process dimensions.

6.3 AI business model value processes

Having identified AI technology's disruption of and contribution to different value aspects of BMs, paper D was undertaken to conduct a structured literature review (Koop & Burgess-Pinto, 2003; Webster & Watson, 2002) to understand existing BM viewpoints, value models, and frameworks. Paper D constitutes a literature review analysis, a cluster and network analysis highlighting the lack of discussions of value in BMI, and a value literature mapping analysis highlighting individual, transactional, and relationship value orientations. This section analyzes paper D together with all previous studies (A–C) to highlight gaps in digital-driven BMs concerning value process matters. Finally, using the opportunities afforded by digital technologies as understood in studies A–C, we work towards a framework for AI-driven value-process–based BMI.

6.3.1 AI contribution to different values within BMs

Analysis of the literature review findings highlights the lack of discussion of value in AI-technology–driven BMI. After the analysis, it was also observed that, although intelligent technology has been studied for quite some time, its impact on the business field has attracted increasing attention only recently. Understandably, as the adoption of intelligent technology has become more comprehensive, industry changes have driven transformation in firms, making such technology a popular topic; however, value-centered studies in the field remain rare. Analyzing the results of technology-related discussions in the reviewed papers highlighted that although technology attracted the most attention (followed by management, information, business, and science), as evident in the RBV (Barney, 1991; Grant, 1991), technology was treated as a resource rather than as a capability that provides competitive advantage within business offerings and value to customers. The above observations stress the lack of value-grounded research on AI technology and on AI-technology offerings in BMI, highlighting the great emphasis on research addressing AI technology from the algorithm and resource perspectives. We also observed that customers were the critical stakeholder group frequently discussed in the reviewed articles, whereas other internal stakeholders such as employees or external stakeholders such as suppliers and business partners were rarely referred to (Wheeler & Sillanpa, 1998).

The cluster network analysis identified the central term as “artificial intelligence,” which was directly or indirectly linked to every other term, indicating that AI technology has gradually impacted all fields and accelerated innovation scope and depth. While business and technology were predominant in the cluster network analysis, value was a relatively minor theme even when all value-related terms were merged. The results revealed numerous and diverse keywords in sub-areas of the business and technology fields, indicating that the literature gap is on the value side. The range of value keywords proposed by the authors and the index values among 252 papers include value chain, value creation, value model, value proposition, customer value, business value, and value engineering, with mean occurrences of only two each. This gap is further emphasized by the fact that only 7% of the authors chose value-related terms as keywords. Based on the phenomenon considered in this thesis and the current lack of discussion of value within AI-driven BMI, a need was identified for further in-depth assessment of value dynamics within AI-driven BMI.

Furthermore, all the identified clusters were classified into either the business or technology fields for analysis. The business cluster highlighted three blocks: business operation, business theory/models, and measurement. The first block, *business operation*, concerns specific processes or functions conducted by cross-functional organization setups, of which product and service receive the most attention. The second block, *business theory/models*, concerns the theoretical concept or basic model that informs the overall business operations and the critical factors such as value and innovation that affect the business. The third block, *measurement*, emerged from standards that measure performance at the business and whole-market scales. The AI technology cluster highlighted the first big block as machine/deep learning involving neural networks and related technologies—a “hot topic” in recent years. The authors of the reviewed literature also frequently created learning models incorporating various statistical techniques for modeling, classification, prediction, or simulation. The second identified block concerned image analysis and computer vision. The third block emerged as data processing, taking note of social media data semantic analysis—again a trend within customer analysis. Finally, the fourth block was a group of independent technologies like IoT, Cloud, Blockchain, etc. Value could not be subjected to a cluster analysis as all the value-related terms were initially merged due to their small number.

Analysis of this part of paper D identifies a lack of discussion of value regarding BMI and AI technology in the recent research literature.

As highlighted in the above analysis of paper D, value could not be considered in the cluster analysis as all the value-related terms were merged to enable them to appear in the cluster diagram in the first place. Hence, the keyword “value” was used to identify all the papers referring to any value aspects, yielding 16 papers. Analyzing them in detail revealed that nine papers focused on AI’s impact on value creation in BMs, one paper each focused on the stakeholder view of value, supplier view of value, and value chains using AI, and four papers focused on customer value models when adopting AI technologies within BMs. As the reviewed value papers were few in number, the value cluster reference motivated us to reassess value theory in the literature, so we analyzed the “value” concept directly through a literature mapping assessment of the existing literature on value. Assessment of this mapping found that value-based studies of BMs could be categorized into one of three perspectives: individual, transactional, or relational.

The individual value perception of every customer has been considered a value measure of individual and personal aspects, such as economic, strategic, and behavioral (Wilson & Jantrania, 1994). Woodruff (1997) proposed using more data elements when determining customer value, such as salesperson reports, research data, and macroenvironment data. Individual value assessment theories consider the monetary aspect, with value being defined as the monetary worth of the various technical, economic, service, and social benefits a customer receives relative to the price paid (Anderson et al., 2006), or even consider value and price as independent of each other such that the value provided nearly always exceeds the price. The difference is the customer’s incentive to purchase (Anderson & Wynstra, 2010). We also categorize the experiential value aspects such as fantasies, feelings, and fun (Holbrook & Hirschman, 1982) within the individual value perspective, and the product value aspects such as the three levels of product values, namely, generic, expected, and augmented. The definition from Neap and Celik (1999) state that the product value reflects the buyer’s desire to obtain the product, which in turn depends on the affiliation of product details or performance with the buyer’s value system, which includes a subjective marginal value.

A transactional view of value has been presented in research: value-in-use and value-in-exchange were discussed by Eggert et al. (2018) and then supplemented with resources, capabilities, shared beliefs, and costs from the customer's standpoint (Eggert et al., 2019). We also categorize customer value aspects concerning price strategy (Keith, 1960) and value (Reichheld, 1996) as parts of a transactional view of value. In a transactional view, value is derived through customer interactions with different touchpoints, possibly during an exchange of goods and services or even during use, thereby creating and delivering value. Concepts such as value chains (Porter, 1985), value networks (Peppard & Rylander, 2006), and value constellations (Normann & Ramirez, 1993) would also be classified under the transactional view of value.

A relational view of value is a more lifecycle-oriented approach (Eggert et al., 2006) in which value creation and delivery are considered longitudinally, along with the customer (Eggert et al., 2006), resulting in the creation of a relationship. This relationship, in turn, still comprises multiple transactions and individual value aspects over a period, aspects such as customer acquisition, customer retention, customer expansion, and customer loyalty (Gupta et al., 2006). The relationship view of value includes the value aspects contributed by other stakeholders and ecosystem partners, both internal and external to the organization (Payne & Holt, 2001). Value creation in a buyer–seller relationship is the key (Lindgreen & Wynstra, 2005; Walter et al., 2001), and the nature of interactions with suppliers is essential to the overall value creation for the firm and its customers (Corsaro & Snehota, 2010). This relationship value is limited to firms, customers, and suppliers and includes other competitors (Doyle, 2000; Miles, 1961). The multidimensional perspective of relationship value towards the perceived value contribution for customers is also an aspect examined by Fiol et al. (2011).

Apart from the individual, transactional, and relationship views of value, it was also noted that value had been considered from an overall perspective (VM, 2020) as a model of firms and customers. Oh (1999) examined customer value from a quality and satisfaction perspective, and Bolton and Drew (1991a) proposed a multi-stage model of customer assessments of quality and value. This overall approach is also found in the servitization literature in the form of value derived for customers and firms, as value is mentioned in papers about service-dominant logic (Vargo & Lusch, 2008), strategic transition to services (Gaiardelli et al., 2015), and the divergence and convergence of this logic (Vargo & Lusch, 2008) to create, deliver, and capture value through multiple and interactive transactions that provide the capability to cater to individual as well as relationship value aspects. Hence, based on the analysis from paper D, the following propositions are formulated:

- *Proposition 8: AI contributes to individual stakeholder value within BMs by introducing new capabilities that enable a more detailed understanding of individual value perceptions.*
- *Proposition 9: AI contributes to transactional value within BMs by introducing new capabilities enabling dynamic pricing and by increasing the transparency of the delivered value.*
- *Proposition 10: AI contributes to relationship value within BMs by introducing new capabilities enabling hyper-personalization, and by enabling continuous value increase over the servitization lifecycle.*

6.3.2 Towards a revised value process framework for BMI

Reflecting on the analysis and proposition assessment from all the studies of this thesis (i.e., studies A–D) highlights the lack of a value focus on AI-driven BMI and the lack of a process orientation within value discussions of BMs. Based on the assessment of conducted studies, a few insights emerged, indicating movement towards an updated view of value dynamics within AI-driven BMs. The insights include the required focus on value identification, merging value aspects, value creation, and value capture due to servitization into the value-manifestation concept, with the dynamic nature of value changing the value perceptions of users throughout the service lifecycle (as highlighted in paper C). Furthermore, there is an observed lack of process orientation in value discussions (Wikström, 1996). This thesis highlights that the process view (Langley et al., 2013) is required for value assessment within BMI to incorporate the emerging, developing, growing, slowing, and changing views of value. Furthermore, AI-driven BMI brings together individual, transactional, and relationship value viewpoints that cannot be encompassed without the process view and only through current value creation, value delivery, and value capture within BMI (Teece, 2010). Hence, this section consolidates the assessment of the propositions from all the papers of this thesis to work towards formulating a value process framework for AI-enabled BMs, folding the three individual, transactional, and relationship perspectives into an overall process view.

By analyzing the value-theory literature assessment from paper D of the individual, transactional, and relational views of value, then synthesizing the AI technology implications for the BMI value dimensions and bringing in the process view of value, this thesis proposes a revised value process framework for AI-enabled BMs incorporating value identification, value manifestation, and value capture (instead of the earlier value creation, value delivery, and value capture). The proposed value framework would not only address both the supplier and buyer perspectives, but would also be relevant specifically within AI-based offerings and services where value transformation is happening much more continuously and almost in parallel during value creation, delivery, and capture, as compared with traditional product-oriented business.

Value identification

The value-identification aspect highlights the required focus on understanding and articulating what values can or should be targeted for stakeholders during the introduction of offerings into the business landscape. During the value identification process, the targeted values of different stakeholders should be identified, updated, or even changed during the service or offering lifecycle, while the offering is being introduced or continuously used. This emphasizes that value is not limited to only certain aspects, such as epistemic, social, emotional, and functional aspects (Sheth et al., 1991), but that there are other value aspects and even combinations of multiple value aspects. Historically, the value-creation dimension of BMs typically begins with the identification of customer or market gaps in a proactive and continuous manner to create solutions and services for customers (Teece, 2010) that, in some ways, include value-identification aspects. However, these gaps are often identified based on certain “assumptions” made by incumbent firms (Jokubauskienė & Vaitkienė, 2017). These assumptions can serve as resources through one or many routes such as the experiences of product managers, the entrepreneurial ideas of the management team, the market research output of a study, competitor analysis reports, and the results of customer surveys. Based on findings regarding the propositions formulated here, we suggest that a shift in focus from value creation to value identification is required for customers’ and other stakeholders’ specific value aspects within BMs as, specifically in AI-driven BMs, value offerings can be fairly disruptive and dynamic.

The value-identification dimension of BMs would include individual value aspects such as the price perceptions (Anderson & Wynstra, 2010), strategic and behavioral aspects (Wilson & Jantrania, 1994), fantasies, feelings, and fun (Holbrook & Hirschman, 1982) of different stakeholders involved in BMs. Value identification requires a thorough and deep understanding of customers, which takes time, causing the firms to make assumptions during value creation. Adopting AI within BMs provides opportunities to capture data about the product/service usage and customers, which can then be augmented with AI technology to predict a value for customers to enable better decisions. The value-identification dimension becomes particularly important due to the advent of data-driven AI predictions incorporated within BMs. As connected products and services capture data about the AI usage and customer interactions, AI-based prediction capabilities re-configure the opportunities engendered by new business insights (Goyal, 2019) and take our understanding of customers’ value perceptions to new levels, co-creating future offerings based on data insights (Buganza et al., 2020).

Value manifestation

Value manifestation combines value-creation and value-delivery aspects through technology usage, offering the resulting business solution to the identified stakeholders within BMI. Value manifestation is essential because, while creating and delivering technology-driven and enabled offerings, the focus should not be on the technology or the solution itself, but on the value it creates and delivers to the stakeholders. It is not very common that the value initially identified during value identification changes or evolves during the creation and delivery of the offering, so it is essential to consider the changed value targets based on learnings and observations and not to lose sight of the value aspect of either the technology or the offering itself. Although value creation and delivery have commonly been considered two separate value dimensions in current BMI discussions (Teece, 2010; Zott et al., 2011), the propositions formulated in the various studies of this thesis suggest they can be combined into one. The creation of value that cannot be delivered or is not desired by customers holds little interest for management from a BM perspective in isolation. With servitization, BMs are becoming increasingly important (Gaiardelli et al., 2015), as value creation and delivery blend as services evolve and mature over time. Servitization drives multiple customer touchpoints and interactions, exposing customers to incumbents over a more prolonged service lifecycle versus that of product-driven BMs.

The value-manifestation dimension of BMs includes the transactional value aspects when the product–service is created and delivered to customers through various stakeholders via a series of transactions, as discussed in theoretical value concepts such as value chains (Porter, 1985), value networks (Peppard & Rylander, 2006), and value constellations (Normann & Ramirez, 1993). Value manifestation also encompasses the value-in-use and value-in-exchange dimensions (Eggert et al., 2018) of the overall BMI. Value manifestation is even more critical in BMs driven by data-driven offerings, as advanced AI algorithms create and deliver simultaneously. Data capture, decision making, and service configurations are processed iteratively within the BM for constant value creation and delivery. For example, the predictive maintenance and anomaly detection cases within intelligent products and services are implemented by creating value through data insights and delivering value through proactive maintenance services to avoid downtime (Opresnik & Taisch, 2015).

Value capture

Value capture is the dimension in which the materialization, monetization, and realization of value occurs for all stakeholders. The types of value captured by this framework dimension are, for example, direct monetary value, gained customer confidence, stickiness, and loyalty. It is important to note that value capture is differentiated from value manifestation (i.e., creation and delivery) as the latter is a complex process that changes multiple times or updates the initial value aspects considered during value identification. Hence, value capture should concentrate on objectively capturing all the different value aspects, including but not limited to monetary, non-financial, functional, emotional, social, conditional, and epistemic aspects, that have been created and delivered for all the different stakeholders under the value-manifestation dimension. Under this dimension, it is essential to capture the real value perceptions of the stakeholders and to allow comparison against the initially identified value aspects and, hence, indicate the next iteration of values that could be realized. Traditionally, value capture was considered only in the case of the end customer who pays for the value proposition (Chesbrough, 2010), which is relevant to product-based BMs. However, with complex BMs enabled by AI such as multi-sided and matchmaking BMs, the direct beneficiary is not always the paying customer. Hence, value capture entails many more stakeholders than just the paying customer, stakeholders such as beneficiaries (Aversa et al., 2015b), and many more value aspects than just direct commerce. The value-capture dimension is proposed to assess the actual value aspects captured by the offering from the supply side (i.e., the firm creating the value proposition) and the demand side (Aversa et al., 2020). The value is captured by the direct beneficiaries, indirect beneficiaries, ecosystem partners, and other stakeholders who are the paying customers.

The value-capture dimension of BMs includes the relationship value aspects over the product's or service's lifecycle (Eggert et al., 2006) across multiple stakeholders within BMI (Payne & Holt, 2001). As value is co-created within new BMs, relationships with the customer (Corsaro & Snehota, 2010) and other stakeholders such as competitors and suppliers are essential in order to incorporate a multi-dimensional view of relationship value (Fiol et al., 2011) into BMI. As value capture provides insights into the actual perceived value of the offered solution, AI-driven BMs are essential as they enable data touchpoints and capabilities that were not possible before. Such touchpoints and capabilities include, for example, customer understanding and insight created using Edge AI, hyper-personalization (Goyal, 2019), and customer engagement predicted by combining datasets from different domains such as the economy and weather, to measure the current value captured under the offering (Chiang, 2019). Also, the entities involved in value capture are expanded by the opportunities provided by AI. Traditional limitations of product-based BMs, digitalization, and big data connections bring the product, supplier, and consumer together for measurement, facilitating the demand view (Baden-Fuller et al., 2020) of value capture within BM transformation.

The three dimensions of the framework are related to one another and are highly interactive and iterative. For example, value identification can occur when value manifestation and value capture happen. This emphasizes that the value transformation process within AI-based BMs is complex, intertwined with various dimensions, and interdependent with many BM factors. The value-process dimensions described within BMs for AI technology highlight the process aspect of value in the proposed framework (Langley et al., 2013). We need to convince the customers only once in product-based BMs, and then the customers are already invested; however, with services, if the value is not identified, manifested, and captured continuously, the customer can quickly leave as there is little investment from the customer's standpoint other than costs that can be transferred to another service provider.

Past researchers have investigated value models from various perspectives, such as customers and BMs. Our focus has been on a value process framework for AI offerings specifically enabled by data technology, which has so far not been extensively explored. Researchers have seldom addressed all three dimensions of the value process within the proposed framework. AI-technology–driven offerings enable us to examine all three dimensions of the value process framework together, helping us improvise and treat this approach as a new capability allowing us to be closer to the customers. It enables learning from customer interactions to predict their future needs and wishes using data touchpoints across the AI-driven offering delivery lifecycle. As a first step, the ambition behind the framework has been to develop a robust and straightforward model that can be applied generically to businesses, industry domains, and customer offerings of various types, all enabled by AI technology. Each dimension could have multiple sub-processes depending on the business, industry, and domain. The dimensions could be merged or skipped in specific scenarios, such as when internal stakeholders create offerings. However, the three high-level value dimensions of the framework still largely remain even though they might interact with one another more or less depending on the case. For example, prototyping a computer-vision–based general object-detection service would be highly iterative and involve highly overlapping value-process dimensions. However, the framework would still provide the required directions and measures for value transformation within an AI-based offering.

6.3.3 Ladder of AI innovation

Structuring the above AI technology implications for existing BM value processes, we highlight a "ladder of innovation" for the impact of AI technology on incumbents. It is depicted in Figure 2, followed by a discussion of the same.

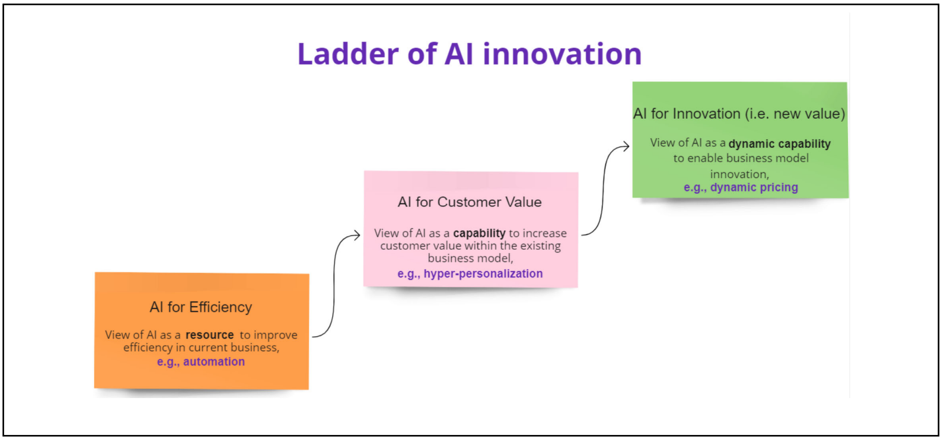

Figure 2: Ladder of innovation.

Step 1 is "AI for efficiency," which is primarily the current business view of AI technology as a resource with implications for business productivity and efficiency gains. This step of AI innovation is very relevant to various industries, and it employs various use cases of AI-driven functionalities and features; for example, intelligence and intelligent products and services are created using advanced analytics and pattern recognition—i.e., better quality through prediction and anomaly detection. Regarding automation using vision-based solutions rather than static programmed robotic solutions, applying AI in such use cases highlights a good use of technology to increase efficiency in different parts of a BM, such as manufacturing, operations, supply chain, and marketing.

Based on the findings of this thesis, we emphasize that AI technology can also be used in Step 2 of innovation, "AI for customer value." In this view, AI technology can be used not only as a resource for improved efficiency but also as a capability for building competitive advantage within BMs. More emphasis can be placed on customer and stakeholder values rather than just on the functionalities and features of products and services. This can create new value through AI technology, value that was not previously possible in the BM offerings of organizations. To illustrate a few, AI enables capabilities such as self-learning, optimizing solutions based on individual customer interactions with the offering, and dynamic pricing that can be adjusted based on actual value perceptions over the contract period. Creating hyper-personalization and mass-customization opportunities in offerings to create value in different parts of the BM is enabled by AI technology.

We further note that AI technology's contribution to BM value does not stop at Step 2 but goes further into Step 3, "AI for innovation." In Step 3, AI technology enables constant change in new value creation and value relationships that were not previously possible by taking a dynamic capability view of AI technology within BMI. This dynamic capability can even create new options within BMs through the insights generated by advanced analytics and AI technology. For example, AI technology utilizes a continuous data stream from customer touchpoints and offerings to understand today's customer experience. It then outlines possible future enhancements of the offerings that can take the current customer experience to the next level. Step 3 can also enable new relationship value generation by including other BM stakeholders, combining their experience and datasets to create new value offerings and BMI relationships with the business stakeholders.

7. Implications and conclusions

Having discussed the AI implications for BM value dimensions and for considerations concerning the proposed value process framework for AI-enabled BMI, this section starts by presenting challenges and opportunities observed during our five research studies and involving AI within the value dynamics of BMs. We continue by discussing these implications from the perspectives of theory and management. Finally, we conclude by identifying limitations of the research and suggesting future research opportunities.

7.1 AI opportunities and challenges for BMI

Organizational value challenges

One of the critical challenges to customer value in product–service offerings is that the value assumptions of incumbents regarding their customers depend greatly on individuals' bounded rationality (Simon, 1991), touching on individuals' narrative cognition at the expense of paradigmaticsm and on reflexivity at the expense of action. Promoted value aspects can be changed considerably as different value aspects may be considered necessary by different individuals due to their individual preferences. Value is a subjective and dynamic concept that constantly changes for customers (Gupta et al., 2006) and is a matter of perception (Cengiz & Kirkbir, 2007), making it challenging to identify, especially up front during the initial phases of business modeling. Another phenomenon to be considered is the role of an organization's dominant logic (Prahalad & Bettis, 1986), driven by the organization's objectives and culture. Although different stakeholders might emphasize different value aspects in different concept development phases, some commonly emphasized value aspects are part of the culture or approach of the organization or department. For example, as highlighted by study D, some firms tend to focus on "functional values" in their customer offerings, providing a good mix of price and features in their portfolios; in contrast, other firms tend to focus on "epistemic values" in their customer offerings, emphasizing innovation and creative solutions in their portfolios. Using data and complex AI technologies such as sentiment analysis (Fjeldstad & Snow, 2017) to understand customer interactions, usage, and feelings can help firms to enter into regular dialogue with their customers, understand their needs (which may be difficult to articulate), and constantly innovate upon their offerings to create, deliver, and capture value.

The value proposition within a BM is sometimes realized using concepts and tools such as design thinking, Voice of the Customer (VoC), and customer journey mappings (Efeoğlu et al., 2013; Liu & Mannhardt, 2019). These tools and processes refer to the cognitive, strategic, and practical processes that develop design concepts for future offerings. These tools and processes are nonlinear and iterative, and they can be employed to understand user values and create innovative solutions for prototyping and testing. These tools and processes consider customer value primarily from the service provider's, rather than the customer's, perspective. While these techniques utilize creative methods and work well to identify value networks for the concept under review, it can be observed that new values dependent on the complex digital offerings of incumbent firms, together with their customers and even ecosystem partners, are sometimes not fully understood. This challenges firms to understand how the value changes throughout the offering lifecycle. Also, while these techniques effectively identify new value during exploration phases, value does get lost during the handover from the exploration to industrialization phases when organizations, individuals, and processes change within firms, highlighting another challenge facing organizations. Application of the proposed value process framework to service design and offering throughout the offering lifecycle will highlight the focus on value identification, which can address the challenge of dynamic and ever-changing value propositions. At the same time, value manifestation focuses on contact value creation and delivery utilizing different stakeholders (both internal and external), which would contribute to handover processes, helping address the faced challenge.

Shared view of value

While the incumbents provide their offerings through ecosystem partners, keeping the end customer at the center of the value proposition, multiple stakeholders are involved in the overall value delivery and capture, playing essential roles in the overall value perceptions. Also, while digital offerings enable capabilities to surpass ecosystem partners, upsetting them may create more challenges than opportunities (Taran et al., 2019). For example, despite connectivity and direct digital touchpoints, it would be impossible for incumbents to reach the entire customer base for education about the technology (which is sometimes crucial) as well as to maintain and support the products and services delivered by the ecosystem partners. Although incumbents can monitor the digital connection with the product and customer, understanding and deriving meaning from the observed digital touchpoint requires customer understanding, which is best retained by the ecosystem partners rather than the incumbent.

Digital-technology–driven capabilities (Verganti et al., 2020) enable value creation by curating customer engagement and interaction data in order to understand customers' needs and expected value aspects and even to predict the insights needed in order to take proactive measures through machine learning and data science, which was challenging to do without AI technologies (Baden-Fuller et al., 2020). However, incumbents, being farther from customers in the value chain than are ecosystem partners, sometimes cannot apply the viewpoint that makes a difference for customers in the offering design. Inclusion of ecosystem partners in the innovation process of incumbents during various BM phases can provide insights into value dimensions to be targeted for customer values within the offering design, and AI together with data access and analysis can foster collaboration and help generate insights in the interest of a combined view.

Including the channel partners in the value-creation and innovation processes would give incumbents better and more timely inputs to incorporate into the value-creation phase, rather than understanding the gap between the created value and the actual perceived value later in the process through the sole feedback mechanism of knowledge collaboration (Eslami et al., 2020). Including ecosystem partners in the incumbent's innovation process and digital innovation arena would make the value-identification and value-creation processes more iterative. This would create an extended knowledge base (Nonaka, 1994) for current products and offerings and for the potential future growth and direction of these products and services using the integrated and iterative approach of value identification, value creation, value delivery, and value capture, which the incumbents could not achieve by themselves.

Ecosystem partners can be better utilized in value identification if they play a new role in incumbents' innovation and industrialization. These ecosystem partners often have a different view of the value of the digital solution from the value initially identified by the incumbent firm during value creation. This different perspective can help incumbents continuously identify new value aspects and target them using the same digital offerings as they go along, which is sometimes either limited or impossible for incumbents to foresee either due to a different view of things or due to non-proximity to the actual customers. It might seem obvious that firms could bypass ecosystem partners by directly reaching customers with their digital offerings, but ecosystem partners' closer dialogue, proximity, and access to customers can foster new insights and opportunities within these offerings, unlocking new customer values. Ecosystem partners can act as an extension of incumbent firms, helping them identify and deliver customer values by considering customer input during decision making in the interest of identifying value before creating it, thereby creating opportunities for multi-sided BMs (Baden-Fuller et al., 2020).

Rather than eliminating ecosystem partners, incumbent firms should consider utilizing them during the their innovation processes for value identification by treating the digital offering as a boundary object (Boland & Tensaki, 1995) in perspective taking and perspective making concerning the value that customers derive from the offering. Also, exploiting ecosystem partners' customer proximity and knowledge through iterative sensemaking (Weick et al., 2005) can provide insights from the demand perspective in BMI, enabling multi-sided BMs. New modes of collaboration need to be explored with ecosystem partners, with more emphasis on gaining insights from their business activities as they possess data on actual customer interactions and associated insights. A significant lesson is that rather than using ecosystem partners only to distribute services, ways need to be found to make ecosystem partners into knowledge centers for customer value and opportunity identification within firms' innovation processes.

7.2 Implications for theory

The theory derived in this thesis has multiple implications, as discussed below.

This thesis suggests that AI technology can create competitive advantages for organizations. In the past, research has discussed the use of technology to create competitive advantages for firms (Chesbrough, 2010; Mitchell & Coles, 2003). This thesis identifies new capabilities such as self-calibration, enhanced sensing, selective capture, and reputation that are enabled by AI technology, which can be used to bolster firms' competitive advantage, thereby extending current research on technology-driven competitive advantage to AI technology in particular. This thesis also highlights AI's contribution to enhancing current capabilities such as predictive and preventive maintenance, efficiency and control, productivity and reliability, and product performance. These findings challenge the resource view of AI (Mikalef et al., 2019; Ristyawan, 2020) as limited and open the discussion to the usage of AI technology as a dynamic capability (Tiguint & Hossari, 2020).

Research has discussed value processes in BMs (Amit & Zott, 2010). However, this thesis highlights the gap in theory and research regarding value processes in BMs in general and in AI-technology–driven BMs in particular, indicating a need for more research and discussion in these areas. Research also discusses how technology enables BMI by contributing to existing BM value creation, delivery, and capture (Kong et al., 2019; Meijer et al., 2019; Zeng et al., 2019). The present findings support the current view of AI technology and extend our understanding of the contribution of AI technology to new value processes such as value manifestation and value identification, as mentioned in the proposed value-process framework. The proposed value-process framework contributes to Khalifa's (2004) more comprehensive view of value, which is driven by the shareholder, stakeholder, and customer categories, and by the new relationships between the value processes of these categories. We emphasize that the current value understanding of BMs is very sequential and linear, ignoring the intricate values arising from interference and interdependence between the value processes in current BMs. With AI-enabled capabilities, BMs become interdependent and intertwined in value processes, depending on stakeholder perception of value during service delivery. Earlier research has considered the influence of functional affiliation and individual entrepreneurial orientation on the perceived value of the offering. This thesis emphasizes that AI technology can improve the perception of overall value by enabling transparency in offerings through rational data collection and assessment techniques.

With a specific focus on AI technology, this thesis advances our understanding of the challenges of integrating AI into BMs, as highlighted by Wuest et al. (2016). The thesis highlights that value is at the core of BMI (Teece, 2010) when merged with intelligent technology such as AI. We also note that the usage of AI is making the value dimensions of BM even more interdependent and the relationships between them even more complex (Aversa et al., 2020), thereby contributing to the BMI literature stream. As this thesis maps existing (i.e., value creation, value delivery, and value capture) and newly proposed (i.e., value manifestation and value identification) value processes onto stakeholders, it also supports and extends our understanding of AI's impact on stakeholders' value models, as Björkdahl (2020) discussed.

The thesis also contributes to our understanding of AI as a driver of BMI, building knowledge of value-based pricing by suggesting that digital technologies, AI, and related platforms may address many of the barriers earlier identified in value-based pricing, such as value-quantification issues (Hinterhuber, 2017). This is a way to address the lack of shared baseline data (Töytäri et al., 2015) and a solution to the need for continuous process monitoring. The findings suggest value-capture strategies such as dynamic pricing, in which customers value some uncertainties in contracts, supplementing earlier findings that contracts are a way to generate defined outcomes (Batista et al., 2017). Our findings regarding specific aspects of contract length and price variations also extend current decision-making theory (Kreye et al., 2014) by empirically demonstrating the management of specific uncertainties in purchase decisions of servitized offerings.

A lack of attention to value identification is also observed in the BM literature, especially concerning AI technology, which could facilitate the acceptance and adoption of AI within BMs through using the proposed framework (i.e., value identification, value manifestation, and value capture) as a meaningful assessment tool. Findings also highlight the importance of value identification within BMI for accelerated adoption and the limitations of current tools and processes regarding different value-identification techniques, limitations that remain to be investigated. The thesis emphasizes that incumbent firms and channel partners may hold complementary views of the dissonance of value, which may have much greater value if combined into a BM portfolio than if BMI and value identification are only approached from the supply side. It also seems that an inclusive BMI approach creates opportunities for more channel partners to be included rather than suggesting that digitalization will make previous distribution patterns obsolete.

While innovation research is a relatively mature field of study, and our understanding of innovation as a process is also quite mature, it is common for the value literature to focus on frameworks and models of value generation at specific instances during the innovation process rather than longitudinally. This thesis applies the process view (Langley, 1999) to advance innovation theory by highlighting that the value created in digital service offerings is sometimes not static; rather, it is dynamic and continues changing during the execution and usage of the service itself. This extends the AI-driven BM process view (Cornelissen, 2017), helps us understand servitization more thoroughly, and could potentially also offer insights into the factors behind the servitization paradox and how it can be avoided (Szasz et al., 2017). For example, even when a new digital service has been co-created by suppliers and customers, realizing the value opportunity could be challenging as it may require a new BM, of which the parties could have different views (Simonsson & Magnusson, 2018), or the value could change throughout the lifecycle of the service.

This research contributes probable approaches and improvement suggestions to the existing digital servitization literature regarding challenges in articulating the value of digital technologies to organizational futures that incumbents face when working on digital offerings in various departments, ranging from exploration to industrialization handover, and in identifying value dissonance with ecosystem channel partners (Kane et al., 2015). This thesis identifies the lack of discussion of new and disruptive value implications when climbing the value chain using technology, extending the discussion of Barbieri et al. (2021) within the servitization literature, which is required to better adopt AI within BMs. While this thesis supports the data-based service design approach of Chiang (2019), it also outlines specific capabilities and approaches to the potential use of AI technology within BMs to generate value for different stakeholders, as highlighted by Goyal (2019), and bridges the gap between technical and business research.

7.3 Implications for practice

There has been a tremendous boom in data-driven and AI technology discussions in industry, but examination of the adoption of AI within BMs has been limited to technology-driven sectors. For AI technology to have a greater impact on incumbent industrial manufacturing firms, this thesis considers that the RBV of AI technology within firms should be changed to a value-based view within BMs. During this research, various case studies revealed multiple AI-enabled capabilities, and concepts such as hyper-personalization (Goyal, 2019) surfaced, which could prove useful in producing competitive advantage. For practitioners, this research stresses that to be relevant as service suppliers, companies would benefit from increased use of big data and AI in customer solutions (Baines & Lightfoot, 2013) and from the use of tools for understanding customer value such as VoC and design thinking (Huang et al., 2009). Findings of this thesis substantiate the need to consider the phenomenon of value changes in customer perception within BM design for better continuous value creation, delivery, and capture and better adoption of servitization (Gebauer et al., 2005).

The proposed AI value process framework for business modeling is a practical tool managers can use when designing and evaluating BMI. The framework is simple, practical, and valuable for clustering, managing, and monitoring value in AI-technology–driven business offerings. The framework can be applied in agile development, iterating the fundamental process of value identification, manifestation, and capture as we explore, introduce, and enhance AI-driven data services and offerings. The proposed value dimensions not only optimize the service offering (Noke & Hughes, 2010) as such over time but do so at a reasonable level of risk for each project and offering in terms of its value. Also, it drives organizational learning in each iteration, thereby supporting the overall BM value. The proposed framework also helps practitioners with their BMI activities by applying AI technology to realize different value processes in action. For example, AI technology can enable new value-capture strategies such as the dynamic pricing of offerings by helping quantify value, and the exact value quantification can help resolve value dissonance between stakeholders. The framework can be applied to various value process dimensions themselves, such as linking value identification to business strategy (Porter, 2001), capturing data for indications of value adaptation during value manifestation, and hypothesizing the next iteration during value capture, but also to the interface between dimensions, such as creating data touchpoints and making objective decisions based on data predictions.

Another observation from this thesis is that companies are still relatively early in their journey towards adopting complex digital offerings. They face value dissonance and see values differing completely from those anticipated from the offering, when compared from the initial exploration to final industrialization phases of the concept. It is therefore crucial to emphasize value identification within BMI. The relationships and roles of an ecosystem's channel partners are evolving and need to be defined by incumbents to make them more inclusive within the value-identification process by involving them early in the firm's innovation process. If we can understand the impact and role of AI technology regarding perceived customer value obtained through the digital offering and other transformed value components, organizations would gain better insights when creating such digital service offerings. This would further help firms appropriate value to their customers and partners within the ecosystem of which the digital offering is part. The findings show that the perceived value (Zeithaml, 1988) of services varies significantly at the level of the individual customer throughout the service lifecycle due to conditional, social, emotional, and epistemic aspects. The observations also indicate end customers' overall perceptions of the value of these offerings. Customers should be segmented and targeted using the innovation and risk-taking traits in their characters rather than other functional traits of the offerings, as has traditionally been the case in product-based offerings.

This research highlights that an individual’s risk-taking ability and innovativeness are vital for his or her value perceptions. It has important organizational implications for AI technology adoption, that usage of AI offerings is based on how innovative and risk-taking individuals are, and this fact can be applied when companies design their offerings. This is an essential insight from both an internal organizational perspective and an external offering design perspective. The internal organizational implication is that the design and offering of AI-technology–enabled services should combine the currently uncoordinated functions within firms taking care of products, services, and contracts. It also highlights that the success of AI-based offerings depends not only on combining the operational and strategic approaches within a single department, but also on interdepartmental cooperation, which calls for new organizational structures. The implication for external offering design is that packaging and branding messages for AI-based offerings should target risk-taking and innovative customer groups for better stickiness.

For practitioners, this thesis emphasizes that, to master the digital transformation, companies need to have exploratory capabilities in digital innovation and to build the required digital leadership capabilities. The thesis also has implications for practice concerning keeping innovative concepts in the exploration and incubation phase for a reasonable period, highlighting the importance of testing, learning, modifying, and handover between organizations, which should be done through a defined process, supported by defined ownership and experience. The present findings also suggest that manufacturing suppliers should embrace certain types of uncertainties within service offerings to generate more value, and that AI technologies can generate transparent solutions to create profitable long-term relationships. Another important finding for practitioners is that the speed to market of new service offerings can be improved through incorporating AI and value-based pricing approaches, as it is sometimes difficult to set an initial price (Hinterhuber, 2017) when both parties are unsure of the value created. The increase in the buyer’s perceived value through digital-technology–enabled transparency has implications for the better visibility of value, resulting in less reluctance to increase the cost when adopting servitization and avoiding the service paradox in which service production costs exceed related revenues (Gebauer et al., 2005).

Overall, the lessons learned from this study can bring clarity to top management about what to do and how to drive the digital transformation agendas of companies into the area of new digital technologies, AI, and BMs. The collective findings can engender additional insights into setting the strategic course of companies and help us understand the needed magnitude of change, future investment levels, and risk-taking to successfully navigate this industrial revolution.

7.4 Conclusions

Reflecting on the observations made during this thesis research and considering the results of its constituent studies, this thesis suggests that AI technology, although commonly used as a resource for efficiency gains within industries through automation and for new functionality creation in products and services, has enhanced existing capabilities and provided new dynamic capabilities with much more significant value implications for BMs. The study observes that AI can improve and create new values in BMs that were not previously possible by providing enhanced and new dynamic value creation capabilities for product and service development. AI technology can deliver value by enabling the quantification of value to increase transparency and perceived value among BM stakeholders. Furthermore, the AI-enabled quantification of value can facilitate value-capture strategies, such as outcome-based contracts and dynamic pricing, that were also previously impossible.

We also observe and conclude that AI is impacting existing and creating new value processes within BMs in fundamentally novel ways by adding new value dynamics such as continuous identification, manifestation, and capture of changes throughout the lifecycle of the product–service within BMs.

The thesis also highlights that the current value view of BMs seems to be derived from a transactional and operational perspective, and it is essential and possible to investigate the process view of value within BMs through the lens of AI technology. We conclude that AI can simultaneously contribute to BMs' individual, transactional, and relationship values and enable a process orientation in BM value discussions. This process dimention is required for the understanding of dynamic nature of value and the impact that AI can drive on BMs. The thesis concludes with a proposed AI value-process framework for BMI, including value identification, manifestation, and capture.

Finally, this thesis highlights challenges incumbents face during AI-enabled BMI in terms of handover between stakeholders throughout the offering lifecycle and in terms of opportunities for incumbents to work more closely with ecosystem partners by making them part of their knowledge base and innovation process.

7.5 Limitations and future research

A future research proposal could combine internal organizational actors, ecosystem partners, and actual product or service-using customers as representatives in a case study, which was not done here. This research explicitly examined one of the use cases of value capture in study C, which could be broadened in future research by studying multiple concept development cases across different organizations within different industries and domains, providing a much more powerful and generic understanding of AI's implications for the value-capture concept within BMI. A similar value-capture study could also be undertaken directly with end customers to substantiate the present findings. Another limitation of the value-delivery study B1 and value-capture study B2 was that the survey assessment was based on data from only two organizations and did not include more companies of different sizes from several industries.

This thesis should be treated as a stepping stone towards more assessment of value identification and of ecosystem partners offering different digital and non-digital use cases spanning various industries and domains. This research focused on industrial use cases of AI based offerings, and how these factors interact in consumer cases merits further observation and analysis.

In the literature review reported in paper D, the search terms focused on AI technology, so the presented findings and observations concerning other technologies and domains need to be carefully valiated. It is also vital to note that peculiarities within the value-process dimensions of the proposed AI framework might not apply to other technologies, businesses, or industrial areas. Slow adoption has been observed of past technologies such as IoT, which took almost two decades to be adopted at large scale, and of other current technologies, such as blockchain. The proposed framework dimensions within other technologies, businesses, or industry areas could be verified and tested in future research.

The framework proposed here is simple and straightforward, but has been described only at a high level; the detailed elaboration and extension of every process dimension, with probable differentiation among various technologies, businesses, and industrial areas, are needed. The proposed framework has not been practically applied in a use case to understand its implications, so it is lacking in support gained from practical experience. We believe that the framework should be applied in an industrial case and be discussed within further research in order to evolve. This would further validate the value-process dimensions and elaborate them with instructions for use and probable translations into key performance indicators (KPIs) for measuring value. Future research could study how the proposed framework is applied to and benefits AI-driven business offerings, specifically as concerns decision making and the introduction, enhancing, and exploring of future business opportunities. Further research could examine how the model could influence technical and commercial risk when implementing BMs. One step following on this thesis could be to use the framework in implementing a case study to obtain practical feedback and observations to advance the development of the proposed value process dimensions.

The proposed new value processes in the framework emphasize that the past BMI approach has been relatively rational, substantiating the need for a more entrepreneurial orientation in sense-making as well as in service design and organizational research.

In this thesis, we considered the value dimensions discussed by Sheth et al. (1991), but many other potentially relevant value-dimension models have been proposed within the literature (Lindgreen et al., 2012; Payne & Holt, 2001; Woodruff, 1997). Future research could map different value dimensions and models onto the value-change process, in an effort to understand whether different patterns emerge as value changes during service execution. Also, the case of value change considered in study C included digitally enabled service offerings and digital data and touchpoints in order to understand and highlight the value change during execution. Studying the same phenomenon in non-digital and B2B settings would also be interesting.

The discussion of BMI diversification in research about moving up and broadening the value coverage (Aversa, 2019) has investigated the role of technology. Different horizontal, vertical, and graphic modes of such diversification have been discussed (Casadesus-Masanell & Ricart, 2011), with differentiation between BM and BMI diversification (Kim & Min, 2015). AI technology can play a significant role in this diversification process, with different value-process implications for BMs—a matter that merits further exploration.

Value is a subjective term encompassing functional, epistemic, conditional, social, emotional, and other aspects. This thesis combined all value aspects into one to form overall perceived value, which contributes to an individual's entrepreneurial orientation. Different value aspects could reflect and impact different entrepreneurial traits within an individual. Further research to understand the correlation between different entrepreneurial traits and different value aspects could provide further insights and explain why individuals with certain entrepreneurial traits see more value in specific offerings than do others, providing useful insights for industry to adopt in service strategies.

Another avenue for future research would be to investigate whether the value-capture approach presented in study B2 through AI-technology–based BMs tends to push pricing into the lower part of the defined negotiation range. For the offering, this would put pressure on supplier margins, which might be managed as goodwill or sunk costs by suppliers. Another interesting aspect that should be further explored is how the negotiating power shifts between the parties during this process. Also meriting further exploration is whether only one party (i.e., suppliers or customers) always ends up with the expectation to prove the value provided. This would call for adjustment of how the negotiation range is defined and of the methods and processes for realigning contract terms.

One of the customer and organizational value areas that has been discussed is the amount and quality of intellectual property (IP) created and held by incumbent firms. AI plays a significant role in IP strategy and therefore has value implications for BMs; this matter has not been investigated within the proposed framework and therefore represents a possible line of future research.

8. Personal reflections on the future of AI

It has been a tremendous opportunity to research an area of technology, AI, that is rapidly evolving and impacting almost every industry and even individual on this planet. AI is not something in the future; it is here and now and everywhere around us. To list a few examples: the alarm clocks that wake us up decide what music to play and at what volume based on our sleep patterns; toothbrushes we use learn from our usage and oral conditions to optimize cleaning patterns; Fitbits connected to pacemakers are connected to our doctors; and insurance companies are utilizing machine-learned models to predict the future and take proactive actions. Body sensors analyze our need for a diet and automatically order the food we might want, for example, in the evening based on how the day has gone. E-commerce services suggest purchases based on our behavior and on the people and communities around us. Home alarm systems recognize our faces and voices to let people in or raise security alarms. Transport solutions utilize movement data to optimize routes and save time and fuel. Using mails and outlooks prediction services for sorting mails and creating automatic replied and action items. The music we listen to is customized by AI-driven playlists based on our taste and mood at a given time. The list can go on and on, illustrating how deep-rooted AI technology has become; it will only continue to become still deeper-rooted in the future.

While every technology has its pros and cons, such as cars offering increased convenience while causing pollution and accidents, screens giving us access to world data and entertainment but causing eyesight concerns, X-rays diagnosing our diseases but causing cancer, and nuclear technology making countries energy self-sufficient but permitting the creation of bombs—and AI is no different. Rather than shying away from a technology, it is essential to understand the technology and its benefits followed by implementing proper regulations for its usage to derive appropriate value.

On the human technological journey, initial inventions helped people with physical tasks such as digging mines in the earth, constructing significant buildings, transporting people faster, making computing faster, and storing large volumes of data. Now we can say that technical inventions are helping us at an emotional level with personalization, convenience, games, communication, connectivity, etc. AI, as a technology, is far more interesting as it can replicate the human brain. One artificial neural network learns and adapts based on environmental and other datasets, like a single brain neuron. We are still at the brink of this technology with "artificial narrow intelligence." These artificial neural network combinations are learning small and specific tasks and getting better than humans at, for example, playing chess, diagnosing cancer, and making supply chain decisions. As this technology advances, I am convinced that we will see "artificial general intelligence" in which a combination of billions of artificial neural networks will be able to perform and even beat humans when it comes to general intelligence and not only specific tasks. We are starting to see this in cases such as the Project Debater from IBM, Emilie the AI Spotify channel, the SoundHound platform to imitate human voices, and the AARON computer program to generate art.

However, the advance of technology does not stop here. The same artificial neural networks might do things we humans cannot do with “artificial super intelligence.” For example, sensors can capture data about day-to-day actions of a specific individual, such as what one eats, what one does, when one sleeps and wakes up, and what one likes and dislikes. Then these data can be analyzed for advanced predictions, for example, that specific individual will go to that specific store to buy that specific item on that specific day at that specific time with an accuracy of over 95%. At the same time, it is just a matter of time until questions such as “Can an artificial neural network, which acts as a brain, have a mind of its own?” will become mainstream concerning AI technology.

In the evolutionary war, the human race has long lost to technology, which is very good at repeatedly doing things much faster and more accurately than people can. With technology now taking over the brain, we never know, but the next evolutionary path for humans might not be limited to brain/consciousness and mental abilities alone. Of course, it sounds uncertain and scary, but as I said before, my standpoint is that running away from this will not change the truth or the reality. It is just a matter of time! Hence, this research tries to address the value aspects that AI technology can drive. Understanding those value dynamics will help us better understand not only AI technology but also its implications and potential future development trajectory. In this research, the phenomenon I address is the value implications of AI-technology–driven BMI. I learned a lot during this research process on so many different fronts, ranging from AI technology specifically to research methodologies, industrial offerings, BMs, customer values, etc. I understand that research requires focus to contribute to science and practice in a specific way to move forward, but my approach has been to strive to understand the phenomenon in general rather than dig deep into one of its aspects.

One of the specific characteristics of AI technology is the collaboration that it requires for its advance. This can be attributed to its requirement of large volumes of varied datasets. To elaborate further, looking closer at history, resource utilization has changed within the economic sphere. More than a century back, resources played an essential role in organizational success. Access to resources such as land, metal, and energy provided the competitive advantage for organizational success. During the age of industrialization, resources themselves lost their luster, and the *development* or *utilization* of resources instead determined what organizations succeeded. For example, using the same resources effectively to distribute and generate better quality was more important than accessing resources. I argue that resource development/utilization as the source of competitive advantage for organizations is changing during this digital age. In this digital technological age, access to data or resources is just a matter of time. For example, in AI technology, machine-learning models from different domains such as sensors, predictive maintenance, and NLP for chatbots will eventually be available to many, if not all, people. However, the success of AI technology is very much dependent on the usage itself, so giving access to the technology and its development/utilization to the masses will be the key. Hence, in this digital age, mass usage of AI technology will play a significant role within organizations and societies when resources (including technology) and their utilization come to constitute a generic knowledge base.

I hope that initiating value discussions concerning AI technology within academia and industry will benefit industry, customers, and society. For example, AI technology in general usage can foster sustainability and touch on multiple UN Sustainable Development Goals (SDGs) within BMs. A few references to specific touchpoints are warranted. As AI can enable intelligence directly on the equipment, an overall reduction in energy consumption will be experienced compared with operations in which all data must be collected on devices, sent to the cloud, analyzed, and then deployed back, thereby contributing to SDG 7: Affordable & Clean Energy. Identifying AI capabilities within BMs would facilitate AI deployment, reducing our need for and dependence on energy in general.

Further assessment needs to be carried out within AI-technology–based BMs to understand other sustainability contributions, such as predicting product failure, providing safety services for operators, and reducing environmental damage, thereby contributing to SDG 9: Industry, Innovation & Infrastructure. Further collaboration enabled by data insights from AI services will unearth some surprising capabilities, supporting innovation in societies and helping them towards SDG 9. Realtime access to information to facilitate rapid on-the-spot action, for example, via "green" KPIs and reduced emissions from products, would help contribute to SDG 11: Sustainable Cities & Communities. AI technology will enable new BMs and services, contributing to overall economic growth. There are reports and discussions in industry about AI potentially contributing up to USD 15.7 trillion to the world economy by 2030. Research should accordingly identify the value transformation promoted by AI-technology–driven capabilities, which would advance the implementation of AI offerings and the deriving of value from them, contributing to SDG 8: Decent Work & Economic Growth. In light of present climate issues, using AI technology to improve sustainability is an urgent task for companies, and research supporting these efforts is critical.

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10. Appendices

10.1. Abbreviations and definitions

Below is the list of abbreviations and definitions of some terms used in this thesis.

Table 3: Abbreviations and definitions.

Term/abbreviation	Description/full form
BM	Business model
BMI	Business model innovation
ICT	Information and communication technology
PSS	Product service system
IoT	Internet of things
IIoT	Industrial Internet of things
Big data	A digital store that can manage large volumes and varieties of data
GPT	General purpose technology
Digital	Signals or data, expressed as series of the digits 0 and 1, typically represented by values of a physical quantity
Digitalization	"Digitalization creates potent digital affordances that likely have a transformative effect upon the organization of economic activity by supporting radical business model innovation" (Autio et al., 2018, p. 76).
Digital technologies	"Digital technologies (viewed as combinations of information, computing, communication, and connectivity technologies) are fundamentally transforming business strategies, business processes, firm capabilities, products and services, and key interfirm relationships in extended business networks" (Bharadwaj et al., 2013, p. 471).
Digital transformation	"Digital transformation is concerned with the changes digital technologies can bring about in a company's business model, which result in changed products or organizational structures or the automation of processes" (Hess et al., 2016, p.124). "Digital transformation has been defined as the use of new digital technologies, such as mobile, artificial intelligence, cloud, blockchain, and the Internet of things (IoT) technologies, to enable significant business improvements to augment customer experience, streamline operations, or create new business models" (Wagner & Wägner, 2019). "Digital transformation is defined as changes in working, roles, and business offerings caused by adopting digital technologies in an organization or the organization's operating environment. This refers to changes at several levels, including the following: • Process level: adopting new digital tools and streamlining processes by reducing manual steps. • Organization level: offering new services and discarding obsolete practices, and offering existing services in new ways. • Business domain level: changing roles and value chains in ecosystems. • Society level: changing society structures (e.g., type of work, influencing decision-making)" (Parviainen et al., 2017, p. 64).
AI	Artificial intelligence
ML	Machine learning
DL	Deep learning
NLP	Natural language processing
RBV	Resource-based view
VRIN	Valuable, rare, imitable, and non-substitutable
VRIO	Valuable, rare, inimitable, and organization

RFM	Recency, frequency, and monetary value
CLV	Customer lifetime value
QFA	Quality factor analysis
CFA	Confirmatory factor analysis
ANOVA	Analysis of variance
VOS-viewer	Software tool for constructing and visualizing bibliometric networks
IEO	Individual entrepreneurial orientation
IP	Intellectual property
Incumbents	Industrial manufacturing firms that have been operating based on traditional product- and supply-chain–based business models for many years.
R&D	Research and development; can be a department within companies
PM	Product manager
OBC	Outcome-based contracts
ROI	Return on investment
KTH	Kungliga Tekniska Högskolan: The Royal Institute of Technology, Sweden
CBS	Copenhagen Business School, Denmark
WASP	Wallenberg AI, Autonomous Systems and Software Program
IJITM	*International Journal of Innovation and Technology Management*
IMM	*Industrial Marketing Management Journal*
JMTM	*Journal of Manufacturing Technology Management*
ICE	International Conference on Engineering, Technology and Innovation
Alpha-GO	AlphaGo is a computer program that plays the board game Go.
ARM	Advanced RISC Machines are a family of reduced instruction set computing architectures for computer processors, configured for various environments.
DIY	Do it yourself

10.2. Paper A interview guides and capability codings

Interview guide Edge AI Projects: Startups

Interview part I *(10 min):*

Permission to continue and record. Individual identity will not be disclosed in any of the external reports. They can be open. Explain the background and format of the interview.

Describe Husqvarna Group Digital Journey together with the importance of AI Lab towards strategic advantage.

- Highlight research collaboration with KTH and VINNOVA.
- Introduce the research topic "How AI-based personalized capabilities would transform perceived value for different stakeholders" and why it is relevant to Husqvarna Group.
- Based on different EDGE projects, introduce the research questions for the paper:
  - What new capabilities does Edge AI create for the development of organizational product service systems?
  - What types of values can Edge AI bring to the product service system, and what significance can this have for an enterprise?
- The objective of this interview is to determine stakeholders' views of Edge AI technology, future capabilities, customer value, and project execution that they have been part of.
- Open question regarding any comments or observations based on the above setup.

Interview part II *(20 min):*

Get inputs on AI/Edge technology capabilities.

- Based on the project execution for Husqvarna use cases and with other customers, what contributions do you think AI technology and specifically Edge AI would make to the offerings that you are planning in future roadmaps?
  - What high-level Edge AI approach was used in the Husqvarna project?
  - What ML algorithms were used in the Husqvarna project?
  - What accuracy percentage was reached for the models?
- What are the main challenges/obstacles that you have noticed within these customer companies that limit them in exploiting the true potential of Edge AI (the following are just a few examples)?

    - AI technical capabilities are limited?
    - Businesses are still not ready?
    - Business models are nonexistent and need to be developed?
    - Customers are still not ready?
    - Use cases do not really offer value?

- With respect to your Edge AI projects with Husqvarna and other clients, in your opinion, do project and technology findings enable *new* capabilities for future offerings or are they just improved features? If so, which capabilities would you mention?

- Could you rank the benefits that could be achieved by companies using Edge AI (the following are just a few examples)?
    - Bring more value to customers?
    - More top line?
    - More bottom line?
    - Better customer stickiness/retention/loyalty?
    - Better marketing and positioning?
    - Any other benefits?

Interview part III *(15 min):*

Walk-through of capabilities and value model worked upon so far.

- Walk-through of the Edge AI capability model, functionalities enabled by Edge AI, and mapping of these functionalities onto the new capabilities enabled in outdoor power products.

- Is there anything from the above list (question 11 or 13) or other (not covered above) new capabilities or improved features that you would like to comment upon?
    - You do not think that any functionality is a new one?
    - You want to add any more functionalities?
    - You do not agree with the capabilities outlined?
    - Any comments on categorization of functionalities into capabilities?

- Which capability do you think companies should focus on the most and do you have any specific reasons for choosing it?
    - Higher value?
    - Ease of appropriation?
    - Ease of implementation?

- What is the main reason for not choosing any of the above capabilities?
    - Lower value?
    - Difficulty of appropriation?
    - Difficult or unknown implementation impact?

- Where do you think AI and Edge specifically can best deliver value to stakeholders?
    - Customers?
    - Internal (e.g., manufacturing, primary, R&D, sales, and after sales)?
    - Channel partners (distributors/dealers)?
    - Others?

Interview part IV *(15 min):*

Feedback on project/experience and feedback for the future.

- What are your opinions on how the project was scoped, approached, and executed?

- What are the top two or three improvements that you would like to propose for the future in case this setup continues for Husqvarna?

- Do you have any specific comment on the setup and experience of working with larger organizations?
    - Anything that works well or difficulties experienced?
    - Any specific collaboration setup within organizations that helps or hinders?

- Expression of thanks, and letting them know:
    - Next actions
    - How these data will be used
    - How they will be kept informed
    - Can we get back with any followup questions?

Interview guide Edge AI Projects: Husqvarna

Interview part I *(10 min):*

Permission to continue and record. Individual identity will not be disclosed in any of the external reports. They can be open. Explain the background and format of the interview.

- Describe the Husqvarna Group Digital Journey together with the importance of AI Lab for strategic advantage.

- Highlight research collaboration with KTH and VINNOVA.

- Introduce the research topic “How AI-based personalized capabilities would transform perceived value for different stakeholders” and why it is relevant to Husqvarna Group.

- Based on different EDGE Projects, introduce the research questions for the paper:
    - What new capabilities does Edge AI create for the development of organizational product service systems?
    - What types of values can Edge AI bring to the product service system, and what significance can this have for an enterprise?

- The objective of this interview is to determine stakeholders’ views of Edge AI technology, future capabilities, customer value, and project execution that they have been part of.

- Open question regarding any comments or observations based on the above setup.

Interview part II *(15 min):*

Get inputs on AI/Edge technology capabilities.

- Based on the roadmap of offerings that you have for the next three to five years, how much focus should be on product-based offerings versus service-based solutions?

- What contribution do you think AI technology and Edge AI specifically can make to the offerings that you are planning in the roadmap?
    4. Could you rank the following reasons for your answer?
        - AI technical capabilities are limited?
        - Husqvarna business is still not ready?
        - Customers are still not ready?

- Use cases do not really offer value?

- With respect to your specific Edge AI Project, in your opinion, do project and technology findings enable *new* capabilities for future offerings or are they just improved features? If so, which capabilities would you mention?
  4. What are the main reasons you would give for your answer?
     - Still a lot of unknown technical aspects?
     - Still a lot of unknown business modelling aspects?
     - Readiness of company/industry?
     - Readiness of customers?

- How could the above *new* capabilities or improved features impact future product- or service-based offerings?
  4. Which of the following (or anything else) do you think could be enabled?
     - Bring more value to customers?
     - More top line?
     - More bottom line?
     - Better customer stickiness/retention/loyalty?
     - Better marketing and positioning?

Interview part III *(10 min):*

Walk-through of capabilities & value model worked upon so far.

7. Walk-through of the functionalities, business impacts, and capabilities of Edge AI regarding consumer products.

8. Mapping the above functionalities, impacts, and capabilities onto one of the value models.

Interview part IV *(15 min):*

Walk-through of the functionalities, business impacts, and capabilities of Edge AI regarding consumer products.

9. Is there anything from the above list or other matter (not covered above) in terms of new capabilities or improved features that you would choose to include in your roadmap of offerings?
   A. What is your main reason for choosing it?
      - Higher value?
      - Ease of appropriation?
      - Ease of implementation?

10. Is there anything from the above list or other matter (not covered above) in terms of new capabilities or improved features that you would *not* choose to include in your roadmap of offerings?
    A. What is your main reason for not choosing it?
        - Lower value?
        - Difficulty of appropriation?
        - Difficult or unknown implementation impact?

11. Where do you think AI and Edge specifically can best deliver value to our stakeholders and partners?
    A. What could it mean or deliver to:
        - Customers?
        - Husqvarna (e.g., manufacturing, primary, R&D, sales, and after sales)?
        - Distributors/dealers?
        - Others?

12. In your opinion, what are the biggest obstacles to realizing the above-mentioned values?

Interview part V *(10 min):*

Feedback on project/experience and feedback for the future.

13. What are your opinions on how the project was scoped, approached, and executed?

14. What are the top two or three improvements that you would like to propose for the future in case this setup continues?

15. Do you have any specific comment on the setup and experience of working with startups?
    A. Anything that works well or difficulties imposed?

16. Expression of thanks, and letting them know:
    - Next actions
    - How these data will be used
    - How they will be kept informed
    - Can we get back with any followup questions?

Step 1 of coding:

V: Valuable	R: Rare	I: Inimitable	N: Non-substitutable O: Organized to exploit
Varied intelligence over time	Varied intelligence over time	Varied intelligence over time	
Anomaly detection			Anomaly detection
Hyper-personalization	Hyper-personalization	Hyper-personalization	Hyper-personalization
Latency			Latency
	Shared deployment		Shared deployment
Self-learning	Self-learning		Self-learning
Performance capture	Performance capture	Software sensors	Performance capture
Orchestration	Orchestration	Orchestration	
	Continuous intelligence	Continuous intelligence	Continuous intelligence
			Software sensors
Quick turnaround			
Continuous intelligence			
Analytics data compliance	Analytics data compliance	Analytics data compliance	Analytics data compliance
	Data sensing	Data sensing	Data sensing
	Relevant filtering	Relevant filtering	Relevant filtering
	Data avalanche	Data avalanche	Data avalanche
Security		Security	
Connectivity agnostic	Connectivity agnostic	Connectivity agnostic	Connectivity agnostic
Technology perception	Technology perception	Technology perception	
Intent capture	Intent capture	Intent capture	Intent capture
Integrity	Integrity		
		Digital operations	Digital operations
			Recurring revenues

<u>Step 2 of coding:</u>

New capabilities	V: Valuable	R: Rare	I: Inimitable	N: Non-substitutable O: Organized to exploit
Self-calibration	Varied intelligence over time Anomaly detection Hyper-personalization Latency Self-learning	Varied intelligence over time Hyper-personalization Shared deployment Self-learning	Varied intelligence over time Hyper-personalization	Anomaly detection Hyper-personalization Latency Shared deployment Self-learning
Enhanced sensing	Performance capture Quick turnaround Orchestration Continuous intelligence	Performance capture Orchestration Continuous intelligence	Software sensors Orchestration Continuous intelligence	Software sensors Performance capture Continuous intelligence
Selective capture	Analytics data compliance Security Connectivity agnostic	Data sensing Relevant filtering Data avalanche Analytics data compliance Connectivity agnostic	Data sensing Relevant filtering Data avalanche Analytics data compliance Security Connectivity agnostic	Data sensing Relevant filtering Data avalanche Analytics data compliance Connectivity agnostic
Reputation	Technology perception Intent capture Integrity	Technology perception Intent capture Integrity	Digital operations Technology perception Intent capture	Digital operations Recurring revenues Intent capture

New capabilities:

<u>Self-calibration:</u>

- Varied intelligence over time: Bring second life to devices by incorporating different intelligences over time and hence different uses
- Anomaly Detection: Prediction of the future state of machines or parts based on current values
- Hyper-personalization: Customization, reconfiguration, or personalization ability with a batch size of one based on individual stakeholder interactions
- Latency: Fast decision making for actions by devices with extreme performance
- Shared deployment: Ability to incorporate basic intelligence across product categories through the same models
- Self-learning: Smartness induced by sub-conscious intelligence on the fly

<u>Enhanced sensing:</u>

- Software sensors: Data and software-driven virtual intelligence without any hardware requirements
- Performance capture: Ability to track downtime, failure prediction, removal of bias during product design, and hence overall degradation or improvement in device operation
- Quick turnaround: Reduced time for scalability by shortening the cycle for data capture, storage, analytics, etc., through Edge deployment
- Orchestration: Ability to relate incoming sensor data on the device to the intelligence provided by Edge AI and to make decisions directly, enabling offerings such as geo-fencing
- Continuous intelligence: Ability to start small and immediately with what we have and to build smartness as we go along

<u>Selective capture:</u>

- Data sensing: Understanding on the device via on-the-fly decision making about when to capture data
- Relevant filtering: Decision making by the product to segregate noise from data for better filtering during device data capture
- Data avalanche: Ability to identify various data streams and associated conditions and to decide locally on the devices what to capture and what not to capture
- Analytics data compliance: Combination of data analytics and compliance on the device itself to deliver towards the sustainability agenda

- Security: Ability to implement compliance requirements directly on the device through realtime data sampling
- Connectivity agnostic: Ability to capture data, deliver product intelligence, take action, and continuously learn even without any sort of connectivity
- Digital operations: Attaining technological leadership not only by understanding but also by mastering the ability to offer solutions such as pay by hour and power by hour

Reputation:

- Technology perception: Impacting customer perception of advanced quality by providing look and feel to software technology that cannot be seen
- Recurring revenue: Enabling new business models such as value- and usage-based offers, which are actually delivery or need based
- Intent capture: Possibility of capturing not only customers' actions but also their interactions to identify what they want to do, i.e., the intentions
- Integrity: Induced trust in product features and data handling rather than controlling it through organizational processes

10.3 Papers B1 and B2: Survey

General information & questions

This survey is conducted by KTH Royal Institute of Technology in collaboration with Husqvarna Group to investigate how and what values can be created by new service offerings utilizing digital technologies.

The survey starts by capturing some general background information.
After this, there are three pages with questions related to one and the same use case.

The survey is fully anonymous and will take approximately five to seven minutes to complete. There are no right or wrong answers; just select the alternative that best fits your view.

Thank you for your participation!

Company?
Role?
How many years have you worked in the company where you are currently employed?
How many years have you worked in your present role?
How many total years of experience do you have in the industry?
Please select the alternative that best fits your view as per the following scale.

1 = Strongly disagree
2 = Disagree
3 = Slightly disagree
4 = Neither agree nor disagree
5 = Slightly agree
6 = Agree
7 = Strongly agree

	1	2	3	4	5	6	7
I prefer to live a challenging life rather than a comfortable one, even though I know I may face many difficulties along the way	☑	○	○	○	○	○	○
I am willing to invest a lot of time and/or money on something that might yield a high return	☑	○	○	○	○	○	○
I tend to act "boldly" in situations where risk is involved	☑	○	○	○	○	○	○
I tend to plan ahead on projects	☑	○	○	○	○	○	○
I love being a champion for my ideas, even against others' opposition	☑	○	○	○	○	○	○
I excel at identifying opportunities	☑	○	○	○	○	○	○
I am always positive about problems arising in my life, and resolve them on my own	☑	○	○	○	○	○	○
When I am confronted with a new task, I am afraid of not being able to handle it	☑	○	○	○	○	○	○
I am able to take a lot of decisions on my own	☑	○	○	○	○	○	○
I often like to try new and unusual activities that are not typical of my routine	☑	○	○	○	○	○	○
I favour experimentation and original approaches to problem solving rather than using methods others generally use for solving their problems	☑	○	○	○	○	○	○
I enjoy working on new things, so I am usually up to date with recent trends	☑	○	○	○	○	○	○

Use case

Assume that you are the purchasing manager for the assembly line of a manufacturing company.

One of the suppliers of an electric motor used in the assembly line has come up with a subscription-based service that includes digital-technology–enabled predictive maintenance and motor performance monitoring.
This subscription agreement implies a monthly fee for a duration of two years.

The supplier delivers on the promised uptime for the motor, with the aim of maximizing the efficiency and productivity of the assembly line.

Every quarter, the agreement allows you to renegotiate the subscription price based on the value delivered, with a maximum increase or decrease of 5%.
If no agreement on the increase or decrease in price is reached, the original subscription price prevails for the next quarter.

As the purchasing manager, please select the alternative that best fits your view as per the following scale.

1 = Not at all
2 = To a small extent
3 = To some extent
4 = Neutral
5 = To a moderate extent

6 = To a great extent

7 = Completely

	1	2	3	4	5	6	7
To what extent does the use of this service enable experimentation with new ways of doing business?	○	✓	○	○	○	○	○
To what extent does the use of this service enable you to learn new things?	○	✓	○	○	○	○	○
To what extent do you feel that this service will improve your assembly-line performance?	○	✓	○	○	○	○	○
To what extent do you consider the predictive maintenance on the motor included in the offer to be valuable?	○	✓	○	○	○	○	○
To what extent do you consider the motor performance monitoring included in the offer to be valuable?	○	✓	○	○	○	○	○
To what extent do you consider the promised uptime for the motor included in the offer to be valuable?	○	✓	○	○	○	○	○
To what extent would you be comfortable with establishing this type of business relationship with the supplier?	○	✓	○	○	○	○	○
To what extent does the use of this service enable you to engage in collaboration activities with your supplier?	○	✓	○	○	○	○	○
To what extent will the use of this service improve the way your company is perceived by your suppliers?	○	✓	○	○	○	○	○
To what extent will the use of this service improve the way your company is perceived by your competitors?	○	✓	○	○	○	○	○
To what extent will the use of this service improve the way your company is perceived by your customers?	○	✓	○	○	○	○	○

	1	2	3	4	5	6	7
To what extent do you find the offering attractive?	○	✓	○	○	○	○	○
To what extent would you be willing to subscribe to this service?	○	✓	○	○	○	○	○
To what extent do you feel comfortable with the overall pricing model of the service?	○	✓	○	○	○	○	○
To what extent do you find this service valuable, as compared to purchasing the motor the way you have done before?	○	✓	○	○	○	○	○
To what extent do you feel comfortable with the contract length of the service?	○	✓	○	○	○	○	○
To what extent do you feel comfortable to purchase this service if the offered motors would require major changes to your current assembly-line set-up?	○	✓	○	○	○	○	○

As the purchasing manager, please select the alternative that best fits your view as per the following scale.

1 = Much more difficult

2 = More difficult

3 = A little more difficult

4 = Neither more difficult nor easier

5 = A little easier

6 = Easier

7 = Much easier

	1	2	3	4	5	6	7
How would the purchasing of this service be as compared to your current way of purchasing the motor?	○	☑	○	○	○	○	○
How would day-to-day assembly-line operations become with the adoption of this service?	○	☑	○	○	○	○	○

As the purchasing manager, please select the alternative that best fits your view as per the following scale.

1 = Much more negative

2 = Very negative

3 = Negative

4 = Neutral

5 = Positive

6 = Very positive

7 = Much more positive

	1	2	3	4	5	6	7
Would your perception of the offering be different if you have had positive prior business relationships with the supplier in question?	○	☑	○	○	○	○	○
Would your perception of the offering be different if the duration of the contract length was longer?	○	☑	○	○	○	○	○
Would your perception of the offering be different if you have had negative prior relationships with the supplier in question?	○	☑	○	○	○	○	○
Would your perception of the offering be different if the duration of the contract length was shorter?	○	☑	○	○	○	○	○
Would your perception of the offering be different if the offered motors would require minor changes to your current assembly-line set-up?	○	☑	○	○	○	○	○
Would your perception of the offering be different if the basis for re-negotiation was clearly supported by actual service performance data?	○	☑	○	○	○	○	○
Would your perception of the offering be different if the analysis used as input for the re-negotiation was provided by a neutral third-party?	○	☑	○	○	○	○	○

As the purchasing manager, please select the alternative that best fits your view as per the following scale.

1 = Much more stress

2 = More stress

3 = A little more stress

4 = Neutral

5 = A little less stress

6 = Less stress

7 = Much less stress

	1	2	3	4	5	6	7
How would the use of this service change your current stress level at work (thanks to product performance monitoring and/or predictive maintenance)?	○	☑	○	○	○	○	○

10.4 Paper C: Interview guide

<u>Interview 1</u>

First interview. Installation is completed and service has been active for one to three weeks. The interview will be held in Swedish (and I will translate the questions below when we are satisfied).

- *Is it ok if we record the interview? (very valuable to our team)*

SECTION 1: BACKGROUND

Conditional

1. How big is your garden?
2. How would you describe your garden? (natural, lawn, rocky)
3. Talk about what hobbies you have. Is gardening one of them?

Epistemic

1. Are you generally interested in innovation and new technology?
2. Have you subscribed to other subscription-based services? What do you like or dislike about them?
3. Do you have other connected machines in your home?

Functional

1. How did you mow your garden before this service?
2. How often do you usually need to trim edges?
3. Are there any parts of the lawn that you find challenging?
4. What do you think of the support and maintenance of tools in general?

Emotional

1. Do you enjoy gardening?
2. What is your previous experience with Husqvarna?
3. What is your previous experience with automowers?
4. What are your feelings about having professionals working in your garden?

Social

1. How important is the appearance of the lawn for you?
2. Have you considered this service to be a contribution to the overall sustainability of the planet?
3. How does your neighborhood look? If you talk about gardening with your neighbors, what would be a recurrent topic?

SECTION 2: EXPERIENCES SO FAR

1. What do you like about the service, so far?
2. How do you think it could be better?
3. What are your expectations? Why? How?
4. What options you would like to have in the service package?
5. What would you like to change or add for a better experience?
6. How can this service make your life better?
7. Are you happy with the quality of the grass?
8. Would you consider this service convenient?
    a. If yes, in what way?
    b. If no, what would make it more convenient for you?
9. Have you already got in contact with the service provider?
10. How was your experience? Tell us how you felt overall about it?
11. Is there anything you would wish to change?

Additional questions:

1. How did you experience the installation?
2. Have you had any issues with the mower so far?
3. (If they have) Did you solve it on your own or did the service provider handle it?
4. Are you happy with the lawn mowing (and trimming) results so far?
5. Have you seen the automower stand still without knowing why? Did it bother you?
6. What are your expectations of the service provider when it comes to response time?

SECTION 3: ENGAGEMENT LEVEL AND PROFILE

Try to get customer to speak freely about the service to understand his/her engagement level. Here are some relevant areas to talk about (use questions if needed):

- Top three reasons you wanted to subscribe to this service
- What is your normal schedule like on one weekday and one weekend day?
- Is the service cost effective?
    - What would you like to add or change in the package?
- What level of involvement would you prefer? (Interest in automower vs. hassle free?)
    - What are the things you want to control in the mower?
    - What is the responsibility of the SP?
    - Would you be interested in any type of statistics?

- Preferred mode and level of communication (more vs. less?)
    - How would you prefer the communication between you and those responsible?
    - Who do you think is responsible for this service?
    - Would you contact him/her if you need support?
    - What would you do if the mower stopped? DIY or contact support?
    - When do you want the service provider to reach out to you?

Interview 2

The customers have had the service running during the summer, for about three to four months (the interview takes place at the end of September).

- Is it ok if we record the interview?
- Start recording!

PART 1: OVERALL—HOW HAS THE EXPERIENCE BEEN?

1. Did you have any difficult areas in the garden and could the mower handle them? (conditional)
2. Have your routines in the garden changed in any way with this service? (functional)
3. What have you experienced as positive about the service? (emotional)
    a. For example, the results, edge trimming, communication
4. What have you experienced as negative about the service? (emotional)
    a. (same as above)
    b. If you were dissatisfied with anything, did you point it out? Has a change been made accordingly?
5. Have any adjustments been made to the initial installation during the summer? (conditional)
    a. Changes in mowing schedule? Who made the changes? How smooth was it?
    b. Have you been able to make the adjustments you wanted (or had them made for you)?
6. Have you done anything in particular with the mower during thunderstorms? (functional)
7. Do you use the app to view data or control the mower? (epistemic)
    a. How often and for what purpose?
8. Have you talked to neighbors or friends about the service? (social)
9. If you were to formulate the advertising message for the service, what would be an important argument in your opinion? (social)
10. Service provider role

11. Last question

PART 2: DATA FROM FLEET

Retrieve and view data about their mower from Fleet (see log of triggered alarms). Open discussion:

- Talk about the log, what it shows and if it matches their experience
- How was the experience when the mower stopped? Who did what? Did it match their expectations?
    - Anything that could have been improved?

PART 3: FURTHER DEVELOPMENT OF THE OFFER

Present and evaluate the offer, this time divided into its components. Let the customer evaluate each component (perhaps relative to the others?).