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How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops

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ABSTRACT

Artificial intelligence (AI) is predicted to radically transform the ways manufacturing firms create, deliver, and capture value. However, many manufacturers struggle to successfully assimilate AI capabilities into their business models and operations at scale. In this paper, we explore how manufacturing firms can develop AI capabilities and innovate their business models to scale AI in digital servitization. We present empirical insights from a case study of six leading manufacturers engaged in AI. The findings reveal three sets of critical AI capabilities: data pipeline, algorithm development, and AI democratization. To scale these capabilities, firms need to innovate their business models by focusing on agile customer co-creation, data-driven delivery operations, and scalable ecosystem integration. We combine these insights into a co-evolutionary framework for scaling AI through business model innovation underscoring the mechanisms and feedback loops. We offer insights into how manufacturers can scale AI, with important implications for management.

1. Introduction

> *We need to transform our value offerings towards optimization of customers processes. To enable this, we are increasingly investing in capabilities for machine learning, AI, and deep learning, and I think we are also quite far ahead in implementing these within our operations. The final component is scaling the business models. So, I think those three are actually the most critical things to get on board for the future.* [Head of digital customer support center, Solutioncorp]

The proliferation of artificial intelligence (AI) technologies holds out the prospect of enabling radical changes in products, services, innovation processes, business models, and the very nature of business activities in industrial ecosystems that embrace the logic of digital servitization (Iansiti & Lakhani, 2020; Sjödin, Parida, Kohtamäki, & Wincent, 2020a; Sklyar, Kowalkowski, Tronvoll, & Sörhammar, 2019). Digital servitization is the "transformation in processes, capabilities, and offerings within industrial firms and their associate ecosystems to progressively create, deliver, and capture increased service value arising from a broad range of enabling digital technologies such as the Internet of Things (IoT), big data, artificial intelligence (AI), and cloud computing" (Sjödin et al., 2020a). A central proposition of digital servitization is that digital technologies such as AI afford radical opportunities for servitization to create and capture value from new revenue streams and to enable differentiation from competitors by assuming greater responsibility for supporting customer outcomes (Kohtamäki, Parida, Oghazi, Gebauer, & Baines, 2019). For example, investment in AI technologies has enabled providers such as GE, Siemens, and ABB to offer enhanced digital customer services such as fleet management and site optimization by monitoring, analyzing, controlling, and automating the performance of connected equipment (Iansiti & Lakhani, 2020; Porter & Heppelmann, 2014). Yet, succeeding with such offerings is far from automatic, and many firms, in setting up business models, fail to realize increased value creation and capture from AI (Linde, Sjödin, Parida, & Gebauer, 2020).

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Although AI technology can provide the foundation for successful digital servitization and business model innovation, simply spending money on digital infrastructure, technologies, and data is not enough. New routines, skills, operational processes, and business models are required in making use of AI technology to create value for customers. For example, many firms have discovered that AI algorithms do not produce definitive answers but offer tentative solutions (e.g., probability-based predictions), which need human interpretation, justification, and action to create concrete, valuable outcomes (Tarafdar, Beath, & Ross, 2019; von Krogh, 2018). Thus, industrial business-to-business (B2B) providers must engage in a large-scale organizational transformation to develop AI capabilities and infuse them into the business model if they are to maintain competitiveness in the era of digital servitization and to benefit generally from digitalization and AI (Iansiti & Lakhani, 2020; Porter & Heppelmann, 2014). This transformation extends beyond back-end R&D to include front-line services and sales and extended ecosystem partnerships (Kamalaldin, Linde, Sjödin, & Parida, 2020). However, most large manufacturing firms have failed to scale AI beyond initial proofs of concepts (Björkdahl, 2020; Brock & Von Wangenheim, 2019) because of the prevailing problems of integrating AI into their value creation, delivery, and capture activities and aligning with customers and extended ecosystems (Wuest, Weimer, Irgens, & Thoben, 2016; Parida, Sjödin, & Reim, 2019). In this domain, we see several research gaps.

First, there is a need to *further understanding on how AI capabilities can be developed in manufacturing firms*. More specifically, there is a need to advance knowledge of the bundles of interrelated yet distinct routines that make up successful AI implementation in manufacturing firms (Parida et al., 2019; Björkdahl, 2020). Indeed, in two large-scale, global top management surveys, the lack of AI capabilities was identified as the primary AI implementation challenge (Brock & Von Wangenheim, 2019). Moreover, such capability gaps are "not always obvious" (Davenport & Ronanki, 2018, p. 8) and "organizations often have trouble assessing their [… AI] capabilities in a candid way" (Desouza, Dawson, & Chenok, 2020, p. 209). Accordingly, the high expectations that executives place on AI often exceed the capabilities of their companies, and few business leaders are well prepared to address the gaps between current and desired AI capabilities (Barro & Davenport, 2018). The importance of data competencies and analytics capabilities is often highlighted (Parida et al., 2019; Björkdahl, 2020), but there is a lack of understanding of the micro-foundational routines and activities that underly successful implementation at larger scale. Hence, several scholars have recently called for further research to overcome this gap in our knowledge (Bailey, Faraj, Hinds, von Krogh, & Leonardi, 2019; Hadjimichael & Tsoukas, 2019; Merendino et al., 2018; von Krogh, 2018). In particular, there is a need for further understanding of the routines, accumulated knowledge, and interdependent action by multiple organizational actors that provide the foundation for large-scale AI implementation and use.

Second, there is a need to advance understanding of the principles on *how AI can be productively used to drive business model innovation on a larger scale*. Indeed, implementation of AI holds the potential to develop organization-wide business model innovation processes for industrial manufacturers – namely, "designed, novel, non-trivial changes to the key elements of a business model and/or the architecture linking these elements" (Foss & Saebi, 2017, p. 201). This new business model calls for a revised logic concerning the underlying principles of how AI technology is incorporated into value offerings and how it interacts with the work of individuals, organizational functions, and the diverse processes across the business to ensure value delivery, capture, and competitiveness (Iansiti & Lakhani, 2020). For example, AI holds the potential to provide multiple business model benefits for customers such as cutting costs, enhancing the quality of services, increasing coordination and productivity, and boosting delivery efficiencies (Davenport & Ronanki, 2018; Iansiti & Lakhani, 2020). By expanding the scale, scope, and learning opportunities, AI-driven business models can leverage new ways of creating, delivering, and capturing value to drive competitiveness (Iansiti & Lakhani, 2020; Majchrzak & Markus, 2013; Nambisan, Wright, & Feldman, 2019). For example, firms with higher AI capability might be better suited to expand the value space (Jovanovic, Sjödin, & Parida, 2021) by using automated insights from the analysis of industrial data to develop data-driven work approaches and co-create customer interaction (Sjödin, Parida, Jovanovic, & Visnjic, 2020b). However, a key challenge is scaling AI services beyond initial proof of concept to larger customer segments though AI business models and demonstrated offerings (Burström, Parida, Lahti, & Wincent, 2021). There is, therefore, a need to better understand the principles that underly AI-enabled business model innovation whereby AI capabilities are assimilated into business activities relating to value creation, delivery, and capture to ensure scalable growth.

The objective of this article is *to explore how manufacturing firms can develop AI capabilities and business model innovation to scale AI in digital servitization*. We build on in-depth case studies of six leading industrial companies engaged in digital servitization that have developed and integrated competitive AI solutions into their operations.

The findings reveal three sets of critical AI capabilities: data pipeline, algorithm development, and AI democratization. To incorporate these capabilities into their businesses, manufacturers need to transform their business models by focusing on the key principles relating to agile customer co-creation, data-driven delivery operations, and scalable ecosystem integration. We combine these insights into a framework for scaling AI underscoring the need for joint investments in AI capabilities development and AI-driven business model innovation. The framework illustrates the interdependences and feedback loops between these AI capabilities and business models, showing that firms must develop routines for each capability and leverage their affordances within the business model to successfully realize the full value potential of AI in digital servitization and enable scaling. Our study has broad implications for management research relating to AI (e.g., Iansiti & Lakhani, 2020; Brock & Von Wangenheim, 2019), digital servitization (Gebauer et al., 2020; Kohtamäki et al., 2019; Sjödin et al., 2020b) and business model innovation (Foss & Saebi, 2017).

2. Theoretical background

2.1. Artificial intelligence enabling business model innovation and digital servitization

AI is typically described as the most advanced form of digitalization (e.g., Parida et al., 2019; Kohtamäki et al., 2019). Digitalization involves the use of digital technology such as sensors, connectivity, and analytics to provide new value-creating and revenue-generating opportunities (Parida et al., 2019); it is a process that is having a profound impact on manufacturing industries (Ardolino et al., 2018; Jovanovic et al., 2021). A key consideration is that digitalization typically goes hand in hand with adopting a servitization strategy for industrial manufacturers (Parida, Sjödin, Lenka, & Wincent, 2015). The emerging literature on digital servitization captures this trend (Kohtamäki et al., 2019; Sjödin et al., 2020b; Vendrell-Herrero, Bustinza, Parry, & Georgantzis, 2017). We follow Sjödin et al. (2020b) in defining digital servitization as the transformation in processes, capabilities, offerings, and business models in industrial firms and their associated ecosystems to progressively create, deliver, and capture increased service value arising from a broad range of enabling digital technologies (such as AI).

We, therefore, consider digital servitization as an *organizational transformation process for business model innovation* (Sjödin et al., 2020b; Foss & Saebi, 2017) where AI (capabilities) can serve as the key enabler. For example, advancements in AI are currently enabling companies to move from product-centric models to more advanced digitally enabled business models (i.e., platform or outcome-based) with higher value-generating potential (Paiola & Gebauer, 2020; Gebauer et al., 2020; Kohtamäki et al., 2019). We argue that AI, as the most advanced form of digitalization, will fundamentally change firms' value propositions and alter how (i.e., through processes and capabilities) a company creates, delivers, and captures value through co-creation with customers to meet their evolving needs (Iansiti & Lakhani, 2020; Lenka, Parida, & Wincent, 2017; Sjödin et al., 2020a).

Indeed, AI offers vast affordances to industrial manufacturers engaged in digital servitization in the shape of added value and competitive advantage (Autio, Nambisan, Thomas, & Wright, 2018; Brock & Von Wangenheim, 2019; Nambisan et al., 2019). AI is "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019, p. 17). The ability to learn and operate in ways that appear intentional makes AI "intelligent" and sets it apart from previous generations of information technology (Bailey et al., 2019; Huang, Rust, & Maksimovic, 2019). These AI affordances can have profound implications for digital servitization as AI creates a foundation for decision support through valuable insights and results that are collected from large and complex data sets and compressed into a manageable form (Iansiti & Lakhani, 2020; Parida et al., 2019).

2.2. Understanding AI capabilities

Research has only just begun to explore the implications of AI for managers and firms (Liu, Chang, Forrest, & Yang, 2020; Paschen, Wilson, & Ferreira, 2020; Phan, Wright, & Lee, 2017). Initial research has been carried out on AI-driven business models (Garbuio & Lin, 2019), organizational decision-making involving AI (Shrestha, Ben-Menahem, & Von Krogh, 2019), and the ways in which firms can foster trust in AI (Hengstler, Enkel, & Duelli, 2016). The practice-oriented management literature repeatedly describes practices and steps that managers can take to integrate AI into their firms (Brock & Von Wangenheim, 2019; Davenport & Ronanki, 2018; Fountaine, McCarthy, & Saleh, 2019; Ransbotham, Kiron, Gerbert, & Reeves, 2017; Tarafdar et al., 2019). Overall, there is a strong consensus that the effects of AI go beyond incremental process improvement and include fundamentally new ways of operating and growing a business. Yet, there is a lack of research on how industrial manufacturers can leverage AI in the form of new capabilities and make the transformation to AI-enabled business models (Brock & Von Wangenheim, 2019; Iansiti & Lakhani, 2020).

Indeed, surveys has identified the lack of AI capabilities as the top AI-implementation challenge (Brock & Von Wangenheim, 2019). It, therefore, seems a fruitful undertaking to investigate the nature of such organizational capabilities in greater depth. Organizational capabilities are frequently defined and operationalized as bundles of interrelated yet distinct routines (e.g., Amit & Schoemaker, 1993; Henderson & Cockburn, 1994; Hult, Ketchen, & Nichols, 2003; Peng, Schroeder, & Shah, 2008; Hamel & Prahalad, 1990). They rely on skills, accumulated knowledge, and interdependent action by multiple actors to make use of organizational resources (Day, 1994). Consequently, organizational capabilities are intangible and socially complex resources, which are hard to imitate and, hence, are a source of sustainable competitive advantage for firms (Barney, 1991). While scholars broadly agree on the relevance of AI capabilities, the literature fails to provide a solid understanding of what AI capabilities actually are. For example, the managerial guidelines of Brock and Von Wangenheim (2019) and Tarafdar et al. (2019) mention some capabilities that are relevant for the purpose of integrating AI into a firm. However, these scholars adopt a rather broad perspective, asserting that the integration of AI requires strategic (business) capabilities in addition to data science and technological capabilities. Consequently, the depth of insight provided by these articles is limited, particularly since depicting these capabilities was not their sole or even primary purpose. To date, scholars and practitioners have no clear understanding of the capabilities and underlying routines that firms require to reap the potential of AI (Barro & Davenport, 2018; Davenport & Ronanki, 2018; Desouza et al., 2020). The current study seeks to deepen our understanding of such AI capabilities. Adopting the established conceptualization of capabilities as a bundle of interrelated yet distinct routines allows us to provide deep insights into AI capabilities by disentangling AI capabilities into specific and identifiable routines. Furthermore, it enables us to outline possible pathways to capability building (Peng et al., 2008).

2.3. AI-driven business model innovation

In addition, there is a need to understand how industrial manufacturers can transform and innovate business models by placing AI capabilities at the core of their business processes (Iansiti & Lakhani, 2020). A business mode describes the "design or architecture of the value creation, delivery, and capture mechanisms" (Teece, 2010, p. 172) of a firm. Although some preliminary suggestions exist (e.g., Parida et al., 2019; Björkdahl, 2020), the development of theory on the topic of AI and business model innovation in digital servitization has been given scant treatment. Our study, therefore, investigates how manufacturing firms go about incorporating AI into the value-creation, value-delivery, and value-capture mechanisms. Indeed, profiting from a digital capability such as AI "is not so much a technology challenge as it is a challenge to harness knowledge to create the organizational knowing to continually optimize the value that can be derived from digital technologies" (Lyytinen, Sørensen, & Tilson, 2017, p. 237).

Value creation relates to the creation of offerings and value propositions for customers. In the digital servitization context, this would relate to AI-enabled services designed to optimize the use and maintenance of products (or fleets of products) in customer operations. A critical assessment is the value to customers as researchers. For example, Sjödin et al. (2020b) emphasize that any value offers created on digital technologies must be (co-)created in agile and customizable manner from the standpoint of customer need. There is, thus, a need to systematically assess AI applications and the potential value that they bring for customer and end-user (Linde et al., 2020; Sjödin, Parida, & Lindström, 2017). Indeed, the application of AI may enable providers to create value closer to the customer's operations since providers can use data from a fleet of equipment to identify areas for improvement in the customer's ongoing operational processes – for instance, optimization of equipment and condition-based maintenance (Kohtamäki et al., 2019).

Value delivery relates to the setting up of operational processes and activities to deliver the value promised. For manufacturer engaged in digital servitization, it could relate to using AI capabilities to improve the work processes of front-line and back-line service staff, and technological support systems. For example, AI capabilities can play an important role in monitoring product flows, process flows, and maintenance processes (Jovanovic et al., 2021). Yet, since full-scale AI implementation is still rare among industrial manufacturers, there is a need to understand the principles required to leverage AI within the core processes of the business model. For example, Iansiti and Lakhani (2020) underline the importance of transforming operating models to increase the scale, scope, and learning opportunities from AI within the organization. Yet, many firms fail to fully consider the value delivery dimension (Linde et al., 2020). The organization must work as an entity, collaborating with other companies and suppliers to adapt to emerging opportunities uncovered by AI capabilities (Sjödin et al., 2020b; Skylar et al., 2019; Kamalaldin et al., 2020).

Value capture relates to elements such as cost structures, potential revenue streams, and revenue-model and financial viabilities. In the case of digital servitization, AI implementation may indeed provide substantial new revenue sources from AI-enabled services but there is also the potentially high cost of maintaining AI infrastructures.

To summarize, the development of AI capabilities holds significant potential to drive business model innovation and new sources of revenue and competitiveness for manufacturers in digital servitization. Yet, many challenges and uncertainties face this transformation head on, with only meagre research insights in place to guide the path forward.

Accordingly, this study seeks to explore how manufacturing firms can develop AI capabilities and business model innovation to scale AI in digital servitization. In the sections that follow, the methods, findings, and contributions of this research are described.

3. Method

3.1. Research approach and case selection

This paper presents an exploratory multiple case study of industrial firms and their digital partners to investigate what AI capabilities firms need in order to advance digital servitization and how firms can leverage their affordances for business model innovation. Case studies enable multiple observations of complex organizational processes (Eisenhardt & Graebner, 2007; Eisenhardt, 1989) and are particularly useful for developing new insights into theoretically novel phenomena (Edmondson & McManus, 2007) such as the development and deployment of AI capabilities.

Our sample comprised globally active Swedish B2B providers and their digital partners engaged in digital servitization. Provider cases from four industries (manufacturing, shipping, construction, and mining) were selected to enhance the generalizability of our findings. This case selection offered an opportunity to contrast various industrial perspectives on organizational processes. Building on recommendations by Glaser and Strauss (1967), we used theoretical sampling to select cases that would illustrate how companies deploy AI (Eisenhardt & Graebner, 2007).

Several factors underpinned the selection of these cases at the time the study was initiated. First, the providers were actively working with AI-enabled digital service offerings (e.g., site optimization) and had several successful collaborations with customers. For example, Solutioncorp had a solid record of delivering AI-enabled digital services that have optimized machine operation by up to 25%. Second, these firms had been developing AI capabilities for some time, with notable development of routines and processes and incorporation into business models. This background meant that we could learn from the experiences of leading companies. For example, Shipcorp described a comprehensive approach of applying AI to develop new digital services. Third, we selected cases where we had established good contacts with stakeholders within the firms. These positive contacts enabled us to collect detailed descriptions of their AI capability development and business model innovation, and obtain in-depth information about the capabilities and how they were deployed.

3.2. Data collection

Data were gathered primarily through individual, in-depth interviews with participants from providers and digital partners that were active in digital servitization. In total, we conducted 42 interviews with key informants. The informants were selected because they were actively involved in developing and deploying AI capabilities to drive business model innovation. Interviewees were identified by snowball sampling, where key informants were asked to recommend people who played an active role in AI. We interviewed various participants exercising different organizational functions to capture a multifaceted view of the process. The interviewees included digital business developers, R&D managers, platform managers, project managers, product managers, and service delivery staff. Table 1 summarizes the cases and the positions of the interviewees within each company.

Table 1
Case study firms and informants.

Focal firm, key products (turnover, employees)	Case description	Informants from focal firm and ecosystem actors (# interviews)
Solutioncorp *Control system and mechanical equipment (SEK 32,400 M / 7,800)*	Comprehensive efforts to drive AI capability application in process industry customer segments. Strategy to connect existing assets and visualize whole operations using digital tools. Examples include fault detection in pulp and paper mills as well as optimization solutions for various equipment such as mine hoists.	Solutioncorp: 11 – 4 contract & account managers, 4 business development managers, 3 digitalization & automation managers. Ecosystem: customers (2), AI/analytics provider (1)
Conglocorp *Mining equipment (SEK 100,000 M / 41,000)*	Large-scale AI transformation of business focusing on digitalization in mining industry through investing in AI, automation, and connectivity. Examples include AI-enabled automation of underground loading, predictive maintenance, and mine optimization services.	Conglocorp: 3 – 2 automation manager, 1 sales manager. Ecosystem: AI and analytics provider (3).
Rockcorp *Mining equipment (SEK 31,000 M / 13,000)*	Effort leveraging use data and AI to drive new business opportunities for mining industry customers. Examples include AI-enabled digital transformation services and automation of drilling systems.	Rockcorp: 5 – head of digital business development, 2 digitalization and automation managers, 2 business development managers. Ecosystem: position system provider (3).
Shipcorp *Ship control systems (66,400 M, 7,600)*	AI initiative with the goal of providing solutions leveraging data from ship control system by sharing it for AI, analytics and support autonomous operations. Examples of applications include fuel optimization, predictive maintenance, and route optimization.	Shipcorp 8: ecosystem manager, digital transformation manager, head of research collaboration, 3 global product manager, business development manager, customer success manager. Ecosystem: Digital service provider (5)
Constructcorp *Heavy construction equipment (SEK 66,500 M / 14,000)*	An AI initiative toward delivering digitally enabled site optimization services for the construction industry. Key focus lies on the customer's core business, maximum uptime potential, and effective cost control. Examples include site optimization, load optimization, and driver assistance.	Constructcorp: 5 – 2 product planning managers, 2 machine services managers, 1 technology manager. Ecosystem: global distributers (2).
Truckcorp *Heavy trucks and transport solutions (SEK 152,000 M./ 38,600)*	AI initiative toward optimizing sustainability and operations of a fleet of connected trucks. Examples include fleet managements systems, fuel efficiency, and driver assistance functionalities.	Truckcorp: 3 – business development manager, digital research manager, digitalization manager. Ecosystem: N/A

The respondents were asked open-ended questions with the support of an interview guide. The guide was developed based on themes about AI, digital servitization, business model innovation principles, and business model innovation outcomes. For example, respondents were asked to consider questions relating to broad themes such as: *How do you develop AI in your organizations? What are examples of AI implementation? How are these leveraged within your service operations? Which AI activities are critical to enable AI business model innovation? How can business models for AI be scaled?* and *How are different ecosystem roles involved in the process?* Follow-up questions were used to clarify points and gain further details, which enabled additional exploration of relevant cases. The interviews took approximately 60–120 min each and were held face to face or via online conference calls. All interviews were recorded and transcribed, and the transcripts provided the basis for the data analysis.

We triangulated our data by applying multiple data collection techniques, including multiple interviews and a review of documents (Jick, 1979). We performed document studies, reviewing company reports, agreements, published material, and project documents to validate and provide context to our respondents' views, thus enabling empirical triangulation. To increase reliability and enhance transparency as well as the possibility of replication, a case study protocol was constructed along with a case study database. The database included case study notes, documents, and analysis.

3.3. Data analysis

As with Clark, Gioia, Ketchen, and Thomas (2010), we followed an interpretive research approach, which "gives voice in the interpretation of events in a first-order analysis to the people actually experiencing those events" (Clark et al., 2010, p. 403). The data analysis was based on a thematic analysis approach, which offers techniques to identify patterns in large, complex data sets (Braun & Clarke, 2006). Moreover, thematic analysis offers a means of effectively and accurately identifying links within analytical themes. Through a series of iterations and comparisons, themes and overarching dimensions can be identified so that an empirically grounded model can be developed. Consequently, we followed a three-step process similar to that described in the literature (Braun & Clarke, 2006; Gioia, Corley, & Hamilton, 2013).

The first step in our data analysis was an in-depth analysis of the raw data (i.e., the interview transcripts). This analysis consisted of reading every interview several times, highlighting phrases and passages related to the overarching research purpose of understanding how AI capabilities are developed and applied within the business model. By coding the common words, phrases, terms, and labels mentioned by respondents, we identified first-order categories of codes that reflect the views of the respondents in their own words.

The second step of the analysis was to further examine the first-order categories to detect links and patterns among them. This iterative process yielded second-order themes that represent theoretically distinct concepts created by combining first-order categories. These themes relate to key AI routines and business model innovation principles. In accordance with validity considerations raised in the literature, the themes were further refined using insights from the literature and data from interviews and secondary sources, such as internal documents, presentations, and newspapers (Kumar, Stern, & Anderson, 1993). We performed this step in the data analysis together, which allowed us to thoroughly discuss the data structure. Internal validity tests were conducted to ensure greater accuracy in the emergent themes through email correspondence and follow-up discussions with selected informants.

The next step involved the generation of aggregate dimensions that represented a higher level of abstraction in the coding. Here, we used insights from the literature to form theoretically sound dimensions relating to capabilities and business model innovation. Thus, the aggregate dimensions built on the first-order categories and second-order themes to present a theoretically and practically grounded categorization. Fig. 1 shows the entire data structure that resulted from the data analysis.

As a final step, we theorized about the logic and linkages across aggregate dimensions, second-order themes, and first-order categories. Because we sought to understand how AI capabilities are developed and applied in business models and how companies manage these processes, we contrasted lines of insight from the cases. This practice of comparing cases allowed us to further refine our data structure and generate an overall model. The initial results of the study were presented to three key informants from case companies to validate the results through discussion. Further adaptations were made where relevant.

4. Findings

Building on empirical data from case companies, we identify and conceptualize the underlying capabilities associated with AI in a digital servitization context. To untangle these capabilities, we specifically focus on various advanced digital servitization initiatives where AI has played a pivotal role. We present our findings in two parts, one relating to AI capabilities, and the other dealing with the principles underpinning AI business model innovation for digital servitization. Following presentation of the findings, we outline the resulting framework and elaborate on how developing AI capabilities and making the transformation to an AI business model for digital servitization can enable scaling of AI with greater depth and breadth across ecosystems.

4.1. AI capabilities

Our analysis uncovers three interrelated AI capabilities that manufacturers must develop to truly profit from digital servitization: *data pipeline capabilities, algorithm development capabilities*, and *AI democratization capabilities*.

4.1.1. Data pipeline capabilities

Data pipeline capabilities lay the foundation for AI capabilities in that they enable firms to sense the industrial environment by capturing data and insights from multiple sources and presenting what they have

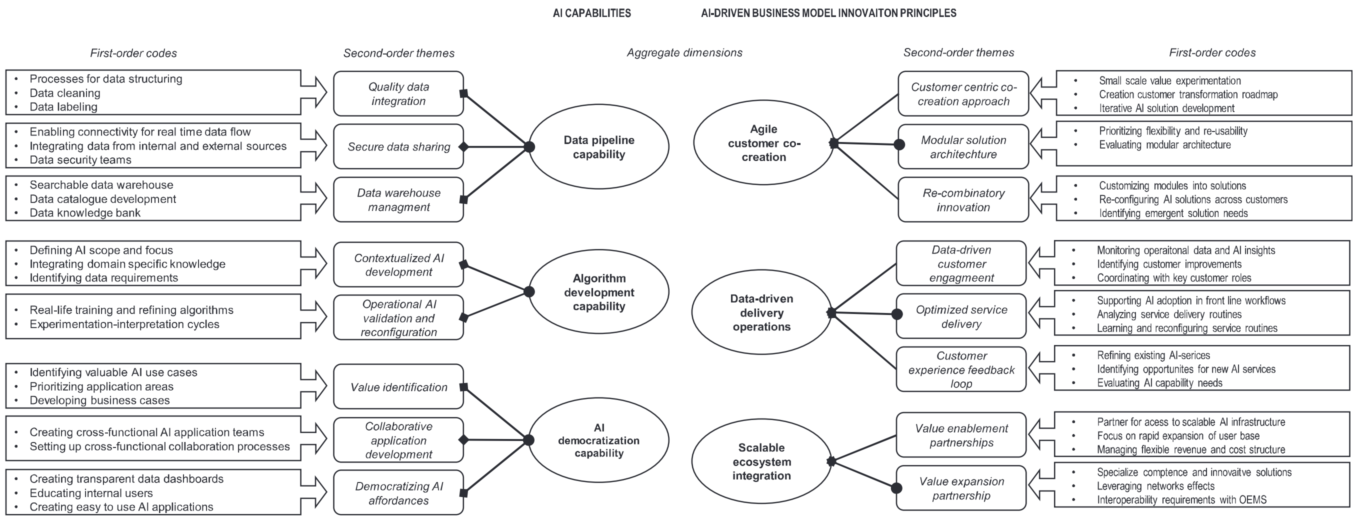

Fig. 1. Data structure.

gleaned in a structured way. Access to vast data sets is often referred to as the fuel that enables the AI algorithm to create its insights. Informants emphasized that the amount and quality of data fed into AI will directly correlate with the output. The goal is to secure a data pipeline by creating routines for gathering, cleaning, integrating, validating, and transferring data in a systematic, secure, sustainable, and scalable way. As noted by many informants, this is easier said than done, and securing the data pipeline proved to be a key challenge they had to overcome in their AI journey.

An important first step in achieving this goal is to develop routines and resources for *quality data integration* from industrial equipment assets and sensors. Thus, data must be made simple and accessible in a secure manner. As our informants recounted, in recent years, the potential insights emerging from data have increased substantially as manufacturers have started to install advanced sensors (e.g., load measurement, hydraulic assessment) in their equipment coupled with sophisticated tools for positioning and situational awareness as well as connectivity. It is important to have processes in place to ensure that these vast data sets are structured in a way that is possible to use. A vital aspect of this routine is focusing on cleaning (i.e., deleting erroneous data) and organizing the data to create a trusted analytics foundation. As the volume of collected data is growing rapidly, major investment is being poured into data integration by labeling, structuring, and correlating data that previously resided in silos. A digital lead from Solutioncorp described the importance of integrating internal and external data in a secure manner:

It is necessary to understand that you have a lot in place already because there is a lot of data to act on if you can access it securely. So, we do not see that there is a lack of information, but the challenge is rather in collecting this data, to consolidate it and create a common worldview so that we can make it useful. And to do this, you need the right toolbox in order to get this collection, structuring, analysis, and feedback loop going.

A second component relates to *secure data sharing*. All equipment providers agreed that expanding the scope of available data by integrating data from different sources, such as OEMs, customer systems, and third parties, was highly relevant in the context of AI-based solutions. One informant from Shipcorp reported that there are more than 2,000 sensors per ship that funnel the data to their cloud-based digital platform. It is also critical to ensure consistent connectivity and real-time data flow to monitor various aspects of machine performance remotely in real time. Indeed, a large portion of securing the data pipeline is connecting existing assets and equipment to create comprehensive data sets for AI to work with. An automation manager from Conglocorp stressed the importance of reliable and structured data flow for AI:

We need to ensure that we have a very good and consistent flow of reliable data from our machines to ensure that we can make sense of the operational environment. Connectivity is critical for many of our artificial intelligence applications; this enables us to have real-time data, and connectivity also provides vital data inputs in terms of positioning.

Another important consideration is combining data from multiple internal and external sources. By way of illustration, third party sources, external data, sensors, and publicly available traffic and weather data can be added on to internal databases and systems (e.g., ERP, CRM) to complement the customer equipment data of a provider. Several firms described the benefits of combining internal (e.g., vibrations in machine) and external data (e.g., road maintenance maps) to build more sophisticated models. Similarly, a digitalization manager from Shipcorp remarked:

We have a lot of data that can be used for AI model development, but we have learned that digital solutions become more customer value adding when we can include data beyond analysis of specific vessel operations. Think about historical weather data from third parties combined with our vessel system data. When we do such data integration, suddenly we can find more accurate models for route optimization.

Yet, obtaining and transferring large data sets in a secure manner can be difficult. For example, some of our firms noted that, in specific segments, the customers would not allow them to transfer operational data beyond the customers' systems and across national boundaries given their security concerns. It is, therefore, important to systematically assess data security aspects to secure customer buy in. For example, several of the studied firms had created dedicated data security teams to manage sensitive customer data and to secure control of how the data is handled.

Several informants highlighted the importance of routines for *data warehouse management* to provide integration of data from different sources and to enable search interface to make it easy to query details of the data landscape. The function of such data warehouses is to provide a repository and a platform for structuring, integrating, and filtering data. Informants noted that, as the volume of collected data grows exponentially, structured databases and platforms are a vital precondition for enabling advanced analytics. Putting data in a centralized data warehouse makes it more efficient for engineers or the AI software to exploit the data so that improvements can be identified. A critical process in data warehouse establishment is development and maintenance of an accurate data catalogue including the location of data, explicit guidelines for what to do with the data, how to protect the data, and standards for when and how to store the data for use and reuse by multiple parties. This provides opportunities for creating a data knowledge bank. For example, informants felt it useful to develop knowledge glossaries to define the terms used in the databases. These, it was affirmed, would facilitate interaction with each other, with external stakeholders, and between digital systems. This activity would allow assets (e.g., machines and data sources) to be linked to the relevant glossary terms, making it easier to find relevant data in the data warehouse catalogue. A business development manager from Truckcorp described the role of handling the data in this way:

Data has become the vehicle that takes us from problem to solution, and the data lake, processing, and data science team have worked with us to build a "map" that can turn this into a reality. The ability to tap into data, trends, and insights is truly powerful and promises to be the foundation for our sustainability mission long into the future.

4.1.2. Algorithm development capabilities

Algorithm development capabilities enable the creation of basic cognitive functions of AI through the development of algorithms that predict the future state or actions of the business. These capabilities are typically the focus of much AI discussion in manufacturing firms, yet few have in-depth knowledge of the underlying routines required.

A crucial step for AI capability is building routines for *contextualized AI development*. AI algorithms holds transformative potential to identify and solve abstract and complex problems. However, developing skills in algorithm development is not easy for traditional manufacturing firms. All of our case-study firms had secured partnerships with IT companies to obtain access to leading AI platforms and algorithms. Yet, this potential can be wasted if it is not executed with an underlying understanding of the business context. For example, many firms described initiatives that tried to outsource algorithm development to global IT leaders, but this had failed because their side lacked the insights to provide contextualization and operational knowledge in the industrial domain. Indeed, leveraging business knowledge in the age of AI requires routines and competencies to define the scope and focus of algorithms internally. The first task is to specify and prioritize – a desired outcome that can be achieved by building a predictive model (e.g., reduce unplanned stops by 15%). As described by many informants, this domain-specific insight into needs and operational knowledge (e.g., failure rates and equipment configurations) is what allows industrial providers to profit from AI.

Because AI systems are “trained” rather than programmed, they often require huge amounts of labeled data to perform complex tasks accurately. A crucial aspect is being able to creatively identify the data needed from existing data catalogues as well as external data sources to build an effective predictive model. For instance, interpreting customer inputs on their key bottlenecks can give vital insights into needed data parameters such as production load, standstills, and common failure modes. Therefore, understanding the key performance indicators (KPIs) being addressed by the new models (e.g., downtime and maintenance costs) provides the metrics required to determine whether existing data structures may be used. Thus, it is critical to involve staff with a clear industrial understanding of the application domain to set up and train the AI models. A business development manager at an AI and analytics provider who partnered with many of the case firms (e.g., Conglocorp, Solutioncorp) described this need from an outside-in perspective:

> *It doesn't make sense that each of these equipment manufacturers should also make their own algorithms. But they still need to have knowledge about AI. You need some data scientist, but what you really need is your domain knowledge. You need to have engineers who know your equipment setup… They need to basically make sure that they have resources to support and the knowledge, and treat it as any other R&D project [following a structured process].*

Another vital aspect concerns routines for *operational AI validation and reconfiguration*. Crucially, the real power of an AI model is in its learning ability and its potential to generate novel insights through machine learning. Thus, the ability to improve algorithms depends on the ability to feed in high quality data to allow the algorithm to learn from real-life applications, but it is also vital to have experienced staff training the algorithm. The informants specifically mentioned that having the help of dedicated staff to interpret algorithm results sustains self-reinforcing learning, re-programmability, and the accuracy of the AI's simulating ability. For example, when setting up models, it is important to accommodate experimentation where hypotheses on new algorithms are tested to ensure that their results and suggestions have the intended effect (i.e., are valid) based on real-life data situations. For instance, Constructcorp mentioned programming AI to avoid driving wheel loaders over potholes, lessening the aging and deterioration of tires. This algorithm could distinguish potholes from other road deformations, substantially increasing a tire's lifespan and reducing maintenance costs. This improvement revealed additional hidden needs, such as road maintenance tracking and situational awareness, which allowed new AI services to be developed. The ability to analyze the data at high speed and accumulate knowledge allows the provider to program new machines with the data and insights from all other preceding machines. An automation manager from Conglocorp described this process of training algorithms using real-life data:

> *The AI system can learn from a really skilled operator how he [or she] fills the bucket. We have been working a lot with this bucket filling system and how to train the algorithms and, over time, this will be a key competence for us … We are learning over time, and our autonomous systems are becoming more competitive.*

4.1.3. AI democratization capabilities

AI democratization capabilities focus on making AI accessible to the entire organization and demonstrating its potential. The objective is to engage the workforce in identifying and experimenting with valuable applications of AI to create data-driven insights so that organizational activities are enhanced. To achieve true benefits for the business, technical capabilities are not enough. Firms need to develop in-house skills in democratizing AI to ensure that their insights are used in the organizational behavior of employees and processes, enabling their companies to create AI value for customers in diverse application areas.

A crucial aspect is to build routines for *value identification* so that high-value application use cases for AI are revealed in both internal and customer processes. To truly deliver groundbreaking value from AI, companies must work actively to utilize business and technical competencies to identify valuable and concrete (e.g., where and for whom) use cases. By creating routines for experimentation involving different competencies, firms focus on identifying and prioritizing specific problems that AI can solve through detailed assessment of customer journeys, business processes, and value chains. For example, Solutioncorp described holding sessions involving customer service staff, key accounts managers, and digital developers to assess customer service data so that priority areas for AI development could be identified. An important consideration in use-case experimentation is instilling procedures for rapid trials of “learn fast and fail fast” to create a culture of AI experimentation. Several companies described methods that they were applying to identify and test use cases, specify AI requirements, and assess their impact and strategic fit in a quick and iterative fashion. A frontline digital manager from Solutioncorp described a collaborative approach of working with frontline personnel and customers to experiment with AI use cases:

> *Together we work with new [AI] technology in a whole new way. The close contact with customers and [Solutioncorp] colleagues around the country is very important in order to quickly find new solutions that help our customers take the next step… Our strong R & D culture is a great asset to us. We have set up the AI lab that helps us to continuously develop our services and to build the solutions of the future together with our customers."*

A key issue is to build routines for *collaborative application development* using cross-functional teams to develop solutions for specific application areas. Dedicated teams of application developers, data scientists, data engineers, business developers, and business-unit experts should work in tandem with each other to leverage the data pipeline and algorithm development, with a focus on improving specific business and operational outcomes. Through collaboration, such teams can envision, build, deploy, and operationalize an end-to-end AI development process in a much more rapid fashion. As informants noted, focusing on target application areas – where solutions would be critical – creates the required urgency to ensure that development is not just focused on proof of concepts but also proof of value. A digital manager from Solutioncorp remarked “if there is no one screaming for a problem to be solved, we probably should not do it.” The implication was that, without agency and commitment, most AI solutions would fail before full scale impementation. Indeed, the key is to integrate the output of AI models into frontline workflows and processes by securing commitment from cross-functional competencies ranging from digital leads and data scientists to key account managers, sales representatives, and service delivery staff. A digital lead from Solutioncorp remarked:

> *Digitization and AI enables a completely different kind of teamwork, where you can twist and turn the information in a team with different skills and get this overview so that you can solve the problem together in a new way, because what it comes down to is really that AI technology is great and all, but if we do not work together and expand the applications and capacity for collaboration, then we still won't be able to solve the challenges in the industry.*

To enable AI democratization, companies must invest in routines for *democratizing AI affordances* so that the action potential of AI analytics is user friendly, understandable, and customized for each user group (e.g., key account managers, service managers, and staff). A key to this is illuminating the possible uses of AI in target application areas and clarifying how AI can or should be used in design and education. This is a critical factor for building transparency and trust in AI among employees. Informants noted that individuals are less prone to trust an AI application if they cannot comprehend how it operates or appreciate the insight it gives. This task requires a combination of basic training and the right support tools, such as intuitive dashboards, recommendation engines, and mobile apps. One critical component relating to AI democratization concerns the development of processes to consolidate business-relevant AI insights through data visualization, so that the insights that flow from AI are capable of being understood by non-experts. For example, several firms mentioned investing in data visualization tools such as analytics dashboards for various staff members. These dashboards can make transparent those hidden insights that inform decisions and actions. A straightforward initial step could provide different individuals with access to simpler applications, readily understood information, and basic recommendations. By starting with simpler, understandable applications, individuals are encouraged to use the data and AI-driven insights to improve their work approaches. Thus, facilitating easy access to AI-based insights is a vital component in developing trust and a culture of experimentation. That is to say, business-unit experts are democratized to work with data-engineering and data-science teams within the organization. A digitalization manager at Rockcorp described the importance of data visualization for enhancing the application of AI:

> *We are using a dashboard to show how much value our machines are really creating by aggregating insights from our AI analytics. We can compare our customers to each other to show how they can do better. When you can visualize it like this, it really allows our internal organization and the customer to understand the value AI can bring and do benchmarking with their industrial peers.*

4.2. AI-enabled business model innovation principles

A key insight from our respondents was the need to define principles to guide the organizational transformation needed to develop AI business models in digital servitization. This represents an important step in explaining the effective utilization of AI capabilities. For example, algorithm development capabilities can generate valuable insights and predictions from customer data but, if these capabilities are not leveraged within actual business operations and concrete customer offerings, the value may be lost. The data reveals three key principles that are central to AI business model innovation: *agile customer co-creation (value creation), data-driven delivery operations (value delivery), and scalable ecosystem integration (value capture)*. As demarcated before each principle has a center of gravity towards one of the business model elements of value creation, delivery and capture.

4.2.1. Agile customer co-creation

Agile customer co-creation focuses on value creation through developing processes capable of rapidly broadening the scope of what the company can do with AI to support its customers while reducing complexity through a modular approach. This is a crucial part of setting up value creation processes to ensure the scalability and profit potential of AI.

A key element is a *customer-centric co-creation approach* to speed up development and to deliver proof of value for AI solutions. The focus is on supporting customer success (i.e., KPIs) by iteratively co-creating AI-enabled service solutions for their most pressing operational needs. Informants noted that the inherent uncertainty of AI development means that agility is required, with small beginnings (i.e., micro-services) on a discrete use case with a clear value proposition that is subsequently refined and implemented in collaboration with the customer to demonstrate proof of value. For example, a strategy manager from Constructcorp explained that an agile co-creative approach entails a different logic of development with an earlier launch of AI micro-services before they are fully developed and tested, allowing users quicker access to the services, and granting them a collaborative role in the final development of a solution that more precisely fits the user's needs. As initial AI investments are proven, trust builds for further development, and the scope of the solution and customer engagement expands over time. To achieve this, the frontline must help customers identify and define their problems, prioritize and assist in creating a transformation roadmap, and provide support throughout the implementation phase. Similarly, a manager for the customer success team at Shipcorp described their approach to working with customers:

> *We need to be very customer focused in our solution development. Every customer will have problems and specific needs that our applications could address, and we need to adapt to that. To be successful, we need to work together with customers in defining the appropriate use cases and together build a roadmap for how to realize value for their operations.*

Informants maintained that the logic of such a co-creation approach means that the manufacturer becomes the customer's partner rather than supplier, which creates an interactive relationship based on increased transparency and mutual exchange. Similarly, a head of digital business development at Conglocorp explained the changed logic in these terms:

> *We have to be much more open to the market. It's no longer possible to have the development process shrouded in secrecy. We must start talking about challenges, not just about solutions.*

Another important aspect for value creation and innovation is to intentionally apply a *modular AI solution architecture*. By leveraging modularity, the complexity of solution development can be reduced, and the scope for adding novel functionalities (i.e. new micro-services) in step with emerging needs is expanded. To achieve this, informants stated that the AI technology must be flexible to be re-used in new application areas, and development teams should prioritize this from the start. Specifically, informants stressed the importance of having algorithms and systems that can be reconfigured to adapt to varying user needs and contexts and that can trigger new solution applications beyond the initial purpose intended. Informants emphasized the importance of having a systematic way of evaluating AI solutions as part of a modular architecture so that new modules are integrated seamlessly into a larger portfolio of integratable offerings. This approach also facilitates efficiency and re-usability. A digital business manager at Rockcorp described this principle:

> *You need to build your AI solutions to be more modular so it can be easy to reconfigure by the people internally and in the ecosystem.*

Finally, *re-combinatory innovation commercialization* is critical to ensure that solutions are scaled. Over time, the agile co-creation approach will lead to the development of a comprehensive portfolio of AI services, enabling the provider to configure customized and potentially more complex solutions using discrete AI-service modules. Respondents frequently mentioned how a successful AI solution that was developed and implemented with one customer often resulted in novel business opportunities. For example, Rockcorp described how an AI-enabled traffic management system can also be used to create a map of an underground mine so that problem areas can be identified. This helps to create novel AI-solution combinations by re-configuring existing service applications across customer segments. Hence, companies must harness flexibility and responsiveness in agile solution development to successfully introduce new functionalities. A digital lead from Solutioncorp described the company's approach:

> *We are starting to build a more comprehensive portfolio of AI service applications building on our work in our different business units. The goals are to be able to transfer these across industries and segments and be able to create new solution combinations. Certainly, there are always adaptations required but, when we have this goal from the start, it also forces us to be more modular and flexible in how we configure our applications.*

4.2.2. Data-driven delivery operations

Data-driven delivery operations focus on transforming value delivery processes to use data and insights from AI in operational and strategic decisions so that continuous improvement, learning, and innovation is achieved. An important function of data-driven learning is that it is disintermediated because it does not always require direct interaction with the customer. Thus, both front-line service technicians and back-line engineers and support staff can hold key roles in ensuring profitable value delivery. Many firms had set up remote data monitoring centers to enable real-time support of customer and internal service operations.

A key use of such centers is *data-driven customer engagement,* which ensures online support and monitoring of customers operations around the clock. A head of digital business development at Conglocorp described the mindset shift involved in working more closely with the customer to utilize data insights:

> *Instead of delivering pure figures into customer systems, we undertake to contribute more directly to their productivity. This means closer collaboration and greater responsibility, which may be felt to be a big step to take. But it's the right way to go.*

The benefit of such centers is that a few skilled engineers can monitor the performance of whole fleets of customer machines and provide concrete suggestions for improvements based on evaluating the AI's recommendations in real time. This means that customers can be offered increasingly detailed and appropriate advice on how certain operations can be performed more efficiently and how their machines can be used optimally in specific situations. Data monitoring centers play an important role in coordinating value delivery and AI usage among remote monitoring centers, internal front-line staff, and customers. For example, a customer may be called up to check the status of the equipment when an anomaly is detected (i.e., increased vibration), spare parts may be ordered well in advance of actual breakdowns, and service staff may receive detailed instructions on where to focus maintenance based on analyzed process data. A head of digital business development at Rockcorp described how they support customers with AI applications in their operations:

> *We have implemented specialized centers for digitalization, AI, and automation in strategic locations across the globe to help improve customer processes and boost productivity.... Customers utilizing this service for their projects can now turn their focus to other areas of the business with the knowledge that [our] team of experts are carefully monitoring progress on site and offering solutions in real time."*

Another affordance of AI is *optimized service delivery* focusing on continuous improvement of the internal service delivery processes for front-line staff. As the informants explained, companies must embed analytics-based decision making in their customer-facing processes (e.g., sales and service). Data monitoring centers exercise a critical role in supporting the transformation of existing workflows and ensuring that front-line workers embrace analytics as an essential tool to challenge established thinking and augment their judgment. For example, Conglocorp had leveraged its data and AI capabilities to implement routines for proactively identifying maintenance needs before a costly breakdown and for making time savings in their service processes. The benefits of such data-driven learning is continuous improvement by focusing on refining operational service routines. As our informants noted, the learning process is accelerated when AI services are quickly implemented and monitored by a dedicated team that support existing service staff so that new routines for value delivery can evolve through combinations of robust data and AI insights, operational experience, and learning by doing. This provides a path to progressively develop AI-service delivery processes, AI-enabled support tools, and procedural knowledge within the front-line organization. A portfolio manager from Constructcorp described how data-driven learning can provide feedback loops to support valuable interactions with customers and increase efficiencies in service delivery:

> *AI will have profound implications for how we can service our customers. Particularly for smaller customers in remote locations who lack own skills in operational analytics. We can cost effectively support their sites remotely and optimize operations... The opportunities for increasing efficiency of use are great, and we can also get an understanding of their operations to drive new service development and refine our internal processes.*

There are also vast opportunities for securing a *customer experience feedback loop*. The active use and monitoring of AI solutions provide many valuable insights for further development of AI capabilities and offerings. Informants stressed that AI services must be tested and improved in operational environments to create an explorative feedback loop for ways to refine the underlying algorithms and data sources powering the AI. Such feedback loops serve to identify new opportunities for the development of next-generation AI services and processes. For example, Conglogcorp explained that dedicated AI monitoring provided the ability to produce ever more accurate and sophisticated customer-behavior models and to tailor applications accordingly. Indeed, the implementation of AI creates powerful opportunities for learning and improvement, which promote the development of new and innovative AI services. By actively monitoring the AI predictions and comparing them to real-life events and contextualized knowledge from front-line staff, the interests of ongoing training and AI model refinement are also served. A digital manager at Shipcorp underlined the importance of the AI feedback loop for innovation and competitiveness:

> *The more we work with our data and algorithms to support our customers business the more we learn. We are uncovering hidden needs and patterns within operations to address in the future, and we are uncovering new application areas. But we are also uncovering limits to our current capabilities and improvement possibilities. This feedback loop will be critical for us to be a leading digitalization partner in the future.*

4.2.3. Scalable ecosystem integration

Scalable ecosystem integration focuses on value capture by stimulating the ability of business units, customers, and ecosystem actors to co-produce new outputs and capture value from the AI in a more rapid and scalable manner. Our informants noted that ecosystems are playing an increasingly prevalent role as scaling catalysts as firms pursue a digital servitization strategy based on AI.

To ensure scalability of AI efforts, informants stressed the importance of *value enablement partnerships* to rapidly scale AI solutions and infrastructure. Of prime importance is the creation of dedicated partnerships to provide access to back-end AI competencies that will support the ongoing development of the business and its scalability. For example, leading global IT firms, such as Microsoft and IBM, were often integrated into the backbone of the business model by providing basic cloud infrastructure and algorithm support. Such partnerships provides the ability to handle the increasing volume of data generated by a rapidly growing number of users. This type of partnership is seen as a critical enabler. For example, Conglocorp had exploited such partnerships to build a comprehensive AI-enabled service portfolio by leveraging their partners' leading back-end AI expertise and their own organization-wide in-depth contextual insights and access to operational data in the mining context. The benefit of this approach is the scalability where infrastructure costs can follow user adoption in a nonlinear way. A digital lead from Solutioncorp recounted:

> "*Our partnership with Microsoft has been a vital enabler for us to be able to scale up our AI initiatives across broader customer segments. They provide a backbone of infrastructure and easily configurable software tools to allow us to quickly ramp up and explore new solution areas. If we would have taken on this role ourselves, we would probably have drowned*

in the cost and lengthy time frame to get such an infrastructure up and running.

A second important domain for value realization is leveraging *value expansion partnerships*. This includes leveraging ecosystem partnerships with SMEs, startups, and OEMs to expand the scope of potential value creation and capture. For example, smaller firms and startups can often serve as vital partners when scaling AI initiatives. These firms often have more specialized and/or industry specific expertise that can augment internal AI capabilities and catalyze AI business model innovation and organizational transformation. A head of digital business at Rockcorp remarked how such a partnership had been vital in transforming its business model:

> *I think the partnership with [Specialized AI SME] has been vital in instigating our transformation. They have filled important gaps in our service portfolio to advance our market presence… But also helped us in thinking how we could run the business more agile and scalable. It is clear that we can't do everything alone, and we need to open up to integrate the ecosystem.*

In this respect, it is important to prioritize open solution configuration. This means focusing from the start on the degree of ease with which AI modules can be reconfigured to create new solutions for the entire ecosystem, including customers, delivery network actors, and partners. A core element is to allow open APIs and SDKs for extended ecosystems. For example, Shipcorp had focused efforts on reducing transaction costs on their AI platform by allowing users and or complementors to customize application interfaces by building on their AI algorithms and structured data. Similarly, a head of digital business at Rockcorp described their open approach:

> *We want to be open and OEM agnostic in developing our solutions. This increases our profit potential by offering analytics services not only on our equipment but also other OEMs. On the other hand, we also gain benefits from an open ecosystem which can develop additional solutions to complement our offerings.*

Indeed, once an AI algorithm or data pipeline is developed, it can often be scaled across users with very low marginal costs and network effects. In addition, the more users connected to an algorithm, the more powerful its base for learning, which further promotes the need for scaling AI across broader ecosystems and customers. This allows external actors to create new value propositions, driving revenue generation without any corresponding cost increases. Informants also highlighted the potential of re-configuring AI solutions by using applications from multiple ecosystem actors. A partnership program manager at Shipcorp explained the innovation potential of the ecosystem:

> *I think the key for us is to get this ecosystem up to scale. The more users and complementary app providers we have leveraging our platform and machine learning algorithms, the more we will gain. A main source of revenue is of course their usage of our platform, but I believe a lot of the future value will come from the solutions they build on top by recombining applications for new types of use.*

4.3. A co-evolutionary framework for scaling AI capabilities through business model innovation

This section brings together our key findings to present a co-evolutionary framework for scaling AI capabilities through business model innovation (see Fig. 2). Indeed, as our informants indicated, AI is on the verge of reshaping the strategies, offerings, operating models, and business models of manufacturing firms as they strive to provide more advanced digital services for their customers. Still, firms struggles to scale AI to unlock this potential. Our results suggest that companies that excel at connecting business routines, aggregating and structuring the data flowing between them, and extracting the value of the data through analytics and AI applications in their business operations and ecosystems will be at an advantage. However, profiting from AI is not easy, and manufacturers need to simultaneously prioritize capability development, innovate their business models, and organize for scalability. For instance, if the last mile of democratizing AI is not completed (i.e., engaging the required organizational resources and establishing proper routines to monitor AI), AI solutions will never be delivered at scale and the potential value of AI may be wasted. Our framework is designed to address these operational and scaling challenges by capturing the insights and knowledge from leading manufacturers at the start of their AI journeys. We illustrate this iterative and co-evolutionary process with reference to three overall, yet interdependent steps.

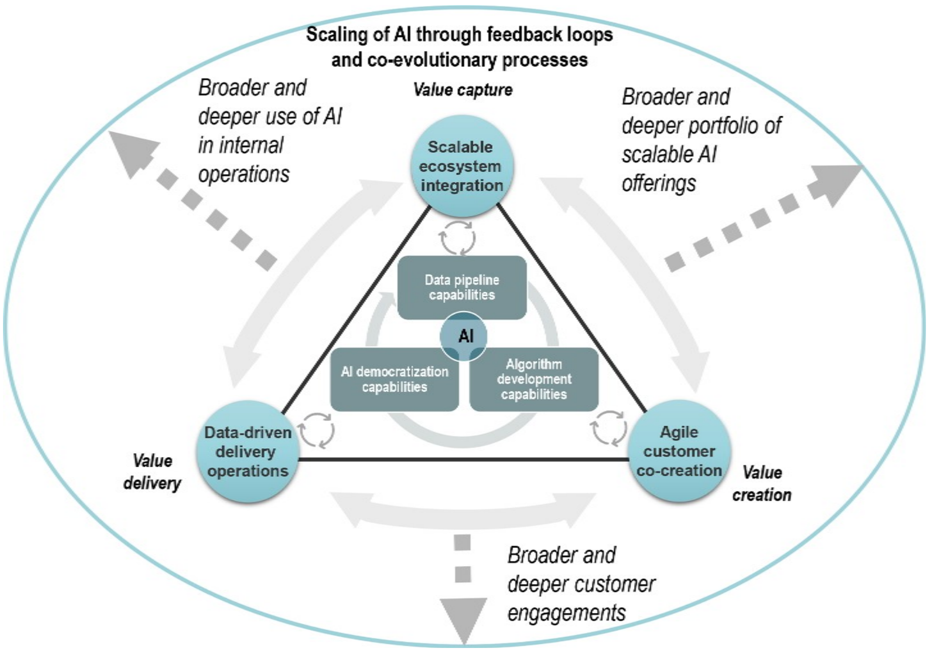

Fig. 2. A co-evolutionary framework for scaling AI capabilities through business model innovation.

Develop interdependent AI capabilities. As a first foundational step, manufacturers should engage in the development of interdependent AI capabilities – namely, *data pipeline capabilities, algorithm development capabilities, and AI democratization capabilities*. Without possessing these capabilities, organizations lack the necessary foundations to identify, assess, and exploit AI-related business opportunities. However, it is important to recognize that significant investment in this process is needed if appropriate routines, infrastructure, and activities are to be developed. Securing the data pipeline is foundational to get AI to work, and defining contextualized algorithms building on internal expertise holds the core value-creating potential. Yet, without involving the organization in democratizing AI to allow for internal experimentation, most AI initiatives will fail to scale and reach their potential. It is important, therefore, to highlight the interdependent and synergistic effects of different AI capabilities and the feeback loops among them. Indeed, possessing higher levels of certain capabilities is not always beneficial if others are absent, implying a tradeoff between the costs and benefits of AI capability development.

Ensure scalability through AI-driven business model innovation principles. Capabilities are not sufficient on their own. Firms need to actively transform and innovate their business models to leverage the application of AI by considering the underlying processes, organizations structures, and usage of AI technology in business activities. We find that, at its core, a scalable transformation of the AI business model is driven by three fundamental principles: *agile customer co-creation, data-driven delivery operations, and scalable ecosystem integration*. First, agility and customer focus in defining AI use cases is key to getting AI operational for paying customers and providing the incentives and feedback loops required for organizational transformation. Embracing a modular approach to AI solutions ensures that the focus is placed on scaling different combinations of AI-enabled services across customer segments. Second, we find that profitable value delivery requires dedicated investments in real-time monitoring of AI solutions. The active monitoring and use of AI is key to creating a data-driven culture where the benefits of AI capabilities are exploited for the purpose of optimizing both customer-facing and internal processes. Finally, the ecosystem is key in making the application of AI scalable, both in creating a scalable infrastructure for AI and in providing trust and inspiration for the transformation. Our informants underlined the importance of openness and the need to harness generativity to let ecosystems drive the recombination and innovation of internal AI resources. Our findings suggest that these principles has synergistic benefits creating feedback loops and learning both within the business model innovation process (i.e. between elements) and also feeding back to AI capability development such as motivating further algorithm development or investments in the data pipeline.

Leverage scaling mechanisms for AI-driven business model innovation. The firms we studied argued that co-evolution of AI capabilities and AI business-model innovation principles reinforces the potential to scale AI-enabled business models and offerings beyond individual use cases to broader customer segments while simultaneously increasing the scope of offerings. We envision this as an iterative process and co-evolutionary process where capabilities, offerings, operational processes, partnerships, and business models for AI co-evolve over time and build on each other. In our conceptualization, scalability refers to the provider's ability to expand its initial AI solution and scope so that it can reach a larger market space and achieve economies of scale internally and externally. This includes increasing the number of customers or users as well as the rate of adoption in internal processes and expanding its portfolio of offerings and revenues from AI. *Scaling towards customers* includes both breadth of AI services offered to multiple customer segments and the depth of AI service value offered to a particular customer or site which is enabled by agile customer co-creation and data driven delivery operations. *Scaling of offerings* includes the breadth of diverse AI offerings and the depth of increasingly complex AI service solutions which is enabled by agile-customer co-creation and scalable ecosystem integration. *Scaling towards service operations* includes the breadth and depth of uptake of AI as a supportive tool in servicing customers which is enabled by data driven delivery operation and scalable ecosystem integration. Our findings suggest that the inherent feedback loops of building AI capabilities and following AI specific business model innovation principles allows firms to achieve these scaling benefits.

5. Discussion

5.1. Theoretical contributions

This study has sought to explore how manufacturing firms can develop AI capabilities and business model innovation principles to scale AI in digital servitization. Due to the recent development of AI as a competitive driver in manufacturing, this field of research is still nascent and in need of further development (Bailey et al., 2019; Iansiti & Lakhani, 2020; Parida et al., 2019; von Krogh, 2018). Our findings provide empirical insights into the intermediate development steps toward AI-driven business model innovation by leading manufacturers engaged in digital servitization. We provide an in-depth characterization of AI capabilities and key principles for business model innovation as a means to assimilate AI into business practice. We further elaborate on the feedback loops and mechanism which enable scaling of AI business models. More specifically, the study makes three theoretical contributions to the AI, digital servitization, and business model innovation literature.

First, *we contribute with an in-depth characterization of what AI capabilities are and their micro-foundational routines and practices*. This is an important first step toward understanding AI capabilities in industrial manufacturers engaged in digital servitization. Indeed, many scholars have emphasized the importance of developing organizational capabilities to profit from AI and digitalization (e.g., Barro & Davenport, 2018; Brock & Von Wangenheim, 2019; Iansiti & Lakhani, 2020; Shrestha et al., 2019; von Krogh, 2018; Sjödin et al., 2020b). However, the management literature sheds little light on what these capabilities actually are (Brock & Von Wangenheim, 2019; Tarafdar et al., 2019) and how industrial firms develop them (Iansiti & Lakhani, 2020; Parida et al., 2019). To overcome this crucial knowledge gap, we conducted the first in-depth analysis and identification of AI capabilities for industrial firms in a business-to-business setting. We conceptualize three sets of interdependent AI capabilities for industrial manufacturers: data pipeline capabilities, algorithm development capabilities, and AI democratization capabilities. Studies such as ours can make a contribution to the rapidly emerging frameworks and literature on digital servitization and the ways in which AI can offer valuable digital opportunities for servitization to create and capture new value (Autio et al., 2018; Kohtamäki et al., 2019). In particular, our conceptualization of AI democratization capabilities is particularly relevant in coming to understand the application of AI in modern business organizations through collaborative application development and democratization of AI affordances. This study encourages scholars to specifically focus on the application of AI as a foundational element in the next generation of digital servitization and expansion of digital service business (Gebauer et al., 2020; Kohtamäki et al., 2019; Sjödin et al., 2020b). Such a view has been largely lacking.

Second, we contribute to the literature on AI and digital servitization by *uncovering key principles for AI-driven business model innovation in digital servitization*. While recent research by Iansiti and Lakhani (2020) has placed strong emphasis on the business model as a vehicle for ensuring AI application in firms, there are still many knowledge gaps, particularly in the industrial domain. Iansiti and Lakhani (2020) provide specific, in-depth examples of how AI has been applied in the business and operation models of leading B2C firms, such as Ant Financials, Amazon, and Google, although less so in the industrial domain. Accordingly, our analysis of six leading industrial companies provides the first empirical evidence of how companies incorporate and scale AI capabilities into their business models by identifying key transformation principles. In our framework, we highlight three underlining principles for AI business models related to agile customer co-creation, data-driven delivery operations, and scalable ecosystem integration. We argue that these principles form the initial key steps for a traditional manufacturing firm to capitalize on its AI capabilities and offer diverse digital servitization business models. In particular, we illustrate intermediate steps in scaling AI from initial proofs of concept towards broader business model adoption which is regarded as a key problem area (Parida et al., 2019) This approach broadly responds to previous calls for research to develop a greater understanding of AI capabilities and business model linkages for value creation (Bailey et al., 2019; Colbert, Yee, & George, 2016; Hadjimichael & Tsoukas, 2019; von Krogh, 2018).

Third, we contribute to the literature on (digital) business model innovation by *illustrating how the scaling of AI-driven business model innovation is supported through interdependencies, feedback loops and co-evolutionary processes.* These findings are nested within and between the processes of development of AI capabilities and key principles for AI business model innovation. While this underlying logic is suggested in the literature on AI (Brock & Von Wangenheim, 2019; Iansiti & Lakhani, 2020; Jovanovic et al., 2021) and business model innovation (Gebauer et al., 2020; Sjödin et al., 2020b), more insights are needed. Our paper offers initial insights into these feedback loops and how value is created, delivered, and captured through the application of AI capabilities to drive business model innovation. In particular, this study illuminates the logics and mechanisms that help explain the linkages between the business model shift toward digital servitization, AI capabilities, business model transformation, and business model innovation. Yet, these processes and linkages are ripe for further research and detailed investigation.

5.2. Managerial contributions

AI is the engine that drives digitalization, and the companies that can execute AI capabilities in scale within their business model are those that will prosper in the future. In today's world, every firm is working on AI-driven transformation in some shape or form. However, the charm of AI fades within a short while, when organization/s realize that they have not been able to scale AI across business processes to meet profit expectations. Indeed, in AI, "the gap between ambition and execution is large at most companies" (Ransbotham et al., 2017, p. 1). A McKinsey survey of executives underscores the relevance of improving our understanding of AI capabilities, revealing that the vast majority of executives consider AI capabilities crucial but only 16% of business leaders felt "well prepared" to address potential capability gaps (Barro & Davenport, 2018, p. 23) and scale AI across the business.

Our findings demonstrate how managers can approach the development of AI capabilities, how they can be implemented and democratized in operations and business models, and how AI can provide valuable growth and revenues. The findings reveal three sets of critical AI capabilities: data pipeline, algorithm development, and AI democratization. To incorporate these capabilities into their businesses, manufacturers need to transform their business models by focusing on the key principles relating to agile customer co-creation, data-driven delivery operations, and scalable ecosystem integration. We envision the scaling of AI as an iterative process where capabilities, offerings, operational processes, partnerships, and business models for AI co-evolve over time and build on each other through active feedback loops. Our findings, provide helpful advice for companies needing to progress along their AI journey from one-off AI experimentation to a robust organization-wide capability that provides a source of competitive agility and growth.

5.3. Limitations and future research

Our study has several limitations that provide opportunities for further research. First, we studied industrial firms engaged in AI-based digital servitization to better understand and define AI capabilities and business model innovation principles. Arguably, AI capabilities are likely to be less context dependent than traditional capabilities (Iansiti & Lakhani, 2020), but we cannot judge the generalizability of the present findings without further research. In particular, business model innovation principles may vary between B2B and B2C. The case firms are all large, well known, and internationally diversified industrial manufacturers. We encourage scholars to examine our findings in other contexts and to extend or modify them as appropriate.

Second, we believe that opportunities exist to move beyond our empirical focus on digital servitization and examine the capabilities and principles that support the successful use of AI for other applications such as the introduction of AI into vehicles, retail stores, or digital shopping platforms and address alternative ways for companies to use AI capabilities. It will be interesting to see whether, to what extent, and how firms working on these applications need different AI capabilities from the ones presented in this study.

Finally, we believe that further research should study the identified capabilities (e.g., AI democratization) and business model innovation principles in greater detail and extend our framework to include related capabilities and business models that allow companies to exploit the identified capabilities fully. For example, ecosystems are becoming increasingly important in the era of AI, and future research could devote increased attention to ecosystem orchestration, governance, partnering, and new types of shared revenue models for AI (Jovanovic et al., 2021; Kamalaldin, Sjödin, Hullova, & Parida, 2021; Sjödin, Parida, & Kohtamäki, 2019). In addition, the role of AI capabilities in driving the transition to autonomous solutions (Thomson, Kamalaldin, Sjödin, & Parida, 2021), smart cities (Linde et al., 2020) and a more sustainable and circular economy appears promising (e.g., circular business models). It seems likely that AI capabilities will play an even more prominent role in the future, and the present article is merely a first step toward an understanding worthy of their importance.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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