Technological Forecasting & Social Change 197 (2023) 122903

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Artificial intelligence enabling circular business model innovation in digital servitization: Conceptualizing dynamic capabilities, AI capacities, business models and effects

David Sjödin [a,b,*], Vinit Parida [a,b,c], Marko Kohtamäki [a,b,c]

[a] Luleå University of Technology, SE-971 87 Luleå, Sweden
[b] University of South Eastern Norway, USN Business School, Norway
[c] University of Vaasa, School of Management, PO Box 700, FI-65101 Vaasa, Finland

ARTICLE INFO

Keywords:
Artificial intelligence
Digital transformation
Circular business models
Digital servitization
Sustainability
Circular economy
Ecosystem
Twin transition
Platform

ABSTRACT

This study explores the potential of AI to enable circular business model innovation (CBMI) for industrial manufacturers and the corresponding AI capacities and dynamic capabilities required for their commercialization. Employing an analysis of six leading B2B firms engaged in digital servitization, we conceptualize the perceptive, predictive, and prescriptive capacities of AI, which enhance resource efficiency by automating and augmenting data-driven analysis and decision making. We further identify two innovative classes of AI-enabled CBMs – augmentation (e.g., optimization solutions) and automation (e.g., autonomous solutions) business models – and their main circular value drivers. Finally, our research reveals novel dynamic capabilities underpinning the innovation of AI-enabled business models – value discovery, value realization, and value optimization capabilities – which enable manufacturers to make economic and sustainable values come to life in collaborating with customers and ecosystem partners. This study represents an important step in our understanding of how AI can drive circularity and sustainable innovation in industrial digital servitization. Overall, our study contributes to practice and the academic literature on AI, circular business models, and digital servitization by highlighting the potential of AI to empower CBMs for industrial manufacturers and the underlying processes of this digital transformation.

1. Introduction

> *"We are starting to think of the emergence of a new class of business models leveraging logics of digitalization, AI, and circularity. The potential is there for us to achieve more sustainable customer relationships, but we need to adapt internally and, in our partnerships, to make this happen."*
>
> *[Digital lead, Solutioncorp reflecting on their future strategy]*

The current climate change crisis calls on industrial manufacturers to assume greater responsibility for transitioning to a more circular and sustainable industrial sector (Bocken et al., 2018; Ritala et al., 2018; Geissdoerfer et al., 2020; Palmié et al., 2021). To address this challenge, artificial intelligence (AI) has been portrayed as an important transformative force to make the industry more sustainable and competitive (Iansiti and Lakhani, 2020; Chauhan et al., 2022; Kristoffersen et al., 2020; Nishant et al., 2020), following the logic of the twin transition (Muench et al., 2022) and digital servitization (Kohtamäki et al., 2022).[1 and 2] Indeed, many industrial companies that put sustainability issues at the top of the corporate agenda are also investing in AI development to enable circular business models (CBMs), which focus on creating value by implementing solutions that reduce, reuse, and recycle material and energy resources (Frishammar and Parida, 2021). We argue that the AI-enabled circular business model (CBM) offers an unprecedented opportunity to support entirely new ways of doing business and unlocking new sources of value, revenue, and sustainability (Davenport and Ronanki, 2018; Paschen et al., 2021; Sjödin

* Corresponding author at: Luleå University of Technology, SE-971 87 Luleå, Sweden.
E-mail addresses: david.sjodin@ltu.se (D. Sjödin), vinit.parida@ltu.se (V. Parida), marko.kohtamaki@uva.fi (M. Kohtamäki).

[1] Digital servitization, has been defined as 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).

https://doi.org/10.1016/j.techfore.2023.122903
Received 17 June 2022; Received in revised form 29 September 2023; Accepted 29 September 2023
Available online 13 October 2023

et al., 2021a) However, practical examples of industrial firms that can successfully create and capture sustainable value from AI-enabled CBMIs are scarce because AI technologies continue to advance faster than the industry can adapt, and they require the development of new resources and capabilities as well as the introduction of radically different business models (Iansiti and Lakhani, 2020; Sjödin et al., 2021a). Indeed, the prime challenge is no longer technology development but putting AI technology capacities to use in concrete business-model applications[2] that make circularity and sustainability come to life.

We argue that, to advance sustainability in the context of industrial business-to-business (B2B), manufacturers engaged in digital servitization must transform their business models, capabilities, and ecosystem partnerships to leverage the inherent potential of AI capacities (Iansiti and Lakhani, 2020; von Krogh, 2018; Sjödin et al., 2021a; Kohtamäki et al., 2022). For example, industrial manufacturers must build the required novel capabilities so that they can identify opportunities to address customers' sustainability challenges with AI capacities, develop appropriate solutions, and manage their evolution over time to realize circular gains. Moreover, industrial firms need to use newly developed AI capacities and capabilities to commercialize new CBMs, which represents a challenging undertaking. However, the literature discourse on linking AI, digital servitization, and CBMI is still in a nascent stage, and several knowledge gaps persist.

First, there is *a need a to conceptualize novel types of industrial AI-enabled circular business models* and delineate their potential sustainability impacts. While the concept of the CBM has gained momentum in recent years (Ritala et al., 2023; Geissdoerfer et al., 2020), the integration of AI and digital servitization (Sjödin et al., 2021a, 2021b) into these models is still a relatively unexplored area. Undeniably, AI systems and technologies have become more pervasive and efficient (Iansiti and Lakhani, 2020) and, consequently, they have become less costly and more effective in tackling prevailing business, societal, and sustainability problems (Phan et al., 2017; Chauhan et al., 2022). In particular, new classes of circular business model that leverage the unique AI capacities of augmentation and automation (Raisch and Krakowski, 2021) need to be conceptualized and developed. Although AI-enabled business models have been established in the related literature on digital servitization (Kohtamäki et al., 2022), there is still much room for exploration and innovation in this area with regard to their effects on sustainability and circularity. For example, AI can be used to support sustainable service offerings, such as optimizing efficiency, reducing waste, and improving sustainability, while enabling smart decision making and predictive maintenance (Kristoffersen et al., 2020). We argue that most knowledge of business model innovation is still rooted in linear models of the take–make–waste paradigm (Bocken et al., 2018; Geissdoerfer et al., 2020). Indeed, updated business model innovation frameworks are required to explain the overall logic of how a firm can leverage AI capacities to create, deliver, and capture value from novel smart solutions in collaboration with their industrial partners in a more sustainable way (Chauhan et al., 2022).

Second, there is a *need to understand the capabilities required to commercialize AI-enabled business model innovations* through effective utilization of AI capacities. As industrial manufacturers increasingly look to AI-enabled CBMs to improve efficiency and realize sustainability, there is a growing need to better understand the capabilities and underlying routines required to implement these models (e.g., Reim et al., 2021). The complex and dynamic interplay of internal and external factors involved in implementing such models can be difficult to navigate (Konietzko et al., 2020), requiring novel routines and capabilities. For example, manufacturers may need to develop routines to assess the economic, social, and environmental impacts of their solutions on customers' operations as well as the needs and expectations of various stakeholders. We argue that the theoretical lens of dynamic capabilities provides an ideal perspective from which to study the underlying routines of AI-enabled circular business model innovation (CBMI) and commercialization and build important insights. Specifically, dynamic capabilities provide a relevant theoretical lens to understand the capabilities and micro-level routines required to sense, seize, and reconfigure (Teece, 2007) the emerging opportunities for AI-enabled CBMI. Yet, no prior studies have investigated dynamic capabilities in this context, leaving various gaps that need to be filled. In particular, there is a need to understand how firms can develop routines to utilize AI capacities to create and deliver new AI-enabled solutions for circularity in collaboration with customers and diverse ecosystem actors.

To address these challenges, the purpose of this paper is twofold. First, it seeks to conceptualize AI-enabled CBMs for industrial firms and their corresponding AI capacities. Second, it aims to understand how dynamic capabilities enable the commercialization of AI-enabled CBMs for industrial customers. We build on the case studies of six leading industrial technology providers engaged in the transformation to AI-enabled CBMI.

Our study findings detail the specific perceptive, predictive, and prescriptive capacities of AI, which enable manufacturers to increase resource efficiency by automating and augmenting data-driven analysis and decisions. We further define the application of these capacities and conceptualize two novel classes of AI-enabled CBMs: augmentation (e.g., optimization solutions) and automation (e.g., autonomous solutions) business models. Specifically, we emphasize the circular effects of these business models in advancing sustainability (e.g., extending product life cycles, optimizing resource usage). Finally, our research reveals novel dynamic capabilities underpinning the commercialization of these AI-enabled CBMs: value discovery, value realization, and value optimization capabilities, which enable providers to make economic and sustainable values come to life. Our results carry several implications for theory and practice relating to AI, digital servitization, CBMI, and business model innovation in general. Moreover, they provide a novel avenue for further research on AI-enabled CBMs.

2. Theoretical background

2.1. Understanding the potential of artificial intelligence capacities

Embracing the limitless possibilities of artificial intelligence (AI), the industrial landscape stands on the brink of an unprecedented revolution, poised to unlock untapped potential and propel industry into a new era of productivity and innovation. For example, consider an underground mining operation entirely manned by autonomous vehicles, where all process parts and energy systems are optimized to achieve net zero. It stands as a remarkable illustration of the potential of AI, enabling unparalleled efficiency, safety, and sustainability in mining operations. Indeed, AI represents the next generation and most advanced form of industrial digitalization and digital servitization (e.g., Parida et al., 2019; Kohtamäki et al., 2022). The growing hype and the industrial AI capacity investments are fuelled by the increasing power of computers, the self-learning capacities of algorithms, and the availability of big data (Iansiti and Lakhani, 2020; Kaplan and Haenlein, 2019). Accordingly, industrial AI capacities involve leveraging digital technology, such as sensors, connectivity, and advanced algorithms, to provide new value-creating and revenue-generating opportunities (Parida et al., 2019) with the potential for increased profits (Kohtamäki et al., 2020), ecosystem collaboration (Kolagar et al., 2022), and industrial sustainability (Nishant et al., 2020). However, we currently lack insights into how to delineate what constitutes AI capacities and their value for industrial firms in enabling advanced digital solutions.

[2] A business model represents the "design or architecture of the value creation, delivery, and capture mechanisms" of a firm (Teece, 2010, p. 172); these elements are increasingly being shaped by circularity principles (Frishammar and Parida, 2019, 2021).

A common definition of 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 and Haenlein, 2019, p. 17). Accordingly, developing diverse AI capacities (i.e. system abilities to achieve certain tasks) is the missing puzzle piece for industrial manufacturers to unlock a world of possibilities and drive unprecedented growth. Developing data-driven AI capacities holds various potential benefits for industrial solution development, such as improved resource efficiency, increased productivity potential, enhanced diagnostics, discoveries of more efficient utilization methods, predictive capabilities for optimizing resource usage, and dynamic and automated resource management (Kristoffersen et al., 2020; Sjödin et al., 2021a, 2021b). The fundamental benefit of AI is creating a platform for decision support through valuable insights and results collected from large and complex data sets and compressed into a manageable form (Iansiti and Lakhani, 2020; Parida et al., 2019) creating an opportunity to augment and automate the solutions to prevailing business problems for industrial manufacturers and their customers (Phan et al., 2017; Sjödin et al., 2021a). In other words, implementing AI further increases the ability to make sense of data, allowing new ways of harnessing value and enabling BMI (Chauhan et al., 2022; Kristoffersen et al., 2020; Liu et al., 2020). Yet, the adoption of AI in traditional industries is not without its challenges. Manufacturers must consciously develop and deploy AI capacities as well as transform their business models, capabilities, and relationships (Sjödin et al., 2021a). Significant research gaps remaining. In particular, the interplay between AI technology capacities and business capabilities for implementing CBM needs further understanding.

2.2. AI-enabled circular business model innovation and digital servitization

Numerous studies have highlighted the enabling role of AI capacities for circular business model innovation (Chauhan et al., 2022; Pan and Nishant, 2023; Dwivedi et al., 2022). For example, AI enables improvements in productivity and efficiency and, therefore, can be linked to making supply chains more "circular" by reducing the leakages in resource loops. Fundamentally, AI offers industrial firms two critical functionalities: augmentation and automation (Jarrahi, 2019; Raisch and Krakowski, 2021). Augmentation leverages the power of AI to enhance human decision-making processes and productivity (Jarrahi, 2019). At the same time, automation entails leveraging AI to automate routine tasks, driving efficiency and reducing costs. These two functionalities can serve as the building blocks for developing and commercializing industrial CBMs, enabling firms to create smart solutions (Kohtamäki et al., 2022) to optimize resource utilization, increase productivity potential, and enhance the overall operational efficiency of their customers. While there is significant promise in these areas, more research is necessary to fully understand the potential of AI-enabled CBMs. Examining the existing CBM literature can provide valuable insights into how firms can leverage AI to advance circularity. Indeed, the effects of AI on addressing sustainability concerns and circular economy objectives have only recently started to receive research attention (Chauhan et al., 2022).

We follow Geissdoerfer et al. (2020, p. 7) in defining CBMs as "*business models that are cycling, extending, intensifying, and/or dematerialising material and energy loops to reduce the resource inputs into and the waste and emission leakage out of an organizational system.*" This definition emphasizes four generic approaches to leveraging circularity in CBMs: *cycling*, *extending*, *intensifying*, and *dematerialising*. Our argument is that AI can assist industrial manufacturers in employing these approaches to enable circular outcomes and effects. First, *cycling* refers to reusing, remanufacturing, refurbishing, and recycling materials and energy within a system (Geissdoerfer et al., 2020). AI can, for example, enhance cycling by identifying hidden patterns, by forecasting future material flows, and by improving product end-of-life strategies (Kristoffersen et al., 2020). Second, *extending* resource loops means that product use time is prolonged through durable and ageless design, services to promote extended usage, maintenance, and repair (Geissdoerfer et al., 2020). For example, AI may enable predictive maintenance or optimized usage with the potential to significantly extend product lifespan (Liu et al., 2020). Similarly, AI algorithms can predict the uncertain performances of various processes, monitor those processes in real time, and detect flaws in industrial systems (Sjödin et al., 2021a). Third, *intensifying* resource cycles entails maximising the utilization of a product through solutions such as the sharing economy or other ways of intensifying usage (Geissdoerfer et al., 2020). For example, implementing AI may intensify the utilization of products via improved optimization, real-time data analysis, and enhanced design (Sjödin et al., 2021a, 2021b). Finally, *dematerialising* refers to providing the functionalities of a product without hardware by substituting service and software solutions (Geissdoerfer et al., 2020). Leveraging AI, for example, is often vital to amplify the dematerialising potential of software through improved resource optimisation. While the prevalent literature (e.g., Geissdoerfer et al., 2020) largely separates these approaches or strategies into distinct business models, we argue that combinations and configurations of these approaches may hold the greatest sustainability potential.

The literature indicates high potential for AI capacities to advance sustainability and circularity by reducing and removing traditional inefficiencies at the system level (Chauhan et al., 2022). However, we lack insights into the different types of AI-enabled CBM in an industrial setting. Empirical examples of how industrial firms conceptualize AI-enabled CBMs to ensure sustainable benefits can be captured from the digital servitization literature (Paiola et al., 2021; Kohtamäki et al., 2022). For example, this literature describes advanced AI-enabled smart solution business models, such as fleet management solutions, optimization solutions, outcome solutions, and autonomous solutions, (Gebauer et al., 2021; Kohtamäki et al., 2022; Sandvik et al., 2022; Thomson et al., 2022). However, the digital servitization literature has yet to provide clear integration of circular economy principles and approaches. This shortfall has been recognized as a research gap in a recent literature review on the topic (Shen et al., 2023). Accordingly, this study seeks to extend the literature on digital servitization by studying the impact of AI and circular strategies in digital servitization. In particular, there is a need to further investigate the potential of AI-enabled CBMs and the required capabilities, processes, and routines for their successful commercialization.

2.3. A dynamic capabilities perspective on AI-enabled circular business model innovation

The increasing prevalence of AI in industrial domains undoubtedly affords the opportunity to create, extend, and modify firms' business models, resources, and competencies to embody AI-enabled circularity. Yet, AI capacities on their own are not sufficient to successfully commercialize AI-enabled CBMIs and advance industrial sustainability. This is because dynamic changes in the industrial and technological environment require manufacturers to rapidly adapt in sensing and seizing AI-enabled circular business opportunities, and in reconfiguring resources and competencies (Teece, 2007). Given the rapid development of AI and circularity practices, we argue that dynamic capabilities, which refer to a firm's "ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments" (Teece et al., 1997, p. 516), provide a promising analytical framework to holistically study key sensing, seizing, and reconfiguring capabilities (Teece, 2007) for AI-enabled CBMI commercialization. Indeed, dynamic capabilities incorporate critical perspectives relevant to AI-enabled CBMI, such as the capacity to identify a need or an opportunity for change, formulate a response to such a need or opportunity, and implement a course of action (Helfat et al., 2009). Yet, little is known of this domain. There is, therefore, a need to further investigate the "distinct skills, processes, procedures, organizational structures, decision rules, and disciplines" (Teece, 2007, p. 1319) that underly dynamic capabilities for commercializing AI-enabled CBMI opportunities. Building on recent research on AI (e.g., Sjödin et al., 2021a, 2021b) and CBMs (Frishammar and Parida, 2021; Blackburn et al., 2022; Kanda et al., 2021), we posit that these will require an ecosystem lens and dynamic adaptions in both internal and external resources and relationships (Ritala et al., 2023).

Sensing capabilities is essentially about identifying AI-enabled CBMI opportunities by gathering and interpreting relevant market intelligence (Teece, 2007). This can involve scanning the business environment to gain an understanding of technologies, customers needs and pain points, competitors, and other ecosystem partners to identify opportunities for novel AI-enabled value propositions (Teece, 2007; Linde et al., 2021). For example, sensing in AI-enabled CBMI can involve cooperating and sharing ideas with customers and ecosystem partners to identify practical problems and discover innovative solutions for complex sustainability challenges (Ritala et al., 2023; Frishammar and Parida, 2021).

Seizing capabilities is about addressing the identified AI-enabled CBM opportunity through the development of novel customer solutions and corresponding business models (Teece, 2007). Seizing AI-enabled CBM opportunities may face significant challenges due to the complex and uncertain nature of AI capacities and circularity objectives in combination. Arguably, resolving this challenge requires a different way of working, incorporating agility, responsiveness, and greater involvement by customers and ecosystem actors in the CBMI process (Parida et al., 2019; Sjödin et al., 2022: Warner and Wäger, 2019; Sjödin et al., 2021b). In essence, the challenge is to simultaneously create novel solutions from evolving AI capacities and corresponding CBMs with a congruent design, mapping out how internal functions, customers, and ecosystem partners will be involved not only in value creation but also in actual value delivery (e.g., service processes) and value capture (Sjödin et al., 2020b).

Finally, *reconfiguring* capabilities has to do with ensuring that AI-enabled CBMs remain competitive over time by adapting resources and structures to changing environments (Teece, 2007). Hence, they can be viewed as the ability to implement and refine AI-enabled CBMs to realize value over time. For example, since AI is gaining access to increasingly larger data sets over time, new opportunities for optimization and improvements may surface (Sjödin et al., 2021a). Similarly, the value of AI solutions may be increased by incorporating novel ecosystem partners with diverse resources and applications (Kolagar et al., 2022). Constant re-evaluation is required, as is the ability to adapt to change (Huikkola et al., 2022).

To conclude our conceptualization of the extant literature, we argue that, to profit from implementing circularity principles, AI-enabled CBMs must be designed to leverage the potential of AI capacities to enable high-value creation and value capture for the focal firm, its ecosystem partners, and its customers while addressing often conflicting financial and environmental goals. However, we still lack insights into the composition of AI capacities, AI-enabled CBMs, and the dynamic capabilities for commercializing such opportunities and their underlying routines and micro-level activities. In particular, specific sensing, seizing, and reconfiguring capabilities are arguably required to achieve sustainable implementation of AI-enabled CBMIs.

3. Methods

3.1. Research approach and case selection

This paper presents an exploratory multiple case study of industrial firms to investigate AI-enabled CBMs for industrial firms and to understand how dynamic capabilities enable the commercialization of AI-enabled CBMs for industrial customers. Case studies generate multiple observations of complex organizational processes and are particularly useful in developing new insights into theoretically novel phenomena (Edmondson and McManus, 2007), such as the development and deployment of novel AI solutions in interorganizational settings.

Our sample comprised globally active Scandinavian B2B manufacturers engaged in AI, digital servitization, and CBMI. We selected cases from five B2B industries (manufacturing, transport solutions, shipping, construction, and mining) to enhance the generalizability of our findings. This case selection offered an opportunity to contrast various industrial perspectives on relational processes. Several factors underpinned the selection of these cases at the time the study was initiated. First, the providers were actively working with AI-enabled CBMI (e.g., site optimization and autonomous solutions) and had several successful collaborations with customers. For example, Conglocorp had a solid record of delivering an AI-enabled CBM that has optimized machine operation by up to 25 %. Second, these firms had been developing AI technologies and commercializing corresponding CBMs for some time, with notable development of routines and processes that were incorporated into business activities. This background meant that we could learn from the experiences of leading companies. For example, Shipcorp described comprehensive processes to make its customers' operations more sustainable. Third, we selected cases where we had established good contacts with stakeholders in the firms. These positive contacts enabled us to collect detailed descriptions of their routines and practices for AI-enabled CBMI. Table 1 summarizes the studied cases.

3.2. Data collection

Data were gathered primarily through individual, in-depth interviews with participants from the manufacturers. In total, we conducted 54 interviews with knowledgeable informants. The informants were selected because they were actively involved in developing and deploying AI-enabled CBMI. We identified relevant informants by means of snowball sampling, where key informants were asked to recommend people who played an active role in AI and CBMI. We interviewed various participants exercising different organizational functions to capture a multifaceted view of the process. The interviewees included digital leads, digital business developers, R&D managers, platform managers, commercial project managers, product managers, and sales managers.

During the interviews, the informants were asked open-ended questions with the support of an interview guide. The guide was developed based on themes relating to the description of relevant AI-enabled CBMI cases, the potential role of AI as an enabler for more sustainable offerings, and the capabilities/routines required for successful commercialization of AI-enabled CBMI, as well as circularity effects and outcomes. For example, respondents were asked to consider questions on broad themes such as: *How does AI implementation contribute to CBMs? Which processes and activities are critical to configure, implement, and improve AI solutions over time? How are customers and ecosystem partners involved in the process? What sustainability improvements and circular effects have you achieved?* We made extensive use of follow-up questions to clarify points and gain further details, which enabled additional exploration of relevant themes in the practical domain. The interviews lasted approximately 60 to 90 min each and were held face to face or via online conference calls. All interviews were recorded and transcribed, and the transcripts provided the main basis for the data analysis.

We triangulated our data by applying multiple data collection techniques, including multiple interviews and a review of documents. We performed document studies (e.g., solution descriptions, ppts), and we reviewed 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.

Table 1
Case study firms and informants.

Focal firm, key products (turnover, employees)	Case description	Interviews
Solutioncorp *Control system and mechanical equipment (SEK 32,400 M/7,800)*	Comprehensive efforts to drive AI capability application in energy and process industry customer segments. Strategy to connect existing assets and visualize and optimize whole operations using AI platforms. Examples include AI augmentation, such as fault detection in pulp and paper mills, and optimization solutions for a range of equipment, such as mine hoists.	11
Conglocorp *Mining equipment (SEK 100,000 M/ 41,000)*	Progressive AI transformation of business focusing on digitalization in the mining industry by investing in AI, automation, augmentation, and connectivity. Examples include AI-enabled autonomous solutions for underground loading, predictive maintenance, and mine optimization services.	5
Rockcorp *Mining equipment (SEK 31,000 M/13,000)*	Efforts leveraging the use of data and AI to drive new augmentation and automation business opportunities for mining industry customers. Examples include AI-enabled digital transformation services and autonomous drilling solutions.	10
Shipcorp *Ship control systems (66,400 M, 7,600)*	AI initiative to provide augmentation solutions leveraging data from ship control system by sharing it for AI, analytics, and autonomous operations support. Examples of applications include fuel optimization, predictive maintenance, and route optimization and autonomous shipping solutions.	10
Constructcorp *Heavy construction equipment (SEK 66,500 M/14,000)*	An AI initiative to deliver digitally enabled site optimization services and autonomy for the construction industry. The key focus lies in the customer's core business, maximum uptime potential, and effective cost control. Examples include site optimization, load optimization, driver assistance, and autonomous loading solutions.	10
Truckcorp *Heavy trucks and transport solutions (SEK 152,000 M./ 38,600)*	AI initiative to optimize sustainability and operations of a fleet of connected trucks and autonomous solutions. Examples include fleet management systems, fuel efficiency, driver assistance functionalities, and autonomous vehicle solutions.	8

3.3. Qualitative data analysis

For the *data analysis*, we deployed thematic analysis as described by Braun and Clarke (2006) and coded the data using four steps. 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-enabled CBMI is developed and applied. 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. In this step, we consulted insights from the literature on dynamic capabilities, AI, and CBMs as well as additional data sources (e.g., internal company reports) to refine our themes on a continuous basis. This step allowed us to eliminate redundant sub-themes and codes that did not have a connection to our research questions.

The next step involved the generation of aggregate dimensions (of themes) that represented a higher level of abstraction in the coding. Here, we used insights from the literature to form theoretically sound dimensions. The aggregate dimension, themes, and codes were then extensively discussed and eventually reviewed to ensure that the findings were relevant to the research questions. Thus, the aggregate dimensions built on the first-order categories and second-order themes to present a theoretically and practically grounded categorization. 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. Fig. 1 shows the entire data structure that resulted from the data analysis.

4. Findings

We present our findings on AI-enabled CBMs in three parts. First, we conceptualize and describe the role of three distinct AI capacities (perceptive, predictive, prescriptive) in enabling sustainability and circularity. Second, we describe and conceptualize two types of AI-enabled CBM (augmentation and automation) and their circularity effects. Finally, we describe dynamic capabilities for AI-enabled CBMs (value discovery, value realization, value optimization) and their underlying routines and activities. Following presentation of the findings, we discuss the resulting framework and elaborate on how developing AI and circularity in combination can contribute to making the transformation to advanced AI-enabled CBMI and a more sustainable industry.

4.1. Understanding AI capacities

Our findings revealed high potential for leveraging AI resource capacities in circular business model innovation and implementation building on quality data and algorithms and democratizing them within business operations. A common theme among informants was that AI capacities can be used as a tool to uncover hidden inefficiencies and opportunities for re-using, reducing, and optimizing energy and resource usage. In particular, informants described the benefits of *perceptive capacities, predictive capacities, and prescriptive capacities*.

4.1.1. Perceptive capacities

The perceptive capacities of AI allow manufacturers to have an increased perception of what is actually happening when their products are being used in industrial customer operations. This perceptive capacity is key to unlocking novel ways of creating value from AI. For example, AI can sense the environment through data from large varieties of connected sensors (e.g., vibrations, temperatures, and lidar) in or near the machines. For example, Constructcorp described connecting entire sites with sensors and analytics to create a real-time perceptive map of what is happening (e.g., traffic congestion areas, idle equipment). These types of capacity allow manufacturing firms to more deeply understand customers operational usage, problems, and requirements. Thus, AI perception offers the prospect of looking deeper into data and, over time, develops insights into customer intelligence. For example, a digital business development manager at Rockcorp described how collecting key AI insights in a simple digital dashboard for customers has given them an enhanced ability to monitor, control, and improve their equipment performance.

A key benefit of AI perceptive capacities is that it is "always on" and cognizant of details (e.g., micro-level trends) in large streams of data, which humans may not have the mental capacity to sift through. The benefit is continuous monitoring of equipment performance, which allows hidden patterns and anomalies to be recognized. Thus, AI helps firms to process a large amount of data and identify hidden patterns that would be difficult to find using traditional analysis – thus, creating

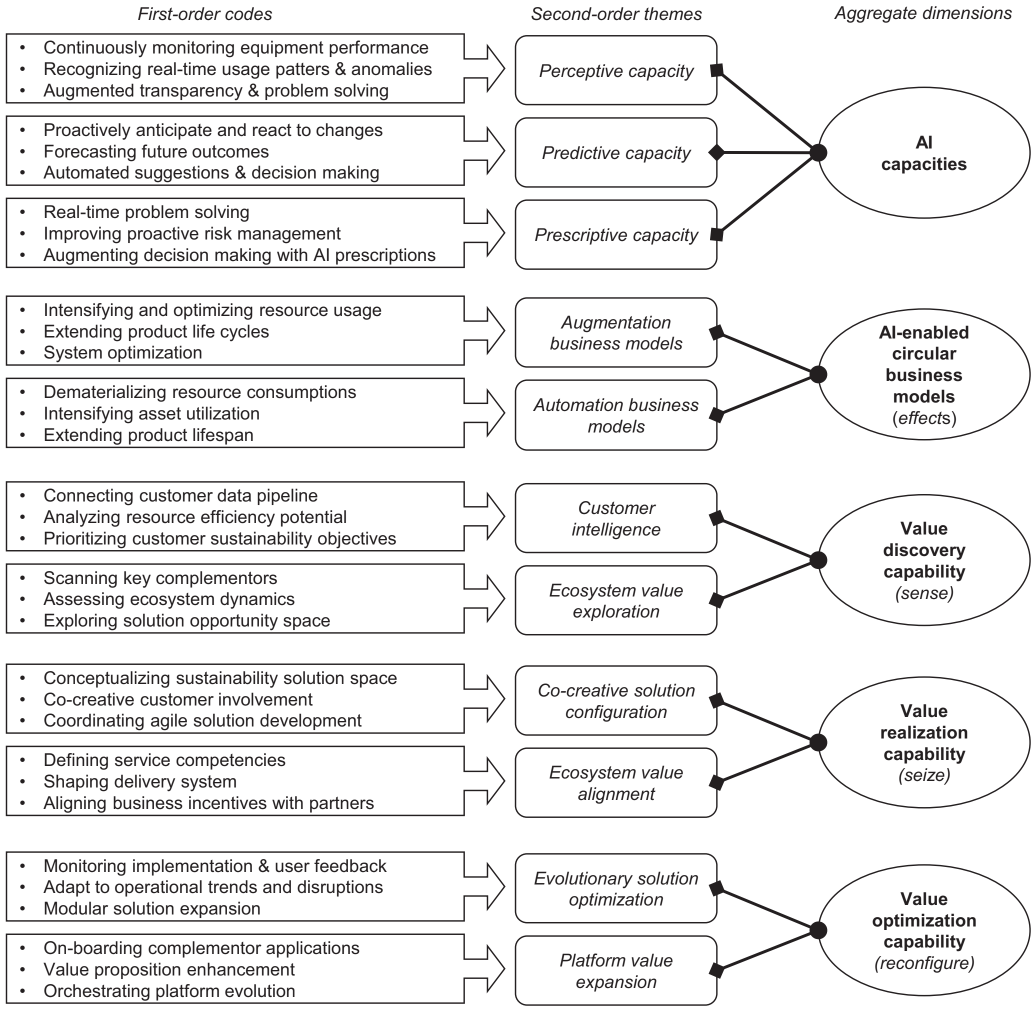

Fig. 1. Data structure.

increased operational transparency. Indeed, it furnishes a key benefit of AI perception by creating a detailed overview of the equipment's health and performance for both internal (e.g., service staff) and customer staff. A senior manager at Solutioncorp described the key perceptive value of AI as follows:

> *"AI doesn't get bored at looking at data for hours and hours… Imagine an event, for example you see a buildup of material, which at some point can disrupt your process, or a component like a heat exchanger at risk of failing, the growing of algae on the hull of a vessel. Those kinds of things people would easily get bored with and not pay sufficient attention to. Algorithms are awake at all times and can thus identify even a gradually creeping trend and alert a human being to what needs to be done or take automatic action depending on the nature of the processes."*

4.1.2. Predictive capacities

Predictive capacities allow firms to use AI to proactively analyze the gathered multi-dimensional data, to seek anomalies and discrepancies from the normal, and to anticipate, predict, and react to changes in the environment for efficient resource usage. Predictive methods convert AI learning from trends in prior data to forecast events and behaviors in the future. This allows AI to make inferences on future probabilities and trends to determine "what is likely to happen" and "when it is likely to happen". The upshot is the creation of actionable insights for planning operations (e.g., when to plan maintenance stops, route planning). Informants underlined the value of foresight in creating circular value. For example, Shipcorp described using machine learning models to predict vessel speed and fuel consumption performance over the course of a given voyage, with a high degree of accuracy that facilitated the creation of services for better decision making. Another critical benefit of predictive capabilities is early warning on the risk of breakdowns and resource waste, thus allowing firms to take pre-emptive actions to realize productivity and sustainability gains. This could take the form of solutions for scheduling maintenance at appropriate intervals or suggesting what action to take to improve machine performance. A vice president at Solutioncorp explained:

> *"AI is particularly useful in situations where things are easily observed but hard to predict, like with equipment failures. Explaining how a material deteriorates is typically very difficult and requires complex calculations. But we can instead measure the effects of degradation by collecting data and using AI functions to detect a developing failure before it happens."*

As informants argued, implementation of predictive capabilities enables increased effectiveness by increasing productivity, saving cost, and reducing time and wastage of material resources. It helps both manufacturers and their industrial customers to make well-informed decisions for more sustainable product usage to be reflected in production plans and maintenance schedules, and it provides the opportunity to monitor and improve the general utilization levels of their equipment. A product manager from Conglocorp stated:

> *"Proactively identifying maintenance needs before something breaks is leading to huge cost and time savings. Our [AI-enabled solution] offer our*

customers a more complete view of their operations for smarter, safer, and more productive work."

4.1.3. Prescriptive capacities

Prescriptive capacities allow manufacturers to create solutions to further optimize the operational usage of their products. As our informants noted, the gaps between the complexity of industrial operations and our problem-solving abilities are widening. With the explosion in data (e.g., CO2, vibrations, engine load, production quality), no single person can keep pace, even with the support of advanced analytics and reporting. Prescriptive AI capacities serve the function of identifying the ideal actions that maximize sustainable value through millions of simulations. As our respondents described, AI can scrutinize all potential possibilities to find those activities that offer the best chance of achieving the desired objectives. A sustainability manager at Minecorp described the potential of leveraging AI to obtain prescriptive insights into how to optimize operations on a system level:

> *"Through data, we see that our large fleet of connected machines are used approximately 30 to 35 percent of the time. It is not because they are not working but because they are on hold. So there is a lot of waste that is at the system level, not at individual machines or processes. It is all the processes together that constitute the big productivity challenge, which we can address with AI."*

For example, Solutioncorp explained that, in the mining industry, digital solutions can optimize and automate ventilation systems to bring air to the right sectors of an underground mine, ensuring worker safety and efficiency in energy consumption. Accordingly, AI can suggest real executable activities that can improve the operational performance of equipment and processes and, in turn, generate new data that can be collected so that this evolutionary computing life cycle can start all over again. For example, Rockcorp described how equipment usage can be optimized to ensure that the "right machine is ready for the right work". Similarly, a product manager from Conglocorp described how AI could help optimize the performance of mining equipment:

> *"We use AI to make the machine learn the cycle and optimizing material routing. We need to train the AI to make better decisions during operation, and this can make our autonomous trucks more competitive over time. Having an AI system that continuously learns and gets smarter is a key enabler for optimizing our customers' processes for more efficient resources extraction and use."*

4.2. AI-enabled circular business models for industrial manufacturers

Our findings identify two main innovative types of AI-enabled CBM as the key focus areas adopted by leading industrial manufacturers engaged in digital servitization. Specifically, these relate to *augmentation business models* (e.g., optimization solutions) and *automation business models* (e.g., autonomous solutions), which link back to current dialogues in the literature on digital servitization and smart solutions (Kohtamäki et al., 2022). In the following sections, we describe the basic properties of these business models and their circular value effects in driving industrial sustainability. A common denominator in the AI-enabled CBMs identified is that they are mainly focused on leveraging circularity principles to increase sustainability in the use phase of their products (i.e., for their customers). A sustainability manager at Constructcorp described why targeting the use phase (use of sold products) is so critical for its sustainability mission:

> *"Our mission is to reduce emissions in the product use phase by 30% and technology plays a key role... [Focusing on our customers' usage] is the highest potential for us to contribute to sustainability as 95% of our emission is corresponding to the use phase."*

4.2.1. Augmentation business models

Augmentation business models are where industrial manufacturers use digital technologies to offer optimization solutions within the use phase of individual equipment, fleets of equipment, and processes. Examples include AI-enabled driver assistance, preventive maintenance, fleet management, productivity services, and even site optimization contracts. A specific example is "site optimization" where whole production sites are optimized by leveraging data from connected equipment to reduce inefficiencies, waste, and emissions in the mining and construction industries. The fundamental objective of these offerings is to increase the efficiency and performance of products, fleets, and even full-scale industrial sites by leveraging AI and analytics to augment decision making. Accordingly, we identified several circular effects of augmentation business models: *intensifying and optimizing resource usage, extending product life cycles, system optimization, and cycling products and parts.*

Intensifying and optimizing resource usage is a key circularity driver of augmentation business models since they are typically focused on optimizing the use of resources, such as energy, fuel, and materials. For example, fleet management solutions can optimize the use of vehicles, reducing fuel consumption and emissions. This can relate to more efficient route planning, appropriate loading, operating speeds, and so on. The opportunities for optimization by leveraging IoT data and AI capacities are vast. For example, Solutioncorp is offering AI-enabled ventilation solutions that reduce energy consumption by 54 % in underground mining operations by optimizing ventilation to areas of the mine where it is needed (e.g., on when needed vs. always on). Specifically, augmentation solutions are often an important enabler in shifting to renewable sources of energy (regenerate) – for example, optimizing route planning and charging of electrified vehicles or optimizing energy usage depending on inputs from solar panels and wind energy. Solutioncorp described the case of an AI-enabled energy optimization platform for a building where energy usage optimization and use of solar panels contributed to making the building a net positive contributor to the energy system. Indeed, great opportunities exist for reducing waste in industrial operations by leveraging AI capacities for augmentation. A portfolio manager from Conglocorp intimated:

> *"As we increasingly shift to actively leveraging technology to optimize our customers' operations, we are looking at AI and digitalization as a game changer. There is significant waste happening in our customers' operations, mainly because no one is looking. But putting these objectives into the business model creates an alignment to drive change in operations and secure future competitiveness and sustainability."*

Extending product life cycles: Augmentation business models can help to extend the life cycle of products, reducing the need for new products to be produced. For example, fleet management solutions can help to extend the life of vehicles by optimizing maintenance schedules and reducing wear and tear, while site optimization solutions can help to extend the life of buildings and infrastructure by optimizing maintenance and energy management. For example, Constructcorp described monitoring the condition of a wheel loader to detect when the risk of breakdown and maintenance needs is too high for intensive industrial operations (e.g., 16 h per day). It then suggested replacement alternatives and found a second life for the current machine with a customer whose operations were less demanding (e.g., 4 h per day). Building on these functionalities, Constructcorp has commercialized an AI-powered fleet management solution for construction vehicles. It monitors error codes and alarms transmitted to the cloud and prioritizes them based on urgency and severity. The technology helps remote monitoring centers to decide whether immediate intervention is necessary or if service technicians can wait until the next scheduled downtime. Additionally, it allows engineers to fix small issues before they escalate into more serious problems. A business development manager from Congolocorp described similar benefits:

"Our solution can help us to identify when the machine is going to fail, understand its state, and intervene before it actually fails… This allows us to deliver customer benefits in terms of productivity, safety, energy, and fuel efficiency."

System optimization is an added circular value driver for augmentation business models. It entails using data to analyze the entire production system (e.g., a mine, quarry, building, factory) to optimize process efficiency, remove waste, and institute better organization. Thus, AI can enable increased process efficiency through continuous analysis of operational data, facilitating the identification of process–performance bottlenecks that can then be eliminated. As our informant noted, augmentation business models can leverage AI to ensure decreased equipment downtime, optimized capacity, and reduced mean time to repair, to name only some of the potential benefits. An AI lead from Solutioncorp stated:

"We are facing demands to optimize all parts of the production system, and there are a lot of co-dependencies. We need to take a system view and not only optimize the individual units but rather the whole production system. AI and digitalization will be key enablers to optimize industrial production sites."

Cycling products and parts. Beyond these benefits, augmentation business models can help to create a more circular supply chain by providing transparency for the end-of-life management of their products. For example, Solutioncorp has added a provision to their smart motor contracts to extend the life cycle of its products, including a take-back system in cooperation with industrial recycling actors. After recycling, products or components can either be used by ABB in the manufacture of new motors or resold to third parties to be used in their production. In addition, optimization solutions provide concrete data on where new product/service combinations can be introduced to increase efficiency (exchange). AI can facilitate the simulation of product configurations in different usage scenarios, the identification of equipment or parts in need of replacement, and the activation of corresponding work processes for recycling. A product manager from Solutioncorp noted:

"With AI, we can plan recycling of old motors in a much more scalable way. We can predict when it's time to replace months before, order a new motor, and make sure that it's delivered to the customer site two weeks in advance with an installation team ready to make sure that everything goes smoothly. But, on the other hand, we can also take back the old motor for refurbishment, sell worn-out parts for recycling, and activate ecosystem partners to make the full cycle run smoothly."

4.2.2. Automation business models

Automation represents a new class of business model driven by virtualization and optimization, which is rapidly emerging among industrial vehicle manufacturers. Autonomous solutions (i.e., self-driving industrial vehicles) are radical innovations that promise great economic and environmental benefits and threaten to disrupt a wide array of industries from logistics to mining. For instance, Shipcorp newly launched a fully autonomous zero-emission container ship aiming to replace 40,000 diesel-powered truck journeys yearly. Automation business models are poised to yield substantial economic and sustainability benefits by embracing circularity principles and by reducing operational expenses through staff reduction and energy optimization. The circularity potential of these offerings is vast. We have identified the following circular effects: *dematerializing resource consumption, intensifying asset utilization*, and *extending product lifespan*.

Dematerializing resource consumption is a key driver of circularity changes in product design, driven by the shift to autonomy. Removing operators offers solid potential for dematerializing by removing the cab-and-driver operation (e.g., no cab, no seat, no climate system). The dematerialization effect of this shift is fundamental. For example, Truckcorp stated that 20 % of the material and engineering resources invested in trucks would be eliminated by removing the cab. Beyond the benefits of shifting to autonomous solutions described above, the design of autonomous solutions can change the overall design (exchange) of the product, enabling more sustainable operation. For example, informants described the benefits of decreasing the size of the vehicles since operator salary cost is no longer an issue. A portfolio manager at Constructcorp described the dematerialization potential of autonomous solutions:

"Autonomous solutions will ultimately have a radical effect on how we design our products. Removing the operator and cab is one thing. But the critical thing is, once you remove operator cost, the whole design of the solution changes. Instead of three large haulers, we can sell a system of five-six smaller ones operating 24/7. The use of resources in the machines and in the operation will be radically reduced."

Intensifying asset utilization is another driver because autonomous vehicles can be used to optimize the use of existing assets, such as vehicles and infrastructure, through efficient route planning and driving style. Informants described how autonomous vehicles can be programmed to take the most efficient routes, which can increase efficiency by reducing fuel consumption and emissions. Similarly, since autonomous solutions can operate around the clock, it reduces the need for vehicles. Indeed, autonomous solutions address the charging time problem of electrified vehicles – since the absence of operator costs and around-the-clock operation means that idle charging time is not an issue. Thus, automation business models have strong potential in the transition to regenerative energy systems. For example, Constructcorp demonstrated that the combination of autonomous and electrified vehicles has reduced CO_2 emissions by 95 % on an industrial customer site. A portfolio manager from Conglocorp described how autonomous intensified asset utilization:

"If you have one operator that can operate five machines, suddenly, you can pretty much… If you need to buy new loaders, maybe you can buy four or three instead of five because you have higher efficiency with utilization of fewer machines."

Extending product lifespan is facilitated because autonomous vehicle solutions can help to extend the lifespan of assets by reducing wear and tear and optimizing maintenance schedules. This can reduce the need for new assets to be produced, which can lead to a more sustainable use of resources. In addition, our informants described how the changed driving styles of autonomous machines use less fuel and spell more efficient operation, which prolongs the life of the machine, reduces maintenance, and prevents unnecessary wear and tear. For example, the deliberate operation of autonomous solutions can be designed to optimize efficiency and the length of life of the vehicle. Truckcorp described how it had found that lowering the driving speed of autonomous trucks led to fewer breakdowns and higher productivity, which was then regulated in the autonomous algorithms. Similarly, a portfolio manager from Conglocorp described how the driving style of autonomous vehicles extends the lifespan and reduces damage:

"An [Conglocorp brand] autonomous truck never crashes. That [removes] one of the big costs in the mine because all machines have to spend a lot of time in the shop because you're smashing the walls. [laughs]. Operators do that. An autonomous vehicle will never do that."

4.3. Dynamic capabilities for AI-enabled circular business model commercialization

Understanding the types of CBM and the benefits of leveraging AI capacities is only an initial step toward sustainable transformation. Our informants described how commercializing AI-enabled CBMIs requires a different way of leveraging AI capacities in solution development and commercialization than the current modus operandi – incentives need to be aligned with the industrial ecosystem actors, such as providers, partners, and customers. Accordingly, our analysis uncovered novel dynamic capabilities to innovate within the collaborative processes to create, deliver, and capture value in a more sustainable way. We discovered three fundamental dynamic capabilities to realize the commercialization of AI-enabled CBMI opportunities: *value discovery capability* (sense)*, value realization capability* (seize)*, and value optimization capability* (reconfigure).

4.3.1. Value discovery capability

Value discovery capability refers to the organizational ability to engage in customer intelligence and ecosystem solution exploration, facilitating the identification and exploration of new AI-enabled CBMI opportunities for the firm. Our informants described the essential role of identifying addressable values because the application of AI capacities is still in its early stages and rapidly evolving, making it uncertain and complex to navigate. Based on our findings, we conceptualize value discovery capability as comprising two fundamental routines: *customer intelligence* and *ecosystem value exploration*.

Our informants underlined the need to develop routines for *customer intelligence* in order to sense opportunities for commercializing AI-enabled solutions. The goal of such routines is to gain a deep understanding of the customers' operations, pain points, and sustainability objectives by listening actively and analyzing the operational data. A critical foundation is connecting customer data pipelines and integrating sensors and data from various sources. Thus, manufacturers can gain a more complete understanding of their customers' operational behavior, preferences, and needs. As our informants described, a deeper understanding of customer needs and operational processes is required since these can vary widely across different markets and segments. For example, Constructcorp described how, even within quite a narrow segment of quarry customers, the key pain points could vary significantly (e.g., from fuel optimization to process bottlenecks), which necessitated a data-driven customer intelligence approach. An added benefit of a data-driven approach to customer intelligence is that the established data platform will facilitate the sensing of novel opportunities over time. An AI lead from Solutioncorp remarked:

> *"Data and information are prerequisites for applying AI solutions. We need to gather all the data from [customers'] assets and operations and aggregate it up to [ERP systems] and all the other data systems. We need to make a synchronization and harmonization of data. As we get access to even more data, that allows us to identify problem areas and develop new advanced AI solutions for our customers over time."*

Having concrete operational data and insights into customers' objectives enables manufacturers to analyze technology's potential for increasing resource efficiency. This analysis helps identify areas where processes can be optimized to reduce waste, energy consumption, and improve efficiency, thereby illuminating circular business opportunities. Furthermore, by prioritizing customers' sustainability objectives, manufacturers can select and initiate the configuration of appropriate AI solutions that aligns with their customers' most pressing issues. Working jointly with customers to determine the target areas is, therefore, a critical foundation for success and ensures that the solution is relevant, valuable, and aligned with the target customers. For example, Shipcorp explained that this need-finding process was key to ensure adoption and to create the required buy-in from customers in order to succeed with novel AI-enabled solutions. Similarly, an AI lead at Solutioncorp asserted that designing the solution with the user in mind is essential to achieve successful commercialization:

> *"The key to AI success is the customer. By starting from the customer's operations, identify the customer's problem and develop solutions that can create added value for the customer and us and bridge different automation systems within the industry."*

Our findings detail that exploring potential opportunities for AI-enabled CBMs requires a level of openness and the development of routines for *ecosystem value exploration*. Clearly, industrial product manufacturers cannot develop AI solutions in isolation. Indeed, informants claimed that they increasingly need to collaborate with complementary partners to jointly configure targeted AI solutions to meet customers' requirements and expand the potential value of the solutions. For example, building and deploying AI solutions often require a range of specialized competencies, including data science, machine learning, and software engineering, which few companies possess entirely in-house. Therefore, partnering with specialized AI solution providers and leveraging their competencies in value discovery can help manufacturers identify and capitalize on the most promising CBM opportunities. As informants described value exploration is built on a culture of openness, where manufacturers are willing to share business information and collaborate with extended sets of complementary partners to achieve customer goals. As informants made clear, an initial step in ecosystem solution exploration is to identify the key potential players in the solution ecosystem. This involves mapping out the various stakeholders, such as suppliers, customers, partners, and competitors, and understanding their roles and relationships within the potential ecosystem. Informants underlined the need to think beyond the traditional setup and assess the dynamics of the ecosystem. This involves assessing potential fit and identifying gaps in the capabilities of ecosystem partners in relation to customer problems that may impact the ecosystem and the solutions that can be developed within it. For example, informants mentioned the need to secure partnerships for connectivity capabilities (e.g., 5G) and the transfer of vast data streams on industrial sites to enable autonomous solutions. A digital lead at Solutioncorp stated:

> *"It's just different constellations of participants. But the same principle applies, that we can jointly create this vision: 'This is what we want to achieve', or: 'This is what the customer wants to achieve.' It's not on the market today, so we kind of have to put a lot of puzzle pieces together to get there, and everyone has different roles."*

Finding valuable applications involves exploring potential solution opportunities that can leverage the ecosystem's strengths to address customer challenges. Thus, manufacturers can leverage customer intelligence and a deep understanding of customer needs, pain points, and behaviors, in combination with an appreciation of the portfolio of complementary ecosystem solutions to address novel business opportunities. For example, a head of innovation at Minecorp described the importance of ecosystem partners in pursuing AI-enabled CBMI opportunities:

> *"Our ecosystem is critical to advance on this journey. We are a traditional manufacturing company, and embracing the digital and AI mindset takes time. Our partners provide us with the innovative potential of AI while we still have the customer knowledge and relationships to explore opportunities for circularity and sustainability."*

4.3.2. Value realization capability

Value realization capability refers to the organizational ability to engage in co-creative solution configuration and ecosystem value alignment, enabling the development and implementation of AI-enabled CBMs in industrial contexts. Our informants stressed that configuring solutions and business models is a critical capability to translate an opportunity into a viable business. It builds on inherent routines for *co-creative solution configuration* and *ecosystem value alignment* with customers and ecosystem partners.

Informants described the need to manage complex AI solution development in a collaborative and iterative way by building routines for *co-creative solution configuration*. This involves a collaborative approach to define, design, and implement solutions for the most pressing needs of customers. Informants underlined the need to avoid overly complex solutions from the start and, instead, to approach solution configuration as an iterative process with initial small-scale solutions, which are progressively refined and expanded in functionality based on operational feedback and data. A key starting point to such processes is conceptualizing the sustainability solution space. This means setting clear goals and metrics (including defining current performance benchmarks) to ensure that the development of AI solutions is aligned with customers' sustainability objectives. This approach delivers by creating a deeper understanding of the problem space, by offering better hypotheses, and by making more accurate estimations. At the heart of this approach is co-creative customer involvement. By involving customers and end users in the development process, manufacturers can ensure that their needs are fully understood and addressed in the final solution. This co-creative work is important since customers often lack the knowledge of what AI can and cannot do. As our informants described, this co-creative approach fosters a shared vocabulary about the business need and potential solutions, enabling solution developers to better visualize and make sense of how end users will actually use the AI solutions. Thus, informants stressed the need to foster trust and a sense of shared ownership, to enable more effective and sustainable AI solution implementation processes. A head of digital solutions at Shipcorp described the changed routines employed to realize AI opportunities:

> *"We now have a process where we actually place the responsibility back to the customer and ask them 'what would you like this system to do for you?', 'what questions do you have?' and 'what answers would you like to get?' Then, we place the responsibility back to the customer, so they are ready to involve my team. Then, we have a meeting and agree on different tasks to build a digital evolution together with the customer. So, we start a journey."*

The upshot is a more agile solution development approach where manufacturers and customers jointly define the solution, break it down into small, manageable pieces, and implement each piece incrementally. Thus, each iteration is tested and validated before moving on to the next. This approach allows incumbent manufacturers to test and refine AI solutions in a more controlled, small-scale, and low-risk environment, build proof of value, and identify and address issues at an early stage in the process. For example, a business development manager from Truckcorp expressed the need to experiment with solutions and build on experience:

> *"We need to start doing things, so we learn, we experience all of these problems that we're going to experience. The sooner we experience these problems, the better. There's a number of things that we haven't really been exposed to yet."*

Another critical component in seizing is to create routines for *ecosystem value alignment*. In essence, this relates to aligning crucial value delivery and capture elements of the business model so that the solution can be configured in the interests of manufacturers, ecosystem partners, and customers. This includes vital discussions on roles, responsibilities, and revenue flows among the actors. For example, informants asserted the vital need to define which service competencies need to be activated to maintain and monitor the solutions – and who should be responsible for the various processes. Essentially, this relates to shaping the delivery system to ensure that AI solutions are delivered proficiently, efficiently, and in line with customer expectations. Due to the contextualized and novel composition of AI-enabled solution offerings, there is often a level of uncertainty on how to align these processes. Informants expressed the need to address potential bottlenecks and showstoppers (e.g., safety routines, data management). Moreover, there are vast opportunities to streamline workflows and to use AI technology to optimize the delivery process across the ecosystem. A key account manager from Truckcorp explained these processes for autonomous truck solutions:

> *"When you talk about a type of solution, it's not just about the hardware. It is about how is that vehicle going to be maintained and who's going to maintain it. How are we going to maintain the upgrades? How do we guarantee you uptime? The most important thing is safety. How do we also do this in a safe way?"*

To succeed with the exploitation of AI opportunities, informants underlined the importance of aligning business incentives with partners to ensure value alignment. For example, informants mentioned that revenue flows need to be aligned to the overall solution configuration and role distribution to ensure a profitable and mutually beneficial partnership. This requires a careful analysis of the cost structure and profit margins of the solution, as well as an understanding of the partners' pricing strategies. A digital lead at Solutioncorp explained:

> *"[Our customer] wants to develop its business and benefit from being an active part of the energy market with its real estate portfolio. There exists no good solution for that, there's not one company that can deliver it. You need a consortium of companies to do it. We need to create an ecosystem of companies that all fulfill different roles and enter into a collaborative process where the value must be distributed in some way fairly. Technically, there are several AI platforms to be implemented, which fulfill different purposes and different competencies to be put in, and this generates a value which should be shared between the partners."*

4.3.3. Value optimization capability

To succeed with implementing AI solutions and ensuring success in value creation over time, value optimization capability is a key foundation for ensuring the reconfiguration of routines and solutions as knowledge develops. This is particularly important in the context of rapid technological development and progressing sustainability concerns, which require ongoing innovation and evolution of solutions to remain effective and relevant. This capability includes two foundational routines: *evolutionary solution optimization* and *platform value expansion*.

Evolutionary solution optimization. Informants explained that, after an AI solution has gone live in industrial operations, it will enter a subsequent life-cycle stage of continuous refinement. For example, over time, the installed sensors will generate more and more data, which can be used to improve the initial models and make better predictions (e.g., machine failures, energy demand). Once the AI solutions have been tested and validated, incumbent manufacturers can then use the feedback and data gathered to make refinements and iterations. Our informants noted that customers' expectations for AI solutions will often change over time as the potential for realizing sustainable operations becomes evident. For example, as AI technology and customer operations change, customers will often begin to measure success by different metrics (e.g., KPIs). Thus, as manufacturers seek to optimize customer value, it is important to check with customers to ensure that the relationship continues to operate under the same shared perceptions of success. Often, when digital maturity increases in the customer organization, new opportunities emerge that were either not contemplated or not considered possible previously. For manufacturers, following this journey is a critical part of ensuring revenue growth by adding new features (e.g., applications) and additional data sources to optimize the performance of AI-enabled CBM solutions. A commercial manager from Truckcorp stressed the importance of continuously improving the solutions and reconfiguring the business model:

> *"It's a bit like a McDonald's, 'Do you want fries with that?' You've got to be about continuous improvement. We currently do it now without autonomous where we go to sites, do site optimization, look at how we can improve them.... Autonomous is exactly the same! There's a solution we are reconfiguring. What's improved? How do we then sell that improvement to the customer and the benefits, and do we get a premium for that? You can't keep giving stuff and not getting something in return. If we can show that improvement is going to drop their cost per ton, then there's got to be a reward for us in that as well."*

Informants specifically underlined the role of data and embracing data as a driver of decision making and value-delivery process improvements to ensure that the potential sustainability benefits are realized. For example, all of the studied manufacturers had set up dedicated remote data monitoring centers to enable real-time support for customer and internal service operations. Such active monitoring and use of AI are key in creating a data-driven culture where circularity principles are used to optimize both customer-facing and internal processes. In the provision of AI solutions, embracing data can lead to effective operational and strategic decisions, which ensure that continuous improvement, learning, and innovation are achieved. A business development manager from Conglocorp described the importance of unlocking the innovation potential over time:

"Once you have the data, you can quickly integrate it with other systems and automate the entire business process…. Using this combined approach of data-gathering and machine learning, we can use our insights to do virtually anything we want: from improving our machines to creating mining sites that are altogether more sustainable…. My motivation is to reach a point where our in-house systems and our customers' systems become one, so that we can unlock the power of data even further."

Platform value expansion. This entails leveraging the existing AI solution infrastructure and the ecosystem to develop new products or services that align with evolving customer needs and, in parallel, exploring new partnerships or collaborations to drive innovation and growth. Essentially, the implementation of initial AI solutions can serve as a platform for the incorporation of complementary offerings, leveraging existing data infrastructure and AI capacities. Informants referenced the importance of actively on-boarding complementor applications to integrate new complementary features and services into their existing AI solutions. This not only improves the customer experience but also opens new revenue streams. Another way to enhance the value proposition is by identifying new market opportunities and creating innovative solutions that meet the evolving needs of customers. A digital lead from Solutioncorp described how the company worked to continuously integrate novel applications from start-ups into its overall solution:

"When we have the solution platform in place, we can shift focus to be an enabler. So [AI-start-up] application is one of a thousand that we could put into it. We don't put a value, we don't say if [AI-start-up] is good or bad, we just say this is what we've found that's great, we've tested, we partner with them. If there's someone else who's great, we'll try to boost them too, make them great. But our mission is that this platform that we have, it should make it easy for these kinds of start-ups and innovations to thrive and expand the overall value of our solutions."

Our informants emphasized the need to maintain a customer dialogue to constantly assess which complementary partners are capable of adding more value. The goal is to orchestrate sustainability evolution for customers by coordinating a larger platform ecosystem of partners in order to progressively target a bigger overall part of the sustainability space (e.g., addressing large-scale environmental problems) in customer operations. An ecosystem partnership manager at Shipcorp described the progressive nature of platform value expansion:

"So, this is work we do with partners…. We do quality assessment on the applications, and our goal is to make sure our customers can pick and choose beyond the best, and they have a full set of applications. Currently, we are working with everything from route optimization, we do a weather routing app with [OEM], we have condition-based maintenance apps, and a growing number of functionalities that sit here."

5. Discussion and implications

This study has sought to conceptualize AI-enabled CBMs for industrial firms and understand how dynamic capabilities enable the commercialization of AI-enabled CBMs for industrial customers. From the primary findings of the empirical study, an AI-enabled CBMI framework can be synthesized, as depicted in Fig. 2. The developed framework describes: i) how perceptive, predictive and prescriptive AI capacities enable diverse types of CBM; ii) the dynamic capabilities needed to accelerate the commercialization process (value discovery, value realization, value optimization); and iii) and the effects in terms of circular outcomes (e.g., intensifying asset utilization) of the respective augmentation and automation business models.

Our framework further details the evolutionary process of AI commercialization by specifying interdependent enabling and evolving effects (arrows in Fig. 2). First, the *enabling effect* details the relationship between the AI capacities (perceptive, predictive, and prescriptive) and the effects they have on AI-enabled CBMs. AI capacities, such as continuous (automated) data analysis and decision making and resource optimization, provide the necessary building blocks to support and enhance CBMs for industrial manufacturers. By leveraging AI technologies, companies can optimize their customer operations, improve resource efficiency, and drive circularity in their business models. The enabling effect of AI capacities allows for the implementation of innovative CBMs that contribute to the circular economy and sustainable practices.

Second, the *evolving effect* relates to the feedback loop between the effects of AI-enabled CBMs and the continued evolution of AI capacities. As industrial manufacturers implement AI-enabled CBMs, they gain valuable insights, data, and experiences that inform the further development and enhancement of AI capacities. Thus, the process of commercialization of AI-enabled CBMs and the continuous leveraging of value discovery, realization, and optimization capabilities provide feedback and drive the evolution of AI capacities. This evolving effect represents a continuous cycle of improvement, where the implementation of AI-enabled CBMs leads to new knowledge and understanding that, in turn, influences the development of more advanced AI capacities and capabilities. This feedback loop facilitates the iterative improvement and refinement of AI technologies in AI platforms to better support CBMs in industrial settings.

Overall, our framework highlights the reciprocal relationship between AI capacities, dynamic capabilities, and the effects of AI-enabled CBMs. It emphasizes how dynamic capabilities enable and enhance CBMs, and how the implementation of these models contributes to the evolution and advancement of AI technologies. We, therefore, contend that, if firms engaged in digital servitization can create capabilities to develop, configure, and effectively utilize AI capacities for commercial CBMs, they can make a significant contribution to sustainability. That is to say, by hitting all the pillars in the so-called triple bottom line, they can derive benefits not only economically but also socially and environmentally. Table 2 summarizes the key insights from the study.

5.1. Theoretical contributions

This study offers several theoretical contributions to the emerging literature on circular business model innovation, digital servitization, and AI in B2B industrial setting.

First, we contribute to the emerging AI, digital servitization, and CBM literature with a *novel conceptualization of distinct AI-enabled CBMs*. Thus, we shed light on issues such as how industrial firms faced with radical AI changes and circularity demands manage to configure novel AI-enabled business models. Specific studies that focus on industrial firms' CBMs have been lacking and, therefore, current attention on this issue greatly benefits the development of the literature (Frishammar and Parida, 2019), especially in the domain of AI. In particular, drawing on the literature on AI and digital servitization, we detail two novel classes of CBM enabled by AI: augmentation and automation business models. We follow the recent literature on smart CBMs (e.g., Kristoffersen et al., 2020) and detail the central role of AI capacities (*perceptive, predictive, and prescriptive*) in enabling these business models and their effects in

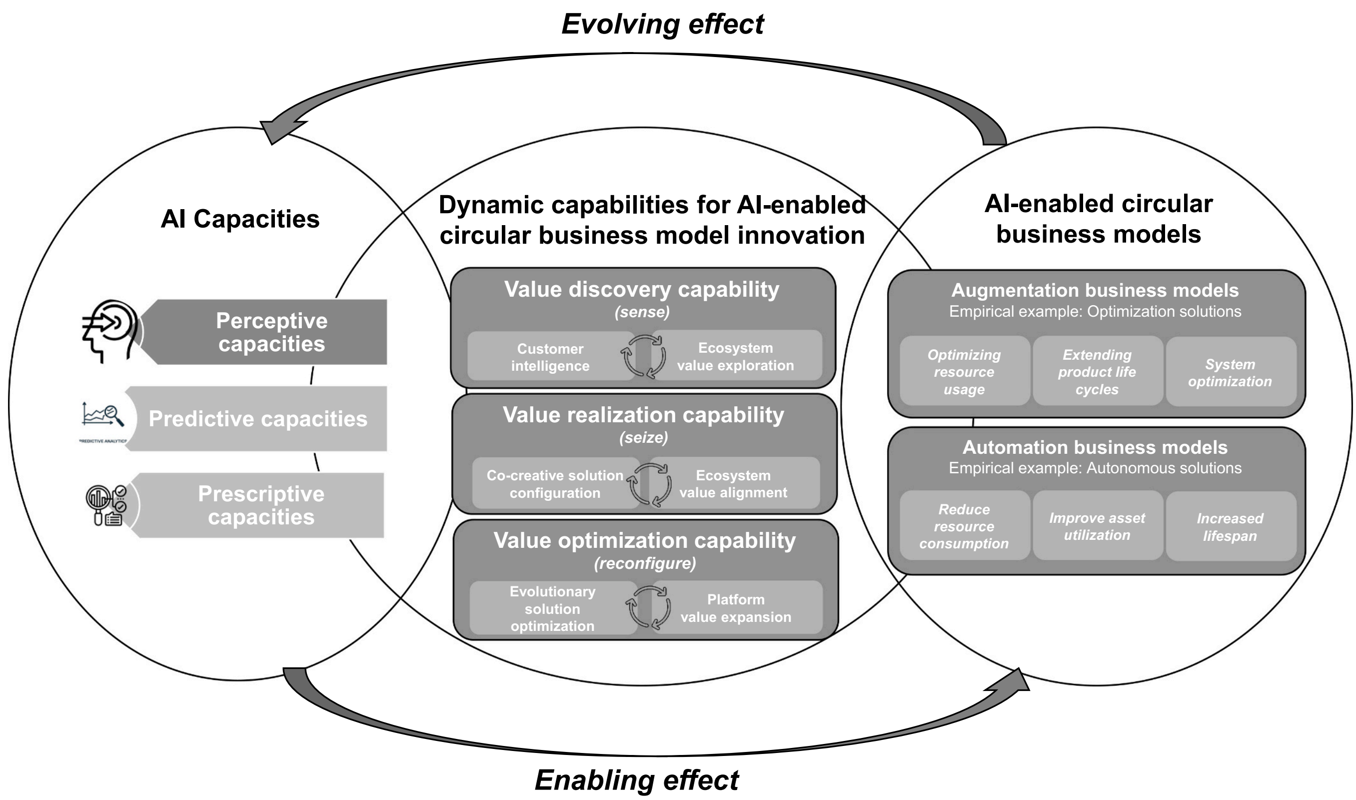

Fig. 2. A framework for AI-enabled circular business model innovation.

Table 2
Summary of identified AI-enabled circular business models and their key circularity strategies.

AI-enabled circular business models	Description of the business model	The role of AI capacities	Dynamic capabilities for realizing AI-enabled CBMI	Circular value drivers
Augmentation business model	*Optimization solutions* designed to create and capture value by optimizing the sustainability of customers' operations. Case examples: *Fleet management *Site optimization *Predictive maintenance *Energy optimization platform *Shipping optimization platform	AI capacities allow the provider to augment human decision making to improve efficiency through continuous analysis of operational data and to guide customers' transformation to perceive and predict anomalies and inefficiencies and prescribe potential solutions.	**Value discovery capabilities* – driven by structured routines for creating customer intelligence and ecosystem solution exploration. **Value realization capabilities* – driven by structured routines for co-creative solution configuration and ecosystem value alignment. **Value optimization capabilities* – driven by structured routines for continuous solution reconfiguration and ecosystem value expansion.	**Optimizing resource usages* (e.g., fuel, energy materials) **Extending product life cycles* (e.g. optimized maintenance, reducing wear and tear) **System optimization* (e.g., process efficiency, removing waste, organization)
Automation business model	*Autonomous solutions* designed to create and capture value by automating customer operations through self-driving industrial vehicles ensuring more sustainable operation. Case examples: *Autonomous trucks *Autonomous ships *Autonomous wheel loaders *Autonomous mining equipment	AI capacities enable automating industrial vehicles to perceive their environment and operate independently or semi-independently leveraging predictive and prescriptive functionalities. The system learns to ensure increasingly efficient operation.		**Reduced resource consumption* waste and emissions (e.g., efficient route planning and driving style, changed product design) **Improving asset utilization* (e.g., 24/7 operation, less need of equipment) **Increased lifespan* (e.g., reducing wear and tear, optimizing maintenance schedules)

driving circularity and industrial sustainability. Prior research (e.g., Geissdoerfer et al., 2020) has illustrated how CBMs can be constructed by following diverse strategies for realizing circular effects: cycling, extending, intensifying, and dematerialization. Our findings illustrate how AI-enabled CBMs allow manufacturers to combine complex configurations of these strategies. For example, automation business models, such as autonomous solutions (Sandvik et al., 2022), allow manufacturers to provide solutions that intensify round-the-clock usage of industrial vehicles, extend the lifespan, and radically change product design to dematerialize the total system. Thus, we delineate the circular effects of AI capacities in industrial CBMs. These distinctions contribute to our understanding of the multifaceted roles AI can play in CBMs and digital servitization. Accordingly, we extend the discussion on digital servitization and AI-enabled CBMs and identify novel research avenues in these domains.

Second, we contribute to the literature on AI transformation and digital servitization by *identifying concrete dynamic capabilities for commercializing AI-enabled business models and solutions*. The literature on AI utilization for novel business models in B2B settings is rapidly growing (e.g., Paschen et al., 2021; Sjödin et al., 2021a). Our study adds to this emerging strand of research by providing evidence on how dynamic capabilities and their corresponding sub-routines allow manufacturers to configure and successfully commercialize AI solutions. Specifically, we detail how dynamic capabilities relating to *value discovery* (sensing), *value realization* (seizing), and *value optimization* (reconfiguring) play a critical role in driving the market success of AI in industrial settings. We demonstrate that neither AI capacities nor individual capabilities are sufficient on their own, but it is the combined use (Linde et al., 2021; Teece, 2007) of the three sets of dynamic capabilities over time that enables manufacturers to successfully commercialize and scale AI solution opportunities. In essence, we provide capability-level insights to untangle the issues related to CBM experimentation (Bocken et al., 2018), business model piloting (Thomson et al., 2023) smart solution development (Huikkola et al., 2022) and innovation (Sjödin et al., 2021a) by industrial firms. In particular, we explain how AI requires platform capabilities and routines for close interaction with the customer, adaptation of the solution to the customer context, and alignment with the requirements of ecosystem partners (Jovanovic et al., 2022). Thus, we provide important theoretical insights into the capabilities and micro level routines and activities required for the commercialization of novel technology-driven business models in established industrial settings.

Third, we contribute by *illustrating the central role of ecosystem partner involvement in AI-enabled CBMs*. For example, to realize the potential of novel AI solutions, manufacturers may require the involvement of many complementary actors, depending on customer requirements and the specific context. Therefore, we provide an in-depth perspective on AI-enabled CBMs, specifying the role of interdependent routines and dynamic capabilities to ensure customer centricity and agility as well as ecosystem orchestration as novel CBMs are sensed, seized, and reconfigured. Thus, while previous studies have offered the firm-centric perspective on CBMs, we extend the dialogue with an ecosystem perspective that encompasses both providers, multiple ecosystem partners, and customers. For example, we contribute by recognizing the need for ecosystem value alignment routines in AI-enabled CBMs where the alignment of value delivery (e.g., roles and processes) and value capture (revenue flows) is not solely a firm-centric requirement but a joint endeavor. In consequence, our study findings suggest that ecosystem involvement in AI-enabled CBMs is more interactive and open than in the traditional product-centric setting because the ecosystem actively participates with the provider in the co-production of the AI solution offering.

Finally, we contribute by offering a novel framework for AI-enabled CBMI. This framework facilitates an increased understanding of how and why incumbent industrial manufacturers engaged in digital servitization innovate their business models by leveraging AI and circularity principles and how this leads to beneficial economic, environmental, and social outcomes for themselves, their customers, the wider ecosystems, and the economy as a whole. Specifically, by focusing on the transformative potential of AI capacities, we foresee an opening up of new dialogues in the AI, digital servitization, CBM, and BMI literature. This will help ensure the cross-pollination of BMI, the circular economy, and AI and digitalization across different theoretical domains and through both emerging and developed literature streams.

5.2. Managerial implications

We view AI and circularity as key enablers of a more sustainable industry. We call on managers in manufacturers engaged in digital servitization to act on this potential, and we offer several recommendations. First, it is critical to recognize the value of different AI capacities (perceptive, predictive, prescriptive). These capacities enable continuous data analysis, decision making, and resource optimization, providing a solid foundation for the development and implementation of AI-enabled CBMs and a path to a more sustainable industry.

Second, to accelerate the commercialization of AI-enabled CBMs, industrial firms need to develop dynamic capabilities that facilitate value discovery, value realization, and value optimization throughout the process of commercialization. These capabilities enable firms to adapt and respond to changing market demands and customer needs, driving the successful implementation and evolution of CBMs. Our findings suggest that the transition to a circular economy is not something a company can achieve on its own – thus, routines incorporating a broader exploration and integration of customers and ecosystem partners are required. In addition, we recommend increased efforts to co-create AI-enabled offerings with customers and ecosystem partners in an iterative way. Given the uncertainty associated with AI solutions, routines to balance the incentives, roles, and data sharing among multiple actors will be key in realizing sustainability in practice.

Third, managers are encouraged to recognize and embrace the circular effects of AI-enabled business models: Business models relating to optimization and autonomous solutions offer opportunities for industrial firms to intensify asset utilization and contribute to the circular economy through efforts to reduce, reuse, and recycle material and energy resources. We argue that the value-creation potential of digital technologies and services can be improved by assuming responsibility for optimizing customers' operations, improving resource efficiency, and driving circularity. Managers engaged in digital servitization should integrate circular thinking and strategies into their strategic decision-making processes and business models, aligning them with the principles of the circular economy.

5.3. Limitations and outlook

Our study has several limitations that provide opportunities for further research. The findings of this study are based on a limited case study sample of five leading companies from Scandinavia, which may not be representative of all industrial manufacturers. The results may not be generalizable to other industries, regions, or company sizes. Future research could expand the sample size and include a broader range of industries to enhance the generalizability of the findings. In particular, other classes of AI-enabled CBMs (e.g., cycling) may be more prevalent depending on the context. Similarly, the types of CBM and the composition of dynamic AI capabilities may vary significantly between B2B and B2C. We encourage scholars to examine our findings in other contexts and to extend or modify them as appropriate.

Furthermore, we provide several potential avenues for future research.

First, this study focuses on the potential of AI to enable CBMI but does not extensively address the challenges associated with the implementation of AI-enabled CBMs in real-world industrial settings. Future research could investigate the barriers and challenges that organizations may face when adopting and implementing AI-enabled CBMs, such as technological infrastructure, organizational culture, and change management processes.

Second, an interesting avenue for future research is to conduct longitudinal studies to assess the long-term impact of AI-enabled CBMs on circularity and sustainability outcomes in industrial settings. This could involve tracking changes in resource efficiency, waste reduction, and economic and environmental performance over time to provide a more comprehensive understanding of the effectiveness of AI-enabled CBMs in driving circular business practices. In addition, future research could compare the performance and outcomes of different types of AI-enabled CBM to identify which approaches are more effective in achieving circular economy goals. This could involve conducting comparative case studies, simulation models, and experiments to systematically compare the impacts of different types of AI-enabled CBM in various industrial contexts.

Third, this study mainly focuses on the perspective of providers of AI-enabled CBMs. Future research could explore the perspectives of other stakeholders, such as customers, suppliers/complementors, regulators, and local communities, to understand their perceptions, motivations, and concerns related to AI-enabled CBMs. For example, our findings demonstrate that 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 model for AI (Sjödin et al., 2022). Finally, our findings specifically detail the importance of platforms yet further studies could further investigate the linkages between industrial digital platforms, AI and circularity (Blackburn et al., 2022; Madanaguli et al., 2023). It seems likely that AI capacities will play an even more prominent role in digital servitization and circularity in the future, and the present article is merely the first step toward an understanding worthy of their importance.

Data availability

The data that has been used is confidential.

Acknowledgments

We gratefully acknowledge the funding support provided from Formas, the Norwegian Research Council and The Swedish Governmental Agency for Innovation Systems (Vinnova) which made this research possible.

References

Blackburn, O., Ritala, P., Keränen, J., 2022. Digital platforms for the circular economy: exploring meta-organizational orchestration mechanisms. Organ. Environ., 108602662211307 https://doi.org/10.1177/10860266221130717.
Bocken, N.M., Schuit, C.S., Kraaijenhagen, C., 2018. Experimenting with a circular business model: lessons from eight cases. Environ. Innov. Soc. Trans. 28, 79–95.
Braun, V., Clarke, V., 2006. Using thematic analysis in psychology. Qual. Res. Psychol. 3 (2), 77–101.
Chauhan, C., Parida, V., Dhir, A., 2022. Linking circular economy and digitalisation technologies: a systematic literature review of past achievements and future promises. Technol. Forecast. Soc. Chang. 177, 121508.
Davenport, T.H., Ronanki, R., 2018. Artificial intelligence for the real world. Harv. Bus. Rev. 96 (1), 108–116.
Dwivedi, A., Moktadir, M.A., Jabbour, C.J.C., de Carvalho, D.E., 2022. Integrating the circular economy and industry 4.0 for sustainable development: implications for responsible footwear production in a big data-driven world. Technol. Forecast. Soc. Chang. 175, 121335.
Edmondson, A.C., McManus, S.E., 2007. Methodological fit in management field research. Acad. Manag. Rev. 32 (4), 1246–1264.
Frishammar, J., Parida, V., 2019. Circular business model transformation: a roadmap for incumbent firms. Calif. Manag. Rev. 61 (2), 5–29.
Frishammar, J., Parida, V., 2021. The four fatal mistakes holding back circular business models. MIT Sloan Manag. Rev. 62 (3), 68–72.
Gebauer, H., Paiola, M., Saccani, N., Rapaccini, M., 2021. Digital servitization: crossing the perspectives of digitization and servitization. Ind. Mark. Manag. 93, 382–388.
Geissdoerfer, M., Pieroni, M.P.P., Pigosso, D.C.A., Soufani, K., 2020. Circular business models: a review. J. Clean. Prod. 277, 123741. https://doi.org/10.1016/j.jclepro.2020.123741.
Helfat, C.E., Finkelstein, S., Mitchell, W., Peteraf, M., Singh, H., Teece, D., Winter, S.G., 2009. Dynamic Capabilities: Understanding Strategic Change in Organizations. John Wiley & Sons.
Huikkola, T., Kohtamäki, M., Ylimäki, J., 2022. Becoming a smart solution provider: reconfiguring a product manufacturer's strategic capabilities and processes to facilitate business model innovation. Technovation 118 (December), 1–13.
Iansiti, M., Lakhani, K.R., 2020. Competing in the age of AI: how machine intelligence changes the rules of business. Harv. Bus. Rev. 98, 3–9.
Jarrahi, M.H., 2019. In the age of the smart artificial intelligence: AI's dual capacities for automating and informating work. Bus. Inf. Rev. 36 (4), 178–187.
Jovanovic, M., Sjödin, D., Parida, V., 2022. Co-evolution of platform architecture, platform services, and platform governance: expanding the platform value of industrial digital platforms. Forthcoming in Technovation. https://doi.org/10.1016/j.technovation.2020.102218.
Kanda, W., Geissdoerfer, M., Hjelm, O., 2021. From circular business models to circular business ecosystems. Bus. Strateg. Environ. 30 (6), 2814–2829. https://doi.org/10.1002/BSE.2895.
Kaplan, A., Haenlein, M., 2019. Siri, Siri, in my hand: who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Bus. Horiz. 62 (1), 15–25.
Kohtamäki, M., Parida, V., Patel, P.C., Gebauer, H., 2020. The relationship between digitalization and servitization: the role of servitization in capturing the financial potential of digitalization. Technol. Forecast. Soc. Chang. 151.
Kohtamäki, M., Rabetino, R., Parida, V., Sjödin, D., Henneberg, S., 2022. Managing digital servitization toward smart solutions: framing the connections between technologies, business models, and ecosystems. Ind. Mark. Manag. 105, 253–267.
Kolagar, M., Parida, V., Sjödin, D., 2022. Ecosystem transformation for digital servitization: a systematic review, integrative framework, and future research agenda. J. Bus. Res. 146, 176–200.
Konietzko, J., Baldassarre, B., Brown, P., Bocken, N., Hultink, E.J., 2020. Circular business model experimentation: demystifying assumptions. J. Clean. Prod. 277, 122596.
Kristoffersen, E., Blomsma, F., Mikalef, P., Li, J., 2020. The smart circular economy: a digital-enabled circular strategies framework for manufacturing companies. J. Bus. Res. 120, 241–261. https://doi.org/10.1016/j.jbusres.2020.07.044.
Linde, L., Sjödin, D., Parida, V., Wincent, J., 2021. Dynamic capabilities for ecosystem orchestration. A capability-based framework for smart city innovation initiatives. Technol. Forecast. Soc. Chang. 166, 120614.
Liu, J., Chang, H., Forrest, J.Y.L., Yang, B., 2020. Influence of artificial intelligence on technological innovation: evidence from the panel data of China's manufacturing sectors. Technol. Forecast. Soc. Chang. 158, 120–142.
Madanaguli, A., Parida, V., Sjödin, D., Oghazi, P., 2023. Literature review on industrial digital platforms: a business model perspective and suggestions for future research. Technol. Forecast. Soc. Chang. 194, 122606.
Muench, S., Stoermer, E., Jensen, K., Asikainen, T., Salvi, M., Scapolo, F., 2022. Towards a Green and Digital Future. Key Requirements for Successful Twin Transitions in the European Union. https://doi.org/10.2760/54.
Nishant, R., Kennedy, M., Corbett, J., 2020. Artificial intelligence for sustainability: challenges, opportunities, and a research agenda. Int. J. Inf. Manag. 53, 102104. https://doi.org/10.1016/j.ijinfomgt.2020.102104.
Paiola, M., Schiavone, F., Grandinetti, R., Chen, J., 2021. Digital servitization and sustainability through networking: some evidences from IoT-based business models. J. Bus. Res. 132, 507–516.
Palmié, M., Boehm, J., Friedrich, J., Parida, V., Wincent, J., Kahlert, J., Sjödin, D., 2021. Startups versus incumbents in 'green' industry transformations: a comparative study of business model archetypes in the electrical power sector. Ind. Mark. Manag. 96, 35–49.
Pan, S.L., Nishant, R., 2023. Artificial intelligence for digital sustainability: an insight into domain-specific research and future directions. Int. J. Inf. Manag. 72, 102668.
Parida, V., Sjödin, D., Reim, W., 2019. Leveraging digitalization for advanced service business models: reflections from a systematic literature review and special issue contributions. Sustainability 11, 391. https://doi.org/10.3390/su11020391.
Paschen, J., Paschen, U., Pala, E., Kietzmann, J., 2021. Artificial intelligence (AI) and value co-creation in B2B sales: activities, actors and resources. Australas. Mark. J. https://doi.org/10.1016/j.ausmj.2020.06.004.
Phan, P., Wright, M., Lee, S.H., 2017. Of robots, artificial intelligence, and work. Acad. Manag. Perspect. 31 (4), 253–255.
Raisch, S., Krakowski, S., 2021. Artificial intelligence and management: the automation–augmentation paradox. Acad. Manag. Rev. 46 (1), 192–210.
Reim, W., Sjödin, D., Parida, V., 2021. Circular business model implementation: a capability development case study from the manufacturing industry. Bus. Strateg. Environ. 30 (6), 2745–2757.
Ritala, P., Huotari, P., Bocken, N., Albareda, L., Puumalainen, K., 2018. Sustainable business model adoption among S&P 500 companies: a longitudinal content analysis study. J. Clean. Prod. 170, 216–226. https://doi.org/10.1016/j.jclepro.2017.09.159.
Ritala, P., Bocken, N.M., Konietzko, J., 2023. 11 Three lenses on circular business model innovation. In: Handbook of the Circular Economy: Transitions and Transformation, p. 175.
Sandvik, H.O., Sjödin, D., Brekke, T., Parida, V., 2022. Inherent paradoxes in the shift to autonomous solutions provision: a multilevel investigation of the shipping industry. Serv. Bus. 16, 227–255. https://doi.org/10.1007/s11628-021-00458-5.
Shen, L., Sun, W., Parida, V., 2023. Consolidating digital servitization research: a systematic review, integrative framework, and future research directions. Technol. Forecast. Soc. Chang. 191, 122478.
Sjödin, D., Parida, V., Kohtamäki, M., Wincent, J., 2020a. An agile co-creation process for digital servitization: a micro-service innovation approach. Accepted for publication in J. Bus. Res. 112, 478–491. https://doi.org/10.1016/j.jbusres.2020.01.009.
Sjödin, D., Parida, Jovanovic, M., Visnjic, I., 2020b. Value creation and value capture alignment in business model innovation: a process view on outcome-based business models. J. Prod. Innov. Manag. 37 (2), 158–183 (doi:10.111/jpim.12516).
Sjödin, D., Parida, V., Palmié, M., Wincent, J., 2021a. How AI capabilities enable business model innovation: scaling AI through co-evolutionary processes and feedback loops. J. Bus. Res. 134, 574–587.
Sjödin, D., Kamalaldin, A., Parida, V., Islam, N., 2021b. Procurement 4.0: how industrial customers transform procurement processes to capitalize on digital servitization. IEEE Trans. Eng. Manag.
Sjödin, D., Parida, V., Visnjic, I., 2022. How can large manufacturers digitalize their business models? A framework for orchestrating industrial ecosystems. Calif. Manag. Rev. 64 (3), 49–77.
Teece, D.J., 2007. Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. Strateg. Manag. J. 28 (13), 1319–1350.
Teece, D.J., 2010. Business models, business strategy and innovation. Long Range Plan. 43 (2–3), 172–194.
Teece, D.J., Pisano, G., Shuen, A., 1997. Dynamic capabilities and strategic management. Strateg. Manag. J. 18 (7), 509–533.

Thomson, L., Kamalaldin, A., Sjödin, D., Parida, V., 2022. A maturity model for autonomous solution provision: the interplay of technology, ecosystem, and business model. Int. J. Entrep. Manag. https://doi.org/10.1007/s11365-020-00717-3.

Thomson, L., Sjödin, D., Parida, V., Jovanovic, M., 2023. Conceptualizing business model piloting: An experiential learning process for autonomous solutions. Technovation 126, 102815.

von Krogh, G., 2018. Artificial intelligence in organizations: new opportunities for phenomenon-based theorizing. Acad. Manag. Discov. 4 (4), 404–409.

Warner, K.S., Wäger, M., 2019. Building dynamic capabilities for digital transformation: an ongoing process of strategic renewal. Long Range Plan. 52 (3), 326–349.

David Sjödin is an associate professor of entrepreneurship and innovation at Luleå University of Technology, Sweden and a professor of entrepreneurship and innovation at University of South Eastern Norway. He conducts research on the topics of servitization, AI and digitalization, innovation ecosystems, and business model innovation in collaboration with leading global firms and regularly consults industry and government. He has published 50+ papers in distinguished international journals, including California Management Review, Long Range Planning, Journal of Product Innovation Management, Journal of Business Research, Industrial Marketing Management, Technovation and others. He is the recipient of multiple awards for his research, including the Entrepreneurship Forum Young Researcher Award 2018 for his research on the servitization of industry.

Vinit Parida (Ph.D.) is a professor at entrepreneurship and innovation at Luleå University of Technology, Sweden. His research interests include servitization, business models, open innovation, and organizational capabilities. He has published more than 100 journal articles, including articles in *Strategic Management Journal, Journal of Management Studies, Long Range Planning, Industrial Marketing Management, Production and Operations Management, Journal of Cleaner Production*, and others.

Marko Kohtamäki is a Professor of Strategy, and a director of the "Strategic Business Development" (SBD) research group at the University of Vaasa, and a Visiting Professor at Luleå University of Technology and University of South-Eastern Norway, and as a Docent at University of Oulu. Prof. Kohtamäki takes special interest in digital servitization, product-service-software innovation, organizational change, strategic practices, business intelligence and strategic alliances. Prof. Kohtamäki has published in Strategic Management Journal, International Journal of Operations and Production Management, Strategic Entrepreneurship Journal, International Journal of Management Reviews, International Journal of Production Economics, Long Range Planning, Technovation, Industrial Marketing Management, Journal of Business Research, amongst others.