



Artificial intelligence capabilities for circular business models: Research synthesis and future agenda

Arun Madanaguli^{a,*}, David Sjödin^{a,c}, Vinit Parida^{a,c,e}, Patrick Mikalef^{b,d}

^a Entrepreneurship and Innovation, Department of Social Sciences, Technology and Arts, Luleå University of Technology, 971 87, Sweden

^b Department of Computer Science, Faculty of Information Technology and Electrical Engineering, Norwegian University of Science and Technology, Trondheim, Norway

^c USN Business School, University of South-Eastern Norway, Vestfold, Norway

^d SINTEF Digital, Department of Technology Management, Trondheim, Norway

^e Department of Management, University of Vaasa, Vaasa, Finland

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ABSTRACT

This study explores the interlink between AI capabilities and circular business models (CBMs) through a literature review. Extant literature reveals that AI can act as efficiency catalyst, empowering firms to implement CBM. However, the journey to harness AI for CBM is fraught with challenges as firms grapple with the lack of sophisticated processes and routines to tap into AI's potential. The fragmented literature leaves a void in understanding the barriers and development pathways for AI capabilities in CBM contexts. Bridging this gap, adopting a capabilities perspective, this review intricately brings together four pivotal capabilities: integrated intelligence capability, process automation and augmentation capability, AI infrastructure and platform capability, and ecosystem orchestration capability as drivers of AI-enabled CBM. These capabilities are vital to navigating the multi-level barriers to utilizing AI for CBM. The key contribution of the study is the synthesis of an AI-enabled CBM framework, which not only summarizes the results but also sets the stage for future explorations in this dynamic field.

1. Introduction

In recent years, the implementation of circularity principles through business models has gained academic and practitioner attention (Frishammar and Parida, 2021; Geissdoerfer et al., 2020; Kanda et al., 2021; Linder and Williander, 2017; Neligan et al., 2022). Recent literature has focused on the role of digital technologies, particularly artificial intelligence (AI), in circular business models (CBM) (Blackburn et al., 2022; Chauhan et al., 2022; Neligan et al., 2022; Rusch et al., 2022; D'Amore et al., 2022; Nishant et al., 2020; Sjödin et al., 2023). Essentially, a CBM entails designing business activities so that resource and energy leakage in the value chain is minimized by introducing processes and services that extend the life of the product and realize positive environmental, social, and economic benefits (Frishammar and Parida, 2019; Geissdoerfer et al., 2020). By AI, we refer to intelligent machines capable of simulating human cognition. This allows them to augment or even replace human intervention (Collins et al., 2021) by leveraging perceptive, predictive, and prescriptive capacities (Sjödin et al., 2023). Although studies highlight the importance of AI for CBM

(Bag et al., 2021; Dwivedi et al., 2023), the mechanisms through which AI can impact CBM are not fully understood.

The value of adopting AI is particularly evident in achieving CBM benefits (Nishant et al., 2020). Specifically, the adoption of AI can lead to significant improvements in productivity and efficiency (Corrado et al., 2021; Damioli et al., 2021; Lin et al., 2020; Makarov, 2020; Mor and Gupta, 2021) and can be linked to making firms more “circular” by reducing resource leakages in resource loops (Sjödin et al., 2023). However, the transition towards AI-enabled CBM is problematic, and the gap between ambition and adoption of AI is contingent on various barriers at the individual, firm, ecosystem, and institutional levels (Åström et al., 2022; Sandvik et al., 2021). Thus, firms, especially large incumbent firms, are stuck in a race to develop the necessary capabilities required to overcome barriers to AI adoption in order to access the value creation, delivery, and capture mechanisms created by AI (Cao, 2021; Paschen et al., 2021; Wang et al., 2021). However, despite these practical and academic interests, how firms can build the necessary capabilities to achieve CBM and, hence, circularity has just begun to garner attention. We argue that AI capabilities can be important for overcoming

* Corresponding author.

E-mail address: arun.madanaguli@ltu.se (A. Madanaguli).

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prevalent AI adoption barriers within CBM by creating capabilities, routines, and processes to realize circularity values (Sjödin et al., 2023). Since the literature is only now developing, the time is now right to step back and examine the AI capability development required to achieve CBM. This will help consolidate and advance this stream of literature.

Several studies exist in the domain of AI and CBM separately, covering topics including CBM and business model innovation for sustainability (Centobelli et al., 2020; Geissdoerfer et al., 2018b; Pieroni et al., 2019), digitalization-enabled BMI of which AI may be a part (Chauhan et al., 2022; Ibarra et al., 2018; Parida et al., 2019), and digitalization-enabled CBM (Caputo et al., 2021). Although these studies hint at the potential of AI capabilities for overcoming barriers to CBM, they do not explicate the AI capabilities that are required. Therefore, to advance our understanding of the same, there is a need for a review that focuses specifically on the key AI adoption barriers in the context of CBM and how organizations should develop AI capabilities for overcoming these barriers.

To address this knowledge gap, the current study employs a scoping review technique and a prospector mindset (Breslin and Gatrell, 2020) to find, catalogue, and synthesize the emerging body of AI and CBM literature. The review advances a research framework for investigating how AI can enable CBM. The review utilizes a capabilities lens to argue that adoption of AI technology, requires the creation of new firm capabilities to leverage AI's potential for achieving CBM.

Our review findings provide several important insights in the context of AI-enabled CBM. Firstly, we detail concrete barriers to AI adoption in the context of CBM, nested at different levels from individual, firm, ecosystem and institutional levels. Secondly, we cluster and conceptualize existing insights from the literature into concrete capabilities for realizing AI implementation in the context of CBM. Specifically, the review identifies four key capabilities essential for AI-enabled CBM: (a) AI infrastructure and platform capability, (b) integrated intelligence capability, (c) automation and augmentation capability, and (d) ecosystem orchestration capabilities. We further describe underlying routines and practices for each of these capabilities. The results underscore the interplay of various technical and non-technical capabilities essential for realizing circularity values using AI. The findings are synthesized into an AI-enabled CBM framework, which forms the basis for advancing a future research agenda and potential future research questions.

2. Underlying concepts and definitions

The topics investigated in this study are current and represent topics that are evolving in their definitions. Therefore, defining the key underlying concepts in the review is essential to assess the scope and define what AI-enabled CBM means. Though existing literature hints at how AI can help with circular business model efforts, a unifying definition of scope is currently lacking. The purpose of this section is to summarize existing definitions and synthesize a working definition of AI-enabled CBM.

2.1. Artificial intelligence

"Artificial intelligence" was initially coined by John McCarthy, who defined it as "the science and engineering of making intelligent machines." Although all definitions revolve around the theme of enabling machines to display some form of "cognition", there is still no definition commonly accepted across disciplines (Collins et al., 2021). Furthermore, the definitions become more diverse as we move into information system literature, and they are often used interchangeably with AI functions and technologies, such as machine learning (ML) (Shollo et al., 2022) and big data. Therefore, for this review, we broadly define AI as *the family of technologies that enable machines to simulate human-like cognitive functions such as learning, thinking, and making decisions based on current and past inputs and outputs*.

However, previous research is unclear about where the boundaries between different levels of AI abilities lie for business researchers. One stream of literature, which can provide some guidance in this regard, is the allied area of business analytics. Prior literature indicates that data and data analytical capabilities are essential prerequisites for exploiting value through AI, which requires an immense quantity of quality data (Sjödin et al., 2021; Mehmood et al., 2019). Business analytics literature differentiates levels of data analytics as (a) descriptive, (b) diagnostic, (c) predictive, and (d) prescriptive analytics, where prescriptive analytics is the stage at which AI integration into the data begins for autonomous decision making. Another lens for looking at AI is through the lens of autonomy. Prior literature classifies these systems as systems that assist human decision making (such as expert systems), augment human action (such as providing analytical insights by analysing large amounts of data), and systems that can take autonomous action (such as autonomous driving) (Kahn et al., 2020; Thomson et al., 2022). For instance, combining the two classifications, assisting human decision making requires diagnostic capabilities, augmenting human action requires both diagnostic and predictive capabilities, and autonomous action requires both predictive and prescriptive business analytical capabilities.

AI can also be classified based on functionality and level of capability into narrow and general AI (Mehmood et al., 2019), where narrow AI refers to specific-use AI, such as chatbots and automatic sensors on websites. In contrast, general AI is designed to mimic human functioning. Although we have made immense leaps in AI technology, industries still mainly use narrow AI. This use includes voice assistants on phones and autonomous driving, which are examples of AI primarily dedicated to accomplishing one purpose.

2.2. Circular business models

On the other hand, CBM, although still a relatively new topic, is one of the most researched areas today. The progress has been marked by the publication of several reviews defining circularity and CBM (Centobelli et al., 2020; Geissdoerfer et al., 2020; Lahti et al., 2018). In this review, we adopt the definition of CBM from Frishammar and Parida (2019, p. 6), who define CBM as: "one in which a focal company, together with partners, uses innovation to create, capture, and deliver value to improve resource efficiency by extending the lifespan of products and parts, thereby realizing environmental, social, and economic benefits." We adopt this definition in our current review because we believe it summarizes the concept quite effectively. The extant literature describes three key mechanisms to achieve this: (a) slowing, (b) narrowing, and (c) closing (Geissdoerfer et al., 2020; Ritala et al., 2023). Here, *slowing* means increasing the timespan of energy and resource loops; *narrowing* means reducing the use of material and energy; and *closing* means converting residual material and energy at the end of the value chain into raw material for the start of the chain, thus effectively closing the loop. We are primarily interested in the processes, activities, and routines that are needed for firms to integrate circular activities into their existing business models.¹

Research suggests that innovation in CBM may happen through the above three different processes depending on the externality or internality of CBM. Existing firms may internally develop them or develop them externally and internalize them through acquisitions and partnerships (Parida et al., 2019). Furthermore, going through the definitions of CBM, we see an emerging pattern of emphasizing ecosystem logic as the means to achieving BMI and, consequently, CBM because it

¹ This is often defined in the literature as circular business model innovation (CBMI) (Guldmann and Huulgaard, 2020). However, to avoid confusion, we use the term CBM throughout the paper. This is because both CBM and CBMI are often defined as dynamic activities that require using capabilities to make changes to existing linear business models.

may be easier to cooperate with a company with needed capabilities than developing them within the firm (Antikainen et al., n.d.; Geissdoerfer et al., 2016; Geissdoerfer et al., 2018b). Thus, the discussion of CBMs would be incomplete without taking the multiple perspectives of the value proposition, firm-centric, and ecosystem lens (Ritala et al., 2023).

2.3. Artificial intelligence capabilities and circular business models

Building on the arguments presented so far, we now define the scope of how AI can enable CBM. AI endows firms with capabilities that translate into the efficiency of processes within the organization (Mehmood et al., 2019; Mor and Gupta, 2021). Therefore, we propose that it is a logical tool for achieving CBM. For instance, the efficiency-enhancing capabilities of AI, along with machine learning, have been used to make the electric grid more efficient in smart buildings (Mehmood et al., 2019). The capabilities perspective is not new in AI research. In particular, prior research indicates that AI capabilities can play a crucial role in enabling any business model innovation (Sjödin et al., 2021; Mikalef and Gupta, 2021). We identified three studies that have worked extensively to identify AI capabilities (Mikalef et al., 2022b; Mikalef and Gupta, 2021; Sjödin et al., 2021). These three studies serve as our guiding light in demystifying AI capabilities by understanding them better through the original capabilities and resource-based view theoretical lenses (Barney, 1991). However, these studies take a static view of resources and capabilities by considering them as tangible, intangible, and human resources and capabilities. Therefore, there is still considerable confusion about what constitutes a capability, primarily driven by a lack of comprehensive literature on AI capabilities (Mikalef and Gupta, 2021).

Furthermore, it can be argued that AI capabilities are just like other IT capabilities that have received extensive attention in the previous literature (Chen and Fong, 2012; Fink and Neumann, 2007). However, we argue that it is important to consider AI capabilities as a distinct capability to existing “regular” IT capabilities, which also endow a firm with capabilities to generate some kind of circular value (Isensee et al., 2020; Parida et al., 2019). To this end, we argue that AI capabilities present an extension of capabilities provided by the existing digitalization capabilities. That is to say, if digitalization through sensors allows a firm to “stand up,” “walk,” and “run”, AI capabilities enable it to perform an intricate dance of “ballet”, whereby the “ballet” cannot be performed without the prerequisites of “walking” and “running”. Similarly, prior digitalization and IT transformations set the stage for companies to develop and deploy use cases because those prior processes enable the firm to process the necessary resources, such as data that are essential to enable AI-based CBM. Thus, AI transformation presents a paradigm shift in digitalization. For example, Sandvik, a prominent B2B company, demonstrates the power of digitalization and AI in optimizing and automating mining operations for its customers. Through its AI platform, Sandvik allows businesses to consolidate operational data and gain valuable insights into its mine planning and operations.

Therefore, AI capabilities are complex and are more than just tangible, intangible, and human resources; they can be operationalized as a bundle of routines that structure the utilization of AI-related resources. These bundles are complex in nature and require active design (Sjödin et al., 2021; Sjödin et al., 2023). More pertinently, AI capabilities are often “inimitable” (Barney, 1991) capabilities that can form the bedrock of competitive advantage. Furthermore, given the need for prior digitalization, AI capabilities enjoy the advantage of time compression diseconomies (Dierickx and Cool, 1989) and are socially complex (Sjödin et al., 2021). In other words, since AI capabilities require quality data and models that need to be trained over time using quality data, it would be difficult for a competitor or a potential customer to replicate them quickly. Therefore, competitive advantage through efficient AI use is likely to be sustainable. Moreover, as new research indicates, AI capabilities afford access to multiple new revenue streams and CBMs

(Sjödin et al., 2023).

To conclude, drawing on literature on the resource-based view and the capabilities view (Barney, 1991; Amit and Schoemaker, 1993), we seek to define AI capabilities and their underlying bundles of routines that enable the leveraging of AI. Our interest in this review involves uncovering AI capabilities for CBM and the complex bundles of routines that enable the CBM activities of narrowing, slowing, and closing resource loops.

3. Review method

Since the conceptual base of the area is still evolving, we utilize a semi-systematic scoping review method to find concepts related to the use of AI in circular initiatives. Scoping reviews are commonly used to provide an exploratory overview of a topic, map the literature, and identify key concepts, theories, and sources of evidence. They work best when an area is complex or needs to be thoroughly reviewed (Grant and Booth, 2009). A semi-systematic approach allows for the utilization of steps that are best suited for the task (Madanaguli et al., 2023). Since the studies on how AI capabilities impact CBM are in their nascent stage, it is best to be flexible and more purposeful in the sampling of literature. Therefore, we combine steps from systematic reviews that require a system search along with a purposeful sampling of CBM literature to build our research sample.

For the systematic search, the current study utilizes two research databases to find literature: Scopus and Web of Science (WOS). The two databases cover almost all sources related to the use of digital technologies in business and the preferred databases in reviews addressing digitalization (Chauhan et al., 2022; Isensee et al., 2020; Matt et al., 2022; Parida et al., 2019) and circular business model innovation (Geissdoerfer et al., 2020; Rosa et al., 2019b; Salvador et al., 2020).

The keywords for the search were extracted from existing reviews covering the topics of AI and circular business models. The list of keywords and their sources are listed in Table 1 below. The keywords were searched in WOS and Scopus databases. The AI/ML, circular, and business model innovation keywords were combined using the intersection operator “AND”, and different keywords in a topic were combined using a union operator “OR”. The search yielded 261 results from WOS and 322 results from Scopus, making a combined yield of 583 works. As is common in systematic methods (Chauhan et al., 2022; Isensee et al., 2020; Matt et al., 2022), duplicated entries were removed by matching DOIs of the documents, resulting in 453 studies.

Each document was then examined and analysed based on the inclusion criteria mentioned in Table 2. After removing conference proceedings and entries with incomplete information, we were left with 433 studies. We then proceeded to read the title and abstract of each paper (Madanaguli et al., 2023; Tranfield et al., 2003). After the first and second rounds of title and abstract filtering, we were left with 145 studies. At this stage, we tried to be broad with our inclusion and did not discount papers that were technical in nature. However, on

Table 1
Keyword selection.

Topic	keywords	Exemplary references
AI/ML	“artificial intelligence”, “machine intelligence”, “intelligent support”, “machine learning”, “intelligent agent*”, “expert system”, “neural network”, “natural language processing”, “digitali*”, “AI capabilities**	Zawacki-Richter et al. (2019), Chauhan et al. (2022), Nishant et al. (2020), Patricio and Rieder (2018)
Circular	“circular economy”, “circularity”, “circle”, “circular”, “closed loops”, “sustainab**	Centobelli et al. (2020), Geissdoerfer et al. (2020), Geissdoerfer et al. (2018a), Pieroni et al. (2019)
Business model	“business model**	Centobelli et al. (2020), Pieroni et al. (2019)

Table 2
Inclusion criteria for the review.

Inclusion	Exclusion
Studies in English	Conference proceedings
Studies addressing the impact of AI on sustainability efforts (how they create value, how it is delivered, and who captured what part)	Studies addressing digitalization without the adoption of AI/ML technologies
Studies with definitions of key concepts	Technical studies discussing algorithms rather than implementation in a firm or its impact on CBM
Studies from the perspective of the firm	
Studies from Scopus and WOS	
Reviews, editorials and book chapters	
Studies discussing AI capabilities	

implementing the condition of papers from the only business domain, we found that the number of papers that fitted our criteria was 32. Using forward and backward citation chaining studies already included in the sample, we added nine more studies, taking the total sample to 41.

Since the literature of how AI influences CBM is still in its infancy, this review approaches the literature from a prospective lens (Breslin and Gatrell, 2020). That is to say, the purpose of the analysis is not only to spot the gaps in the extant literature but also to leave the options open for new conceptualizations and to invite new thoughts and theoretical perspectives. Therefore, we supplemented the identified studies with studies investigating the role of AI in other business processes, such as innovation studies on CBM and studies on CBM processes and their antecedents and consequences.

3.1. Analysis of the literature

The selected studies were analysed thematically to those topics in the literature that were of interest to the current scoping review.

- (i) Internal and external factors that could act as enablers or barriers to AI-enabled CBM with a focus on AI capabilities and the mechanisms through which they can contribute to CBM.
- (ii) Key barriers to the implementation of AI-enabled CBM initiatives.
- (iii) Conceptual models or empirical studies that have investigated how AI can contribute to CBM.
- (iv) AI capabilities that enable CBM initiatives.

However, due to the limited number of studies in the area, the studies from the review were augmented with publicly available examples of companies that have implemented AI-enabled CBM.

4. Results

4.1. AI-enabled circular business models

Prior literature has identified three mechanisms for innovating CBMs: (a) narrowing, (b) slowing, and (c) closing the resource loop (Geissdoerfer et al., 2020). In this theme, we explain how different circular business models are suited to the adoption of AI. However, this classification should be considered with caution because the principles of CBM are often implemented with synergy in mind (Bocken et al., 2016). In other words, an initiative aimed at narrowing is also likely to impact slowing initiatives, which ultimately leads to closing initiatives.

4.1.1. AI-enabled narrowing business models

Narrowing refers to reducing the resource flows in a product by using fewer resources (Bocken et al., 2016). For example, Toyota's production system emphasizes efficiency to reduce wastage (Ritala et al., 2023). Considering that AI technologies allow for better business analytics through their diagnostic and predictive abilities, AI can help the narrowing process by identifying sources of resource inefficiency from data

(Mehmood et al., 2019). For instance, Schneider Electric, a global energy management and automation company, employs AI to reduce energy consumption in commercial and industrial buildings. Through its EcoStruxure platform, Schneider Electric utilizes AI algorithms to analyse data from sensors, meters, and building systems, optimizing energy usage, identifying inefficiencies, and recommending targeted energy-saving measures. This helps businesses reduce their environmental footprint and achieve cost savings (Schneider Electric, no date).

Narrowing using AI often takes the form of employing AI capabilities to increase efficiency in the value chain. In the context of AI for narrow-based circular business model innovation, "narrowing" refers to the application of AI technologies to optimize and streamline specific aspects of the circular business model (Sjödin et al., 2023). It involves leveraging AI to focus on areas of the business process, enabling more efficient and effective implementation of circular practices. This may include using machine learning in data analytics to create expert systems that aid managerial decision making. However, following an automation route, machine learning systems can make decisions independently, creating a "human out of the loop" system (Ross and Taylor, 2021). This complexity was not previously seen in digitalization, where human intervention was more prominent.

The primary value created in this business model is usually increasing efficiency by reducing wasteful practices in the supply chain, leading to waste reduction and increased resource use efficiency (Bocken et al., 2016), thus narrowing the loop. Most studies in our sample focus on a narrowing CBM due to the infancy of AI adoption in most industries. By leveraging AI, businesses can identify opportunities to optimize energy usage (Mehmood et al., 2019), pinpoint inefficiencies (Hina et al., 2022), enhance supply chain speed (Lopez et al., 2021; Butollo et al., 2022), and achieve material efficiency, waste reduction, and circular product design. Therefore, value creation occurs through the development of innovative solutions addressing specific circular challenges (Bag et al., 2021).

4.1.2. AI-enabled slowing business models

In the context of circular business model innovation, "slowing" refers to all activities aimed at prolonging the life of a product and its components, as well as reducing consumption in the first place (Bocken et al., 2016; Ritala et al., 2023). AI's predictive and prescriptive capabilities, through machine learning on usage and maintenance data, can enable firms to slow down resource loops.

To this end, AI technologies can help create "slowing" circular business models in three ways. Firstly, AI can play a crucial role in extending product lifespans. Leveraging AI algorithms for predictive maintenance, businesses can monitor the condition of products in real time, identify potential issues before they occur, and take proactive measures to address them (Gasser et al., 2021; Sjödin et al., 2023). This approach prevents premature product obsolescence and enables timely repairs or replacements, maximizing the product's usable life and minimizing waste. Secondly, AI enables businesses to reduce consumption by facilitating demand-driven production. AI can gather insights into consumer preferences, behaviours, and market trends through data analysis and machine learning, which helps in targeting the right customers (Ho and Chow, 2023). This information can inform product customization, inventory management, and production planning, allowing businesses to produce goods based on actual demand rather than speculative forecasts (Amirkolaii et al., 2017). By aligning production with demand, businesses can minimize overproduction, reduce waste, and optimize resource utilization (Toorajipour et al., 2021). Furthermore, AI contributes to sustainable resource usage in circular business models. AI algorithms can analyse data on resource availability, usage patterns, and environmental impacts to identify optimization and circularity opportunities (Talwar et al., 2021). By making data-driven decisions powered by AI, businesses can achieve more efficient and sustainable practices throughout their value chains. A notable example is Siemens' Mindsphere platform, which offers predictive

maintenance solutions for industrial machinery, leveraging AI and IoT data to optimize equipment reliability and reduce downtime (Petrik and Herzwurm, 2019). Another significant way AI assists in slowing is through its ability to simulate materials and suggest substitutes for existing materials (Deviatkin et al., 2022; Pyzer-Knapp et al., 2022), thus enabling companies to build longer-lasting products.

Overall, the strategic integration of AI in “slowing” in circular business model innovation holds significant potential. By leveraging AI technologies to extend product lifespans, reduce consumption through demand-driven production, and optimize resource usage, businesses can enhance their sustainability performance, minimize waste generation, and contribute to a more circular economy.

4.1.3. AI-enabled closing business models

Closing business models in circular business models focus on closing the loop of resources post-consumption. These “closing” activities may begin even before production through effective designs that allow for easy disassembly and disposal or occur after consumption through systems for reverse logistics and remanufacturing, among others (Chauhan et al., 2022; Hina et al., 2022). Although research on how AI can enable closing business models is still nascent, it has been observed that AI’s predictive and prescriptive data analytics capabilities play a major role. An example is how Cisco utilizes AI and data analytics to enable predictive maintenance and remanufacturing processes, optimize product lifecycles, and facilitate sustainable business practices.

AI enables closing business models by facilitating post-consumer recycling, end-of-life design for disassembly, reverse logistics, take-back or rental systems, and other sustainable practices (Schlüter et al., 2021; Abd Aziz et al., 2021; Kerin and Pham, 2020). Firstly, AI-driven data analytics and predictive capabilities help optimize reverse logistics by identifying efficient routes for product returns and by enabling better inventory management for refurbishment or recycling. For instance, a B2B technology company, such as Dell, uses AI algorithms to predict customer return patterns and streamline reverse logistics, ensuring timely collection of used products and minimizing transportation emissions. Secondly, AI-assisted end-of-life design optimization ensures products are designed with disassembly and recycling in mind, making the recycling process more feasible and efficient. For example, Siemens employs AI-driven simulations to create modular industrial equipment designs that facilitate easy disassembly and recycling of component parts. Lastly, AI-driven rental or take-back models benefit from data analysis to match customer preferences with available products, reducing waste and extending product lifecycles. A notable example is Michelin’s tire-as-a-service programme, where AI algorithms analyse tire usage data to offer predictive maintenance, optimize tire performance, and enable circular economy practices through tire retreading and recycling. Through these processes and real-life examples, AI plays a crucial role in supporting circular economy practices and promoting environmentally conscious business operations in the B2B sector.

4.2. Barriers to AI-enabled CBM

Achieving CBM requires simultaneous efforts across organizational and ecosystem dimensions (Ritala et al., 2023). The use of AI in CBM has great potential, but it introduces new barriers for firms to overcome. However, these barriers are often at different levels and may be beyond the control of the firm. They may require active actions outside the firm with ecosystem (Sjödin et al., 2023) or even community and policy actors. Thus, taking a multi-level and multi-actor perspective is essential to make sense of the barriers (Ritala et al., 2023). To this end, we identify four key barriers discussed in the literature: 1) *organizational AI resistance* (individual/team level), 2) *inadequate AI business integration* (firm level), 3) *deficient ecosystem collaboration* (ecosystem level), and 4) *uncertain institutional environment* (institutional level).

Firstly, *organizational AI resistance* is related to individual, team, and

leadership-level resistance in firms to developing and using AI. For example, this barrier is related to issues such as the unwillingness of employees to use AI, mistrust of AI, and organizational leaders not being ready to relinquish their decision-making power to AI. Particularly, the automation aspect of AI has been investigated as a key reason for fear among workers and teams in adopting AI (Ångström et al., 2023). Thus, using AI requires significant organizational adjustments and restructuring of existing routines and structures to enable data-driven resource tracking, which can be met with resistance from both employees and management, hindering a smooth integration process (Kolbjørnsrud et al., 2017; Nam et al., 2021). Furthermore, using AI for CBM means that other concerns about AI’s impact on workers must be considered. This includes job displacement and ethical considerations, which create psychological barriers affecting people’s perceptions of its implementation (Mutascu, 2021; Nguyen and Vo, 2022). At the leadership level, barriers are raised, such as not trusting the recommendations of AI algorithms, which are manifestations of leaders’ unwillingness to relinquish control to machines (Raisch and Krakowski, 2021).

The second cluster of challenges, *inadequate AI business integration*, arises from the organization’s inability to develop and integrate AI for CBM effectively. Establishing AI in organizations is challenging due to a lack of specialized skills, different ways of working, and the relative novelty of applying AI in circular models. This is because AI resources and CBM are complex and intertwined, and decision makers are often unsure how changes brought about by AI would propagate through the organization (Davenport, 2018). Other AI-specific organizational problems exist – for example, biased algorithms due to inappropriate machine learning models or biased data (Mikalef et al., 2022a; Straw and Wu, 2022; Tilmes, 2022). Furthermore, AI implementation requires the organization to look beyond its “silos” of knowledge and short-term priorities to actively engage in experimentation and long-term focused projects (Ångström et al., 2023). The issue is made worse when considering the riskiness of both CBM (Linder and Williander, 2017) and AI (Åström et al., 2022), specifically, the risk of cannibalizing existing products and business models. Another stream of interest here is the automation augmentation paradox, where a firm cannot pursue one direction without closing opportunities in another (Raisch and Krakowski, 2021). Thus, even though a firm would like to automate everything, if a firm opts for AI that augments human actions, it will face difficulties later in introducing systems that replace humans. However, it cannot create an automated system without investing in augmentation systems to collect the necessary data required.

The third key barrier is *deficient ecosystem collaboration*. On an ecosystem level, effective CBM hinges on collaborative partnerships among diverse stakeholders (Burström et al., 2021; Sjödin et al., 2023; Ritala et al., 2023). Indeed, the need for ecosystem partnerships seems amplified in the context of AI adoption. Specifically, securing crucial AI resources, including high-quality data and advanced technologies, transcends the confines of individual organizational boundaries and demands inter-organizational collaboration (Burström et al., 2021). This integration, contextualized within an ecosystem framework, hinges on congruent objectives and navigation of intellectual property issues and competitive dynamics. However, aligning disparate interests and priorities among these entities presents formidable challenges, mandating intricate coordination mechanisms.

The fourth level of barriers, *uncertain institutional environment*, is at the institutional level and reflects what is called the dark side of AI and the uncertain AI legislative environment. Some research attention has been witnessed on the “dark side” of AI transformation, where the adoption of AI can have an unintended negative impact on the stakeholders involved (Mikalef et al., 2022a; Raisch and Krakowski, 2021). This includes issues such as algorithm bias fuelling discrimination (Mikalef et al., 2022a; Straw and Wu, 2022; Tilmes, 2022) and unemployment (Mutascu, 2021; Nguyen and Vo, 2022) among others. For instance, an article by Fortune notes that companies have already started replacing humans with ChatGPT (Williams, 2023). This fear has led

Table 3
AI-enabled CBM typologies, barriers, and sustainability benefits.

Business model typology	Key AI technologies	Barriers	Sustainability benefits
AI-enabled narrowing CBM Leveraging AI to increase the descriptive and prescriptive nature of business analytics by identifying inefficiencies in current processes and suggesting human comprehensible suggestions for better resource allocation and optimization. <i>Example:</i> Siemens Mindsphere, C3.ai, Cat Asset Intelligence	<ul style="list-style-type: none"> • Data analytics • Machine learning • Simulation • Decision systems • Generative AI 	Organizational AI resistance (Individual/team-level) <ul style="list-style-type: none"> • The inability of managers to relinquish control. • Fear of AI among employees. • Lack of organizational processes to accommodate the use of AI for generating circular value. 	<ul style="list-style-type: none"> • More efficient operation • Cost efficiency • Better descriptive capability of data
AI-enabled slowing CBM Using AI to enhance diagnostic and predictive data analytics to augment and automate design and delivery processes through data-based designs, which are long-lasting and pre-emptively repair before a fault occurs through analysis of usage patterns. <i>Example:</i> Siemens Healthineers, Bosch Maintenance 4.0, ABB	<ul style="list-style-type: none"> • Data analytics • Machine learning • Digital twins • Data-driven design • Predictive maintenance 	Inadequate AI business integration (Firm-level) <ul style="list-style-type: none"> • Automation augmentation paradox • Integrating AI into existing processes • Cannibalization of existing products and services • Inability to see business value • Unclear business and revenue models 	<ul style="list-style-type: none"> • Products and services with longer life cycle • Lower downtime due to faults and breakage • Modular products and offerings • Usage and maintenance instructions to users in natural language to prolong life • Better customer relationships
AI Enabled Closing CBM Using descriptive, diagnostic, predictive, and prescriptive capabilities of AI with partners through novel business model configurations by data-driven design that allows for easy assembly and disassembly while simultaneously identifying aftermarket for reuse and refurbished parts through customer matching. <i>Example:</i> Xerox, Dell, Renault Refactory	<ul style="list-style-type: none"> • Data-driven design • Digital twins • Analytics and forecasting • Generative AI 	Deficient ecosystem collaboration (Ecosystem-level) <ul style="list-style-type: none"> • Finding the right partners with complementary AI skills • Aligning incentives between ecosystem partners • Customer hesitancy to AI Uncertain institutional environment (institutional level) <ul style="list-style-type: none"> • Algorithm bias • Unclear AI regulations (for mitigating the dark side of AI) • Balancing the triple bottom line considering the efficiency orientation of AI 	<ul style="list-style-type: none"> • More value is captured at the end of life through refurbishment, reuse, and partial recycling. • Recurrent revenue from service business models that focus on continuance and closing through modular product design.
Example references	Toorajipour et al. (2021); Nishant et al. (2020); Ahmed et al. (2023)	Mutascu (2021); Nguyen and Vo (2022); Mikalef et al. (2022a); Straw and Wu (2022); Tilmes (2022); Raisch and Krakowski (2021); Ångström et al. (2023)	Toorajipour et al. (2021); Giuggioli and Pellegrini (2023); Jovanovic et al. (2022)

governments to either not act on regulations or act on haphazard regulations on the use of AI, which is bound to slow down how AI is used. Another argument is that, whereas AI can help with the environmental dimension of sustainability, the use of AI can have a detrimental impact on other dimensions of sustainability. For instance, consider the use of AI in highly polluting industries, such as mining. While the adoption of AI can result in significant cost as well as process efficiency, this can mean faster depletion of resources and an expansion bringing about fallout social consequences (Mikalef et al., 2022a). Considering the triple bottom line argument, increased efficiency can help with the economic dimension while simultaneously exerting a negative impact on social and environmental outcomes of sustainability. Therefore, currently, it is unclear how powering CBM through AI will impact sustainability outcomes. It therefore requires further investigation.

In summary, there is immense potential in using AI for CBM. Yet, its intricate landscape requires a nuanced approach to overcome multiple barriers at the individual, firm, ecosystem, and institutional levels. Thus, there is a strong need to develop novel capabilities, routines, and processes within the organization to ensure a smooth transition to AI-enabled CBM. Table 3 summarizes the values AI offers and the sustainability benefits that can be drawn from it considering different barriers at different levels.

4.3. AI capabilities for CBM

Capability theory serves as the theoretical lens for overcoming the

barriers to adoption of AI for CBM. However, considering the business model typologies discussed prior, it is apparent that adopting a simple tangible, intangible, and human lens to identifying and developing the capabilities is insufficient because the involved processes may be too complex. Utilizing AI for CBM is a complex process that involves careful coordination and orchestration of several routines and capabilities from different functional areas to create new routines and processes (Mikalef and Gupta, 2021). For example, consider narrowing the loop; it requires simultaneous data management, leadership, and people capabilities to sustain effective change in processes to encourage data-driven decision making. Therefore, it is important to define these capabilities in light of the development of AI. Furthermore, it can be noted that, as we move from narrowing to slowing to closing, the complexity and interconnection of the capabilities needed increase substantially, requiring the orchestration of an ecosystem to deliver circular values (Ritala et al., 2023; Sjödin et al., 2023).

Considering the above, the review of the extant literature shows that these “higher order capabilities” are a combination of IT and management practices and are required to create the necessary routines and structure within the organization to adopt AI. We identify four such capabilities: (a) *AI infrastructure and platform capabilities*, (b) *process automation and augmentation capabilities*, (c) *integrated intelligence capability*, and (d) *AI ecosystem orchestration capabilities*. In this section, we discuss the capabilities and the routines under each heading.

4.3.1. AI infrastructure and platform capabilities

Developing AI infrastructure and platform capabilities is a fundamental part of enabling AI value creation in the context of CBM. Unlike digitalization, which requires only connectivity, storage, and limited data analytical technology, AI capabilities are more resource-hungry and play a critical role as an antecedent of the adoption of AI processes and, consequently, circular economy capabilities (Bag et al., 2021). Some important tangible resources related to AI that are reported in the literature are cloud computing and database systems (Lee et al., 2022). Here, tangible resources refer to those resources that can be transacted in a resource market (Barney, 1986, 1991; Mikalef and Gupta, 2021; Teece et al., 1997). Tangible computational infrastructure provides the basic platform for not only utilizing existing data generated through prior digitalization (if any) but also for enabling the development of advanced capabilities. Combined, they constitute what we term “AI infrastructure and platform capabilities”, which not only include the data management where data from different internal sources, such as machine-level telematic data, are combined and housed in a single platform for AI use within the organization (Madanaguli et al., 2023; Baabdullah et al., 2021). We identify three routines for this capability: *AI data allocation and management routine*, *AI platform infrastructure development*, and *data pipeline configuration and deployment routine*.

Firstly, the organization needs to move beyond just holding data to investing in developing *AI data allocation and management* routines that allow for CBM activities, such as data-enabled sustainable manufacturing (Baabdullah et al., 2021; Bibri, 2021; Chauhan et al., 2022; Kusiak, 2022). This means procedures for making the data easy to access and reuse within the organization and building data pipelines for effective identification of value, particularly circular value, in the data (Sjödin et al., 2023). Data capabilities refer to the accumulated stock and capability of the firm to collect, process, and gain insights from the data (Mikalef and Gupta, 2021; Sjödin et al., 2021). This is the ability to manage data that needs to work in tandem with developing the requisite hardware and platform. Here, organizations need to collect data and process it to examine patterns in resource usage and optimization. Prior research indicates that reliable data is essential to train AI and produce insights and, when done effectively, it can result in significant business value, such as enhanced cost effectiveness, more efficient resource usage within the organization (Butollo et al., 2022; Chauhan et al., 2022), reduced wastage, and enhanced customer value due to greater customizability from better customer insights.

However, hardware tangible resources and data management are only two pieces of the infrastructure puzzle. A key routine discussed in the literature is *AI platform infrastructure development* (Sjödin et al., 2021). It is not enough to have just an organization with a repository of usable data to realize this circular value. Often, the data that is collected is unsuitable for AI algorithm training (Ben-Israel et al., 2020) and, thus, cannot be used to build useful algorithms and models (Mikalef and Gupta, 2021). Moreover, it is possible that data comes from multiple sources (sensors, user reviews, and sales data, among others) and is difficult to put together (Kar and Kushwaha, 2021). Therefore, it is important that processes and activities are in place to help structure this data and associated AI models into reusable formats on a common organizational platform. This platform is a combination of the necessary tangible hardware and the data required to utilize the data for CBM activities, which may afford the firm the capabilities to predict and prescribe actions rather than describe and react (Sjödin et al., 2023).

Furthermore, it is vital to have routines that string together data from multiple sources in such a way that an AI algorithm is created. This is called a *data pipeline configuration and deployment routine* (Sjödin et al., 2021), which supports the creation of a platform standard within the organization that can help to integrate partners in the future through data integration and co-creation (Madanaguli et al., 2023). The data pipeline routine is more pertinent in ecosystem settings where data from multiple stakeholders need to be combined to enable value creation. These stakeholders may include suppliers, customers, and even

competitors. For instance, consider the AEMP 2.0 API, which is a data management standard that enables mixed construction equipment fleet owners to track and manage data from different brands (Volvo, 2023). The data standard allows customers to have a better data pipeline with fewer “leaks” than manually integrating data from different OEMs. The AI infrastructure and platform capabilities, as with other platform architectures, allow for a common platform on which the firm can internally and externally manage data and draw insights that can help drive a data-driven efficiency routine.

4.3.2. Process automation and augmentation capabilities

As discussed in the literature background, prior literature shows that AI creates value through two mechanisms: automation and augmentation of organizational tasks and routines (Raisch and Krakowski, 2021). Here, AI capabilities offer value by processing data through algorithms to make resource loops faster and more efficient in an organization by either automating certain processes away from human intervention or by augmenting human work by making better data available for decision making (Thomson et al., 2022). However, accomplishing these values is not easy and requires balancing what is called the “augmentation automation paradox” as prioritizing one over the other can cause long-term negative business and societal outcomes for the firm (Raisch and Krakowski, 2021). To this end, we identify three key fundamental routines for AI-enabled processes, (a) *intelligent task allocation*, (b) *automated decision support*, and (c) *continuous stakeholder integration*.

One key point to consider in leveraging AI is to create routines for *intelligent task allocation*. Intelligent task allocation refers to using AI for the strategic and automated assignment of tasks to individuals or systems based on their capabilities, expertise, and availability. This routine is a crucial component of leveraging AI in operational processes to enhance efficiency and optimize resource utilization. AI systems can use machine learning and analyse real-time data to adapt task assignments dynamically, ensuring that the workload is distributed optimally and is responding to changes in the operational environment (Sjödin et al., 2021). For example, global mining equipment provider Sandvik leverages AI to help select the most appropriate machine and human operators for various tasks in mining operations. What this means is that tasks can be scheduled in such a way that waste can be reduced even before it is generated, thus narrowing and slowing the resource and energy loop. One example of this is how AI affords predictive and prescriptive capabilities that can be utilized to schedule and reduce time and resource wastage (Sjödin et al., 2023; Mahmood et al., 2019). This use case has been exploited extensively in the energy sector to reduce energy wastage.

However, the key strength of AI lies in emerging technologies, such as GenAI, that can create *automated decision systems*. These systems, particularly in AI-enabled circular business models, facilitate the optimization of resource usage and waste reduction (Mahmood et al., 2019). By analysing vast amounts of data, AI can identify patterns and opportunities for circularity and guide expert decision makers in the firm. Gen AI technologies can also create human-understandable outputs that can be integrated into decision systems to make human decision making better (Thomson et al., 2022; Ross and Taylor, 2021). This integration is vital in CBM because it allows for real-time adaptation and innovation in processes, ensuring that resources are utilized most effectively, and waste is minimized. Furthermore, AI-enabled agility has the agility of human teams and, thus, plays a crucial role in enabling creativity and innovation (Song et al., 2022). Moreover, the literature on AI capabilities shows that the adoption of AI increases agility by augmenting workers’ tasks and reducing their workloads (Shollo et al., 2022), and it enhances managerial decision making (Ross and Taylor, 2021). Thus, the overall efficiency of the system is increased, creating more value than just slowing, narrowing, or closing loops.

Another key aspect is the need to develop routines for *continuous stakeholder integration*. Effective stakeholder engagement helps align the objectives of the AI efforts with the overall organizational goals and

processes, and it ensures that the implemented solutions meet the needs of all relevant parties, such as internal functions, customers, and ecosystem partners (van Eechoud and Ganzaroli, 2023). For example, Sjödin et al. (2023) found that successful commercialization of AI-enabled CBM requires continuous integration of customers and ecosystem partners. Indeed, it is important to understand that there are multi-level and multi-stakeholder barriers to using AI (Toorajipour et al., 2021), which can be managed through stakeholder integration. For example, ABB has developed a closing CBM for electrical motors where AI-driven insights on the remaining useful life and recycling plans need to be integrated with internal service staff, recycling partners, and customers. Thus, it is imperative to identify and map stakeholders. This involves identifying all parties either involved in or impacted by AI initiatives and comprehensively mapping their respective roles, responsibilities, and levels of influence (Sjödin et al., 2023). This enables the establishment of clear communication channels to ensure stakeholders remain consistently informed and engaged throughout the AI journey.

4.3.3. Integrated intelligence capability

Good data and technological know-how cannot be leveraged to their potential without an enabling, data-driven culture that is curious about AI technologies rather than fearful of them (Ångström et al., 2023; Baabdullah et al., 2021; Spataro, 2023). Fear of change and new technology is often a concern due to the automation risks and loss of employment (Mutascu, 2021; Nguyen and Vo, 2022). In addition, supportive leadership is an essential component for the development of AI technologies (AlSheibani et al., 2020). Thus, several organizational factors need to work together to encourage the use of data in decision making to realize circular value. We term this enabling, data-driven environment of leadership, capability, and experimental culture as “integrated intelligence capability”, or the capability of a firm and its leadership to bring together people and processes to enable the exploration of AI for CBM. To achieve this, firms need to develop routines related to *developing a data-driven culture, AI competence development and upskilling, and AI leadership development*.

Firstly, deploying integrated intelligence capability involves a change in organizational culture that encourages the use of data at every level to track and control resource leakage in the value chain or otherwise (Mikalef and Gupta, 2021). This *data-driven culture* is an essential part of adopting AI because it creates a standard way of doing things within the organization. For example, Siemens, through its Siemens AI Lab, has embraced a shift in organizational culture, which not only enables it to offer AI-enabled CBM offerings but also helps in integrating AI throughout its operations by encouraging a cultural shift. Accomplishing this integrated intelligence culture requires careful coordination of employees and teams, routines, structures, and processes, and supervision and leadership (Sjödin et al., 2021, 2023; Mikalef and Gupta, 2021). In other words, the organization needs to break through traditional silos so that different complementary resources can work together and not be separated by departmental or other barriers (Keding, 2021).

Secondly, a skilled workforce is essential to utilizing AI capabilities (Baabdullah et al., 2021). Thus, *AI competence development and upskilling of employees* is essential to bring in the data-driven culture mentioned earlier (Sjödin et al., 2023). Technical skills refer to the skills possessed by employees regarding AI and how to use them (Mikalef and Gupta, 2021). Due to its complex nature, AI requires experts with various skills, such as algorithm design, database management, and data analytics, among others (Mikalef and Gupta, 2021). Bag et al. (2021), in their study of AI's impact on sustainable management practices, show that workforce skills are an important antecedent to the adoption of big data-powered AI. However, motivating the workforce to embrace AI has been considered a difficult task because the automation potential can make human labour redundant (Raisch and Krakowski, 2021). Thus, motivated employees require specific upskilling in addition to conducive

organizational processes, routines, and structures that enable them to utilize these capabilities (Plastino and Purdy, 2018). Moreover, it is essential that the firm creates initiatives to democratize AI use. That is to say, AI resources within the organization should be easy to access and AI use should be encouraged and incentivized (Sjödin et al., 2021). This will ensure AI is used at lower levels of the organization and will ultimately contribute to the overall CBM goal.

The third key routine of interest is *AI leadership development*. These routines are essential for firms to ensure that leaders have the vision and skills required to lead the AI adoption processes for CBM. The role of leadership cannot be understated in any AI innovation endeavour (Giraud et al., 2022). Prior research examining CMB also notes that participatory leadership is one of the key antecedents of CBM (Bocken and Konietzko, 2022). For instance, we know that leadership needs to evolve to play new roles (Wilson et al., n.d.) and requires training in AI and circularity to enable democratization, which may, in turn, enable an AI-driven culture of resource tracking and minimization. Realizing circular efficiency values requires decision makers in the firms to trust and embrace AI-enabled data-driven insights as the means to make decisions (Raisch and Krakowski, 2021). Thus, leaders are vital in order to enable an environment in the organization that encourages data-driven decision making. This is particularly true for AI transformation, as discussed by Mikalef and Gupta (2021), who show that the leadership capabilities of managers are key in recognizing and realizing the business value of AI. They make AI a key component of the business, they communicate it effectively to everyone, and they enable all staff to use and make sense of it (Sjödin et al., 2021). However, it is important to recognize that leadership in an AI-driven world itself requires evolution and courageous experimentation with AI technologies either augmenting or automating leadership activities (Giraud et al., 2022). Key people, processes, and leadership working together can leverage the integrated intelligence capability by making best use of data and AI capabilities throughout the organization.

4.3.4. AI ecosystem orchestration capabilities

Prior research indicates that CBM using AI enable new value creation, capture, and delivery mechanisms that were previously impossible since they required close collaboration with various ecosystem partners to accomplish effectively (Toorajipour et al., 2021). This means that firms need the capability to not only identify these partners but also to know how to work with them over time. Therefore, we observe that AI ecosystem orchestration capabilities are key. We identify three key routines that need development under this capability: (a) *AI partner exploration*, (b) *ecosystem relationship management* and (c) *customer- and partner-driven scaling*.

The first task in building an ecosystem is to identify the right partners and to keep exploring new partners as customer demand changes (Kolagar et al., 2022). Thus, *AI partnership exploration* is about identifying the right partners to work with. Nishant et al. (2020) argue that taking a multi-level approach involving various actors at different levels is essential in using AI for sustainability-related outcomes. Firms should leverage their ecosystem capabilities to find the right partners for their skills and capabilities as the required AI capabilities may lie outside the confines of the firm (Sjödin et al., 2021, 2023). Furthermore, the extant literature shows that incumbent companies can either develop their own CBMs or develop them outside the firm, or they can acquire the capabilities for the CBM they desire (Geissdoerfer et al., 2018b; Kanda et al., 2021). This imparts significance to startups armed with the requisite AI capabilities, positioning them as attractive targets for acquisition or investment. Alternatively, startups boasting flexibility unencumbered by legacy systems and data can devise CBMs that potentially eclipse those of incumbents. For instance, in 2018, Blue River Technology, a startup specializing in AI-driven agricultural equipment, was acquired by John Deere. Blue River's “See & Spray” technology uses machine learning to identify and spray only weeds, reducing the amount of herbicide used in farming. This acquisition aligned with John Deere's

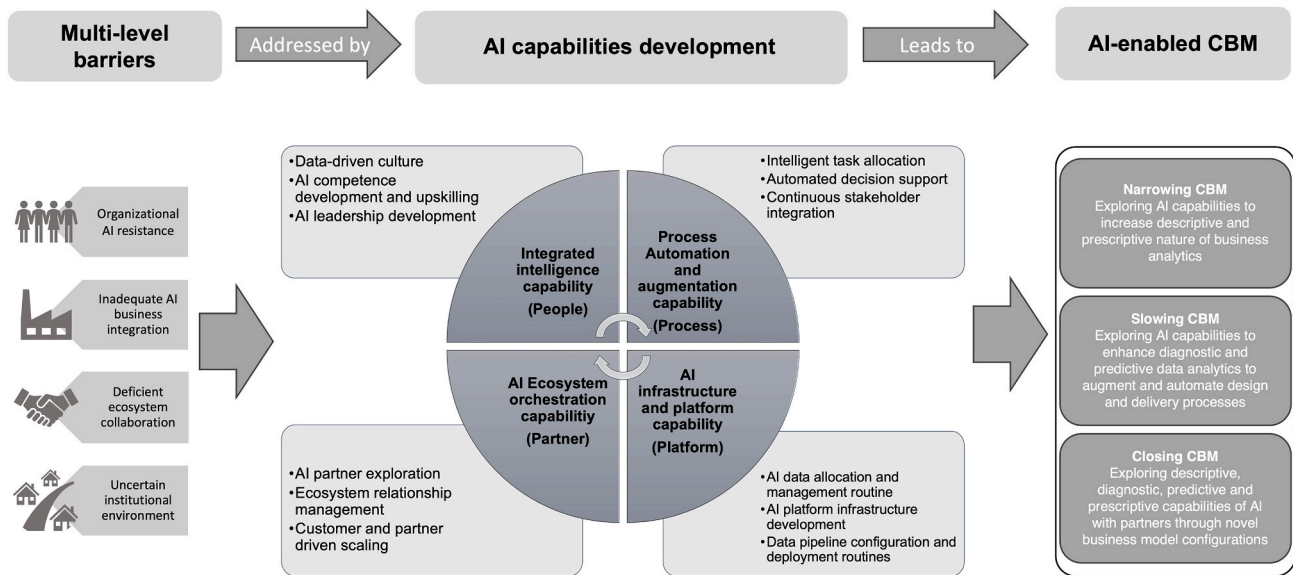


Fig. 1. AI-enabled CBM framework.

sustainability goals to create more efficient and environmentally friendly agricultural practices (Deere, 2018). However, startups are different from large firms: they have much smaller decision time frames, suffer from resource poverty, and require special care in identification and engagement (Garcia Martin et al., 2023).

The second factor to consider is how the ecosystem leader can deliver *ecosystem relationship management over time* (Madanaguli et al., 2023). AI integration means gradually inculcating a data-driven culture in partners and negotiating or forcing standards on the different ecosystem participants (Madanaguli et al., 2023; Jovanovic et al., 2022; Parida et al., 2019). In particular, a closing CBM would require all four capabilities to work together, particularly ecosystem capabilities, with several different actors simultaneously due to the nature of remanufacturing (Parida et al., 2019). Several actors would need to be brought together with aligning incentives to ensure the product can be disassembled for remanufacturing. Another important factor to consider, particularly in B2B settings, is the role of the customer in the CBM. As observed in the digitalization literature, a compelling paradigm unfolds where customers evolve from passive recipients to active co-creators of circular value. For instance, Baabdullah et al. (2021), in their study of SMEs in Saudi Arabia, show that acceptance of AI-related practices has an influence on customer relationships. Viewing this transformation through the lens of ecosystem orchestration underscores the intricacies involved (Burström et al., 2021). Within the realm of AI's integration for circular value, the cultivation of customer relationships emerges as a key activity as we see an increasing trend for customer to demand sustainable products and services.

Building on the concept of customer integration, the next key activity that needs to be performed is *customer- and partner-driven ecosystem scaling*. The prior literature on ecosystem orchestration can guide us in finding the right orchestrating mechanism to develop scalable solutions (Parida et al., 2019). Since the use of AI requires the sharing of proprietary data with the provider, cultivating trust through standardization of data, negotiation on common processes, and nurturing underdeveloped customers, such as startups, may be vital in setting up a shared infrastructure that may be scaled both within customer sites and across customers (Madanaguli et al., 2023). AI's impact transcends mere efficiency gains, beckoning enterprises to revolutionize engagement strategies and empower customers as essential partners in shaping their circular value propositions. For example, the ABB ability platform offers a compelling example. ABB ability is an industrial IoT platform that integrates AI and machine learning to optimize manufacturing

processes, from predictive maintenance to energy efficiency. ABB collaborates with various startups, hardware and software providers, creating an ecosystem that extends beyond a single factory's walls, thus enabling narrowing and slowing business models simultaneously. Thus, ecosystem orchestration capabilities, which may be called a "soft capability", assume a pivotal role along with the "hard technological" capabilities discussed earlier, serving as the conduit for translating the vision of using AI for CBM into reality.

5. Discussion – a future research agenda

Examining the literature on AI and CBM enables us to explicate details on how AI capabilities can enable CBM. We discuss how existing circular business typologies can be empowered by using AI to facilitate new types of internal value for the firm and external value for the customer. In particular, taking a capability lens, we argue that new routines and processes powered by the orchestration of complex AI and ecosystem capabilities are required to overcome barriers at different levels.

However, there is a need to consolidate this information into a comprehensive framework to not only guide future research but also to provide a comprehensive overview of the barriers, capabilities, and CBM outcomes. Considering the nature of the AI capabilities uncovered and the CBM routines outlined, we draw inspiration from the three-pillar framework. This has three key components: (a) people, (b) process, and (c) technology, which has been used to understand the impact of advanced technologies on business models (Sjödin et al., 2018; Blackburn et al., 2017). Here, the people dimension refers to challenges and activities that need to occur at the individual and team levels. Process refers to challenges and activities that need to be addressed in existing organizational processes and routines. Finally, technology refers to technological challenges and the associated activities needed to address those challenges. However, in our case, though people and process can be adopted directly, we see a need to extend the framework with two additional components. These are needed to adequately represent the barriers and the routines required if AI capabilities are to address the challenges associated with CBM. We, therefore, define the four vital components of the AI transformation as *people, process, platform, partner* (4P). Specifically, we identify the following capabilities relating to these dimensions: *integrated intelligence capability* (people), *process automation and augmentation capability* (process), *AI infrastructure and platform capability* (platform), and *ecosystem orchestration capability* (partner). As

Table 4
Summary of future research avenues.

Future research avenue	Key gaps in knowledge	Research questions	Related references
1. <i>Connecting AI capabilities to CBM types</i>	Unclear mechanisms of AI capabilities' interaction with each other in firm environments for CBM	<ul style="list-style-type: none"> How do different higher-order AI capabilities interact to accomplish certain AI-enabled CBM types? How do firm level factors like culture moderate this relationship? 	Mikalef and Gupta (2021)
2. <i>Acquiring AI capabilities for CBM</i>	Strategies and activities to acquire AI capabilities for CBM are not well understood	<ul style="list-style-type: none"> What are the ecosystem and network strategies followed by firms to acquire AI resources and capabilities for CBM purposes? What are the barriers and enablers of the creation of infrastructure standards? How do these strategies vary by CBM type? 	Geissdoerfer et al. (2016), Mikalef and Gupta (2021), Kanda et al. (2021), Linder and Willander (2017)
3. <i>The in-between mechanism of how AI capability can impact CBM</i>	Unknown mechanisms at individual, team, firm, and interfirm levels through which AI capabilities can impact CBM	<ul style="list-style-type: none"> What is the role of AI in enhancing organizational creativity? How does organizational creativity mediate the relationship between AI capabilities and CBM? 	Mikalef and Gupta (2021), Morris (2010), Hotho and Champion (2011), Mobarakeh (2011), Tesluk et al. (1997)
4. <i>Role of leadership</i>	Role of leadership in AI-enabled CBMs and necessary cultural changes within an organization	<ul style="list-style-type: none"> How can leaders effectively guide capability-building decisions to balance between new AI-enabled CBMs and old BMs? How can firms create a culture of AI and data-driven circular value exploration within a firm? How can firms train managers to embrace and cultivate an AI-driven culture for CBM? 	Giraud et al. (2022), Wilson et al. (n.d.)
5. <i>Business value of AI</i>	Unclear actual business value of AI for CBM and its impact on firm performance	<ul style="list-style-type: none"> Does CBM serve as a mediator/moderator between AI adoption and firm performance? How do industrial customers perceive the value of AI-enabled CBM? 	Ångström et al. (2023), D'Amore et al. (2022), Nishant et al. (2020), Rosa et al. (2019a), Lee et al. (2022), Mikalef and Gupta (2021) Sjödin et al., 2023
6. <i>Balancing strategies</i>	Strategies for balancing new CBM with existing BMs and planning CBMs for startups	<ul style="list-style-type: none"> What are the strategies incumbent companies can use to balance new CBM with existing BM? How can startups plan their CBMs to effectively cannibalize/appeal to incumbent companies and CBMs? 	Linder and Willander (2017), Åström et al. (2022)
7. <i>Dark side of powering CBM through AI</i>	Negative impact of AI on stakeholders and sustainability outcomes when implementing AI-enabled CBM	<ul style="list-style-type: none"> How to balance the triple bottom line when implementing AI-enabled CBM? How can fair value creation through AI-enabled CBM in socially sensitive contexts be ensured? 	Mikalef et al. (2022a), Raisch and Krakowski (2021), Mutascu (2021), Nguyen and Vo (2022), Williams (2023), Frishammar and Parida (2019), Geissdoerfer et al. (2016), Geissdoerfer et al. (2018b)

highlighted in the results, its essential for the four higher order AI capabilities to work together in synergy to extract circular value using AI. The overall role of AI in enabling CBM is summarized in the AI-enabled CBM framework shown in Fig. 1.

5.1. Future research avenues

Although the review addresses several issues concerning the use of AI capabilities in CBM, several questions remain unanswered. In this section, we summarize the different knowledge gaps and associated research questions that were discussed in the results section. The summary has been presented in Table 4 below.

6. Implications, limitations, and conclusion

6.1. Academic implications

The current study presents a distinctive review of the literature that delves into the role of AI in the realm of CBM. This inquiry makes a significant contribution to expanding conceptual boundaries within the CBM domain by introducing a novel perspective on integrating AI capabilities. In doing so, we extend the work of previous authors who have investigated the impact of digitalization on circular sustainable business model innovation (Chauhan et al., 2022; Hina et al., 2022; Isensee et al., 2020; Parida et al., 2019) by arguing that AI capabilities are logical extensions of digitalization capabilities that empower an organization

with capabilities required to enable CBM. As AI's multifaceted impact on circular value creation comes to light, it becomes evident that a holistic approach that balances the use of several AI and non-AI capabilities is essential to unlock the transformative potential of AI in CBM. Though several studies have examined AI capabilities (Mikalef and Gupta, 2021; Sjödin et al., 2021), a more comprehensive examination of capabilities as bundles of routines was missing from the literature. We have addressed this knowledge gap by considering the various routines that AI enables and how a combination of routines is essential for adopting AI in CBM. Although this has been defined in the CBM context, it can be translated to other AI applications.

Furthermore, we uncover the key barriers to adopting AI for CBM and define the AI-enabled CBM typologies. In doing so, we augment the literature investigating barriers to AI adoption (Ångström et al., 2023). Consequently, this research offers an academic imperative that urges researchers to venture beyond conventional silos and embrace a broader view that accommodates the intricate interplay between AI, circular economy principles, and business model innovation.

Finally, the review is presented at an opportune time when the literature is coping with issues of AI implementation and sustainability. The inherent efficiency-increasing nature of AI presents a paradoxical tension (Raisch and Krakowski, 2021), which requires closer inspection. Our review extends this argument by presenting several individual-, team-, firm-, ecosystem-, and community-level barriers and argues that AI transformation, particularly for CBM, requires careful coordination of capabilities to address these barriers. We synthesize this relationship

from the literature into an AI-enabled CBM framework that can guide future research in this area.

6.2. Managerial implications

Managers of B2B firms embarking on integrating AI capabilities into their CBM must adopt a multifaceted approach. The conventional categorization of tangible, intangible, and human capabilities falls short due to the intricate nature of AI's impact. Successful AI adoption demands a synchronized orchestration of capabilities from diverse functional domains and a comprehensive strategy (Keding, 2021). The results highlight that it is important for managers to be aware of different routines that need to be developed to make the organization capable of using AI in CBM.

The results indicate that it is imperative to establish a robust AI infrastructure and platform encompassing tangible computational resources, adept data management, and optimal technology utilization. Nurturing data capability emerges as a pivotal cornerstone for effective insight extraction. Simultaneously, constructing a proficient data pipeline ensures seamless integration across varied sources, particularly in intricate ecosystem contexts. Effective AI deployment demands a cultural shift that endorses AI exploration over apprehension, reinforced by visionary leadership that drives widespread adoption.

Finally, collaborative ecosystem orchestration emerges as an indispensable avenue, enabling firms to acquire AI capabilities externally while honing customer partnerships. It is essential to strategically approach startup acquisitions or partnerships, capitalizing on their AI expertise to enhance CBM efforts. Furthermore, as customers evolve into active co-creators of circular value through AI, managers should adroitly pivot engagement strategies, fostering trust through standardized data practices, adept negotiations, and the cultivation of a shared infrastructure. Overall, managers must encompass ethical considerations, sustain a proactive learning mindset, and meticulously balance circular and sustainability values to successfully navigate the intricate terrain of AI-enabled CBM.

6.3. Limitations of the study

The current review has some limitations. Firstly, due to the relative lack of literature directly addressing AI and CBM, the current study takes a prospective approach to review (Breslin and Gatrell, 2020). Instead of focusing on presenting a detailed review of the extant literature, we focus more on tying together relevant concepts to advance a future research agenda. Secondly, we use only literature in the English language. Although this is standard practice in most reviews (Madanaguli et al., 2023; Talwar et al., 2021; Chauhan et al., 2022), it is conceivable that some studies that were relevant might have been ignored during the actual search and elimination phase of the review.

6.4. Conclusion

The purpose of the current paper was to advance a future research direction for research on how AI can enable CBM. To this end, we have covered some distance. The current review has not only synthesized how barriers to AI-enabled CBM can be overcome with capabilities, but we also highlighted key gaps in our knowledge. In particular, we use a capabilities lens to highlight how four key capabilities of AI infrastructure and platform capability, integrated intelligence capability, process automation and augmentation capability, and ecosystem capabilities need to be balanced to achieve CBM. We summarize our future research suggestions from the synthesized AI-enabled CBM framework, which will guide future research in the area. The review highlights the important role AI plays in enabling CBM and how the complex change is perhaps best achieved if done with partnerships with other companies. Indeed, it highlights how non-technical skills and capabilities are as important as technical skills in the adoption of AI for CBM due to the

complexity of the activities involved. This is particularly pertinent for closing business models, which require several partners to work together to close the resource loop by bringing resources back to production. However, AI is not a flawless solution, and the review shows that, despite the immense potential, there is also a dark side, of which managers intending to use AI in their CBM ought to be aware.

CRedit authorship contribution statement

Arun Madanaguli: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **David Sjödin:** Writing – review & editing, Supervision, Software, Resources, Project administration, Funding acquisition, Formal analysis, Conceptualization. **Vinit Parida:** Writing – review & editing, Validation, Supervision, Software, Resources, Investigation, Funding acquisition, Conceptualization. **Patrick Mikalef:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Conceptualization.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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Arun Madanaguli is a postdoctoral researcher in the Entrepreneurship and Innovation subject at Luleå University of Technology. His research interests include digitalization, AI-enabled business transformation, electrification business models, and sustainability. His research appears in international journals such as *Business Strategy and Environment*, *Technovation*, *Technological Forecasting and Social Change* and *Journal of Business Research*.

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, 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.

Vinit Parida is a Chaired Professor of Entrepreneurship and Innovation at Luleå University of Technology and Scientific Leader for NorrlandsNavet-A Kamprad center for SMEs business development and growth. He is also member of Swedish Ministry's high-level group (regeringens samverkansgrupper) on digital transformation of Swedish Industry. His research interests include digitalization transformation, business model innovation,

organizational capabilities, servitization, industrial ecosystem, and circular economy. He has published 200+ international journal articles, conference papers and industry reports.

Patrick Mikalef is a Professor in Data Science and Information Systems at the Department of Computer Science. In the past, he has been a Marie Skłodowska-Curie post-doctoral research fellow working on the research project "Competitive Advantage for the Data-driven Enterprise" (CADENT). He received his B.Sc. in Informatics from the Ionian University, his M.Sc. in Business Informatics for Utrecht University, and his Ph.D. in IT Strategy from the Ionian University. His research interests focus the on strategic use of information systems and IT-business value in turbulent environments. He has published work in international conferences and peer-reviewed journals including the *Journal of Business Research*, *British Journal of Management*, *Information and Management*, *Industrial Management & Data Systems*, and *Information Systems and e-Business Management*.