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AI-Enabled Circular Business Model Transition for Mitigating Climate Change: A Natural Resource-Based View Perspective on Business Strategies

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ABSTRACT

The role of artificial intelligence (AI) in achieving sustainability goals has garnered attention in academic literature. While AI has been argued to be crucial in addressing circularity challenges, organizations face challenges in configuring a business model. Designing new business calls for insights on how AI can be integrated into value creation and capture mechanisms. There is a lack of clarity on how organizations deploy AI as they transition to circular business model innovation. The purpose of the study is to explore how AI is integrated into organizational processes while adopting circular business models. We conducted online open-ended interviews with 55 participants to explore the potential role of AI in enabling the adoption of circular business models. Our findings have implications for theory building relating to AI business model innovation and provide a novel avenue for further research on business model innovation literature. Building on a natural resource-based view, the findings indicate that while implementing a circular business model is challenging, AI enables organizations to create, transfer, and capture value through resource efficiency and the reuse of resources. As AI technologies continue to evolve, organizations must develop adaptive capabilities to continually explore opportunities. AI enables organizations to reduce costs, develop novel value-creation strategies, and capture opportunities, resulting in improved efficiency. Transitioning to a circular business model requires developing routines, and organizations must adapt existing systems to ensure these systems result in pollution prevention, product stewardship, and sustainable development. It is important for managers to develop organizational resources and capabilities that enable the development of AI capabilities.

1 | Introduction

The climate change crisis calls on organizations to assume social and environmental responsibilities by pursuing business model innovation (Burström et al. 2021; Oluleye et al. 2023; Sjödin et al. 2023), and there is agreement that waste reduction and regenerating resources are crucial for achieving long-term economic viability (Geissdoerfer et al. 2020; Rusch et al. 2023). Many organizations have made sustainability issues a strategic goal and are investing in novel technologies to achieve them (Sjödin et al. 2023; Del Vecchio et al. 2024; Frishammar and Parida 2019). The key premise is the role of "reuse", "reduce", and "recycle" strategies while reconfiguring existing business models (Barreiro-Gen and Lozano 2020).

Nonetheless, organizations face various challenges while transitioning to circular models, specifically, financial and technological constraints (Bocken and Geradts 2020; Pascucci et al. 2024). Shifting to circularity requires a swift interpretation of external changes and collaboration with stakeholders (Köhler et al. 2022; Luqman et al. 2024; Re and Magnani 2022; Schneider and Clauß 2020). A successful transition towards a circular business model (CBM) calls for a paradigm shift, as existing organizational practices are not environmentally sustainable (Hart and Dowell 2011). Accordingly, numerous organizations have made sustainability issues a strategic goal and are investing in novel technologies to achieve them (Sjödin et al. 2023; Del Vecchio et al. 2024; Frishammar and Parida 2019).

Interestingly, digital technologies can be a potential enabler, offering analytic tools for resource optimization and product lifecycle management (Abideen et al. 2021; Del Vecchio et al. 2024; Tutore et al. 2024; Wilson et al. 2022). Scholars agree that digital technologies hasten circular transition by facilitating real-time data collection, ensuring virtual inspection, value chain transparency, and allowing collaboration with actors (Chen et al. 2023). Digitalization supports predictive maintenance, waste minimization, and fosters collective behavior by encouraging various stakeholders to engage in circular practices (Sjödin et al. 2024). Nonetheless, despite the promise of digital technologies shaping sustainable outcomes, their intersection with CBMs remains underexplored (Palmié et al. 2021; Roshan et al. 2024), and critical gaps remain in academic research and practice (Rusch et al. 2023). A research gap remains concerning the role of digital technologies in enabling business model transformation (Parida et al. 2019) and capturing value in the form of resource efficiency (Liu et al. 2024). Specifically, there is a need to investigate the impact of artificial intelligence (AI) on CBM implementation (Revathi et al. 2024; Sjödin et al. 2023), a topic of growing relevance (De Angelis 2022; Frishammar and Parida 2019).

Lately, the emergence of AI has been argued to be a catalyst for change, requiring organizations to restructure existing business models and develop new value propositions (Kanbach et al. 2024). AI, often referred to as intelligent machines, is capable of simulating cognition and has the potential to augment and/or require human intervention in decision-making by leveraging data analytic capabilities (Puranam 2021). There is an agreement that AI has the potential to facilitate the transition to circularity by allowing “slowing”, “narrowing”, and “closing” the resource loop (Jogarao et al. 2024; Madanaguli et al. 2024), and creating new business opportunities (Fallahi et al. 2023; Sjödin et al. 2023). AI supports human actions by enhancing the ability to predict inefficiencies, optimize resource use, and forecast future needs (Sjödin et al. 2023). In a nutshell, AI can potentially enhance the product life cycle by scheduling maintenance, reducing wear and tear, and taking a system view.

Despite the crucial role of AI (Brock and von Wangenheim 2019), several gaps exist in the current literature (Mikalef and Gupta 2021). Reconfiguring the business model represents a high-risk strategy (Sjödin et al. 2020), and we lack theory-driven insights on how organizations can deploy digital technologies to redevelop new business models and reconfigure existing ones (Chauhan et al. 2022; Kanbach et al. 2024). Extant research has focused predominantly on the structure of business models rather than organizational processes (Frishammar and Parida 2019; Parida et al. 2019). It is unclear what challenges organizations face while integrating AI into business models (Pascucci et al. 2024; Toorajipour et al. 2024), and how they mitigate challenges including high costs of AI integration (Kanbach et al. 2024). There is a lack of clarity on the capabilities that organizations need to develop and how organizations integrate value creation and capture (Chauhan et al. 2022; Sjödin et al. 2021). Investing in AI is not sufficient, and organizations need to invest in new resources and capabilities to capture value (Madanaguli et al. 2024; Sjödin et al. 2021). In brief, ambiguity remains regarding the economic, social, and environmental value of implementing AI-enabled circular business models (Sjödin et al. 2023). There is a lack of understanding of how organizations can harness AI technologies for circularity (Frishammar and Parida 2019; Kanbach et al. 2024) and what the value of AI is in shaping business model innovation (Madanaguli et al. 2024).

We consider AI technologies as a capability, which is necessary to develop circular business models. Essentially, organizations need to develop complementary resources and capabilities to leverage AI technology (Mikalef and Gupta 2021). We applied the qualitative method (Bouncken and Aslam 2023) and employed a flexible pattern-matching approach. Flexible pattern matching involves observing theoretical patterns in prior literature, then allowing new patterns to emerge from the data (Sinkovics et al. 2021). Using open-ended interviews, we explore participants' experiences regarding using AI in implementing circular business models. Our methodology aligns with the study's exploratory nature, allowing for a deep dive into the lived experiences of organizational members and their perceptions of AI-driven CBM implementation. We draw on the natural resource-based theory (NRBV) and seek to explore the role of resources that are required to leverage AI (Santa-Maria et al. 2022). The findings extend past research by showing that the NRBV is an appropriate lens for leveraging resource efficiency and extending the product life cycle in dynamic and turbulent environments (Coppola et al. 2023; Farrukh et al. 2022).

We extend existing literature by offering an understanding of the interplay between AI and CBMs. First, we contribute to the emerging debate on business model innovation literature (Foss and Saebi 2017; Spieth et al. 2023) and examine the impact of AI on business models. The findings enhance our understanding of opportunities and challenges associated with AI-driven circular practices and offer practical recommendations for business owners and policymakers. Our analysis reveals that the transition to circularity reveals novel challenges (Ritala et al. 2023). Second, our research is based on a natural resource-based view as the theoretical underpinning of AI-enabled business models, enabling organizations to create economic, social, and environmental values. Our key thesis is that the sustainability transition by firms calls for the transformation of business models by leveraging the potential of AI capabilities (Sjödin et al. 2023).

The remainder of this paper is structured in the following way. Section 2 provides a brief overview of the literature on circular economy (CE), circular business models, and artificial intelligence. We provide a brief discussion on the theoretical framework, a natural resource-based view of the firm. The methodology is described in Section 3. In Section 4, the findings are presented in Section 4. We illustrated the emergent themes based on thematic analysis. Finally, in Section 5, we conclude with discussions on findings, implications, and limitations.

2 | Theoretical Background

2.1 | Circular business model (CBM)

In the current business environment, organizations struggle to take a comprehensive view of products' life cycles, leading to inefficiency in resource consumption (Goyal et al. 2018; Le et al. 2023; Schneider and Clauß 2020). An alternative to unsustainable resource consumption is a circular economy CE, a regenerative system aimed at minimizing wastage by "slowing", "closing", and "narrowing" resource loops (Al Halbusi et al. 2025; Geissdoerfer et al. 2018; Lüdeke-Freund et al. 2019). The key principles include designing products with minimal wastage (Palmié et al. 2021; Vilariño et al. 2017), extending product life (Fontana et al. 2021), and regenerating resources (Hart and Dowell 2011). Slowing loops imply slower resource consumption based on an extended product lifecycle (Triguero et al. 2022); the "narrowing" loop implies the use of fewer resources based on efficient product design. Finally, "closing" loops implies recycling of materials used in products (Kara et al. 2022).

A Circular business model (CBM) clarifies how to "create", "deliver", and "capture" value sustainably (Jesus and Jugend 2023; Dagilienė and Varaniūtė 2023; Ritala et al. 2023). In contrast to traditional linear models, which follow a "take, make, and dispose" approach, circular business models focus on efficient resource deployment by extending lifespans, minimizing resource usage, and recycling resources through strategies such as reuse, repair, and remanufacturing, all while collaborating with partners. The concept of the CBM is theoretically linked to the 3R strategy, i.e., slowing, narrowing, and closing the resource loop (Madanaguli et al. 2024). Developing a CBM calls for developing customer-facing promises that emphasize sustainability and circularity (Gomes 2025; Palmié et al. 2021). It requires innovative business models, including novel value propositions, value delivery mechanisms, and capture (Zhao et al. 2020; Geissdoerfer et al. 2023; Scarpellini 2022). Value creation in circular business models implies designing products using fewer materials, optimizing processes to reduce waste, and closing the loop (Ertz et al. 2019; Ünal et al. 2019). Value delivery and capture calls for collaboration with different stakeholders, including suppliers, customers, and recycling partners, and creating a circular ecosystem (Moggi and Dameri 2021).

Despite the importance of the transition to a circular business model, there is considerable uncertainty on how to implement CBMs effectively within the value chain (Madanaguli et al. 2024). For example, the paradoxes faced by organizations include learning, performing, belonging, and organizing (Pascucci et al. 2024). The organizations face tensions while shifting from the old and new business models. They need to learn new skills and unlearn and simultaneously balance short-term and long-term goals. Table 1 provides an overview of the extant literature on the circular business model.

2.2 | AI and Business Model Innovation

The academic literature on CBMs has extensively documented their economic and environmental value (Donner and de Vries 2021; Lüdeke-Freund et al. 2019; Madanaguli et al. 2024). Prior studies have also highlighted key enablers of CBM, such as stakeholder collaboration (Calabrese et al. 2024; Frishammar and Parida 2019; Ritala et al. 2023), the ability to manage paradoxes (Pascucci et al. 2024), institutional support (Wijewardena and Rammal 2025), resource orchestration (Palmié et al. 2021), and minimizing resource consumption (Madanaguli et al. 2024). Concurrently, existing literature highlights the role of digital technologies such as machine learning and blockchain in implementing sustainability principles (Nishant et al. 2020; Ragazou et al. 2022), providing an opportunity to reconfigure business models by reducing waste and facilitating recycling processes (Jogarao et al. 2024). There is a growing debate in the literature on how digital technologies can transform business models across industries (Ferrigno et al. 2023; Moggi and Dameri 2021; Mouazen et al. 2025; Rohn et al. 2021). Scholars agree that AI-driven data analytics are a critical resource for decision-making (Madanaguli et al. 2024; Trunk et al. 2020; Toorajipour et al. 2024), and integrating AI with business processes can automate and streamline decision-making and, in turn, boost overall business performance (Araujo et al. 2020; Jesus and Jugend 2023; Kanbach et al. 2024). AI enhances organizational creativity, optimizes resource allocation, and forecasts trends by leveraging data and analytics, which helps identify and target specific customer segments more effectively (Åström et al. 2022; Davenport 2018; Mikalef and Gupta 2021). AI allows routine task automation and enables organizational actors to focus on strategic decision-making (Baabdullah et al. 2021).

In a nutshell, AI has emerged as a potential catalyst for reconfiguring business models as it facilitates the development of new revenue models with potential for low resource consumption (Åström et al. 2022; Kanbach et al. 2024; Mishra and Tripathi 2021). Successful integration, in turn, fosters an innovative culture and training to leverage AI's potential for sustainable development (Goralski and Tan 2020). Nonetheless, the integration of AI and circular practices necessitates the navigation of varied risks and ethical issues (Etzioni and Etzioni 2017; Madanaguli et al. 2024; Mikalef and Gupta 2021). Challenges include implementation lag (Mikalef and Gupta 2021), algorithmic bias (Panch et al. 2019), and data privacy (Martin and Zimmermann 2024), which must be critically examined and addressed. Table 2 below provides an overview of the extant literature on the intersection of AI and circular business models.

3 | Methodology

3.1 | Research Context

3.1.1 | Method

Given the complexity and fine-grained tacit processes that explain how firms deploy AI while transitioning to the circular business model, qualitative inquiry is considered (Sjödin

TABLE 1 | Key empirical papers in circular business model research.

References	Purpose of study	Definition (circular business model)	Methodology	Key findings
Pascucci et al. (2024)	What paradoxical tensions do incumbent firms face during the implementation of circular business model innovation?	A circular business model enables organizations to create and capture value by improving resource efficiency and extending the lifecycle of products.	Longitudinal single-case study. Nine interviews with multiple respondents supplemented by field notes.	Tensions faced while implementing circular business model: new and old knowledge, circularity and profitability, closed and open systems. Dynamic capabilities enable incumbent firms to manage paradoxes
Palmié et al. (2021)	How do organizations implement a circular business model?	A circular business model reduces resource usage, improves resource efficiency, and minimizes leakage to create economic value.	Multi-case study. Nine firms in Germany and Switzerland, 40 interviews (17 initial interviews and 23 follow-up) with participants in Virtual power plants (VPP). 7 interviews with resource providers.	Asset sharing plays a crucial role in implementing a circular business model. The role of digital technologies is crucial while reconfiguring internal resources and facilitating interaction between actors.
Hartmann and Long (2025)	How does circularity training influence the implementation of a circular business model?	Implementing circularity calls for designing a circular business model in line with circularity principles.	Ten interviews	Circularity training enables the implementation of circular business models.
Rao et al. (2024)	How organizations overcome barriers while adopting a circular business model.	A circular model is a closed-loop resource recovery model, as it allows the transformation of residual output into new value.	Single case study	Adapting to the regulatory and institutional environment, trust-based relationships, and employee engagement are crucial while implementing circular business models.
Aarikka-Stenroos et al. (2022)	How does supply chain collaboration shape the circular business model transition?	A circular business model is defined as a business strategy focused on value creation and capture	Multiple case studies	Implementing a circular business model necessitates collaboration with various stakeholders. Digital technologies enable supply chain collaboration.
Santa-Maria et al. (2022)	How can an organization implement a circular business model in a dynamic business environment?	Circular business models aim at aligning stakeholders to ensure the implementation of the CE.	Ten firms	Dynamic capabilities support the implementation of circular business models.

(Continues)

TABLE 1 | (Continued)

References	Purpose of study	Definition (circular business model)	Methodology	Key findings
Ritala et al. (2023)	How firms develop a circular value proposition	Circular business models are model applying CE strategies	Conceptual	Implementing a circular business model calls for innovation at multiple levels. Firms need to leverage support from various actors in the ecosystem to pursue a circular transition.

et al. 2020). Qualitative interviews are employed to understand the participants' lived experiences. We employed open-ended essays to collect qualitative data. Open-ended questions are well accepted in management research as they help elicit narratives from informants concerning the phenomenon by asking questions related to their individual experiences. Written open-ended essays allow online qualitative data collection for participants through predefined questions. There are several advantages of open-ended interviews. First, participants can answer as per their convenience rather than time-bound face-to-face interaction with the researcher, as participants can answer questions within 2–3 days. Second, the open-ended approach offers anonymity in participation, and they can answer without any bias. While demographic data of participants were collected, their identity is kept anonymous. Third, researchers can reach out to the same or different participants to conduct further stages of the study. The selected participants can again be contacted to probe them about the phenomenon under study and ask follow-up questions. In nutshell, open-ended essays allow participants to share their experiences without any social desirability bias. The key benefits include the ease of data collection, flexibility to address a wide range of research questions, an opportunity to collect data from a large body of participants, giving voice to participants, and choice of anonymity (Braun et al. 2021).

3.1.2 | Participant Selection and Data Collection

We recruited participants from "Prolific Academic", a crowdsourcing platform, an accepted resource for qualitative data collection employed in prior studies. The platform connects researchers with organizational members with the desired profile who can answer open-ended essays. We employed purposeful sampling, and our sample included senior managers working in diverse industries and actively engaged in leveraging AI while implementing business model innovation. We engaged with participants who had experience of AI deployment in work processes. We followed the following protocols before launch of study. We informed the prospective participants about the purpose of study. We specifically clarified that interview data collected would be used only for academic purposes. We promised participants about anonymity and confidentiality of responses (Flick 2004). In addition, we briefed them about questions, and the procedure for writing responses was explained. We employed the following criteria to identify appropriate respondents for the study. First, individuals who participate in the study must be strategic leaders in the organizations implementing circularity. Second, they should have knowledge about the role of circularity in achieving competitive advantage. Third, they should have implemented AI in their organization. The participants were selected based on questions regarding the nature of the work they perform, the main activities of the organization they work with, their daily job responsibilities linked to the circular business model, their awareness about AI, and whether their organization uses AI to pursue circularity.

We interviewed 55 participants deploying AI in their decision-making (e.g., see Table 3). We first asked about demographic information and participants' perspectives on the role of AI. We asked participants to describe recent developments in AI in the second stage, and the questions focused on the role

TABLE 2 | Key empirical papers on AI and business models.

Reference	Purpose of study	Methodology	Key findings	Implications
Chauhan et al. (2022)	How does digitalization influence circular business model implementation?	Review	AI shapes the implementation of circular business models by enabling efficient decision-making and resource utilization. AI's ability to process large amounts of data and identify hidden patterns is crucial while implementing circular business models.	AI facilitates circular business models by ensuring data-driven decision-making.
Sjödin et al. (2021)	How AI capabilities and routines are developed in manufacturing firms. How do organizations deploy AI capabilities while implementing circular business models? What are the distinct routines that shape AI-driven circular business model implementation?	Swedish B2B firms and their service providers. Multiple case studies with 42 interviews with participants (business developers, R&D persons, platform managers, product and service managers, and delivery staff) involved in deploying AI capabilities.	The findings help clarify how AI can be integrated into the value creation, delivery, and capture. First, AI enables firms to sense and collect data from multiple sources. It is important to have routines that allow the use of data. Second, algorithm development capabilities and the ability to improve algorithms help firms make sense of complex data. Third, engaging the workforce in implementing AI is crucial.	Co-creation, data-driven capabilities, and ecosystem integration are crucial. To implement an AI-enabled business model, the role of three AI capabilities, i.e., “data pipeline”, “algorithm development”, and “AI democratization” is crucial.
Sjödin et al. (2023)	What role does AI play in implementing circular business model innovation?	Five B2B firms. Fifty-four interviews with key participants actively involved in the implementation of the circular business model. Review of documents (secondary data)	The crucial role of AI-enabled “perceptive”, “predictive”, and “prescriptive” capabilities resulting in resource efficiency.	The two phases of AI-enabled business model implementation are augmentation and automation. AI-enabled value discovery, optimization, and realization result in economic and environmental benefits. The role of dynamic capabilities is crucial in discovering, realizing, and optimizing value.
Madanaguli et al. (2024)	What are the drivers of AI-enabled circular business model implementation?	Review	The roles of “people”, “process”, “platform”, and “ecosystem” are crucial	AI implementation leads to “narrowing”, “slowing”, and “closing” resource loops.
Jorzik et al. (2024)	How do startups use AI to implement circular business models?	Nine cases	The role of AI-driven innovation in shaping environmental impact	AI shapes value creation, delivery, and capture.
Toorajipour et al. (2024)	What are value creation and value capture mechanisms in a data-enabled ecosystem?	Archival data from 28 companies, followed by 19 in-depth interviews	The findings help categorize business models into four archetypes: adaptive partnership, user-centric, standardized efficiency, and flexible transaction	Balancing control and customization is crucial to navigating the complexities of an AI-based data ecosystem

(Continues)

TABLE 2 | (Continued)

Reference	Purpose of study	Methodology	Key findings	Implications
Kanungo et al. (2024)	How does responsible AI lead to business model innovation?	Four hundred seventy-two responses from stakeholders	Responsible AI shaped by cognitive analytics enables business model innovation.	The role of responsible AI in business model implementation.
Lee et al. (2019)	How does AI transforms business model	Case study. Two cases. Both Cases A and B employed AI in area of talent management	Business model innovation process involves (1) execute the pilot project, (2) build AI team in-house, (3) train team, (4) develop AI strategy, and (5) communicate	The role of top management is crucial to foster AI-enabled BMI
Åström et al. (2022)	How AI providers align value creation and value capture?	Single case study. twenty-three interviews with Senior Managers.	The findings exhibit three qualifiers for BMI: (1) identifying pre- requisites for value creation, (2) value capture mechanism, and (3) developing business model.	Feedback loop between value creation and capture is crucial.
(Kohtamäki et al. 2020)	What are the micro practices that underline business model innovation	Six cases, 20 interviews with representative of selected cases and 11 interviews with experts.	The three practices are (1) "proactive idea generation", (2) "value-driven product development", and (3) "market-driven product commercialization".	Entrepreneurial orientation and absorptive capacity enhance innovation

TABLE 3 | Demographic profile of the study participants.

Participant ID	City and country participant is based	Total work experience (in years)	Number of employees working in participant's organization	Participant age (in years)	Annual income (USD)	Management level	Organization type
1	Ohio, United States	20	500	51–60 years	[110,000 up to 140,000]	[Middle management—operational]	[Private]
2	Fremont, California, United States	6	12	18–30 years	[50,000 up to 80,000]	[Above middle management—tactical]	[Private]
3	New York, United States	25	500	51–60 years	[110,000 up to 140,000]	[Top management]	[Private]
4	Effort, United States	17	10,000	41–50 years	[80,000 up to 110,000]	[Above middle management—tactical]	[Public]
5	Afton, United States	40	180	Above 60 years	[Above 140,000]	[Top management]	[Private]
6	Texas, United States	12	20	31–40 years	[Above 140,000]	[Top management]	[Private]
7	Wausau, Wisconsin, United States	5	2	Above 60 years	[< 50,000]	[Top management]	[Private]
8	West Des Moines, United States	12	85	31–40 years	[50,000 up to 80,000]	[Above middle management—tactical]	[Public]
9	San Bernardino, United States	8	2	31–40 years	[< 50,000]	[Top management]	[Public]
10	Rogers, USA	11	7000	31–40 years	[80,000 up to 110,000]	[Middle management—operational]	[Private]
11	El Dorado, AR, United States	7	24	31–40 years	[50,000 up to 80,000]	[Top management]	[Private]
12	Gwinn, United States	16	7	31–40 years	[< 50,000]	[Top management]	[Public]

(Continues)

TABLE 3 | (Continued)

Participant ID	City and country participant is based	Total work experience (in years)	Number of employees working in participant's organization	Participant age (in years)	Annual income (USD)	Management level	Organization type
13	California, United States	9	250	31–40 years	[50,000 up to 80,000]	[Middle management—operational]	[Private]
14	Hopkins, Minnesota, United States	10	79	31–40 years	[80,000 up to 110,000]	[Middle management—operational]	[Private]
15	Caldwell, NJ, United States	11	700	31–40 years	[110,000 up to 140,000]	[Senior leadership]	[Private]
16	Sterling Heights, United States	2	2	41–50 years	[< 50,000]	[Top management]	[Private]
17	United States	5	1000	18–30 years	[Above 140,000]	[Above middle management—tactical]	[Public]
18	Virginia, United States	25	1000	41–50 years	[80,000 up to 110,000]	[Top management]	[Private]
19	Acworth, Gam United States	13	8	31–40 years	[50,000 up to 80,000]	[Above middle management—tactical]	[Private]
20	Maryland, United States	21	8	41–50 years	[Above 140,000]	[Top management]	[Private]
21	Boston, MA, United States	18	12,000	31–40 years	[Above 140,000]	[Senior leadership]	[Private]
22	Punta Gorda, United States	9	200	41–50 years	[50,000 up to 80,000]	[Middle management—operational]	[Private]
23	Aldie, United States	21	45	41–50 years	[80,000 up to 110,000]	[Top management]	[Private]
24	Caldwell, NJ, United States	11	700	31–40 years	[110,000 up to 140,000]	[Senior leadership]	[Private]

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TABLE 3 | (Continued)

Participant ID	City and country participant is based	Total work experience (in years)	Number of employees working in participant's organization	Participant age (in years)	Annual income (USD)	Management level	Organization type
25	Mississippi, United States	18	500	31–40 years	[Above 140,000]	[Middle management—operational]	[Private]
26	Florida, United States	2	50–100	31–40 years	[80,000 up to 110,000]	[Senior leadership]	[Public]
27	California, United States	3	100	18–30 years	[50,000 up to 80,000]	[Above middle management—tactical]	[Public]
28	Lycnhburg, VA, United States	28	950	41–50 years	[Above 140,000]	[Senior leadership]	[Private]
29	Florida, United States	40	600	41–50 years	[110,000 up to 140,000]	[Middle management—operational]	[Private]
30	San Bernardino United States	40	1	51–60 years	[Above 140,000]	[Top management]	[Private]
31	United States	15	500	41–50 years	[Above 140,000]	[Senior leadership]	[Public]
32	California, United States	4	250	18–30 years	[Above 140,000]	[Senior leadership]	[Private]
33	New York, United States	11	850	41–50 years	[110,000 up to 140,000]	[Above middle management—tactical]	[Private]
34	Kinston, United States	5	600	31–40 years	[50,000 up to 80,000]	[Above middle management—tactical]	[Public]
35	Appleton, Wisconsin, United States	35	100	51–60 years	[Above 140,000]	[Senior leadership]	[Private]
36	California, United States	5	100	18–30 years	[50,000 up to 80,000]	[Senior leadership]	[Public]
37	New York, United States	12	50–249	31–40 years	[50,000 up to 80,000]	[Top management]	[Public]

(Continues)

TABLE 3 | (Continued)

Participant ID	City and country participant is based	Total work experience (in years)	Number of employees working in participant's organization	Participant age (in years)	Annual income (USD)	Management level	Organization type
38	New Jersey, United States	6	45	41–50 years	[50,000 up to 80,000]	[Middle management—operational]	[Private]
39	Washington, United States	6	9	18–30 years	o	[Middle management—operational]	[Private]
40	United States	20	20	51–60 years	[< 50,000]	[Middle management—operational]	[Private]
41	Medford, United States	30	5	41–50 years	[50,000 up to 80,000]	[Top management]	[Private]
42	Terra Alta, United States	3	200	18–30 years	[50,000 up to 80,000]	[Above middle management—tactical]	[Public]
43	Corolado, United States	35	> 50	Above 60 years	[50,000 up to 80,000]	[Top management]	[Public]
44	New York, United States	32	87	51–60 years	[Above 140,000]	[Middle management—operational]	[Private]
45	Riverton, United States	8	135	31–40 years	[Above 140,000]	[Above middle management—tactical]	[Private]
46	Atlanta, GA, United States	22	252	41–50 years	[50,000 up to 80,000]	[Senior leadership]	[Private]
47	United States	7	1	41–50 years	[Above 140,000]	[Top management]	[Private]
48	Houston, United States	30	100	Above 60 years	[Above 140,000]	[Senior leadership]	[Private]
49	Maud, Texas, United States	20	3200	41–50 years	[< 50,000]	[Top management]	[Private]

(Continues)

TABLE 3 | (Continued)

Participant ID	City and country participant is based	Total work experience (in years)	Number of employees working in participant's organization	Participant age (in years)	Annual income (USD)	Management level	Organization type
50	Atlanta, GA, United States	10	14	31–40 years	[Above 140,000]	[Top management]	[Private]
51	Milwaukee, United States	14	400	31–40 years	[Above 140,000]	[Above middle management—Tactical]	[Private]
52	New York, United States	7	3000	31–40 years	[110,000 up to 140,000]	[Middle management—operational]	[Public]
53	FLORIDA, United States	6	3	18–30 years	[80,000 up to 110,000]	[Senior leadership]	[Private]
54	Elizabethtown Pennsylvania, United States	3	10,001	31–40 years	[80,000 up to 110,000] USD	[Above middle management—tactical]	[Private]
55	United States, Pennsylvania	20	65	51–60 years	[Above 140,000] USD	[Senior leadership]	[Private]

of AI, challenges, and experiences with the use of AI. During the open-ended written interviews, the participants were asked to reflect on the role of AI in implementing business models.

Specifically, we asked participants to describe any recent developments in AI that are geared toward enhancing usability.

How do they perceive the role of AI in enabling the transition from a linear to a CE?

We asked participants to elaborate on the challenges they foresee in integrating AI.

What are the key challenges and opportunities that AI technologies present for the CE?

How do AI technologies influence the way businesses and consumers think about resource use and waste management?

How do they view the role of AI in developing a circular business model? How can AI contribute to improving resource efficiency and product lifecycle management in a CE?

3.1.3 | Data Analysis

We analyzed interview data using thematic analysis, a robust method of data analysis well-used in organizational research due to its ability to discover new patterns in data that explain the organizational phenomenon. Thematic analysis involves data *familiarization, identifying patterns and developing, defining, and naming themes, and writing the results* (Braun and Clarke 2013). In particular, we employed the Gioia method to identify our codes (Gioia and Chittipeddi 1991). Microsoft Excel was used for data analysis. We first employed open coding to interview data. In this step of data analysis, we performed an in-depth analysis of interview data. This stage involves employing meaningful and descriptive data that was used by the participants in the study and understanding their views, assumptions, and beliefs (Gioia and Chittipeddi 1991). We read the interviews multiple times and marked passages related to the research question. We coded words and phrases mentioned by participants to identify first-order codes expressing participants' voices.

This is followed by axial coding focuses on iteratively discovering the patterns in the data and developing broad themes by grouping open codes at the theoretical level (Braun and Clarke 2021). The second-order codes are not apparent to participants but are meaningful to other researchers. The step involved developing aggregate dimensions representing a higher level of abstraction. We used insights from literature to guide the formation of aggregate dimensions. This involves analyzing data across participants and identifying convergence among patterns. This procedure involves "constant comparison", as participants' responses were repeatedly compared to discern the themes (Grandgirard et al. 2003). In this stage, we sought to discover patterns within the first-order codes and develop second-order codes. This step continued until we achieved saturation in the coding structure. We developed aggregated dimensions by performing theoretical coding at an abstract level (Gioia et al. 2013). The aggregate dimensions—built on the first-order codes—present a theoretically grounded categorization. In the final step, we theorized the linkages between second-order themes and sought to uncover how AI shapes business model innovation and how firms manage value creation and value capture.

Overall, our methodology was designed to provide a thick description and allow a "way of seeing" the role of AI in entrepreneurial organizations (Gioia and Chittipeddi 1991). Our approach helped us provide a comprehensive understanding of the potential of AI in establishing circularity.

4 | Results

While prior research has explored the process of business model innovation in the form of value creation, transfer, and value capture, how digital technologies can be used to develop business model innovation, and the potential of developing a circular business model, it has not yet captured the role of AI. The findings reveal the role of AI in developing a circular business model. First, AI as a digital technology is a resource with the potential to optimize processes and improve sustainability performance (Kanbach et al. 2024; Madanaguli et al. 2024; Parida et al. 2019). AI can shape CBM innovation (CEP) by enhancing resource efficiency and reducing energy and material consumption (Yavuz et al. 2023). AI can enhance resource management by monitoring resources and improving decision-making processes (Ye et al. 2023). Second, AI as digital technology provides access to new knowledge (Kanbach et al. 2024) and plays a crucial role in improving value chain transparency by tracking resource overconsumption and aiding resource conservation efforts.

4.1 | AI Challenges

The findings revealed that transitioning to a CBM is an alternative to the current linear economic model (Bidmon and Knab 2018; Sarasini and Linder 2018) (see Figure 1). Adoption of AI can drive sustainable competitive advantage by optimizing processes and improving environmental responsibility, which can be challenging. The resource management challenges include a fit between AI and existing resources (Pascucci et al. 2024), developing new organizational capabilities (Palmié et al. 2021), developing new employee competencies (Hartmann and Long 2025; Kanbach et al. 2024), and managing interdependencies between internal and external processes (Palmié et al. 2021).

While AI aids in designing sustainable products and facilitates the development of new circular business models, the participants faced challenges in implementing a circular business model, including the need for a fundamental shift in business models (Frishammar and Parida 2019; Hartmann and Long 2025; Madanaguli et al. 2024; Parida et al. 2019). The potential challenges during AI integration of digital technologies include adaptation challenges, resource management, and ethical issues such as data privacy concerns, algorithmic bias,

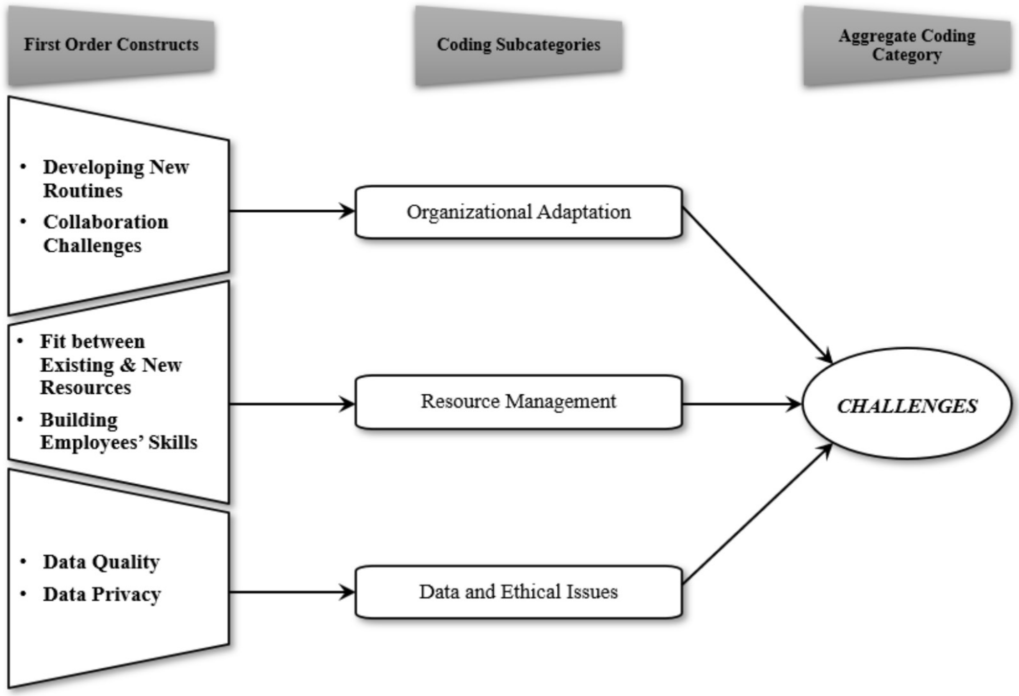

FIGURE 1 | AI-Implementation challenges.

and the need for specialized technical expertise. The participants discussed their challenges during value creation, delivery, and capture (Pascucci et al. 2024). The resource management challenges include the high input cost of AI implementation, risks associated with input data, training needs, and privacy risks. The resource management issues include the potential for increased resource consumption and the environmental impact of digital technologies. The participants faced an initial technology adoption hurdle while initially adapting the AI-enabled business model, which involved training, planning, and determining how to integrate and use AI (Madanaguli et al. 2024). "The first challenge is adaptation. Internal training and planning, modeling, and determination of integration and usage within corporations is critical" (#P33). Successful implementation of CBMs requires the integration of new technology adoption and engagement of multiple organizational functions. This involves aligning various departments and ensuring collaboration among stakeholders, which can be complex and resource-intensive.

Resource management emerged as a challenge as the participants disclosed that developing AI-driven capabilities calls for reskilling employees and building competencies (Hartmann and Long 2025; Kanbach et al. 2024). While the findings revealed that AI drives cost saving and resource efficiency (Madamaguli et al., 2024), the participants disclosed the need to incur new costs, participants need to incur new input costs. "AI utilizes a lot of energy, much of which currently comes from non-renewable sources" (#P9). The participants emphasized that ensuring data accuracy is crucial for training AI systems. The participants elaborated on the complexity of creating value-delivery systems and identified challenges like the need for incremental capability development and managing resource reconfiguration (Madanaguli et al. 2024). There's also mention of difficulties managing cultural shifts towards technology reliance and risks associated with radical transformations. In addition, the initial investment required for AI adoption is a concern, as transitioning to circular business models has financial implications, such as higher initial capital investment.

Ethical concerns, such as data privacy, algorithmic bias, and transparency, pose significant challenges. The participants need to navigate these issues carefully to maintain trust and comply with regulatory standards. The participants expressed concerns regarding how personal data is protected. They sought transparency on how AI-driven systems operate and make decisions. "Customers are concerned about data privacy and the transparency of AI-driven systems, but they also want AI to improve environmental practices, recycling, and product durability" (#P53). Another significant ethical challenge in adopting AI for CBMs is the lack of robust data quality. The participant often struggled with the insufficient data quality and the expertise required to effectively leverage AI. Ensuring the accuracy of data and addressing security concerns are fundamental to the successful adaptation of new systems. Proper training with accurate data and strong security protocols can help mitigate these concerns and meet expectations. AI can generate misleading information, and triangulation is crucial to ensure the reliability of AI-generated insights. "I think expectations and concerns If the data isn't accurate, then there's no point in using it. Training it to be relevant and accurate data is initially crucial" (#P10). AI systems need to be transparent while recommending decision-making processes. They need to identify and mitigate biases in AI algorithms and establish clear accountability mechanisms to monitor and address any ethical concerns. "The key challenges, in my eyes, are to ensure the scaling of AI technology remained ethical, truthful and helpful as to benefit society in meaningful and sustainable ways and avoid corruption and cruelty" (#P55).

4.2 | AI-Enabled Value Creation

The findings revealed the crucial role of AI as a resource in novel value creation (Parida et al. 2019), for example, through *waste reduction* and energy efficiency by leveraging predictive analysis, data-driven design to support predictive maintenance, and AI-enabled *product life cycle extension* (see Figure 2). The role of AI is critical in accelerating the transition from a linear economy to a circular economy (CE), as the deployment of AI enables organizations to optimize product design for longevity, deploy predictive maintenance, implement recycling strategies, and ensure that resources are utilized more effectively. The findings reveal that AI contributes to reducing energy and material consumption, which is crucial for CE practices. AI significantly enhances operational efficiency by ensuring optimum resource utilization and cost reduction (Parida et al. 2019). Data-driven practices influenced how value is created by eliminating waste. Innovative products and processes helped them eliminate waste and pollution.

The participants emphasized the importance of "designing out waste" and highlighted the role of AI in sustainable design, innovation, and process improvement. AI significantly enhances operational efficiency by ensuring optimum resource utilization and cost reduction (Parida et al. 2019). Data-driven practices influenced how value is created by eliminating waste. Innovative products and processes helped them eliminate waste and pollution. AI enables the development of innovative circular business models by predicting consumer behavior, analyzing environmental impacts, and managing risks associated with new products (Parida et al. 2019). AI contributes to reducing energy and material consumption, which is crucial for CE practices. The participants noted that the deployment of AI helped them manage waste and reduce resource use and carbon footprints. By utilizing AI, organizations can reduce waste and enhance their sustainability outcomes. "I think it really depends on the company and the scenario context they are dealing with. On one hand, AI can streamline your operations to a point where most, if not all, of your resources are being used more efficiently. You may even cut down on waste because you are using fewer conventional resources" (#P16).

The findings revealed that AI enhances value propositions by enabling autonomous and adaptive solutions, leveraging data, and fostering stronger collaboration within ecosystems. For instance, AI-driven resource optimization in data centers can potentially cut resource consumption and reduce emissions. Specifically, AI aids idea generation and provides organizations with deep insights into their operations (Sjödin et al. 2021), enabling them to identify areas of improvement in resource optimization. "I think businesses feel that using AI in its business operations gives them more knowledge on how to cut down on waste materials, especially in the manufacturing process, and also conserving natural energy resources" (#P22). AI automates waste sorting, increasing recycling rates, resulting in improved efficiency and effectiveness in waste management. "One previous project is AMP Robotics, which automates waste sorting using AI to increase recycling rates. The significance of data quality, the scalability of AI solutions, and striking a balance between automation and job creation are among the lessons learned (#P53)." In brief, AI can significantly reduce resource consumption through automation, such as automating asset utilization. For example, using AI to predict future trends based on real-time data (see Figure 3).

The findings revealed that AI-enabled value creation through product design optimization based on predictive maintenance

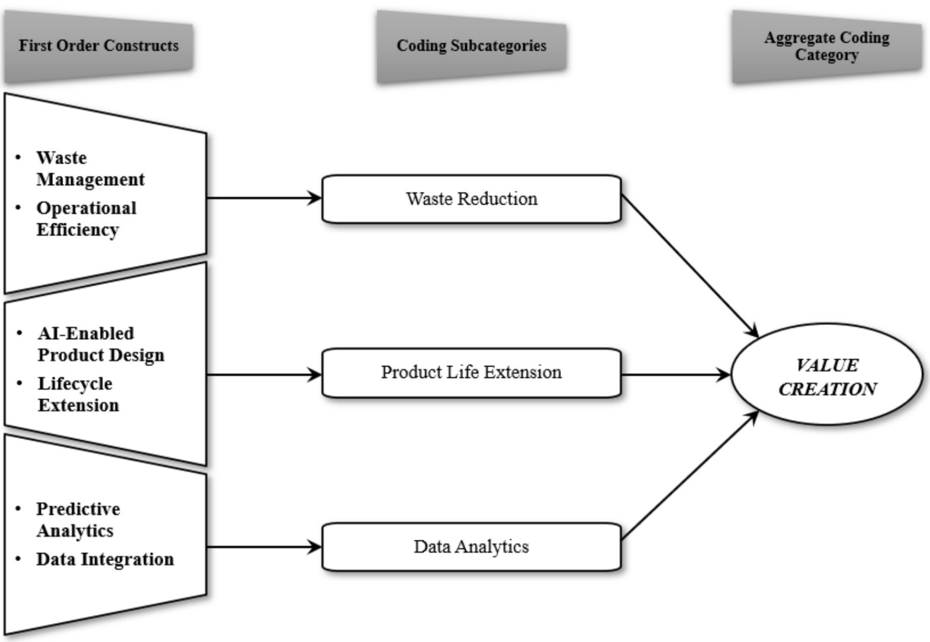

FIGURE 2 | AI-Enabled Value Creation.

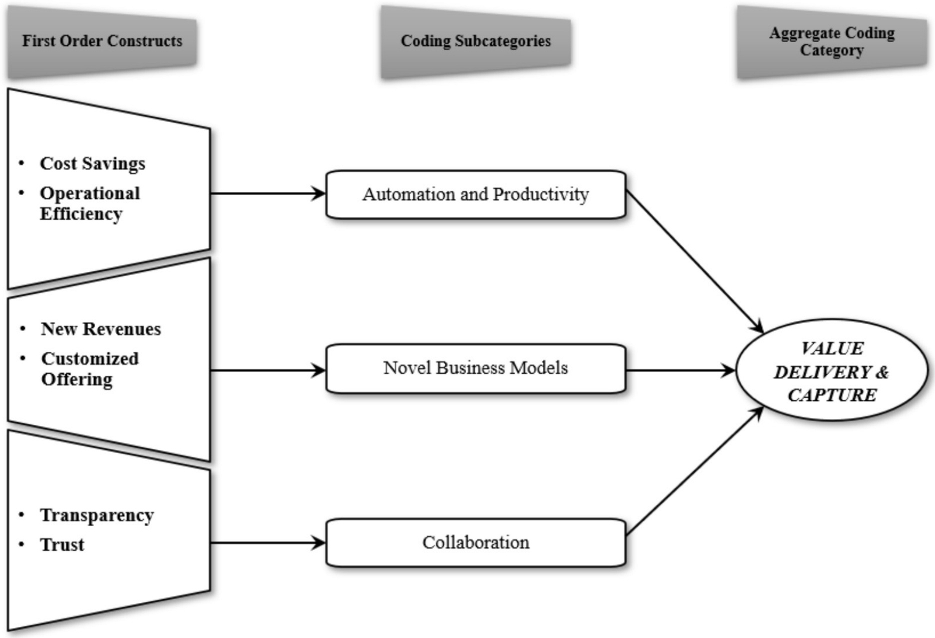

FIGURE 3 | AI-enabled value delivery and capture.

and recycling ensured that materials were used for longer periods (Åström et al. 2022). AI-powered decision support systems enable informed choices about product design, resource recovery, and supply chain management, ultimately leading to more sustainable practices. Likewise, AI-driven predictive analytics help businesses design products for durability and recyclability, reducing material waste; this results in building capabilities for product lifecycle extension (Åström et al. 2022). The participants revealed the crucial role of AI in extending product lifecycles via reuse, repair, remanufacturing, and recycling. AI reduces overproduction and enhances resource utilization through demand forecasting and real-time adjustments, aligning with circular principles. AI offers opportunities to optimize resource use by improving recycling processes. "It is likely that AI would be a boon to the CE while posing problems at the same time. Some of the primary opportunities include optimization of resource use, recycling approaches, and predictive maintenance (#P50)".

The finding revealed the role of AI-based data analytics in value creation through *narrowing*, *slowing* and *closing* strategy. AI-powered systems monitor and analyze the condition of products, facilitating decisions on the best recovery path, such as repair or remanufacture, thus extending product lifespans. AI integrates data across product design, energy use, waste streams, and supply chains to create closed-loop systems. AI optimizes resource usage by analyzing data, leading to enhanced processes. AI optimizes material flows and identifies novel resource recovery and reuse opportunities. "AI also supports sustainable supply chains through blockchain and IoT integration, tracking product lifecycles for reuse and refurbishment. Additionally, AI-driven design tools assist manufacturers in creating sustainable, modular, and recyclable products, further advancing CE principles (#P50)". AI can predict when a product is likely to fail, enabling timely maintenance and reducing downtime, thereby extending the product's useful life. AI can predict when equipment will likely fail, allowing for timely maintenance, preventing unexpected downtime, and extending product life. "Due to its brilliance, AI can prevent equipment failure. It is easy to identify and solve an issue" (#P47).

4.3 | AI-Enabled Value Capture and Value Delivery

The findings revealed the crucial role of AI in capturing and delivering value through cost savings and new revenue streams (Burström et al. 2021). Value delivery encompasses processes and activities required to deliver value through a collaborative network (Chauhan et al. 2022). AI-driven value capture is linked with the role of AI technology in maximizing value through superior asset utilization and cost reduction. The findings revealed the crucial role of AI in delivering novel value through circular systems (e.g., sharing, reuse, and recycling), as well as automating customer needs assessment, forecasting, monitoring, and control using data analytics (Sjödin et al. 2023). AI can significantly reduce resource consumption through automation, such as automating asset utilization. For example, Figure 3 highlights the use of AI to predict future trends based on real-time data.

AI support organizations build new capabilities and analyze vast amounts of market data to identify trends, opportunities, and potential risks, thereby enabling businesses to make informed decisions (Åström et al. 2022). AI systems quickly identify and diagnose issues, providing solutions faster than traditional methods. "We use AI-driven behavioural analytics to understand customer habits, enabling personalized sustainability recommendations. A success story is our EcoTrade Program, where AI tracks product lifespans, reminding customers to return used furniture for refurbishment" (#P24). AI-based technologies helped them simulate product lifecycles before production, reducing material waste and enhancing the durability and recyclability of products. AI-enabled waste tracking systems ensure returned products are efficiently reintegrated into new production.

Furthermore, AI technologies significantly enhance operational efficiency, which is crucial for capturing value in a CBM. AI optimizes the use of materials, energy, and water, thereby reducing consumption and waste. AI helps organizations save costs and gain a competitive advantage by improving process efficiency and reducing waste. AI assists organizations in analyzing data to predict equipment failures and maintenance needs, reducing downtime and extending the life of assets. This predictive maintenance leads to cost savings and improved resource utilization. While predictive analytics help organizations reduce costs by leveraging data-based decisions and improving market competitiveness, automation increases productivity by streamlining processes.

The deployment of AI helps organizations optimize existing revenue models and reduce costs through improved efficiency and automation (Madanaguli et al. 2024). AI can support firms in transitioning from product sales to service-based models (e.g., product-as-a-service), where customers pay for the use of a product rather than ownership. This model encourages firms to design products for longevity and recyclability. AI can analyze customer data to offer personalized recommendations and services, enhancing customer loyalty and engagement. "From cost savings and efficiency to increasing productivity across the board, the possibilities are plentiful, and we honestly haven't even scratched the surface of its core capabilities (#P50)". AI platforms can enable knowledge sharing and collaboration across industries, fostering innovation and best practices in CE initiatives. The deployment of AI ensures transparency in sourcing, compliance with regulations, and balancing profit with sustainability goals.

Collaborative feedback is essential for refining the product's design and extending its lifespan. The participants revealed the potential of AI in consumer engagement, and the use of analytics helped them understand customer habits and provide personalized sustainability recommendations (Parida et al. 2019). AI helped them track product lifespans and encourage customers to return used furniture for refurbishment. "AI technologies enable collaborative environments, encouraging customers and supply chain partners, or R&D firms, to achieve resource efficiency through enhanced product lifetimes and reuse. Companies use AI-driven insights to optimize product designs, predict maintenance needs, and improve recycling processes" (#P38).

5 | Discussion

The integration of circularity with the business model has garnered significant attention in both academia (Burström et al. 2021). There is growing agreement that circular business models (CBMs), emphasizing "*resource efficiency*" and "*resource reuse*", are crucial for addressing environmental challenges and achieving long-term economic viability (Geissdoerfer et al. 2020; Frishammar and Parida 2019). However, despite the theorized potential of AI to optimize resource use and facilitate product lifecycle management (Bocken et al. 2021), its intersection with circular business model remains relatively underexplored (De Angelis 2022; Lee et al. 2019). While extant research has focused on the perspective of digitalization and business model innovation (Sjödin et al. 2022), and its impact on value creation and capture (Åström et al. 2022); there is a lack of understanding of the wider adoption of AI in reconfiguring business models. Our study seeks to provide an explanation of how AI can be employed to design and reconfigure value creation and capture. We explore how AI can support the implementation of CBM and the potential challenges during the implementation of AI during business model reconfiguration. We answer the following research question: **RQ:** How can organizations deploy AI while pursuing CBM innovation?

We present empirical evidence from interviews with fifty-five participants working in various organizations. Participants are selected through purposive sampling, and data is analyzed using thematic analysis and identified themes (Grogan et al. 2018). Employing a thematic analysis of fifty-five interviews with participants engaged in CBM transitions, we conceptualize the role of AI in enabling value creation and capture, which enhances resource efficiency through pollution control and stewardship.

While AI is a key resource during business model reconfiguration (Åström et al. 2022) the implementation requires surmounting significant barriers. The findings revealed that transitioning to AI-driven sustainable transition calls for new capabilities development, and organizations must navigate strategic challenges as transition calls align digital technologies with existing resources, reconfiguring existing capabilities (e.g., predictive maintenance systems), and managing interdependencies between internal processes (Ferrigno et al. 2023). Furthermore, the high upfront costs of AI adoption, the quality of data, and the high costs associated with energy-intensive AI systems conflict with sustainability goals. Training employees and ensuring data accuracy is critical as organizations face risks due to privacy concerns, algorithmic bias, and transparency issues, which can undermine stakeholder trust.

The findings underscore AI's pivotal role in reconfiguring existing business models by sharing, reusing, and recycling resources and assessing customer needs through forecasting (Madanaguli et al. 2024). AI's ability to analyze big data helps organizations identify novel opportunities and make informed decisions (Åström et al. 2022). AI's potential to enable stakeholder collaboration is crucial, as collaborations facilitate product lifecycle extension and promote resource reuse (Chen et al. 2023). AI-generated insights enable organizations to optimize product designs, predict maintenance needs, and improve recycling processes.

Finally, in Figure 4 we propose a conceptual framework and argue that the transition to circularity enabled by AI encompasses an interplay of technology adoption, opportunity recognition, and adaptation (Awan et al. 2025). Building on the natural resource-based view, we theorize the importance of leveraging natural resources to build novel capabilities and gain a competitive advantage (Farrukh et al. 2023; Caldera et al. 2018). The key thesis is that the efficient deployment of

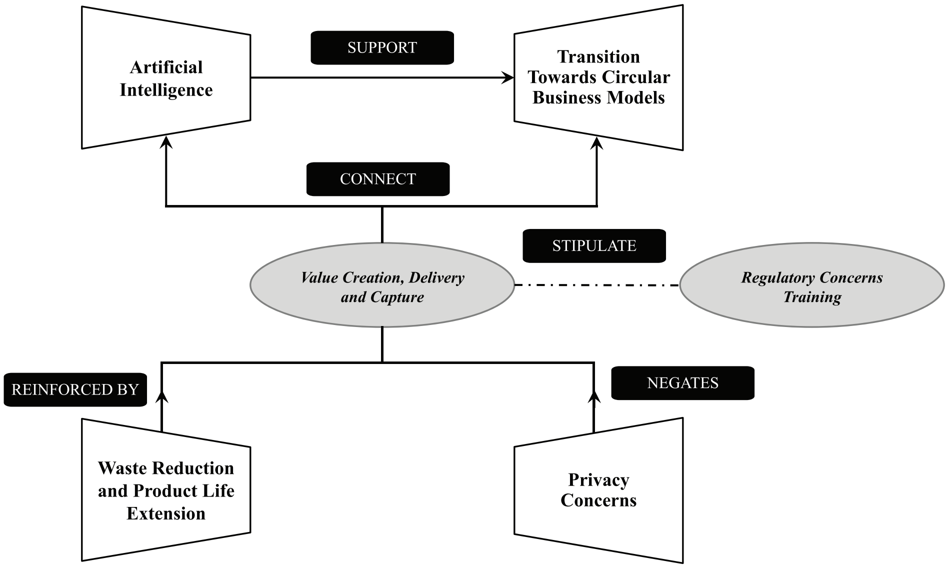

FIGURE 4 | AI-Enabled Circular Transition.

natural resources is crucial to developing operational excellence and pursuing technological innovation. Building a CBM calls for reducing waste while designing products (Hart 1995), and extending the product life cycle by ensuring products and materials are repaired, refurbished, and reused (Geissdoerfer et al. 2020).

Moreover, the role of AI-enabled activities is crucial to capture value. AI can help organizations build novel resources and capabilities, for example, analyzing big market data to identify hidden trends, tap new opportunities, and forecast new risks, thereby helping businesses take data-driven decisions (Åström et al. 2022). AI allows value capture through cost savings and novel revenue models. Ultimately, AI can play the role of a catalyst by offering new pathways to improve efficiency, extending product life, and achieving profitability with sustainability principles. Nonetheless, the contextual factors, for example, regulations, shape the AI implementation and require transparency, training, and reinvestment. In a nutshell, the natural resource-based view theory, proposed by Hart and Dowell (2011), helped us understand the role of AI in supporting the implementation of circular business models.

5.1 | Theoretical Implications

First, the findings significantly contribute to the NRBV, emphasizing three key strategies: "*pollution prevention*", "*product stewardship*", and "*sustainable development*". The NRBV has been previously used to understand how organizations develop dynamic capabilities while transitioning to circular economy (Coppola et al. 2023). Building on existing on NRBV, we argue that the role of digital technologies is crucial in reconfiguring internal resources and capabilities (Palmié et al. 2021). Specifically, AI's role in optimizing processes to reduce waste and emissions aligns with the NRBV's emphasis on minimizing environmental impact through efficient resource use. AI technologies-supported predictive maintenance and data analysis help firms achieve continuous improvement in pollution prevention strategies, reduce costs, and enhance their operational efficiency (Chen et al. 2023). The deployment of AI leads to product stewardship, as the ability to analyze vast amounts of data supports the integration of environmental considerations into product design and product lifecycle extension. By designing products for low resource consumption, durability, and reuse, firms minimize product lifecycle costs and integrate diverse stakeholder interests. In a nutshell, AI's role in pollution prevention and extending product lifecycles through reuse, repair, remanufacturing, and recycling supports the reduction of the environmental burden and drives collaboration within ecosystems.

Second, the findings contribute to the CBM literature by demonstrating AI's ability to configure existing business models through effective resource management (Bocken et al. 2016) and value creation (Åström et al. 2022; Palmié et al. 2021). The findings highlight the pivotal role of AI in advancing CE practices. AI supports the development of innovative circular business models by predicting consumer behavior, analyzing environmental impacts, and managing risks. It integrates value chains to create closed-loop systems, optimizing resource usage and identifying opportunities for resource recovery and reuse.

Third, the findings empirically validate theoretical claims that the deployment of AI technologies shapes sustainability transitions and highlight the need for collaborative technology-human interface systems that augment human expertise rather than replace it (Sjödin et al. 2023). AI-enabled CBMs require a holistic redesign of value chains, i.e., not just technological adoption, but emphasizing interdependencies between data infrastructure, employee competencies, and cross-departmental collaboration. Digitalization encourages learning-by-doing, allowing organizations to adapt their strategies based on iterations. This iterative approach enables organizations to refine their strategies over time, improving their environmental performance and competitive positioning. Collaborative technologies address workforce reskilling and ethical concerns often overlooked in technocentric CBM literature. It contributes to debates on responsible AI by linking CE principles (e.g., transparency and equity) to algorithmic governance, urging a dual focus on environmental and social sustainability.

Finally, the findings have key implications for NRBV literature (Hart 1995). Resource responsibility, combined with digital transformation, improves financial performance. AI-enabled decision support systems incorporating environmental and economic goals aid organizations in making strategic decisions (Sartori and Theodorou 2022). AI systems help organizations evaluate the trade-offs between different strategic options, ensuring that decisions align with financial performance and environmental sustainability (Shi et al. 2012). This approach aligns with the NRBV by integrating environmental considerations with economic growth. In addition, the role of dynamic capabilities is crucial to mitigate the tensions that arise during the transition to the CBM (Pascucci et al. 2024).

5.2 | Practical Implications

We propose the following managerial implications. First, managers need to leverage AI while addressing challenges associated with circular business models. AI can help mitigate barriers to CBM adoption by improving resource utilization (Chauhan et al. 2022). Organizations need to develop a unique resource and AI-enabled capabilities to generate value (Mikalef and Gupta 2021). Managers integrating AI capabilities into business models must orchestrate diverse capabilities from diverse stakeholders. Moreover, managers must be aware of various challenges related to the integration of AI with existing business models. It is important to nurture data processing capabilities to successfully integrate diverse data (Rusch et al. 2023).

Second, implementing circular business models requires continuous adaptation based on feedback, and subsequent adjustment to changes (Chauhan et al. 2022). Innovations linked to circularity, such as resource efficiency, can help improve a firm's competitive position (Ritala et al. 2023). Collaboration with different stakeholders is crucial while integrating data (Calabrese et al. 2024). Managers need to leverage both the breadth and depth of knowledge accessed while collaborating with stakeholders. Particularly, while broad knowledge assists in value creation, existing knowledge expertise is crucial for value capture. AI allows understanding of customer needs and ensures customer satisfaction. AI analysis helps find hidden patterns and provide a novel offering, resulting in improved sales and customer satisfaction. In a nutshell, transitioning to circular business models can help firms create value from underused resources, develop stronger collaborative relationships, and develop resilience (Ritala et al. 2023; Sarasini and Linder 2018). Collaborating with actors in the ecosystem based on trust is crucial for effective transition towards circularity (Rao et al. 2024).

We propose AI-enabled business model innovation across the ecosystem. Different actors in the ecosystem play a role in facilitating AI implementation and circular transition. Opportunities to co-create and capture value help firms further reconfigure the value proposition (Ritala et al. 2023). Policymakers should promote practice-academia collaboration to foster the development of new knowledge.

Third, different actors in the ecosystem play a role in facilitating AI implementation and circular transition. Opportunities to co-create and capture value help firms further reconfigure the value proposition (Ritala et al. 2023). Managers need to leverage activities of various actors in the ecosystem. Inter-firm collaboration leveraging digital technologies is crucial to hasten the transition towards circularity (Ritala et al. 2023). Managers need to play the role of brokers in the ecosystem and orchestrate resources from various actors in the ecosystem (Palmié et al. 2021). Effective communication can help them communicate the benefits of circularity to various stakeholders (Ritala et al. 2023).

6 | Conclusion

The purpose of the paper is to explore how AI can facilitate the transition to the circular business model. We investigate how barriers to AI implementation can be overcome with capabilities based on natural resources. Building on the natural resource-based view lens to highlight the role of pollution control and product stewardship in enabling value creation and capture, we argue the importance of AI in enabling the transition to the circular business model. Despite the theorized contributions, we propose the following limitations and avenues for future research. The study relied on interviews with only one interviewee per organization, posing a risk of one-sided perspectives. Future research needs to obtain participant narratives from multiple sources. Second, the microfoundation of natural resource-based dynamic capabilities was not assessed, and future research needs to dive deep into the microfoundations of dynamic capabilities linked to pollution control and stewardship.

Author Contributions

Jian Wang: conceptualization, investigation, methodology, supervision, validation, writing – original draft preparation. **Sanjay Chaudhary:** conceptualization, data curation, formal analysis, methodology, supervision, validation, writing – original draft preparation. **Muhammad Mustafa Kamal:** conceptualization, methodology, writing – review and editing (final round) and preparation of final draft. **Salwa Saleh Almasabi:** conceptualization, funding acquisition, investigation, writing – review and editing (first round). **Sándor Remsei:** methodology, writing – review and editing (second round).

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