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Systematic Review

Artificial Intelligence (AI) in the Circular Economy: A Systematic Literature Review

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Abstract

The transition from linear production and consumption to a circular economy (CE) requires organizations to manage complex information about products, materials, waste streams, and supply-chain activities. Artificial intelligence (AI) may support this transition, but research on its role across business and organizational contexts remains fragmented. This study systematically reviews how AI is applied to CE practices and identifies the main thematic areas in the literature. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement, Scopus was searched for English-language studies published up to 2025. After screening 301 records and assessing 56 full texts, 25 studies were included and analyzed through qualitative content analysis and thematic narrative synthesis. Four clusters emerged: AI-enabled circular operations and supply-chain transformation; resource recirculation, recovery, and loop closure; organizational and ecosystem capabilities for circular innovation and business-model transformation; and green marketing, stakeholder engagement, and corporate disclosure. Across these clusters, AI is reported primarily to improve visibility, prediction, classification, optimization, and coordination. Evidence is strongest for operational efficiency and waste-related applications, while support for higher-value circular strategies and system-level loop closure remains limited. AI should therefore be regarded as a conditional enabler rather than a sufficient driver of circular transformation; its contribution depends on circular objectives, organizational capabilities, human expertise, infrastructure, financing, governance, and interorganizational cooperation.

Keywords: artificial intelligence (AI); circular economy; circular innovation; circular supply chains; resource recirculation; circular business models; organizational capabilities; systematic review

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1. Introduction

The prevailing linear model of production and consumption has contributed to resource depletion, waste generation and environmental degradation. The circular economy (CE) offers an alternative aimed at retaining products and materials in use while reducing resource extraction and waste [1,2]. At the business level, however, the transition toward circularity requires more than isolated environmental practices. It involves the redesign of products, operations, supply chains, organizational capabilities, interorganizational relationships and mechanisms of value creation and capture.

This transition depends on organizations' ability to obtain and use information about products and materials and coordinate activities across their life cycles. Artificial Intelligence (AI) may support these requirements across operations and supply-chain activities [3], resource recovery [4], and circular product design, maintenance, business-model development, and supporting infrastructure [5]. However, AI adoption does not necessarily result in greater circularity. Its contribution depends on infrastructure and skilled resources [6], collaborative intelligence, knowledge integration, and ecosystem cooperation [7], and technological characteristics, organizational capabilities, financing, employee participation, and the external task environment [8]. AI should therefore be examined as a potential enabler of CE practices rather than as evidence of circular transformation in itself.

Previous reviews have established the relevance of the AI–CE research area. Acerbi et al. [9] examined AI in circular manufacturing, and Agrawal et al. [3] used structural topic modeling to identify major AI applications in CE. Madanaguli et al. [10] focused on AI capabilities for circular business models, while Raut et al. [11] and Percuoco et al. [12] mapped the development and intellectual structure of the field through bibliometric and network analyses. Despite these contributions, the literature remains fragmented across operational, organizational, ecosystem and stakeholder-facing perspectives. A business and organizational synthesis is therefore needed to integrate these perspectives and clarify how AI is applied across different areas of CE activity.

Against this background, the purpose of this study is to systematically examine how AI contributes to the implementation and advancement of CE practices in business and organizational contexts. The review addresses the following research questions:

RQ1. How is AI applied to support CE practices and outcomes in business and organizational contexts?

RQ2. What main thematic areas characterize the business and organizational literature on AI and CE?

The study makes two principal contributions. First, it provides a systematic synthesis of the AI–CE literature from an explicitly business and organizational perspective. Second, it integrates the fragmented literature into four thematic clusters: AI-enabled circular operations and supply-chain transformation; AI-enabled resource recirculation, recovery and loop closure; organizational and ecosystem capabilities for circular innovation and business-model transformation; and AI-enabled green marketing, stakeholder engagement and corporate disclosure. Based on this synthesis, the study develops theoretical and practical implications and identifies directions for future research.

The remainder of the paper is structured as follows. Section 2 presents the theoretical background, Section 3 describes the review methodology, Section 4 reports the thematic findings, Section 5 discusses their broader implications and Section 6 concludes the study and identifies directions for future research.

2. Theoretical Background

2.1. Circular Economy: Definition, Principles and Organizational Application

CE represents an alternative to the linear "take–make–dispose" model. It seeks to retain products, materials, and value within the economy for as long as possible by narrowing, slowing, and closing resource loops through strategies such as reduction, reuse, repair, refurbishment, remanufacturing, recycling, and recovery [13–15]. More broadly, CE aims to decouple economic activity from resource depletion and environmental degradation by redesigning production and consumption systems so that waste is minimized and resources remain in circulation [16].

A central premise of CE is that economic value can be retained beyond the initial production and sale of a product. Firms can extend product lifetimes through design

for disassembly [17] and develop circular business models that create and capture value through circular strategies [18,19]. These models can be centred on repair and maintenance, reuse and redistribution, refurbishment and remanufacturing, recycling, cascading and repurposing, and organic feedstock [20]. CE therefore shifts organizational attention from isolated waste-management practices toward the broader redesign of how firms create, deliver, and capture value through their business models, operations, supply chains, and innovation activities [18–22].

Implementing CE requires changes in product design, organizational decision-making, operational processes, and interorganizational relationships. Because products and materials frequently move across organizational boundaries, circularity depends on coordination among firms, suppliers, customers, recovery organizations, and other stakeholders rather than on isolated firm-level action [23]. Its implementation also requires appropriate indicators and assessment frameworks that allow organizations to evaluate circularity and guide their decisions [24–26]. CE is thus both an organizational strategy and a systemic transformation whose definitions, boundaries, and measurement approaches continue to evolve [1,21].

CE has the potential to reduce waste, conserve finite resources, mitigate environmental impacts, and strengthen economic resilience [14,23]. Nevertheless, circular practices do not automatically produce positive sustainability outcomes. Their effects depend on the technological, organizational, market, and policy conditions under which they are implemented, and some interventions may shift burdens across environmental, economic, or social dimensions [16,25,27]. Circular initiatives must therefore be evaluated according to their actual outcomes rather than assumed to be sustainable by definition.

2.2. Artificial Intelligence as an Enabler of Circular-Economy Transformation

AI refers broadly to computational systems capable of performing functions associated with human intelligence, including learning, reasoning, prediction, classification, problem-solving, and decision-making. Such systems use data to recognize patterns, generate insights, and act autonomously or support human decisions in pursuit of defined objectives [28,29]. AI encompasses technologies such as machine learning, deep learning, computer vision, natural language processing, and predictive analytics, which enable organizations to analyze complex data, forecast outcomes, automate activities, and optimize processes [30–32].

For organizations, however, deploying an AI tool is not equivalent to developing AI capability. AI capability refers to an organization's ability to combine and coordinate complementary technological, human, and organizational resources, including data, technical infrastructure, employee expertise, and managerial knowledge [33]. Without such integration, AI applications may remain fragmented and fail to generate meaningful improvements in organizational decisions or performance. Their value therefore depends not only on technical adoption but also on data quality, employee expertise, governance, and process integration [33,34].

This distinction is particularly relevant to CE because managing circular systems is highly information- and decision-intensive. Organizations need information about products, materials, assets, inventories, waste streams, and supply-chain activities across different stages of their life cycles. AI can process complex information through prediction, classification, optimization, and decision support [29,31], capabilities that may improve visibility and inform decisions concerning resource use and circular practices. Its analytical capabilities can also facilitate operational coordination, resource planning, and process improvement [31,35], potentially supporting the integration of circular objectives into organizational decision-making.

3. Methodology

A systematic literature review was conducted to examine how artificial intelligence (AI) contributes to the implementation and advancement of CE practices within business and organizational contexts. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 reporting framework to enhance the transparency, replicability, and completeness of the selection process (Supplementary Materials) [36,37]. Consistent with established guidance for systematic literature reviews, the process involved three stages: planning the review, conducting the search and screening, and analyzing and synthesizing the selected studies [38].

The literature search was conducted in the Scopus database on 5 July 2026. Scopus was selected because of its broad multidisciplinary coverage and its inclusion of research from business, management, environmental science, economics, energy, and related disciplines [39]. The search was applied to the titles, abstracts, and keywords of indexed publications using the following search string:

("artificial intelligence" OR "AI") AND ("circular economy") AND ("business*" OR firm* OR compan* OR enterprise* OR organization* OR corporat* OR manag* OR strateg* OR "supply chain*" OR "operation*")

No lower publication-date boundary was imposed. However, the search was restricted to studies published up to and including 2025, thereby excluding incomplete records from the year in which the search was conducted. The initial search produced 2366 records. Application of the publication-period restriction reduced this number to 1623. Restricting the results to English-language publications resulted in 1602 records. The document-type filter retained journal articles, book chapters, and conference papers, reducing the sample to 1149 records.

To preserve the business and organizational orientation of the review, the results were further restricted to the following Scopus subject areas: Business, Management and Accounting; Environmental Science; Economics, Econometrics and Finance; Social Sciences; Energy; Decision Sciences; and Agricultural and Biological Sciences. Following these database-level filters, 301 records remained for screening.

Studies were included when they examined AI and CE as central and interconnected concepts rather than referring to either concept only peripherally. Eligible studies were required to adopt a business, corporate, organizational, managerial, strategic, operational, entrepreneurial, or supply-chain perspective. They also had to examine the application, adoption, implementation, role, impact, or implications of AI in CE practices, processes, business models, strategies, operations, value chains, supply chains, or organizational decision-making.

Studies were excluded when AI or CE was mentioned only in the title, abstract, keywords, introduction, or conclusion without substantive analysis of their relationship. Research focusing primarily on algorithm development, materials science, chemical processes, sensor or product design, robotics control, wastewater systems, waste-treatment technologies, or other technical optimization problems was excluded when it lacked an identifiable business, managerial, organizational, or supply-chain contribution.

Studies examining digital technologies such as blockchain, the Internet of Things, big data, digital twins, robotics, or Industry 4.0 were excluded unless AI constituted a substantial element of the analysis. Editorials, notes, book reviews, systematic literature reviews, dissertations, theses, reports, conference abstracts, magazine articles, duplicate records, non-English publications, and studies for which the full text was unavailable were likewise excluded.

The screening process was conducted in two stages. First, two authors independently screened the titles and abstracts of the 301 records against the predefined inclusion and

exclusion criteria. This stage excluded 242 records, leaving 59 reports sought for retrieval. Three reports could not be retrieved; therefore, the remaining 56 reports were assessed in full by the same two authors to determine their alignment with the review objectives and eligibility criteria. Of these, 31 were excluded because they did not satisfy the inclusion criteria. The final sample comprised 25 studies for detailed analysis and synthesis (Table A1). The complete selection process is presented in the PRISMA flow diagram (Figure 1).

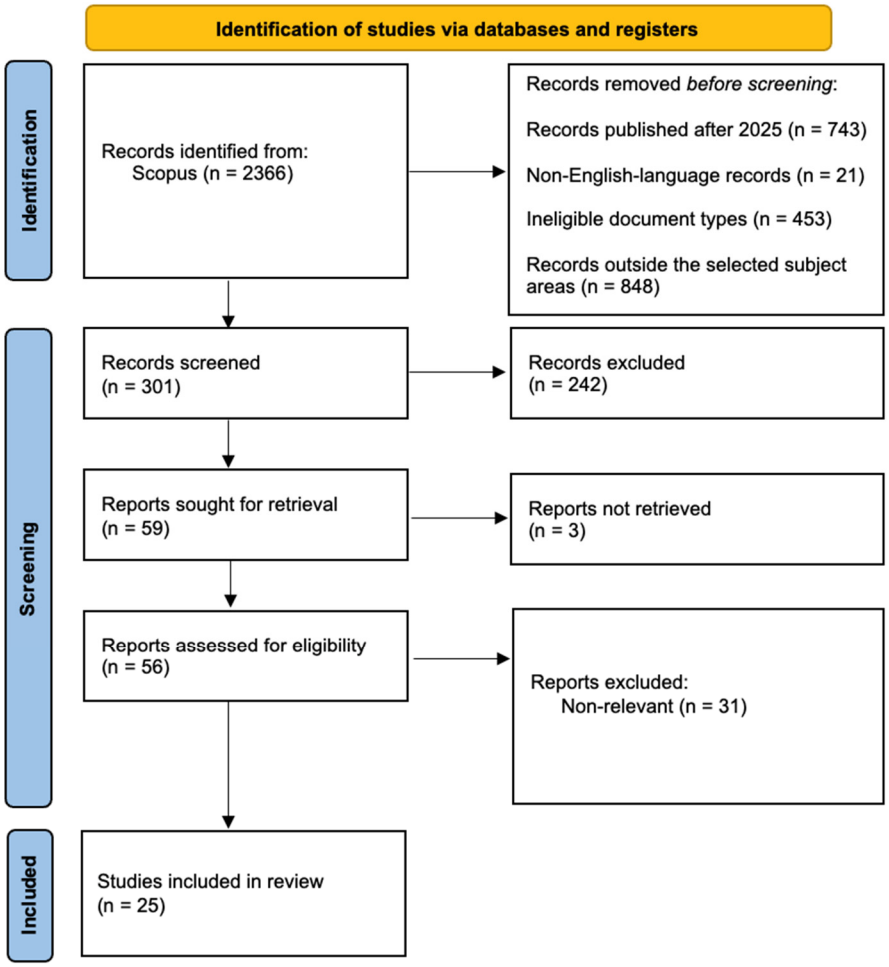


Figure 1. Study-selection flow diagram adapted from the PRISMA 2020 template.

The 25 included studies were analyzed through qualitative content analysis. A structured coding framework was used to record each study's research objectives, geographical and sectoral context, methodological approach, AI application, CE practice, level of analysis, principal findings, enabling conditions, implementation barriers, and reported organizational or sustainability outcomes.

The analytical process combined deductive and inductive coding. Deductive categories were derived from the review objectives and focused on the role of AI in circular operations, supply chains, resource recirculation, organizational innovation, business-model transformation, and stakeholder engagement. Inductive coding was subsequently used to identify recurring relationships, mechanisms, opportunities, challenges, and contextual conditions emerging from the studies themselves. Related codes were compared and progressively consolidated into higher-order themes.

This iterative process produced four thematic clusters: (1) AI-enabled circular operations and supply-chain transformation; (2) AI-enabled resource recirculation, recovery, and loop closure; (3) organizational and ecosystem capabilities for circular innovation and business-model transformation; and (4) AI-enabled green marketing, stakeholder engage-

ment, and corporate disclosure. Each study was assigned to the cluster that most closely reflected its principal analytical contribution, although connections across clusters were considered during the integrative synthesis. Given the methodological and contextual heterogeneity of the included studies, a thematic narrative synthesis was considered more appropriate than statistical meta-analysis.

4. Results

The final sample of 25 publications was subjected to qualitative content analysis. The included literature is highly recent, with the studies concentrated between 2022 and 2025. This temporal pattern indicates that scholarly interest in the intersection of AI and CE has developed rapidly and that the field remains at an emerging stage. The studies vary in their methodological approaches, sectoral settings, and levels of analysis, ranging from firm-level operations and supply-chain management to business-model innovation, ecosystem collaboration, and stakeholder communication.

The content analysis identified four thematic clusters. The first and largest cluster, AI-enabled circular operations and supply-chain transformation, comprises nine studies and examines the application of AI to operational decision-making, manufacturing, resource efficiency, and supply-chain coordination. The second cluster, AI-enabled resource recirculation, recovery, and loop closure, includes seven studies addressing waste prediction and classification, reuse, remanufacturing, reverse logistics, and secondary-resource flows. The third cluster, organizational and ecosystem capabilities for circular innovation and business-model transformation, comprises six studies focusing on knowledge integration, organizational capabilities, collaborative innovation, financing, and circular business-model development. The fourth cluster, AI-enabled green marketing, stakeholder engagement, and corporate disclosure, contains three studies examining how AI supports sustainability communication, consumer engagement, green marketing, and corporate reporting (Table 1).

Table 1. Thematic clusters, thematic focus and allocation of the included studies.

Cluster Name	Thematic Focus	Documents
AI-enabled circular operations and supply-chain transformation	Manufacturing and operational optimization, circular supply-chain capabilities, logistics transformation, resource efficiency, and sustainability and performance outcomes	[6,8,40–46]
AI-enabled resource recirculation, recovery and loop closure	AI-enabled forecasting, identification, classification, inspection, routing and inter-organizational matching that keep post-use products, components, materials, energy and by-products in circulation through reuse, reverse logistics, remanufacturing, recycling, recovery and industrial symbiosis.	[47–53]
Organizational and ecosystem capabilities for circular innovation and business-model transformation	Managerial and technical AI knowledge, organizational change capabilities, circular entrepreneurship and startups, knowledge integration, open innovation, ecosystem collaboration, circular financing and business-model transformation.	[7,54–58]
AI-enabled green marketing, stakeholder engagement and corporate disclosure	Strategic green marketing, AI-enabled personalization and consumer engagement, sustainability communication, stakeholder accountability, integrated reporting and the disclosure of AI-enabled circular practices.	[59–61]

Although each publication was assigned to the cluster that best represented its primary contribution, the clusters are interconnected. Together, they illustrate that AI's role in the CE extends from the optimization of internal operations and material flows to organiza-

tional transformation, ecosystem collaboration, and the communication of circular value to external stakeholders (Figure 2).

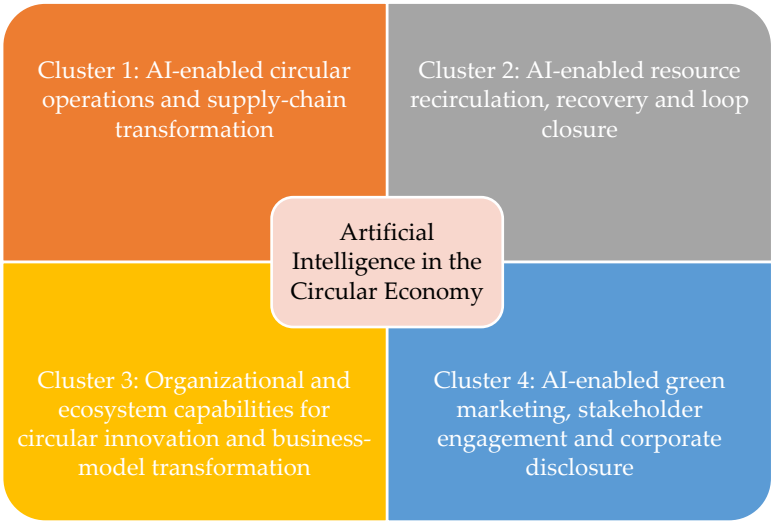


Figure 2. Thematic clusters linking AI and CE.

4.1. Cluster 1. AI-Enabled Circular Operations and Supply-Chain Transformation

The nine studies in this cluster examine how AI supports circular production, logistics, warehousing, and supply-chain processes [6,8,40–46]. Collectively, they indicate that AI contributes by monitoring resource and material flows, forecasting demand, optimizing operational decisions, and improving coordination across supply chains.

The principal applications include demand forecasting, inventory management, production planning, predictive maintenance, quality control, warehouse automation, route optimization, and resource monitoring [40,41,43,44]. These applications can improve supply-chain flexibility and operational efficiency while reducing costs, energy consumption, inventory, product damage, and downtime [6,44]. In agricultural supply chains, AI can also be combined with digital twins and the Internet of Things to support water conservation, reuse, recycling, and resource recovery [40].

However, operational improvements do not necessarily demonstrate that products and materials remain in circulation. Warehouse automation, for example, may improve energy management and reduce waste without establishing whether materials are reused or recovered [44]. Similarly, reduction, reuse, and recycling receive greater attention than recovery, redesign, and remanufacturing, suggesting that more advanced circular practices remain less consistently developed [40]. Operational efficiency should therefore be understood as a potential contributor to circularity rather than evidence of circular transformation.

The extent to which AI supports circular outcomes also depends on organizational capabilities and technological readiness. Financial resources, managerial support, employee participation, and AI-related knowledge influence firms' ability to adopt and integrate these technologies [8]. Circular supply-chain capabilities and broader organizational competencies further help translate AI adoption into improved operational and sustainability performance [6,42,45]. AI should therefore be considered an enabling resource whose value depends on its integration with existing processes, workforce skills, and circular practices.

Technological integration may also involve short-term difficulties. Evidence of a U-shaped relationship between AI adoption and circular performance suggests that early implementation may initially reduce performance, potentially reflecting investment costs, operational disruption, and misalignment between digital systems and established green capabilities [46]. The mixed effects of supply-chain integration similarly indicate that

technological adoption does not automatically produce benefits without alignment among organizational processes, capabilities, and strategic objectives [45].

Responsible implementation represents an additional condition for effective adoption. Explainability, traceability, data protection, cybersecurity, human oversight, and accountability can support trust and coordination across circular supply chains, although the effectiveness of these mechanisms requires further empirical validation [41,43]. The social consequences of automation also warrant attention, particularly its implications for workplace safety, job displacement, employee stability, and workforce retraining [43,44].

Overall, AI can support circular operations by improving firms' ability to monitor, predict, optimize, and coordinate complex processes. However, its contribution depends on organizational readiness, alignment with circular practices, and responsible implementation. Its value should ultimately be assessed not only through operational efficiency but also through demonstrable improvements in resource circulation and environmental performance.

4.2. Cluster 2. AI-Enabled Resource Recirculation, Recovery and Loop Closure

The seven studies in this cluster examine how AI supports reuse, reverse logistics, remanufacturing, recycling, recovery, and industrial symbiosis [47–53]. Collectively, they show that AI can support resource recirculation by identifying products and materials, assessing their condition, forecasting waste flows, and identifying opportunities for reuse, recovery, and exchange.

The principal applications involve operational activities such as recognition, sorting, and inspection. Computer vision and machine learning can classify second-hand products and construction waste, improve the purity of recovered materials, and determine whether used components are suitable for remanufacturing [47,48,52]. AI-based reverse logistics and predictive waste analytics can also support material-flow management and CE performance [49,50]. However, the available evidence largely concerns specific applications, perceived organizational improvements, or modeled outcomes rather than direct, long-term measurements of resource circulation.

The circular contribution of these applications also depends on the strategies they support. Although automated sorting can improve recycling and material recovery, direct reuse and remanufacturing may preserve greater product and component value. Evidence concerning second-hand products, AI-assisted component inspection, and the contribution of AI and robotics to reuse highlights the potential importance of these higher-value strategies [47,51,52]. AI applications should therefore be assessed not only according to processing efficiency but also according to their contribution to product-life extension, resource conservation, and environmental performance. AI and robotics may also contribute to reuse, recovery, or recycling even when these outcomes were not among the original objectives of their implementation [51].

Effective implementation further depends on human, organizational, and institutional conditions. Technological readiness, management support, trust, regulatory conditions, and government assistance influence the adoption of AI-based reverse logistics [50]. Mistrust, perceived complexity, and concerns about job displacement may also limit the effectiveness of predictive waste analytics [49]. Conversely, human involvement can improve both the acceptance and performance of AI systems when workers review uncertain classifications, identify potential errors, and contribute information for system improvement [52].

Resource recirculation also requires coordination beyond individual organizations. Decision-support tools and related digital applications can help identify potential industrial-symbiosis opportunities and connect secondary resources with possible users [53]. However, their implementation depends on material availability and quality, transportation

costs, market demand, and cooperation among participating organizations. AI can support the identification of circular opportunities, but it cannot independently establish the infrastructure and relationships required to realize them.

In sum, AI can support resource recirculation by improving the identification, assessment, and management of post-use products and materials. Its contribution depends on explicit circular objectives, appropriate infrastructure, organizational readiness, human involvement, and interorganizational cooperation. Further research should establish whether these applications produce measurable increases in material circulation, product longevity, and environmental performance.

4.3. Cluster 3. Organizational and Ecosystem Capabilities for Circular Innovation and Business-Model Transformation

The six studies in this cluster present AI as a conditional catalyst of circular transformation rather than a stand-alone operational technology [7,54–58]. Collectively, they suggest that AI resources and skills can support knowledge integration, collaborative innovation, and business-model transformation. However, these contributions depend on organizational change capabilities, human expertise, financial resilience, data availability, stakeholder alignment, and effective governance.

A central finding is that AI capability is organizational rather than purely technical. Managerial and technical AI knowledge can stimulate disruptive innovation, but its translation into circular practices depends on firms' capacity to finance and manage organizational change [54]. Similarly, AI-enabled circular transformation can support organizational adaptability and innovation when combined with collaborative intelligence and knowledge integration [7]. AI capability should therefore be understood as a combination of technical infrastructure, managerial understanding, human expertise, organizational learning, and the ability to reconfigure established routines. Technology investment alone is unlikely to generate substantial circular transformation.

Knowledge management consequently becomes an ecosystem-level capability. Circular innovation depends on information and expertise distributed among manufacturers, suppliers, customers, technology providers, financial institutions, and other stakeholders. Digital intelligence can connect internal organizational knowledge with open-innovation networks, while collaborative intelligence combines algorithmic outputs with stakeholder expertise [7,57]. However, greater openness also raises concerns about data protection, cybersecurity, intellectual property, and human oversight. Effective governance arrangements are therefore necessary to balance knowledge sharing with the protection of commercially sensitive information.

Circular business-model transformation also extends beyond process optimization. AI can support the narrowing, slowing, and closing of resource loops through predictive analytics, condition monitoring, resource allocation, and product-life extension [58]. Its contribution to value creation and delivery is nevertheless more evident than its contribution to value capture, which depends on viable revenue models and the allocation of ownership, costs, and risks. In product-as-a-service arrangements, AI-based residual-value estimation can reduce financial uncertainty but cannot independently resolve capital requirements, delayed revenues, financing arrangements, or stakeholder incentives [55]. Without suitable financial and organizational conditions, technically promising circular initiatives may remain difficult to implement or scale.

Circular startups face a related tension between flexibility and limited resources. Their capacity for experimentation can support circular innovation, but they frequently lack the capital, technical expertise, infrastructure, and historical data required for AI adoption. Among the five startups examined in one study, all regarded data as central to their circular solutions, yet only two were using AI technologies [56]. This suggests that new

circular ventures may benefit from AI but often lack the reliable datasets and organizational resources needed to develop or implement it. Shared infrastructure, accessible AI services, supportive entrepreneurial ecosystems, appropriate financing, and targeted training could help reduce these barriers [7,56].

Important limitations nevertheless constrain the evidence. Several studies examine AI alongside broader digital technologies, making it difficult to isolate its independent contribution to circular outcomes. Circularity is also frequently assessed through managerial perceptions, innovation indicators, or business-model characteristics rather than direct changes in virgin-material use, waste generation, or environmental impact. Cross-sectional designs, small case samples, and limited longitudinal evidence further restrict causal inference and generalizability. Potential trade-offs, including the energy requirements of AI systems, algorithmic bias, reduced human oversight, and the distribution of value among stakeholders, also remain insufficiently examined [7,57].

Taken together, the cluster shows that AI is an enabling but insufficient condition for circular transformation. Its contribution depends on the integration of technical and managerial capabilities, human expertise, knowledge sharing, ecosystem collaboration, and suitable financing arrangements. Circular innovation and business-model transformation therefore require not only technological functionality but also the organizational, financial, and institutional conditions needed to translate digital capabilities into viable circular practices.

4.4. Cluster 4. AI-Enabled Green Marketing, Stakeholder Engagement and Corporate Disclosure

The three studies in this cluster extend AI's contribution to CE beyond operational optimization to the external communication of circular practices [59–61]. Collectively, they suggest that credible communication can enhance the market and legitimacy value of circular initiatives by enabling stakeholders to understand and respond to them.

Green marketing and reporting therefore emerge as mechanisms through which internal circular practices acquire external meaning. Strategic green marketing translates resource efficiency, recycling, and waste reduction into market positioning and stakeholder relationships [59]. AI supports this process through consumer segmentation, personalization, and sentiment analysis [60], while integrated reporting connects AI-enabled circular initiatives with resource use, organizational value creation, and stakeholder information needs [61].

However, AI does not strengthen all dimensions of circular strategy uniformly. Keskin et al. [59] find that AI reinforces the relationship between CE capacity and environmental performance but modestly weakens the contribution of strategic green marketing orientation. AI may therefore improve the technical execution of circular practices while weakening the relational value of green marketing when communication becomes excessively automated. Although personalization can increase the relevance of sustainability messages, extensive automation may reduce their perceived authenticity. A hybrid approach combining AI-supported analysis with human judgment and transparent dialogue may consequently help preserve stakeholder trust.

The evidence also reveals an important gap between engagement and circular behavior. Interview participants reported that AI can identify environmentally conscious consumers and increase their interaction with sustainable brands [60], but the study does not establish whether such engagement leads to repair, reuse, sharing, resale, product returns, or reduced consumption. The studies rely primarily on managerial perceptions and corporate disclosures rather than direct consumer evidence or observed behavior. The extent to which AI-enabled communication produces measurable circular outcomes therefore remains uncertain.

Corporate disclosure similarly creates both opportunities and governance challenges. AI could improve data collection and connect internal circular practices with external accountability. Nevertheless, references to AI and circularity in corporate reports do not demonstrate that the reported practices are effective, material, or independently verified [61]. Greater disclosure does not necessarily improve accountability without comparable indicators, methodological transparency, and appropriate assurance. Whether AI-enhanced communication increases the persuasiveness of environmental claims without improving underlying performance remains a question for future research.

The evidence base remains limited and concentrated among relatively capable adopters. Infrastructure limitations, implementation costs, data shortages, and limited technical expertise constrain adoption, particularly among smaller firms in African markets [60]. Cross-sectional survey evidence, qualitative managerial accounts, and measures of disclosure presence rather than quality further restrict causal inference and generalizability [59–61]. Overall, the cluster presents AI as a capability linking circular practices with external communication and accountability, but its benefits depend on whether enhanced communication reflects substantive and verifiable circular performance.

5. Discussion

This review shows that AI's contribution to the CE is neither direct nor technologically determined. Across the 25 studies, AI primarily strengthens organizations' ability to observe resource conditions, predict changes, optimize decisions, and coordinate actors. These capabilities can support circularity, but their effects depend on circular practices, organizational readiness, human expertise, infrastructure, financing, and interorganizational cooperation.

5.1. AI as an Informational Capability for Circularity

The most consistent contribution of AI is the reduction in informational uncertainty. AI increases visibility over production processes, equipment, inventories, products, and material flows. It can classify post-use products, assess component condition, predict waste generation, and support decisions concerning reuse, remanufacturing, and recycling [47–50,52]. It can also support industrial-symbiosis matching, residual-value assessment, ecosystem knowledge exchange, and stakeholder communication [53,55,57,61].

Better information, however, does not automatically close resource loops. Waste predictions require collection and treatment infrastructure, component assessments require remanufacturing capacity, and industrial-symbiosis opportunities depend on viable transportation, regulation, market demand, and agreements over costs and benefits. AI's value therefore depends on the circular routines, organizational capabilities, and interorganizational relationships in which it is embedded [6,8,42,45].

5.2. Operational Efficiency and the Depth of Circular Outcomes

A major limitation of the literature is the tendency to interpret operational efficiency as circular transformation. Forecasting, predictive maintenance, route optimization, energy monitoring, and warehouse automation can reduce costs, downtime, inventories, and resource consumption. Nevertheless, these improvements do not necessarily demonstrate that products and materials remain in circulation for longer.

Evidence is most frequently reported for operational efficiency, while findings on reuse, recovery, and recycling are less consistent. Evidence of remanufacturing networks, repeated product-life extension, and regenerative systems remains limited. Warehouse automation, for example, can reduce energy consumption and product damage without changing the underlying linear flow of resources [44]. Similarly, reduction, reuse, and recycling are

more common than recovery and redesign in the cases examined by Ali et al. [40]. The circular contribution of predictive maintenance is also more convincing when it produces measurable extensions in asset life and reductions in material demand.

The purpose for which AI is introduced also matters. Reuse, recovery, and recycling were not among the original objectives of most of the AI and robotics projects examined by Sigüenza Tamayo et al. [51]. This helps explain why these technologies may improve operational efficiency without generating clear circular outcomes. Circular targets such as product longevity, component reuse, secondary-material use, and recovery value should therefore be incorporated into system design and performance measurement. AI-supported reuse and remanufacturing may also preserve more embedded value than recycling alone [47,52]. AI applications should consequently be evaluated according to the extent to which they extend product life, preserve material value, and reduce demand for virgin resources.

5.3. Organizational and Ecosystem Conditions for AI-Enabled Circularity

Material circulation can depend on effective knowledge sharing and access to appropriate financing. Relevant information is distributed among manufacturers, suppliers, customers, repairers, recyclers, technology providers, financial institutions, and regulators. AI can help integrate these knowledge sources, but incompatible data, limited trust, cybersecurity concerns, and intellectual-property protection may restrict cooperation [7,57].

Circular business-model transformation also requires more than operational efficiency. AI can support value creation through resource optimization, value delivery through predictive services and coordination platforms, and value capture through pricing and residual-value assessment [55,58]. However, the evidence is stronger for value creation than for sustainable value capture. AI may reduce uncertainty about product condition and future value, but it cannot independently resolve ownership, delayed revenues, contractual responsibility, financing requirements, or the distribution of benefits among ecosystem participants.

These challenges are particularly relevant to circular startups and resource-constrained firms. Such organizations may regard data as central to their circular value propositions while lacking the historical data, financial resources, infrastructure, and technical expertise needed to implement AI effectively [7,56]. More generally, the translation of AI knowledge into circular innovation depends on firms' ability to manage organizational change and absorb the associated financial demands [54]. Shared digital infrastructure, accessible AI services, workforce training, and suitable financing arrangements may therefore help reduce adoption barriers.

5.4. Risks and Responsible Governance of AI-Enabled Circularity

Digital and circular capabilities are not automatically complementary. Nonlinear and mixed relationships suggest that AI adoption may initially reduce circular performance before benefits emerge at higher levels of technological maturity and organizational alignment [45,46]. AI may also reinforce operational circular capabilities while weakening the relationship between green marketing and environmental performance when communication becomes excessively automated or impersonal [59]. Digital systems, circular routines, workforce skills, and decision rights must therefore be aligned for AI to produce credible circular benefits.

AI can itself generate environmental, social, and governance-related risks. Developing AI systems and the associated data-processing, storage, and hardware infrastructure consumes energy and material resources; consequently, using AI to optimize narrowly defined CE objectives may create harmful trade-offs and undermine broader environmental

priorities. Data-intensive AI applications may create privacy and security risks, particularly when product, consumer, and supply-chain data circulate through interoperable inter-organizational networks. They may also reproduce bias, while black-box models and complex allocations of responsibility can make resulting harms difficult to trace and redress [5]. Related privacy, bias, fairness, traceability, and explainability concerns have also been identified in AI-enabled supply chains [41]. These risks should be treated as part of circular-performance assessment rather than as external implementation issues.

Human expertise remains central to this alignment. Managers connect AI with organizational strategy, workers evaluate uncertain classifications, and ecosystem partners provide contextual knowledge. In remanufacturing, employees can review uncertain AI recommendations, identify errors, and provide information that improves the system [52]. Resistance to AI may also reflect legitimate concerns about mistrust, complexity, job displacement, or reduced decision authority rather than a simple reluctance to change [49]. AI is therefore more likely to gain acceptance when it supports rather than replaces human judgment.

Responsible AI practices represent an additional governance condition. Explainability, traceability, privacy protection, transparency, and human oversight can strengthen confidence in AI-supported material and supplier decisions and facilitate cross-organizational data sharing [41,43]. These safeguards are also relevant to marketing and reporting, where AI-supported personalization requires ethical data use and credible communication of environmental practices [60,61].

Green marketing and integrated reporting can make circular activities understandable to consumers, investors, and regulators [59,61]. However, communication should not be treated as evidence of implementation. References to AI and circularity in corporate reports do not demonstrate that the reported activities are effective, material, or independently verified. Credible communication therefore requires comparable indicators, methodological transparency, and verifiable evidence of operational and environmental performance.

6. Conclusions

Within the 25 studies meeting the predefined eligibility criteria, AI was most consistently associated with improved visibility, prediction, classification, optimization, and coordination. These reported benefits were concentrated in operational efficiency and waste-related applications, whereas evidence concerning repair, reuse, remanufacturing, sustained product-life extension, verified resource recirculation, and system-level loop closure was limited and methodologically heterogeneous. The findings should therefore be interpreted as recurring patterns within this narrowly defined evidence base, not as demonstrating a uniform or causal effect of AI on CE performance across sectors or countries.

6.1. Theoretical Implications

The findings contribute to the resource-based view and dynamic capabilities perspective by showing that AI resources support circular performance when combined with managerial knowledge, employee involvement, circular capabilities, and the capacity to reconfigure routines [6,8,42,45]. The nonlinear relationship identified between AI adoption and circular performance further indicates that adoption alone does not generate circular value [46]. Knowledge-based and socio-technical perspectives explain the need to integrate algorithmic capabilities with human expertise and knowledge distributed across organizational boundaries [7,52,57]. Business-ecosystem and stakeholder perspectives further show that AI can support coordination, residual-value assessment, and disclosure but cannot independently resolve ownership, financing, value distribution, or stakeholder trust [55,59,61].

Taken together, these insights advance theory by reframing AI from a stand-alone technological resource into an informational capability whose circular value emerges through alignment with organizational, human, and ecosystem capabilities. They also shift the focus from AI adoption itself to the multilevel conditions that translate AI-enabled efficiency into verifiable circular outcomes.

6.2. Practical Implications

Managers should link AI investments to explicit circular objectives and assess outcomes through product-life extension, material reuse, waste reduction, and reduced demand for virgin resources. Improvements in cost, speed, or efficiency are insufficient evidence of circular transformation [40,44]. Before adoption, organizations should assess data quality, employee skills, managerial support, and capacity for change while retaining human oversight of classification, inspection, and recovery decisions [8,49,52,54].

Circularity frequently spans organizational boundaries, requiring firms to establish arrangements for data sharing, ownership, financing, and the distribution of risks and benefits. Policymakers and industry associations can assist smaller firms through shared infrastructure, training, interoperable standards, reverse logistics, and secondary-material markets [53,56]. AI-enabled marketing and reporting should also be supported by transparent and verifiable evidence [60,61].

6.3. Limitations and Directions for Future Research

This review used only Scopus and English-language publications in selected subject areas and focused on business and organizational applications; relevant technical, interdisciplinary, or non-English studies may therefore have been omitted. The relatively small number of eligible studies also limits the breadth and generalizability of the conclusions. The findings should therefore be interpreted as a structured thematic synthesis of the literature meeting the predefined eligibility criteria rather than as definitive conclusions applicable to all sectors, countries, or AI-enabled CE practices. Coverage through 2025 limits timeliness, while assigning each study to one principal cluster involved interpretive judgment and may underrepresent cross-theme connections. Future reviews should extend database, language, disciplinary, and temporal coverage and permit multi-cluster classification.

Beyond these review limitations, the evidence remains fragmented across sectors, designs, definitions, and performance measures and frequently relies on cross-sectional surveys, managerial perceptions, or small case samples. Future empirical research should use longitudinal, comparative, and quasi-experimental designs and direct measures of product life, material recirculation, waste, environmental impact, and virgin-resource demand. It should track products and materials across life-cycle stages, give greater attention to repair, reuse, remanufacturing, and system-level loop closure, and test nonlinear effects across sectors, countries, and firm sizes.

Research should also examine how ecosystems manage data, knowledge, financing, ownership, and risk; whether shared infrastructure, accessible AI services, and collaborative financing reduce barriers for smaller firms; and whether AI-enabled business models distribute costs and benefits sustainably. Finally, studies should evaluate whether AI-supported communication changes return, repair, reuse, and resale behaviors and how transparency, privacy, human interaction, and independent verification shape trust in circular claims.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/su18199790/s1. Table S1: PRISMA 2020 Checklist [36].

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
CE	Circular Economy
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses

Appendix A

Table A1. Main contributions and relevance of the studies included in the review.

Reference	Main Contribution and Relevance to the Review
AlDhaheri et al. [6]	Examines how AI-based and CE practices mediate the relationships among supply-chain sustainability, flexibility, and performance. Included as firm-level evidence connecting AI-enabled practices with circular supply-chain outcomes.
Hwang, Puntha, and Jitanugoon [7]	Shows how AI-driven circular transformation contributes to startup adaptability and circular innovation through collaborative intelligence and knowledge integration.
Ronaghi [8]	Identifies technological characteristics, organizational capabilities, and the external task environment as determinants of AI adoption and finds that AI adoption positively affects internal environmental management, eco-design, and corporate asset management and recovery. Included as manufacturing-sector evidence connecting AI-adoption conditions with organizational CE practices.
Ali et al. [40]	Examines how AI, digital twins, and related technologies support resource optimization, waste reduction, reuse, recycling, and recovery in Chinese agricultural industries.
Allam et al. [41]	Synthesizes AI applications in sustainable supply chains, including demand forecasting, logistics optimization, waste management, resource allocation, and closed-loop activities.
Le et al. [42]	Tests how AI-enabled dynamic capabilities and circular manufacturing influence competitive advantage and sustainable firm performance in Vietnamese manufacturing firms. It finds that competitive advantage partially mediates the effects of both dynamic capabilities and circular manufacturing on sustainable performance.
Meena et al. [43]	Organizes AI applications, enablers, and barriers in circular supply chains through the triple-bottom-line perspective and emphasizes transparent and responsible AI.

Table A1. *Cont.*

Reference	Main Contribution and Relevance to the Review
Saha et al. [44]	Develops a consensus-based q-rung orthopair fuzzy decision model for prioritizing AI-based material-handling technologies for smart logistics in sustainable warehouses under CE principles. The application ranks autonomous mobile robots as the preferred alternative.
Waqas et al. [45]	Tests the direct effects of AI and big data on CE performance and their indirect effects through the circular supply chain, while examining the moderating roles of explorative and exploitative supply-chain integration.
Ye and Zhang [46]	Identifies a U-shaped relationship between AI adoption and CE performance and examines the moderating role of green innovation capability.
Badran et al. [47]	Uses AI-based image classification and social-media data mining to identify commonly reused product categories in online thrift shops and draws on LCA evidence to compare the environmental implications of reuse, recycling, and disposal.
Farshadfar et al. [48]	Compares machine-learning-based and conventional construction-waste sorting in terms of material recovery, sorting performance, circularity, and long-term costs.
Hwang, Jitanugoon, and Puntha [49]	Examines how AI-based predictive waste analytics supports regenerative resource integration and material-flow optimization in tourism, while identifying resistance to adoption.
Mukherjee et al. [50]	Identifies the technological, organizational, and environmental drivers of AI-based reverse-logistics adoption and its relationship with CE performance.
Sigüenza Tamayo et al. [51]	Assesses how AI and robotics contribute to reuse, recovery, and recycling, including circular effects that were not among the technologies' original objectives.
Süße et al. [52]	Examines human–AI interaction in remanufacturing and shows how workers interpret, review, and respond to AI-supported component-classification decisions.
Yazan et al. [53]	Explains how AI- and IT-based decision-support tools can identify, assess, and manage industrial-symbiosis opportunities across the business life cycle.
Al Halbusi et al. [54]	Shows that managerial and technical AI skills foster disruptive innovation, which is positively associated with CE, and that organizational change capability and financial resilience strengthen the relationship between disruptive innovation and CE.
Fallahi et al. [55]	Examines financing barriers to circular product-as-a-service business models and demonstrates how AI-supported residual-value estimation may reduce financial uncertainty.
Ghoreishi et al. [56]	Explores how circular start-ups use data and AI, identifying limited AI uptake associated with skills shortages, high technology costs, and gaps in data integration and accessibility.
Huang and Zhou [57]	Develops a knowledge-management model explaining how digital intelligence supports the integration of open innovation and CE through knowledge acquisition, sharing, and ecosystem collaboration.
Montes-Pineda and Garrido-Yserte [58]	Explains how AI may support circular business-model innovation, including value creation, delivery, and capture and the narrowing, slowing, and closing of resource loops.
Keskin et al. [59]	Tests how strategic green marketing mediates the relationship between CE capacity and environmental performance and how AI moderates the effects of CE capacity and green marketing on environmental performance.
Muduva and Kiwa [60]	Explores how AI-enabled green marketing supports resource efficiency and consumer engagement in African markets while identifying financial, infrastructural, data, and skills barriers.
Nazir et al. [61]	Examines how leading companies implement and disclose combined AI and CE activities and connects these disclosures with resource-use and organizational indicators.

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