



ORIGINAL CONTRIBUTION

Artificial Intelligence and Circular Economy: A Systematic Literature Review

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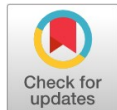
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Abstract— Research on Artificial Intelligence (AI) for the circular economy remains fragmented across separate literatures on reuse, recycling, remanufacturing, waste reduction, and resource optimization. Following PRISMA 2020, this review synthesizes 53 studies published between 2019 and 2026, all identified through systematic searches of Scopus and Web of Science; a supplementary Google Scholar search yielded no additional eligible studies. Four AI capability clusters recur across the five strategies: predictive assessment, automated classification, process optimization, and system-level integration. Recycling is the most mature area (16 studies, 30.2%). In this area, computer vision and deep learning sorting systems have been validated in real operating settings, although contamination and inconsistent packaging still reduce accuracy. Waste reduction (11 studies) has a growing base of empirical and pilot evidence, with machine learning forecasting reducing overproduction and food waste, but almost entirely in food and retail supply chains. Resource optimization (7 studies) is concentrated in energy-intensive, data-rich manufacturing, where AI supports energy management and fills data gaps in life cycle assessment. Remanufacturing (6 studies) mainly relies on predictive maintenance and remaining-life estimation, while AI-assisted disassembly remains largely conceptual. Reuse (5 studies) is the least developed strategy: it focuses mainly on condition assessment and reverse logistics and pays little attention to organizational strategy. Across all strategies, adoption depends on data quality, organizational readiness and cost, and regulatory and market pressure. The review proposes a framework that positions AI as a shared, cross-cutting enabler of circular economy transformation. It also sets out a research agenda on field validation, cross-strategy capability transfer, and underexplored sectors and regions.

Index Terms— Artificial intelligence, Circular economy, Systematic literature review, Reuse, Recycling, Remanufacturing, Waste reduction, Resource optimization

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Introduction

The transition from the linear take-make-waste model to a circular model is a major issue in current industrial and environmental policy. The circular economy, including reducing, reusing, recycling, remanufacturing, and optimizing resources, aims to close material loops, extend product

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life cycles, and minimize raw material consumption. Meanwhile, businesses in manufacturing, retail, agriculture, and urban planning are working to make this a reality, and Artificial Intelligence (AI) is proving to be a technology that can help accelerate and scale the circular economy in ways manual or conventional digital methods cannot.

AI is a major component in achieving a circular economy and can be applied across all phases of the product life cycle, including prediction, classification, optimization, and automation (MacArthur & Cowes, 2019; Özsoy, 2023). In the past few years, there has been a beginning of conceptual and empirical efforts that explore the link between the application of AI technologies, such as machine learning, computer vision, robotics, and digital twins, and CE actions at the firm and system levels (Percuoco et al., 2026; Tutore et al., 2024). In general discussions on digital technologies and the transition towards the circular economy, AI is frequently used alongside the other components of the increasingly integrated technologies, namely the Internet of Things, blockchain, and big data analytics, but its applications remain scattered across isolated, strategy-specific bodies of literature (Handoyo & Sueb, 2026; Neri et al., 2024; Turkolmez et al., 2024).

Research that integrates AI and the circular economy coherently remains scarce, and most existing work is confined to a single discipline or strategy. AI-supported reuse research typically focuses on reverse logistics and product condition assessment (Habazin et al., 2025; Psarommatis et al., 2025). Research on AI for recycling is more abundant and includes computer vision and deep learning techniques for waste sorting, contamination detection, and material categorization (Dawar et al., 2025; Jin et al., 2023; Mohammed et al., 2023). The study of remanufacturing has been conducted on predictive maintenance (Dudkowiak et al., 2025), disassembly planning (X. Chen, 2022; Z. Chen & Huang, 2021), and the integration of digital twins (Xiao & Huang, 2024). Waste-reduction research focuses on the food supply chain, retail pricing, and inventory systems (Carpitella & Izquierdo, 2025; Dong et al., 2025; Sharma et al., 2020). A final stream focuses on resource optimization by life cycle assessment, energy efficiency, and smart resource allocation (Popowicz et al., 2025; Waltersmann et al., 2021).

While each of these five research streams has produced useful domain-specific insights, none has yet been integrated into a coherent perspective that treats AI as a cross-cutting lever for the five circular economy strategies examined in this review, namely reuse, recycling, remanufacturing, waste reduction, and resource optimization, rather than as a collection of isolated applications. These five strategies were selected because they are the R strategies most frequently addressed in AI and circular economy research (Khulbe, 2025; Percuoco et al., 2026). This fragmentation limits theoretical progress and complicates AI adoption in organizations that aim to connect the dots and adopt AI across their circular economy initiatives rather than in isolation.

This review aims to fill this gap and follows the guidelines of a Systematic Literature Review (SLR) as described by the PRISMA 2020 guidance (Page et al., 2021). It integrates results of the five circular economy strategies and draws on the Resource-Based View (RBV), Dynamic Capabilities Theory (DCT), and the Technology-Organization-Environment (TOE) framework (Mailani et al., 2024; Nguyen et al., 2022; Shahzad & Ferreira, 2026). The review is guided by 3 research questions. First, how can AI support each of the five circular economy strategies: reuse, recycling, remanufacturing, waste reduction, and resource optimization? Secondly, which theoretical frameworks have the primary studies on AI and the circular economy applied? Third, what discrepancies in the literature suggest a future research agenda?

The review's key contribution is an integrative framework that outlines how AI capabilities relate to CE outcomes, along with a structured agenda of research and empirical studies to guide the field's future trajectory. The remainder of the paper is organized as follows. Section 2 introduces the circular economy and AI. Section 3 presents the review methodology, including quality appraisal and reliability procedures. Section 4 reports the findings for each of the five strategies. Section 5 develops the integrative framework. Section 6 discusses the findings, Section 7 sets out theoretical and practical implications, Section 8 presents limitations and a future research agenda, and Section 9 concludes.

Background and Conceptual Foundations

Circular economy principles

The circular economy represents a shift from the linear economy (take-make-waste) to a system that uses resources and materials as efficiently as possible. Circular economy principles extend the useful life of products, components, and materials, and they promote the regeneration of natural systems instead of the take-make-dispose (Jogarao et al., 2024; MacArthur & Cowes, 2019). Circularity has been tackled by different R strategies such as reduction, reuse, recycling, remanufacturing, and resource optimization (Khulbe, 2025; Percuoco et al., 2026). Reduction involves reducing the amount of material and energy used, while reuse extends the life of materials and components with minimal changes (Dong et al., 2025). Recycling uses discarded material as input for further production, whereas remanufacturing returns used products or parts to a condition comparable to a new product (Farshadfar et al., 2025).

These strategies are implemented together and are not mutually exclusive. Effective reverse logistics, product tracking, condition assessment, and recovery systems support reuse and remanufacturing (Grosse Erdmann et al., 2025). Recycling and reduction (Habazin et al., 2025; A. R. Singh et al., 2025) are closely related to efficient waste management and optimal material utilization. Resource optimization is broader, as it improves material, energy, and production-capacity utilization (Olawade et al., 2026). Therefore, understanding the relationship between these strategies is important (Palakurti, 2025) a strategy-specific perspective may overlook technologies that support several circular goals at once.

Artificial intelligence technologies relevant to circular economy

AI is among the most important technological tools for achieving the circular economy because it can process massive amounts of data, extract intricate patterns, predict outcomes, and support automated decision-making (Kim et al., 2024; Xiao & Huang, 2024). In particular, the following AI technologies have been singled out for their potential applications in the field of circular economy: machine learning, deep learning, computer vision, robotics, digital twins, predictive analytics, and optimization algorithms (Bitzenis et al., 2025). Machine learning and deep learning have been widely used in various applications, such as prediction, classification, demand forecasting, and material identification (X. Chen, 2022; Jin et al., 2023). Computer vision automates product and recyclable recognition, classification, sorting, and product quality assessment (Mohammed et al., 2023; J. Singh et al., 2025).

AI-based perception and decision-making, combined with robotics, enable physical operations such as sorting, disassembly, material handling, and product recovery, especially in recycling, reuse, and remanufacturing (Ali et al., 2025; Xiao & Huang, 2024). Digital twins simulate processes and test circular interventions before implementation in the physical world (Z. Chen & Huang, 2021; Sajadieh & Noh, 2025). Predictive analytics and optimization algorithms help optimize resources by improving demand forecasting, inventory management, production planning, energy management, and capacity utilization, as Dong et al. (2025) and Jayaprakash et al. (2021) discuss. The presence of computer vision and robotics in recycling and reuse, and of digital twins and predictive technologies in remanufacturing and resource optimization, highlights the need for an integrated perspective on AI's capabilities across circular economy strategies.

Theoretical lenses

To structure the integrative synthesis, the authors selected three theoretical lenses: The Resource-Based View (RBV), Dynamic Capabilities Theory (DCT), and the Technology-Organization-Environment (TOE) framework. RBV explains why AI capabilities can create value across several circular strategies. DCT explains how organizations build and adapt these capabilities over time, and TOE explains why adoption differs across contexts. These lenses were chosen by the authors to organize the synthesis. They differ from the theories applied in the primary studies.

Under RBV, knowledge and data skills, technological infrastructure, and AI-related analytical capability become strategic organizational resources. If these resources are valuable, rare, difficult to imitate, and effectively organized, they create competitive advantage and strengthen an organization's ability to implement circular practices (Mailani et al., 2024). The Dynamic Capabilities Theory can be used in tandem, with emphasis on the capability of an organization to sense opportunities, seize new technology, and reconfigure resources and processes to fit new environments; AI can help with that, in the form of better environmental scanning, predicting, experimenting, and adapting processes to new environments (Shahzad & Ferreira, 2026). The Technology-Organization-Environment framework incorporates technological readiness, organizational traits, and external environmental influences that shape AI adoption (Arroyabe et al., 2024; Nguyen et al., 2022).

Together, these frameworks suggest that AI-enabled circularity occurs at the intersection of technology, organization, and environment: The Resource-Based View focuses on the strategic value of AI resources, Dynamic Capabilities Theory on organizational adaptations, and the Technology-Organization-Environment framework on the conditions that shape adoption.

Positioning AI as an enabler

AI must be understood as a supporting technology (Abdullah et al., 2025) that can enhance both organizational and technological processes related to waste reduction, reuse, recycling, remanufacturing, and resource optimization (Hernandez et al., 2024). AI can enhance existing circular practices through analytical capabilities, predictive modeling, perceptual capabilities, and automated processes, making them more efficient, accurate, and scalable (Neri et al., 2024; Tutore et al., 2024). Machine learning can forecast the demand and failure events, computer vision can be used to sort materials, robotics can support material recovery, and digital twins can simulate and optimize circular production systems (Rahman et al., 2025).

This review therefore adopts an enabling perspective: Circular economy outcomes depend not only on the technology used but also on the wider system in which it operates. AI's potential can be realized only with the right data, infrastructure, staff skills, organizational support, and operational integration (Palakurti, 2025), and with the organizational capability to achieve circular outcomes (Bitzenis et al., 2025). The approach to AI presented in this review is therefore a cross-cutting technological enabler relevant to several circular economy strategies, moving beyond single-technology and single-strategy studies to examine how AI technologies and R strategies interact.

Methodology

Review protocol

This review is conducted following a systematic literature review approach following PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses; Page et al., 2021) which is the current evidence synthesis reporting standard, and is structured into four evidence

synthesis stages: Identification, screening, eligibility assessment and inclusion. At each stage, we recorded the number of records retained and excluded, along with the reasons for exclusion, so the process can be audited and replicated.

A purely narrative review is less transparent than a PRISMA-based systematic approach, and bibliometric or citation-mapping reviews suit reporting publications but not summarizing substantive results (Linnenluecke et al., 2019). This review was most suitable as a PRISMA-guided approach to integrating findings and aligns with recent methodological guidance for systematic reviews in management and sustainability research (Sauer & Seuring, 2023). The review was not formally registered in a protocol repository like PROSPERO, which is mostly designed for health and clinical reviews. Still, the review team agreed on an internal protocol before screening began and followed it throughout.

Database selection

Scopus and Web of Science were selected because they offer the broadest coverage of peer-reviewed journals, established citation indexing, and reliable metadata for systematic reviews in management, engineering, environmental science, and interdisciplinary sustainability research. We also conducted a second (non-systematic) search in Google Scholar to find more recently published conference proceedings. We edited book chapters that were not fully indexed in Scopus or Web of Science. Consistent with the peer-review requirement in Table III, we excluded preprints and other non-peer-reviewed early-access material identified through this supplemental search.

Search strings, fields, and reproducibility

A combination of two sets of keywords with Boolean operators was used: AI vocabulary set ("artificial intelligence", "machine learning", "deep learning", "computer vision", "robotics") and a circular economy strategy set ("circular economy", "reuse", "recycling", "remanufacturing", "waste reduction", "resource optimization"). To avoid the retrieved record set being dominated by subthemes of the circular economy that were highly published, as well as to avoid undersampling subthemes that were not as highly published, the 5 circular economy strategies were searched individually against the AI term set, as opposed to as a single search (Table I).

Table I
Database search strategy and retrieval results

CE strategy	AI term set	CE/strategy term set	Database search field	Search string	Scopus <i>n</i>	WoS <i>n</i>
Reuse	"artificial intelligence" OR "machine learning" OR "deep learning" OR "predictive analytics"	reuse OR "product life extension" OR "product reuse"	Scopus: TITLE-ABS-KEY; WoS: TS	("artificial intelligence" OR "machine learning" OR "deep learning" OR "predictive analytics") AND (reuse OR "product life extension" OR "product reuse")	74	61
Recycling	"artificial intelligence" OR "machine learning" OR "deep learning" OR "computer vision"	recycling OR "waste sorting" OR "material recovery"	Scopus: TITLE-ABS-KEY; WoS: TS	("artificial intelligence" OR "machine learning" OR "deep learning" OR "computer vision") AND (recycling OR "waste sorting" OR "material recovery")	132	105
Remanufacturing	"artificial intelligence" OR "machine learning" OR "deep learning" OR robotics	remanufacturing OR disassembly OR refurbishment	Scopus: TITLE-ABS-KEY; WoS: TS	("artificial intelligence" OR "machine learning" OR "deep learning" OR robotics) AND (remanufacturing OR disassembly OR refurbishment)	76	59
Waste reduction	"artificial intelligence" OR "machine learning" OR "deep learning" OR "predictive analytics"	"waste reduction" OR "waste minimization" OR "waste prevention"	Scopus: TITLE-ABS-KEY; WoS: TS	("artificial intelligence" OR "machine learning" OR "deep learning" OR "predictive analytics") AND ("waste reduction" OR "waste minimization" OR "waste prevention")	118	91
Resource optimization	"artificial intelligence" OR "machine learning" OR "deep learning" OR optimization	"resource optimization" OR "resource efficiency" OR "life cycle assessment"	Scopus: TITLE-ABS-KEY; WoS: TS	("artificial intelligence" OR "machine learning" OR "deep learning" OR optimization) AND ("resource optimization" OR "resource efficiency" OR "life cycle assessment")	94	73
Total retrievals					494	389

CE relevance was not defined by the search string alone. At title and abstract screening, each record also had to address at least one of the five named CE strategies, in line with the topical relevance criterion in Table III; records that discussed sustainability in general terms without

specific relevance to any of the five strategies were excluded at this stage.

The formal database search was conducted on 15 January 2026 in Scopus (TITLE-ABS-KEY field) and the Web of Science Core Collection (Topic, TS, field), using the strategy-specific search strings reported in Table I. Both searches included English-language journal articles, conference papers, and book chapters published between 2019 and 15 January 2026. The searches returned 494 records from Scopus and 389 from Web of Science (883 in total). After 397 duplicates were removed, 486 unique records remained for title and abstract screening (Table II). A supplementary, non-systematic search was run in Google Scholar using combinations of “artificial intelligence” or “machine learning” with “circular economy” and each of the five strategies. We reviewed the first 200 results for each query (600 records total). A record was retained only if it could be verified as a peer-reviewed article, conference paper, or book chapter published within the review window. We then compared the verified records with the 486 unique database records and screened them using the same criteria (Table III). Every eligible record identified through Google Scholar was already present in the Scopus and Web of Science set, and no additional eligible study was found. The Google Scholar search therefore served only as a completeness check on the database search. It contributed no new studies, and all 53 included studies came from the Scopus and Web of Science flow reported in Table II and Figure 1.

Table II
Search and screening numbers

Stage	Number
Scopus records	494
Web of Science records	389
Google Scholar records screened separately	600
Database records before duplicates	883
Duplicates removed	397
Unique database records	486
Title/abstract records screened	486
Records excluded at title/abstract stage	383
Full texts sought	103
Full texts unavailable	0
Full texts assessed	103
Full texts excluded	50
Evidence studies included	53

Inclusion and exclusion criteria

Studies published between 2019 and 2026 were included if they focused on adoption, implementation, and/or theory of AI in one or more of the five circular economy strategies. The lower bound of 2019 was chosen for three reasons. First, 2019 marks the publication of the Ellen MacArthur Foundation’s report on artificial intelligence and the circular economy (MacArthur & Cowes, 2019). That report was the first systematic statement that AI enables circularity. Following its publication, the AI and circular economy literature began to form a distinct research stream. Second, the AI techniques that dominate the included studies, such as deep learning-based computer vision, reinforcement learning, and digital twins, only became mature and accessible enough for applied circular economy research in the late 2010s—earlier work mainly concerns rule-based or expert systems that are not comparable to current applications. Third, the European Union’s Circular Economy Action Plan (Commission, 2020) and related policy initiatives sharply increased regulatory and industry attention to circular practices from 2019 onward, which is reflected in the growth of publications shown in Figure 2. The upper bound is the final search date (15 January 2026). In total, 433 records were excluded (383 at title and abstract screening and 50 at full-text assessment) because they were either broader studies on the circular economy or sustainability (with only minor elements involving AI), studies on AI outside the scope of the circular economy or sustainability, lacked full text in either the institutional or open access repository, or duplicates across the databases (Table III).

Table III
Inclusion and exclusion criteria applied during screening and eligibility

Criterion	Inclusion	Exclusion
Language	English	Non-English
Publication type	Peer-reviewed journal article, conference paper, book chapter	Non-peer-reviewed, editorial, opinion piece
Publication window	2019-2026	Outside 2019-2026
Topical relevance	Substantive AI component within a CE strategy	CE topic without meaningful AI component, or AI topic unrelated to CE
Accessibility	Full text accessible	Full text inaccessible
Duplication	Unique record	Duplicate across databases

The thematic synthesis includes only the 53 evidence studies. Four additional background and methodological references for example, (Page

et al., 2021) were cited to support the review's concepts and methods. They did not meet the inclusion and exclusion criteria and are not included in the 53 studies.

Screening, selection, and reliability

Of the 883 database records identified, 397 duplicates were removed, leaving 486 unique records for title and abstract screening. At this stage, 383 records were excluded because they lacked a substantive AI component, did not address any of the five circular economy strategies, or were duplicates with differing metadata. The remaining 103 records were assessed at the full-text stage, and a further 50 were excluded for the reasons reported in Table IVa. This left 53 studies for thematic synthesis (Figure 1). Of these, 45 studies address one of the five circular economy strategies that form the review's main analytic domains: Reuse (5), recycling (16), remanufacturing (6), waste reduction (11), and resource optimization (7). The remaining 8 studies are general or cross-cutting AI and circular economy frameworks that do not have one dominant strategy; they are treated as a separate category and inform the integrative framework in Section 5 rather than the strategy-specific findings in Section 4 (Table IV).

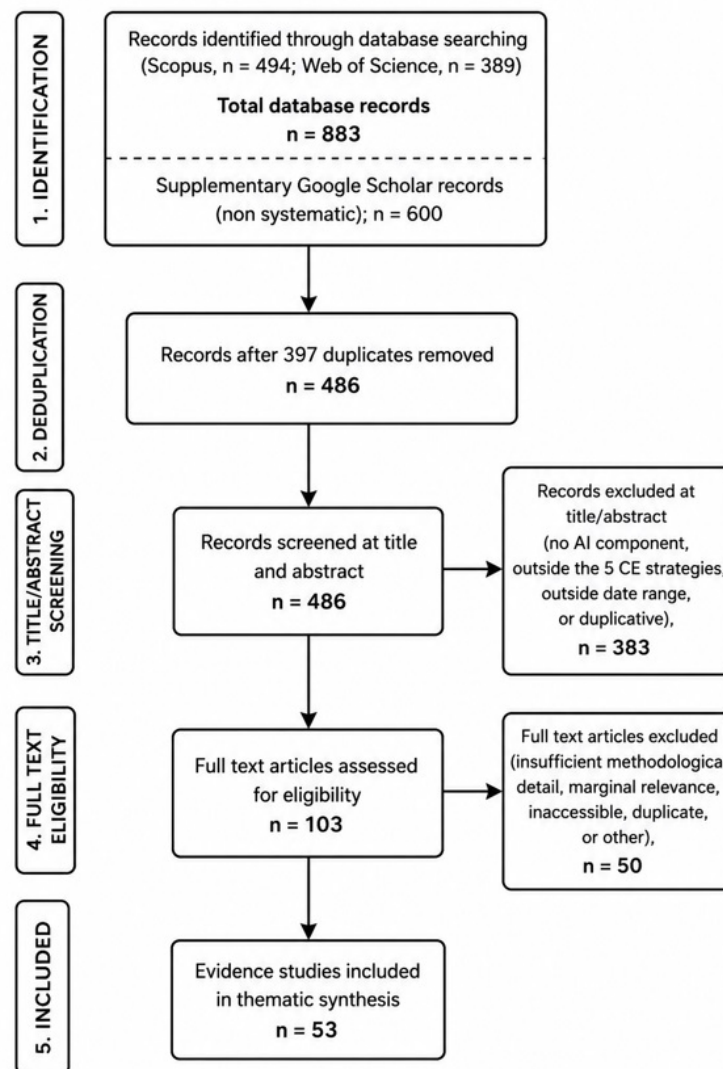


Fig. 1 PRISMA 2020 flow diagram

A single reviewer conducted title and abstract screening and full-text eligibility assessment consistently throughout the study, using the criteria in Table III; this is acknowledged as a limitation in Section 8. To check consistency, a second reviewer independently re-screened a 20 percent sample of the full texts (21 of 103) and re-coded a 20 percent sample of the included studies (11 of 53); disagreements were resolved through discussion.

The included studies range from 2019 to 2026. Publication output rose sharply in 2024 and 2025, which together account for 30 of the 53 studies (56.6 percent). The low count for 2026 reflects only the partial year covered by the search (to 15 January 2026), not a decline in interest. The included studies are published in journals including Sustainability, Environment, Development and Sustainability, IEEE Access, Waste Management, and Artificial Intelligence Review, as well as conference proceedings and edited book chapters. They are systematic and scientometric reviews, bibliometric analyses, conceptual and framework papers, and empirical machine learning, deep learning, and case study applications. The contributing research teams are spread across Europe, Asia, North America, and the Middle East, with empirical and applied research focused in China, Italy, and Southeast Asia, and conceptual and/or review-based research focused in European research institutions.

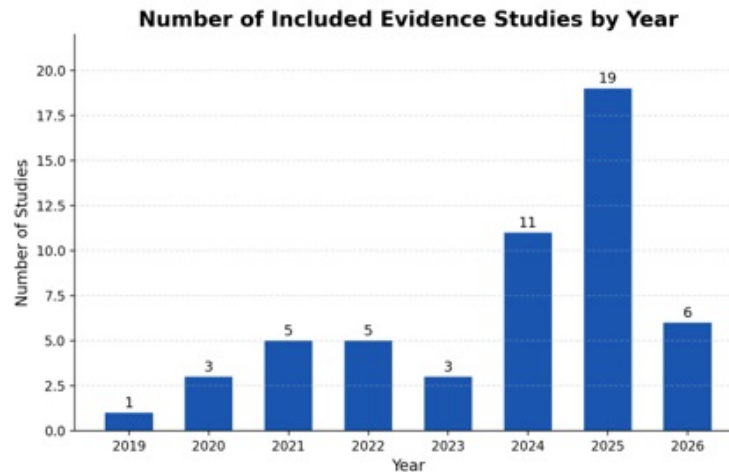


Fig. 2 Number of included evidence studies by publication year (2019-2026), $n = 53$

Coding, thematic analysis, and classification rule

For each of the 53 included studies, four dimensions were coded: The circular economy strategy addressed, the type of AI technology or method used, the theoretical framework applied (if any), and the key findings reported. A representative sample was used for testing the coding scheme, and this was then adapted for use with the entire sample. Where a study presented a linking or combination of more than one approach to circular economy, it was assigned to one primary strategy category for Table IV, and the corresponding Findings subsection, with the strategy that was most clearly addressed in the study's aims and results; secondary strategy linkages for multi strategy studies are instead discussed narratively in the Integrative Framework section. Because of this primary-strategy assignment rule, the categories in Table IV are mutually exclusive, and all categories sum to the included sample.

Table IV
Distribution of the 53 included studies across circular economy strategies

Category	Number of Studies	Percentage
General/cross-cutting AI-CE framework	8	15.1%
Reuse	5	9.4%
Recycling	16	30.2%
Remanufacturing	6	11.3%
Waste reduction	11	20.8%
Resource optimization	7	13.2%
Total	53	100%

Table IVa: Full-text exclusion reasons ($n = 50$)

Reason for full-text exclusion	Number of records
Insufficient methodological detail for synthesis	11
Marginally relevant to research questions	14
Duplicate not caught at earlier stage	4
Other	21
Total excluded at full text	50

Study quality appraisal

There are two reasons that a comprehensive checklist for assessing the quality of one type of study would not be suitable for this entire group of studies included in the evidence: First, the studies vary in type, from empirical to case studies, to reviews, bibliometric analyses, conceptual papers, conference proceedings, and book chapters; and second, the studies do not all feature the same quality measures. During coding, each included study was classified into one of four categories: Tier 1: Empirical validated, studies with field or real-world deployment that report measured performance outcomes; Tier 2: Empirical pilot or lab-tested, studies with controlled or simulated results that were not yet deployed at scale; Tier 3: Conceptual or framework, studies proposing a model or argument that has not been empirically tested; Tier 4: Secondary synthesis, systematic reviews, bibliometric analyses, or scientometric studies summarizing other primary work. This four-tier classification was developed by the authors for this review and is not a validated appraisal instrument. It was designed because established tools, such as the Mixed Methods Appraisal Tool (Hong et al., 2018), assume a primary empirical study with a defined design. In contrast, a large share of the evidence base here consists of conceptual papers, framework proposals, and secondary syntheses to which such criteria cannot be applied. The tiers therefore indicate each study's evidence strength and maturity (from field-validated deployment to conceptual argument) rather than scoring methodological quality within a design. The tiers were used to weight the synthesis and not to exclude studies, and tier assignment was included in the 20 percent second reviewer re-coding check described in section screening, selection and reliability.

Table V
Study quality appraisal tiers

Tier	Label	Criteria
1	Empirical, validated	Field or real-world deployment with measured performance outcomes
2	Empirical, pilot/lab tested	Controlled or simulated results, not yet deployed at scale
3	Conceptual/framework	Proposed model or argument without empirical testing
4	Secondary synthesis	Systematic reviews, bibliometric or scientometric studies

Findings

AI's role in reuse

Reuse avoids the material and energy required for recycling or remanufacturing by prolonging product use. Here, the primary role of AI is product condition assessment, reverse logistics coordination, and demand prediction for product reuse. Psarommatis et al. (2025) identify issues with scaled reuse, such as non-uniform condition-assessment approaches and a lack of connection between reusability decisions and manufacturing planning, and propose machine-learning models based on sensor and usage data to improve reusability-decision precision and automation. Xiong et al. (2024) use reinforcement learning to support maintenance decisions for second-hand machines to demonstrate that the performance and failure history can be used to guide the maintenance schedule and extend the life of equipment.

In reverse logistics, AI improves route optimization, demand forecasting, and inventory management, although AI adoption remains less mature than in forward logistics (Habazin et al., 2025). Khulbe (2025) and Rahman et al. (2025) both highlight AI's ability to identify reuse opportunities earlier and more proactively and to predict product life cycle stages before waste generation. Overall, reuse research is primarily technical (Tier 2 and Tier 3 evidence dominate) and relatively under-researched in organizational reuse strategy.

AI's role in recycling

Recycling turns waste into resources for new production, and AI applications focus on automatically classifying waste, detecting contamination, and monitoring material streams. Sorting applications are the most developed, with (Jin et al., 2023) demonstrating that automatic garbage detection via deep learning is superior to manual sorting and (Mohammed et al., 2023) linking neural networks with feature fusion for automated garbage sorting in a smart city, both highlighting that contamination and inconsistent packaging still affect performance. (Kebisek et al., 2026) provide an AI-based approach to contamination detection other than cameras: A radar-based approach. System-level reviews support this: Dawar et al. (2025) note a shift from proof of concept to integrated monitoring for municipal solid waste, hampered by data standardization issues.

J. Singh et al. (2025) report rapid growth in recent years, focused on high-income urban contexts; Fuqaha and Nursetiawan (2025) show that IoT-connected infrastructure makes continuous monitoring of municipal solid waste systems feasible. Recycling research has started to focus on certain material streams, such as textiles (Lopes et al., 2026) and construction and demolition waste (Alimi et al., 2025), where the sorting process is not as well developed as in municipal waste, and on the integration of recycling into smart city infrastructure (X. Chen, 2022). Compared with other strategies, recycling has the most technically mature, Tier 1-validated applications in this review. Still, it remains vulnerable to contamination, and the transition from pilot to operational deployment remains challenging.

AI's role in remanufacturing

Remanufacturing restores used products or components to near-new condition but must cope with uncertain input quality, so AI is applied to condition assessment, disassembly planning, and recovery scheduling. The most common application reported is predictive maintenance, where Hossain and Hoque (2026) and Kim et al. (2024) state that predictive models are used to estimate the remaining lifespan of a component and to identify parts that can be remanufactured. However, these models are often implemented in a specific product category and are therefore not easily transferable. According to Dudkowiak et al. (2025), predictive and diagnostic applications dominate the remanufacturing literature, while disassembly sequencing support remains comparatively underdeveloped and mostly conceptual.

Xiao and Huang (2024) demonstrate AI-assisted robotic perception that adapts disassembly sequences based on the changing condition of returned products, which is far less standardized than forward assembly. Digital twin applications, as discussed by Z. Chen and Huang (2021) in the context of supply chain information sharing and by Sajadieh and Noh (2025) in general, are most useful if they are populated with real-time condition details, and not as fixed design models. Remanufacturing applications are conceptually mature (Tier 3 evidence is common) and have less empirical evidence of large-scale validation than recycling, and disassembly planning is less technically mature than predictive maintenance.

AI's role in waste reduction

Waste reduction does not require reprocessing waste; it involves forecasting, inventory control, and supply chain coordination to reduce waste at the source. Machine learning models outperform traditional statistical forecasting in e-commerce supply chains by reducing overproduction (Dong et al., 2025) and in the food supply chain (Palakurti, 2025). A specific focus is food waste: (Sharma et al., 2020) outline three mechanisms, demand forecasting, quality inspection, and near-expiry redistribution, with the latter example showing how AI can change consumer purchasing habits to minimize food waste. (Carpitella & Izquierdo, 2025), Khang et al. (2024) expand the scope of AI waste reduction to other inventory management and waste-monitoring automation, while Hernandez et al. (2024) and Dzreke (2025) use precision agriculture and farm-to-fork systems approaches to prevent waste at the production stage. This literature is more empirical than that on reuse or remanufacturing (Tier 1 + Tier 2 evidence), although it remains concentrated in food and retail settings.

AI's role in resource optimization

Optimization of resources is not limited to a certain stage of a product's life cycle but can be applied to manufacturing, energy, computing, etc. Popowicz et al. (2025) suggest hybrid approaches that combine AI with traditional Life Cycle Assessment (LCA), where AI primarily fills data gaps and automates impact calculations but faces challenges in model transparency and data quality, especially for regulatory reporting. Waltersmann et al. (2021) Machine learning is commonly used to optimize energy use, minimize material waste, and uncover inefficiencies that traditional monitoring misses; Li et al. (2022) show similar gains in thermal energy system optimization. A third application is adaptive resource allocation, where clustering and optimization algorithms reallocate resources in response to changing demand. For example, (J. Singh et al., 2025) propose a real-time grid optimization framework based on deep learning and IoT that adapts to demand fluctuations better than static allocation. Bitzenis et al. (2025) show that research interest is concentrated in manufacturing and energy, while Olawade et al. (2026) confirm that waste management and resource optimization go hand in hand. Resource optimization applications are best established in energy-intensive, data-rich environments and are comparatively underrepresented in smaller-scale and service settings.

Integrative Framework: Connecting AI and Circular Economy

Synthesis across the five domains

The five strategies share four recurring AI functions: Predictive assessment, automated classification, process optimization, and system-level integration. Predictive assessment is seen as condition and remaining life prediction in reuse (Xiong et al., 2024), predictive maintenance and quality forecasting in remanufacturing (Hossain & Hoque, 2026; Kim et al., 2024), demand forecasting in waste reduction (Dong et al., 2025), and life cycle impact estimation in resource optimization (Popowicz et al., 2025). The clearest evidence for automated classification appears in recycling, where computer vision is used for sorting (Jin et al., 2023; Mohammed et al., 2023), with less evidence of the same function in product condition grading for reuse and component assessment for remanufacturing. Process optimization appears in waste-reduction inventory and pricing systems (Abdullah et al., 2025; Carpitella & Izquierdo, 2025) energy and manufacturing resource allocation (A. R. Singh et al., 2025) (Waltersmann et al., 2021) and remanufacturing scheduling (Kim et al., 2024). System-level integration in remanufacturing and recycling can be identified in smart city and digital twin-enabled environments (Z. Chen & Huang, 2021; Fuqaha & Nursetiawan, 2025; Sajadieh & Noh, 2025).

Table VI compares all four capability clusters across all five strategies, based on the evidence identified above. Coverage is uneven: Predictive assessment and process optimization are well documented across most strategies; automated classification is well documented mainly in recycling; and system-level integration is mainly in remanufacturing, with weaker evidence in recycling. Cells labeled "not evidenced" do not mean the

capability is not applicable; they reflect current literature limits and are included as findings to support the future research agenda outlined in section limitations and future research agenda.

Table VI
AI capability clusters evidenced across the five circular economy strategies

CE Strategy	Predictive Assessment	Automated Classification	Process Optimization	System-Level Integration
Reuse	Yes (Xiong et al., 2024)	Limited, condition grading only	Not evidenced	Not evidenced
Recycling	Not evidenced as distinct	Yes, strongly evidenced (Jin et al., 2023; Mohammed et al., 2023)	Limited (Kebisek et al., 2026)	Limited (X. Chen, 2022)
Remanufacturing	Yes (Hossain & Hoque, 2026; Kim et al., 2024)	Limited, conceptual only	Limited (Dudkowiak et al., 2025)	Yes (Z. Chen & Huang, 2021; Sajadieh & Noh, 2025)
Waste reduction	Yes (Dong et al., 2025)	Not evidenced as distinct	Yes (Abdullah et al., 2025; Carpitella & Izquierdo, 2025);	Not evidenced
Resource optimization	Yes (Popowicz et al., 2025)	Not evidenced as distinct	Yes (A. R. Singh et al., 2025; Waltersmann et al., 2021)	Not evidenced

Note. "Not evidenced" indicates that no included study reported that capability cluster for that strategy; this reflects the current boundaries of the reviewed literature rather than a theoretical absence of applicability.

Proposed conceptual framework

The proposed framework links the four AI capability clusters to the five circular economy outcomes through many-to-many rather than one-to-one pathways, and the strength of each pathway varies with the technical maturity and data availability of each strategy. In a Resource-Based View approach, the capability clusters are strategic resources that are hard to imitate and create "multiplication effects" when deployed across multiple circular strategies (Mailani et al., 2024). Dynamic Capabilities Theory explains how organizations continuously adapt through iterative sensing, seizing, and reconfiguring (Shahzad & Ferreira, 2026). The Technology Organization Environment framework accounts for variation in technology's contribution to the circular economy outcomes, driven by differences in organizational readiness and external regulatory or market pressures (Arroyabe et al., 2024; Nguyen et al., 2022).

Contextual and enabling conditions

The contextual and enabling conditions are not moderators, but they still strongly influence the relationship between AI capabilities and circular economy outcomes, as the included studies often identify them as barriers or enablers to AI and circular economy. One recurring challenge is the lack of clean, representative training data, especially for contamination detection and life cycle assessment modeling (Kebisek et al., 2026; Popowicz et al., 2025). Organizational readiness and firm size influence adoption, with cost and technical capacity issues more critical for smaller firms and municipalities (Arroyabe et al., 2024; Fuqaha & Nursetiawan, 2025). Adoption intensity also depends on regulatory and market context; for example, sustainability reporting requirements encourage the use of AI for resource optimization and life cycle assessment (Popowicz et al., 2025).

Visual model description

Figure 3 presents the proposed integrative framework as three connected layers. The first layer contains the four AI capability clusters identified in section synthesis across the five domains: Predictive assessment, automated classification, process optimization, and system-level integration. These clusters are not tied to any single strategy. Each is a generic capability an organization can build once and deploy across several circular economy settings, consistent with the resource-Based View perspective in section proposed conceptual framework.

The second layer contains the four contextual and enabling conditions that recur across the included studies: Data infrastructure, organizational readiness, regulatory context, and market pressure. These conditions do not change the direction of the relationship between AI capabilities and circular outcomes, but they determine the strength of that relationship in practice. For example, automated classification produces reliable sorting outcomes only where clean, representative training data are available (Kebisek et al., 2026). Organizational readiness and cost determine whether smaller firms and municipalities can adopt AI at all (Arroyabe et al., 2024; Fuqaha & Nursetiawan, 2025), and regulatory reporting requirements encourage firms toward AI-supported life cycle assessment (Popowicz et al., 2025).

The third layer contains the five circular economy strategy outcomes: Reuse, recycling, remanufacturing, waste reduction, and resource optimization. The pathways between the capability layer and the outcome layer are many-to-many rather than one-to-one, and their strength

reflects the evidence summarized in Table IV. Predictive assessment is linked strongly to reuse, remanufacturing, waste reduction, and resource optimization. Automated classification is linked most strongly to recycling, with weaker links to reuse and remanufacturing through condition grading. Process optimization is linked strongly to waste reduction and resource optimization, with weaker links to recycling and remanufacturing. System-level integration is linked mainly to remanufacturing and, more weakly, to recycling. Pathways marked "not evidenced" in Table VI are kept in the framework as untested propositions rather than removed, because they show where future research is needed (Table VIII). Taken together, Figure 3 captures this review's central finding: AI is not a set of separate, strategy-specific tools but a shared set of capabilities whose contribution to circularity depends on the conditions in which it is deployed. The same predictive or classification capability can therefore produce strong outcomes in one organization and weak outcomes in another, depending on its data infrastructure, organizational readiness, and regulatory and market context.

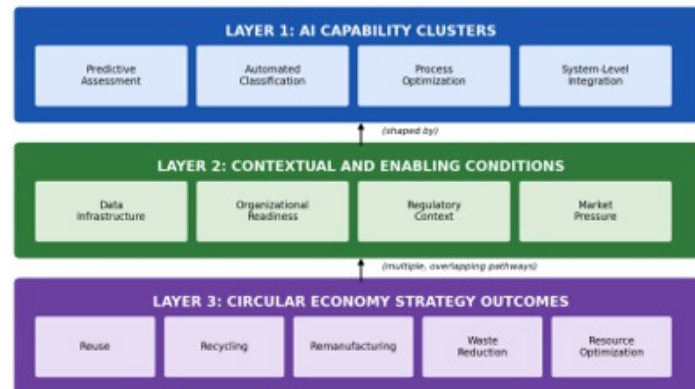


Fig. 3 Proposed integrative framework connecting AI capability clusters, contextual and enabling conditions, and circular economy strategy outcomes

Discussion

This review shows a significant lack of uniformity in research maturity, technology readiness, and empirical validation across these five AI-supported circular economy strategies, despite clear technical progress. The most numerous included studies (16 of 53, 30.2 percent) focus on recycling, with reuse included 3.2 times as often (5 of 53, 9.4 percent), and are concentrated on mature computer vision and deep learning applications with relatively large and well-labeled training sets, Tier 1 and Tier 2 applications. Reuse research, by contrast, remains highly technical, focusing on areas such as predictive maintenance (Xiong et al., 2024) or reverse logistics (Habazin et al., 2025) but without exploring an organizational reuse strategy.

While research on reuse is less developed than that on remanufacturing, it is evident that there are conceptual approaches, like with digital twin applications (Z. Chen & Huang, 2021; Sajadieh & Noh, 2025) and predictive maintenance models (Hossain & Hoque, 2026; Kim et al., 2024), that are being proposed and tested in lab settings, and only rarely reported as applied at scale (Dudkowiak et al., 2025). Although the number of publications varies considerably between the various strategies, the central AI functions used in each of these strategies are very consistent: Life prediction for reuse, predictive maintenance for remanufacturing, demand forecasting for waste reduction, and life cycle impact estimation for resource optimization are all different names for the same underlying predictive assessment function, yet studies in one strategy rarely cite or build on studies in another. This suggests that the field's fragmentation reflects how the literature is organized rather than genuine technical divergence.

Although the barriers are conceptually similar, strategy-specific literatures frame them differently. From a recycling research perspective, the barriers are mainly technical, focusing on the accuracy of contamination detection in textiles (Lopes et al., 2026) and construction waste (Alimi et al., 2025), respectively. Waste reduction research in food chains views barriers through a behavioral lens, focusing on whether dynamic pricing can change consumer behavior (Abdullah et al., 2025). Resource optimization research is centered on data quality and model transparency issues, particularly in the context of regulatory reporting that demands explainability that is not delivered by many AI models (Popowicz et al., 2025). This variation indicates that, in general, the barriers to adoption are similar across strategies but take different forms across operational and regulatory contexts and are examined in different ways.

Empirical and applied research tends to focus on manufacturing and energy-intensive industries, especially in China, Italy, and Southeast Asia, and conceptual and review-based contributions tend to focus on European institutions. This pattern may reflect regional differences in the maturity of industrial AI adoption, although differences in research funding and publication norms cannot be ruled out.

Implications

Theoretical implications

This review advances the theory, as it proves that AI is not strategy-dependent, but rather a common resource that can be applied to reuse, recycling, remanufacturing, waste reduction, and resource optimization; it thus provides a Resource-Based View reading for the use of AI capabilities across multiple circular strategies, rather than one. Table VII shows that the 53 included studies contain 46 theory or framework applications; this count reflects applications, not studies. Descriptive frameworks dominate: Industrial ecology and circular economy frameworks (8) and life cycle approaches (4) account for 26.1 percent, describing material loops rather than explaining how AI creates circular value. Organizational theories, namely RBV (7), TOE (6), and DCT (5), account for 39.1 percent, while adoption theories (Diffusion of Innovations, Institutional Theory, and TAM) add 19.6 percent. Theory use is strategy-specific: RBV appears mainly in resource optimization and waste reduction, DCT in reuse and remanufacturing, and TOE in recycling. The recorded gaps, including limited longitudinal validation, cross-country comparison, and empirical testing, indicate an early theoretical stage. Applying RBV, DCT, and TOE jointly across all five strategies therefore extends existing theory rather than importing new theory, and Table VIII links each gap to a specific lens and research design.

Table VII
Theoretical frameworks identified among included evidence studies

Theory/framework	No. of studies	CE strategy most frequently associated	Level of analysis	Representative application	Identified gap
Resource-Based View (RBV)	7	Resource optimization; waste reduction	Firm	AI capability as an organizational resource for improving resource efficiency	Limited longitudinal validation
Technology–Organization–Environment (TOE)	6	Recycling; resource optimization	Firm/organizational	Organizational readiness and technological infrastructure for AI adoption	Limited cross-country comparison
Dynamic Capabilities Theory (DCT)	5	Reuse; remanufacturing	Firm/supply chain	AI-enabled sensing, adaptation and reconfiguration of circular processes	Limited empirical testing
Diffusion of Innovations (DOI)	4	Recycling; waste reduction	Organizational/industry	Adoption of AI-enabled circular technologies	Limited evidence from developing economies
Transaction Cost Economics (TCE)	3	Reuse; remanufacturing	Supply chain	AI-supported coordination and transaction efficiency	Few empirical studies
Institutional Theory	3	Recycling; waste reduction	Institutional/industry	Regulatory and institutional pressures affecting AI adoption	Weak causal evidence
Technology Acceptance Model (TAM) / related adoption models	2	Resource optimization	Individual/organizational	User acceptance of AI-enabled systems	Mostly pilot-level evidence
Industrial Ecology / Circular Economy frameworks	8	All five strategies	System/supply chain	AI contribution to material and resource loops	Frameworks often descriptive rather than tested
Life-Cycle Assessment (LCA) / life-cycle approaches	4	Recycling; remanufacturing	Product/system	AI-supported environmental and material-flow assessment	Limited integration with real-time AI
Other/explicit theoretical frameworks	4	Multiple	Mixed	Study-specific conceptual explanations	Fragmented theoretical base
Total theory/framework applications	46	—	—	—	—

Practical implications

The review suggests treating AI support for the circular economy as a capability-development journey for practitioners, rather than a series of isolated, strategy-specific projects. As an organization establishes the ability to maintain its remanufacturing processes predictively, it is also investing in data infrastructure and modeling skills that may be applied to another part of the organization where waste is being reduced, or resources are being optimized, further lowering the marginal cost of spreading AI-enabled circular practice. While municipalities and policy makers are familiar with the technical maturity of AI for recycling, less focus has been placed on the infrastructure enabling AI at scale in less well-resourced urban areas, suggesting that supporting the technology through policy might be better achieved by targeting shared infrastructure and data, rather than technology pilots that are hard to scale beyond their initial setting.

Limitations and Future Research Agenda

This review has a few limitations. The search was restricted to Scopus, Web of Science, and a supplementary, non-systematic, Google Scholar search; studies that were only indexed in other regional or disciplinary databases might not have been identified. Only English-language publications were reviewed so relevant non-English work may have been missed. The studies presented here are a snapshot of the fast-moving research fields of AI and circular economy and do not necessarily reflect current research. Studies were classified into a single main category, circular economy, and screening and coding were done largely by one coder and verified by a second coder for a 20 percent sample, leaving the possibility of individual coding bias, even though the coding scheme was piloted and iteratively refined.

Future reuse research should move from the technical to the organizational level by examining how condition assessment and reverse logistics are embedded in business models. Research in plastics and municipal solid waste sorting has been well developed using AI. However, the same is not true of other, mostly under-researched material streams, such as textiles and construction and demolition waste. Remanufacturing research should focus on full-scale industrial tests, as much existing work is conceptual or based on laboratory testing. Waste-reduction research should not be limited to food supply chains; it should also include other resource-intensive industries, such as construction, textiles, and electronics. In addition, the authors developed the evidence tiers for quality appraisal rather than adapting them from a validated instrument, so they indicate evidence maturity. They should not be read as a formal risk of bias assessment. Resource optimization research should also address smaller-scale and service sectors, which are underrepresented compared with energy-intensive manufacturing. Finally, longitudinal studies testing whether AI capabilities transfer across circular economy strategies within the same organization over time would directly examine the integrative framework proposed in this review. Table VIII maps each gap to a suggested theoretical lens, method, and context.

Table VIII
Future research agenda linked to identified gaps

Gap Identified	Recommended Theory	Recommended Method	Recommended Context
Reuse research remains narrowly technical, not integrated into organizational strategy	Dynamic Capabilities Theory	Longitudinal case study	Manufacturing firms with active reverse logistics
Recycling underdeveloped in textiles and construction/demolition waste	Resource Based View	Empirical, field-validated model testing	Textile and construction/demolition waste processors
Remanufacturing applications remain conceptual or lab-tested	Technology Organization Environment	Multi-site empirical validation	Full-scale industrial remanufacturing facilities
Waste reduction research concentrated in food supply chains	Resource Based View	Empirical, cross-sector comparative study	Construction, textiles, electronics industries
Resource optimization underexplored in smaller-scale/service settings	Technology Organization Environment	SME-focused empirical study	Service sector and small/medium manufacturers
No study tests cross-strategy capability transfer over time	Dynamic Capabilities Theory	Longitudinal, multi-strategy case study	Organizations pursuing more than one CE strategy

Conclusion

This systematic review brings together 53 evidence studies on AI and the circular economy in reuse, recycling, remanufacturing, waste reduction, and resource optimization. The review approach is designed to be an integrative approach in which four AI capability clusters (Predictive Assessment, Automated Classification, Process Optimization, and System-Level Integration) stand in for shared and cross-cutting resources, the strength of which and the resulting outcomes depend on the enabling and contextual conditions (such as data infrastructure, organizational readiness, regulatory context, etc.). Research maturity varies: Recycling has the most technically advanced and empirically well-supported applications, while reuse and remanufacturing are less developed. Addressing the identified challenges, validation gaps, cross-strategy transferability questions, and underexplored organizational and geographical contexts would support both theoretical and practical understanding of AI as an enabler of circular economy transformation

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