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Review Article

# Large Language Models in the Circular Economy: A Scoping Review of Applications, Emerging Patterns, and Governance Challenges

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**ABSTRACT**

Large language models represent a qualitatively new development within generative artificial intelligence and have recently begun to appear in circular economy research, yet no review has pulled together what is actually known about how and where these tools are being used in this field. This study aims to map current applications of large language models and generative artificial intelligence in circular economy contexts, examine how these tools are being deployed methodologically, and identify what the evidence says about their benefits, limitations, and risks. Following PRISMA-ScR guidance, a scoping review was conducted in Scopus in February 2026, returning 127 records, which were screened down to 30 peer-reviewed journal articles published between 2024 and 2026 and analyzed through a matrix-based coding approach. The findings show that large language models are used less as standalone decision-making tools and more as ways of organizing and mobilizing knowledge for practitioners and researchers, with roles ranging from design assistants and knowledge integrators to analytical components in larger modelling workflows. Most applications are found in industrial symbiosis, circular supply chains, sustainable product and materials innovation, and the built environment, while newer work is beginning to emerge in waste sorting, policy analysis, and skills mapping. The studies consistently show that the most reliable results come when large language models are combined with domain-specific knowledge bases and expert validation, rather than used autonomously. Across these application areas, several governance challenges remain unaddressed, including the absence of domain-specific validation standards, insufficient data infrastructure for circular economy contexts, and the largely unaccounted environmental footprint of generative AI hardware itself. Based on these findings, future research should focus on comparative evaluations and better integration with established tools such as life cycle assessment. Policymakers need to invest in domain-specific data infrastructure and clear governance frameworks, and practitioners should treat human oversight as a necessary part of any workflow that uses these tools.

## 1. INTRODUCTION

Circular economy (CE) has gained prominence as a response to escalating resource depletion, pollution, and climate change, by proposing a shift from linear "take–make–dispose" models to systems in which materials, components, and products remain in use for as long as possible through strategies such as reuse, repair, remanufacturing, and recycling. Implementing CE in practice, however, is information-intensive: organizations must understand complex material flows, product life cycles, and environmental impacts across supply chains, while coordinating diverse stakeholders and business models. Digital technologies, and artificial intelligence (AI) in particular, are increasingly viewed as key enablers that can help manage this complexity and support the design and scaling of circular strategies [1], [2].

Over the past few years, a substantial body of work has explored how AI and machine learning (ML) can support CE across domains such as waste management, recycling and reuse, reverse logistics, sustainable manufacturing, and circular supply chains. For example, Noman et al. (2022) present a bibliometric and systematic review of AI and ML in CE, identifying thematic clusters around sustainable development, reverse logistics, waste management, supply chain management, recycling and reuse, and manufacturing [3]. Acerbi et al. (2021) focus on AI in circular manufacturing and show that applications are relatively mature at the micro (firm) level but less developed at meso (industrial symbiosis) and macro (regional, national) scales [4]. Pathan et al. (2023) review the role of AI in CE and sustainable supply chains, emphasizing AI's potential to enable new circular business models and improve traceability and coordination [2]. More recently, Huang et al. (2025) link AI to stages of firm-level "circular economy maturity," while Raut et al. (2025) provide a critical analysis

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of AI applications in CE and propose future research directions [5], [6]. Collectively, these studies consolidate AI as a strategic technological catalyst for circular transitions.

Within this broader AI–CE nexus, the rapid emergence of generative AI and large language models (LLMs) such as ChatGPT represents a qualitatively new development. LLMs are trained on massive text corpora and can perform a wide range of natural-language tasks summarization, information extraction, classification, code generation, and open-ended dialogue often with minimal task-specific training. These capabilities are highly relevant to CE, where much of the key knowledge is embedded in unstructured textual sources such as policy documents, standards, patents, technical reports, scientific articles, and social media content. Early conceptual work already positions ChatGPT as a potential enabler of a "digital circular economy," highlighting its possible roles in STEM education, research, and the development of circular business models and innovations [7]. At the same time, the computational and energy demands of LLMs raise questions about their own environmental footprint and about how their deployment aligns with CE principles.

LLMs have already been applied to classify textual business descriptions into the International Standard Industrial Classification for waste-to-resource repositories [8], to construct large-scale waste-to-resource knowledge graphs for industrial symbiosis identification[9], to support life cycle analysis of circular bio-manufacturing processes [10], and to analyse social-media engagement with public-sector CE communication [11]. Taken together, these applications indicate that LLM-based tools are beginning to affect multiple stages of the circular value chain, from knowledge infrastructures to assessment and public communication. However, the scholarly understanding of LLMs in CE remains fragmented. Existing reviews on AI and CE synthesize applications of AI at a high level and emphasize their importance for CE transitions, but they typically treat AI as a broad category and do not systematically examine generative models or LLM-specific applications and do not differentiate between predictive models, computer-vision systems, and LLM-based tools in terms of capabilities, risks, or suitability for particular CE tasks. At the same time, the emerging LLM-focused studies are developed in different disciplinary communities, employ heterogeneous data sources and evaluation metrics, and use varying conceptions of what constitutes a "circular" outcome. As a result, there is currently no integrated synthesis that maps where and how LLMs are being used in CE, what kinds of circular strategies they support, and how their benefits and risks are understood. This lack of synthesis makes it difficult for researchers, practitioners, and policymakers to learn across cases, identify robust use patterns, or develop guidelines for the responsible design and deployment of LLMs in circular contexts. Engineers, sustainability managers, procurement specialists, and industrial ecology practitioners who are currently evaluating or deploying generative AI tools in circular operations face the same absence of integrated guidance, with no structured evidence base from which to assess which tools, configurations, or validation practices are appropriate for their specific contexts.

Against this backdrop, the study aims to systematically map and critically assess the emerging literature on ChatGPT and other LLMs within CE. To this end, the study adopts a scoping review design following PRISMA-ScR guidance, using Scopus as the primary bibliographic database, in order to provide a transparent and replicable synthesis of the available evidence. Specifically, it addresses the following research questions:

- RQ1: In which circular economy domains, sectors, and value-chain stages are generative AI and LLMs currently applied?
- RQ2: What methodological approaches, model types, and data sources underpin these applications?
- RQ3: What benefits, limitations, and risks are reported regarding the use of generative AI and LLMs to support circular strategies?
- RQ4: What research and practice directions emerge for the responsible and effective use of generative AI in circular economy contexts?

This review makes several distinct contributions to the existing literature. As the first scoping review to systematically map generative AI and large language model applications within circular economy and industrial ecology contexts using PRISMA-ScR guidance, it addresses a gap left open by prior AI-for-CE reviews, which treat artificial intelligence as a broad category without differentiating generative models as a functionally distinct subset. Beyond mapping the field, the review introduces a taxonomy of functional roles through which large language models engage with circular economy tasks, spanning knowledge and design assistance, analytical extraction, organizational capability constructs, and circular scrutiny of AI infrastructure itself. It also identifies cross-cutting governance and validation gaps that are specific to generative models and that remain under addressed in the existing literature, which neither focuses on large language models as a distinct category nor systematically examines human-AI complementarity and environmental accountability in circular economy contexts.

The remainder of the paper is organized as follows: Section 2 details the review methodology; Section 3 reports the results, first providing a descriptive overview of the identified literature and then presenting a thematic synthesis of generative AI and LLM applications along the circular value chain; Section 4 discusses cross-cutting issues, implications and limitations; and Section 5 concludes with key insights, recommendations and directions for future research.

## 2. METHODOLOGY

This study follows a scoping review design to map how generative and conversational AI tools are being used in circular economy and industrial ecology contexts. The approach is inspired by systematic review procedures in management research, which emphasize transparency, replicability, and an explicit link between review questions and search, screening and synthesis steps [12], [13], [14]. In line with these guidelines, the review focuses on peer-reviewed journal articles and aims to provide a conceptually structured synthesis rather than a descriptive listing of studies. Reporting of the identification, screening, and selection process follows the PRISMA extension for Scoping Reviews (PRISMA-ScR) reporting guidelines [15], which comprises 20 essential and 2 optional reporting items. Twenty of these items were applicable to and addressed in the present review, covering the title, structured summary, rationale, objectives, protocol and registration, eligibility criteria, information sources, search, selection of sources of evidence (both screening and reporting stages), data charting process, data items, synthesis of results (both methods and reporting stages), characteristics of sources of evidence, results of individual sources of evidence, summary of evidence, limitations, conclusions, and funding. The two optional items (Items 12 and 16), concerning the critical appraisal of individual sources of evidence, were not applied, as the objective of this review was to map the breadth and nature of the existing evidence rather than to formally appraise the methodological quality of individual studies.

### 2.1 Search Strategy

The bibliographic search was conducted on 6 February 2026, using Scopus as the primary database. Scopus was chosen because it offers broad coverage of journals in sustainability, industrial ecology, engineering, and information systems, and has been widely used in related circular economy and industrial symbiosis reviews. The search was applied to titles, abstracts, and author keywords, combining terms for generative or conversational AI with terms capturing circular economy and industrial ecology contexts. The exact search string used was:

(ChatGPT OR Gemini OR Grok OR Copilot OR "Generative Artificial Intelligence" OR "Conversational Artificial Intelligence" OR "Conversational AI” OR "Generative AI" OR "GPT" OR "LLM" OR "Large Language Model") AND ("Industrial Ecology" OR "Industrial Park" OR "Eco Industrial Park" OR "Closed-Loop Economy" OR "Circular Economy" OR "Industrial Symbiosis")

The first part of the query was designed to capture different ways in which generative and conversational AI tools are labelled. The second part of the query targeted key concepts at the intersection of circular economy and industrial ecology, including “circular economy,” “industrial symbiosis,” “eco-industrial park,” “industrial park,” “closed-loop economy,” and “industrial ecology.” This structure was chosen to account for the fact that some studies may describe circular initiatives primarily under industrial ecology or industrial symbiosis labels rather than explicitly using the term circular economy. The search returned 127 records. No restrictions were imposed ex ante on publication year.

### 2.2 Inclusion Criteria, Study Selection and PRISMA Flow

Consistent with evidence-informed review principles [13], [14], the following inclusion criteria were applied:

- Topical relevance – circular economy context: The article had to address circular economy, industrial symbiosis, eco-industrial parks, closed-loop economy, or industrial ecology in a substantive way.
- Topical relevance – generative or conversational AI: The article had to discuss, design, or empirically apply generative or conversational AI tools in relation to circular economy, industrial ecology, or related industrial systems.
- Document type and quality filter: Only peer-reviewed journal articles were included; books, book chapters, conference proceedings and non-refereed material were excluded.
- Accessibility: Full text had to be accessible to the authors to allow detailed coding.

Study selection followed an iterative screening procedure consistent with PRISMA-ScR recommendations for transparent reporting [15]. First, all 127 records were exported from Scopus and screened by document type. Books, book chapters, note, editorial and conference papers were excluded to focus the review on peer-reviewed journal articles, resulting in 68 remaining records. Second, review papers were removed because the present work seeks to synthesize primary empirical and conceptual contributions on generative/conversational AI in circular economy, rather than to meta-review existing reviews; this step reduced the set to 60 articles. This exclusion is consistent with scoping review practice in adjacent fields, where the focus on primary contributions is maintained to avoid conflating first-order empirical evidence with second-order syntheses [14]. In the third step, the full texts of the 60 articles were read to assess substantive relevance. Articles that mentioned generative or conversational AI tools only tangentially, without engaging with their role in circular economy, industrial symbiosis, or closely related industrial ecology contexts, were excluded. At this stage, 30 articles were excluded for insufficient relevance, yielding a final corpus of 30 journal articles for in-depth analysis.

This number is a direct consequence of the narrow focus adopted in this review; namely, applications of generative and conversational large language AI tools within circular economy and industrial ecology contexts, and the stringent inclusion criteria applied. The identification and screening process started from 127 records and followed PRISMA-ScR guidance, meaning that the small sample size reflects the current maturity of the field rather than weaknesses in the search strategy. This is consistent with methodological guidance that emphasizes the fit between review purpose, field maturity and design, rather than any fixed minimum number of included studies [13], [14]. The sequence of identification, screening, eligibility assessment, and inclusion is visualized in Figure 1.

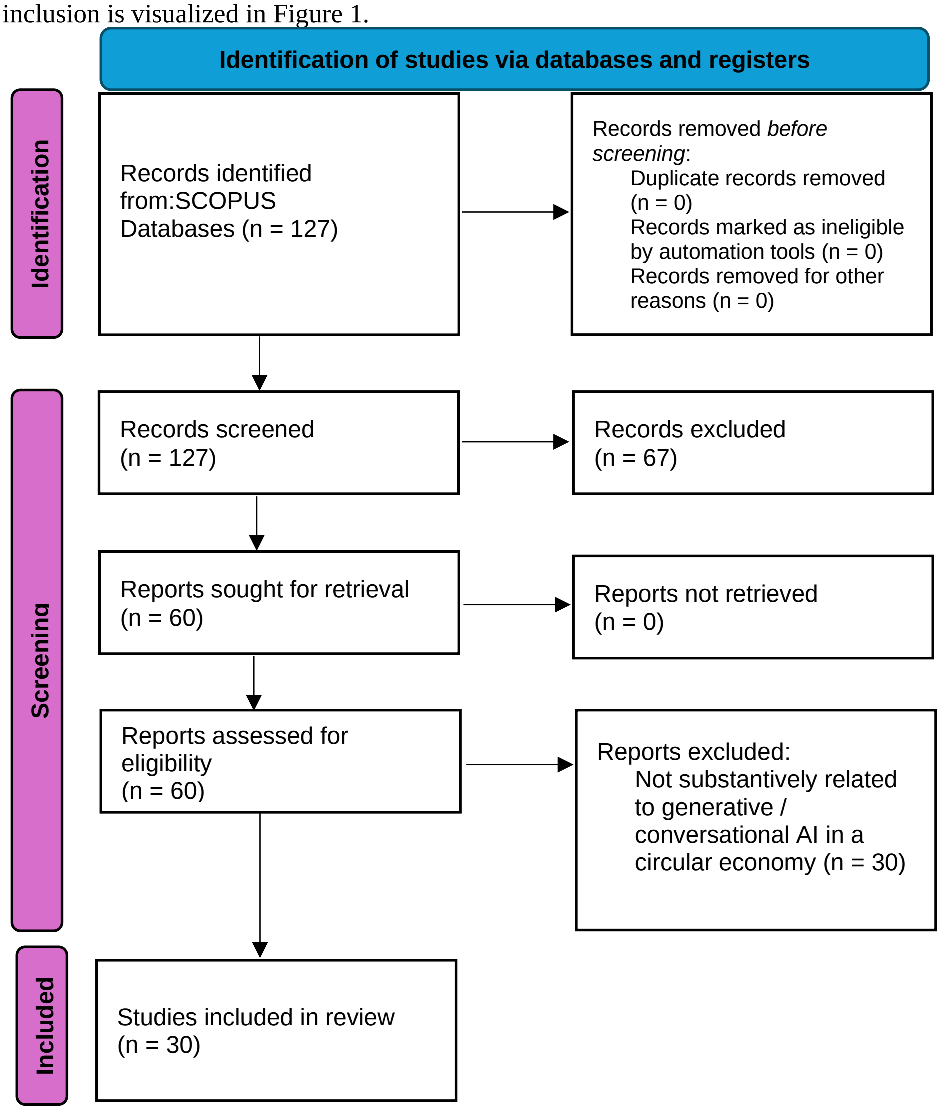


Fig. 1. Prisma flow diagram

All screening and eligibility decisions were carried out by the sole author. Given the single-author nature of this review, independent verification of screening decisions was not possible. To mitigate this limitation, a structured and pre-defined set of inclusion criteria was applied consistently throughout the screening process, and borderline cases were resolved through re-examination of the full text against each criterion. In accordance with PRISMA-ScR guidelines, formal risk of bias assessment at the study level was not conducted, as this is an optional rather than required component of scoping reviews. Instead, methodological heterogeneity and study-level limitations are acknowledged where relevant in the thematic synthesis and discussed in the Limitations section. This scoping review was not registered, and no formal protocol was published in advance. The review followed an a priori set of inclusion criteria and a structured search and charting procedure, as described above, but these were not deposited in a public registry such as the Open Science Framework.

### 2.3 Data Extraction and Synthesis using Matrix-Based Coding

To structure the analysis and avoid a fragmented "paper-by-paper" narrative, a matrix method was used to organize information from the selected articles. The matrix method has been proposed as a practical way to obtain both a high-level framework and a systematic roadmap for navigating dispersed literature, by arranging studies in rows and key analytical

dimensions in columns [16]. This approach has recently been adapted to conduct comprehensive reviews and shown to be effective for integrating heterogeneous evidence [17], [18], [19].
The coding dimensions used in the matrix were defined a priori, prior to full-text reading of the included studies, drawing on the research questions and the analytical framework established during the search and screening phase. This approach was adopted to minimize the risk of post hoc category construction and to ensure that the thematic synthesis reflects a pre-specified rather than data-driven organizational logic. For each of the 30 included articles, bibliographic and methodological information was extracted into a spreadsheet-based matrix. The columns captured: (i) bibliographic details (authors, year, journal), (ii) type of contribution (empirical case study, conceptual paper, framework or tool development), (iii) circular economy domain (e.g., industrial symbiosis, eco-industrial parks, life-cycle assessment, circular supply chains, policy and communication), (iv) value-chain stage(s) addressed (e.g., design, production, use, reuse/repair, end-of-life), (v) type and role of generative or conversational AI tool (e.g., ChatGPT-based assistant, LLM-based classifier, generative AI recommender), (vi) data sources (e.g., scientific publications, policy documents, social media data, industrial case data), (vii) evaluation approach and performance metrics, (viii) reported circular outcomes or implications (e.g., identification of symbiosis opportunities, support for LCA, improved stakeholder engagement), and (ix) limitations, risks, and future research directions identified by the authors. The matrix was then used as the basis for a concept-driven thematic synthesis, in line with recommendations to structure literature reviews around key concepts and themes rather than individual studies [12]. Descriptive statistics such as publication year, journal outlet, and distribution across circular economy domains were derived from the matrix, while qualitative coding supported the development of higher-level themes regarding the roles of generative and conversational AI in enabling circular strategies, the methodological patterns adopted, and the gaps and risks that remain underexplored. In line with scoping review methodology, a formal critical appraisal or risk of bias assessment of individual sources was not undertaken, as the aim was to map the breadth of existing evidence rather than to evaluate the methodological quality of individual studies.

## 3. RESULTS

This section presents the findings of the review in two steps. It first provides a descriptive overview of the included studies and then identifies the main cross-cutting themes and emergent patterns regarding how generative AI and LLMs are being applied across circular economy and industrial-ecology contexts.

### 3.1 Descriptive Overview of the Included Studies

This section provides a descriptive overview of the 30 studies included in the final sample. It summarizes their publication characteristics, methodological profiles, application domains, and the different roles assigned to generative AI and LLMs, thereby establishing the empirical basis for the thematic analysis that follows.

#### 3.1.1 Publication trends and outlets

The final corpus comprises 30 peer-reviewed journal articles that explicitly connect generative AI, often, but not exclusively, in the form of large language models such as ChatGPT, to circular economy (CE), industrial ecology or closely related domains. All identified studies are very recent, with publications clustered in 2024–2026, which mirrors the rapid diffusion of generative AI as a topic in sustainability and operations research. The articles are distributed across interdisciplinary outlets in sustainable production and consumption, industrial ecology, energy systems, and operations and supply chain management.
Table I summarises the publication outlets of the reviewed studies, showing that current work on generative AI and LLM applications in circular economy and industrial ecology is dispersed across a diverse set of management, sustainability, engineering and computer science journals.

TABLE 1. PUBLICATION OUTLETS, YEARS AND CITATION COUNTS OF THE REVIEWED ARTICLES

| Journal Title | Year | Number of Articles | Citations |
|---|---|---|---|
| ACS Central Science | 2025 | 1 | - |
| Advanced Engineering Informatics | 2025 | 1 | 10 |
| At-Automatisierungstechnik | 2025 | 1 | 0 |
| British Food Journal | 2025 | 1 | 0 |
| Cleaner Waste Systems | 2026 | 1 | 0 |
| Computers and Industrial Engineering | 2024, 2025 | 2 | 25 |
| Engineering, Construction and Architectural Management | 2025 | 1 | 4 |
| Environment, Development and Sustainability | 2025 | 1 | 4 |
| Environmental Impact Assessment Review | 2026 | 1 | 1 |
| IEEE Engineering Management Review | 2025 | 1 | 5 |
| International Journal of Production Economics | 2024 | 1 | 83 |
| Journal of Building Engineering | 2026 | 1 | 0 |
| Journal of Engineering Design | 2026 | 1 | 0 |

| Journal Title | Year | Number of Articles | Citations |
|---|---|---|---|
| Journal of Hydroinformatics | 2025 | 1 | 0 |
| Journal of Industrial Ecology | 2025 | 1 | 3 |
| Journal of Mechanical Design | 2026 | 1 | 0 |
| Nature Communications | 2026 | 1 | 0 |
| Nature Computational Science | 2024 | 1 | 50 |
| Resources, Conservation and Recycling | 2025, 2026 | 3 | 6 |
| SN Computer Science | 2025 | 1 | 2 |
| Sustainability (Switzerland) | 2026 | 1 | 0 |
| Sustainable Futures | 2025 | 1 | 2 |
| Technological Forecasting and Social Change | 2026 | 2 | 0 |
| Technology in Society | 2026 | 1 | 0 |
| Transportation Research Part E: Logistics and Transportation Review | 2024 | 1 | 67 |
| Water Science and Technology | 2024 | 1 | 3 |

### 3.1.2 Study types and methodological approaches

The sample combines conceptual essays, analytical modelling studies, and empirical applications or prototypes. A first subset of contributions develops, or tests concrete generative AI or LLM based tools. For example, Jiang et al. (2025) introduce a two-stage retrieval augmented generation (RAG) framework that couples an LLM with two specialized knowledge bases (one for product architecture and one for sustainable design strategies) to generate component specific guidelines for sustainable product development aligned with CE principles [20]. In the industrial symbiosis (IS) domain, Genc (2024, 2025) benchmarks several leading conversational AI assistants on their ability to answer IS/CE concept questions, classify wastes into European Waste Catalogue (EWC) and NACE categories, and suggest construction-sector IS opportunities, combining quantitative similarity metrics with expert evaluation [21], [22]. This tool-oriented stream has expanded considerably in the newer studies. Zhao et al. (2026), for instance, develop an LLM-enabled pipeline to extract waste-to-resource relations from published articles and organize them into a knowledge graph for industrial symbiosis identification [9]. In product and design-oriented contexts, Peitzmeier et al. (2026) present AutoPCM, an automated LLM-based approach that transforms manufacturing documents into product architecture representations and circularity assessments for automotive electronics [23], while Forth and De Wolf (2026) combine semantic textual similarity and a fine-tuned LLM to enrich BIM models for automated circularity assessment in buildings [24]. Other studies in this subset test concrete prototype or application settings, such as blockchain-supported LLM scheduling for distributed manufacturing in new-energy-vehicle production [25], multimodal large-language-model classification of waste in zero- and few-shot settings [26], and LLM-assisted web-based reporting and compliance support for water-smart circular-economy projects [27].

A second subset of papers relies on quantitative modelling and survey-based analysis rather than tool prototyping. Li et al. (2024) use structural equation modelling on firm-level survey data to examine how generative-AI usage relates to sustainable supply chain performance, mediated by green collaboration and circular-economy implementation practices [28]. Akhtar et al. (2024) similarly apply survey-based modelling to investigate how smart product platforming and big-data analytics, supported by AI and generative AI, shape environmentally oriented product outcomes in the automotive sector [29]. The enlarged sample also includes several modelling-heavy studies in which generative AI functions as an analytical component rather than a standalone prototype. Lin and Ma (2025) use multimodal GPT to interpret circular-economy system diagrams, translate them into executable system-dynamics models, and simulate policy scenarios using Taiwan's material-flow data [30]. Yu et al. (2026), by contrast, propose a generative inverse-design model based on a conditional invertible neural network to design sustainable concrete mixtures using recycled waste glass, combining computational generation with experimental validation [31]. Related empirical analyses also use LLMs for large-scale extraction or interpretation tasks, including the mapping of material stocks in the built environment [32], circularity-related metrics extraction from environmental product declarations in construction [33], and the analysis of public-sector circular-economy communication or circular-transition skills using GPT-based text analysis [11], [34]. Other contributions, such as Chen et al. (2025) on circular supply chain safety management [35] and Schoemaker et al. (2025) on recyclable automotive materials, adopt conceptual or forward-looking perspectives that synthesise existing literature and propose research and practice agendas without implementing specific models [36]. This conceptual strand is also extended by Graessler et al. (2025), who outline an "information circularity assistance" concept combining digital twins, scenario techniques, and LLM-supported natural-language interaction for strategic product planning, and by recent studies on circular-construction transition risks that use LLMs as part of policy-document analysis and validation workflows rather than as operational decision tools [37].

A complete overview of all 30 studies, including their contribution type, methodological approach and primary data sources, is provided in Table II.

TABLE II. OVERVIEW OF THE INCLUDED STUDIES, METHODOLOGICAL APPROACHES AND DATA SOURCES

| ID | Reference | Type of contribution | Methodological approach | Primary data source(s) |
|---|---|---|---|---|
| S1 | [21] | Empirical tool evaluation | Comparative assessment of several conversational AI assistants (e.g., ChatGPT, Gemini, Copilot) for industrial symbiosis tasks in the construction sector | Structured prompts; construction-sector IS scenarios; expert judgement on correctness and usefulness |
| S2 | [22] | Empirical tool evaluation | Use of ChatGPT-4 as an advanced language model to explain CE/IS concepts, interpret EWC and NACE codes, and suggest potential symbiotic partners | MAESTRI industrial symbiosis database; European Waste Catalogue and NACE classifications; expert evaluation of AI outputs |
| S3 | [20] | Prototype / framework | Two-stage retrieval-augmented generation (RAG–LLM) framework for generating sustainable and circular product design guidelines | Patents and scientific publications on sustainable design and circular strategies; expert assessment of generated guidelines |
| S4 | [38] | Empirical modelling | Unsupervised clustering of inlet water quality in industrial parks; comparison with human-designed clusters and a ChatGPT-based clustering baseline | Water-quality measurements from multiple industrial-park reuse stations; engineers' cluster designs; LLM-generated cluster suggestions |
| S5 | [39] | Empirical modelling / big-data text analysis | LLM-assisted extraction and synthesis of multi-stakeholder narratives on smart circular supply chains in fast fashion; integration into an influential-factor model | Large-scale online text corpora on fast fashion and circular supply chains; ChatGPT-4-mediated text synthesis; structural modelling of drivers and barriers |
| S6 | [35] | Conceptual framework | Forward-looking framework for integrating generative AI into circular supply chain safety management | Literature on circular supply chains, safety management and generative AI; illustrative safety use cases |
| S7 | [28] | Survey-based empirical study | Structural equation modelling of links between generative-AI usage, circular economy implementation and sustainable supply-chain performance | Survey data from manufacturing firms; multi-item constructs for generative-AI usage, CE practices and performance |
| S8 | [29] | Survey-based empirical study | SEM analysis of how AI-enabled smart product platforming and big-data analytics affect environmentally oriented and circular product outcomes | Survey data from automotive industry professionals; constructs for smart product platforms, analytics and CE-related product outcomes |
| S9 | [36] | Conceptual / perspective | Narrative synthesis on bio-based and recyclable chemicals and materials for circular automotive design, with discussion of generative AI in materials discovery | Literature on bio-based plastics, recycling targets and regulatory context; conceptual mapping of AI-assisted materials discovery |
| S10 | [40] | Modelling study | Computational-power-driven material flow analysis of e-waste arising from generative-AI hardware under different circular-economy strategies | Scenario data on generative-AI deployment; estimates of hardware stocks and flows; assumptions on reuse, refurbishment and recycling |
| S11 | [41] | Empirical modelling | Use of a domain-specific generative model to create synthetic fault data for smart/circular production and maintenance | Vibration and fault data from smart production equipment; synthetic data generation and classification performance |
| S12 | [42] | Empirical classification | Transformer-based text classification of digital-transformation products into domains including smart circular economy | Large corpus of product descriptions; supervised learning to assign domain labels (e.g., smart circular economy, AI & analytics) |
| S13 | [43] | Survey-based empirical study | Difference-in-Differences (DiD) and fuzzy-set Qualitative Comparative Analysis (fsQCA) of how GenAI adoption affects environmental, operational, and social outcomes in responsible and circular supply chains | Firm–quarter panel data from 320 South Korean firms (2023Q1–2025Q2); survey data, administrative records, and ESG/HR disclosures |
| S14 | [11] | Empirical modelling / big-data text analysis | Zero-shot LLM-based classification of public-sector circular-economy communication on X, combined with causal discovery (DirectLiNGAM) and causal estimation (DoWhy) | More than 20,000 public-sector X posts collected between 2015 and 2024; GPT-4o-mini classifications of elaboration, emotional tone, and message purpose, validated against manual coding |
| S15 | [44] | Survey-based empirical study | Structural equation modelling of how generative-AI-enabled enablers, circular innovation alignment, transparency, and sustainability-oriented decision empowerment shape equitable and resilient supply-chain outcomes | Questionnaire data from 279 U.S.-based supply-chain and logistics professionals with at least 3 years of industry experience; Likert-scale survey items analysed using PLS-SEM and bootstrapping |

| ID | Reference | Type of contribution | Methodological approach | Primary data source(s) |
|---|---|---|---|---|
| S16 | [33] | Empirical modelling / large-scale automated data extraction | LLM-based extraction and standardisation of environmental and circularity metrics from Environmental Product Declarations (EPDs) for construction products | 8,463 construction-product EPDs from The International EPD System, processed from PDF text using GPT-4o to extract circularity metrics, material composition, and environmental/biodiversity indicators |
| S17 | [24] | Prototype / framework | Semantic enrichment of BIM models for circularity assessment using semantic textual similarity, fine-tuned LLM matching, and labeled property graphs | studies used to calculate Architectural BIM models (IFC), archetypal construction assemblies from the TOTEM database, and three building case studies used to calculate disassembly potential and the Building Circularity Indicator (BCI) |
| S18 | [25] | Empirical modelling / prototype | Blockchain-based LLM-driven energy-efficient scheduling for distributed multi-agent manufacturing in new-energy-vehicle production within the circular economy | Distributed manufacturing task, scheduling, and production-interaction data from new-energy-vehicle manufacturing scenarios; blockchain transaction and agent-level production data used for case-based validation |
| S19 | [30] | Empirical modelling / scenario simulation | Multimodal GPT-assisted interpretation of circular-economy system diagrams and translation into executable system-dynamics models for policy scenario simulation | Taiwan's material flow data (2013–2022), including stock-flow and causal-loop representations, historical subsystem indicators, and GPT-generated scenario parameters for 2030 policy simulations |
| S20 | [31] | Modelling study with experimental validation | Generative inverse design of sustainable concrete using a conditional invertible neural network (cINN) and ANN-based screening, followed by laboratory validation | Literature-derived dataset of 331 concrete mixtures from 45 studies, including physical and chemical properties of raw ingredients and 28-day compressive-strength data; additional experimental validation data from 10 newly produced concrete mixtures containing waste glass |
| S21 | [45] | Prototype / framework | Knowledge- and function-augmented LLM approach for optimal remanufacturing process design, combining RAG-based knowledge retrieval with function learning for multi-objective decision support | Remanufacturing process database including process documents, technical standards, flow diagrams, work instructions, historical gearbox remanufacturing cases, and a function database of objective formulas validated through an automobile gearbox case study |
| S22 | [26] | Empirical tool evaluation | Comparative evaluation of vision–language models and multimodal large language models for zero-shot and few-shot waste classification, including a training-free Tip-Adapter for VLMs | Four waste-image datasets: TrashNet, RealWaste, MultiWaste, and FPWaste; public benchmark datasets plus proprietary conveyor-belt and sorting-environment image collections used for model evaluation |
| S23 | [37] | Conceptual framework / survey | Systematic literature survey and conceptual synthesis combining Scenario-Technique, Digital Twins, artificial intelligence, and large language models to propose an Information Circularity Assistance approach for circular product creation | Literature from Scopus, Web of Science, and Google Scholar on scenario-based strategic product planning, Digital Twins, extreme data, and AI/LLM approaches for circular product development |
| S24 | [23] | Prototype / framework | Automated LLM-based workflow (AutoPCM) that transforms manufacturing documents into product-architecture decompositions, matrix-based representations, and circularity assessments for automotive electronics | Bills of materials and assembly instructions for automotive electronic/electrical products; two automotive case studies (a headlight electronic control unit and a camera sensor) used for validation |
| S25 | [34] | Empirical modelling / big-data text analysis | Big-data-driven text mining and topic modelling using Large Language Models and Transformers to profile employability skills for the digital and circular transition in the agri-food sector | Large corpus of online job advertisements collected via web scraping from major employment platforms, specifically focused on the European agri-food labour market |
| S26 | [32] | Empirical modelling | LLM-assisted extraction of building-material data from energy performance certificates and machine-learning-based spatiotemporal mapping of exterior wall material stocks | More than 20,000 Swiss building energy performance certificates (GEAK/CECB/CECE dataset), linked with the Swiss building and dwelling registry and construction-history sources to estimate exterior wall material stocks, mass, and embodied $CO_2$ emissions |
| S27 | [27] | Prototype / application | AI-enhanced web-application development integrating a third-party LLM for data management, visualization, risk assessment, regulatory compliance checks, and automated report generation in a water-smart circular-economy project | Demonstration case-study data from the WIDER UPTAKE project, including real-time sensor measurements, laboratory test data, regulatory/standards documents, and project database records from multiple water-reuse cases |
| S28 | [46] | Empirical ideation study | Prompt-based LLM ideation study using the Repurposable Attribute Basis (RAB) to generate and evaluate repurposing opportunities for decommissioned products | Prompt-generated repurposing ideas for a decommissioned Cisco IP phone 7945 and its handset, evaluated with human-rater and NLP-based novelty/feasibility metrics; additional validation on a commercial aircraft nacelle |

| ID | Reference | Type of contribution | Methodological approach | Primary data source(s) |
|---|---|---|---|---|
| S29 | [9] | Prototype / framework | Automated construction of a waste-to-resource knowledge graph for industrial symbiosis identification using LLM-based retrieving, structured extraction, and fusion modules | 4,499 Scopus-indexed research papers on waste-to-resource practices published after 2017, including abstracts of all papers and full texts of 77 review papers used to build the W2RKG database |
| S30 | [47] | Empirical qualitative analysis / policy text analysis | Mixed human–AI qualitative content analysis combining manual expert coding in NVivo with LLM-based validation and scaling using Kimi K2, GLM 4.6, and a GPT-5 Mini audit agent | 101 European Green Deal policy and guidance documents published between 2019 and February 2025, analysed as a corpus of PDF texts for transition-risk references affecting the construction sector |

### 3.1.3 Application domains and circular value-chain stages

The 30 studies collectively span several CE and industrial-ecology domains. One prominent area is industrial symbiosis and eco-industrial parks. Genc (2024, 2025) focuses on IS opportunities in the construction sector and also all sectors, using LLMs to explain IS concepts, interpret EWC/NACE codes and suggest potential waste-to-resource exchanges, while emphasising that domain experts remain essential for validation [21], [22]. Chen et al. (2024) examines water reuse in Chinese industrial parks, comparing unsupervised clustering algorithms and ChatGPT-based clustering for inlet-water classification, and show that specialised clustering methods outperform both human and LLM-based baselines in terms of purity and stability [38]. This domain has recently expanded beyond conversational support and clustering tasks. Zhao et al. (2026), for example, develop an LLM-based pipeline to construct a waste-to-resource knowledge graph from the literature in order to support industrial symbiosis identification at scale [9]. In a related but more application-oriented context, Strogonov and Pollert (2025) use an AI-enhanced web platform with LLM support for data management, compliance checking, risk assessment, and reporting in a water-smart circular-economy project centred on water reuse [27].

A second cluster of applications relates to circular and sustainable supply chains. Li et al. (2024) analyse how generative-AI usage in manufacturing firms supports sustainable supply chain performance through green collaboration and circular-economy implementation [28], while Chen, Sarkis and Yildizbasi (2025) conceptualise the role of generative AI in circular supply chain safety management, highlighting potential uses in hazard identification, incident analysis and training [35]. Akhtar et al. (2024) address CE at the product and business-model level, arguing that AI-enabled smart product platforming can facilitate environmentally friendly products and circular product strategies in the automotive industry [29]. Newer studies broaden this cluster in two directions. First, Park (2026) examines responsible and circular supply chains at the firm level and shows, through Difference-in-Differences and fsQCA analysis, how GenAI adoption relates to environmental, operational, and social performance outcomes [43]. Second, Xia et al. (2026) analyse how generative-AI-enabled enablers, circular innovation alignment, transparency, and sustainability-oriented decision empowerment shape equitable and resilient supply-chain outcomes using survey-based structural modelling [44].

A third set of studies focuses on sustainable product and materials innovation. Jiang et al.'s (2025) RAG–LLM framework directly targets the early design stage, generating design guidelines that more comprehensively cover product life-cycle stages, including use and end-of-life, than non-RAG baselines according to expert evaluations [20]. Schoemaker et al. (2025) discuss how AI and generative models can accelerate the discovery of bio-based and recyclable chemicals and materials for "fully recyclable cars," positioning generative AI as a key enabler of circular materials innovation [36]. This product- and materials-oriented stream has grown substantially in the enlarged sample. Forth and De Wolf (2026) use semantic similarity, fine-tuned LLM matching, and graph-based modelling to enrich BIM data for circularity assessment in buildings [24]. Peitzmeier et al. (2026) develop AutoPCM, an automated LLM-based workflow that extracts product-architecture information from manufacturing documents and links it to circularity assessment in automotive electronics [23]. Zhang et al. (2025) propose a knowledge- and function-augmented LLM approach for remanufacturing process design, extending CE-oriented decision support into the remanufacturing stage [45]. Yu et al. (2026), meanwhile, apply a generative inverse-design model to sustainable concrete mixtures containing recycled waste glass, combining AI-based mixture generation with experimental validation [31]. Hewa Witharanage et al. (2025) also contribute to this domain by using LLMs to generate and evaluate repurposing opportunities for decommissioned products, thereby addressing product life extension and second-life use [46].

A fourth group of studies is concentrated in the built environment and construction. Vergés et al. (2026) use GPT-based extraction to derive circularity-related and environmental metrics from thousands of construction-product Environmental Product Declarations, while Schmid et al. (2025) combine LLM-assisted text extraction with machine learning to map exterior wall material stocks and embodied emissions in the Swiss building stock [33], [32]. At the sectoral and policy level, Li et al. (2026) analyse public-sector circular-economy communication on X using zero-shot LLM classification, Smaldone et al. (2025) use LLMs and transformers to identify skills for the digital and circular transition in the agri-food sector, and Mubasher et al. (2026) examine transition risks in circular construction through mixed human–AI policy-document analysis [11], [34], [47].

Finally, one article explicitly treats generative AI as an object of circular-economy analysis rather than solely as an enabler. Wang et al. (2024) quantify the future e-waste associated with generative-AI hardware, particularly LLM training and inference infrastructure, and demonstrate that CE strategies such as reuse, refurbishment and recycling along the AI hardware value chain could substantially reduce projected e-waste by 2030 [40]. This systems-level perspective complements the more application-oriented studies by highlighting that LLMs contribute to both circular opportunities and new resource challenges. As shown in Table III, the enlarged sample spans a broader set of domains, with the strongest concentrations still found in industrial symbiosis, circular or sustainable supply chains, and product or materials innovation, while newer studies also extend the field into the built environment, construction, waste classification, policy communication, and skills-related governance issues.

TABLE III. APPLICATION DOMAINS AND CIRCULAR VALUE-CHAIN STAGES ADDRESSED IN THE REVIEWED STUDIES

| Application domain | Design & product development | Production & operations | Use phase | End-of-life / recovery | Cross-cutting (policy, safety, governance) |
|---|---|---|---|---|---|
| Industrial symbiosis & eco-industrial parks | – | S1, S2, S4 | – | S29 | S27, S29 |
| Circular / sustainable supply chains | S8 | S5, S11, S13, S15, S18 | S7, S8 | – | S6, S7, S12, S13, S15 |
| Product and materials innovation | S3, S9, S20, S23, S24 | – | S3 | S3, S9, S20, S21, S28 | – |
| Built environment and construction | S16, S17 | - | S26 | S16, S17 | S30 |
| Cross-sector policy, communication, and skills | - | - | - | - | S14, S19, S25 |
| Waste management and recycling | - | - | - | S22 | - |
| Generative-AI infrastructure and e-waste | – | – | – | S10 | S10 |

## 3.2 Cross-cutting themes and emergent patterns

To provide a more structured interpretation of the reviewed evidence, the cross-cutting themes are organized into four interrelated areas. These themes were derived inductively from the charted matrix rather than being defined in advance. The application domains, AI tool roles, and reported outcomes recorded for each study were examined for recurring patterns, and studies sharing similar functional roles and circular economy contexts were grouped together, yielding the four themes presented below. Studies relevant to more than one theme were assigned to the category most closely aligned with their primary contribution. These sub-sections highlight the main functional roles of generative AI and LLMs across CE and industrial-ecology contexts, while also showing how application domains, methodological approaches, and governance concerns converge around a limited set of recurring patterns.

### 3.2.1 Knowledge Integration in Circular Design and Industrial Symbiosis

LLMs as knowledge integrators for circular design and industrial symbiosis emerge as a first theme across the reviewed studies. Generative and conversational models are used to connect fragmented bodies of knowledge, such as eco-design strategies, product architectures and industrial classification schemes, and to present them in a form usable by designers and practitioners [20], [21], [22]. In sustainable product development, retrieval-augmented LLM setups organise large corpora of design and sustainability literature into targeted guidance at component or system level, so that circularity requirements such as reparability or modularity are explicitly surfaced at early stages [20]. In the industrial symbiosis and water-reuse context, LLMs are used to interpret waste and process descriptions, map them to formal taxonomies such as EWC and NACE, and articulate candidate exchange or reuse options, often alongside more traditional clustering or database approaches [21], [22], [38]. More recent work shows that this role is no longer limited to conversational support but also includes knowledge-graph construction and operational platforms. Zhao et al. (2026), for example, use LLM-based retrieval, extraction and fusion modules to build a waste-to-resource knowledge graph from thousands of publications, thereby formalizing industrial-symbiosis knowledge in machine-readable form [9]. Likewise, Strogonov and Pollert (2025) embed LLM support into a web-based environment for water-smart circular-economy projects, where AI assists with data management, regulatory compliance checks, risk assessment and reporting across multiple reuse cases [27]. In product-oriented settings, Peitzmeier et al. (2026) show that LLMs can also integrate manufacturing-document knowledge into product-architecture representations and circularity assessments for automotive electronics, while Zhang et al. (2025) combine retrieval and function augmentation to support remanufacturing process design with knowledge drawn from process databases, technical documents and historical cases [23], [45]. Similar language-based representations underpin work that classifies digital-transformation products and domains, where smart circular economy and generative AI appear as distinct clusters within broader innovation landscapes [42].

### 3.2.2 Generative AI in Circular and Sustainable Supply Chains

Generative AI in circular and sustainable supply chains forms a second prominent theme. Survey-based studies conceptualise generative-AI usage as an organisational capability embedded in supply-chain practices, and quantify its association with sustainable performance and circular-economy implementation at firm level [28]. In parallel, modelling and empirical work explores more specific capabilities, including smart predictive maintenance enabled by generative models for synthetic fault data in circular production environments and the role of AI-enabled smart product platforming in supporting environmentally oriented and circular product strategies in the automotive sector [29], [41]. Further contributions in this theme incorporate generative AI into broader smart circular supply-chain frameworks in fast fashion, where large text corpora and LLM-mediated synthesis help to characterise stakeholder narratives, technological drivers and social expectations around circular practices [39]. Conceptual analyses of circular supply-chain safety management extend the scope by outlining how generative AI could support hazard identification, incident analysis and training in circular logistics and reverse flows [35]. The enlarged sample reinforces this theme with additional firm-level and operations-oriented evidence. Park (2026) shows, using Difference-in-Differences and fsQCA, that GenAI adoption in South Korean firms is associated with configurations of environmental, operational and social performance in responsible and circular supply chains [43]. Xia et al. (2026) similarly model how generative-AI-enabled enablers, circular innovation alignment, transparency and sustainability-oriented decision empowerment contribute to equitable and resilient supply-chain outcomes [44]. At the operational level, Liu and Nie (2025) move beyond organizational capability arguments by embedding an LLM into blockchain-based scheduling for distributed new-energy-vehicle manufacturing, linking generative AI directly to energy-efficient production coordination in a circular manufacturing context [25].

### 3.2.3 Design, Materials, and End-of-Life Applications

Design and materials innovation for circularity represent a third area where generative AI appears as an enabling technology. In product design, LLM-based assistants augment conventional engineering workflows by generating design guidelines that explicitly reference life-cycle stages and circular strategies, thereby linking functional requirements to circular outcomes within the same design brief [20]. In the automotive sector, smart product platforming arrangements draw on AI and generative tools to support configurable yet platform-based vehicles, which can accommodate personalised demands while maintaining reuse and commonality that are favourable to circularity [29]. At the materials level, work on recyclable and bio-based chemicals and polymers for an entirely recyclable car highlights machine learning and generative models as accelerators of materials discovery and optimisation within constraints defined by recyclability, toxicity and regulatory targets [36]. Process design aspects also surface in water-reuse studies where data-driven clustering and LLM-based interpretation jointly inform the configuration of industrial reuse stations, linking process-level decisions to circular water management in industrial parks [38]. Newer studies broaden this theme from design guidance to concrete assessment, remanufacturing, repurposing and inverse materials design. Forth and De Wolf (2026) use semantic similarity, fine-tuned LLM matching and graph-based modelling to enrich BIM data for circularity assessment in buildings, showing how language models can support design-stage evaluation of disassembly potential and building circularity [24]. Yu et al. (2026) apply a generative inverse-design model to sustainable concrete mixtures containing recycled waste glass, combining AI-based mixture generation with laboratory validation [31]. Hewa Witharanage et al. (2025) address life extension more explicitly by using LLMs to generate and evaluate repurposing opportunities for decommissioned products, while Funk et al. (2026) focus on end-of-life sorting through multimodal model evaluation for waste classification in zero-shot and few-shot settings [26], [46]. Vergés et al. (2026) and Schmid et al. (2025) further show that LLMs can support circularity-related extraction tasks in the built environment, from environmental product declarations to building-energy certificates, thereby linking language models to material-stock intelligence and circularity metrics at scale [32], [33].

### 3.2.4 Complementarity, Validation, and Governance

Human–AI complementarity, limitations and governance challenges cut across all of these thematic areas. Evaluations of LLM-based assistance for industrial symbiosis, waste classification and water-reuse categorisation consistently report a mixture of useful suggestions and systematic errors, leading to a positioning of generative AI as a support tool whose outputs require expert review rather than as an autonomous decision-maker [21], [22], [38]. Taken as a pattern across these studies, rather than as an explicit finding of any single contribution, this positioning reflects a recurring convergence in how authors frame the role of human oversight in generative AI-assisted circular economy workflows. Survey-based work indicates that generative-AI usage contributes to sustainable and circular supply-chain outcomes only in conjunction with specific collaboration and implementation practices, suggesting that technology and organisational routines are tightly intertwined [28], [29]. Conceptual contributions on circular supply-chain safety and on the e-waste implications of generative-AI infrastructure emphasise issues of model transparency, data security, bias, accountability and hardware lifecycles, and point to the need for explicit governance arrangements when generative AI is embedded into CE and industrial-ecology systems [35], [40]. The newer studies reinforce this pattern rather than overturning it. Li et al. (2026) show that LLM-based analysis can be used to classify and interpret public-sector circular-economy communication at scale but also rely on human validation and causal interpretation to make the findings policy-relevant [11]. Smaldone et al. (2025) and Mubasher et al. (2026) likewise position LLMs as analytical partners in cross-cutting governance tasks, including the identification of circular-transition skills in labor-market data and the validation of transition risks in European Green Deal policy documents [34], [47]. Taken together, these studies do not support a fully automated model of CE decision-making. Instead, they show that LLMs are most useful when they speed up extraction, synthesis, or scenario exploration, while experts remain responsible for interpretation and validation. The directional implications of these patterns for future research, practice, and policy, which correspond to the fourth research question, are elaborated in the Discussion and Conclusion sections, where the cross-cutting evidence is interpreted in relation to the broader AI-CE literature

Table IV differentiates the main roles played by generative AI and LLMs in the CE context: knowledge and design assistants, analytical components within modelling and extraction frameworks, organizational capabilities captured via survey constructs, and, in a smaller number of cases, objects of circular-economy scrutiny in their own right. The enlarged sample also highlights more specific variants of these roles, including compliance and reporting assistants, knowledge-integration tools, and generative design or ideation models.

TABLE IV. ROLES OF GENERATIVE AI AND LARGE LANGUAGE MODELS IN THE REVIEWED STUDIES

| ID | Tool / model type | Role of generative AI / LLM | Primary CE purpose |
|---|---|---|---|
| S1 | Conversational AI assistants (ChatGPT, Gemini, Copilot) | Knowledge & design assistant | Exploring industrial symbiosis concepts and opportunities in the construction sector |
| S2 | ChatGPT-4 (large language model) | Knowledge & design assistant | Explaining CE/IS concepts; suggesting waste classifications and potential IS partners |
| S3 | Retrieval-augmented LLM | Knowledge & design assistant | Generating sustainable and circular product design guidelines across life-cycle stages |
| S4 | ChatGPT (LLM baseline) | Benchmark / auxiliary tool | Providing a clustering baseline for industrial-park water reuse design |
| S5 | ChatGPT-4 and LLM-assisted text synthesis | Analytical component in modelling framework | Extracting and synthesising multi-stakeholder narratives and drivers of smart circular supply chain practices in the fast-fashion industry |
| S6 | Generative AI (LLMs and multimodal models, conceptual) | Analytical engine in circular-supply-chain safety framework | Envisioned applications in hazard identification, incident analysis and training |
| S7 | Generative-AI usage (organisational practice) | Organisational capability (survey construct) | Explaining sustainable supply-chain performance via CE implementation and collaboration |
| S8 | AI and generative AI in smart product platforms | Organisational capability (survey construct) | Enabling environmentally oriented and circular product outcomes in automotive supply chains |
| S9 | Generative models (conceptual) | Knowledge & design assistant (envisioned) | Accelerating discovery of recyclable and bio-based materials for circular automotive design |
| S10 | Generative-AI / LLM hardware infrastructure | Object of circular-economy scrutiny | Quantifying and mitigating e-waste from generative-AI hardware through CE strategies |
| S11 | Domain-specific generative model | Analytical component in modelling framework | Generating synthetic fault data to support circular/smart production and maintenance |
| S12 | Transformer-based language models | Analytical component in classification | Mapping digital-transformation products into domains such as smart circular economy |
| S13 | Firm-level generative AI adoption | Organisational capability (survey / quasi-experimental analysis) | Improving environmental, operational, and social performance in responsible and circular supply chains |
| S14 | GPT-4o-mini (zero-shot LLM classification) | Analytical component in policy / communication analysis | Classifying and analysing public-sector circular-economy communication |
| S15 | Generative-AI-enabled supply-chain enablers | Organisational capability (survey) | Strengthening equitable and resilient supply-chain outcomes through circular innovation alignment and transparency |
| S16 | GPT-4o-based extraction pipeline | Analytical component in large-scale metric extraction | Extracting circularity-related and environmental metrics from construction-product EPDs |
| S17 | Fine-tuned LLM + semantic textual similarity + labeled property graph | Knowledge & assessment assistant | Automating circularity assessment in buildings, including disassembly potential and building circularity indicators |
| S18 | Blockchain-based LLM scheduling system | Analytical component in operational decision support | Optimising energy-efficient distributed manufacturing in a circular-economy production setting |

| ID | Tool / model type | Role of generative AI / LLM | Primary CE purpose |
|---|---|---|---|
| S19 | Multimodal GPT | Analytical component in scenario simulation | Interpreting circular-economy system diagrams and simulating policy scenarios from material-flow data |
| S20 | Conditional invertible neural network (cINN) + ANN screening | Generative design model | Designing sustainable concrete mixtures with recycled waste glass |
| S21 | Knowledge- and function-augmented LLM | Knowledge & decision assistant | Optimising remanufacturing process design and decision-making |
| S22 | Vision-language models / multimodal LLMs | Analytical component in waste classification | Supporting end-of-life waste sorting and classification for recycling / recovery |
| S23 | LLM-supported Information Circularity Assistance concept | Knowledge & strategic planning assistant | Supporting circular product creation through scenario-based and digital-twin-enabled planning |
| S24 | AutoPCM (automated LLM-based workflow) | Knowledge & assessment assistant | Identifying circular design potentials in automotive electronics from manufacturing documents |
| S25 | Large language models and transformers | Analytical component in skills / labour-market analysis | Identifying skills for the digital and circular transition in the agri-food sector |
| S26 | LLM-assisted text extraction + machine learning | Analytical component in material-stock intelligence | Mapping building material stocks, mass, and embodied $CO_2$ for circular construction analysis |
| S27 | Third-party LLM embedded in a web application | Knowledge, compliance, and reporting assistant | Supporting water-smart circular-economy data management, risk assessment, and regulatory compliance |
| S28 | Prompt-based large language model ideation | Knowledge & ideation assistant | Generating and evaluating repurposing opportunities for decommissioned products |
| S29 | LLM-based retrieval, extraction, and fusion modules | Knowledge integrator / analytical extraction tool | Constructing a waste-to-resource knowledge graph for industrial symbiosis identification |
| S30 | Kimi K2, GLM 4.6, and GPT-5 Mini audit agent | Analytical component in policy-risk validation | Identifying and validating transition risks in circular construction policy documents |

## 4. DISCUSSION

This discussion interprets the reviewed evidence in relation to the broader AI–CE literature and highlights the main conceptual, practical, and policy implications of the findings. To structure this interpretation more clearly, the discussion is organized into four parts: the shifting role of generative AI in circular systems, its potential and constraints in supporting circular practices, the implications for research and practice, and the key limitations of the review.

### 4.1 From Optimization Tool to Knowledge Infrastructure

The studies reviewed here sit at the intersection of two fast-moving conversations: the broad literature on artificial intelligence as an enabler of circular economy, and a much narrower stream where generative AI and large language models are explicitly embedded in circular and industrial-ecology tasks. Earlier reviews on AI and CE portray AI largely as a family of analytical tools that improve forecasting, optimisation and classification in circular manufacturing, reverse logistics and waste management [2], [3], [4], [6], [48]. In that work, specific algorithms vary, but the underlying narrative is that AI increases efficiency and visibility along circular value chains. When attention narrows to generative AI and LLMs, a somewhat different picture appears. Rather than functioning mainly as optimisation engines, these models are configured as interfaces to bodies of domain knowledge: eco-design heuristics and life-cycle strategies, industrial taxonomies such as EWC and NACE, or large corpora of stakeholder narratives. In the reviewed studies, retrieval-augmented LLMs assemble design guidance from technical and sustainability literature, conversational assistants translate free-text waste descriptions into standardised codes and potential exchanges, and generative models help to structure complex supply-chain and maintenance data. The reviewed studies also show that this interface role now appears in a wider set of tasks, including knowledge-graph construction, circularity-metric extraction, BIM enrichment, policy-document interpretation, and scenario simulation. LLM-based systems are not only retrieving or rephrasing knowledge but increasingly transforming unstructured CE-related information into databases, graphs, circularity indicators, and executable models that can support decisions in remanufacturing, construction, industrial symbiosis, and policy analysis. This suggests that, in CE contexts, generative AI often plays a different role from the optimization-oriented AI described in earlier reviews. Rather than replacing analysis, it more often helps connect people, data, documents, and formal models [4], [49]. This is visible, for example, in work that builds waste-to-resource knowledge graphs for industrial symbiosis, extracts circularity metrics from Environmental Product Declarations, maps building-material stocks from energy certificates, and translates circular-economy system diagrams into system-dynamics simulations [9], [30], [32], [33].

### 4.2 Generative AI as a Driver of Circular Practices: Potentials and Constraints

The reviewed evidence also refines earlier claims about AI as a driver of circular practices. Large-sample surveys on AI adoption and CE in manufacturing and agri-food sectors report positive associations between AI usage and circular practices, often mediated by digital capabilities and collaboration [50], [51]. Within the smaller generative-AI subset, similar patterns appear, but with more clearly articulated mediators. Generative-AI usage in supply chains is linked to sustainable performance through green collaboration and circular-economy implementation, and smart product platforming augmented by generative tools is connected to environmentally oriented product outcomes. The expanded sample strengthens this conclusion by adding further firm-level and supply-chain evidence. In particular, recent survey and quasi-experimental studies suggest that generative-AI adoption is associated not only with sustainable performance, but also with combinations of environmental, operational, social, resilience, transparency, and circular-innovation outcomes. This shifts the focus away from AI as a pure efficiency tool and toward generative AI as something that works through organizational routines, managerial decision processes, and circular supply-chain practices [43], [44]. These findings resonate with broader conceptualisations of AI not as an automatic source of circularity but as a capability whose effects depend on complementary organisational routines and governance [2], [5]. At the same time, the results from industrial symbiosis, water reuse and circular-safety applications show that generic LLMs are far from reliable stand-alone decision-makers. In tasks that require precise technical classification or safety-critical judgements, such as assigning waste codes or categorising inlet water for reuse, domain-specific clustering and expert-designed methods continue to outperform LLM baselines. This aligns with more general observations in the AI–CE literature that sector-specific models and high-quality data infrastructures remain indispensable, and that AI should be integrated into existing industrial-ecology toolkits rather than seen as a replacement [52], [53]. The same point is reinforced by studies in waste classification, public-sector communication analysis, and policy-risk assessment, where LLMs and multimodal models are useful for scaling extraction and interpretation, but still depend on benchmark datasets, expert coding, or human validation to become trustworthy in CE settings [11], [26], [47]. Finally, the inclusion of work on the hardware footprint of generative AI complements existing concerns about the environmental implications of digitalisation in CE. Reviews and conceptual papers have begun to discuss “green AI” architectures and the need to align AI deployments with sustainable resource use [49], [54], [55]. The generative-AI-specific analysis of e-waste adds quantitative evidence on how LLM-driven infrastructures may generate new material flows, and how circular strategies such as refurbishment and recycling can mitigate them. At the same time, the enlarged corpus shows that generative AI is now being mobilized across a wider range of circular functions, from design guidance and remanufacturing planning to product repurposing, waste sorting, and compliance support, making the balance between circular benefit and environmental burden even more important to assess explicitly. Overall, the evidence suggests that generative AI can support circular practices, but it can also create new governance and environmental problems that need to be addressed directly.

### 4.3 Implications for Research, Practice, and Policy

Several implications follow from this synthesis for research, practice and policy. Conceptually, the findings suggest that generative AI in CE should be seen not only as a predictive or optimization tool, but also as an intermediary that connects users, classification systems, documents, and domain-specific models. In the reviewed studies, generative tools are most effective when they surface codified CE and industrial-ecology knowledge at the point of design or decision-making, rather than when they operate in isolation. This perspective is compatible with capability-based accounts of AI in CE and sustainability, which argue that digital technologies create value through the routines and knowledge structures they enable [5], [50], [51]. For managers and practitioners, the findings caution against treating LLMs as plug-and-play solutions for circular transition. The most promising applications in the corpus combine generative AI with curated knowledge bases, industrial taxonomies and clear human-in-the-loop validation, for example in sustainable product design assistants or industrial-symbiosis opportunity exploration. The enlarged sample points to several additional practice implications. Firms can also use generative AI to extract circularity data from technical documents, enrich BIM or product-architecture representations, support remanufacturing planning, and explore repurposing options for decommissioned products. However, these benefits depend on documentation quality, standardized data structures, and the availability of domain experts who can interpret outputs and intervene when model suggestions are incomplete or incorrect. This implies that firms seeking to leverage generative AI for CE should invest in domain-specific data infrastructures, documentation of circular practices and training for staff who will interpret and challenge AI-generated suggestions. Evidence from Ireland and other contexts indicates that current AI use in industry is still primarily driven by efficiency and cost motivations rather than explicit circular goals [2], [51], [56]. Aligning generative-AI deployments with circular metrics and governance structures remains an open managerial challenge. Policy implications arise at both the enabling and constraining ends. On the enabling side, regional and national CE strategies that aim to use generative AI for industrial symbiosis matchmaking, circular-supply-chain coordination or urban circular planning will need robust data infrastructures and standardised reporting, as highlighted in many AI–CE reviews [2], [4], [6]. The reviewed studies also suggest that this enabling agenda will require interoperable document standards, better access to environmental and product data, and clearer governance frameworks for AI-supported communication, compliance, and policy evaluation. These issues become especially salient in construction and built-environment contexts, where LLM-based extraction from EPDs, energy certificates, BIM models, and policy documents is already beginning to shape circularity assessment and transition-risk analysis [24], [32], [33], [47]. On the constraining side, the material and energy footprint of generative-AI hardware suggests a role for regulation that internalises these impacts, for example through extended producer responsibility for data-centre equipment, incentives for refurbishment and high-quality recycling, and transparency requirements on the environmental profile of AI services used in CE initiatives. Work on AI as a risk-treatment tool in circular transitions also indicates the value of integrating AI governance into broader risk and safety frameworks, rather than treating it as a separate technical issue [55]. Mapping the governance gaps that emerge across the four thematic clusters reveals a set of challenges that are both cross-cutting and domain-specific. In the knowledge integration and industrial symbiosis cluster, the primary governance gap concerns validation standards: the reviewed studies consistently show that LLM outputs for waste classification, symbiosis identification, and taxonomy interpretation require expert review, yet no agreed protocols exist for what constitutes adequate validation in these contexts, who is responsible for it, or how validation outcomes should be documented and communicated. In the circular and sustainable supply chain cluster, governance concerns centre on organizational accountability, as the association between generative AI adoption and circular performance outcomes is mediated by routines and practices that remain largely invisible to external auditors or regulators. In the design, materials, and end-of-life cluster, the governance gap relates primarily to data infrastructure: the most effective applications in this cluster, including LLM-based extraction from Environmental Product Declarations, BIM models, and energy performance certificates, depend on standardized, interoperable, and publicly accessible document formats that do not yet exist consistently across sectors or jurisdictions. Finally, and cutting across all clusters, the environmental footprint of the generative AI infrastructure on which these applications depend remains almost entirely unaccounted for within the circular economy initiatives they are intended to support. Addressing these gaps requires governance mechanisms that are differentiated by application domain rather than applied uniformly, and that treat validation, accountability, data standardization, and environmental transparency as equally necessary conditions for responsible deployment. Taken together, the evidence suggests that policy should not only promote AI-enabled circular innovation but also shape the conditions under which generative AI is documented, validated, audited, and environmentally accounted for.

### 4.4 Limitations

This review also has several limitations. First, the included studies are highly heterogeneous in their aims, methods, and levels of maturity, ranging from conceptual papers and prototype demonstrations to survey-based studies, modelling papers, and document-analysis applications. This methodological diversity limits direct comparability across studies and makes formal synthesis difficult. Second, much of the evidence is still based on case-specific applications, simulated settings, expert evaluations, or single-sector datasets, which constrains the generalizability of findings across CE and industrial-ecology contexts. Third, the field is evolving rapidly, and both the capabilities of generative AI systems and their modes of deployment are changing faster than the academic literature can stabilize, meaning that some conclusions may quickly become outdated. Fourth, several studies evaluate AI-assisted outputs with human judgement, but use different validation procedures, performance criteria, and benchmark baselines, which makes it difficult to assess robustness consistently across the corpus. Finally, the review focuses deliberately on studies that explicitly engage generative or conversational AI within circular economy or industrial ecology contexts; while this strengthens conceptual precision, it also excludes adjacent work on broader AI-enabled sustainability, non-generative machine learning, or circularity-related digitalization that may still be relevant to practice. Additionally, all screening and selection decisions were made by a single author, which introduces the possibility of selection bias that independent verification would have mitigated. Similarly, no formal risk of bias assessment was conducted at the study level, consistent with the optional nature of this step-in scoping review methodology. These limitations suggest that the findings should be interpreted as a structured synthesis of an emerging and uneven body of evidence, rather than as a definitive assessment of effectiveness across all CE applications.

## 5. CONCLUSION

The reviewed evidence collectively points to a field that has moved past early experimentation and is consolidating around a recognizable set of application patterns, functional roles, and unresolved governance challenges. Large language models have found their most productive footing not in replacing domain expertise but in making dispersed and unstructured circular economy knowledge more accessible and actionable, whether by extracting circularity metrics from technical documents, constructing waste-to-resource knowledge graphs, enriching product and building data for circularity assessment, or supporting the interpretation of policy and communication content at scale. The field remains concentrated in industrial symbiosis, circular supply chains, and product and materials innovation, with a growing presence in the built environment and construction sector. Across all of these domains, the pattern that emerges most consistently is that performance and reliability improve substantially when generative AI is embedded within structured workflows that include curated data, domain taxonomies, and human validation, and deteriorate when these conditions are absent.

This review establishes that generative AI in the circular economy is better understood not simply as an efficiency tool, but as a means of linking people, documents, classification systems, and analytical models. This perspective helps distinguish the generative-AI literature from earlier AI-for-CE work centred mainly on prediction, optimisation, and automation. It also offers a structured basis for interpreting the field through recurring functional roles, including design assistance, knowledge integration, analytical extraction, organisational capability, and circular scrutiny of AI systems themselves. In this sense, the review not only maps an emerging domain but also provides a conceptual language for comparing studies that differ substantially in sector, method, and maturity. The review also has clear implications for practice. For managers, engineers, and circular-transition practitioners, the findings suggest that value is most likely to emerge when generative AI is embedded in well-documented workflows such as circular design support, material and product data extraction, remanufacturing planning, industrial-symbiosis screening, and compliance-oriented reporting. For policymakers and ecosystem actors, the results underline the importance of interoperable data infrastructures, reporting standards, validation routines, and governance mechanisms that can make AI-assisted circular applications reliable, auditable, and environmentally accountable.

Several directions follow from these findings. Future research should move toward comparative evaluations across sectors and task types, stronger benchmarking against domain-specific baselines, and closer integration between LLM-based systems and established CE tools such as life-cycle assessment, material-flow analysis, and industrial-ecology modelling. More longitudinal and real-world implementation studies are also needed to examine whether the benefits reported in prototypes, case studies, and modelling environments translate into durable organisational and environmental outcomes. In practice and policy, the next step is not simply wider adoption, but more responsible deployment: generative AI should be implemented with explicit attention to transparency, human oversight, data quality, and the environmental consequences of the infrastructures on which these systems depend. Taken together, the evidence suggests that generative AI can become a valuable layer within circular and industrial-ecology systems, but only when its deployment is guided by domain knowledge, robust governance, and clearly defined circular objectives.

## Data availability statement

The data is available from the corresponding author upon reasonable request.

## Competing interests

The author declares no competing interests.

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## Declaration of using Generative AI and AI-assisted technologies

During the preparation of this work, the author used Generative AI tools in order to synthesize information from diverse sources, paraphrasing and language editing. After using these tools, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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