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THE AI-ENABLED CIRCULAR ECONOMY: EXTRACTING AND SYNTHESIZING DESIGN KNOWLEDGE

Completed Research Paper

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Abstract

Artificial intelligence (AI) increasingly enables circular economy (CE) practices like sustainable material design, robotic disassembly, and waste sorting. However, studies on AI-enabled artifacts rarely articulate design knowledge; prescriptive insights remain implicit through performance comparisons, trade-off analyses, or context-specific recommendations, limiting theoretical accumulation and practical guidance for organizations adopting AI for CE transitions. We conduct a meta-synthesis across four databases and abstract 99 empirically grounded design principles. Using structured coding and an AI-assisted extraction pipeline, we generalize one design principle per study and synthesize them into four meta-principles (MPs): MPs 1–3 capture physical-technical mechanisms that operationalize CE strategies of slowing (predictive insight), closing (material sensing and actuation), and narrowing (hybrid AI optimization) resource loops; MP4 represents socio-technical orchestration capabilities that enables organizations to sense, seize, and reconfigure circular opportunities. The synthesis links technical optimization with organizational sustainability practices, contributing cumulative, transferable design knowledge for AI-enabled circularity in information systems research.

Keywords: Circular economy, Artificial intelligence, Design knowledge, Meta-Synthesis

1 Introduction

Awareness of the circular economy (CE) has increased in response to ecological and social challenges, with the CE emerging as a paradigm for aligning industrial growth with environmental sustainability (Geissdoerfer et al., 2017; Kirchherr et al., 2018). Meanwhile, artificial intelligence (AI) has been recognized as a general-purpose technology with significant implications for business operations and sustainability transitions (Brynjolfsson & McAfee, 2017; George et al., 2021). AI techniques are applied in fields such as manufacturing, construction, waste management, and energy to optimize processes, reduce waste, and generate insights that support environmental and economic sustainability (Kar et al., 2022). Thus, the intersection of AI and the CE offers considerable technological and societal promise.

A growing body of engineering and applied science research documents AI-enabled artifacts that enhance CE practices. For instance, machine learning (ML) models predict sustainable construction material properties (Kazemi & Mirjalili, 2024), multimodal sensor fusion improves detection of fasteners during robotic disassembly of electronic waste (Zhou et al., 2024), and hybrid AI-life cycle assessment frameworks reduce uncertainty in sustainability assessment (Shafiq et al., 2024). These artifacts are innovations operating at the intersection of engineering and sustainability. Consequently, AI-enabled CE artifacts can be viewed not merely as tools but as socio-technical objects (Carlile, 2002) that mediate between communities of practice with differing logics and priorities.

Despite AI's evident potential for a CE (Sagnier Eckert et al., 2026), design knowledge (DK) remains fragmented and under-theorized. Our meta-review reveals a pattern: while many studies report prototypes, lab systems, or field pilots with rigorous evaluations, few articulate findings into explicit design principles (DP) or guidelines. Instead, prescriptive insights are conveyed implicitly through interpretations of experiments, performance benchmarks, or context-specific recommendations. For instance, one study finds pyrolysis of waste face masks can be optimized by adjusting catalyst ratios and temperature settings, yet these insights remain embedded in parameter choices rather than abstracted as generalizable principles for AI-enabled waste valorization (Hooda & Mondal, 2024). Similarly, research on textile recycling reports that under constrained data conditions, less data-intensive AI approaches may be preferable to more complex deep learning models (Karmali & Valilai, 2025), yet these prescriptive implications often remain implicit rather than articulated as a reusable design heuristic.

This poses both theoretical and practical challenges. Theoretically, the absence of DK limits cumulative insights that guide the design of AI-enabled CE systems across domains. Engineering papers are replete with technical recipes (e.g., which neural network (NN) variant achieved the highest accuracy on a given dataset), but these are often too specific to travel beyond their immediate context. Without abstraction, the findings remain locked within silos. Practically, organizations face difficulties translating domain-specific findings into actionable guidance for their particular settings. For instance, managers may know that AI can enhance sorting accuracy or predictive maintenance, but they lack generalizable principles that guide them on when certain design choices are preferable, how to weigh trade-offs, or what socio-technical factors influence successful adoption.

For information systems (IS) research, this is both an opportunity and a responsibility. IS research has long positioned itself as centrally concerned with the design, use, and impact of digital artifacts (Gregor & Hevner, 2013; Orlikowski & Iacono, 2001). Design science research (DSR) emphasizes the development of generalizable DK, principles, theories, and frameworks that extend beyond specific instantiations (Chandra Kruse et al., 2016; Gregor & Jones, 2007). From this perspective, the current landscape of AI–CE research represents a vast but underexploited repository of instantiations from which DK can be systematically extracted and generalized.

We address these issues with a meta-study on AI applications in CE contexts. We ask: *How can design knowledge embedded in AI studies for the CE be extracted and synthesized into reusable design principles?* To answer this question, we adopt a structured coding protocol that distinguishes between instantiation, DK, artifact type, empirical evidence, and research approach. This enables us to classify the existing work, identify the forms of DK currently produced, and analyze the mechanisms that explain artifact performance across domains. Doing so advances both the academic discourse on design theory and the practical discourse on CE transitions. Building on these mechanisms, IS research can abstract cross-domain DPs that capture reusable guidance for AI-enabled CE systems. Such principles move beyond technical recipes to provide prescriptive knowledge that is both generalizable and actionable.

This study makes three contributions. First, we provide a systematic classification of AI-enabled CE instantiations, showing that prototypes, lab experiments, and field pilots are common, yet DK remains fragmented. Second, we identify causal mechanisms that underpin artifact performance, such as multimodality mitigating occlusion, offering explanatory depth beyond individual case findings. Third, we abstract these mechanisms into four cross-domain meta-principles (MPs) that link physical-technical mechanisms with socio-technical orchestration capabilities. Together, these contributions advance IS scholarship by transforming domain-specific findings into generalizable DK that informs both theory and practice. In doing so, we respond to calls for IS research to engage with grand societal challenges (Majchrzak et al., 2016; Markus et al., 2021).

2 Theoretical Background

2.1 AI-enabled CE

The CE is a systems approach that keeps products and materials at their highest value through circulation and regeneration while decoupling economic activity from resource consumption. Emphasizing resource efficiency, reuse, and extended product lifecycles, the CE seeks to transform how organizations act (Geissdoerfer et al., 2017; Ghisellini et al., 2016). Building on early concepts such as Stahel's (2020) "performance economy", which emphasizes maintenance, reuse, and remanufacturing, the concept has evolved into a holistic framework encompassing product design, production processes, consumption patterns, and end-of-life (EoL) management. At its core, the CE aims to eliminate waste and pollution, keep products and materials in use, and regenerate natural systems (EMF, 2012). The operationalization of CE principles has led to the development of strategic frameworks guiding implementation across organizations and sectors. Bocken et al. (2016) conceptualized three core strategies: *narrowing* resource flows through increased efficiency and reduced material use per unit of service; *slowing* resource loops by extending product lifespans through design for durability, repair, and remanufacturing; and *closing* material loops through recycling and recovery at EoL. CE has become a central topic in the IS discipline (Zeiss et al., 2021) since CE depends on the availability, quality, and interoperability of data across organizational boundaries (Ixmeier et al., 2023). Digital technologies enable circular supply chains and manufacturing by improving visibility, traceability, and coordination across products, materials, and actors over the lifecycle (Bag et al., 2021; Kristoffersen et al., 2021). These capabilities support the implementation of CE strategies within circular business models through lifecycle monitoring, take-back systems, and service-based offerings (Bressanelli et al., 2018, Hoppe-Ludwig et al., 2025) while also highlighting the importance of circular ecosystems, where value creation also depends on information sharing and coordination across actors (Aryee et al., 2025; Sagnier Eckert et al., 2025).

AI is increasingly recognized as an enabler of the CE (Pathan et al., 2023). Since its emergence in the 1950s, when researchers first explored how computers could simulate aspects of human cognition (McCarthy et al., 2006), AI has come to encompass methods that enable systems to learn and act under uncertainty (e.g., ML, neural networks (NN), deep learning, and fuzzy logic) (Pathan et al., 2023). Recent breakthroughs have accelerated AI toward generative AI systems that autonomously generate novel content from multimodal inputs (e.g., text, images, audio, sensor data), approximating human creativity and reasoning. This marks a paradigm shift, fundamentally reshaping knowledge work, innovation processes, and decision-making (Strobel et al., 2024). From a CE perspective, AI's enabling mechanisms are manifold. For instance, AI methods support the design of circular products and circular business models, optimize circular processes (Bag et al., 2021; Tutore et al., 2024), enhance resource efficiency, predict material lifetimes, improve product life-cycle transparency, and strengthen circular supply chains (Acerbi et al., 2021; Pal Singh, 2023). Additionally, AI supports material recovery, waste management, and the development of knowledge-based services (Roberts et al., 2024). Overall, AI's capacity to sense, learn, and generate insights positions it as a pivotal enabler of the CE, continuously improving the circular performance of products, processes, organizations, and ecosystems.

2.2 Design Knowledge and Dynamic Capabilities for an AI-enabled CE

Within IS, established frameworks guide the study of the design, implementation, and consequences of digital artifacts (Gregor & Hevner, 2013). In the CE context, AI-enabled artifacts act as socio-technical objects facilitating circular transitions (Carlile, 2002; Star & Griesemer, 1989). DSR, which builds and evaluates artifacts and extracts actionable DK for reuse, offers a foundation for capturing and structuring the knowledge that accumulates around such artifacts (Baskerville et al., 2018; Peffers et al., 2007).

In DSR, DK represents the overarching prescriptive insight that enables the creation of artifacts, integrating descriptive problem understanding with prescriptive solution guidance (Strohmann & Khosrawi-Rad, 2025; vom Brocke et al., 2020). A *design theory* provides the coherent logic for this knowledge, explaining key constructs and expected outcomes to guide how artifacts are built (Gregor & Hevner, 2013). This theoretical guidance is often articulated as *design principles*, which constitute a nascent design theory by defining concise, actionable prescriptions that link configurations to objectives; specifically, they follow a structural anatomy comprising an aim, a context, a mechanism, and a theoretical rationale (Gregor et al., 2020; Chandra et al., 2022; Walls et al., 1992). *Instantiations* act as the concrete application of this design theory, embodying the prescriptions in prototypes or processes to demonstrate feasibility and provide evaluation evidence (Baskerville et al., 2018; Peffers et al., 2007). However, AI-enabled CE is not only a matter of artifact design, but also of how such artifacts are embedded in organizational action and coordination.

While DK focuses on *how* digital artifacts are created, dynamic capabilities (DC) explain how organizations translate these artifacts into competitive advantage, enabling them to adapt and evolve in dynamic environments (Steininger et al., 2022). DCs are defined as *"the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments"* (Teece et al., 1997, p. 516). They encompass *sensing* opportunities, *seizing* them through strategic decision-making, and *reconfiguring* organizational resources to sustain innovation (Teece, 2007). Scholars have examined AI-enabled CE processes through the lens of DCs, analyzing digitally enabled DCs in cloud technologies, cybersecurity (Neri et al., 2023), blockchain applications (Meier et al., 2023), and the influence of industrial IoT on CE outcomes (AL-Khatib, 2023).

3 Methodological Approach

We conduct a meta-synthesis of DK to extract and synthesize prescriptions dispersed across AI and CE publications. Our approach looks beyond formally articulated DPs and unearths DK embedded in artifacts from other fields, a method akin to design archaeology (Chandra Kruse et al., 2019). This is crucial because while DSR, particularly within IS research, has made significant efforts to formalize the contribution and accumulation of DK (Chandra Kruse et al., 2022; Gregor & Jones, 2007; vom Brocke et al., 2020), this paradigm is not yet common in the applied sciences and engineering from which we draw our sample. These fields produce substantial, valuable DK, but it often remains implicit within artifact descriptions rather than being formalized. We extract this knowledge and translate it into the formalized structures of DSR, thereby increasing its potential for theoretical accumulation.

We opted for a pragmatic meta-synthesis (see Figure 1). We follow the method for a DSR meta-synthesis proposed by Khosrawi-Rad et al. (2024), but with one modification: we do not search exclusively for DK formulated according to established DSR principles. Instead, we draw on design archaeology, looking for diverse forms of prescriptive insight. This use of meta-analysis for crafting new theoretical contributions also appears in other IS genres (e.g., Berente et al., 2019). Given that DK can exist at various levels of abstraction (Winter & Albani, 2025), we narrowed our approach as follows: we first synthesized one core DP per study from our literature corpus. We then use this set of DPs as the input to abstract overarching MPs, which in turn map back to the specific DPs they were derived from.

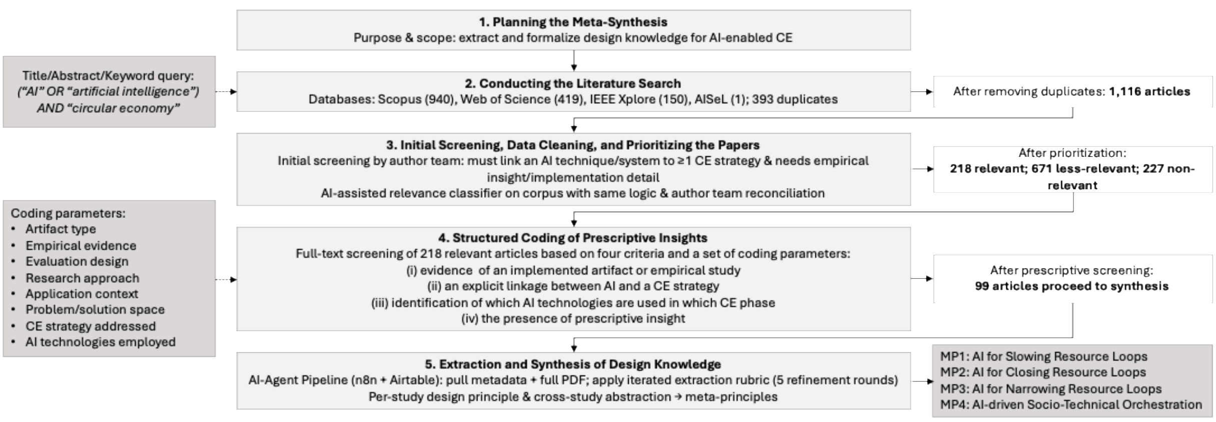

Figure 1. Meta-synthesis approach for synthesizing AI-enabled CE design knowledge.

Step 1: Planning the meta-synthesis (purpose & scope). The purpose is to identify and abstract reusable DK. We defined scope and eligibility criteria to ensure our corpus focuses on empirically grounded AI applications linked to circular strategies. Inclusion required that a manuscript be written in English, published within the last five years to reflect the rapidly evolving AI-enabled CE field,and available as a peer-reviewed journal article or conference paper, thereby focusing the synthesis on academic empirical research. Additionally, the publication had to address an AI technique or system in the context of at least one CE strategy or practice, and provide empirical insight or implementation detail, such as a case study, experimental results, or a deployment.

Step 2: Conducting the literature search. Guided by PRISMA (Moher et al., 2015), an evidence-based approach widely applied in meta-analyses (Parmentola et al., 2022; Tutore et al., 2024), we searched four databases to balance interdisciplinary breadth, technical depth, and IS-specific coverage: Scopus, Web of Science, IEEE Xplore, and the AIS eLibrary (AISeL). We used a title/abstract/keyword query: *("AI" OR "artificial intelligence") AND "circular economy"*, harmonizing time window, language, and document types. Initial retrieval returned 940 records in Scopus, 419 in Web of Science, 150 in IEEE Xplore, and only 1 record in AISeL, underscoring that IS research has been comparatively quiet on AI and CE. After removing 393 duplicates, the working corpus comprised 1,116 unique records.

Step 3: Initial screening, data cleaning, and prioritizing the papers. We harmonized metadata and excluded items outside scope (e.g., no AI applications linked to circular strategies). To calibrate judgments, we piloted full-text coding on two papers, then two authors independently screened title and abstract of 30 randomly selected papers to refine criteria for instantiations and DK outputs. Using the pilot set, we applied an AI-assisted relevance classifier to the remaining corpus under the same decision logic. A subsequent manual reconciliation adjusted labels as follows: 24 items moved from non-relevant to less-relevant, 1 from non-relevant to relevant, 2 from less-relevant to relevant, and 4 from less-relevant to non-relevant. The final counts were 218 relevant, 671 less-relevant, and 227 non-relevant.

Step 4: Structured coding of prescriptive insights. The coding parameters were developed and refined through pilot coding and team discussion for the AI–CE corpus, while the overall approach was informed by prior work on design archaeology and DSR meta-synthesis (Chandra Kruse et al., 2019; Khosrawi-Rad et al., 2024). We distributed papers for full-text assessment against four verification criteria: (i) evidence of an implemented artifact or empirical study, (ii) an explicit linkage between AI and a CE strategy, (iii) identification of which AI technologies are used in which CE phase, and (iv) the presence of prescriptive insight. Inconsistencies were resolved in team discussions. Because we aim to extract DK, we prioritized studies that report instantiations and contain actionable guidance. We define an instantiation as an AI-enabled artifact evaluated on CE tasks; studies using AI solely for literature mining or data preprocessing for non-AI artifacts were excluded (Larsen et al., 2020). After coding, 119 papers were excluded, yielding 99 articles for synthesis.

Step 5: Extraction and synthesis of DK. We synthesized one core DP per study in our final corpus. To accomplish this, we constructed an AI-agent-based pipeline using N8N (https://n8n.io/). This pipeline accessed structured analysis data from Airtable (https://airtable.com/), retrieved the full-text PDF for each study, and applied guidelines to extract and synthesize embedded DK. The extraction instructions were a critical component of this process. To validate AI-generated DPs, the author team reviewed outputs against the source articles for fidelity to the reported artifact, completeness of the DP anatomy, consistency of abstraction level, and plausibility of the inferred mechanism. We iterated them five times, with the author team rechecking the quality of AI-generated extraction and generalization at each step to ensure accuracy, consistency, and alignment with our research goals. In the final iteration, the AI agent was instructed as an expert DSR assistant. For each paper, it constructed a complete DP that adheres to the anatomy of a DP (Gregor et al., 2020). This required synthesizing information from both the full PDF text and our analysis metadata to define the DP's title, aim, implementer, user, context, mechanism, and rationale. The output was structured as a JSON object to ensure consistency for subsequent synthesis, which another AI agent used to derive four overarching MP. Figure 2 illustrates how one study (Dong et al., 2022) moves through the pipeline, from structured coding to AI-assisted DP generation and final aggregation into the corresponding MP.

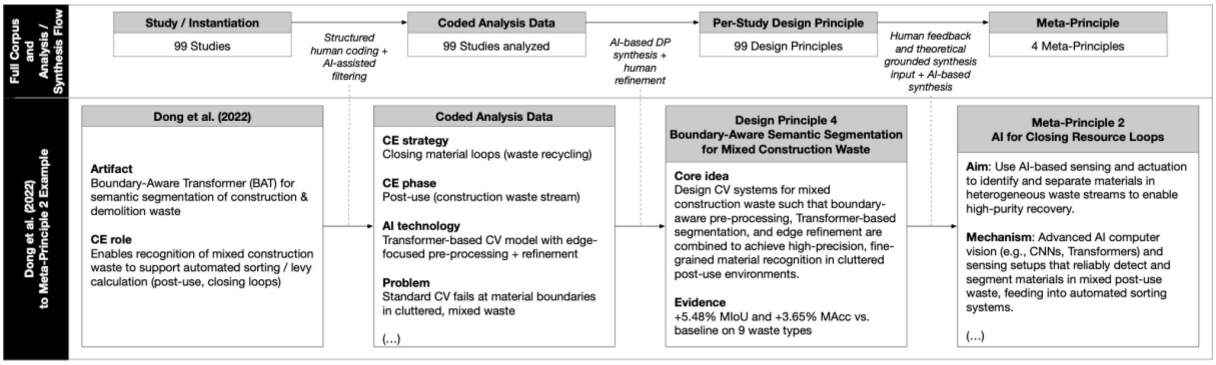

Figure 2. Mapping of a single study through the meta-synthesis pipeline.

4 The AI-enabled Circular Economy

The analysis of 99 AI-enabled CE instantiations yields a two-layered architecture that explains how AI generates circular value in practice. For readability, the papers in the final sample are cited by ID in parentheses (e.g., 26; 42; 99). Full references, DP, justification for DP categorization, and a glossary of technical abbreviations appear in the online appendix [10.6084/m9.figshare.30627287]. The physical-technical layer comprises mechanisms that operationalize the core CE strategies of slowing, closing, and narrowing resource loops (Bocken et al., 2016). These mechanisms correspond to MPs 1–3 and describe what AI systems do to materials, components, and processes: forecasting degradation to prolong asset life (MP1), sensing and actuating to recover materials from heterogeneous waste streams (MP2), and computationally exploring design and process spaces to minimize resource and energy inputs (MP3). Underpinning these physical-technical mechanisms, MP4 captures the socio-technical orchestration capability that enables organizations to sense opportunities for circularity, seize them through deployment and business model choices, and reconfigure assets, workflows, and inter-organizational arrangements to scale successful solutions.

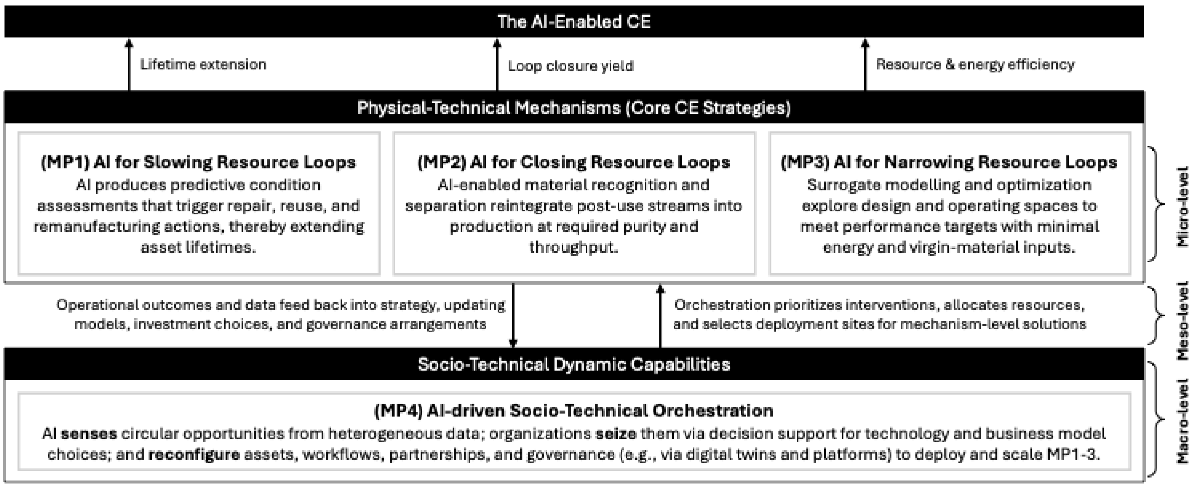

Figure 3. Meta-logic of design knowledge for the AI-enabled circular economy.

Conceptually, this foundational layer functions as an AI-augmented DC in Teece's sense of sensing, seizing, and reconfiguring (Teece, 2007), acting upon and amplifying the physical-technical mechanisms and creating feedback loops in which operational outcomes inform strategic choices. This layered view clarifies how DK from individual instantiations transfers across domains: MPs 1–3 provide mechanism-outcome patterns that specify how particular AI configurations generate circular effects at the object or process level, while MP4 specifies how organizations identify, integrate, and scale such mechanisms across contexts through policy-aware planning, worker-in-the-loop deployment, and platform-based orchestration and governance. Together, the four MPs define a coherent design space for AI-enabled circularity that links micro-level model choices to meso-level workflows and macro-level governance arrangements, offering a vocabulary for explaining and shaping how AI becomes embedded in circular transition pathways. Figure 3 provides an overview of this meta-logic.

4.1 Meta-Principle 1: AI for Slowing Resource Loops

MP1 captures how AI-driven predictive insight extends the functional life of products, components, and infrastructure. It aims to slow resource loops by shifting organizations from reactive failure response toward proactive, evidence-based maintenance, repair, reuse, and remanufacturing. In in-use contexts such as structural health monitoring, predictive maintenance, AI/ML, and engineering, models that learn from vibration signals, process variables, images, or acoustic patterns are configured to infer remaining useful life, classify fault states, or estimate damage severity (Fraguela Díaz et al., 2025; Gordan et al., 2023; Rebahi et al., 2023). In post-use contexts such as disassembly and remanufacturing, the same communities design perception and guidance systems that help managers, technicians, and remanufacturing planners assess condition and reusability with sufficient accuracy to justify life-extending interventions rather than replacement. The vignettes operationalize each MP by showing how the synthesized design logic is instantiated across representative studies, implementation contexts, and typical enactors.

Aim: To slow resource loops by extending the functional life of products, components, and infrastructure through proactive, evidence-based maintenance, repair, reuse, and remanufacturing.
Implementer: AI/ML engineers, data scientists, structural, mechatronics & robotics engineers
User: Asset & facility managers, maintenance personnel, disassembly technicians, remanufacturing planners
Context: In in-use (e.g., structural health monitoring, predictive maintenance) and post-use (e.g., EoL disassembly, remanufacturing) scenarios, where accurate assessment of an asset's condition, degradation, or reusability is critical for extending its value.
Mechanisms:
M1-A: Employ AI-driven predictive models (e.g., LSTMs, ANNs) to forecast degradation, detect faults, or assess remaining useful life based on real-time sensor data.
M1-B: Utilize AI-based assessment (e.g., CV/OCR, multi-modal sensor fusion, AR) to guide optimal disassembly, identify components for remanufacturing, and assess reuse potential.
Enactors: The predictive maintenance algorithm, the fault-detection system, the component identification model, or the AI-guided disassembly planner.
Rationale: Because this directly operationalizes the CE strategy of slowing resource loops. AI's ability to predict failures, identify parts, and assess conditions before they become critical enables a shift from reactive to proactive maintenance, repair, and reuse.
Foundational principles IDs: 19; 26; 35; 42; 57; 67; 70; 73; 74; 75; 79; 80; 82; 98; 99

Vignette 1. Meta-Principle 1: AI for Slowing Resource Loops

MP1 instantiations generate convergent DK on mechanisms and enactions. For in-use assets, effective systems employ predictive models – i.e. long short-term memory networks (LSTM), NN or regression-based predictors as enactors to forecast degradation or detect faults from real-time sensor data in heating, ventilation, and air conditioning (HVAC) plants, bridges, computer numerical control (CNC) tools, and water networks (26; 42; 99). A recurring design choice is to structure outputs into lifecycle-relevant categories (e.g., reuse as-is, repair, remanufacture, discard) rather than reporting only continuous health scores, aligning model behavior with maintenance and replacement policies (42). Another concern is model scope: predictor families tuned to specific asset classes and operating environments outperform universal anomaly detectors and better reflect the constraints of structural and mechatronics engineering (35; 73). Predictive maintenance algorithms also localize faults, such as leak positions in smart water pipes, allowing for minimally invasive interventions that are both economically and environmentally viable (74). These patterns jointly articulate a principle that slowing loops requires models not only to detect degradation but to represent it in forms that directly trigger and target life-extending actions.

In post-use and remanufacturing scenarios, MP1 DK centers on AI-based assessment embedded in human-AI workflows. Computer vision (CV), optical character recognition (OCR), multimodal sensor fusion, and augmented reality (AR) interfaces serve as enactors that identify components, read worn serial numbers, and guide disassembly of automotive modules and electronics (57; 80; 98). Multimodal fusion improves detection of small but critical features such as screws under occlusion, which is essential for robot-assisted disassembly (98), while AR-guided workflows overlay AI-derived instructions and quality checks onto the artifact, reducing cognitive load and error rates for technicians (67). Several studies further embed AI-derived condition indicators into multi-criteria decision frameworks that compare reuse, remanufacturing, and recycling options for returned cores and construction elements, explicitly valuing life-extending strategies (19; 70; 75; 79).

In synthesis, MP1 can be stated as follows: begin with the CE decisions to be supported in in-use and post-use scenarios, then configure sensing infrastructures, predictive and perceptual models, and guidance and decision frameworks backward from these decision points so that AI's predictive and classificatory capacities directly operationalize the CE strategy of slowing resource loops.

4.2 Meta-Principle 2: AI for Closing Resource Loops

MP2 concerns AI for closing resource loops by enabling high-throughput, high-purity, and economically viable sorting, classification, and recovery of materials from heterogeneous and often contaminated post-use streams. Implemented primarily for waste management operators and recycling plant managers, MP2 instantiations are evident in various applications, including waste sorting, demolition processing, e-waste, textile recycling, as well as specialized streams such as medical waste and incineration residues. Across these contexts, the core mechanism is an integrated AI–robotic sorting system that couples perception (e.g., convolutional neural networks (CNNs) or transformer-based detection and segmentation) with physical actuation (e.g., robotic pickers, programmable logic controller (PLC)-controlled conveyors) so that "waste" can be reclassified and physically separated into clean technological or biological cycles rather than being disposed.

Aim: To close resource loops by enabling high-throughput, high-purity, and economically viable automated sorting, classification, and recovery of materials from heterogeneous, complex, and often contaminated waste streams.
Implementer: AI/robotics engineers, CV specialists, automation engineers, mechatronics engineers
User: Waste management facility operators, recycling plant managers, dismantling stakeholders
Context: Post-use scenarios (e.g., waste sorting, recycling) characterized by cluttered, heterogeneous, and overlapping materials (e.g., construction waste, e-waste, plastics, textiles, municipal solid waste), where manual sorting is inefficient, hazardous, or unfeasible.
Mechanisms:
M2-A: Employ AI-driven CV models (e.g., CNNs, YOLO, U-Net, Transformers) to perform object detection, instance segmentation, and classification of waste items.
M2-B: Utilize diverse sensors (e.g., RGB, Hyperspectral, Raman spectroscopy, 3D laser) to identify materials based on visual, chemical, or physical properties.
M2-C: Integrate these sensing models with physical robotic systems (e.g., robotic arms, PLC-controlled conveyors) for automated actuation and sorting.
Enactor: The integrated AI-robotic sorting system.
Rationale: Because this operationalizes the CE strategy of closing resource loops. AI's sensory and actuation capabilities are necessary to achieve the high-purity separation required to create clean technological/biological material cycles, transforming waste back into valuable feedstock.
Foundational principles IDs: 2; 3; 6; 7; 9; 11; 14; 18; 20; 22; 23; 24; 29; 32; 39; 45; 48; 49; 60; 62; 64; 66; 69; 71; 76; 90; 93; 94; 95

Vignette 2. Meta-Principle 2: AI for Closing Resource Loops

The papers extract convergent DK on how to configure sensing and modeling under MP2. A set of studies shows that standard image-based architectures, such as You Only Look Once (YOLO)-like detectors, U-Net segmenters, and related CNN variants, can reliably classify and separate paper, plastics, glass, metals, and organics in mixed municipal waste when trained on images reflecting real operating conditions, including clutter, variable lighting, occlusion, and contamination (6; 22; 39; 60; 64; 71), with domain-specific variants extending these to medical waste items or used electronic components (18; 24). Here, DK centers on representation: training data should replicate the vantage point, camera geometry, and illumination of the actual sorting line, and should intentionally include deformed, partially occluded, and contaminated items to avoid brittle performance. A second cluster shows that when downstream processes require more finer or compositionally precise distinctions, such as polymer types in plastics or fiber blends in textiles, upgrading the sensing stack is often more consequential than complicating the neural architecture. Hyperspectral imaging, Raman spectroscopy, and 3D laser scanning expose spectral or geometric signatures correlated with material composition and contaminant levels, enabling AI models to meet stringent purity thresholds beyond those achievable with standard color imaging (14; 32; 45; 48; 90; 95). The resulting principle is that designers should start from the material distinctions required by recycling routes, then choose sensing modalities and fusion strategies that make those distinctions observable, rather than pursue incremental gains in image-only accuracy.

A complementary body of work frames MP2 as a system integration problem requiring the co-design of perception, actuation, and plant architecture. Several studies integrate AI models with robotic arms, grippers, and PLC-controlled conveyors into end-to-end sorting cells, emphasizing constraints such as conveyor speed, robot reach, and cycle time (2; 7; 9; 11; 20; 93; 94). Others deploy compressed or quantized models on embedded devices for real-time bin- or container-level classification at collection points (23; 66; 76). These instantiations yield a shared design heuristic: modular system architectures that decouple sensing, classification, and actuation layers enable facilities to update models, reroute material flows, and adjust purity–throughput trade-offs without redesigning mechanical hardware, while maintaining low-latency communication and integration with plant control logic and dashboards.

MP2 thus advises implementers to begin from required purity levels, throughput targets, and plant constraints, and then configure sensor suites, AI models, and robotic or conveyor-based actuators backward from these requirements so that AI's material sensing and actuation capacities directly operationalize the CE strategy of closing resource loops.

4.3 Meta-Principle 3: AI for Narrowing Resource Loops

MP3 concerns AI-driven optimization for resource efficiency. It aims to narrow resource loops by identifying designs, material compositions, and process parameters that minimize energy and virgin material inputs while maintaining required levels of performance and value. Implemented for product designers, operators, and R&D managers, MP3 spans pre-use eco-design and in-use process control. The central mechanism is a hybrid AI-optimization framework in which predictive models approximate complex input-output relationships and optimization algorithms search vast, multi-objective solution spaces. In this pattern, AI models encode the relationships among design variables, technical performance (e.g., strength, yield, energy efficiency), and environmental outcomes (e.g., emissions, virgin material share), enabling stakeholders to explore trade-offs and identify configurations that meet technical and regulatory requirements with substantially lower resource footprints.

Aim: To narrow resource loops by identifying optimal designs, material compositions, or process parameters that minimize the input of energy and virgin materials while maximizing performance and value.
Implementer: AI/ML engineers, operations researchers, process engineers, materials scientists, building design engineers
User: Product designers, process/facility operators, construction engineers, R&D managers
Context: In pre-use (e.g., sustainable material design, eco-design) and in-use (e.g., process control) scenarios involving complex, multi-variable optimization problems where the goal is to balance performance (e.g., strength, yield) with sustainability (e.g., low emissions, low resource use).
Mechanisms:
M3-A: Employ computational optimization (e.g., metaheuristics, gradient-based optimization, incremental learning) to search vast solution spaces.
M3-B: Utilize predictive AI models (e.g., ANNs, surrogate models, neuro-fuzzy) as a "fitness function" or efficient process model to rapidly evaluate the performance of countless design permutations or learning steps without physical experimentation.
Enactor: The hybrid AI-optimization framework or the energy-efficient learning model.
Rationale: Because this operationalizes the CE strategy of narrowing resource loops. AI's ability to solve complex, multi-objective optimization problems allows for the discovery of novel, resource-efficient solutions.
Foundational principles IDs: 10; 16; 21; 25; 27; 34; 41; 44; 46; 51; 53; 59; 63; 81; 88; 91; 92; 97

Vignette 3. Meta-Principle 3: AI for Narrowing Resource Loops

Across the corpus, a prominent cluster of MP3 instantiations uses surrogate modelling and metaheuristic optimization for sustainable materials and product design. NN, neuro-fuzzy systems, and hybrid predictors estimate properties such as compressive strength, durability, or life-cycle emissions of cementitious mixes, asphalt, composites, and other materials that incorporate recycled or waste-derived constituents (21; 41; 44; 46; 51; 53; 59; 91; 92; 97). These models serve as rapid "fitness functions" within optimization loops, utilizing genetic algorithms, particle swarm optimization, biogeography-based optimization, or gradient-based search to generate, for example, mix designs or crop configurations that meet mechanical or agronomic targets while reducing clinker content, embodied CO_2, or fertilizer use. Similar hybrids appear in chemical processes and building design, where surrogate models predict flowsheet performance or building energy use and emissions, enabling engineers and architects to tune process structures or envelope parameters to meet energy codes and sustainability goals (25; 44; 88). The resulting DK emphasizes that when high-fidelity simulation or physical experimentation is costly, surrogate models should be trained within the valid operating envelope and embedded into optimization routines whose objective functions explicitly balance performance with resource and emission reductions, rather than treating sustainability as a secondary constraint.

A second cluster applies MP3 to in-use industrial and energy processes and, in some cases, to the AI learning process itself. Studies integrate NN with multi-objective optimization to tune co-combustion and pyrolysis conditions, maximizing useful outputs while minimizing emissions and residues (27; 41). Others optimize operating windows for water treatment and metal recovery, embedding energy efficiency and greenhouse gas reductions directly into the optimization objectives (10; 16; 63). Here, AI models serve either as controllers that continually adjust process parameters or as decision-support tools during design and commissioning. Complementary work extends the narrowing of loops to digital infrastructure, where "green incremental learning" reduces training energy costs by adapting models incrementally and aligning complexity with the marginal value of accuracy gains (81).

Synthesized as an MP, MP3 advises implementers to begin with the sustainability objectives and hard constraints that define feasible operations–regulatory limits, safety margins, and physical laws–and then configure surrogate models, optimization algorithms, and, where relevant, energy-aware learning schemes backward from these requirements. Effective MP3 systems treat resource and energy efficiency as primary considerations in the optimization problem, yielding solutions that are not only technically optimal but also materially and energetically frugal.

4.4 Meta-Principle 4: AI for Socio-Technical Orchestration

MP4 concerns AI-driven socio-technical orchestration and provides the organizational DCs required to deploy the physical mechanisms of slowing, closing, and narrowing (MPs 1–3) in a coordinated way. It conceptualizes AI as part of a firm- and ecosystem-level sensing, seizing, and reconfiguring capability (Teece, 2007): AI systems help organizations detect circularity opportunities and risks, commit resources to specific CE strategies and business models, and reconfigure assets, workflows, and partnerships as conditions evolve. Implemented for top management, policymakers, supply-chain managers, planners, and frontline workers, MP4 operates in complex, multi-stakeholder contexts such as cities, supply chains, and industrial symbioses. In practice, these actors enact orchestration through interfaces such as dashboards, decision-support tools, workflow systems, digital twins, and collaboration platforms, using AI-generated insights to prioritize interventions, allocate resources, and coordinate changes across assets, processes, and actors. The core design problem is to assemble AI-enabled socio-technical workflows that make circular options visible, comparable, and governable at scale.

In its sensing and seizing dimensions, MP4 aggregates heterogeneous signals and translates them into strategically usable insight and commitments, operationalized through decision-support, monitoring, and coordination systems. Archetypical examples are forecasting models for waste generation and municipal waste flows, supporting planners in anticipating where CE interventions are most urgent or impactful (8; 31; 87). Natural language processing (NLP) and sentiment analysis extract stakeholder concerns and emerging reuse trends from social media, policy documents, and industry reports, revealing social and institutional enablers and barriers (12; 61). Remote sensing and CV detect illegal activities, while models on financial and market data assess the circularity performance of firms or investments (5; 52; 54; 56).

Aim: To provide the organizational-level dynamic capabilities required to effectively identify, assess, implement, and manage CE strategies (slowing, closing, narrowing) by integrating AI into decision-making, knowledge workflows, and human-machine systems.
Implementer: AI/NLP engineers, system architects, digital twin and decision-support system developers
User: Top management, policymakers, supply chain managers, planners, designers, human workers
Context: In complex, organization-wide, or multi-stakeholder CE contexts that require strategic and operational decision-making, knowledge synthesis from diverse sources (e.g., text, sensors, business data), human-machine collaboration, and end-to-end system traceability/management.
Mechanisms:
M4-A: Employ AI to sense opportunities and threats. This involves using NLP/LLMs to extract stakeholder sentiment and technical knowledge, and XAI or predictive models to identify policy drivers, environmental impacts, or market trends.
M4-B: Employ AI to seize opportunities. This involves using AI for complex decision-support (e.g., supplier selection, investment evaluation), creating new incentive models, and augmenting human workers with AR and real-time guidance.
M4-C: Employ AI to reconfigure assets and workflows. This involves creating integrated digital twins, managing self-adapting AI pipelines, and orchestrating complex value chains via platforms (e.g., Blockchain, GIS).
Enactor: The integrated AI-driven decision-support system, digital twin, socio-technical workflow, or incentive-management platform.
Rationale: Because implementing physical CE strategies requires profound organizational change. This MP provides the DC, the firm's capacity to sense, seize, and reconfigure, which are the essential managerial and organizational foundations for any CE transformation. AI acts as the "orchestration" engine for this capability.
Foundational principles IDs: 1; 4; 5; 8; 12; 13; 15; 17; 28; 30; 31; 33; 36; 37; 38; 40; 43; 47; 50; 52; 54; 55; 56; 58; 61; 65; 68; 72; 77; 78; 83; 84; 85; 86; 87; 89; 96

Vignette 4. Meta-Principle 4: AI for Socio-Technical Orchestration

DK here centers on how to build sensing infrastructures that integrate diverse data sources and provide interpretable, policy- and management-relevant outputs instead of black-box scores (36; 86). Seizing-focused systems in this category then embed these insights into multi-criteria decision-support tools for technology choice, business model design, and incentive schemes (55; 72). They quantify residual value, cost-benefit trade-offs, or tariff options for product-as-a-service and refurbish-to-host models (30; 40), and design nudging and reward mechanisms that make CE strategies acceptable and attractive to users (50; 77; 96). The emerging DP is to treat AI-based sensing and decision support as organizational instruments that combine technical performance metrics with economic, behavioral, and institutional dimensions, thereby making circular options actionable and investable.

The reconfiguring dimension captures AI-enabled restructuring of physical and digital assets, workflows, and inter-organizational arrangements, with human–AI collaboration and explainability as recurring concerns. Digital twins of factories, infrastructures, or waste systems support simulation-based redesign of layouts, control policies, and capacity expansions, often paired with optimization to coordinate multiple CE levers (4; 47). Platform solutions, frequently using geographic IS or blockchain, orchestrate reverse logistics, industrial symbioses, and shared facilities across firms and municipalities, turning dispersed actors into coordinated CE value chains (28; 33; 58; 65; 68; 78). Some systems even reconfigure the AI infrastructure itself, e.g., via "self-X" pipelines that detect and repair failures in optimization models (43) or evolutionary algorithms that integrate renewables system-wide (85).

Across these instantiations, DK emphasizes modularity, interoperability, and traceability: orchestrating MPs 1–3 at scale requires standard data models, APIs, and governance mechanisms so that new assets, models, and partners can be added without destabilizing existing operations. MP4 thus synthesizes into a MP for implementers: start from the CE strategies and governance context to be realized, then configure AI-driven sensing, decision-support, digital-twin, and platform infrastructures–and the associated human-in-the-loop workflows–so that organizations can continuously sense where to apply MPs 1–3, seize promising options under real-world constraints, and reconfigure socio-technical systems as learning from circular experiments accumulates.

5 Discussion and Conclusion

This study set out to excavate and synthesize DK from a rapidly growing yet fragmented body of AI-enabled CE research. While engineering and applied science papers report a rich variety of AI instantiations in areas such as waste management, sustainable materials, and process optimization, they rarely articulate reusable DK. Through a meta-synthesis of 99 empirically grounded studies, we reconstructed one core DP per paper. We abstracted them into four MPs that explain how AI contributes to slowing, closing, and narrowing resource loops and to orchestrating these mechanisms at organizational and ecosystem levels. This two-layered architecture links micro-level model and system design with meso- and macro-level capabilities, advancing IS design science, CE scholarship, and research on AI-enabled CE transitions (George et al., 2021; Zeiss et al., 2021).

First, we contribute to CE scholarship by specifying how AI instantiations operationalize circular strategies. Prior work has conceptualized narrowing, slowing, and closing resource loops and emphasized the importance of data and digital infrastructures for CE (Bocken et al., 2016; Geissdoerfer et al., 2017; Ixmeier et al., 2023; Kristoffersen et al., 2021). Our MPs show how predictive models and hybrid AI-optimization frameworks render degradation, efficiency, and sustainability trade-offs actionable at the level of assets, materials, and processes (MP1, MP3); how AI-driven sensing and actuation yield high-purity material streams (MP2); and how AI-augmented DCs help organizations sense circularity opportunities, seize them through investments and business models, and reconfigure assets and relationships (MP4; Teece, 2007). This mechanism-based view complements largely conceptual CE-AI accounts (Pathan et al., 2023; Roberts et al., 2024) and clarifies how AI-enabled artifacts function as socio-technical objects that translate between informational and material realms and between engineers, operators, managers, and policymakers (Carlile, 2002; Star & Griesemer, 1989).

Our second contribution is to design science in IS. We demonstrate how “design archaeology” can extract DK from fields that do not explicitly follow DSR conventions (Chandra Kruse et al., 2019; vom Brocke et al., 2020). By distinguishing instantiations, DK, artifact type, empirical evidence, and research approach, and by reconstructing full DPs from these elements, we show that engineering papers contain more prescriptive insight than their formal contributions reveal. The four MPs propose a mid-range design theory that connects concrete AI configurations to CE outcomes, expressed through artifacts, mechanisms, contexts, and justificatory rationales (Gregor et al., 2020; Gregor & Jones, 2007). In doing so, we respond to calls for IS to deepen its theorization of digital artifacts and their design logics rather than treating AI solutions as opaque tools (Gregor & Hevner, 2013; Orlikowski & Iacono, 2001).

A third contribution is methodological. We combine a PRISMA-guided meta-review (Moher et al., 2015; Tutore et al., 2024) with an AI-assisted extraction pipeline that generates structured DPs adhering to established DSR anatomies (Gregor et al., 2020; Winter & Albani, 2025). This shows how generative AI can alleviate cognitive overload in synthesizing large corpora and support cumulative theorizing (Berente et al., 2019; vom Brocke et al., 2020). At the same time, our approach highlights the need for reflexive scrutiny: choices about prompting, model configuration, and validation shape which aspects of DK are emphasized, introducing novel loci of bias even as others (e.g., selective reading) are reduced. Such scrutiny is particularly important because AI-assisted theory extraction is still a relatively novel methodological approach. More specifically, AI assistance may privilege patterns that are more explicit, repetitive, or easily verbalized in the source material, while underrepresenting contextual nuance, contradictory findings, or latent design logic. This may affect validity at the level of abstraction and emphasis, for example, by shaping which mechanisms appear central or how broadly a design principle is generalized. Because abstraction is itself a theory-generating act, AI assistance may shape not only which patterns are extracted, but also how design knowledge is generalized and ordered into more coherent theoretical structures. To mitigate these risks, we iteratively refined prompts, constrained outputs through a structured DP schema, and embedded repeated human review and team discussion at key stages of extraction, generalization, and synthesis, including repeated checks of AI-generated outputs against the source articles.

These contributions are subject to several *limitations*. Our corpus includes only English-language, peer-reviewed work from the last five years, thereby excluding grey literature, earlier studies, and nonacademic implementations that may follow different design logics. As a result, the MPs are grounded primarily in academic empirical research and may require adaptation in industry or policy contexts, where implementation constraints, regulatory conditions, and practitioner priorities can differ from those emphasized in scholarly studies. We focus on instantiations where AI is an integral part of the artifact, rather than a purely analytical tool, which omits some policy and planning applications. Despite detailed protocols, AI assistance, and multiple rounds of human review, coding and abstraction remain interpretive; other teams might formulate partly different DPs or MP boundaries. This is particularly relevant for the AI-assisted stages of the process, where prompt design, model behavior, and schema choices may influence which aspects of design knowledge are foregrounded or abstracted across studies. Finally, our synthesis operates at a relatively high level of abstraction appropriate for cross-domain theorizing but necessarily leaves out domain-specific constraints and trade-offs that matter in concrete implementation contexts. The MPs should therefore be understood as synthesized from prior empirical studies rather than tested in new settings, and as a foundation for future research and design rather than final prescriptions.

These limitations open several avenues for *future research*. A first direction is to empirically instantiate and refine the MPs in longitudinal IS studies. Engaged DSR and case-based work could co-design MPs 1–3 artifacts with industrial or municipal partners and investigate how MP4-type orchestration capabilities emerge around them (Baskerville et al., 2018; Peffers et al., 2007; Steininger et al., 2022). Such work would validate and nuance our DK, clarifying how AI-enabled CE solutions interact with existing enterprise systems, data infrastructures, and institutional arrangements (Neri et al., 2023). A second direction is to examine organizational readiness and capabilities for AI-enabled CE. Many instantiations assume data quality, interoperable infrastructures, and MLOps practices that may be lacking in CE-focused firms with limited digital maturity. IS research can theorize how digital infrastructures, data governance, and cross-functional competencies condition the feasibility and impact of MPs 1–4 (Meier et al., 2023).

A third promising avenue concerns the evolution from singular AI artifacts toward agentic, multi-AI systems enabling CE. Most studies in our corpus focus on isolated solutions for specific tasks; emerging work on generative and agentic IS suggests constellations of interacting AI agents that coordinate sensing, decision-making, and actuation across lifecycle and organizational boundaries (Strobel et al., 2024). Building on our MPs, IS scholars could explore how MPs 1–3 might be realized as specialized agents whose outputs are orchestrated by MP4-type coordination agents, pointing toward design research on AI-enabled circular ecosystems. Finally, the scarcity of IS papers at the AI-CE intersection contrasts with the discipline's longstanding interest in sustainability and digital innovation (Majchrzak et al., 2016; Markus et al., 2021). IS research can assume a stronger integrative role by systematically extracting and synthesizing DK from adjacent disciplines, proposing reference architectures and patterns for AI-enabled CE systems, and theorizing how these systems reshape organizational processes, business models, and ecosystems. In doing so, IS can help ensure that AI technologies are purposefully harnessed for the socio-technical transformations required to realize a CE.

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