ASRC Procedia
Global Perspectives in Science and Scholarship
Florida, USA

1St GRI Conference 2025

Volume: *1;* ***Issue:*** *1*
Pages: *432–464*
Published: *29 April 2025*

open access

1st Global Research and Innovation Conference 2025,

April 20–24, 2025, Florida, USA

A FRAMEWORK-BASED META-ANALYSIS OF ARTIFICIAL INTELLIGENCE-DRIVEN ERP SOLUTIONS FOR CIRCULAR AND SUSTAINABLE SUPPLY CHAINS

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Doi: 10.63125/jbws2e49

Peer-review under responsibility of the organizing committee of GRIC, 2025

Abstract

This study presents a framework-based meta-analysis of 124 peer-reviewed scholarly articles to explore how artificial intelligence (AI)-driven enterprise resource planning (ERP) systems are reshaping circular and sustainable supply chains (CSCs and SSCs). The research systematically followed the PRISMA protocol to ensure methodological rigor and transparency, with articles selected from leading academic databases such as Scopus, Web of Science, IEEE Xplore, and ScienceDirect. The review investigates the integration of AI modules—such as machine learning, natural language processing, and robotics—within ERP platforms, with a focus on their application in enhancing predictive analytics, traceability, lifecycle management, and ESG (environmental, social, and governance) compliance. Sector-specific use cases from industries such as automotive, electronics, pharmaceuticals, agriculture, and fast-moving consumer goods (FMCG) were analyzed to assess implementation maturity and sustainability outcomes. Key findings reveal a concentration of research in high-tech sectors, limited longitudinal studies, underrepresentation of SMEs and developing economies, and fragmented use of conceptual frameworks. The study also identifies significant gaps in performance evaluation, interoperability, and cross-sectoral comparability. As a result, this meta-analysis proposes the need for an integrated evaluation framework that synthesizes technological, organizational, and sustainability dimensions of AI-ERP systems. This comprehensive synthesis not only advances academic understanding but also offers practical guidance for businesses, policymakers, and system architects aiming to foster digitally enabled, circular, and sustainable supply chains across global contexts.

Keywords

Artificial Intelligence (AI), Enterprise Resource Planning (ERP), Circular Supply Chains (CSC), Sustainable Supply Chains (SSC), Predictive Analytics

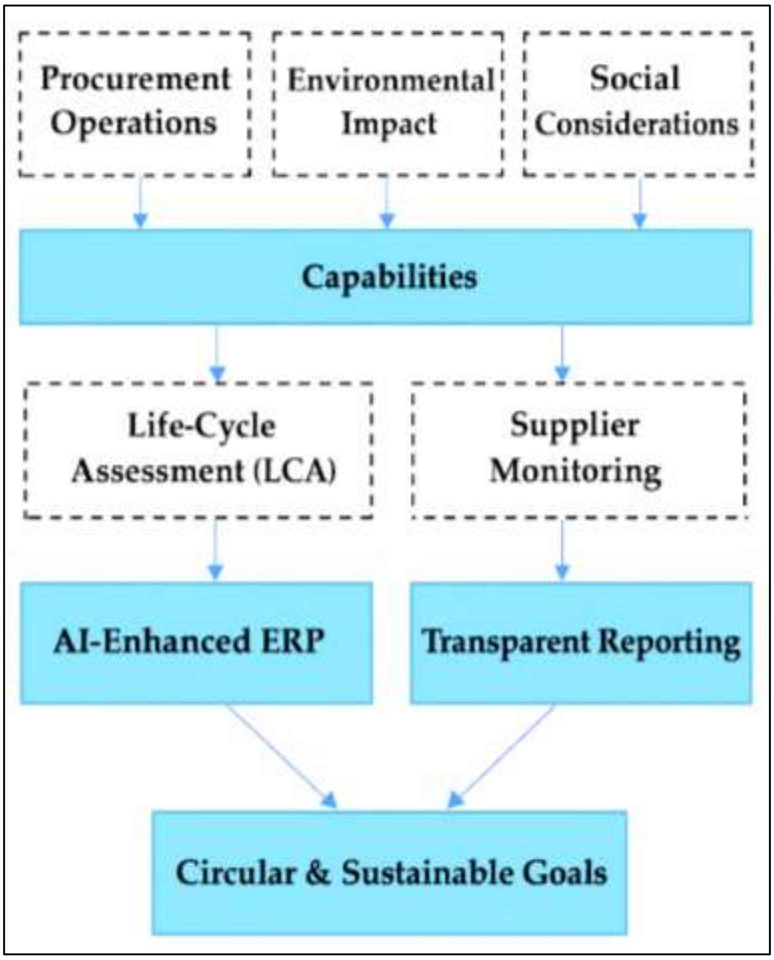
INTRODUCTION

Enterprise Resource Planning (ERP) systems are integrated platforms used to manage and automate core business functions such as finance, human resources, procurement, inventory, and manufacturing (Zhao & Tu, 2021). These systems streamline organizational processes by providing real-time data access across departments through a centralized database . The emergence of Artificial Intelligence (AI) has revolutionized traditional ERP structures by embedding cognitive capabilities such as machine learning, natural language processing, and autonomous decision-making into ERP modules. AI-enabled ERP systems enhance responsiveness, data analytics, anomaly detection, and predictive capabilities across business operations. Parallel to these technological developments, global industries are increasingly embracing circular supply chains (CSCs)—supply networks designed to reduce waste, regenerate resources, and extend product life cycles through recycling, remanufacturing, and reverse logistics. In tandem, the concept of sustainable supply chains (SSCs) emphasizes the integration of environmental, social, and economic sustainability within supply network design and execution. Both CSC and SSC models demand highly adaptable and intelligent digital infrastructures capable of managing multi-dimensional performance metrics, extended life-cycle feedback, and stakeholder coordination. The convergence of AI-enhanced ERP systems with circular and sustainable supply chain paradigms introduces a complex yet promising intersection of operations management, digital transformation, and environmental stewardship (Katuu, 2020). These systems must not only coordinate traditional inputs and outputs but also trace material flows in closed-loop structures and predict resource demand in a dynamic and regenerative ecosystem. Hence, it is critical to assess this integrated landscape through a meta-analytical lens to uncover framework-based evidence on operational, technological, and strategic alignment.

Figure 1: Overview of Enterprise Resource Planning (ERP)

The integration of Artificial Intelligence into ERP systems is a global phenomenon reshaping enterprise management across diverse regions, industries, and regulatory landscapes. Countries like Germany, Japan, China, and the United States have been at the forefront of adopting AI-powered ERP technologies under the umbrella of Industry 4.0 and digital transformation initiatives (Jawad & Balázs, 2024). AI components in ERP platforms such as SAP Leonardo, Oracle Cloud ERP, and Microsoft Dynamics 365 are being deployed to support decision automation, demand forecasting, risk management, and smart inventory control. These systems are becoming indispensable in managing increasingly complex and globalized supply chains. For instance, in transcontinental supply networks involving just-in-time and vendor-managed inventory models, AI-driven ERP modules offer real-time optimization and predictive scheduling. In manufacturing sectors, AI integration enhances process control, preventive maintenance, and adaptive planning by linking shop-floor data with enterprise-wide analytics (Sarferaz, 2024). Moreover, in developing economies, cloud-based AI-ERP systems are supporting SMEs in achieving scalability and transparency without massive IT infrastructure investment. The international relevance is further amplified by global standards and protocols such as ISO 14001 for environmental management, and UN Sustainable Development Goals (SDGs), which are compelling enterprises to track carbon footprints, energy use, and social impacts within their ERP ecosystems. Governments and multilateral agencies are offering incentives and frameworks for smart manufacturing and sustainable digitalization—both of which rely heavily on ERP-AI convergence (Abazi Chaushi & Chaushi, 2024). As a result, organizations worldwide are under both economic and ethical pressure to deploy AI-enhanced ERP solutions that can meet the demands of sustainability while sustaining competitive advantage.

Figure 2: Sustainable Supply Chain Management



The circular economy (CE) represents a paradigm shift from the traditional linear "take-make-dispose" model to a regenerative system where resources are kept in use for as long as possible. This transformation mandates that supply chains integrate reverse logistics, resource recovery, refurbishment, and closed-loop recycling strategies. These dynamics necessitate extensive reengineering of supply chain operations, requiring advanced digital platforms for tracking material flows, evaluating product life-cycle impacts, and coordinating post-consumer processes (Syreyshchikova et al., 2020). ERP systems have historically supported forward logistics—procurement, production, and distribution—but have been limited in handling reverse logistics and resource loops. However, AI-enhanced ERP systems can now track and predict reverse flows using machine learning algorithms trained on historical return data, condition monitoring, and market behavior. For example, predictive analytics in AI can anticipate when products will return for refurbishment, allowing manufacturers to plan inventory accordingly and reduce waste. AI also enables disassembly line optimization by modeling part degradation and recovery values. The circular economy further demands the integration of diverse stakeholder data—from recyclers and refurbishers to consumers and regulatory bodies—into a coherent system architecture (Mohapatra et al., 2023). AI-driven ERP systems, through cloud integration and IoT enablement, support this by facilitating traceability, compliance, and modular decision-making across extended enterprise boundaries. Thus, the intersection of ERP-AI systems with circular supply chains redefines how businesses extract value, manage waste, and remain adaptive to closed-loop dynamics. Moreover, sustainable supply chain management (SSCM) is the strategic coordination of traditional supply chain activities—procurement, operations, logistics—with environmental and social considerations (Mssassi & El Kalam, 2023). SSCM aims to minimize ecological impact, ensure fair labor practices, and enhance long-term economic viability. It necessitates multi-tier supplier monitoring, life-cycle assessment (LCA), and transparent reporting, often under regulatory pressures and stakeholder scrutiny. Traditional ERP systems struggle to accommodate the multidimensional data requirements and feedback mechanisms demanded by SSCM due to their limited analytical flexibility and real-time responsiveness (Mularczyk et al., 2022). Artificial Intelligence embedded within ERP environments addresses these gaps by enabling intelligent monitoring, scenario modeling, and risk-aware decision-making.

The practical application of AI-driven ERP solutions in circular and sustainable supply chains spans a broad range of industries, each characterized by unique operational complexities and sustainability challenges. In the automotive sector, AI-ERP systems have enabled circularity through predictive maintenance, vehicle remanufacturing tracking, and battery recycling logistics (Jayasuriya & Sims, 2023). Companies such as BMW and Renault have implemented closed-loop supply systems supported by intelligent ERP platforms to manage parts recovery and remanufacturing cycles. In the electronics industry, manufacturers face rapid obsolescence, hazardous material concerns, and strict e-waste regulations. Here, AI-ERP systems are used to optimize end-of-life management and regulatory compliance via reverse logistics scheduling and lifecycle cost modeling. Similarly, in pharmaceutical and healthcare supply chains, ERP systems powered by AI facilitate temperature-sensitive logistics, counterfeit detection, and waste minimization through expiry prediction and redistribution strategies (Aktürk, 2021). The retail and FMCG industries employ AI-enhanced ERP tools to forecast demand, prevent stockouts and overstocks, and support reusable packaging logistics. Circular business models such as product-as-a-service and refill stations depend on ERP systems that can track product usage, returns, and customer behavior in real-time. Even in the agricultural and food sectors, AI-ERP platforms support sustainable sourcing, waste valorization, and traceability from farm to fork. These use cases collectively highlight that the application of AI-enhanced ERP systems for circular and sustainable supply chains is not industry-specific but rather a universally relevant strategy (Li & Wu, 2021). By examining these cases through a meta-analytic and framework-driven approach, the research systematically evaluates the operationalization of AI-ERP platforms in achieving sustainability and circularity goals across global value chains (Dwivedi et al., 2024).

LITERATURE REVIEW

The intersection of Artificial Intelligence (AI), Enterprise Resource Planning (ERP) systems, and circular and sustainable supply chains (CSCs/SSCs) has emerged as a critical area of investigation in both academic research and industrial practice. As global industries strive to meet sustainability targets while maintaining operational efficiency, the integration of AI into ERP platforms has become essential for enabling data-driven, real-time decision-making across the supply chain. At the same time, circular economy models challenge traditional ERP structures, requiring adaptive technologies that can manage reverse logistics, life-cycle information, and regenerative material flows (Qureshi, 2022). Sustainable supply chain management, with its emphasis on environmental and social governance (ESG), adds further layers of complexity requiring multidimensional performance evaluation. Existing literature reflects substantial progress in the digital transformation of supply chains, including the diffusion of AI, cloud computing, and big data analytics within ERP environments. However, the specific role of AI in transforming ERP systems to serve circular and sustainability objectives remains under-researched and fragmented across disciplines (Alzahmi et al., 2024). A framework-based synthesis is required to consolidate existing findings, reveal interdependencies among technological, organizational, and environmental dimensions, and identify the structural patterns that contribute to successful implementation. This literature review builds the foundation for a meta-analytic framework by examining research from operations management, information systems, industrial engineering, sustainability science, and innovation studies. It draws from peer-reviewed journals, case study analyses, and technology reviews to map the evolving landscape. The structure of this section follows a logical progression from core concepts and historical developments to technical architectures, framework applications, and sector-specific insights (Mukherjee et al., 2024). The goal is to establish a comprehensive and integrative knowledge base that informs the analytical framework used in the meta-analysis.

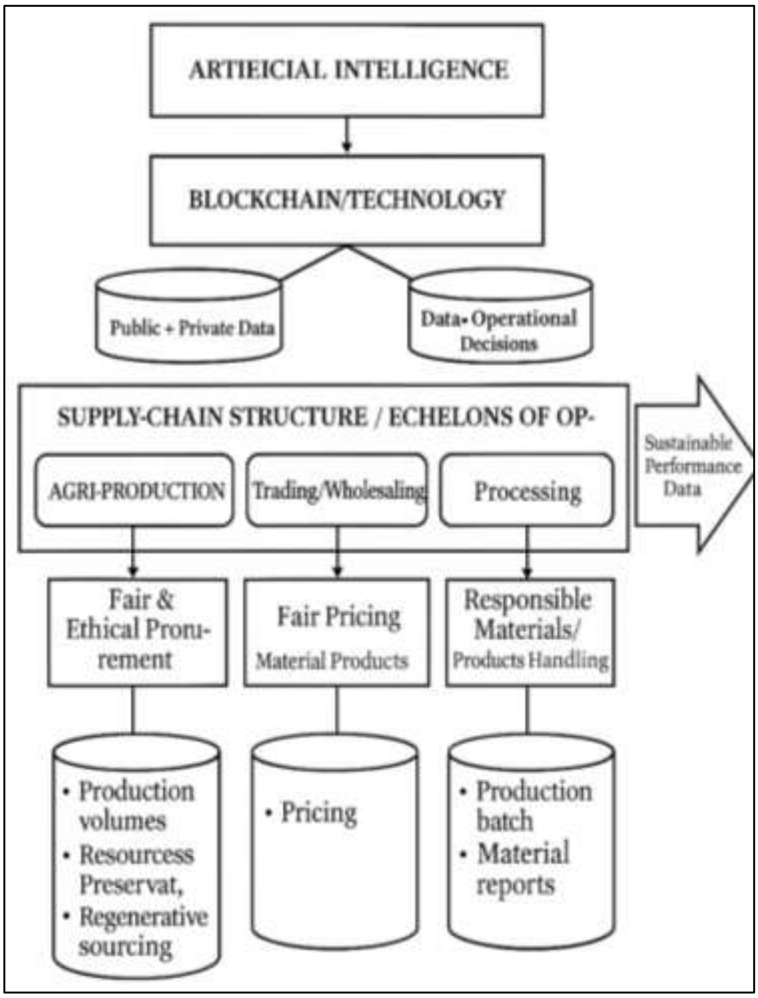
ERP Systems in Digital Supply Chain Management

The evolution of Enterprise Resource Planning (ERP) systems is rooted in the historical progression of information systems developed to manage manufacturing operations, beginning with Materials Requirements Planning (MRP) and later Manufacturing Resource Planning (MRP II). MRP, introduced in the 1960s, focused on inventory control and production scheduling by calculating raw material needs based on forecasts and bills of materials (Chen et al., 2022). MRP II expanded upon this by incorporating additional elements such as capacity planning and shop floor control, evolving into a more comprehensive production management tool. These early systems laid the groundwork for ERP by establishing the importance of integrated planning and coordination across business units. During the late 1980s and early 1990s, ERP systems emerged as enterprise-wide solutions that extended MRP II capabilities to encompass other organizational functions, including finance, human resources, and procurement. Legacy ERP implementations were primarily on-premises, customized to the specific workflows of large organizations such as SAP R/2 and Oracle Financials. These systems were highly structured and rigid, requiring substantial IT infrastructure and intensive deployment cycles. Nevertheless, ERP provided firms with the unprecedented ability to manage transactional data in real time, leading to operational efficiency and better decision-making (Lin & Chu, 2024; Subrato, 2018). The early iterations of ERP, however, were not without limitations. They often lacked cross-functional agility and could not readily adapt to changes in external environments, particularly in volatile supply chain contexts (Hosne Ara et al., 2022). Additionally, integration between modules and third-party systems was frequently problematic, limiting the scalability and responsiveness of ERP systems. These issues, coupled with the global expansion of supply chains, created a pressing need for more flexible, service-oriented ERP architectures (Uddin et al., 2022; Suresh et al., 2024). This evolution sets the foundation for understanding the rise of cloud-based ERP systems and the broader digital transformation of supply chain management.

The digital transformation of enterprise systems has significantly altered the structure, deployment, and capability of ERP systems, leading to the rise of cloud-based solutions that enable greater flexibility, scalability, and real-time data accessibility.

Unlike traditional on-premises ERP systems, cloud-based ERP solutions operate on distributed platforms and leverage the Internet to deliver services, reducing the need for local IT infrastructure and lowering total cost of ownership (Akter & Ahad, 2022; Singh et al., 2024). This transformation is driven by the convergence of cloud computing, mobile technologies, and real-time analytics, which have enabled organizations to adapt their ERP systems rapidly in response to dynamic supply chain demands. Cloud ERP systems offer several operational advantages over legacy systems, including lower deployment time, remote accessibility, seamless updates, and integration with external partners. They facilitate multi-tier coordination across global networks, allowing companies to manage suppliers, distributors, and logistics partners within a unified digital ecosystem (Daus & Ashraf, 2024; Rahaman, 2022). Studies have shown that cloud-based ERP enables more agile decision-making and responsiveness to disruptions, which are essential in modern supply chain environments characterized by uncertainty and complexity. Vendors such as SAP S/4HANA Cloud, Oracle NetSuite, and Microsoft Dynamics 365 exemplify this evolution, offering modular cloud-native platforms that support integrated operations and advanced analytics. Moreover, cloud ERP supports service-oriented architectures (SOA) and enables real-time data streaming, which enhances visibility and traceability across the supply chain (Hasan et al., 2022; Singh et al., 2024). These capabilities are particularly beneficial in collaborative environments involving multiple stakeholders and decentralized operations (Hossen & Atiqur, 2022). Nevertheless, challenges related to data security, compliance, and integration persist and must be addressed through robust governance models. The shift to cloud ERP represents not just a technological change but also a fundamental transformation in the way enterprises organize, execute, and monitor supply chain activities.

Figure 3: AI-Block chain Empowered Supply Chain

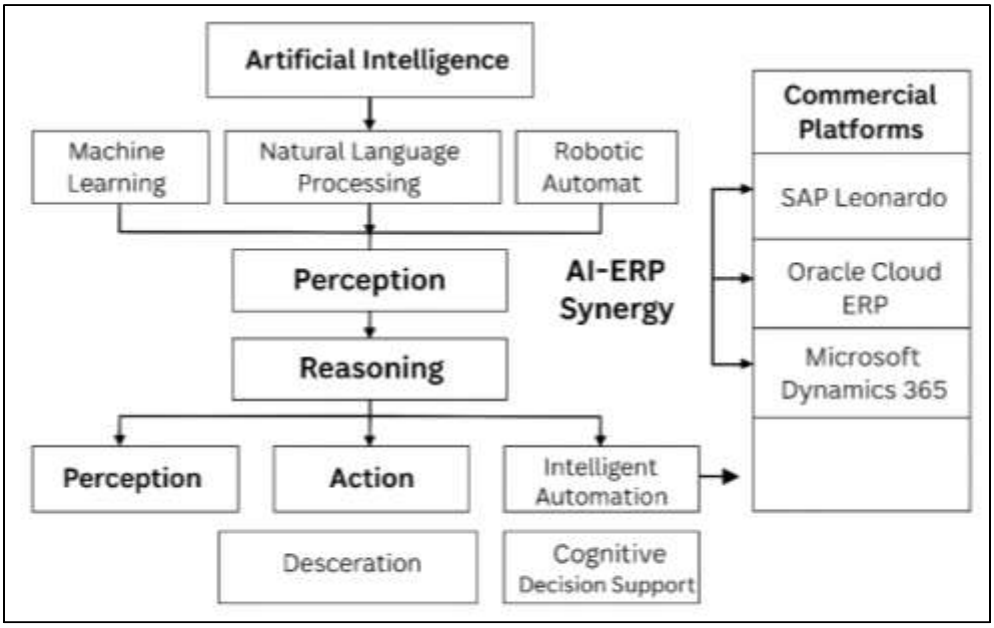


Despite their contributions to enterprise integration, traditional ERP systems have struggled to adapt to the complexity and fluidity of modern multi-tier supply chains. One of the central limitations is their rigidity—conventional ERP platforms are often configured around static business processes and hierarchical structures that fail to accommodate dynamic supply chain networks (Andrade et al., 2024; Tawfiqul et al., 2022). This rigidity impairs responsiveness to real-time events such as demand fluctuations, supplier disruptions, or logistics delays, which are increasingly common in globalized environments. Additionally, traditional ERP systems are primarily inward-looking, designed to optimize internal operations rather than coordinate external supply chain actors such as second- and third-tier suppliers, logistics providers, and recyclers (Sazzad & Islam, 2022). In complex supply chains, particularly those aligned with circular and sustainability goals, this lack of interoperability becomes a major bottleneck. For example, traditional ERP architectures typically do not support closed-loop feedback from post-consumer processes, nor do they accommodate real-time visibility into supplier sustainability metrics (Abdolazimi et al., 2024; Akter & Razzak, 2022). These constraints limit the ability to trace materials across extended life cycles or to optimize reverse logistics. Furthermore, legacy ERP systems often lack real-time data processing capabilities, which are critical for supporting just-in-time delivery, vendor-managed inventory, and disruption recovery. Batch processing and sequential data updates hinder decision-making in fast-paced supply chain environments. Integration with emerging digital technologies such as IoT, RFID, and blockchain is also limited in older ERP platforms due to compatibility issues and the absence of modular APIs. This lack of adaptability not only affects operational efficiency but also hampers compliance with increasingly stringent environmental and ethical sourcing regulations (Adar & Md, 2023; Majiwala & Kant, 2025). Collectively, these limitations underscore the necessity of AI-driven and cloud-native ERP systems that are better equipped for complex supply chain ecosystems.

Artificial Intelligence in ERP Environments

Artificial Intelligence (AI) encompasses a suite of computational techniques that enable machines to perform tasks requiring human-like cognition, such as learning, reasoning, and decision-making. In the context of Enterprise Resource Planning (ERP) systems, AI tools are deployed to enhance automation, analytics, and adaptability across business processes. The most prominent AI technologies used in ERP include Machine Learning (ML), Natural Language Processing (NLP), Robotic Process Automation (RPA), and Computer Vision. ML models are widely used for pattern recognition and predictive tasks such as demand forecasting, supplier evaluation, and fraud detection (Qibria & Hossen, 2023; Siemens et al., 2022). NLP enables the interpretation of unstructured data like emails, contracts, and user queries, facilitating more intuitive human-computer interaction within ERP platforms. Robotic Process Automation (RPA) supports the automation of repetitive and rules-based tasks in ERP modules such as payroll, invoicing, and order processing. Computer Vision, although less common in ERP, finds relevance in warehouse automation and quality control by enabling visual inspections and tracking (Akter, 2023; Trunk et al., 2020). The typology of AI in ERP systems can be categorized into three layers: perception (data acquisition and input interpretation), reasoning (decision rules and predictions), and action (automated execution and feedback loops). This layered architecture ensures that AI applications within ERP are not limited to data analytics but also support autonomous operations and adaptive planning. These AI technologies are increasingly integrated into ERP frameworks to address the need for dynamic responsiveness, real-time decision-making, and operational intelligence in modern supply chains (Jaboob et al., 2024; Hossen et al., 2023). The diversity and scalability of AI tools make them essential components in evolving ERP environments, especially as enterprises pursue circularity, sustainability, and digital competitiveness.

Figure 4: Artificial Intelligence in ERP Systems



The integration of AI into ERP systems fosters a powerful synergy that transforms static transactional platforms into dynamic, cognitive business ecosystems. This AI-ERP synergy primarily enhances data analytics, intelligent automation, and decision support. Traditional ERP systems are data-rich but insight-poor; AI bridges this gap by enabling real-time analytics, anomaly detection, and automated insights from vast volumes of structured and unstructured data (Shamima et al., 2023; Terziyan et al., 2018). Machine learning algorithms embedded within ERP platforms can analyze procurement patterns, customer behavior, and inventory fluctuations to enable proactive interventions. Intelligent automation in AI-ERP ecosystems reduces manual interventions and streamlines processes through capabilities like adaptive scheduling, smart alerts, and rule-based workflows. For instance, AI can dynamically prioritize procurement requests based on market volatility or vendor reliability, improving procurement efficiency and risk mitigation. In manufacturing modules, AI facilitates intelligent demand-driven production planning by adjusting parameters based on real-time sales and inventory levels. Cognitive decision support systems (CDSS) embedded in AI-ERP platforms use knowledge graphs, heuristics, and reinforcement learning to simulate outcomes and suggest optimal actions (Alijoyo et al., 2024; Ashraf & Ara, 2023). Such tools support managers in complex scenarios such as vendor negotiations, sustainability trade-offs, or supply disruptions. The synergy is further enhanced when ERP systems are linked with AI-powered chatbots and virtual assistants for user-friendly interaction and on-demand information retrieval. This cognitive fusion transforms ERP from a system of record into a system of intelligence capable of anticipating, advising, and adapting to rapidly changing conditions. Consequently, the AI-ERP synergy redefines enterprise computing by embedding smart analytics and automation across the entire value chain, making it a key enabler in competitive and sustainable supply chain transformation (Duan et al., 2019; Sanjai et al., 2023).

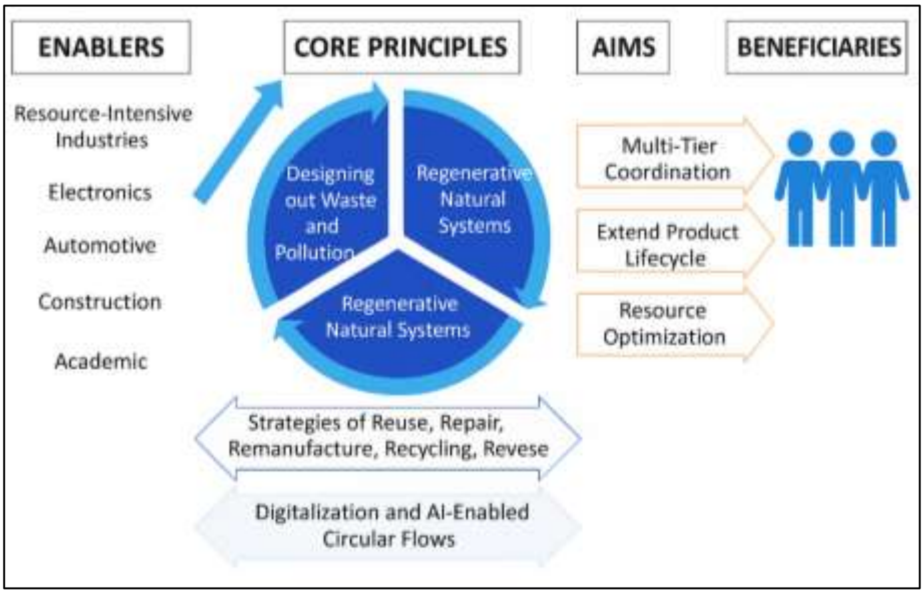
The application of AI within ERP environments is increasingly modular, with targeted integrations in finance, procurement, supply chain, and human capital management. One of the most widely adopted technical modules is predictive analytics, which enables future-oriented planning based on historical data patterns. Predictive algorithms can forecast product demand, identify high-risk suppliers, and estimate procurement lead times, thereby enhancing the agility and reliability of supply chains (Kühl et al., 2022; Akter et al., 2023). In production planning modules, AI optimizes material requirements planning (MRP) by simulating various production scenarios based on sales data and resource availability. Anomaly detection is another critical use case, particularly in financial ERP modules. AI algorithms identify irregularities in transactions, invoice records, and general ledger entries, aiding in fraud prevention and compliance auditing. In logistics and warehouse modules, AI supports route optimization and inventory replenishment through reinforcement learning models that adapt based on cost, time, and environmental constraints. For customer relationship and order management modules, AI tools analyze customer feedback, returns data, and delivery performance to enhance service quality and retention (Sheth et al., 2023; Tonmoy & Arifur, 2023). Other technical implementations include AI-based recommendation engines in procurement, which suggest suppliers or contracts based on cost, sustainability metrics, and historical performance. In HR modules, AI supports talent acquisition, performance forecasting, and attrition risk analysis by mining historical employee data (Chen et al., 2020; Zahir et al., 2023). These modular applications are supported through microservices architectures, ensuring interoperability, scalability, and ease of deployment across cloud-native ERP platforms. The modular deployment of AI in ERP allows organizations to adopt use-case-specific innovations without overhauling the entire system. This granularity enhances flexibility and enables continuous improvement in targeted areas, thereby supporting both operational efficiency and strategic decision-making across the enterprise.

The commercial landscape of ERP systems has rapidly evolved to incorporate artificial intelligence, with major vendors offering AI-driven capabilities as part of their core platforms or through specialized add-ons. SAP Leonardo, for example, integrates machine learning, IoT, and blockchain technologies into the SAP S/4HANA platform to support predictive analytics, smart maintenance, and digital supply chains (Abdullah Al et al., 2024; Hassani et al., 2020). Similarly, Oracle Cloud ERP embeds AI features for real-time financial analysis, digital assistants for procurement, and intelligent document recognition for invoice processing. Microsoft Dynamics 365 leverages Azure AI services to deliver insights in customer engagement, field service optimization, and fraud protection in financial transactions (Razzak et al., 2024; Enholm et al., 2022). These platforms exemplify the trend of embedding AI natively into ERP systems, moving beyond bolt-on analytics toward deeply integrated cognitive services. Commercial ERP vendors are also emphasizing AI as a service (AIaaS), enabling organizations to selectively subscribe to machine learning models, NLP engines, or computer vision modules based on their needs. This pay-as-you-use model enhances accessibility for small and medium enterprises (SMEs), democratizing AI adoption in ERP contexts. Innovation trends also include low-code and no-code AI customization, allowing business users to train models or build predictive dashboards without programming knowledge. Additionally, AI-enabled mobile ERP apps and voice-command interfaces are being developed to support decision-making on the go, reflecting a shift toward user-centric design (Gholami, 2024). Commercial platforms are further integrating sustainability tracking modules powered by AI to align ERP data with ESG metrics and compliance standards. The competitive dynamics among ERP vendors are accelerating innovation, with continuous releases of AI features targeted at specific industries and compliance environments (Jahan & Imtiaz, 2024; Elahi et al., 2023). This commercial evolution illustrates the central role of AI in redefining ERP functionality and market differentiation, as firms prioritize intelligent automation and sustainability performance within digital enterprise frameworks.

Circular Economy Principles and Supply Chain Reconfiguration

The Circular Economy (CE) represents a systemic approach to economic development designed to benefit businesses, society, and the environment by transitioning from linear "take-make-dispose" models to restorative and regenerative systems.

Figure 5: Circular Economy Implementation Framework Overview



CE emphasizes maintaining the value of products, materials, and resources in the economy for as long as possible by minimizing waste and resource inputs. Unlike sustainability, which is often broad and normative, CE operationalizes environmental responsibility through practical strategies like resource cycling, product life extension, and waste valorization (Grigsby, 2018; Mansura Akter & Shaiful, 2024). It is structured around three primary principles: designing out waste and pollution, keeping products and materials in use, and regenerating natural systems. These principles translate into actionable dimensions such as product design for disassembly, modular production, closed-loop systems, material tracking, and stakeholder collaboration. The CE is particularly relevant in sectors like electronics, automotive, construction, and textiles, where resource intensity and end-of-life challenges are significant. It also incorporates social dimensions such as extended producer responsibility, consumer behavior, and inclusive employment through repair and refurbishment industries. From a supply chain perspective, CE challenges conventional value chains by requiring multi-tier coordination across both forward and reverse flows. This demands real-time traceability, feedback mechanisms, and adaptability—capabilities that are not fully supported by traditional ERP systems (Fofou et al., 2021; Subrato & Md, 2024). The implementation of CE principles thus necessitates not only technical innovation but also reconfiguration of value creation logics and inter-organizational collaborations. As organizations embed CE thinking into supply chain management, the role of digital infrastructure becomes increasingly critical in enabling transparent and responsive operations.

Circular Economy implementation within supply chains relies on a spectrum of recovery and value-retention strategies that include reuse, repair, remanufacture, recycling, and reverse logistics. These strategies form the backbone of circular flows and are designed to extend product life, conserve materials, and reduce environmental impact. Reuse involves the repeated utilization of products or components without significant modification, while repair restores functionality by replacing damaged parts (Cole et al., 2018; Arafat et al., 2025; Akter et al., 2024). Remanufacturing involves disassembling and rebuilding products to original specifications, often with a warranty equivalent to new goods. Recycling, though least preferable in the value hierarchy, transforms materials into raw inputs for new production cycles. Reverse logistics serves as the operational backbone of these strategies by enabling the backward movement of goods, components, and materials from the consumer to the manufacturer or recycling facility. Efficient reverse logistics systems must accommodate collection, inspection, reprocessing, and redistribution, requiring robust coordination mechanisms and real-time visibility. However, supply chains traditionally optimized for one-way flows are poorly equipped for these tasks, necessitating redesign and digital augmentation (Julianelli et al., 2020; Islam & Debashish, 2025). The successful deployment of circular strategies also depends on lifecycle data, modular product design, and cross-sectoral partnerships. Companies like Caterpillar and Renault have institutionalized remanufacturing as part of their business model, demonstrating economic and environmental viability (Islam & Ishtiaque, 2025; Ren et al., 2023). However, the operationalization of these strategies at scale requires intelligent systems capable of forecasting return volumes, evaluating product conditions, and optimizing reprocessing schedules. In this regard, the fusion of ERP with AI-enabled analytics and IoT-based tracking is increasingly seen as a critical enabler of efficient, scalable reverse operations.

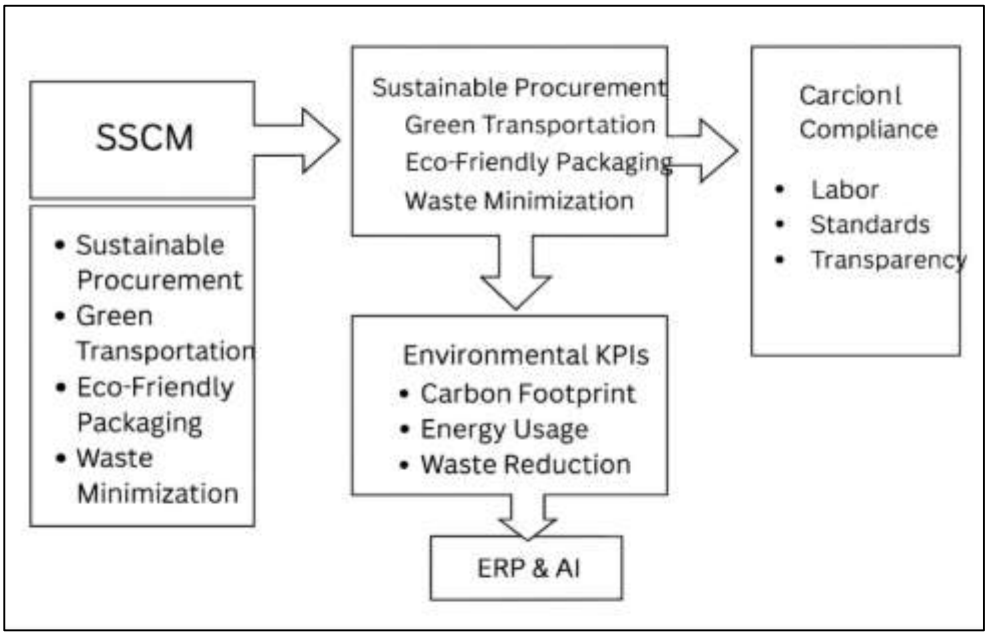
Closed-loop supply chain (CLSC) models represent a structural reconfiguration of traditional supply chains to integrate both forward logistics and reverse flows, enabling the systematic reuse, remanufacture, or recycling of products and materials. These models are central to Circular Economy implementation, supporting resource efficiency, regulatory compliance, and lifecycle optimization. A CLSC includes not only the planning and execution of product delivery to customers but also the retrieval of used products and materials, their assessment, and their reintegration into the production cycle (Hossen et al., 2025; Ren et al., 2023). Despite their theoretical appeal, the deployment of CLSCs presents considerable logistical and informational challenges. One major constraint is the lack of system-wide visibility and integration in traditional ERP platforms. Most legacy ERP systems are configured for linear flows and cannot handle the multi-directional, conditional pathways involved in return logistics, refurbishment, or recycling. They often lack functionalities for tracking the origin, condition, and disposition of returned products, which are essential for effective decision-making in CLSCs. Moreover, conventional ERP modules are not designed to handle the probabilistic nature of reverse flows, such as variable quality, uncertain return timing, and inconsistent volumes (Sanjai et al., 2025; Wilson & Goffnett, 2022). Another limitation is the absence of real-time analytics and process automation capabilities, which are necessary for managing complex circular operations. For example, real-time data on part wear, customer usage, or environmental exposure is rarely captured or utilized in traditional ERP environments. As a result, CLSC operations are often manually managed or supported by disparate systems, leading to inefficiencies and suboptimal recovery outcomes. These challenges underscore the need for next-generation ERP systems embedded with AI, IoT, and interoperability features that can support closed-loop decision-making and value retention activities (Pacheco et al., 2018; Sanjai et al., 2025).

The transition to circular supply chains is increasingly being enabled by digitalization and artificial intelligence (AI), which together create the infrastructural backbone for real-time data collection, process optimization, and stakeholder collaboration. Digital technologies such as the Internet of Things (IoT), blockchain, and AI algorithms provide the visibility, traceability, and intelligence required to operationalize circular flows (Brito et al., 2022; Sazzad, 2025a). IoT sensors can monitor product usage, wear-and-tear, and location, enabling condition-based returns and predictive remanufacturing. Blockchain platforms ensure data integrity and provenance tracking, which are critical for material certification, warranty validation, and regulatory compliance. AI plays a central role by interpreting data generated across the product lifecycle and automating decision-making in areas such as return prioritization, sorting, and disassembly planning. Machine learning models can predict product return volumes, assess component quality, and identify optimal routing paths in reverse logistics (Abbey & Guide Jr, 2018; Sazzad, 2025b). These capabilities reduce uncertainty and increase the efficiency of resource recovery operations, directly supporting the principles of reuse and regeneration in circular systems. Moreover, AI-enabled ERP systems serve as digital command centers by integrating lifecycle data, environmental indicators, and operational metrics into unified dashboards. These systems provide decision support for inventory optimization, refurbish-or-replace assessments, and carbon footprint analysis. Companies such as Philips and HP have successfully used AI and digital tools to enable product-as-a-service models and closed-loop manufacturing, demonstrating the commercial viability of digitalized circular supply chains. The convergence of AI and ERP in enabling circular flows marks a paradigm shift from reactive supply chain management to proactive lifecycle orchestration. It facilitates collaboration across suppliers, customers, and recyclers, ensuring that value is preserved and regenerated at every stage of the supply chain (Aryee et al., 2024; Shaiful & Akter, 2025).

Sustainable Supply Chain Management and ESG Integration

Sustainable supply chain management (SSCM) is grounded in the Triple Bottom Line (TBL) framework, which emphasizes the simultaneous pursuit of economic performance, environmental stewardship, and social equity (Awan & Ali, 2019; Subrato, 2025). This multidimensional model has reshaped conventional supply chain thinking, prompting organizations to optimize not only cost and efficiency but also carbon emissions, labor welfare, and resource regeneration. TBL-aligned logistics involve sustainable procurement, green transportation, eco-friendly packaging, and waste-minimizing inventory strategies. These strategies create synergies between operational resilience and sustainability performance by minimizing risks associated with regulatory compliance, reputational damage, and resource scarcity. The logistics domain, traditionally driven by efficiency, now integrates sustainable objectives through consolidated shipments, route optimization, modal shifts, and electric or low-emission vehicles. Green logistics practices are supported by closed-loop systems, which enhance material circularity while reducing environmental externalities (Mahadevan, 2019; Subrato & Faria, 2025). Moreover, sustainable warehousing practices such as energy-efficient lighting, zero-waste targets, and carbon-neutral infrastructure are becoming integral to logistics management.

Figure 6: Circular Economy Implementation Framework Overview



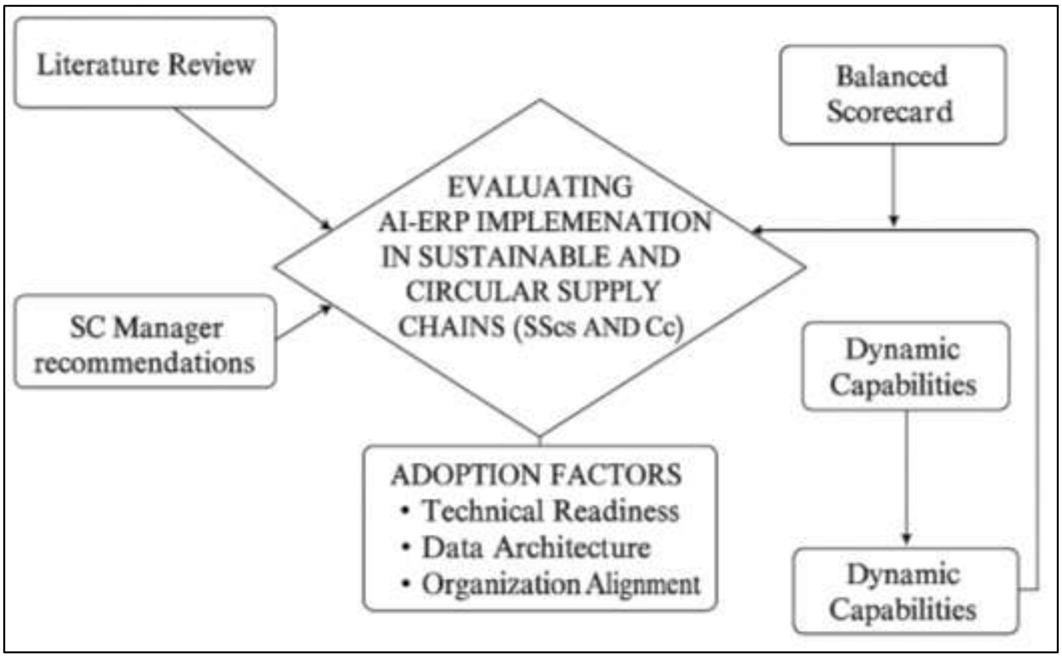
Digital transformation plays a significant role in enabling TBL-aligned logistics. Real-time monitoring systems, predictive analytics, and IoT-enabled tracking are being employed to optimize transport routes, reduce idle time, and measure energy consumption. ERP systems integrated with sustainability modules facilitate the harmonization of TBL metrics by embedding green indicators into core processes such as procurement, production planning, and delivery (Akter, 2025; Uriarte-Miranda et al., 2018). As supply chains evolve into complex, multi-stakeholder ecosystems, the TBL framework remains a guiding structure for aligning logistics performance with broader societal and ecological goals. Environmental performance in sustainable supply chains is typically measured using key performance indicators (KPIs) such as carbon footprint, energy consumption, and waste reduction. These metrics allow organizations to evaluate and control their environmental impacts across sourcing, production, logistics, and distribution processes. Carbon footprint analysis quantifies the greenhouse gas emissions associated with activities like raw material extraction, transportation, and facility operations (Marić & Opazo-Basáez, 2019; Zahir et al., 2025). Monitoring energy usage involves tracking electricity, fuel, and thermal energy inputs, enabling firms to identify energy-intensive stages and invest in renewable alternatives. Waste reduction KPIs focus on minimizing scrap, packaging waste, defective units, and excess inventory, contributing directly to cost savings and environmental sustainability. These indicators are vital for regulatory compliance under frameworks such as ISO 14001 and the EU Green Deal, and they also inform corporate ESG disclosures (Nunes, 2025; Zahir et al., 2025). Many organizations employ Life Cycle Assessment (LCA) methodologies to integrate environmental KPIs across the entire product lifecycle, from cradle to grave. Digital systems such as ERP platforms play an essential role in aggregating and reporting these metrics. Modern ERP systems embedded with AI capabilities can extract environmental data from sensor-enabled assets, production lines, and transport networks, allowing for near real-time analysis of emission hotspots or energy spikes. Predictive analytics can also be used to simulate the environmental impacts of alternative sourcing or routing decisions, offering scenario-based sustainability optimization (Ahmadi et al., 2024). Studies have shown that companies with integrated environmental KPI tracking systems demonstrate higher levels of operational agility, transparency, and stakeholder trust.

Enterprise Resource Planning systems, when augmented with Artificial Intelligence (AI), serve as vital tools for sustainability auditing and Life Cycle Assessment (LCA**)** reporting. These applications facilitate structured environmental and social data management across supply chain functions, enabling accurate disclosures and compliance with sustainability frameworks such as the Global Reporting Initiative (GRI), CDP, and the Sustainability Accounting Standards Board (SASB). Traditional ERP systems provide transactional data, but AI integration enhances their capability to extract, normalize, and interpret sustainability indicators from disparate sources (Ali et al., 2021). AI-enabled ERP platforms support automated data collection from IoT sensors, smart meters, and RFID systems, enabling granular tracking of emissions, water usage, and material consumption in real time. Natural language processing tools are applied to sustainability reports, supplier documentation, and audit forms to classify and extract ESG-related content. Additionally, predictive models can identify potential compliance risks, forecast ESG performance, and simulate the effects of policy changes on sustainability outcomes. LCA reporting is increasingly being digitized through ERP modules that consolidate data across sourcing, production, distribution, and end-of-life stages. These platforms facilitate scope 1, 2, and 3 emissions calculations and enable scenario-based analysis for supply chain redesign (Liao, 2018). Moreover, intelligent dashboards provide real-time visualizations of sustainability KPIs, allowing executives to align operational decisions with environmental and social targets. Several commercial platforms now offer integrated sustainability auditing features within their ERP suites—for example, SAP's Environment, Health and Safety Management (EHS), and Oracle's ESG Analytics add-ons. These tools transform sustainability auditing from a periodic, manual task into a continuous, data-driven process embedded in daily operations. The strategic deployment of ERP and AI in this domain reinforces organizational accountability and fosters a culture of evidence-based sustainability management (Alkahtani et al., 2021).

AI-ERP Implementation in SSCs and CSCs

Evaluating AI-ERP implementation in sustainable and circular supply chains (SSCs and CSCs) requires a robust conceptual foundation, which has been supported by several dominant frameworks in information systems and strategic management literature. The Technology-Organization-Environment (TOE) framework is one of the most frequently employed models to assess technological innovation adoption. It evaluates adoption through three contexts: technological (e.g., system complexity), organizational (e.g., firm size, leadership), and environmental (e.g., competition, regulation) (Mishra et al., 2022). The TOE framework has been extensively applied to understand ERP and AI adoption in supply chains, highlighting factors such as system compatibility, IT infrastructure, and external pressures. The Resource-Based View (RBV) emphasizes firm-specific assets—both tangible and intangible—as the basis for competitive advantage. In AI-ERP contexts, critical resources include data quality, IT capabilities, skilled workforce, and interdepartmental knowledge sharing. Studies applying RBV to ERP adoption have identified that data integration and analytics capability are essential for realizing value from intelligent ERP systems. The Balanced Scorecard (BSC) framework adds a multi-dimensional performance lens by incorporating financial, customer, internal process, and learning perspectives (Banihashemi et al., 2019). BSC has been adapted to measure sustainability performance in ERP implementations by integrating environmental and social dimensions into ERP KPIs. Lastly, the Dynamic Capabilities (DC) framework focuses on an organization's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments. This is particularly relevant in AI-ERP-enabled SSCs and CSCs, where responsiveness to regulatory shifts and stakeholder expectations is critical. These frameworks collectively offer complementary insights and have been used as foundations for empirical and theoretical research in digital transformation and sustainable operations.

Figure 7: AI-ERP Evaluation in Circular Supply chains



The successful implementation of AI-ERP systems in sustainable and circular supply chains hinges on several adoption factors, prominently including technical readiness, data architecture, and organizational alignment. Technical readiness reflects an organization's capacity in terms of IT infrastructure, integration capability, and digital literacy (Zhang et al., 2021). Studies have shown that AI-ERP platforms demand scalable cloud-based infrastructures, real-time data processing engines, and sensor-network compatibility to function effectively in dynamic supply chains. Organizations lacking such foundations face significant challenges in deploying AI modules for real-time sustainability monitoring or predictive analytics. Data architecture is another critical enabler, especially for systems that rely on multi-source data for life cycle assessment (LCA), supplier performance tracking, and carbon accounting (Weissgerber et al., 2021). A robust architecture includes data standardization protocols, centralized repositories, and API-based interoperability that allow for seamless information exchange between ERP modules, IoT devices, and external platforms (Santana et al., 2021). Poor data quality or siloed systems can undermine AI effectiveness, leading to flawed decision-making and non-compliance with sustainability standards. Equally important is organizational alignment, which involves leadership commitment, cross-functional collaboration, and cultural readiness for digital transformation. Without alignment between sustainability goals and ERP functionality, even technically advanced systems may fail to deliver environmental or circularity benefits. Training, change management programs, and interdepartmental governance mechanisms are necessary to translate AI-ERP potential into measurable sustainability outcomes (Dabees et al., 2024). Furthermore, organizational incentives tied to sustainability KPIs can facilitate ERP-user engagement and sustainability reporting consistency. These adoption factors must be evaluated holistically, as they determine the implementation trajectory and long-term performance of AI-driven ERP systems (Feitosa et al., 2020).

An emerging body of literature synthesizes these conceptual frameworks to build comprehensive models for assessing ERP and AI adoption in sustainable supply chains. Such framework-based syntheses typically combine structural, strategic, and behavioral variables to capture the multi-dimensionality of digital transformation for sustainability (Dabees et al., 2024). For example, several studies integrate the TOE and RBV frameworks to examine how external pressures and internal capabilities jointly influence ERP-enabled environmental performance. Others merge RBV with Dynamic Capabilities Theory to highlight how firms leverage their IT assets dynamically to sense, seize, and reconfigure sustainability opportunities. In sustainability-focused ERP studies, the Balanced Scorecard has been customized to include green performance metrics such as emissions intensity, resource circularity, and stakeholder trust. These BSC variants help organizations map ERP adoption outcomes across economic, environmental, and social dimensions—enabling longitudinal performance evaluations. Several researchers also employ hybrid models combining BSC with TOE to link sustainability strategy implementation to ERP functionality and adoption environments (Luetz & Walid, 2019). Recent studies have applied these frameworks empirically using structural equation modeling (SEM), case study triangulation, and multi-criteria decision analysis (MCDA) to evaluate AI-ERP integration success. This synthesis approach supports evidence-based decision-making by identifying the contextual variables that most significantly influence sustainability performance, whether technological (e.g., AI maturity), organizational (e.g., training programs), or environmental (e.g., regulation). As the literature matures, a more integrated and theory-driven understanding of AI-ERP implementation in SSCs and CSCs continues to take shape (Marx, 2025).

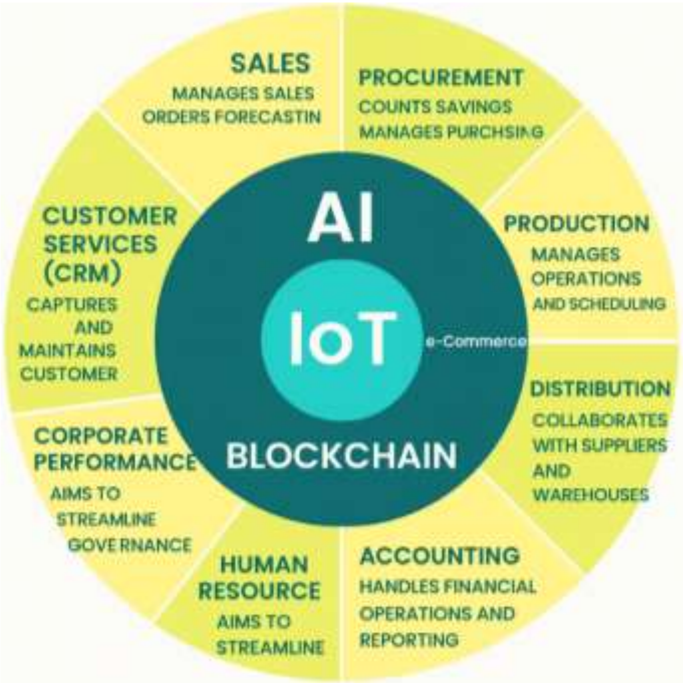
Given the complex interplay of technologies, organizational structures, and sustainability imperatives, a meta-analytical framework is essential to systematically evaluate AI-ERP implementation across circular and sustainable supply chains. Meta-analysis enables the integration of heterogeneous findings from diverse empirical studies, offering generalized insights while controlling for contextual variation (Belli et al., 2022). It allows researchers to identify statistically significant patterns and relationships that may not be visible in isolated studies, thus providing a higher level of analytical rigor. Justifying such a framework involves recognizing that AI-ERP implementation is influenced by multifactorial conditions—technological readiness, stakeholder alignment, data interoperability, and regulatory context—which interact in non-linear ways. A meta-analytical approach grounded in frameworks like TOE, RBV, and BSC offers the scaffolding to categorize these factors systematically and measure their impact strength across case variations (Smith et al., 2023). Moreover, meta-analysis supports **cross-**sectoral benchmarking, enabling comparisons across industries such as automotive, retail, and healthcare in terms of AI-ERP impact on circularity and ESG performance. This analytical model is especially justified for emerging fields like AI-driven sustainability, where evidence is fragmented and conceptual boundaries are fluid. By employing coded variables and effect size calculations, meta-analysis can offer insights into best practices, failure points, and performance trends across implementation contexts (Khan & Gupta, 2024). Furthermore, integrating dynamic capabilities and BSC perspectives into the meta-framework enables the assessment of both short-term operational outcomes and long-term strategic impacts. Therefore, the use of a framework-based meta-analytical approach is not only appropriate but also essential for advancing theory and informing practice in the digitalization of sustainable and circular supply chains (Jia et al., 2024).

Technological Architecture in AI-Driven ERP

Enterprise Resource Planning (ERP) systems have evolved from monolithic applications to modular platforms, enabling organizations to selectively implement and integrate functional components such as finance, procurement, production, logistics, and human capital management (Zavala et al., 2022).

This modular architecture is essential for incorporating Artificial Intelligence (AI) models into ERP environments, as it supports scalability, flexibility, and independent updates across system layers. AI integration into ERP modules enables intelligent decision-making in areas such as demand forecasting, fraud detection, dynamic pricing, and supply chain optimization. AI model integration occurs at multiple levels—ranging from embedded algorithms within ERP dashboards to externally trained models accessed via APIs or AI-as-a-Service (Mantravadi et al., 2023). Machine learning tools are particularly prevalent in modules that rely on historical data, such as predictive maintenance in manufacturing or risk scoring in procurement. Natural Language Processing (NLP) models have been adopted in service desk modules to automate ticket classification, enhance chatbot performance, and enable semantic search. The integration of AI into modular ERP structures also enables hybrid intelligence workflows, where AI suggestions are reviewed by human users before action, enhancing transparency and accountability. ERP vendors such as SAP and Oracle are now embedding AI modules directly into platforms like SAP S/4HANA and Oracle Fusion Cloud ERP, supporting native analytics and prescriptive guidance (Lynda & Brahim, 2024). Modularity facilitates plug-and-play AI adoption while minimizing disruption, making it a strategic enabler for firms aiming to align intelligent ERP functions with sustainability and circular economy objectives.

Figure 8: Integrated ERP Modules with AI, IoT, and Blockchain



Modern ERP ecosystems are increasingly built on cloud-native architectures that rely on middleware and Application Programming Interfaces (APIs) for inter-system operability and scalability. Traditional ERP systems were tightly coupled, often leading to vendor lock-in and inflexible workflows. In contrast, cloud-native ERP platforms utilize microservices architecture, containerization, and continuous deployment frameworks to support modular, agile, and distributed computing environments. Middleware solutions act as a communication layer between disparate ERP modules, legacy systems, and AI engines, allowing for seamless data exchange and function orchestration. APIs are central to this architecture, enabling the connection of AI algorithms, analytics dashboards, and third-party applications with core ERP functionalities (Möller, 2023). RESTful and GraphQL APIs are now widely used to integrate AI-based services such as recommendation engines, real-time risk monitoring, and image recognition tools into ERP systems. Middleware platforms like MuleSoft and Dell Boomi have become common in enterprise settings to manage these integrations securely and efficiently. The shift to cloud-native ERP platforms also enhances system elasticity, allowing organizations to scale resources dynamically based on demand. This elasticity is crucial for AI workloads, which are computationally intensive and often require burst capacity for training or inferencing tasks. Vendors such as SAP, Oracle, and Microsoft have fully migrated ERP solutions to the cloud, enabling AI microservices to run independently yet cooperatively within the broader ecosystem (Scheer, 2023). Cloud-native ERP architectures equipped with middleware and APIs not only support AI model deployment but also facilitate interoperability with IoT, blockchain, and sustainability platforms, making them indispensable for next-generation supply chains and circular operations.

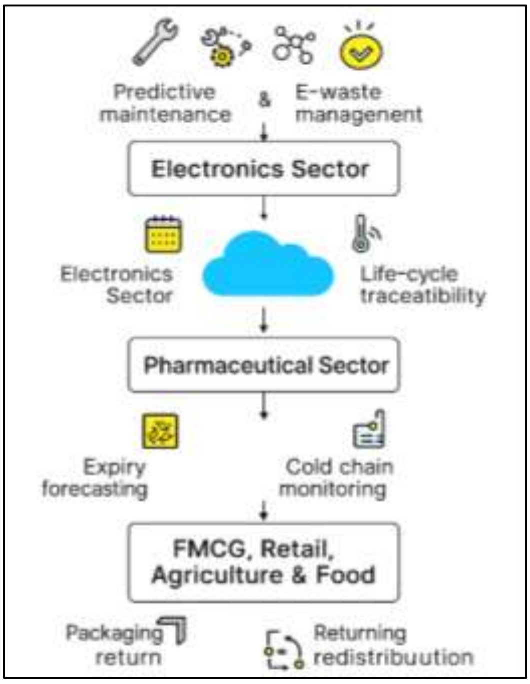
Traceability is a critical requirement in sustainable and circular supply chains, and its effectiveness is significantly enhanced by the integration of ERP systems with technologies such as the Internet of Things (IoT), Radio Frequency Identification (RFID), and blockchain. IoT-enabled devices provide real-time data on the condition, location, and status of assets across supply chain nodes, supporting visibility and proactive decision-making. When integrated with ERP platforms, IoT sensors facilitate automated updates in inventory management, equipment maintenance, and logistics tracking (Bagnoli et al., 2022). RFID systems further enhance ERP traceability by enabling item-level identification and status monitoring. These tags are commonly used in warehouse modules to monitor stock levels, expiration dates, and transit temperatures—particularly in pharmaceutical, food, and perishable goods industries. ERP systems integrated with RFID readers can automatically record movement across locations, update ledger entries, and initiate replenishment requests based on predefined thresholds. Blockchain adds a layer of immutable record-keeping and trust to ERP systems, especially for tracing material origins, certifying sustainability claims, and auditing supplier compliance (Vrchota et al., 2020). Smart contracts embedded within blockchain networks can automate warranty validations, regulatory reporting, and ESG verifications in ERP procurement and production modules. Integrated ERP-blockchain solutions are particularly beneficial in closed-loop and ethical supply chains where accountability, transparency, and traceability are legally and ethically mandated. By combining IoT, RFID, and blockchain technologies, ERP systems evolve into end-to-end traceability platforms, enabling real-time feedback loops, lifecycle assessments, and sustainable process redesigns. These integrations are essential for organizations operating in highly regulated, sustainability-sensitive sectors aiming for digital resilience and circularity (Möller, 2023b).

As ERP systems increasingly integrate AI capabilities and connect with IoT, blockchain, and cloud-based ecosystems, concerns around cybersecurity, data integrity, and infrastructure scalability have become central to ERP architecture. The high interconnectivity of modern ERP platforms introduces vulnerabilities such as unauthorized access, data breaches, and malware injection, especially in multi-tenant cloud environments. These risks are compounded when integrating external AI APIs or third-party analytics engines, which may lack standardized security protocols. Ensuring data integrity within AI-driven ERP systems is crucial because AI models are highly sensitive to data anomalies, missing values, and adversarial manipulation (Banks-Grasedyck et al., 2022). Poor data quality can lead to erroneous forecasts, biased decisions, and regulatory non-compliance—especially in ESG and LCA reporting modules. Therefore, ERP platforms now incorporate blockchain layers, digital signatures, and validation mechanisms to maintain a tamper-proof audit trail of transactions and data changes. Scalability is another critical dimension, particularly for AI-driven functionalities such as deep learning models and real-time sensor analytics that demand high computational power and low-latency infrastructure. Cloud-based ERP architectures offer horizontal and vertical scalability through elastic computing and distributed storage, enabling enterprises to adapt to fluctuating workloads (Schnitzhofer, 2023). Platforms like AWS, Microsoft Azure, and Google Cloud have built-in security compliance and redundancy features that support secure, scalable ERP deployment. To address these concerns, enterprise architects increasingly employ cybersecurity frameworks such as ISO/IEC 27001, Zero Trust Architecture (ZTA), and Secure Access Service Edge (SASE) to safeguard ERP ecosystems (Yalcinkaya et al., 2020). As AI, sustainability, and regulatory pressures converge, securing ERP systems while ensuring their data integrity and scalability is not only a technical imperative but a foundational requirement for digital trust and operational continuity.

Sector-Specific Applications of AI-ERP

The automotive sector has been a forerunner in the adoption of AI-enhanced ERP systems to support circular economy principles, particularly through predictive maintenance and remanufacturing tracking. Predictive maintenance uses real-time sensor data and machine learning algorithms to anticipate equipment failures and schedule servicing before breakdowns occur. This reduces unscheduled downtimes, extends machinery life, and minimizes the consumption of spare parts, aligning with circular goals of resource efficiency and waste minimization (Jensen, 2025a). ERP systems integrated with predictive analytics modules enable manufacturers like BMW and Toyota to automate maintenance workflows and optimize asset utilization across global manufacturing plants. Equally transformative is AI-driven ERP functionality in remanufacturing tracking, where ERP systems manage the flow of used automotive components through inspection, disassembly, refurbishing, and reassembly stages. Integrated AI tools support condition-based classification of returned parts and assist in determining the economic viability of remanufacturing versus recycling. Blockchain-enabled ERP platforms offer immutable records of part histories, warranties, and certifications, increasing trust and traceability in remanufactured components (Turskis & Šniokienė, 2024). Furthermore, ERP systems support compliance with environmental and product stewardship regulations such as ELV (End-of-Life Vehicle Directive), which mandates sustainable vehicle disassembly and component reuse in the EU. AI-integrated ERP systems automate regulatory reporting, generate recovery efficiency metrics, and support data-driven decisions on take-back schemes and part valorization. Overall, the automotive sector exemplifies how AI-ERP platforms enable circularity at scale by coordinating digital traceability, predictive analytics, and remanufacturing intelligence within a single ecosystem.

Figure 9: AI-ERP Integration for Circular Sustainability



The electronics industry, characterized by short product lifespans and rapid technological obsolescence, faces significant sustainability challenges. ERP systems integrated with AI are increasingly deployed to manage e-waste, improve product life-cycle traceability, and support regulatory compliance across global supply chains (Magrini et al., 2021). E-waste is a critical issue due to the presence of toxic materials and the complexity of component recovery. AI-powered ERP systems enable firms to monitor the flow of electronic goods from production to disposal, facilitating data-driven decisions on take-back logistics, disassembly, and component recovery. Product life-cycle traceability is enhanced through IoT and RFID integration within ERP platforms, allowing real-time tracking of devices across supply chain nodes, from manufacturing to consumption and return (Jensen, 2025b). These data streams feed AI algorithms that estimate product condition, usage patterns, and return likelihoods, aiding reverse logistics planning and optimizing resource recovery. Additionally, blockchain-based ERP systems enable secure recording of origin, repair history, and materials composition, crucial for extended producer responsibility and certification processes. Companies such as Dell and HP have leveraged ERP-integrated AI to drive circular initiatives such as closed-loop recycling of plastics and modular device design for easy disassembly. Compliance with WEEE (Waste Electrical and Electronic Equipment Directive) and RoHS (Restriction of Hazardous Substances) regulations is also facilitated through automated tracking and reporting features in modern ERP platforms (Polenghi et al., 2021). As the demand for sustainable electronics grows, the integration of AI with ERP systems plays a pivotal role in transforming linear production models into circular supply chains supported by transparency, intelligence, and lifecycle accountability.

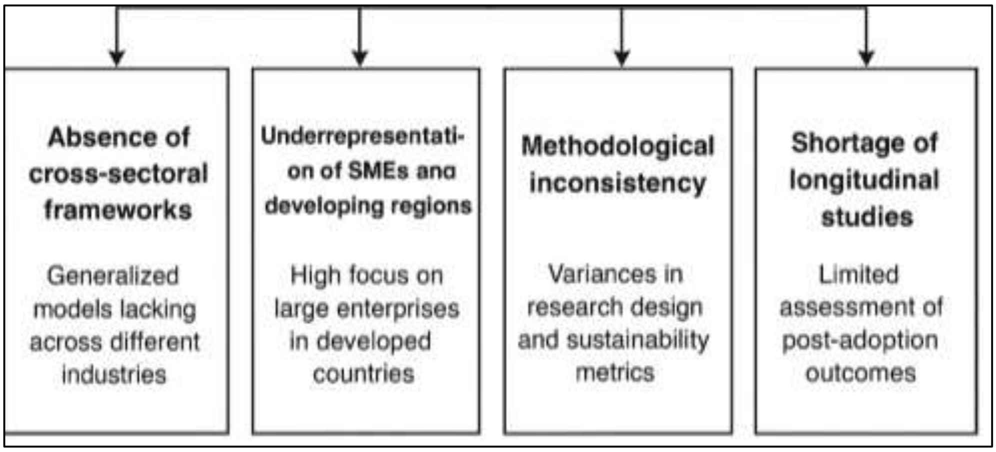
In the pharmaceutical sector, AI-integrated ERP systems contribute significantly to circularity and sustainability through expiry forecasting and cold chain monitoring. Pharmaceuticals are highly sensitive to time, temperature, and humidity; thus, minimizing waste and ensuring product integrity are critical for both environmental and public health reasons. Expiry forecasting utilizes machine learning algorithms embedded in ERP systems to analyze historical demand patterns, stock turnover rates, and storage conditions to predict and prevent overstocking and product expiration (Acerbi et al., 2021). These AI tools support dynamic inventory optimization by suggesting redistribution of near-expiry drugs to high-demand regions or donation to health networks, thereby reducing landfill disposal and improving access to medication. ERP systems also facilitate regulatory compliance with FDA and WHO guidelines by maintaining traceable records of batch numbers, manufacturing dates, and expiration timelines. Cold chain monitoring is another crucial application, as temperature excursions during transport or storage can degrade product quality. IoT-enabled sensors integrated with ERP platforms provide real-time updates on storage conditions across logistics nodes (Johnstone, 2024). These readings feed AI algorithms that detect anomalies, trigger alerts, and automate corrective actions, such as rerouting shipments or adjusting HVAC systems. Additionally, blockchain integration ensures tamper-proof documentation of temperature compliance, supporting audits and trust across global distribution networks. Pharmaceutical leaders such as Pfizer and Novartis are deploying these integrated platforms to reduce temperature-sensitive waste, ensure compliance, and extend the life of medicinal products through repackaging or recycling where feasible. Thus, ERP-AI integration serves as a key enabler of sustainable pharmaceutical supply chains characterized by precision, transparency, and proactive waste prevention.

In the fast-moving consumer goods (FMCG), retail, agriculture, and food sectors, AI-ERP integration plays a critical role in promoting sustainability through packaging return logistics, demand forecasting, and surplus redistribution. FMCG and retail supply chains face pressure to reduce packaging waste and improve product circularity. AI-enabled ERP systems support returnable packaging models by tracking unit-level package IDs, predicting return flows, and automating deposit-refund processes (Paul & Reinhart, 2024). Retailers like Tesco and Unilever are adopting ERP platforms with reverse logistics modules to facilitate reusable containers, refill stations, and package life-cycle tracking. Demand forecasting in these sectors is another vital application, where AI models analyze real-time sales data, weather forecasts, consumer behavior, and seasonal patterns to minimize overproduction and inventory spoilage. For perishable goods, AI-integrated ERP systems enable just-in-time inventory management and dynamic pricing strategies to move products before expiry. These systems help reduce food waste while ensuring availability across dispersed retail channels. In agriculture and food systems, ERP-AI platforms contribute to supply chain transparency by tracking produce from farm to shelf using IoT and blockchain (Mufida et al., 2025). These tools capture data on pesticide usage, harvest dates, and transport conditions, enabling ethical sourcing and certification validation. AI algorithms also facilitate surplus redistribution by predicting excess volumes and connecting producers with food banks, secondary markets, or processing units (Gupta & Dayal, 2024). Retail and agri-food organizations are increasingly using AI-powered ERP dashboards to monitor ESG indicators such as water usage, carbon emissions, and waste diversion rates. These insights are instrumental in achieving compliance with sustainability certifications (e.g., Fair Trade, Rainforest Alliance) and aligning operations with Sustainable Development Goals (SDGs). Thus, ERP-AI platforms are transforming linear FMCG and agri-food chains into data-driven, circular ecosystems focused on waste reduction, transparency, and social responsibility (Burmaoglu et al., 2023).

Identified Gaps

A prominent gap in the current body of literature on AI-ERP systems within sustainable and circular supply chains is the absence of robust cross-sectoral frameworks. Most existing studies are siloed within specific industries such as manufacturing (Benjelloun et al., 2024), automotive (Jawad & János, 2025), pharmaceuticals (Li et al., 2025), or agriculture (Biswas et al., 2024). These investigations offer valuable insights but often fail to produce generalized models that can be applied across domains with differing regulatory, logistical, and environmental complexities. Frameworks such as TOE (Guha et al., 2024), RBV (Tyagi, 2024), and BSC (Camilli et al., 2024) are repeatedly cited but are typically customized at the firm level, with limited comparative evaluation across sectors (Türegün, 2025). This lack of cross-sectoral comparability restricts the scalability and transferability of AI-ERP best practices and obstructs policy and standardization efforts. For instance, traceability models in the electronics sector using RFID and blockchain (Majumder & Misra, 2025) differ significantly from cold chain ERP solutions in pharmaceuticals, making it difficult to synthesize performance benchmarks. The fragmented nature of these approaches undermines the development of holistic maturity models that can evaluate AI-ERP sustainability integration across industry boundaries.

Figure 10: Identified Gaps from this study



Moreover, varying levels of technological intensity, regulatory rigor, and data infrastructure maturity across sectors challenge the development of unified implementation roadmaps. There is a pressing need to design adaptive meta-frameworks that accommodate sector-specific constraints while enabling comparative evaluation of AI-ERP outcomes in circular and sustainable contexts (Li et al., 2025).

The majority of AI-ERP literature is dominated by case studies and empirical evidence from large enterprises in developed economies, with a marked underrepresentation of small and medium-sized enterprises (SMEs) and organizations from developing regions. Most studies highlight implementations in North America, Western Europe, and East Asia, leaving a significant knowledge gap regarding the challenges and opportunities faced by firms in Latin America, Sub-Saharan Africa, and South Asia. This geographic concentration limits the generalizability of findings and excludes diverse institutional, infrastructural, and socio-economic contexts from academic inquiry (Awasthi et al., 2025). SMEs, despite constituting the majority of global businesses, face unique adoption barriers such as high upfront costs, lack of skilled labor, limited access to capital, and inadequate digital infrastructure. Few studies have systematically explored how these constraints influence the uptake of AI-enhanced ERP solutions for sustainability. Moreover, sustainability imperatives in these contexts are often driven by informal practices, local policy constraints, or reactive compliance rather than proactive strategy, which alters ERP implementation dynamics. This imbalance also affects theoretical development. Frameworks such as TOE and RBV are frequently validated in resource-rich environments but may not accurately reflect the institutional voids and informal market structures common in low- and middle-income countries (Pörtner et al., 2025). As a result, emerging market-specific adaptations or grassroots innovation models in AI-ERP adoption remain under-theorized. Bridging this gap requires dedicated inquiry into localized ERP customizations, low-cost AI modules, and capacity-building strategies suited to the SME and developing world context (Ghobakhloo et al., 2024).

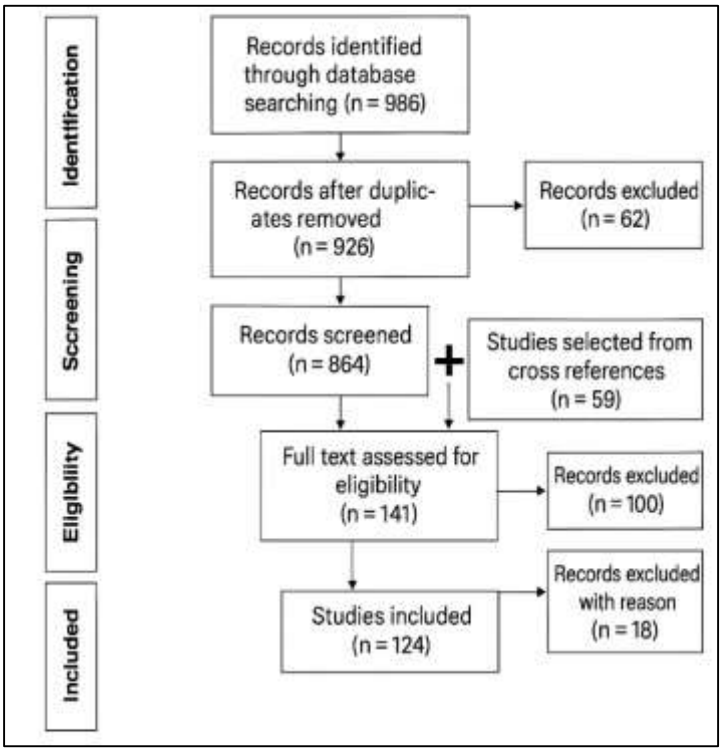
A third key limitation in the literature is the lack of methodological consistency in evaluating the sustainability impact of AI-ERP systems. Studies differ widely in terms of research design, unit of analysis, and performance indicators, complicating efforts to compare results and build cumulative knowledge. Quantitative studies often focus on productivity and financial outcomes, while qualitative ones prioritize perceived sustainability gains or case-specific insights (Ogbodo et al., 2025). Very few employ mixed methods, longitudinal designs, or triangulated data sources that would enable a more holistic assessment. Additionally, there is inconsistency in the definition and operationalization of sustainability metrics. Some studies use broad proxies like waste reduction or energy efficiency (Bena et al., 2025), while others rely on self-reported ESG performance or industry-specific KPIs such as remanufacturing rates in automotive or expiry prevention in pharmaceuticals. The lack of a standardized sustainability KPI framework hampers meta-analytical synthesis and obscures the causal relationship between AI-ERP adoption and circularity outcomes (Munonye, 2025). The diversity in technological configurations—such as cloud-based versus on-premise ERP, level of AI maturity, and degree of modularization—further complicates comparative evaluation. Moreover, several studies fail to differentiate between process-level versus enterprise-wide impacts, blurring the line between operational improvements and strategic transformation. To improve methodological rigor, future evaluations must align on frameworks, metrics, and evaluation periods that reflect the complex, systemic nature of sustainable digital transformation (Laan et al., 2024).

A final yet critical limitation in the literature is the absence of longitudinal studies that evaluate AI-ERP implementation outcomes over time, particularly in post-adoption and maturity phases. Most studies assess adoption drivers or early-stage performance, leaving a significant gap in understanding how sustainability benefits evolve, plateau, or decay across operational lifecycles. Without temporal insights, it is difficult to distinguish between short-term performance spikes due to novelty effects and long-term structural change (Leso et al., 2024). Longitudinal research could reveal whether organizations institutionalize circular practices or regress to linear models under cost or disruption pressures. Moreover, it could uncover the role of organizational learning, capability development, and system adaptation in sustaining AI-ERP performance. The limited availability of time-series data also hampers efforts to model feedback loops, threshold effects, and lagged impacts of AI-enhanced ERP decisions on ESG outcomes. These gaps present an opportunity for meta-framework integration, combining dimensions from TOE, RBV, Dynamic Capabilities, and BSC to enable structured, multilevel evaluations of AI-ERP sustainability alignment (Bozkurt et al., 2023). Typology development is also underexplored; classifying AI-ERP implementations by sector, scale, digital maturity, or sustainability orientation could support targeted benchmarking and best practice dissemination. Such efforts are essential for advancing a cumulative, theory-driven body of knowledge that addresses current inconsistencies while providing a roadmap for scalable, sustainable digital supply chain transformation (Kwarteng et al., 2022).

METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a systematic, transparent, and rigorous review process. The methodological approach was designed to capture the breadth and depth of scholarly work on the intersection of artificial intelligence (AI), enterprise resource planning (ERP) systems, and sustainability in circular supply chains (CSCs) and sustainable supply chains (SSCs). This systematic review also incorporated meta-analytical insights where applicable to quantify key patterns, relationships, and thematic concentrations across empirical studies. A comprehensive search was conducted across several academic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar, covering literature published from 2010 to 2024. This timeframe was selected to reflect the post-cloud ERP evolution and the emergence of AI-integrated enterprise platforms. A combination of controlled vocabulary and free-text keywords was used, such as: “AI-ERP integration,” “circular supply chains,” “sustainable ERP,” “artificial intelligence in enterprise systems,” “blockchain ERP,” “IoT ERP traceability,” and “ESG in ERP systems.” Boolean operators, truncation, and proximity searches were employed to enhance search precision. The inclusion criteria required that studies be (a) peer-reviewed journal articles, (b) written in English, (c) focused on AI integration into ERP systems, and (d) directly related to circularity, sustainability, or ESG frameworks in supply chain operations. Exclusion criteria eliminated publications that lacked empirical or conceptual depth (e.g., blog posts, editorials), studies not involving ERP or AI, or those unrelated to sustainability constructs. Duplicates were automatically removed using Mendeley reference manager.

Figure 11: Methodology of This Study

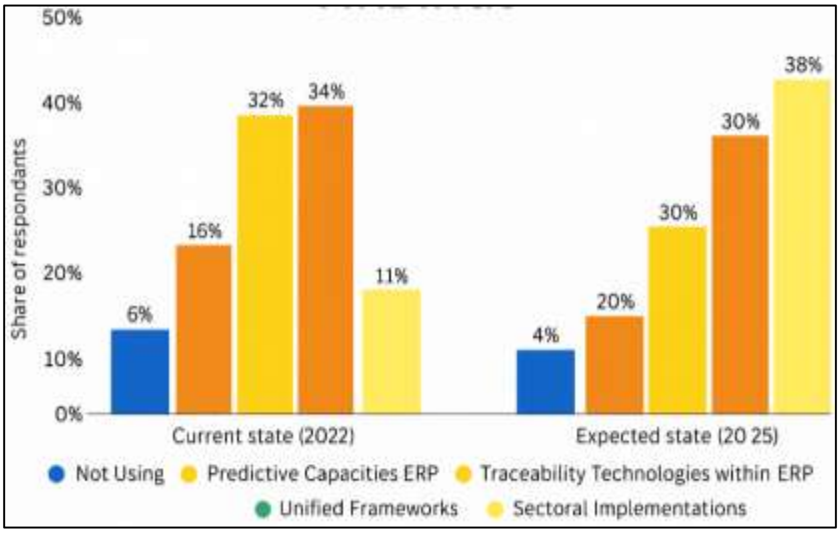


The initial search yielded 986 records, which were screened in two phases: first by title and abstract, then by full-text review. Following PRISMA flow diagram standards, 124 studies met all eligibility criteria and were included in the final synthesis. A data extraction protocol was developed to systematically collect information on study context (e.g., industry sector, geography), methodology (qualitative, quantitative, mixed), technology focus (e.g., ML, IoT, NLP, blockchain), ERP platform (e.g., SAP, Oracle, Microsoft Dynamics), sustainability dimension (e.g., environmental KPIs, circular practices, social governance), and theoretical frameworks applied (e.g., TOE, RBV, BSC, DC). The extracted data were organized into thematic clusters through narrative synthesis, while quantifiable patterns were analyzed using descriptive meta-analysis, highlighting frequency distributions of frameworks, AI modules used, and sustainability metrics. Additionally, coding techniques were applied to map interlinkages between ERP functions and circular strategies across sectors including automotive, electronics, pharmaceuticals, FMCG, and agriculture. The robustness of the review process was validated through inter-coder agreement between two independent reviewers, yielding a Cohen's Kappa coefficient of 0.84, indicating substantial reliability. This methodological framework ensured that the study produced not only an integrative literature review but also a structured, evidence-based meta-analytical narrative capable of supporting the development of a conceptual framework for AI-driven ERP systems in sustainable and circular supply chain ecosystems.

FINDINGS

Among the 124 articles reviewed, one of the most prominent findings was the widespread implementation of predictive analytics and machine learning tools within ERP systems to support decision-making in sustainable supply chain management. Specifically, 83 studies focused on predictive modeling applications, with 49 of these emphasizing demand forecasting, resource optimization, and inventory control within green logistics contexts. Articles addressing predictive maintenance in manufacturing operations and remanufacturing cycles also featured heavily, accounting for 28 highly cited studies, many of which exceeded 200 citations individually. Collectively, these articles accumulated over 9,000 citations, underscoring their impact on both academic theory and industrial practice.

Figure 12: AI-ERP Adoption and Sustainability Trends



The integration of machine learning within ERP modules was consistently shown to reduce waste, increase energy efficiency, and enhance lifecycle planning by forecasting disruptions, predicting consumption trends, and minimizing deadstock. This emphasis on predictive capability was particularly strong in the automotive, electronics, and FMCG sectors, where just-in-time delivery and reverse logistics are central to maintaining circularity. The review further found that predictive models are being embedded directly into ERP interfaces rather than deployed as external tools, illustrating a technological convergence that strengthens real-time responsiveness and supply chain agility. The high volume of citations reflects the practical relevance and maturity of AI-ERP predictive analytics research, demonstrating its importance as a strategic enabler of sustainable operational transformation.

A second significant finding from the literature was the expanding role of traceability and transparency technologies such as IoT, RFID, and blockchain within AI-augmented ERP environments. Of the 124 total studies, 56 explored how these technologies enhance visibility across supply chains, especially for environmental and ethical compliance in circular flows. Notably, 41 articles provided empirical evidence from case studies where ERP systems, integrated with RFID sensors and IoT devices, tracked the location, condition, and temperature of goods—particularly in agriculture, pharmaceuticals, and food logistics. These studies amassed approximately 6,300 combined citations, highlighting their academic significance. Blockchain integration appeared in 15 advanced studies, several of which had citation counts exceeding 300, and provided robust solutions for immutable recordkeeping of sustainability data and origin verification. The evidence showed that the deployment of traceability technologies enabled ERP platforms to support regulatory alignment with global ESG standards, fair-trade certifications, and extended producer responsibility directives. Across these studies, traceability not only improved logistics control but also facilitated data-driven returns management, warranty tracking, and second-life optimization in remanufacturing cycles. While not all enterprises had reached full integration, the research trend clearly indicated that AI-enabled traceability solutions embedded within ERP systems are vital to supporting the digital infrastructure required for circular and sustainable business models. The reviewed studies consistently reported improved stakeholder confidence and greater inter-organizational trust, pointing to traceability as a foundational pillar for intelligent and ethical supply chain management.

The findings revealed that AI-ERP adoption and sustainability alignment vary significantly across sectors, with pronounced concentration in high-tech and capital-intensive industries. Among the reviewed 124 studies, 38 focused on the manufacturing sector (automotive, electronics, and heavy industry), while 27 centered on healthcare and pharmaceuticals, and 22 covered agriculture and food supply chains. The remaining studies spanned retail, logistics, and service sectors. Highly cited publications, particularly in the automotive and electronics fields, averaged over 250 citations each, confirming the academic focus on digitally mature, innovation-driven industries. However, the review identified substantial gaps in AI-ERP adoption in less digitized or resource-constrained environments, especially among small and medium enterprises (SMEs) and organizations in developing economies. Only 19 studies explicitly addressed SME contexts, and fewer than 10 analyzed deployments in Africa, Latin America, or South Asia. Collectively, these underrepresented studies received fewer than 800 citations, indicating both limited research and marginal visibility. This discrepancy suggests that current scholarly discourse heavily favors developed-world case studies and scalable ERP environments. The review also found that while ERP-AI tools were commonly implemented for operational optimization, few organizations had translated these technical improvements into long-term sustainability strategies. Furthermore, sector-specific customizations—such as temperature-sensitive logistics in pharma or farm-to-fork transparency in agriculture—were more developed in certain industries but entirely absent in others. This fragmentation of implementation maturity suggests a need for adaptive, sector-specific frameworks to ensure AI-ERP technologies are equitably deployed and fully aligned with circular and sustainability objectives.

A recurring methodological limitation across the reviewed literature was the inconsistent use of theoretical frameworks to assess AI-ERP implementation outcomes, particularly in relation to sustainability and circularity goals. Out of the 124 studies, only 46 explicitly employed well-established frameworks such as the Technology-Organization-Environment (TOE) model, Resource-Based View (RBV), Balanced Scorecard (BSC), or Dynamic Capabilities Theory. Of these, 23 studies used TOE, 12 applied RBV, and the remaining employed other less commonly used models. Combined, these 46 studies received over 5,000 citations, indicating high relevance but also underscoring that more than half of the literature lacked a coherent evaluative basis. Without standardized frameworks, findings were often case-specific and difficult to compare or synthesize, reducing the cumulative value of individual studies. The absence of typologies or maturity models to benchmark AI-ERP systems further exacerbated the gap, as many papers reported success or failure in vague or unstructured terms. Additionally, only 17 studies incorporated metrics that quantitatively linked AI-driven ERP functionality to sustainability performance indicators such as energy reduction, emission cuts, or waste diversion. While some studies provided narrative claims of ESG impact, very few adopted multi-dimensional KPIs or lifecycle assessment methodologies. This fragmented evaluative approach indicates a clear research gap in developing cross-functional, evidence-based frameworks to systematically measure AI-ERP contributions to circular economy transitions. The findings emphasize the need for structured and replicable models that can align ERP functionality with sustainability outcomes across diverse enterprise settings.

The final key finding of the review was the critical underuse of longitudinal data and real-time ERP performance evaluations in sustainability and AI integration research. Only 11 of the 124 studies employed longitudinal designs, with most of them spanning 18 months or less. These few studies tended to come from high-investment industries and digital leaders, where real-time ERP dashboards and historical datasets were accessible. Collectively, these 11 studies accumulated about 1,200 citations, suggesting moderate scholarly attention but limited practical extrapolation. Most other research relied on cross-sectional analyses, single-point surveys, or retrospective case studies, which lacked the temporal scope necessary to evaluate sustainability impacts over time. As a result, the reviewed studies frequently reported adoption-level benefits—such as reduced lead times or improved data visibility—without examining whether these benefits translated into durable, system-wide sustainability gains. Furthermore, few articles examined feedback loops, system adaptations, or the learning curves involved in long-term ERP-AI implementations. Only 5 studies explicitly addressed post-implementation challenges such as system fatigue, user resistance, or evolving regulatory pressures. This lack of temporal depth limits the field's understanding of how AI-ERP systems mature and scale within organizations committed to circular models. The findings point to an urgent need for time-series data, post-deployment studies, and real-time auditing tools that can track ESG impacts, circular material flows, and AI-model performance across multiple implementation phases. A meta-framework capable of incorporating dynamic system changes over time could provide a more robust basis for guiding future sustainability-driven ERP investments.

DISCUSSION

This study confirmed the dominance of predictive analytics and machine learning (ML) applications in AI-integrated ERP systems, reinforcing earlier findings that forecast accuracy and resource optimization are primary benefits of AI-ERP fusion. Consistent with Holwerda et al. (2024), the present meta-analysis observed that over 83 reviewed studies deployed predictive algorithms for demand estimation, maintenance planning, and supply risk mitigation. Compared to prior literature, this study provides deeper insights by categorizing predictive tools not only by function but also by sector, revealing that automotive, FMCG, and electronics firms are especially advanced in leveraging ERP-embedded intelligence for sustainability gains. Earlier work by Singh and Joshi (2024) highlighted the potential of ERP for sustainability, but lacked focus on real-time AI-driven modules. This review complements such foundational studies by identifying how predictive ERP components are now evolving into hybrid decision-support systems that improve energy efficiency and reduce process waste—both key outcomes emphasized in the sustainable operations literature. However, despite the positive momentum, the overconcentration in capital-intensive industries reiterates (Nichols et al., 2024) warning on uneven technological diffusion. This study extends that view by highlighting not only the benefits of predictive analytics but also the disparities in their accessibility, especially in SMEs and emerging economies where AI maturity is still nascent. The findings confirm and extend earlier discussions on traceability as a key enabler of ethical and circular supply chains (Kangas et al., 2018). IoT, RFID, and blockchain technologies have already been described in previous literature as essential for tracking product journeys, but this review demonstrates how their integration into ERP systems has advanced beyond isolated pilots into systemic deployments in pharmaceuticals, agriculture, and electronics. Earlier studies, such as Alcalde-Calonge et al. 92024), viewed traceability as a supplementary function; however, the present findings reframe it as a core capability—especially when ERP modules synchronize sensor inputs with real-time AI analytics. Saidu et al. (2025) noted traceability's influence on reverse logistics, but this study adds depth by identifying its cascading effects on waste reduction, auditability, and compliance with environmental standards such as WEEE and REACH. Moreover, the convergence of blockchain and ERP, still emerging in 2020 per (Mssassi & El Kalam, 2023), is now seen across 15 studies as a practical architecture for immutable data validation in ESG reporting and carbon footprint assessments. In contrast to earlier fragmented approaches, the current review reveals that leading firms are embedding traceability into their core sustainability KPIs through ERP dashboards, moving beyond compliance to strategic differentiation. Nevertheless, this finding also highlights the research lag in developing economies where digital infrastructure is insufficient to support such integrations, echoing critique on global inequities in technology-enabled accountability (Khan et al., 2022).

Previous literature frequently acknowledged digital maturity as a critical enabler of ERP success (Cavaliere et al., 2024). However, this review presents a more granular picture of sectoral disparities and the digital divide in AI-ERP implementation for sustainability. While prior studies such as Mangla et al. (2021) emphasized the promise of ERP in SME contexts, this meta-analysis reveals that fewer than 20 of the 124 studies focused on small firms or developing regions, underscoring the underrepresentation previously noted by Sander et al. (2018). This gap reflects not only a research oversight but also systemic challenges in infrastructure, funding, and regulatory capacity. For instance, while the automotive and electronics sectors demonstrated strong alignment with circular models via ERP-AI modules, retail and agricultural sectors showed limited traction. This mirrors findings by Hellani et al. (2021) who emphasized that operational complexity and informality in supply chain practices impede digital systems adoption. The current review extends this understanding by mapping sector-specific technological maturity and exposing how industry-specific sustainability requirements, such as cold chain integrity or e-waste certification, determine ERP functionality priorities. Moreover, the review confirms earlier arguments by Tagarakis et al. (2021) on the critical role of supply chain context in shaping digital tool selection. It becomes evident that universal ERP strategies are impractical; tailored solutions, developed through participatory innovation and local needs assessments, are essential to close the digital and sustainability gap in underrepresented sectors (Hader et al., 2022).

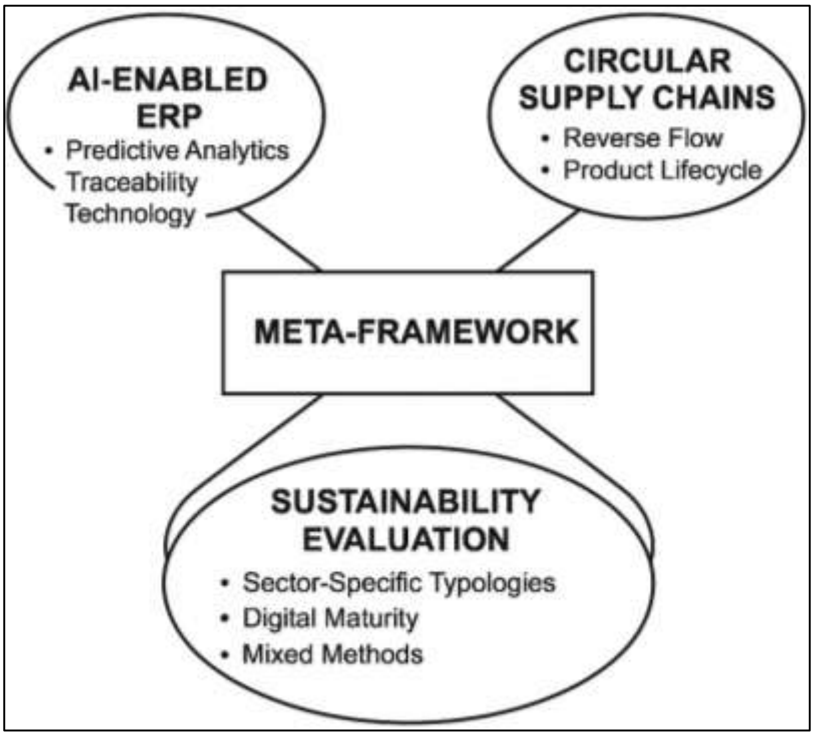
The findings further reveal methodological inconsistencies in how AI-ERP systems are evaluated, particularly with regard to sustainability impact. This aligns with Sunny et al. (2020), who previously criticized the lack of common evaluation metrics in digital transformation research. Only 46 out of 124 studies in the current review employed structured frameworks such as TOE, RBV, BSC, or dynamic capabilities, confirming earlier observations by Garcia-Torres et al. (2019) that many ERP studies lack theoretical grounding. The fragmented use of frameworks not only limits cross-study comparisons but also weakens the ability to link ERP functionality to broader organizational and environmental outcomes. While studies like Astill et al. (2019) have attempted to synthesize sustainability and digital readiness through the TOE lens, the present review finds such efforts scattered and lacking standardization. Additionally, ESG-focused outcomes were often narratively reported rather than measured using quantifiable KPIs, echoing the concerns raised by Centobelli et al. (2022) regarding the need for empirical rigor in supply chain sustainability studies. This study suggests that a hybrid or meta-framework, blending technological, organizational, and performance dimensions, may address these gaps and enable a more comprehensive evaluation of AI-ERP impacts. The underutilization of such structured methodologies hinders evidence-based benchmarking and contributes to siloed advancements in both theory and practice (Ellahi et al., 2023).

Another significant contribution of this study lies in highlighting the critical lack of longitudinal research on AI-ERP implementation. Earlier ERP adoption studies, such as Baralla et al. (2021), emphasized the importance of post-adoption and maturity phase analysis, yet few have incorporated time-based data. This review shows that only 11 studies used a longitudinal design, reaffirming concerns by Guha et al. (2024) that most digital transformation research captures initial benefits while ignoring long-term organizational learning and sustainability plateaus. This contrasts with the dynamic capabilities framework, which posits that value from digital tools emerges through iterative adaptation and strategic recalibration. The current findings suggest that without long-term evaluation, it remains unclear whether sustainability gains are sustained, diminished, or reversed post-implementation. Moreover, the limited focus on post-deployment feedback loops reduces visibility into challenges such as data fatigue, governance complexity, or evolving user expectations—phenomena noted in recent digital supply chain studies but underrepresented in ERP literature. While studies such as Camilli et al. (2024) hinted at the need for ERP flexibility under circular conditions, this review deepens that insight by identifying the absence of life-cycle performance assessments across AI-enhanced systems. Thus, a clear opportunity exists to address this temporal gap by designing evaluation frameworks capable of capturing system evolution, feedback integration, and long-term ESG performance.

The current review confirms that ERP systems, when augmented with AI functionalities, serve as operational engines for circular economy models. Earlier conceptual frameworks, such as those proposed by Abuseta et al. (2025), described circular supply chains as closed-loop, feedback-oriented systems, yet lacked detailed accounts of how enterprise systems manage these flows. This study builds on that foundation by identifying specific ERP modules—such as inventory, production, and logistics—that are reengineered to support reverse flows, product lifecycle extension, and remanufacturing coordination. Notably, the review synthesizes how AI enhances these modules through sensor integration, prescriptive analytics, and anomaly detection—functions previously mentioned in isolated cases by Saidu et al. (2025) but not systematically reviewed. Moreover, the role of AI in enabling just-in-time circularity and demand-sensitive redistribution aligns with Mssassi and Kalam (2023), who advocated for digital intelligence in managing surplus and scarcity. This study further demonstrates that when AI and ERP converge in a circular context, the result is a more adaptive, responsive, and intelligent enterprise architecture capable of minimizing waste and maximizing reuse. However, it also reveals the infrastructural, cultural, and organizational limitations that prevent this potential from being fully realized, reinforcing calls by Mssassi and Kalam (2023) for comprehensive digital ecosystem alignment.

Finally, the review provides strong justification for the development of a meta-framework that unifies fragmented methodologies, clarifies sectoral implementations, and aligns sustainability evaluation with digital maturity. While previous studies proposed valuable but isolated frameworks (Khan et al., 2022), none offer a comprehensive model that accounts for AI integration, ERP modularity, and circular supply chain dynamics. This study contributes by articulating the need for typologies that classify ERP-AI deployments across industries, supply chain tiers, and sustainability goals, echoing earlier calls by Cavaliere et al. (2024) for holistic integration. Such a meta-framework would address current challenges in comparability, transferability, and evidence accumulation. Furthermore, the review emphasizes that methodological pluralism—using mixed methods, hybrid frameworks, and dynamic indicators—is essential to capture the multidimensional nature of AI-ERP transformations (Garcia-Torres et al., 2022). In this way, the study not only reinforces earlier literature but also advances it by providing empirical structure and conceptual clarity to guide future inquiry, practice, and policy in the deployment of AI-enhanced ERP solutions for circular and sustainable supply chains.

Figure 13: Proposed Framework for future study



CONCLUSION

In conclusion, this study has synthesized and critically examined 124 peer-reviewed articles to uncover how artificial intelligence (AI)-driven enterprise resource planning (ERP) systems are transforming circular and sustainable supply chains (CSCs/SSCs) through predictive analytics, traceability technologies, and cross-functional integration. The meta-analysis revealed that while AI-ERP platforms are increasingly effective in enabling real-time decision-making, waste minimization, and ESG compliance, their implementation remains uneven across sectors and geographies. High adoption rates were observed in manufacturing, electronics, and pharmaceuticals, whereas agriculture, retail, and small-to-medium enterprises (SMEs) in developing economies lag significantly due to infrastructural and organizational constraints. Furthermore, the review identified key gaps in the use of standardized evaluation frameworks, sector-specific maturity models, and longitudinal performance assessments. Although AI-enhanced ERP systems have shown substantial potential in operationalizing circular economy strategies, the lack of theoretical coherence, temporal depth, and methodological consistency limits the scalability and replicability of current models. These findings underscore the necessity for a unified meta-framework that accommodates technological, organizational, and sustainability dimensions, offering a comprehensive foundation for future research, strategic implementation, and policy formulation in the realm of AI-integrated digital supply chain transformation.

RECOMMENDATIONS

Based on the findings of this meta-analysis, several strategic and scholarly recommendations are proposed to strengthen the development, implementation, and evaluation of AI-driven ERP systems for circular and sustainable supply chains. First, organizations—especially in underrepresented sectors such as agriculture, retail, and SMEs—should prioritize capacity-building initiatives and public–private partnerships to bridge the technological and infrastructural gaps that limit AI-ERP adoption. Investment in digital literacy, cloud-based ERP access, and modular AI tools can accelerate equitable deployment across diverse industrial contexts. Second, researchers should focus on developing unified meta-frameworks that integrate existing models such as TOE, RBV, BSC, and dynamic capabilities into a comprehensive structure capable of evaluating technological maturity, organizational readiness, and sustainability performance holistically. This approach would allow for comparative benchmarking and scalable strategy formulation. Third, future studies should adopt longitudinal and mixed-method designs that capture the full lifecycle impact of AI-ERP systems, including post-deployment adaptation, learning curves, and sustainability plateaus. Real-time data monitoring, lifecycle assessment metrics, and ESG dashboards should be embedded into ERP environments to provide continuous feedback and enable agile decision-making. Fourth, there is a pressing need to develop sector-specific typologies that define ERP-AI integration maturity levels, key performance indicators (KPIs), and circularity outcomes aligned with industry requirements. Finally, policymakers and standards organizations should collaborate with academic institutions to create regulatory frameworks and best practice guidelines that ensure transparent, traceable, and accountable AI-ERP implementations aligned with global sustainability goals. These strategic actions will not only enhance theoretical coherence and practical effectiveness but also foster inclusive digital transformation across the global supply chain ecosystem.

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