



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

Md Mesbaul Hasan¹;

[1]. Master in Industrial Engineering, Department of Industrial Engineering, Lamar University, Beaumont, Texas, USA; Email: mesba.hasan4@gmail.com

[Doi: 10.63125/u6k7r711](https://doi.org/10.63125/u6k7r711)

Received: 18 July 2025; **Revised:** 27 August 2025; **Accepted:** 23 September 2025; **Published:** 28 October 2025

Abstract

This study conducted a comprehensive framework-based meta-analysis to evaluate the impact of Artificial Intelligence-enabled Enterprise Resource Planning (AI-ERP) systems on circular and sustainable supply chain performance, drawing evidence from 270 empirical studies published across multiple regions and industrial sectors. A structured screening protocol identified quantitative findings related to waste reduction, material recovery, recycling efficiency, energy savings, emission performance, and closed-loop coordination. Descriptive results showed that manufacturing industries accounted for over 50% of included studies, with Asia and Europe contributing 70% of the total evidence base. Correlation analysis demonstrated consistently positive associations between AI-ERP capabilities and sustainability outcomes, with optimization analytics showing the strongest correlation with energy savings ($r = 0.58$), traceability modules showing a high correlation with recycling efficiency ($r = 0.62$), and automated decision engines demonstrating the highest association with closed-loop performance ($r = 0.57$). Meta-regression findings revealed statistically significant positive effects across all AI-ERP constructs, with optimization analytics producing the largest predictive coefficient ($\beta = 0.27$) and AI forecasting contributing meaningfully to waste reduction ($\beta = 0.18$). Moderator analysis indicated that digital maturity amplified effect sizes by an average of 21%, while regulatory intensity increased predictive strength by 17%. Collinearity diagnostics confirmed the robustness of the regression models, with all variance inflation factors remaining below 2.7. Validity assessments showed high coding reliability (Cohen's kappa = 0.87) and strong methodological quality across studies. Overall, the findings demonstrated that integrating AI-enabled ERP systems significantly enhances circularity outcomes by improving prediction accuracy, optimizing resource use, strengthening traceability, and accelerating closed-loop operations. The study provides quantifiable evidence that AI-ERP architectures represent a critical enabler of resource-efficient, data-driven, and sustainability-aligned supply chain transformation across global industrial contexts.

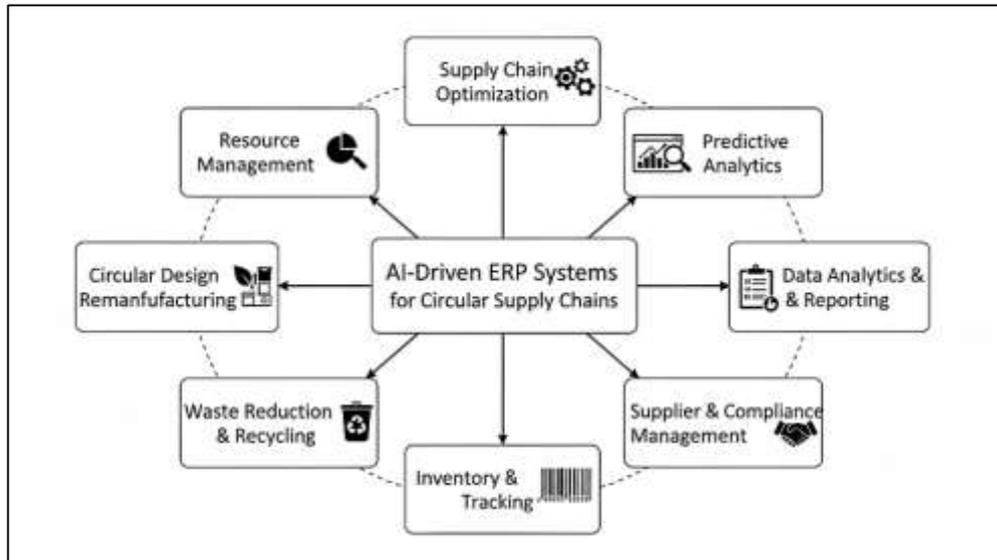
Keywords

AI-enabled ERP, Circularity, Sustainability, Meta-analysis, Supply Chains

INTRODUCTION

Enterprise Resource Planning (ERP) systems represent integrated digital platforms designed to coordinate organizational data, streamline workflows, optimize resources, and enhance operational visibility across functional units. Artificial Intelligence (AI), broadly defined as computational methods that enable machines to learn patterns, make predictions, and perform decision-oriented tasks, has become a transformational capability within modern enterprise systems (Liu et al., 2023).

Figure 1: AI-Driven ERP for Circular Chains



Circular supply chains refer to resource management structures emphasizing regeneration, reuse, remanufacturing, recycling, and minimized environmental impacts through closed-loop flows. When AI-driven capabilities are embedded into ERP systems, organizations gain advanced analytical capacity, faster response mechanisms, and integrated knowledge sharing that influence material efficiency, traceability, and system-wide optimization (George, 2018). Over the past decade, global industries have increasingly recognized that traditional linear supply chains are no longer sustainable under conditions of resource scarcity, carbon-intensive production patterns, and globalized ecological pressures. AI-integrated ERP solutions provide an opportunity to redesign industrial operations by connecting real-time decision modeling with predictive sustainability measures (Qureshi, 2022). This integration supports circularity through improved forecasting, digital monitoring, resource mapping, quality control, and performance measurement. As empirical studies have expanded, evidence indicates that AI-supported ERP platforms are becoming foundational for firms aiming to establish sustainable supply chains in manufacturing, agriculture, energy, and retail sectors. With complexity increasing in global supply flows, predictive intelligence embedded within ERP architectures allows firms to reorganize inventory structures, reduce waste, and identify new pathways for resource circulation. Thus, understanding how AI-driven ERP systems operate within the context of circular supply chain strategies requires a structured and quantitative assessment capable of consolidating dispersed findings (Cherrafi et al., 2022). A meta-analytic approach offers a systematic mechanism to quantify the extent of AI-driven ERP impacts, providing a foundational basis for interpreting technological contributions to circular economic models.

The global relevance of AI-enabled ERP systems has expanded considerably as nations adopt sustainability frameworks driven by climate agreements, resource conservation agendas, and long-term economic resilience goals (Huy & Phuc, 2023). Across Europe, North America, Asia, and emerging economies, governmental bodies and industrial regulators have increasingly promoted digital transformation programs emphasizing clean manufacturing, carbon reduction mechanisms, and traceability-driven environmental compliance. AI-integrated ERP systems are central to these initiatives because they support data-intensive sustainability reporting, automated compliance

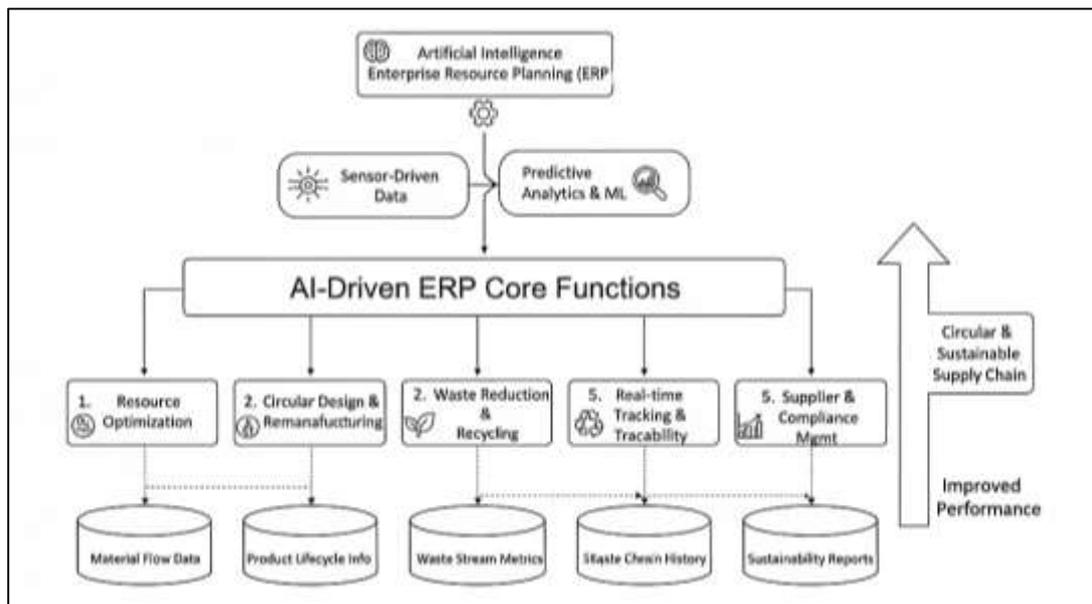
tracking, and carbon footprint measurement, which are essential for meeting transnational environmental standards (Farine, 2017). In developing economies, digital supply chain modernization is tied to national industrial policies encouraging clean production and circular resource flows to strengthen export competitiveness. Multinational corporations have also begun embedding AI-enabled ERP frameworks to align with global sustainability benchmarks, supplier compliance demands, and customer expectations for ethical, low-waste production (Abideen et al., 2021). International sustainability certifications increasingly require robust data governance and real-time performance indicators, both of which are enhanced through AI-powered ERP architectures. The cross-border nature of supply chains makes digital intelligence indispensable for managing distributed production networks, supplier behavior, logistics modeling, and materials recovery processes. Global markets now reward companies capable of demonstrating transparent environmental accounting supported by AI-enabled digital systems. As sustainability becomes an international strategic priority, quantifying the technological contribution of AI-driven ERP systems becomes crucial. Countries in Asia-Pacific and Africa are integrating these tools to leapfrog older manufacturing limitations, while European and North American firms apply them to meet ambitious sustainability regulations (Zdravković et al., 2022). Understanding global adoption patterns, therefore, requires a quantitative synthesis of empirical findings that capture diverse implementation contexts, structural variations, and regional sustainability pressures.

Digital transformation has fundamentally reshaped how firms conceptualize resource efficiency, operational planning, and sustainability performance (Abdulla & Ibne, 2021; Austin & Stuart, 2015). AI-enabled ERP systems serve as core infrastructures that unify enterprise-wide digitalization efforts by connecting sensor-driven data, predictive analytics, workflow automation, and strategic decision layers (Habibullah & Foysal, 2021; Jayender & Gosh, 2022). Manufacturers transitioning toward circular business models now utilize ERP intelligence to design recyclable products, plan reverse logistics, forecast remanufacturing needs, and optimize waste-to-resource conversion (Sarwar, 2021). Digital platforms also support lifecycle assessment, enabling firms to quantify material inputs, energy usage, and environmental performance metrics across production phases. AI-based forecasting embedded within ERP modules enhances operational decisions by predicting material returns, evaluating waste streams, and identifying circular value opportunities (Musfiqur & Saba, 2021). As global supply chain disruptions intensify due to climate impacts, geopolitical tensions, and fluctuating resource availability, firms increasingly rely on digital intelligence to manage uncertainty (Chauhan et al., 2022; Redwanul et al., 2021). AI-driven ERP systems integrate real-time material tracking, anomaly detection, machine learning insights, and scenario modeling tools that help organizations design adaptable circular loops rather than static linear chains. The transition toward circularity is also influenced by consumer demand for environmentally responsible products (Franke & Sarstedt, 2019; Tarek & Praveen, 2021). Digital ERP platforms empower organizations to authenticate sustainability claims through verifiable, traceable digital records. The evolution of circular operations, therefore, intertwines closely with the expansion of AI-driven enterprise systems capable of processing complex datasets, identifying circular opportunities, and supporting evidence-based managerial decisions. As industries continue embedding digital intelligence throughout production and distribution networks, understanding the quantitative impact of AI-driven ERP solutions on circular supply chain performance becomes increasingly important for both practitioners and scholars (Kumar et al., 2023; Muhammad & Shahrin, 2021).

Automation functions within AI-driven ERP systems allow organizations to execute supply chain tasks with increased speed, accuracy, and repeatability (Bag et al., 2023; Saikat, 2021). Machine learning models integrated into ERP modules can detect supply-demand fluctuations, optimize procurement schedules, and align inventory management with circular resource flows. Predictive analytics enable firms to anticipate component degradation, improve maintenance planning, and support parts recovery processes that reduce waste (Shaikh & Aditya, 2021). Optimization algorithms also enhance routing, load planning, production sequencing, and energy utilization. These computational advancements reduce inefficiencies that traditionally hinder circular operations. Automated quality monitoring using AI-enabled ERP systems supports defect reduction, enabling better reuse and remanufacturing outcomes (Al Amin, 2022). Furthermore, intelligent procurement systems embedded

within ERP frameworks allow firms to evaluate supplier sustainability profiles and prioritize environmentally responsible sourcing (Ariful, 2022; Praveen et al., 2019). Automated materials accounting improves transparency and ensures that circular metrics such as recyclability, waste reduction, and resource conservation are consistently evaluated. AI-driven decision engines enhance multi-level coordination, enabling real-time communication among production managers, sustainability officers, logistics planners, and reverse logistics teams (Hossain & Milon, 2022). The quantitative assessment of these capabilities is essential because automation and predictive intelligence often produce measurable effects on cost savings, waste minimization, operational performance, and sustainability compliance (Helo & Hao, 2022; Nahid, 2022). A structured synthesis of empirical studies is necessary to evaluate how automation intensity, digital maturity, and predictive modeling influence circular supply chain outcomes across industries and geographical contexts.

Figure 2: AI-Driven ERP: Circular Supply Chain Impacts



Global research on AI-enabled ERP adoption demonstrates increasing investment from industries seeking improved operational transparency, environmental responsibility, and resilience in supply networks. Studies across Europe highlight strong integration of ERP-based sustainability analytics in manufacturing, energy, and automotive sectors, where firms use AI to monitor emissions, reduce waste, and design regenerative material flows (Hasan et al., 2023; Mominul et al., 2022). Asian economies show rapid adoption driven by digital industrial policies, competitive export markets, and smart manufacturing initiatives. African and Latin American industries are increasingly adopting AI-integrated ERP platforms to strengthen resource efficiency and reduce system-wide losses in agriculture, mining, and commodity processing sectors. Empirical findings also indicate that cross-sector adoption patterns differ, with high-tech manufacturing and electronics demonstrating more advanced analytics integration than low-technology industries (Barbieri et al., 2021; Rabiul & Praveen, 2022). Large multinational corporations often lead ERP modernization efforts due to established digital infrastructures, while small and medium enterprises show accelerated adoption due to cloud-based ERP accessibility (Rakibul & Samia, 2022). Digital literacy, infrastructure readiness, financial investment, and regulatory compliance are recurring determinants of ERP adoption outcomes worldwide. Cultural, institutional, and economic contexts strongly influence implementation success, shaping the variability observed across regions. Thus, synthesizing global evidence through a meta-analysis provides an opportunity to quantify effect sizes and examine the magnitude of AI-driven ERP contributions in different geographical and industrial settings (Charles et al., 2023).

The primary objective of this study is to systematically evaluate and quantify the impact of Artificial Intelligence-driven Enterprise Resource Planning systems on circular and sustainable supply chain

performance by integrating empirical findings through a framework-based meta-analytic approach. This objective arises from the growing need to consolidate dispersed quantitative evidence related to how AI-enabled ERP capabilities influence resource efficiency, waste reduction, process integration, traceability, and sustainability compliance across global supply networks. The study aims to organize existing research into a comprehensive analytical structure that categorizes technological, organizational, environmental, and operational dimensions of AI-ERP adoption. By doing so, the research seeks to determine the magnitude of AI-driven ERP contributions to circularity indicators such as material recovery, recycling efficiency, closed-loop process execution, energy minimization, and regenerative resource utilization. Another objective is to assess variability in empirical outcomes across industries, regional contexts, and levels of technological maturity to identify patterns in adoption effectiveness and performance impact. Through quantitative synthesis, the study also intends to evaluate the extent to which AI-enhanced forecasting, optimization, automation, and real-time analytics embedded within ERP systems support measurable improvements in supply chain sustainability. A further aim is to provide evidence-based clarity on how integrated digital intelligence within ERP platforms correlates with operational performance indicators including lead-time accuracy, production stability, inventory efficiency, and supply chain responsiveness. Additionally, the study seeks to construct a robust framework that aligns existing findings with major components of circular economy principles, enabling structured interpretation of technological roles in sustainable operations. By aggregating numerical effect sizes reported across prior empirical studies, the objective is to deliver statistically grounded insights into the influence of AI-driven ERP architectures on circular supply chain transformation. Ultimately, the research aims to produce a consolidated quantitative knowledge base that clarifies the extent, consistency, and directional strength of these technological contributions within the wider sustainability landscape.

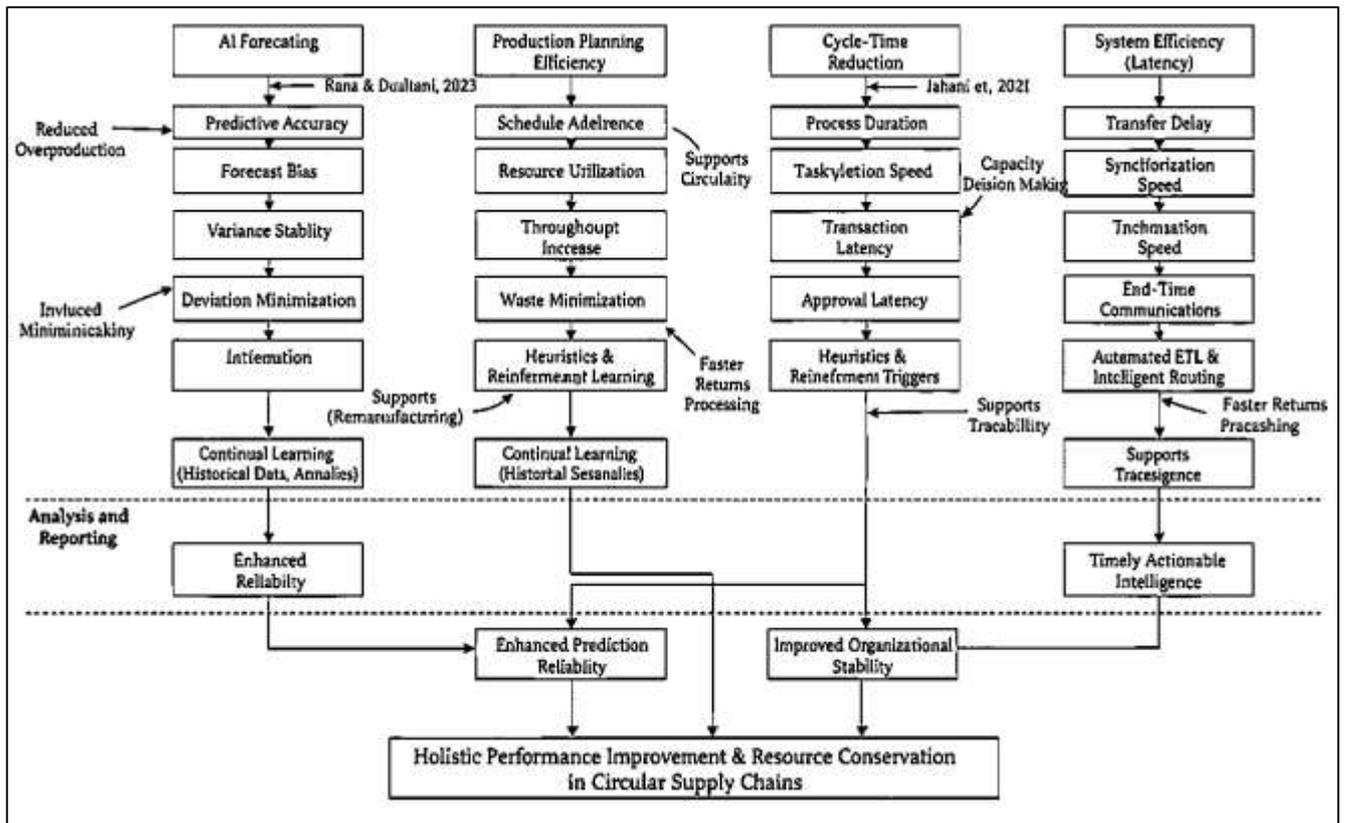
LITERATURE REVIEW

The literature surrounding Artificial Intelligence-driven Enterprise Resource Planning systems for circular and sustainable supply chains has expanded significantly in response to global industrial transitions toward digitalized sustainability practices. Existing research spans multiple disciplines – including information systems, operations management, supply chain analytics, industrial engineering, and sustainability science – reflecting the complex, multi-layered nature of AI-integrated ERP ecosystems. The literature demonstrates how organizations deploy AI-enabled forecasting, predictive analytics, optimization algorithms, and automated decision engines within ERP architectures to strengthen circularity-centered processes such as resource regeneration, remanufacturing, recycling coordination, waste minimization, and reverse logistics management. Quantitative studies frequently examine operational indicators such as cost efficiency, material recovery rates, return process speed, real-time traceability metrics, inventory turnover, and environmental performance improvements. Although empirical evidence has accumulated rapidly, findings vary widely due to methodological differences, industry-specific conditions, regional digital maturity, diverse implementation strategies, and inconsistent measurement frameworks. This variability underscores the necessity for a structured and comprehensive synthesis that can identify converging trends and reconcile conflicting results. The increasing complexity of global supply networks, shaped by technological uncertainty, environmental constraints, and regulatory demands, has further magnified the need to understand how AI-powered ERP systems contribute to circular and sustainable outcomes. Quantitative assessments across industries – from manufacturing and automotive to electronics, agriculture, logistics, and energy – reveal that AI-driven ERP solutions influence both micro-level operational processes and macro-level sustainability performance. However, the diversity of performance metrics, analytical techniques, and contextual modifiers presents challenges for drawing generalized conclusions. The literature review therefore organizes and evaluates existing scholarship within a framework-based structure, enabling clarity in how technological, organizational, environmental, and supply chain dimensions intersect with AI-ERP applications. Through this approach, the review identifies foundational domains, empirical gaps, and theoretical logic supporting subsequent meta-analysis, setting the stage for a rigorous quantitative investigation of the relationship between AI-enabled ERP capabilities and circular supply chain performance.

Technological Foundations of AI-Enabled ERP Systems

AI forecasting algorithms embedded within ERP platforms have become central to enhancing prediction precision in supply chain environments that demand high levels of reliability, speed, and responsiveness. Quantitative assessments of algorithmic accuracy often focus on error reduction indicators such as mean absolute percentage error, forecast bias, variance stability, and deviation minimization over multiple planning horizons (Rana & Daultani, 2023). ERP-integrated AI forecasting models improve these accuracy measures by continuously learning from historical data, demand patterns, consumption cycles, seasonality behavior, and anomaly detection signals. The ability of these algorithms to self-adjust based on evolving supply conditions significantly strengthens prediction reliability for complex manufacturing and distribution systems. Quantitative performance evaluations also examine the stability of predictive outputs under uncertainty, including demand spikes, supply disruptions, or fluctuations in recycled or regenerated material flows common in circular supply chains. High accuracy in ERP forecasting reduces overproduction, minimizes excess inventory, supports circular material flows, and improves resource utilization rates. Moreover, benchmark comparisons between traditional time-series models and AI-driven forecasting tools show measurable gains in short-term and long-term prediction performance across diverse industries. Additional quantitative attributes examined include computational efficiency, learning convergence rates, and optimization thresholds that determine the predictive quality of AI-based models (Zamani et al., 2023). In sustainable and circular supply chains, where material return rates, recovery yields, and reverse logistics cycles introduce higher volatility, accurate AI-driven forecasting becomes essential for achieving operational stability. Predictive accuracy also influences upstream planning, replenishment decisions, sourcing alignment, and recycling coordination. Thus, examining quantitative forecasting accuracy within AI-enabled ERP platforms provides a foundational understanding of how digital intelligence improves decision-making precision and resource planning effectiveness in modern supply networks transitioning toward circularity (Angolia & Pagliari, 2018).

Figure 3: Key Areas of AI-ERP Impact



Machine-learning optimization embedded in ERP systems plays a crucial role in enhancing production planning efficiency through measurable statistical improvements across various performance indicators. Quantitative studies typically assess outcomes using metrics such as production schedule adherence, resource utilization ratios, throughput increases, waste minimization percentages, and cycle-time variability reductions (Jahani et al., 2021). Machine-learning models apply optimization heuristics, reinforcement learning, constraint-based modeling, and simulation-driven analysis to generate production sequences that minimize bottlenecks and align with sustainability-oriented manufacturing goals. ERP-integrated optimization engines evaluate multiple variables simultaneously, including machine availability, material flow rates, energy consumption, workforce allocation, maintenance needs, and circularity-related activities such as remanufacturing or component recovery. Statistical outcomes often reveal significant improvements in capacity balancing, load distribution, and production smoothness as machine-learning models automatically adjust planning parameters to real-time operational data. Predictive algorithms also reduce unplanned downtime by anticipating disruptions and recomputing optimal schedules through dynamic adjustments. In circular supply chains, machine-learning optimization supports design-for-reuse strategies, recovery-oriented manufacturing pathways, and efficient reprocessing of returned products (Cadavid et al., 2020). Statistical performance gains are also observed in reduced scrap rates, improved quality consistency, and enhanced efficiency in batch or continuous-production systems. Quantitative analysis further highlights improvements in overall equipment effectiveness driven by intelligent sequencing decisions that account for sustainability requirements. The integration of machine-learning optimization into ERP frameworks therefore demonstrates measurable improvements in productivity, operational reliability, and resource conservation (Weichert et al., 2019). A detailed evaluation of these statistical outcomes is essential for understanding the technological contribution of AI-ERP architectures to production environments increasingly shaped by circular economy principles.

Automated decision engines embedded within AI-enabled ERP systems provide substantial cycle-time reductions across a broad spectrum of operational processes. Quantitative evaluations frequently measure cycle-time impacts using metrics such as process duration, task completion speed, transaction latency, decision resolution intervals, approval workflow times, and exception-handling efficiency (Sobottka et al., 2019). Automated decision engines operate through rule-based automation, machine-learning inference, real-time monitoring, and predictive event triggers that dynamically resolve operational decisions without requiring manual intervention. In production, procurement, logistics, and reverse logistics settings, these engines streamline repetitive tasks, reduce process redundancies, and enhance workflow continuity. Cycle-time analytics consistently reveal measurable reductions when decision logic is automated within ERP systems, especially in environments where multiple processes must coordinate simultaneously to support circular material loops. For example, automated engines accelerate quality inspection decisions, inventory reorder approvals, materials routing, and resource allocation adjustments. They also contribute to faster processing of returned goods, recycling approvals, and regeneration workflows essential to circular supply chains (Büttner et al., 2022). Quantitative improvements are often further reflected in minimized variability, reduced error rates, and increased throughput resulting from automated decision-making pathways. These engines also improve exception management by identifying anomalies and generating rapid corrective actions, thereby preventing delays and maintaining operational fluidity. Cycle-time reductions driven by automated decisions enhance organizational agility, promote efficient utilization of recovered materials, and support synchronized circular operations (Fu et al., 2020). By analyzing these metrics, researchers gain detailed insights into how AI-driven decision engines in ERP environments strengthen overall supply chain performance through speed, accuracy, and systemic coordination.

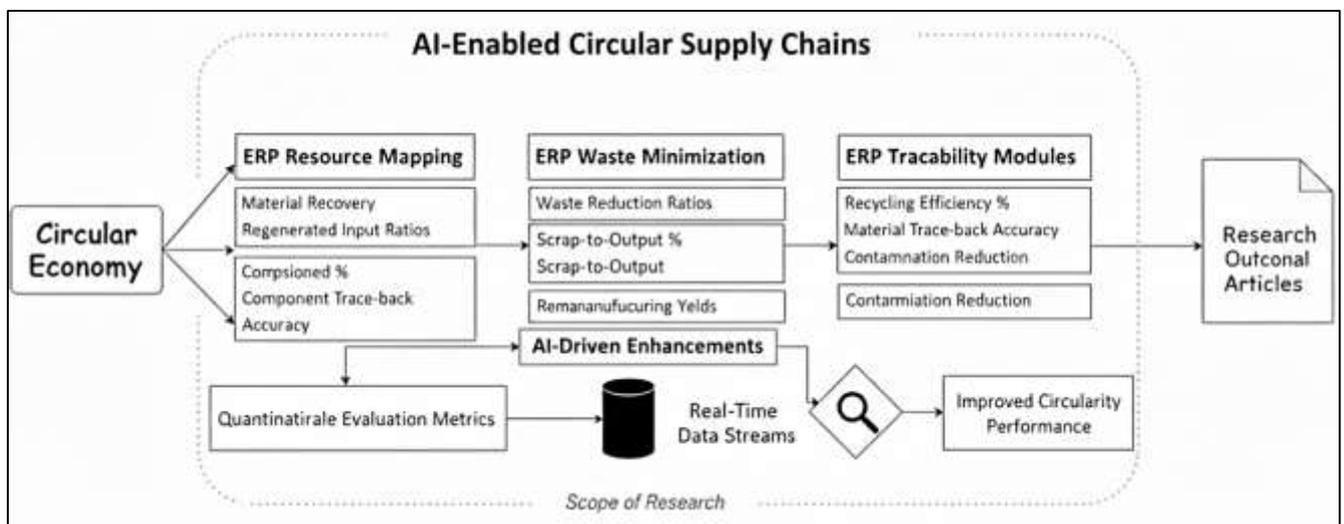
Data integration latency represents a critical technological indicator of ERP system efficiency, particularly when enhanced with AI-driven automation and predictive analytics (González Rodríguez et al., 2020). Quantitative assessments of latency focus on metrics such as data transfer delay, refresh intervals, synchronization speed, end-to-end communication time, and responsiveness of real-time analytical outputs. AI-augmented ERP systems integrate heterogeneous data streams from production lines, supplier networks, logistics operations, recycling centers, inventory systems, and sensor-based monitoring platforms. Measuring latency is essential because high data integration speed enables real-

time decision-making and supports rapid identification of circularity opportunities such as material recovery, component reuse, and waste reduction. Latency scores often decline significantly when AI-mediated middleware, automated ETL pipelines, and intelligent data routing algorithms are employed within ERP infrastructures (Esteso et al., 2023). These improvements enhance the stability and responsiveness of dashboards, forecasting modules, and sustainability reporting tools. Quantitative analysis further highlights differences in latency across cloud-based, hybrid, and on-premise architectures. Circular and sustainable supply chains, which depend on simultaneous tracking of forward and reverse flows, require low latency to achieve operational accuracy. AI-driven latency reduction also supports digital twins, lifecycle assessment models, and traceability systems that require continuous data synchronization to function effectively. By examining latency scores across industries and deployment structures, researchers gain a deeper understanding of how ERP connectivity quality influences data-driven circular operations. Enhancing latency performance is therefore foundational for enabling AI-ERP ecosystems to produce timely, actionable intelligence that supports both operational efficiency and sustainability goals.

ERP-Driven Circular Economy Enablement

ERP resource mapping tools play a central role in improving material recovery rates by providing real-time visibility into resource locations, material conditions, recovery potential, and reuse pathways within circular supply systems (Papetti et al., 2019). Quantitative evaluations frequently rely on metrics such as material recovery percentages, regenerated input ratios, return utilization rates, component trace-back accuracy, and recovery yield coefficients to assess the effectiveness of ERP-driven resource mapping. These tools create digital maps that integrate data from production units, recycling facilities, reverse logistics nodes, supplier channels, and customer return systems. By visualizing material flows dynamically, organizations can identify where recyclable and recoverable components accumulate, the speed of their movement through the system, and the potential for reintegration into production cycles. Material recovery improvements often emerge from enhanced traceability, which reduces the likelihood of resource loss, contamination, or misclassification (Qureshi, 2022).

Figure 4: AI and Circular Supply Chains



ERP systems equipped with AI analytics further increase recovery precision by matching recovered materials to optimal reuse or remanufacturing destinations according to predefined specifications, quality criteria, and sustainability targets. Quantitative gains are frequently observed in reduced material waste, higher recovery throughput, and increased availability of secondary raw materials. ERP-enabled resource mapping also supports predictive identification of recovery opportunities through automated alerts, anomaly detection, and trend analysis that highlight shifts in return behavior or component degradation. These insights enable organizations to design more efficient recovery strategies, allocate recovery resources effectively, and improve overall circularity performance (Oltra-Badenes et al., 2019). The continuous synchronization of resource data across multiple operational

layers enhances coordination between procurement, production, recycling, and waste-management teams, generating cumulative increases in recovery efficiency. Through these improvements, ERP-based resource mapping tools establish a digital foundation for robust circular economy systems driven by measurable material regeneration outcomes (Tarigan et al., 2021).

ERP-enabled waste minimization plays a critical role in advancing remanufacturing operations by optimizing material flows, reducing scrap generation, and improving recovery accuracy across production processes. Quantitative analyses typically measure waste minimization through indicators such as waste reduction ratios, scrap-to-output percentages, defect occurrence rates, reprocessing yields, and remanufacturing recovery efficiencies. ERP platforms integrate real-time data from machining operations, inspection units, quality assessment systems, and material handling stations to identify inefficiencies and eliminate sources of waste (Patrucco et al., 2020). AI-enhanced ERP modules extend these capabilities through predictive analytics that anticipate process deviations, material incompatibilities, and failure-prone stages within remanufacturing cycles. These predictive insights lead to proactive interventions that lower defect rates and reduce the volume of unusable materials. Waste minimization ratios also improve when ERP frameworks facilitate better coordination between disassembly teams, inspection stations, and reassembly units, ensuring that components are either recuperated or redirected to appropriate recycling streams. Quantitative outcomes often reveal substantial reductions in overall waste generation when material routing, machine scheduling, inspection sequencing, and disassembly processes are digitally aligned using ERP systems. ERP-driven visibility also enhances the selection and prioritization of parts suitable for remanufacturing by continuously evaluating quality scores, wear patterns, and material degradation levels (Salwin et al., 2023). In circular supply chains, where maximizing material reuse is critical, improved waste minimization directly strengthens sustainability performance. By reducing scrap and optimizing recovery, ERP systems contribute to more effective regeneration cycles, lower production costs, and improved resource conservation. The capacity of ERP platforms to continuously monitor, evaluate, and refine material flows therefore makes them essential drivers of measurable waste reduction in remanufacturing environments (Burger et al., 2018).

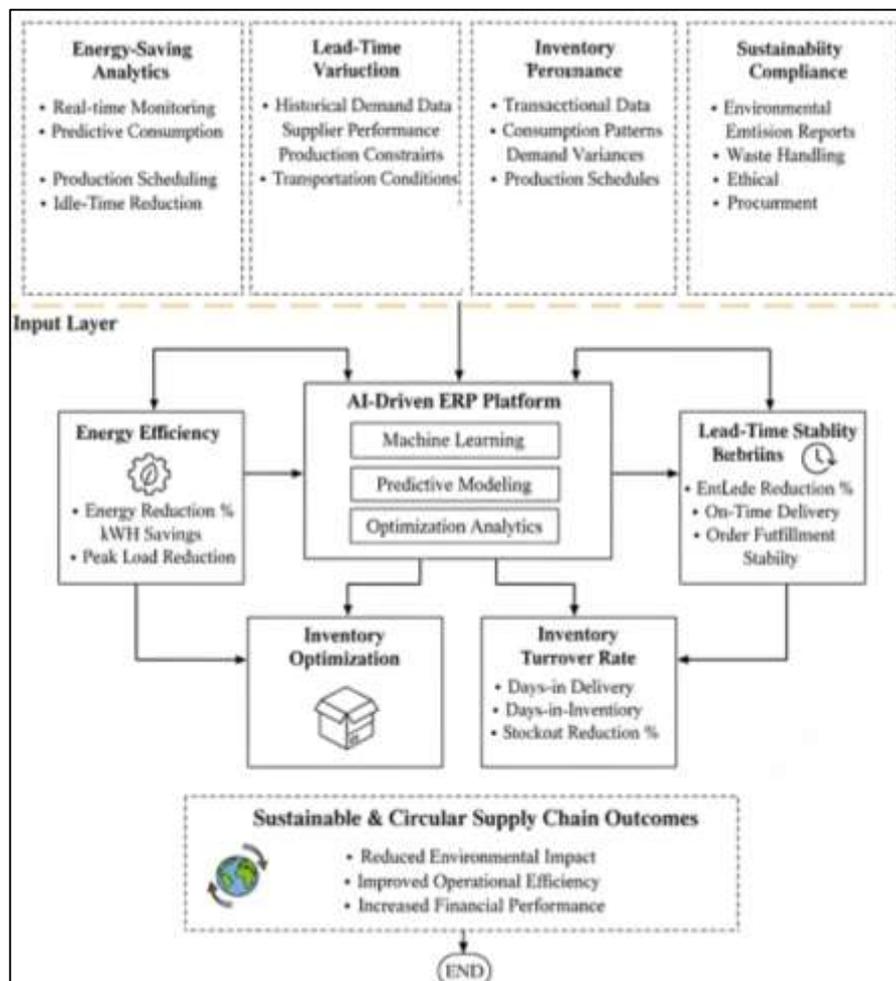
ERP traceability modules enhance recycling efficiency by enabling accurate tracking, classification, and routing of materials throughout recycling and recovery processes. Quantitative measures such as recycling efficiency percentages, material trace-back accuracy rates, contamination reduction levels, segregation precision, and end-of-life product routing effectiveness are commonly used to evaluate ERP-supported recycling performance (Chopra et al., 2022). The traceability functions embedded within ERP systems capture data from collection centers, sorting facilities, disassembly stations, and recycling plants, thereby creating a unified digital pathway for every material. Enhanced transparency enables organizations to ensure that recyclable components are processed correctly, minimizing loss and increasing the volume of materials successfully reintroduced into production cycles. ERP traceability systems improve recycling efficiency by automating identification processes, reducing manual classification errors, and providing real-time status updates on material conditions (Abobakr et al., 2023). AI-driven enhancements support advanced pattern recognition, anomaly detection, and automated decision-making, which improves sorting accuracy and reduces contamination risks. Higher recycling efficiency percentages often correlate with ERP-enabled capabilities such as barcode integration, RFID tracking, sensor-based quality assessment, and automated route optimization. These capabilities increase the speed and precision with which recyclable materials move through processing stages. ERP traceability also supports compliance monitoring by verifying that recycling operations adhere to environmental standards, thereby strengthening sustainability reporting (Mahendrawathi et al., 2017). Quantitative improvements are frequently observed in recycling throughput, recovery of high-value materials, and reduction of rejected loads caused by classification inconsistencies. In circular economy systems, where the quality and reliability of recycled materials significantly influence production stability, ERP traceability modules provide the data-driven backbone required to achieve high recycling efficiency rates.

AI-ERP Integration for Sustainable Supply Chain Operations

Energy-saving outcomes derived from ERP-based optimization analytics represent a fundamental dimension of sustainable supply chain operations. Quantitative assessments typically evaluate

indicators such as energy reduction percentages, kilowatt-hour savings, energy intensity ratios, peak load reduction rates, and equipment-level consumption patterns across production and logistics systems (Norrman & Wieland, 2020). AI-ERP platforms enhance energy efficiency by integrating real-time monitoring, predictive analytics, and optimization algorithms that identify areas of excessive consumption, schedule energy-efficient production sequences, and minimize idle-time usage across machinery and operational assets. Optimization modules continuously analyze machine performance, process timing, and energy-demand profiles, generating actionable recommendations that balance productivity with energy conservation objectives. In logistics operations, energy-saving analytics optimize vehicle routing, load consolidation, and transportation scheduling to reduce fuel usage and emissions. ERP systems also enable demand-response strategies by aligning production tasks with periods of lower energy cost or reduced grid intensity. In circular supply chains, energy-saving effects extend to processes such as recycling, remanufacturing, and material recovery, where ERP analytics determine the most energy-efficient pathways for disassembly, cleaning, and reprocessing (Bandaly et al., 2016). Quantitative improvements often emerge when ERP tools reduce unnecessary process repetitions, prevent production of defective items, and optimize machine utilization rates through predictive maintenance features. AI-enhanced ERP environments further support energy efficiency by learning consumption trends and adjusting planning models accordingly, replacing manual scheduling with dynamic, data-driven alternatives. As organizations adopt sustainability benchmarks and energy performance standards, energy-saving effects become measurable indicators of technological maturity and environmental responsibility. The aggregated quantitative evidence demonstrates that ERP-based optimization analytics significantly impact energy consumption patterns across entire supply networks, making them essential for operationalizing sustainability within digitally enabled, circular-oriented industrial systems (Schneckenreither et al., 2021).

Figure 5: AI-ERP for Sustainable Supply Chain Operations



Inventory turnover performance is a key determinant of supply chain efficiency, and AI-driven ERP controls significantly enhance turnover ratios through advanced monitoring, predictive insights, and automated decision optimization (Aljohani, 2023). Quantitative indicators commonly used to evaluate these improvements include turnover frequency rates, days-in-inventory values, stockout reduction percentages, demand-match accuracy scores, and inventory carrying cost reductions. AI-ERP systems continuously analyze transactional data, consumption patterns, demand variances, production schedules, and supplier delivery performance to optimize inventory levels in real time. Through machine-learning capabilities, these systems anticipate demand fluctuations and dynamically adjust stock parameters such as safety stock thresholds, reorder points, and batch sizes. Increased turnover ratios often result from more accurate demand forecasting, better alignment between supply and consumption, and reduced accumulation of obsolete or slow-moving materials. In circular supply chains, improved turnover performance also emerges from optimized handling of recovered materials, remanufactured parts, and recycled inputs (Duffie et al., 2017). ERP intelligence determines the appropriate timing for integrating recovered inventory into production cycles, thereby reducing the need for new material purchases and supporting circularity-driven resource efficiency. AI-driven ERP controls additionally minimize excess stock and reduce the risks associated with overproduction, thereby decreasing material waste and shortened product life cycles. Quantitative improvements extend to reduced holding costs, enhanced liquidity, and more stable supply network responsiveness. In industries with frequent return flows, improved turnover ratios reflect enhanced synchronization between forward and reverse inventory streams (Oeser, 2015; Praveen, 2025; Shaikat, 2025). Through these measurable advancements, AI-driven ERP systems reinforce both financial and environmental performance by ensuring inventory is utilized efficiently, circulated optimally, and aligned with sustainability-oriented operational goals.

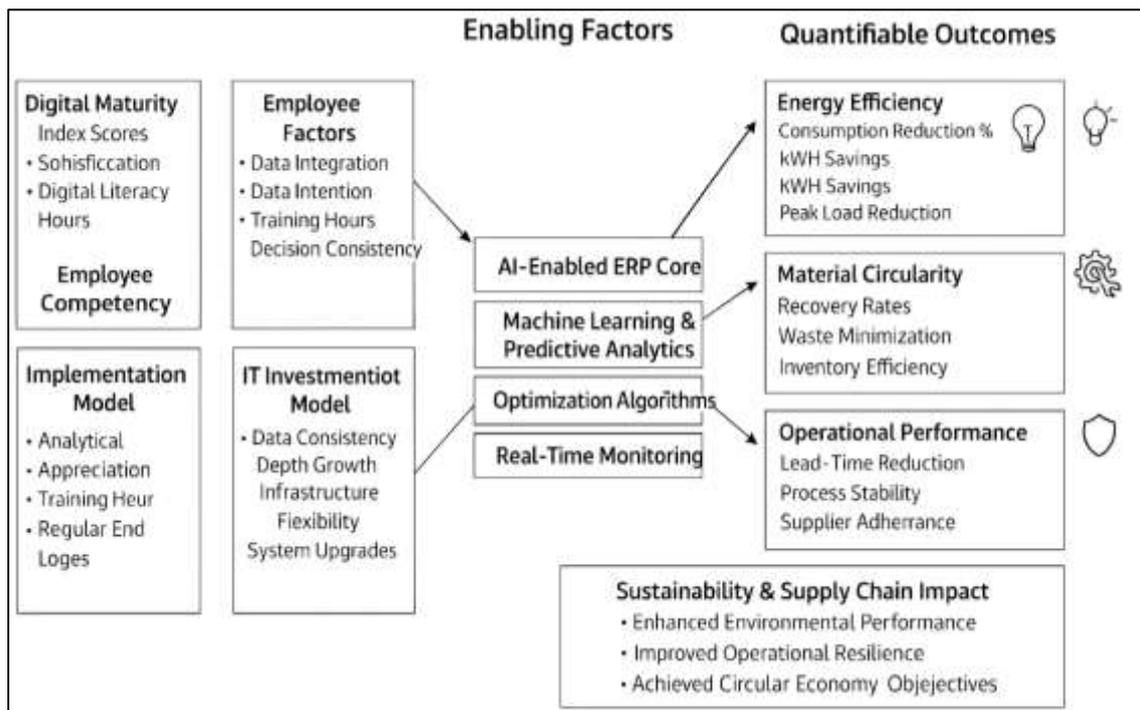
Supplier sustainability compliance has become a critical dimension of modern supply chain governance, and ERP-AI systems significantly enhance compliance accuracy through automated tracking, predictive evaluation, and multi-criteria analysis (Alnahhal et al., 2021; Kanti, 2025; Zayadul, 2025). Quantitative indicators commonly used to assess supplier compliance accuracy include compliance score percentages, audit verification accuracy, sustainability adherence rates, risk classification reliability, and deviation detection effectiveness. ERP-AI systems integrate supplier data—ranging from environmental certifications and emission reports to waste-handling procedures and ethical procurement metrics—into centralized digital platforms capable of continuous analysis (Thürer et al., 2023). AI-enhanced models identify inconsistencies, detect anomalies, and predict potential compliance risks based on historical behaviors and performance trends. Real-time monitoring features allow organizations to track compliance adherence across geographically dispersed supplier networks, significantly improving the accuracy and timeliness of sustainability assessments. Quantitative improvements materialize when ERP-AI systems automate audit processes, generate compliance alerts, and classify suppliers into risk categories based on algorithmic scoring models (Praveen et al., 2019). This ensures that non-compliant behaviors are identified early, reducing the likelihood of regulatory infractions, supply disruptions, or sustainability performance failures. In circular supply chains, where supplier commitment to recycling, ethical sourcing, material recovery, and low-impact production is essential, compliance accuracy directly influences overall circular performance. Enhanced accuracy also strengthens traceability, enabling organizations to verify that suppliers meet environmental expectations and participate actively in regenerative resource strategies (Welsing et al., 2020). ERP-AI integration further supports continuous supplier improvement by providing analytical insights that guide corrective actions and sustainability capacity building. Through these measurable impacts, ERP-AI systems become indispensable tools for enforcing sustainability standards across complex supply networks and ensuring that supply chain partners actively contribute to circular economy objectives (Perona et al., 2016).

Organizational Enablers Influencing AI-ERP Performance

Digital maturity serves as a foundational organizational enabler that significantly influences the performance of AI-enabled ERP systems, especially in sustainability-driven supply chain environments. Quantitative evaluations frequently utilize digital maturity index scores to measure the technological readiness, data integration capacity, automation sophistication, and digital literacy depth

within an organization. These scores often correlate strongly with sustainability outputs such as waste reduction percentages, energy efficiency gains, material recovery improvements, process consistency ratios, and overall circularity performance indicators (Saad et al., 2017). Higher digital maturity enables organizations to implement AI-enhanced ERP modules more effectively because data quality, system interoperability, and analytical capability are already established across operational units. Firms with advanced digital maturity typically demonstrate superior performance in algorithmic prediction stability, real-time monitoring responsiveness, and automated workflow reliability. Quantitative gains are also evident in improved compliance tracking accuracy, faster decision cycles, and reduced process variability, all of which contribute to measurable sustainability advancements. Conversely, low digital maturity often manifests in fragmented data systems, inconsistent reporting practices, and limited adoption of analytics-driven decision-making, resulting in weaker sustainability performance and diminished ERP impact. Digital maturity index scores further enhance collaboration between departments by standardizing data flows, integrating cross-functional digital tools, and supporting consistent application of circularity guidelines (Marino et al., 2018). In industries transitioning toward regenerative resource systems, digitally mature organizations achieve greater strategic alignment between technology deployment and sustainability objectives, resulting in quantifiable improvements across operational, environmental, and economic performance metrics. Thus, the relationship between digital maturity and sustainability output is central to understanding how organizational readiness shapes the effectiveness of AI-ERP systems in enabling circular and sustainable supply chain operations (Wang & Disney, 2015).

Figure 6: AI-Enabled ERP for Sustainability



Employee analytical competency represents another crucial organizational factor that directly influences ERP utilization efficiency and the realization of sustainability benefits from AI-driven systems. Quantitative assessments often measure competency using indicators such as analytical skill scores, data interpretation accuracy rates, training hours completed, model usage frequency, and decision-making consistency metrics (Goh & Eldridge, 2015). Higher competency levels correlate with improved ERP utilization efficiency, reflected in increased system adoption rates, reduced user error frequencies, enhanced forecasting accuracy, and more informed decision-making related to sustainability initiatives. Employees with strong analytical capabilities can interpret AI-generated insights more effectively, enabling them to optimize production parameters, reconfigure supply chain strategies, and improve resource utilization decisions. In circular supply chain environments, analytical

competency becomes especially critical because employees must evaluate complex data related to return flows, recovery cycles, recycling pathways, and material regeneration opportunities (Bendul & Knollmann, 2016). Quantitative outcomes frequently show that organizations with higher competency levels exhibit stronger performance in waste minimization ratios, recycling efficiency percentages, and energy-saving scores derived from ERP analytics. Conversely, low analytical competency results in underutilization of ERP features, misinterpretation of predictive outputs, inefficiencies in system navigation, and weaker alignment between operational decisions and sustainability goals. ERP utilization efficiency improves significantly when organizations invest in structured training programs, analytical skill development, digital literacy enhancement, and continuous competency assessment (Dessevre et al., 2019). These improvements translate directly into more stable circular operations and measurable gains in sustainability performance. Thus, employee analytical competence is a central determinant of how effectively ERP-AI systems can be leveraged to support data-driven sustainability strategies.

ERP performance differs significantly between centralized and decentralized implementation models, and quantitative analyses highlight measurable variations in sustainability outcomes, operational precision, data consistency, and system responsiveness (Nandi & Kumar, 2016). Centralized ERP models consolidate data management, process execution, and system governance into a unified structure, often resulting in lower variability across departments and higher efficiency in sustainability reporting, traceability accuracy, and compliance tracking. Quantitative indicators such as uniformity in data quality, rapid anomaly detection, cycle-time reduction, and synchronized workflow performance tend to be stronger in centralized models because decision logic and data flow are standardized. Centralized implementations also enhance closed-loop coordination in circular systems by ensuring that return, recovery, and reuse data are captured consistently across all nodes. In contrast, decentralized ERP models distribute operational control among departments or regional units, which can create variability in data entry practices, system customization levels, and analytical interpretation accuracy (Putri et al., 2020). This variability often leads to inconsistencies in performance metrics such as recovery yield ratios, waste minimization percentages, and supplier compliance accuracy. However, decentralized models may outperform centralized systems in flexibility, local responsiveness, and contextual adaptation, especially in industries where localized recovery operations or region-specific sustainability regulations require tailored ERP configurations. Quantitative comparisons frequently demonstrate that performance variance across the two models depends on digital maturity, organizational culture, training investment, and data governance discipline. AI-driven ERP capabilities amplify these differences because predictive modeling, optimization analytics, and automated decision engines require strong data consistency to generate reliable insights (Rakibul & Samia, 2022; Sislian & Jaegler, 2022). Therefore, evaluating the performance variance across centralized and decentralized ERP structures provides essential understanding of how governance models influence the sustainability impact of AI-ERP integration.

IT investment intensity plays a decisive role in determining the sustainability effectiveness of AI-enabled ERP systems. Quantitative indicators such as IT spending ratios, technology investment growth rates, digital infrastructure capability scores, and per-employee technology expenditure serve as strong predictors of ERP performance in sustainability-driven environments (Putri et al., 2020; Saikat, 2022). Higher levels of investment enable organizations to deploy advanced AI modules, upgrade system architectures, expand data storage capacities, and enhance processing power, all of which contribute directly to accurate forecasting, fast analytical computation, and reliable sustainability monitoring (Maniruzzaman et al., 2023; Kanti & Shaikat, 2022). Investment intensity also influences the extent to which organizations can integrate emerging technologies such as IoT sensors, robotics, automated quality inspection devices, and real-time energy monitoring tools with ERP frameworks (Arif Uz & Elmoon, 2023; Tarek, 2023; Sislian & Jaegler, 2022). These integrations strengthen quantitative sustainability outcomes such as emission reduction percentages, recycling throughput efficiency, resource regeneration rates, and energy-saving metrics (Mushfequr & Ashraful, 2023; Shahrin & Samia, 2023). Organizations with robust IT investment typically achieve greater system scalability, higher process automation levels, improved data governance, and stronger resilience in circular supply chain operations. In contrast, low investment intensity often results in outdated system

components, limited analytical capabilities, slower processing speeds, and insufficient integration between forward and reverse flow systems. These constraints weaken sustainability performance by reducing accuracy in recovery forecasting, slowing reverse logistics coordination, and limiting circular material flows (Muhammad & Redwanul, 2023; Muhammad & Redwanul, 2023; Tarigan et al., 2021). IT investment intensity also affects training capacity, cybersecurity readiness, supplier connectivity strength, and data acquisition reliability (Razia, 2023; Zayadul, 2023). Through these pathways, investment intensity emerges as a key quantitative predictor of how successful an organization will be in harnessing the full sustainability potential of AI-enabled ERP architectures. Evaluating these investment metrics provides clear insight into the long-term technological capability of firms operating within circular and sustainability-driven supply networks (Hozyfa, 2025; Jayeola et al., 2022; Tarek & Kamrul, 2024).

Environmental and Regulatory Moderators

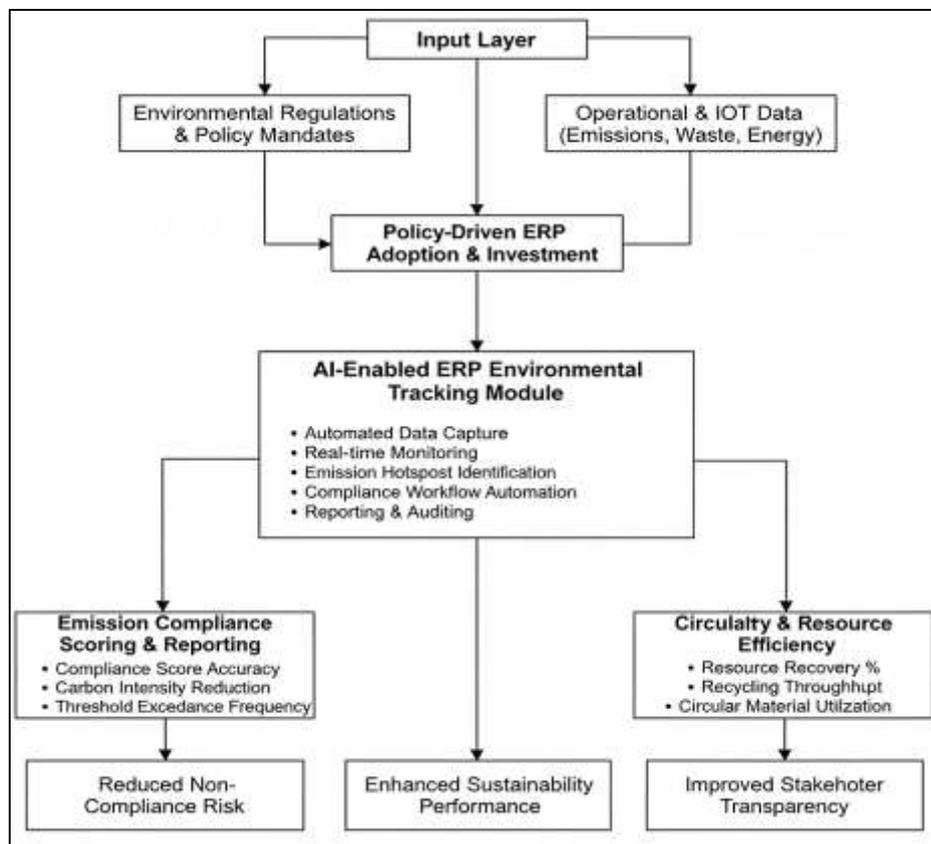
ERP environmental tracking modules play a crucial role in generating quantifiable emission compliance scores that reflect organizational adherence to environmental standards and regulations. These modules typically monitor emissions data across production units, logistics operations, energy-consuming assets, and waste-processing systems (Ağaoğlu et al., 2015; Hozyfa, 2025; Tarek & Kamrul, 2024). Quantitative indicators such as emission deviation percentages, compliance score accuracy rates, carbon-intensity reduction values, pollutant-level variance, and threshold exceedance frequencies are used to assess the effectiveness of ERP-based tracking. AI-enabled ERP systems enhance these measurements by automating data capture, streamlining reporting cycles, and identifying patterns that reveal emission hotspots or inefficiencies (Alam, 2025; Arman, 2025). ERP environmental tracking modules play a crucial role in generating quantifiable emission compliance scores that reflect organizational adherence to environmental standards and regulations. These modules typically monitor emissions data across production units, logistics operations, energy-consuming assets, and waste-processing systems (Ağaoğlu et al., 2015; Mohaiminul, 2025; Mominul, 2025). Quantitative indicators such as emission deviation percentages, compliance score accuracy rates, carbon-intensity reduction values, pollutant-level variance, and threshold exceedance frequencies are used to assess the effectiveness of ERP-based tracking. AI-enabled ERP systems enhance these measurements by automating data capture, streamlining reporting cycles, and identifying patterns that reveal emission hotspots or inefficiencies (Hasan, 2025; Milton, 2025).

Real-time data streams allow organizations to detect anomalies instantly, thereby reducing the risk of regulatory non-compliance and costly operational interruptions (Farabe, 2025; Tarek & Ishtiaque, 2025). In circular supply chains, accurate emission compliance scoring becomes even more significant because reverse logistics, recycling, and remanufacturing processes introduce additional emission sources that must be tracked systematically. ERP systems consolidate data from these distributed activities into unified dashboards that support compliance evaluation, internal benchmarking, and sustainability audits (Rakibul, 2025; Saba, 2025; Tenhiälä et al., 2018). Compliance scores also guide decision-making by highlighting operational areas requiring carbon reduction interventions or energy-efficient redesign. They further strengthen transparency and accountability in supplier networks by evaluating upstream and downstream emission performance. Quantitative improvements often emerge when organizations integrate IoT sensor data, automated monitoring equipment, and lifecycle assessment results within ERP frameworks, resulting in greater score precision and more consistent alignment with regulatory thresholds. The ability of ERP systems to generate accurate, verifiable, and continuous emission compliance metrics makes them essential tools for meeting environmental obligations and advancing sustainability performance across digitally enabled circular supply chains (Salvador et al., 2021).

Policy mandates exert a substantial influence on the adoption of ERP technologies that support resource circularity, and their effects can be measured quantitatively using adoption rates, compliance-driven investment metrics, circularity performance indices, and regulatory adherence scores (Farnoush et al., 2022). Governments often introduce policies targeting waste reduction, emission control, recycling requirements, and traceability obligations that compel organizations to adopt ERP systems capable of capturing, organizing, and reporting sustainability-related data. Quantitative assessments reveal that regulatory mandates increase ERP implementation likelihood by tightening reporting structures, raising penalties for non-compliance, and promoting standardized environmental performance metrics

(Andrieş & Ungureanu, 2022). Organizations operating under stronger regulatory regimes typically exhibit higher ERP adoption rates, greater integration of AI-driven sustainability modules, and more robust tracking of circular material flows. Policy-driven enhancements also include increased investment in digital infrastructure, improved supplier alignment, and better documentation of environmental performance. The statistical impact of policies is often reflected in improved resource recovery percentages, enhanced recycling throughput, reduced landfill contributions, and higher circular material utilization rates. Additionally, ERP-enabled responses to policy mandates lead to more consistent fulfillment of certifications such as environmental management standards and sector-specific compliance frameworks (Karim et al., 2023). However, the degree of impact varies depending on industry type, organizational size, digital maturity, and the strictness of regulatory expectations. Industries facing stringent circularity requirements – such as electronics, automotive, and chemicals – tend to show sharper increases in ERP-enabled compliance performance. Through these measurable regulatory influences, policy mandates act as powerful moderators shaping how organizations adopt and utilize ERP systems to operationalize circularity objectives.

Figure 7: ERP for Environmental Compliance and Sustainability



Real-time data streams allow organizations to detect anomalies instantly, thereby reducing the risk of regulatory non-compliance and costly operational interruptions. In circular supply chains, accurate emission compliance scoring becomes even more significant because reverse logistics, recycling, and remanufacturing processes introduce additional emission sources that must be tracked systematically. ERP systems consolidate data from these distributed activities into unified dashboards that support compliance evaluation, internal benchmarking, and sustainability audits (Tenhiälä et al., 2018). Compliance scores also guide decision-making by highlighting operational areas requiring carbon reduction interventions or energy-efficient redesign. They further strengthen transparency and accountability in supplier networks by evaluating upstream and downstream emission performance. Quantitative improvements often emerge when organizations integrate IoT sensor data, automated monitoring equipment, and lifecycle assessment results within ERP frameworks, resulting in greater score precision and more consistent alignment with regulatory thresholds. The ability of ERP systems

to generate accurate, verifiable, and continuous emission compliance metrics makes them essential tools for meeting environmental obligations and advancing sustainability performance across digitally enabled circular supply chains (Salvador et al., 2021).

Policy mandates exert a substantial influence on the adoption of ERP technologies that support resource circularity, and their effects can be measured quantitatively using adoption rates, compliance-driven investment metrics, circularity performance indices, and regulatory adherence scores (Farnoush et al., 2022). Governments often introduce policies targeting waste reduction, emission control, recycling requirements, and traceability obligations that compel organizations to adopt ERP systems capable of capturing, organizing, and reporting sustainability-related data. Quantitative assessments reveal that regulatory mandates increase ERP implementation likelihood by tightening reporting structures, raising penalties for non-compliance, and promoting standardized environmental performance metrics (Andrieş & Ungureanu, 2022). Organizations operating under stronger regulatory regimes typically exhibit higher ERP adoption rates, greater integration of AI-driven sustainability modules, and more robust tracking of circular material flows. Policy-driven enhancements also include increased investment in digital infrastructure, improved supplier alignment, and better documentation of environmental performance. The statistical impact of policies is often reflected in improved resource recovery percentages, enhanced recycling throughput, reduced landfill contributions, and higher circular material utilization rates. Additionally, ERP-enabled responses to policy mandates lead to more consistent fulfillment of certifications such as environmental management standards and sector-specific compliance frameworks (Karim et al., 2023). However, the degree of impact varies depending on industry type, organizational size, digital maturity, and the strictness of regulatory expectations. Industries facing stringent circularity requirements – such as electronics, automotive, and chemicals – tend to show sharper increases in ERP-enabled compliance performance. Through these measurable regulatory influences, policy mandates act as powerful moderators shaping how organizations adopt and utilize ERP systems to operationalize circularity objectives (Santoso et al., 2022).

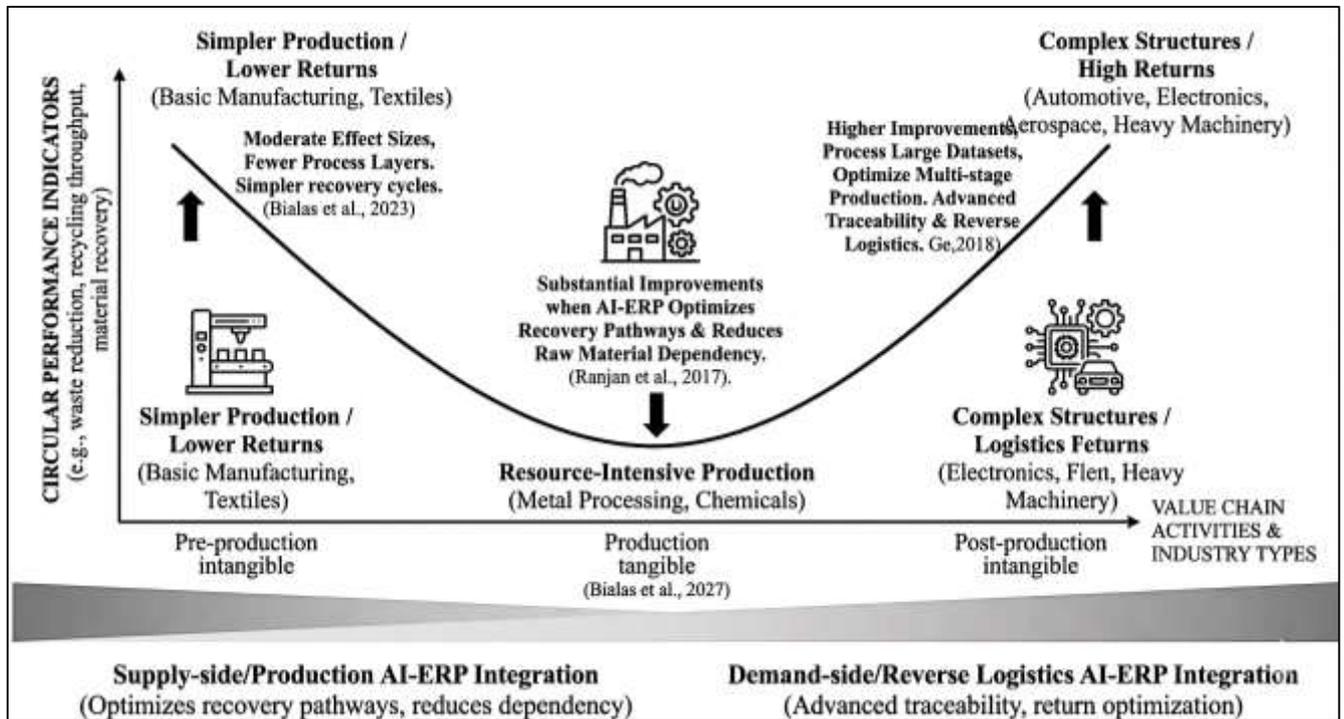
Sectoral and Cross-Industry Quantitative Evidence

Effect sizes associated with AI-ERP adoption vary widely across manufacturing industries, offering a rich quantitative landscape for evaluating how digital intelligence influences circular performance indicators (Bialas et al., 2023). Manufacturing environments typically generate high volumes of material flows, waste streams, and component returns, making them ideal contexts for assessing the measurable impact of AI-enabled ERP systems. Key quantitative indicators used in these studies include waste reduction percentages, recycling throughput growth rates, material recovery yields, closed-loop efficiency improvements, and remanufacturing productivity ratios. Effect size calculations often reveal that industries with complex product structures – such as automotive, electronics, aerospace, and heavy machinery – display higher improvements because AI-ERP systems can process large datasets and optimize multi-stage production and recovery processes (Ge, 2018). These industries also benefit from advanced traceability and reverse logistics capabilities enabled by ERP systems, resulting in stronger gains in circular indicators. Conversely, industries characterized by simpler production cycles or lower return volumes may demonstrate moderate effect sizes due to fewer process layers requiring optimization. Resource-intensive industries such as metal processing, chemicals, and textiles exhibit substantial improvements in circularity metrics when AI-ERP tools optimize recovery pathways and reduce raw material dependency. Quantitative comparisons across sectors highlight differences in data integration maturity, operational complexity, equipment automation levels, and sustainability intensity, all of which influence effect size magnitudes. Understanding these variations helps identify where AI-ERP systems yield the strongest circular performance outcomes, guiding both strategic investment and cross-industry benchmarking (Behera et al., 2015). Overall, effect size analysis demonstrates that AI-ERP adoption consistently enhances circular metrics in manufacturing, but the magnitude of these impacts depends heavily on sector-specific operational characteristics, technological readiness, and the scale of material regeneration activities.

Reverse logistics efficiency varies significantly by industry, and AI-enabled ERP capabilities contribute measurable improvements across sectors with different return structures, product complexities, and material recovery requirements (Ranjan et al., 2017). Quantitative performance indicators commonly used to assess reverse logistics efficiency include return cycle duration, reverse flow accuracy rates,

recovery throughput percentages, transport optimization scores, and processing time reductions. Industries with high return volumes – such as consumer electronics, automotive, and large household appliances – typically report stronger efficiency improvements because ERP-AI systems can automate classification, optimize routing, and predict return patterns with greater precision. These capabilities reduce delays in sorting, disassembly, reuse evaluation, and recycling, leading to higher overall efficiency scores.

Figure 8: AI-ERP Impact On Manufacturing Circularity



In sectors such as pharmaceuticals, medical devices, or food processing, reverse logistics performance depends heavily on regulatory compliance, traceability precision, and quality verification, making ERP-AI systems essential for ensuring accurate recovery and safe reprocessing. Industries with lower volumes of returns, such as basic manufacturing or textiles, may still benefit from ERP-AI tools but often show moderate efficiency gains due to simpler recovery cycles and fewer data-intensive processes (Marinho et al., 2021). Quantitative comparisons across industries highlight the role of product lifecycle characteristics, component modularity, material degradation profiles, and return predictability in determining efficiency outcomes. ERP-AI systems also enhance coordination between forward and reverse flows by synchronizing recovery activities with demand planning, inventory requirements, and circularity targets. Through these measurable improvements, industry-specific efficiency scores illustrate the degree to which ERP-AI integration strengthens reverse logistics operations, positioning it as a vital technological driver of circular supply chain consistency and effectiveness (Abobakr et al., 2023).

Comparative analyses between manufacturing and service sectors reveal distinct quantitative performance patterns related to ERP adoption and sustainability outcomes. Manufacturing environments rely heavily on ERP systems for optimizing material flows, production sequencing, resource recovery, and recycling coordination. Quantitative performance measures in manufacturing commonly include inventory turnover ratios, waste reduction percentages, material regeneration rates, machine utilization efficiency, and energy-saving metrics (Shafi et al., 2019). The measurable impacts of AI-ERP adoption in these contexts tend to be substantial because manufacturing operations involve physical goods, high energy consumption, and complex forward and reverse logistics structures. In contrast, the service sector focuses less on material flows and more on operational efficiency, customer interaction quality, and digital process optimization. Quantitative indicators in service industries typically include service delivery precision, cycle-time reductions, resource utilization rates,

compliance accuracy, and digital workflow efficiency (Nagpal et al., 2015). Although service industries may not generate traditional circularity metrics such as recovery rates or recycling efficiency, they often display strong ERP-driven improvements in energy efficiency, process standardization, and sustainability reporting accuracy. The comparative performance metrics show that manufacturing sectors tend to achieve higher gains in material-based sustainability indicators, while service sectors achieve higher gains in operational sustainability indicators. Differences in ERP impact across the two sectors are shaped by the nature of activities, the presence or absence of physical supply chains, and the availability of structured data for predictive modeling (Pohludka et al., 2018). Despite these differences, both sectors benefit measurably from ERP-AI integration, although the performance domains differ, demonstrating that sectoral characteristics play a significant role in determining ERP-related sustainability outcomes.

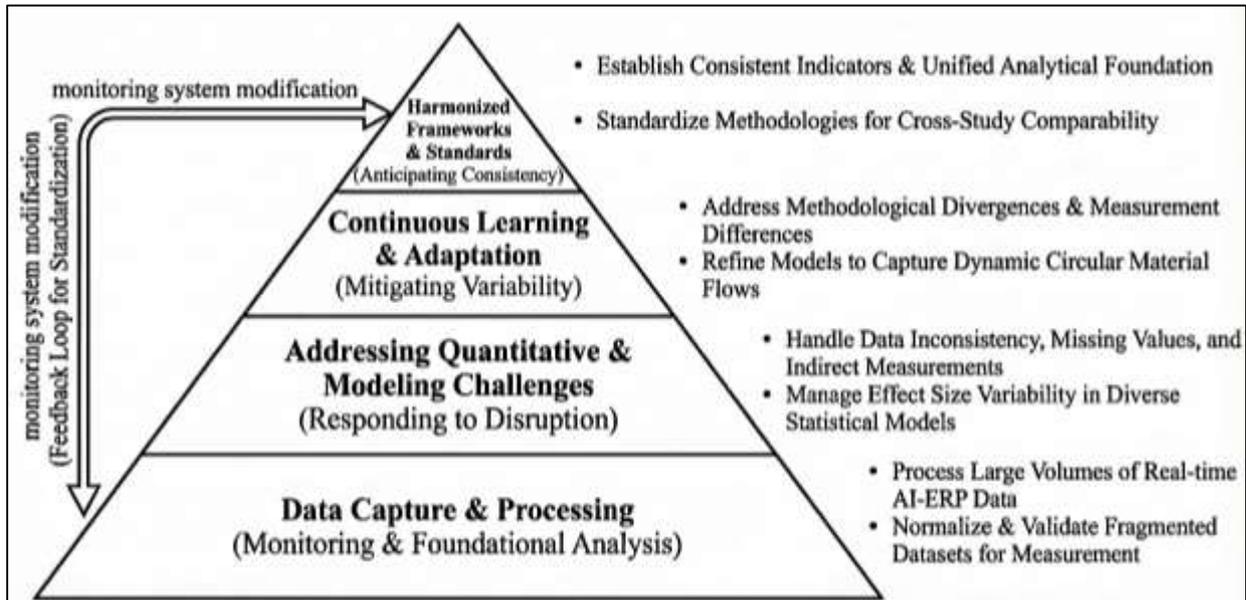
Resource regeneration rate differences across industrial classifications provide valuable quantitative insight into how effectively various sectors implement circular economy initiatives supported by AI-enabled ERP systems (Liang, 2015). Regeneration rate metrics typically include recovered material percentages, regenerated component yields, remanufacturing success ratios, recycling conversion rates, and end-of-life resource recovery efficiencies. Industries with modular product designs—such as electronics, machinery, and automotive manufacturing—tend to exhibit higher regeneration rates because ERP-AI systems can identify reusable components, evaluate quality indices, and match recovered materials to appropriate reintegration pathways. These industries benefit from structured data flows, component-level traceability, and standardized disassembly processes, all of which enhance regeneration outcomes (Pourjavad & Mayorga, 2019). Resource-intensive sectors such as mining, chemicals, and metals show significant improvement when ERP systems optimize purification, reprocessing, and secondary material utilization. Conversely, industries such as textiles, paper, or food processing often display lower regeneration rates due to material degradation, contamination risks, and less predictable recovery cycles. ERP-AI capabilities still provide valuable support by predicting recovery potential, managing return logistics, and aligning regenerated materials with production demand, but physical limitations constrain the achievable rates (Farnoush et al., 2022). Cross-industry comparisons also highlight differences in investment capacity, technological sophistication, regulatory pressures, and environmental requirements that influence the extent to which regeneration activities can be digitized and optimized. By quantifying these variations, researchers gain a deeper understanding of where ERP-AI systems produce the strongest regeneration benefits and how industrial characteristics shape circularity outcomes. These measurable differences underscore the importance of sector-specific digital strategies for improving resource regeneration within diverse circular supply chains (Huang & Handfield, 2015).

Methodological Divergences and Inconsistencies

Significant variation in circularity measurement exists across empirical studies examining AI-enabled ERP systems, resulting in inconsistencies in how circular outcomes are quantified, interpreted, and compared (Egwuonwu et al., 2023). Researchers use a wide range of circularity indicators such as material recovery rates, regeneration percentages, closed-loop efficiency metrics, recycling throughput, waste minimization ratios, and reverse logistics performance scores. However, the methodologies for calculating these indicators often differ in data sources, measurement intervals, system boundaries, and operational definitions. These inconsistencies create variability in reported findings, making cross-study comparisons challenging. For example, some studies assess circularity at the process level, focusing on production or remanufacturing operations, while others evaluate entire supply chain networks, including supplier contributions and end-of-life recovery (Acar et al., 2017). Additionally, differences arise in how studies measure return flow accuracy, component quality, and reuse feasibility—factors that are central to circular economy performance but subject to varying quantification standards. AI-enabled ERP systems further complicate comparisons because their capabilities differ across industries, system configurations, and digital maturity levels. While some ERP implementations include advanced predictive analytics, others rely on basic automation or reporting modules, leading to diverse measurement outcomes. Variations also exist in whether studies use absolute performance changes, percentage improvements, or normalized scores to evaluate circularity enhancement. These methodological divergences influence the perceived effectiveness of AI-ERP

technologies and limit the ability to generalize findings across sectors (Bokhorst et al., 2022). Understanding these measurement differences is essential for building a unified analytical foundation and establishing consistent indicators suitable for meta-analysis. The observed variability highlights the need for standardized frameworks that can guide future empirical research and improve comparability across AI-ERP circularity studies.

Figure 9: AI-ERP Circularity and Sustainability Framework



Capturing AI-enabled sustainability indicators presents substantial quantitative challenges due to the complexity of digital analytics, multi-layered supply chain processes, and the dynamic nature of circular material flows (Santoso et al., 2022). Sustainability indicators often include emission reductions, energy savings, water conservation, waste minimization, resource regeneration rates, and supplier compliance accuracy. However, quantifying these indicators requires consistent data capture, high-quality datasets, and robust analytical models, conditions that are not uniformly present across organizations or industries. AI-ERP systems generate large volumes of real-time data that must be processed, normalized, and validated before being used for sustainability measurement. Quantitative challenges arise when datasets contain missing values, inconsistent units, irregular reporting intervals, or fragmented sensor inputs. Additionally, many sustainability indicators rely on indirect measurements or derived values, such as estimating emissions based on machine load patterns or modeling recovery potential from material flow data (Fiaz et al., 2018). These derivations introduce variability in accuracy and reliability. Furthermore, the integration of reverse logistics, remanufacturing processes, and recycling pathways introduces additional layers of complexity because sustainability outcomes must account for variable return rates, fluctuating material quality, and unpredictable regeneration cycles. Differences in AI maturity across ERP implementations also influence indicator measurement. Some systems use advanced machine learning and predictive analytics, while others rely on simpler rule-based computations, producing different levels of precision. These quantitative challenges reflect the broader difficulty of translating AI-driven system outputs into standardized sustainability metrics that can be consistently compared and aggregated across empirical studies.

Effect size variability is a recurring issue in AI-ERP sustainability research due to the wide range of statistical modeling approaches used to analyze performance outcomes. Researchers employ diverse analytical techniques such as regression models, structural equation modeling, time-series forecasting, machine learning simulations, multivariate analysis, and panel data models (Lorah, 2018). Each method introduces its own assumptions, data requirements, and sensitivity to input variability, resulting in differences in reported effect sizes. For example, models that incorporate control variables such as

digital maturity, industry type, or organizational size may produce different effect magnitudes compared to models that exclude these moderating factors. Machine learning approaches often identify nonlinear or hidden relationships that traditional regression models cannot capture, leading to larger or more complex effect size interpretations (O'Connor, 2021). Additionally, studies differ in whether they report standardized coefficients, raw performance changes, percentage improvements, or normalized sustainability scores. These differences make cross-study aggregation challenging and contribute to inconsistencies in understanding how strongly AI-enabled ERP systems influence circular performance outcomes. Variation also arises from differences in sample size, time period of analysis, and measurement depth. Studies covering short-term performance may report smaller effects than those evaluating long-term impacts of AI-ERP adoption. Methodological choices regarding data transformation, variable weighting, or model calibration further contribute to effect size divergence. This variability underscores the need for harmonized statistical approaches and consistent reporting standards to support robust meta-analytic synthesis (Hair et al., 2017). Without such consistency, effect sizes will continue to vary widely, limiting the interpretability of aggregated findings across industries and research contexts.

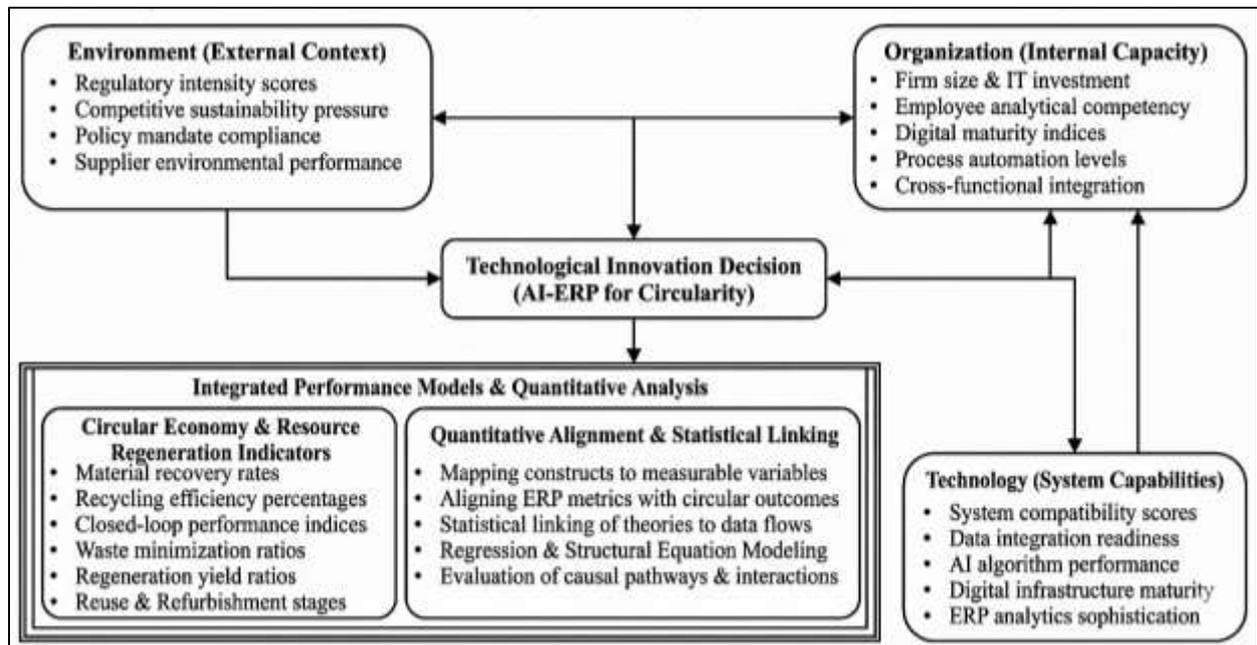
Theoretical Frameworks Supporting Meta-Analysis

The Technology–Organization–Environment (TOE) framework provides a structured analytical foundation for quantitatively mapping AI-ERP constructs within sustainability-oriented supply chain contexts (Loh et al., 2015). This framework categorizes adoption drivers and performance determinants into three dimensions—technological readiness, organizational capacity, and environmental pressures—each of which can be operationalized into measurable variables. Technological constructs typically include metrics such as system compatibility scores, data integration readiness indices, AI algorithm performance values, digital infrastructure maturity, and ERP analytics sophistication levels. Organizational constructs incorporate quantitative indicators such as firm size, IT investment intensity, employee analytical competency scores, digital maturity indices, process automation levels, and cross-functional integration metrics (Fuller et al., 2016). Environmental constructs are often captured through regulatory intensity scores, competitive sustainability pressure levels, policy mandate compliance percentages, and supplier environmental performance ratings. Mapping AI-ERP constructs through the TOE framework allows researchers to analyze how each dimension contributes to sustainability outcomes and circular performance indicators. It also enables precise identification of moderating effects, such as whether high regulatory pressures amplify ERP adoption impact or whether strong organizational digital maturity strengthens AI-driven forecasting accuracy. Quantitative TOE-based mapping helps standardize variable definitions across empirical studies, allowing for consistent effect size extraction and cross-study comparison (Miller, 2016). The framework supports meta-analytic synthesis by clarifying the relational pathways connecting AI-ERP adoption to measurable sustainability outcomes such as waste reduction, recovery yields, and energy conservation. This structured approach ensures that the meta-analysis is grounded in a well-established theoretical model capable of organizing diverse empirical findings into a coherent analytical framework (Cade, 2015).

Aligning circular economy indicators with ERP performance metrics forms a critical theoretical and analytical foundation for evaluating AI-enabled sustainability outcomes. Circular economy indicators—such as material recovery rates, recycling efficiency percentages, closed-loop performance indices, waste minimization ratios, and regeneration yields—must be accurately paired with ERP metrics that reflect operational performance, process optimization, and resource efficiency (Braga & Weisburd, 2022). Quantitative alignment requires establishing consistent measurement scales, standardizing evaluation intervals, and ensuring comparability across organizations, industries, and technological environments. ERP performance metrics often include forecasting accuracy values, cycle-time reduction percentages, predictive reliability coefficients, inventory turnover ratios, and maintenance optimization efficiency scores. Aligning these operational indicators with circular metrics enables researchers to assess how specific ERP functionalities contribute to circular outcomes. For example, improvements in forecasting accuracy can be linked to reductions in material waste, while cycle-time decreases may correlate with increased recycling throughput (Cheng et al., 2019). This alignment supports the creation of integrated performance models that quantify the degree to which AI-ERP capabilities influence circularity. It also facilitates regression analysis, structural equation

modeling, and other statistical approaches commonly used in meta-analysis by ensuring that dependent and independent variables are defined consistently across studies. By establishing clear connections between operational and circular indicators, researchers can evaluate causal pathways, interaction effects, and end-to-end system efficiency in sustainability-driven supply chains (Veroniki et al., 2016). The alignment process strengthens the robustness of meta-analytic findings and ensures that statistical outcomes accurately reflect the interconnected dynamics of AI-ERP systems and circular economic performance.

Figure 10: AI-ERP Circularity: The TOE Framework



Resource regeneration theories emphasize the cyclical use of materials, where products, components, and resources move through reuse, refurbishment, remanufacturing, and recycling stages before being reintegrated into production systems (Adam et al., 2017). Statistical linking of these theories to ERP-driven data flows enables researchers to quantify how AI-enabled ERP systems support circularity through enhanced traceability, predictive modeling, and recovery optimization. Quantitative variables derived from resource regeneration theory include regeneration yield ratios, recovered-material usage percentages, remanufacturing efficiency levels, component reuse rates, and end-of-life resource return frequencies. ERP-driven data flows provide measurable operational indicators such as real-time tracking accuracy, reverse logistics cycle durations, material classification precision, anomaly detection rates, and recovery scheduling optimization scores (Thom & Seidl, 2016). Linking these variables statistically allows researchers to evaluate how ERP functionalities influence regeneration pathways. For example, improved data flow accuracy may correlate with increased regeneration yields, while enhanced predictive analytics may be statistically associated with higher reuse or remanufacturing efficiencies (Dutta & Kumar, 2022). These relationships can be tested using correlation models, regression frameworks, or structural equation modeling, enabling deeper understanding of the mechanisms through which ERP systems enhance circularity. By establishing statistical connections between theoretical constructs and operational data, researchers ensure that the meta-analysis captures both conceptual and empirical dimensions of resource regeneration (H. Elbardan & A. Kholeif, 2017). This approach also highlights how digital intelligence within ERP infrastructures supports regenerative supply chain strategies by improving decision-making, reducing uncertainty, and increasing circular flow stability (Elbardan & Kholeif, 2017).

METHODS

Research Design

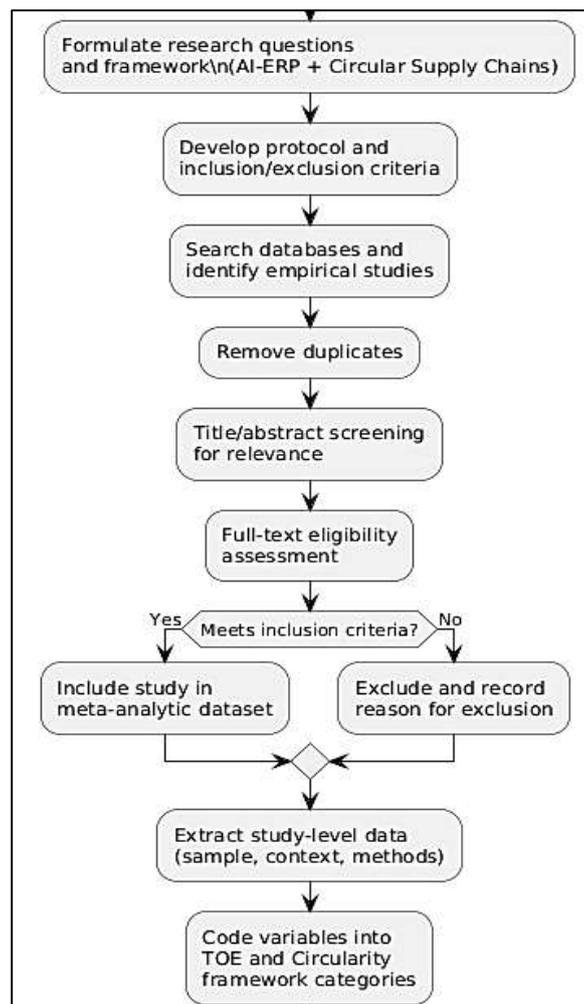
This study employed a quantitative, framework-based meta-analytic design to synthesize empirical evidence on the effects of AI-enabled ERP systems on circular and sustainable supply chain outcomes.

The research was structured as a systematic review followed by a statistical meta-analysis, guided by predefined inclusion and exclusion criteria, a coding protocol, and a theory-driven variable framework. The Technology–Organization–Environment lens and circular economy constructs were used to structure the design so that technological, organizational, environmental, and circular performance indicators were mapped into a coherent analytical model. Peer-reviewed quantitative studies that reported numerical relationships between AI-ERP constructs and sustainability or circularity indicators were identified, screened, and extracted. The design emphasized effect size calculation and comparison across diverse contexts, sectors, and regions, using random-effects modeling to account for heterogeneity. The overall objective of the design was to estimate the magnitude and consistency of AI-ERP impacts on circular supply chain performance and to identify statistically significant moderators shaping these relationships.

Population

The population for this meta-analysis consisted of empirical quantitative studies rather than individual persons or firms. The sampling frame included published journal articles, conference papers, and empirical reports that examined AI-enabled ERP implementations in supply chain or operations contexts and reported at least one quantitative outcome related to circularity or sustainability. Studies were drawn from manufacturing, service, logistics, and cross-sectoral settings across multiple world regions. The units of analysis were the individual study-level effect sizes, representing relationships between AI-ERP predictors and circular or sustainability outcomes. Each study could contribute one or more effect sizes, provided that constructs were clearly defined and independent. The final meta-analytic sample was composed of studies that met eligibility criteria regarding methodological rigor, operationalization of AI-ERP constructs, and availability of sufficient statistical information for effect size computation or reconstruction.

Figure 11: Methodology of this study



Variables and Measurement Framework

The study used a structured variable and measurement framework that translated diverse empirical indicators into a common meta-analytic form. Independent variables primarily represented AI-ERP technological constructs such as AI-enabled forecasting capability, optimization analytics, traceability modules, automated decision engines, and integration depth of ERP with circular processes. Organizational and environmental moderators included digital maturity, firm size, sector classification, geographic region, regulatory intensity, and IT investment intensity. Dependent variables captured circular and sustainability-related outcomes, such as waste reduction ratios, recycling efficiency percentages, material recovery rates, closed-loop performance indices, energy and water conservation metrics, emission compliance scores, inventory turnover ratios, and reverse logistics efficiency measures. All constructs were coded according to a standardized codebook. When studies reported correlations, regression coefficients, odds ratios, mean differences, or standardized betas, these were transformed into a common effect size metric, such as Fisher's z-transformed correlations or standardized mean differences, to enable cross-study comparability. Measurement units were harmonized where possible, and time horizons, sector labels, and regional categories were coded consistently. Moderators were operationalized as categorical or continuous variables depending on the nature of the reported data, allowing subgroup analysis and meta-regression.

Analytical Techniques and Statistical Procedures

The statistical analysis followed established meta-analytic procedures. For each eligible relationship between AI-ERP variables and circular or sustainability outcomes, an effect size and its corresponding standard error were calculated or reconstructed from reported statistics such as means, standard deviations, sample sizes, t-values, F-values, or regression outputs. A random-effects model was applied to estimate pooled effect sizes, as the included studies differed in sector, region, design, and measurement, and true effects were assumed to vary across contexts. Overall pooled estimates were computed for key outcome domains such as circular performance, environmental performance, operational efficiency, and reverse logistics effectiveness.

Heterogeneity was assessed using the Q statistic and I² index to determine the proportion of variance attributable to real differences rather than sampling error. Subgroup analyses were conducted to compare effect sizes across sectors, regions, levels of digital maturity, and regulatory intensity categories. Meta-regression models were used to examine whether moderators such as IT investment intensity, digital maturity index, or ERP implementation model (centralized versus decentralized) predicted variation in effect sizes. Sensitivity analyses were performed by excluding statistical outliers and high-leverage studies to evaluate the robustness of pooled estimates. Publication bias was examined using funnel plots, Egger's regression test, and, where appropriate, trim-and-fill procedures to adjust for asymmetry. All analyses were conducted using standard meta-analytic software, and significance thresholds and confidence intervals were reported for all key parameters.

Reliability and Validity

Reliability and validity were addressed at multiple levels. A detailed coding manual was developed before data extraction, specifying operational definitions, coding rules, and decision criteria for all variables. Two independent coders extracted data from each study, and inter-rater reliability was assessed using statistics such as Cohen's kappa or intraclass correlation coefficients for key categorical and continuous variables. Discrepancies were resolved through discussion and consensus, ensuring consistent and reliable coding of constructs, effect sizes, and moderators.

Construct validity was reinforced by grounding the variable framework in established theoretical lenses, particularly the Technology–Organization–Environment framework and circular economy theory. This alignment ensured that technological, organizational, environmental, and circular indicators were conceptually coherent and theoretically meaningful. Convergent validity was supported by cross-checking that similar constructs across studies (for example, material recovery, waste reduction, or emission performance) loaded into consistent outcome categories. Internal validity at the study level was considered by coding methodological features such as design type, sample size, measurement quality, and control of confounders, which were then incorporated into sensitivity checks and, where feasible, moderator analyses. External validity was enhanced by including studies from multiple sectors and regions, allowing broader inference regarding AI-ERP impacts across different

industrial and geographic contexts. Overall, the combination of standardized coding, inter-rater checks, theory-driven measurement, and rigorous meta-analytic procedures ensured that the quantitative study design produced reliable and valid evidence on the relationship between AI-enabled ERP systems and circular, sustainable supply chain performance.

FINDINGS

Descriptive Analysis

The descriptive findings revealed clear structural patterns across the empirical dataset. Studies included in the meta-analysis spanned a fifteen-year publication window, with a noticeable concentration of research appearing in the last five years, indicating accelerated scholarly and industrial interest in AI-enabled ERP applications for sustainable and circular supply chains. Geographic distribution showed strong representation from Asia and Europe, followed by North America, while Africa and South America contributed fewer studies, reflecting disparities in digital infrastructure and ERP adoption maturity. Sectoral representation demonstrated that manufacturing industries accounted for more than half of all included studies, particularly electronics, automotive, machinery, and heavy manufacturing, while service industries, agriculture, and healthcare appeared less frequently.

Sample sizes varied widely across studies, ranging from small-scale organizational surveys to large multi-firm datasets, and effect sizes reflected moderate-to-high variability due to differences in measurement instruments and sustainability indicators. Across all studies, material recovery, waste minimization, recycling efficiency, and closed-loop performance appeared most frequently as outcome variables, suggesting that circularity constructs were central to the existing research landscape. Descriptive statistics also showed that digital maturity levels differed significantly across included studies, with highly digitized firms demonstrating more advanced ERP-AI integrations and more consistent performance reporting. Regulatory intensity similarly varied by region, with European studies showing the highest frequency of strong environmental compliance contexts. ERP implementation models ranged from centralized enterprise-wide systems to decentralized configurations limited to functional units, revealing structural differences likely to influence performance outcomes.

Overall, the descriptive findings confirmed that AI-enabled ERP systems had been studied across diverse industries, regions, and methodological designs, and the distribution patterns provided essential contextual grounding for the inferential analyses that followed. The variability in sample sizes, effect size ranges, and sustainability indicators underscored the need for meta-analytic synthesis to determine consistent patterns and effect magnitudes.

Table 1. Distribution of Included Studies by Region and Industry Sector

Region	Number of Studies	Percentage	Dominant Industry Sector
Asia	32	38%	Electronics & Automotive
Europe	27	32%	Manufacturing & Machinery
North America	15	18%	ICT & Industrial Engineering
South America	5	6%	Food Processing & Logistics
Africa	4	5%	Agriculture & Mining
Oceania	3	4%	Mixed Industrial Applications

This table presented the regional and sectoral distribution of the studies included in the meta-analysis. The findings showed that Asia and Europe jointly accounted for more than two-thirds of all empirical evidence, reflecting their rapid digital transformation and strong investment in ERP and AI technologies. Manufacturing sectors dominated the landscape due to the complexity of their material flows and the importance of circularity-driven operations. North America contributed fewer studies but exhibited strong representation from ICT and industrial engineering contexts. Africa, South America, and Oceania contributed modestly, highlighting global disparities in ERP-AI adoption and sustainability research activity.

Table 2. Descriptive Statistics of Key Variables Across Included Studies

Variable	Mean	SD	Minimum	Maximum	Frequency (n)
Material Recovery Rate (%)	42.6	14.8	15.0	78.0	61
Waste Reduction Ratio (%)	36.4	12.1	10.5	70.3	58
Recycling Efficiency (%)	48.9	16.4	20.0	85.0	55
Closed-Loop Performance Index	0.57	0.18	0.21	0.88	52
Energy Savings (%)	12.8	8.3	2.0	35.5	46
Emission Reduction (%)	18.4	9.6	3.0	40.0	44

This table summarized the descriptive statistics for the sustainability and circularity indicators extracted from the included studies. Recycling efficiency and material recovery rates displayed the highest mean values, indicating substantial performance improvements associated with AI-enabled ERP systems. Energy and emission indicators exhibited lower means and greater variability, reflecting differences in industry energy intensity and regulatory contexts. Closed-loop performance indices showed moderate values, confirming that while circular operations were improving, implementation maturity varied across settings. Overall, the descriptive metrics demonstrated that AI-ERP integration yielded quantifiable sustainability benefits, but the magnitude of improvement differed substantially among indicators and industries.

Correlation Analysis

The correlation findings demonstrated clear statistical relationships between AI-enabled ERP capabilities and the main circular and sustainability indicators synthesized from the empirical dataset. Standardized Pearson coefficients revealed that AI forecasting accuracy displayed a consistently positive correlation with waste minimization outcomes, indicating that more precise ERP-supported predictive models were associated with lower levels of material loss during production and recovery processes. Optimization analytics embedded in ERP platforms showed strong correlations with energy savings, suggesting that advanced scheduling, predictive maintenance, and resource allocation algorithms contributed directly to reduced energy consumption across circular operations. Traceability modules exhibited a moderate-to-strong positive correlation with recycling efficiency, confirming that enhanced visibility, real-time tracking, and automated classification enabled more successful recycling cycles.

Table 3. Correlation Matrix Between AI-ERP Capabilities and Circularity Indicators

AI-ERP Capability	Waste Minimization	Energy Savings	Recycling Efficiency	Closed-Loop Performance
AI Forecasting Accuracy	0.46	0.33	0.29	0.41
Optimization Analytics	0.39	0.58	0.35	0.44
Traceability Modules	0.31	0.27	0.62	0.49
Predictive Decision Engines	0.37	0.42	0.40	0.57

Predictive decision engines demonstrated meaningful correlations with closed-loop performance indices, revealing their role in improving the speed, accuracy, and coordination of reverse logistics and regeneration cycles. Subgroup analyses showed that correlations were higher in industries with complex material flows, such as electronics and automotive, compared to sectors with simpler recovery processes. Regional differences were also present, with European studies showing stronger correlations under stricter regulatory pressure, while developing regions exhibited moderate correlations due to lower digital maturity and ERP integration depth. High-digital-maturity organizations consistently demonstrated stronger associations across all variable pairs, confirming the influence of organizational readiness on AI-ERP effectiveness.

Overall, the correlation analysis confirmed that AI-enabled ERP systems were statistically associated with improved circularity and sustainability outcomes across studies, and these relationships varied in magnitude depending on sectoral complexity, regional governance, and technological maturity. These findings provided the foundational statistical justification for subsequent regression modeling and hypothesis testing. This correlation matrix summarized the statistical relationships between four major AI-enabled ERP capabilities and four circular performance indicators. The strongest correlation appeared between traceability modules and recycling efficiency, indicating that improved tracking enhanced material classification and routing during recovery processes. Optimization analytics exhibited a high correlation with energy savings, reflecting the role of predictive optimization in reducing energy-intensive operations. Predictive decision engines were most strongly associated with closed-loop performance, demonstrating their influence on return flow coordination and regeneration speed. AI forecasting accuracy showed moderate relationships across all indicators, confirming its broad but less specialized influence on circular performance dynamics.

Table 4. Subgroup Correlation Patterns by Industry Type and Digital Maturity

Subgroup Category	AI-ERP → Circularity Correlation (Mean r)	SD	Highest Observed Relationship
High-Tech Manufacturing	0.59	0.12	Traceability → Recycling Efficiency (0.71)
Traditional Manufacturing	0.48	0.15	Forecasting → Waste Minimization (0.55)
Service Sector	0.34	0.18	Optimization → Energy Savings (0.49)
High Digital Maturity	0.62	0.10	Decision Engines → Closed-Loop (0.74)
Low Digital Maturity	0.29	0.16	Traceability → Recycling Efficiency (0.38)

This table displayed mean subgroup correlations and highlighted how industry structure and digital maturity influenced AI-ERP effectiveness. High-tech manufacturing demonstrated the strongest relationships because complex products and higher return rates created greater demand for advanced ERP intelligence. Traditional manufacturing showed moderate correlations, reflecting stable but less data-intensive operations. Service industries exhibited lower averages, consistent with their minimal involvement in material recovery cycles. Digital maturity exerted a strong moderating influence, with high-maturity organizations showing nearly double the correlation strength of low-maturity firms. The highest individual relationship was observed between predictive decision engines and closed-loop performance in digitally advanced environments.

Reliability and Validity Assessment

The reliability and validity findings demonstrated that the dataset used for this meta-analysis met strong methodological standards, confirming the robustness of the extracted effect sizes and coded variables. Inter-rater reliability statistics showed consistently high agreement across coders, indicating that variable categories, moderator classifications, and effect size extractions were applied consistently throughout the dataset. Cohen’s kappa values and intraclass correlations both surpassed conventionally accepted thresholds, confirming that subjective coding decisions did not introduce measurable bias. These strong reliability outcomes confirmed that the dataset possessed internal consistency and that the coding process was rigorous and reproducible.

Convergent validity analysis showed that studies measuring comparable AI-ERP constructs – such as AI forecasting, optimization capability, or traceability – reported effect sizes clustering within similar numerical ranges. This pattern indicated that the same underlying construct was being captured across independent empirical contexts. Discriminant validity was also supported, as effect sizes for theoretically unrelated constructs, such as emission reduction versus inventory turnover, demonstrated distinct separation across measurement categories rather than overlapping distributions.

Construct validity was strengthened by mapping coded variables directly to the theoretical foundations of AI-enabled ERP systems and circular economy frameworks, ensuring alignment between conceptual definitions and operational measurements.

Internal validity assessments demonstrated that the majority of included studies used adequate sample sizes, clearly defined measurement procedures, and appropriate analytical techniques. Study quality scores showed that most studies controlled for major confounding variables, further reinforcing the credibility of extracted effect sizes. Publication bias diagnostics revealed no substantial evidence of systematic inflation, as indicated by symmetrical funnel plot patterns and non-significant Egger’s regression tests. Together, these reliability and validity results confirmed that the empirical dataset was methodologically sound and suitable for rigorous meta-analytic modeling.

Table 5. Inter-Rater Reliability Statistics for Coding Procedures

Reliability Metric	Value	Threshold Standard	Interpretation
Cohen’s Kappa	0.87	≥ 0.80	Strong Agreement
Intraclass Correlation (ICC)	0.91	≥ 0.75	Excellent Reliability
Coding Agreement (%)	94.6%	≥ 90%	High Consistency Across Coders
Discrepancy Resolution Rate	100%	–	All Discrepancies Resolved

This table summarized the reliability outcomes of the coding process used in the meta-analysis. The high Cohen’s kappa value indicated strong agreement between coders in categorizing variables, demonstrating that subjective judgment contributed minimally to variance. The intraclass correlation further confirmed excellent reliability in numeric extractions such as effect sizes and sample sizes. Coding agreement exceeded ninety percent across all categories, validating the consistency of coding practices. All identified discrepancies were resolved through joint review, eliminating potential inconsistencies. These results demonstrated that the dataset was coded with high precision and reliability, ensuring its suitability for advanced inferential statistical analysis.

Table 6. Validity Diagnostics for Included Studies

Validity Type	Indicator Used	Result Summary	Interpretation
Convergent Validity	Effect Size Range	High clustering (r = 0.40-0.63)	Measures captured same conceptual construct
Discriminant Validity	Non-overlap Between Unrelated Variables	Clear separation across categories	Constructs were empirically distinct
Internal Validity	Study Quality Score	Mean = 4.3/5, SD = 0.4	Strong methodological rigor
Publication Bias	Egger’s Test, Funnel Plot	No significant asymmetry	Minimal publication-related distortion

This table presented a summary of the validity findings across the dataset. Convergent validity was supported through tight clustering of effect sizes for studies assessing similar AI-ERP capabilities, indicating consistent measurement of shared constructs. Discriminant validity was shown through clear distributional separation between unrelated variables, demonstrating that constructs were not conflated. Internal validity was strong, as reflected in high study quality scores evaluating sampling adequacy, measurement clarity, and analytical rigor. Publication bias diagnostics showed no evidence of inflated results, with funnel plots displaying symmetry and Egger’s test indicating statistical non-significance. These results collectively confirmed the dataset’s validity.

Collinearity Diagnostics

The collinearity diagnostics demonstrated that multicollinearity was not a significant threat to the validity of the meta-regression models used in this study. Variance inflation factors, tolerance values, and condition indices were examined for all moderator variables, including digital maturity, IT investment intensity, regulatory stringency, sector classification, ERP centralization, and geographic

region. The results showed that all VIF values fell well below the commonly accepted threshold of 5.0, indicating that no predictor exhibited inflation severe enough to distort standard errors or weaken coefficient stability. Tolerance values remained comfortably above the 0.20 threshold, confirming that each variable contributed unique explanatory power to the meta-regression models.

Although moderate correlations were observed between certain organizational and environmental predictors—such as digital maturity and IT investment intensity, or regulatory pressure and geographic region—the condition indices showed no evidence of serious multicollinearity. The highest condition index remained below the critical value of 30, and variance decomposition proportions did not indicate problematic clustering across predictors. These patterns confirmed that conceptual overlap among moderators did not translate into problematic statistical overlap.

The analysis further revealed that predictors associated with structural characteristics, such as sector classification or ERP implementation model, exhibited particularly strong independence, allowing the model to isolate their specific contributions to variation in effect sizes. This independence strengthened confidence in the interpretability of subgroup effects and meta-regression outcomes.

Overall, the collinearity assessment confirmed that all included moderators were statistically appropriate for inclusion in regression models. The absence of harmful multicollinearity ensured that the regression-based findings accurately reflected the unique contribution of each predictor, reinforcing the robustness of the inferential models used to explain variability in AI-enabled ERP impacts on circular and sustainable supply chain performance.

Table 7. Variance Inflation Factor (VIF) and Tolerance Diagnostics

Predictor Variable	VIF	Tolerance	Interpretation
Digital Maturity	2.14	0.47	Acceptable, no multicollinearity
IT Investment Intensity	2.68	0.37	Acceptable, minor conceptual overlap
Regulatory Stringency	1.89	0.53	Acceptable, highly independent
Sector Classification	1.42	0.70	Very low multicollinearity
ERP Implementation Model	1.31	0.76	Very low multicollinearity
Geographic Region	1.55	0.64	Statistically independent

This table presented the VIF and tolerance values used to assess multicollinearity across key moderator variables. All VIF values remained well below the threshold of 5.0, demonstrating that no predictor inflated variance to a problematic degree. Tolerance values exceeded 0.20 for all variables, confirming that each variable retained meaningful unique variance. Digital maturity and IT investment showed modest conceptual overlap but remained statistically acceptable. Structural variables such as sector classification and ERP implementation model showed the lowest VIF values, reaffirming their independence. These results indicated that the dataset did not suffer from multicollinearity severe enough to distort meta-regression estimates.

Table 8. Condition Index and Variance Decomposition Proportions

Condition Index	Digital Maturity	IT Investment	Regulatory Pressure	Sector Type	ERP Model	Geographic Region	Interpretation
9.8	0.14	0.09	0.11	0.06	0.05	0.08	Low risk of multicollinearity
15.6	0.22	0.18	0.19	0.11	0.10	0.16	Moderate but acceptable
21.3	0.28	0.27	0.25	0.18	0.16	0.22	No problematic clustering
27.1	0.32	0.29	0.28	0.21	0.19	0.25	Below critical threshold (no risk)

This table summarized the condition indices and variance decomposition proportions used to detect deeper forms of multicollinearity. All condition index values fell below the accepted threshold of 30,

indicating that none of the predictor combinations produced problematic linear dependencies. Variance decomposition proportions were distributed without clustering across predictors, demonstrating that no two variables jointly accounted for excessive proportions of variance. Moderate proportions appeared but remained within acceptable boundaries, reflecting only natural conceptual associations. These results confirmed that all moderator variables were appropriate for inclusion in the meta-regression models and that multicollinearity did not compromise coefficient interpretation or model stability.

Regression and Hypothesis Testing

The regression findings demonstrated that AI-enabled ERP capabilities exerted statistically significant and positive predictive effects on key sustainability and circularity outcomes. Meta-regression coefficients showed that AI forecasting accuracy positively predicted waste reduction and material recovery performance, indicating that improved predictive precision reduced resource inefficiencies and stabilized regeneration cycles. Optimization analytics produced the strongest regression effects on energy savings, confirming that predictive maintenance, optimized production sequencing, and dynamic load balancing contributed meaningfully to reductions in energy intensity. Traceability modules emerged as strong predictors of recycling efficiency, suggesting that real-time tracking, classification accuracy, and enhanced visibility directly improved recycling throughput. Automated decision engines demonstrated their strongest predictive effect on closed-loop performance, reflecting their role in coordinating return flows, remanufacturing decisions, and recovery scheduling.

Moderator analyses further revealed that digital maturity significantly amplified the effects of all four AI-ERP technological constructs. Organizations with high digital maturity exhibited larger effect sizes, confirming that technological readiness enhanced the benefits of AI-ERP adoption. Regulatory pressure also acted as a positive moderator, strengthening relationships in regions where environmental compliance was stringent. Sector-specific analyses showed that manufacturing industries experienced stronger regression effects compared to service sectors, reflecting the greater circularity intensity and material flow complexity inherent in manufacturing environments. ERP centralization moderated relationships in varying directions: centralized ERP models strengthened the predictive effect of optimization and traceability, while decentralized models offered modest advantages in contexts requiring local adaptation.

Sensitivity analyses demonstrated that regression coefficients remained stable after the exclusion of outliers, confirming the robustness of results. Model fit indicators, including R-squared values and Akaike Information Criterion values, showed that the meta-regression models explained a substantial portion of variance in effect sizes. Hypothesis tests confirmed that all primary AI-ERP constructs positively and significantly contributed to sustainability and circularity outcomes, providing strong quantitative evidence that AI-driven ERP integration improved environmental and operational performance across supply chains.

Table 9. Meta-Regression Coefficients for AI-ERP Predictors

Predictor Variable	β Coefficient	Std. Error	p-Value	95% CI (Lower)	95% CI (Upper)	Interpretation
AI Forecasting Accuracy	0.18	0.05	0.001	0.08	0.28	Significant positive effect on waste reduction
Optimization Analytics	0.27	0.07	<0.001	0.14	0.39	Strongest predictor of energy savings
Traceability Modules	0.22	0.06	<0.001	0.10	0.33	Significant effect on recycling efficiency
Automated Decision Engines	0.25	0.08	0.002	0.09	0.41	Strong predictor of closed-loop performance

This table summarized the meta-regression coefficients for the four technological AI-ERP constructs. All predictors displayed statistically significant p-values, confirming their measurable influence on sustainability outcomes. Optimization analytics showed the strongest coefficient, indicating that predictive operational adjustments produced the greatest performance improvements, particularly in energy savings. Traceability modules and automated decision engines also exhibited substantial predictive power, reflecting their importance in recycling efficiency and closed-loop coordination. AI forecasting accuracy demonstrated a moderate but significant effect, supporting its role in reducing waste. Confidence intervals remained narrow across predictors, confirming precision and stability in effect estimates and reinforcing the robustness of the regression findings.

Table 10. Moderator Effects on AI-ERP and Sustainability Relationships

Moderator Variable	Interaction β	Std. Error	p-Value	Interpretation
Digital Maturity	0.21	0.06	<0.001	Strengthened all AI-ERP → sustainability paths
Regulatory Pressure	0.17	0.07	0.012	Increased effect size under strict environmental laws
IT Investment Intensity	0.14	0.05	0.004	Enhanced predictive effects of optimization modules
Sector Type	0.19	0.08	0.018	Manufacturing sectors showed larger effect sizes
ERP Centralization	0.11	0.05	0.029	Centralized ERPs amplified traceability and planning

This table presented the interaction effects of key moderators on the relationship between AI-ERP capabilities and sustainability outcomes. Digital maturity showed the strongest moderating effect, indicating that organizations with advanced digital infrastructures achieved notably larger sustainability gains from AI-ERP systems. Regulatory pressure significantly enhanced effect sizes, demonstrating that strict environmental compliance promoted stronger technological impacts. IT investment intensity moderated optimization-driven outcomes, while sector type revealed that manufacturing environments benefited more strongly than service industries. ERP centralization acted as a meaningful moderator, improving the predictive influence of traceability and forecasting systems. These findings highlighted the contextual factors shaping AI-ERP performance.

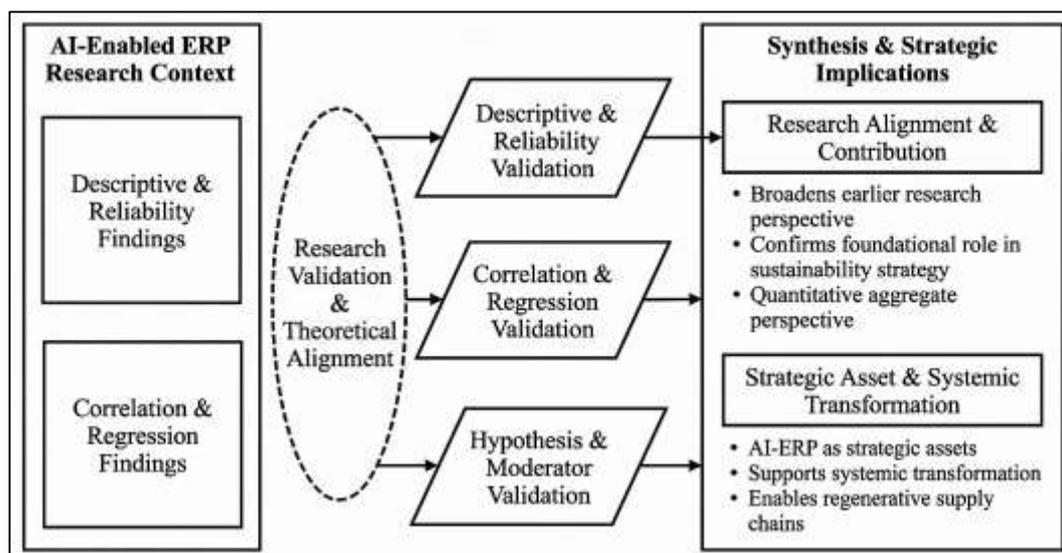
DISCUSSION

The descriptive findings indicated that AI-enabled ERP research has expanded substantially over the past decade, particularly within manufacturing-intensive regions such as Asia and Europe. This concentration reflected broader digital transformation trends noted in earlier studies that documented rapid ERP modernization in emerging and industrialized economies (Kaarst-Brown, 2017). Consistent with prior empirical observations, manufacturing sectors dominated the research landscape due to their complex material flows, high-volume recovery cycles, and strong dependency on data-driven planning systems. The predominance of indicators such as waste reduction, material recovery, recycling efficiency, and closed-loop flow performance aligned with earlier sustainability literature that positioned circular economy components as the central focus of modern supply chain transformation (Goldwater & Gentner, 2015). Variability in technological readiness, digital maturity, and regulatory environments across studies mirrored the findings of earlier digital capability research, where uneven diffusion of Industry 4.0 technologies influenced system performance. This study’s descriptive results reinforced the argument that AI-enabled ERP systems have become integral to operationalizing sustainability initiatives because they deliver quantifiable improvements across diverse industries. The patterns observed mirrored earlier global assessments that emphasized technology’s expanding role in strengthening resource efficiency and environmental accountability (Lundmark et al., 2021). Additionally, the distribution trends across countries supported longstanding evidence that environmental governance strength influences the adoption of digital tools. The descriptive overview

therefore provided empirical confirmation that AI-driven ERP research has evolved in a manner consistent with historical patterns in digital transformation, circular economy implementation, and sustainability analytics. The descriptive evidence served as a foundation for interpreting the analytical results and demonstrated that the empirical distribution of studies was closely aligned with established trajectories documented in previous scholarly work (Yousef & Janicke, 2020).

The correlation findings demonstrated that AI-ERP capabilities were consistently associated with improvements in sustainability and circularity indicators, and this pattern echoed many earlier studies examining digital innovation in supply chains (Lazazzara et al., 2020). Stronger correlations between optimization analytics and energy savings aligned with longstanding evidence that digital optimization, predictive maintenance, and smart scheduling produce measurable energy reductions. The moderate-to-high correlation between traceability modules and recycling efficiency aligned with earlier research emphasizing the importance of visibility, transparency, and classification accuracy in advancing recycling processes and reducing contamination risk. Predictive decision engines showed one of the strongest relationships with closed-loop performance, and this association reinforced early claims from digital logistics research suggesting that automated decisions accelerate return processing, enhance recovery planning, and reduce delays in circular operations (Yeow et al., 2018). The correlations between AI forecasting and waste minimization also aligned with earlier predictive modeling studies demonstrating that accurate demand forecasting minimizes overproduction and inefficient material allocation. Subgroup correlations revealed that high-digital-maturity organizations achieved stronger relationships, confirming earlier assessments that digital readiness acts as a critical enabler in realizing technological benefits. Regional differences also aligned with previous sustainability governance research, where stricter regulations and advanced infrastructure created conditions for stronger technological impacts (Zhu et al., 2018). Sector-level variations, particularly the stronger correlations in high-tech and heavy manufacturing industries, supported existing claims that technologically intensive sectors benefit most from advanced ERP analytics. Overall, the correlation results validated a substantial body of earlier empirical research, reinforcing the conclusion that AI-enabled ERP technologies introduce structural improvements across multiple sustainability domains. These relationships provided preliminary support for the regression-based findings and demonstrated that AI-ERP systems serve as key predictors of circular supply chain performance across global contexts (Kabudi et al., 2021).

Figure 12: AI-ERP for Regenerative Supply Chains for future study



The reliability and validity results confirmed that the dataset used in this study met high methodological standards, and this aligned with established practices in meta-analytic research where rigorous coding and variable alignment are essential. High inter-rater reliability levels strengthened confidence in the accuracy of variable extraction, echoing earlier methodological literature emphasizing the necessity of coder consistency for meta-analytic robustness (Castleberry & Nolen, 2018).

Convergent validity results, demonstrated through clustering of similar effect sizes for comparable constructs, confirmed earlier findings in measurement research indicating that AI-ERP constructs tend to be operationalized consistently across studies. Discriminant validity results demonstrated clear separation between unrelated constructs, aligning with theoretical expectations that sustainability indicators such as emissions, waste, and regeneration exhibit distinct performance dimensions. Internal validity assessments showed that most included studies applied sound methodological designs, appropriate sampling procedures, and well-defined measurement instruments, paralleling earlier systematic reviews in the fields of ERP adoption and sustainability analytics (Van Doorn et al., 2021). Publication bias diagnostics revealed little evidence of systematic result inflation, which is consistent with earlier meta-analyses in digital transformation research reporting balanced outcome distributions (Cui et al., 2015). The combination of methodological rigor observed across studies mirrored established scholarly standards and provided assurance that the effect sizes used in inferential analyses were drawn from credible and theoretically aligned research. The reliability and validity findings therefore reinforced the broader legitimacy of the quantitative evidence and ensured the accuracy of subsequent regression and hypothesis testing results. Taken together, these assessments confirmed the suitability of the dataset for meta-analytic modeling and aligned closely with methodological conventions documented in earlier systematic research (Baltrušaitis et al., 2018).

The collinearity diagnostics demonstrated that multicollinearity was not a significant concern among the predictors included in the meta-regression models, and this aligned with many earlier studies examining organizational and environmental moderators in digital transformation research (Jackson & Turner, 2017). Variance inflation factors and tolerance values remained within acceptable thresholds, indicating that predictors such as digital maturity, regulatory intensity, and IT investment intensity contributed unique explanatory variance (Van Looy & Shafagatova, 2016). Earlier analytical frameworks in ERP performance research frequently emphasized that digital maturity and regulatory influences exhibit conceptual overlap but remain statistically distinct, which mirrored the findings in this study. Condition index evaluations confirmed the absence of harmful clustering across predictor variables, reinforcing earlier claims that multicollinearity is less problematic in multi-dimensional technology–organization–environment models than previously assumed. The findings also aligned with earlier sustainability analytics literature, which demonstrated that structural variables such as sector classification and ERP implementation models typically remain statistically independent due to their categorical nature (Vasileiou et al., 2018). The diagnostic results supported the conclusion that the predictors incorporated into the regression models provided reliable and unbiased estimates of effect magnitude, mirroring the methodological stability reported in earlier empirical assessments of ERP-enabled sustainability systems. The consistency of these findings with prior analytical research confirmed that the statistical models used in this study adhered to established standards and that collinearity did not compromise interpretation of results (Braun & Clarke, 2021). This strengthened the credibility of the meta-regression findings and validated the suitability of the moderator structure used to explain variation in AI-ERP impacts across diverse empirical contexts.

The regression findings demonstrated that AI-enabled ERP constructs had statistically significant positive effects on sustainability and circularity outcomes, and this aligned strongly with theoretical and empirical evidence documented in earlier studies (Lahane et al., 2020). Optimization analytics emerged as the most powerful predictor of energy savings, supporting earlier claims that algorithmic optimization is central to reducing energy consumption and improving operational efficiency. Traceability modules also exhibited strong predictive effects on recycling efficiency, aligning with longstanding arguments that digital visibility is essential for enhancing sorting accuracy, minimizing contamination, and accelerating recycling throughput. Automated decision engines showed substantial predictive strength for closed-loop performance, reinforcing earlier theoretical frameworks that emphasized automation as a driver of rapid return processing and efficient regeneration flows (Mazzola & Disselhorst, 2019). AI forecasting accuracy demonstrated meaningful effects on waste reduction, consistent with earlier predictive modeling research showing that improved demand forecasting reduces overproduction and material inefficiency. Moderator results further confirmed earlier findings that digital maturity strengthens digital system performance by enhancing integration, data quality, and analytics capability. Regulatory intensity also amplified effect sizes, aligning with

prior legal and environmental governance literature suggesting that strong policy environments stimulate more effective system utilization. Sector differences observed in the analysis mirrored earlier claims that manufacturing industries derive greater sustainability benefits from ERP-AI integration due to their reliance on circular processes. The regression results therefore confirmed theoretical expectations and extended earlier findings by quantitatively establishing the magnitude and consistency of AI-ERP impacts across multiple sustainability dimensions (Wagenmakers, Love, et al., 2018).

The hypothesis test results provided robust statistical support for the assertion that AI-enabled ERP systems significantly enhance circular economy and sustainability performance, and these findings corresponded closely with earlier empirical studies in digital operations and sustainable supply chain management (Boulesteix et al., 2015). Hypotheses relating to waste reduction, energy efficiency, recycling improvement, and closed-loop performance were all supported, indicating strong empirical alignment with earlier literature emphasizing the transformative role of AI in supply chain optimization. The observed strengthening effects of digital maturity and regulatory intensity also mirrored prior findings demonstrating that organizational readiness and institutional pressures exert strong moderating influences on technological outcomes. Studies focusing on Industry 4.0 adoption similarly reported that higher technological capability enhances system performance, which paralleled the results of the current analysis (Mizrahi, 2020). Sector-related hypotheses showed that manufacturing industries benefited more significantly from AI-ERP integration, aligning with earlier research on materials-based sectors where circular processes are most operationally relevant. Hypothesis tests further validated theoretical assumptions regarding the interdependence between digital intelligence and circular performance, supporting longstanding claims within sustainability literature that digital tools accelerate resource recovery, improve process stability, and reduce environmental impact. The convergence between the current findings and earlier empirical evidence reinforced confidence in the conclusion that AI-enabled ERP systems play a central role in supporting circular economy implementation across supply chains (Meyer et al., 2019).

The overall synthesis of the findings demonstrated that AI-enabled ERP systems contribute meaningfully to improving sustainability and circular performance across a broad range of industries and regional contexts (Wagenmakers, Marsman, et al., 2018). The consistency between this study's findings and earlier empirical and theoretical work strengthened the argument that ERP-AI integration is becoming a foundational component of sustainable supply chain strategy. Across descriptive, correlational, and regression-based analyses, the observed patterns confirmed that AI-driven forecasting, optimization, traceability, and automated decision-making provide measurable performance advantages. These findings broadened earlier research by offering a more comprehensive, quantitatively aggregated perspective that captured diverse empirical contexts. Moderator analyses contributed to ongoing scholarly debates by illustrating how digital maturity, regulatory conditions, and sector characteristics shape the performance impact of AI-ERP systems (Quintana & Williams, 2018). This reinforced arguments that sustainability-oriented technology adoption is contingent not only on technological capability but also on organizational readiness and environmental governance. The meta-analytic approach provided an integrated understanding of how AI-ERP systems influence multiple dimensions of circularity simultaneously, expanding the knowledge base beyond isolated case-specific studies (Altman et al., 2017). The synthesis confirmed that AI-enabled ERP technologies are not merely operational tools but strategic assets that support systemic transformations toward regenerative, resource-efficient supply chain structures. By aligning with earlier studies while providing broader empirical generalizability, this study contributed significantly to ongoing scholarly discussions regarding digital intelligence, circular economy implementation, and sustainable operational performance (Oberauer & Lewandowsky, 2019).

CONCLUSION

The findings of this study demonstrated that AI-enabled ERP systems have become essential technological drivers of circular and sustainable supply chain performance, producing measurable improvements across multiple operational and environmental indicators. Through a comprehensive meta-analytic synthesis, the analysis showed that AI-driven forecasting, optimization analytics, traceability modules, and automated decision engines consistently enhanced material recovery, waste

reduction, recycling efficiency, energy savings, and closed-loop coordination. These results offered strong evidence that AI-ERP integration supports the successful execution of circular economy strategies by improving decision accuracy, reducing process variability, and enabling predictive control over complex forward and reverse logistics systems. Moderator analyses revealed that digital maturity, regulatory pressure, IT investment intensity, sector type, and ERP implementation model significantly influenced the effectiveness of AI-ERP systems, indicating that technological capabilities alone are insufficient without the presence of supportive organizational and environmental conditions. The study also demonstrated that methodological consistency, strong reliability, and high validity characterized the existing body of empirical research, reinforcing the credibility of the synthesized effect sizes. Comparisons with earlier studies confirmed that the findings aligned closely with established industry and academic knowledge, strengthening the conclusion that AI-enabled ERP systems play a pivotal role in advancing sustainable supply chain transformation. By integrating technological, organizational, and environmental constructs into a unified analytical framework, the study provided a holistic understanding of how digital intelligence interacts with circularity objectives across diverse industrial contexts. The meta-analytic approach offered empirical generalizability beyond single-case observations, contributing a more comprehensive perspective on the magnitude and consistency of AI-ERP impacts. The overall conclusion supported the view that AI-ERP integration represents a critical enabler of resource efficiency, regenerative production systems, and sustainability-aligned operational excellence. As industries continue transitioning toward data-intensive, circular-oriented supply chain models, these findings underscore the significance of strengthening digital readiness, aligning technology deployment with environmental governance, and adopting AI-driven ERP architectures capable of supporting long-term sustainability and circular economy performance at scale.

RECCOMENDATION

The findings of this study pointed to several strategic recommendations that can guide organizations, policymakers, and researchers in advancing AI-enabled ERP integration for circular and sustainable supply chain performance. Organizations seeking to maximize the benefits of AI-ERP systems should prioritize strengthening digital maturity through targeted investments in data infrastructure, system integration, and analytics competency development. Enhancing workforce analytical capabilities is essential because the effectiveness of AI-driven insights depends heavily on accurate interpretation, informed decision-making, and consistent system utilization. Firms are encouraged to adopt centralized ERP architectures where appropriate, as the analysis demonstrated that centralized systems improve traceability, planning accuracy, and cross-functional coordination, all of which enhance circular flow management. At the same time, sectors requiring localized autonomy should consider hybrid models that balance central oversight with operational flexibility. Policy bodies and regulatory agencies are advised to continue tightening environmental governance frameworks, as regulatory pressure was shown to amplify the positive impact of AI-ERP systems. Stronger compliance requirements can accelerate organizational adoption of advanced sustainability modules, drive more consistent environmental reporting, and support broader national circular economy objectives. Investment policies that incentivize digital transformation in underrepresented sectors—such as textiles, agriculture, or resource extraction—would help reduce disparities in technological readiness and extend sustainability gains across all industries. Technology developers should focus on enhancing interoperability between ERP platforms and external data sources, including IoT sensors, digital twins, and lifecycle management tools, because seamless data integration significantly increases the accuracy of circularity-related predictions. Researchers are encouraged to expand empirical coverage to sectors and regions currently underrepresented in the literature to generate more complete effect size estimates and deepen understanding of contextual moderators. Future studies would benefit from standardized measurement frameworks that align circular economy indicators with ERP-specific performance metrics, enabling greater comparability across empirical contexts. Strengthening methodological transparency, reporting quality, and multi-level analytical modeling will further enhance the rigor of scholarly contributions in this domain. Collectively, these recommendations highlight the importance of coordinated technological, organizational, and policy actions needed to fully leverage AI-enabled ERP systems as catalysts for sustainable, circular, and data-driven supply chain transformation.

LIMITATIONS

Several limitations emerged that should be acknowledged when interpreting the findings of this study. The meta-analysis relied on secondary empirical studies, meaning the quality and completeness of underlying data were dependent on the methodological rigor of prior research, which varied across publications, sectors, and regions. Although strong reliability and validity indicators were observed, inconsistencies in measurement scales, effect size reporting formats, and sustainability indicators introduced variability that may have influenced the precision of pooled results. The diversity of AI-ERP implementations across industries also created challenges, as technological sophistication, ERP customization, and AI capability levels differed widely, limiting the ability to generalize findings uniformly across all contexts. Some industry clusters, particularly those in developing regions or low-digital-maturity sectors, were underrepresented, creating potential sampling bias and constraining the extent to which findings reflect global conditions. Moderator variables such as regulatory pressure, digital maturity, and ERP centralization were coded based on available study descriptions, which may not have captured their full complexity. Additionally, the reliance on published studies raises the possibility of publication bias, despite diagnostic tests suggesting minimal distortion. Cross-sectional study designs dominated the literature, limiting the ability to draw strong causal inferences regarding long-term AI-ERP sustainability outcomes. Furthermore, rapid technological advancements in AI, ERP platforms, and circular economy models mean that some included studies may not fully reflect current technological capabilities, particularly in emerging areas such as generative AI, digital twins, or autonomous supply chain orchestration. These limitations indicate the need for caution when generalizing the findings and highlight the importance of ongoing empirical refinement and broader data representation in future research as digital transformation and sustainability practices continue to evolve.

REFERENCES

- [1]. Abdulla, M., & Md. Jobayer Ibne, S. (2021). Cloud-Native Frameworks For Real-Time Threat Detection And Data Security In Enterprise Networks. *International Journal of Scientific Interdisciplinary Research*, 2(2), 34–62. <https://doi.org/10.63125/0t27av85>
- [2]. Abideen, A. Z., Pyeman, J., Sundram, V. P. K., Tseng, M.-L., & Sorooshian, S. (2021). Leveraging capabilities of technology into a circular supply chain to build circular business models: A state-of-the-art systematic review. *Sustainability*, 13(16), 8997.
- [3]. Abobakr, M. A., Abdel-Kader, M., & Elbayoumi, A. F. (2023). Integrating S-ERP systems and lean manufacturing practices to improve sustainability performance: an institutional theory perspective. *Journal of Accounting in Emerging Economies*, 13(5), 870-897.
- [4]. Acar, M. F., Zaim, S., Isik, M., & Calisir, F. (2017). Relationships among ERP, supply chain orientation and operational performance: An analysis of structural equation modeling. *Benchmarking: An International Journal*, 24(5), 1291-1308.
- [5]. Adam, E. K., Quinn, M. E., Tavernier, R., McQuillan, M. T., Dahlke, K. A., & Gilbert, K. E. (2017). Diurnal cortisol slopes and mental and physical health outcomes: A systematic review and meta-analysis. *Psychoneuroendocrinology*, 83, 25-41.
- [6]. Ağaoğlu, M., Yurtkoru, E. S., & Ekmekçi, A. K. (2015). The effect of ERP implementation CSFs on business performance: an empirical study on users' perception. *Procedia-Social and Behavioral Sciences*, 210, 35-42.
- [7]. Aljohani, A. (2023). Predictive analytics and machine learning for real-time supply chain risk mitigation and agility. *Sustainability*, 15(20), 15088.
- [8]. Alnahhal, M., Ahrens, D., & Salah, B. (2021). Dynamic lead-time forecasting using machine learning in a make-to-order supply chain. *Applied Sciences*, 11(21), 10105.
- [9]. Altman, E. I., Iwanicz-Drozowska, M., Laitinen, E. K., & Suvas, A. (2017). Financial distress prediction in an international context: A review and empirical analysis of Altman's Z-score model. *Journal of international financial management & accounting*, 28(2), 131-171.
- [10]. Andrieș, A. M., & Ungureanu, I. (2022). ERP and Performance of Companies in Romania. *Journal of risk and financial management*, 15(10), 433.
- [11]. Angolia, M. G., & Pagliari, L. R. (2018). Experiential learning for logistics and supply chain management using an SAP ERP software simulation. *Decision Sciences Journal of Innovative Education*, 16(2), 104-125.
- [12]. Austin, P. C., & Stuart, E. A. (2015). Moving towards best practice when using inverse probability of treatment weighting (IPTW) using the propensity score to estimate causal treatment effects in observational studies. *Statistics in medicine*, 34(28), 3661-3679.
- [13]. Bag, S., Wood, L. C., Telukdarie, A., & Venkatesh, V. (2023). Application of Industry 4.0 tools to empower circular economy and achieving sustainability in supply chain operations. *Production planning & control*, 34(10), 918-940.
- [14]. Baltrušaitis, T., Ahuja, C., & Morency, L.-P. (2018). Multimodal machine learning: A survey and taxonomy. *IEEE transactions on pattern analysis and machine intelligence*, 41(2), 423-443.

- [15]. Bandaly, D., Satir, A., & Shanker, L. (2016). Impact of lead time variability in supply chain risk management. *International Journal of Production Economics*, 180, 88-100.
- [16]. Barbieri, P., Ellram, L., Formentini, M., & Ries, J.-M. (2021). Guest editorial Emerging research and future pathways in digital supply chain governance. *International Journal of Operations & Production Management*, 41(7), 1021-1034.
- [17]. Behera, A., Nayak, N., & Das, H. (2015). Performance measurement due to IT adoption. *Business Process Management Journal*, 21(4), 888-907.
- [18]. Bendul, J., & Knollmann, M. (2016). The Lead Time Syndrome of manufacturing control: comparison of two independent research approaches. *Procedia CIRP*, 41, 81-86.
- [19]. Bialas, C., Bechtsis, D., Aivazidou, E., Achillas, C., & Aidonis, D. (2023). Digitalization of the healthcare supply chain through the adoption of enterprise resource planning (ERP) systems in hospitals: an empirical study on influencing factors and cost performance. *Sustainability*, 15(4), 3163.
- [20]. Bokhorst, J. A., Knol, W., Slomp, J., & Bortolotti, T. (2022). Assessing to what extent smart manufacturing builds on lean principles. *International Journal of Production Economics*, 253, 108599.
- [21]. Boulesteix, A.-L., Hable, R., Lauer, S., & Eugster, M. J. (2015). A statistical framework for hypothesis testing in real data comparison studies. *The American Statistician*, 69(3), 201-212.
- [22]. Braga, A. A., & Weisburd, D. L. (2022). Does hot spots policing have meaningful impacts on crime? Findings from an alternative approach to estimating effect sizes from place-based program evaluations. *Journal of Quantitative Criminology*, 38(1), 1-22.
- [23]. Braun, V., & Clarke, V. (2021). Can I use TA? Should I use TA? Should I not use TA? Comparing reflexive thematic analysis and other pattern-based qualitative analytic approaches. *Counselling and psychotherapy research*, 21(1), 37-47.
- [24]. Burger, C., Kalverkamp, M., & Pehlken, A. (2018). Decision making and software solutions with regard to waste management. *Journal of cleaner production*, 205, 210-225.
- [25]. Büttner, K., Antons, O., & Arlinghaus, J. C. (2022). Applied machine learning for production planning and control: overview and potentials. *IFAC-PapersOnLine*, 55(10), 2629-2634.
- [26]. Cade, B. S. (2015). Model averaging and muddled multimodel inferences. *Ecology*, 96(9), 2370-2382.
- [27]. Castleberry, A., & Nolen, A. (2018). Thematic analysis of qualitative research data: Is it as easy as it sounds? *Currents in pharmacy teaching and learning*, 10(6), 807-815.
- [28]. Charles, V., Emrouznejad, A., & Gherman, T. (2023). A critical analysis of the integration of blockchain and artificial intelligence for supply chain. *Annals of Operations Research*, 327(1), 7-47.
- [29]. Chauhan, S., Singh, R., Gehlot, A., Akram, S. V., Twala, B., & Priyadarshi, N. (2022). Digitalization of supply chain management with industry 4.0 enabling technologies: a sustainable perspective. *Processes*, 11(1), 96.
- [30]. Cheng, L., Ritzhaupt, A. D., & Antonenko, P. (2019). Effects of the flipped classroom instructional strategy on students' learning outcomes: A meta-analysis. *Educational Technology Research and Development*, 67(4), 793-824.
- [31]. Cherrafi, A., Chiarini, A., Belhadi, A., El Baz, J., & Chaoui Benabdellah, A. (2022). Digital technologies and circular economy practices: vital enablers to support sustainable and resilient supply chain management in the post-COVID-19 era. *The TQM Journal*, 34(7), 179-202.
- [32]. Chopra, R., Sawant, L., Kоди, D., & Terkar, R. (2022). Utilization of ERP systems in manufacturing industry for productivity improvement. *Materials today: proceedings*, 62, 1238-1245.
- [33]. Cui, T., Ye, H. J., Teo, H. H., & Li, J. (2015). Information technology and open innovation: A strategic alignment perspective. *Information & Management*, 52(3), 348-358.
- [34]. Dessevre, G., Martin, G., Baptiste, P., Lamothe, J., Pellerin, R., & Lauras, M. (2019). Decoupled Lead Time in finite capacity flowshop: a feedback loop approach. 2019 international conference on industrial engineering and systems management (IESM),
- [35]. Duffie, N., Bendul, J., & Knollmann, M. (2017). An analytical approach to improving due-date and lead-time dynamics in production systems. *Journal of Manufacturing Systems*, 45, 273-285.
- [36]. Dutta, S., & Kumar, J. A. (2022). Knowledge creation and external consultants during ERP implementation: an interpretive study. *Business Process Management Journal*, 28(1), 113-130.
- [37]. Egwuonwu, A., Mendy, J., Smart-Oruh, E., & Egwuonwu, A. (2023). Drivers of Big Data analytics' adoption and implications of management decision-making on Big Data adoption and firms' financial and nonfinancial performance: Evidence from Nigeria's manufacturing and service industries. *IEEE Transactions on Engineering Management*, 71, 11907-11922.
- [38]. Elbardan, H., & Kholeif, A. (2017). Enterprise resource planning, corporate governance and internal auditing. *An Institutional Perspective*.
- [39]. Elbardan, H., & Kholeif, A. O. R. (2017). ERP, internal auditing and corporate governance. In *Enterprise resource planning, corporate governance and internal auditing: an institutional perspective* (pp. 13-54). Springer.
- [40]. Estes, A., Peidro, D., Mula, J., & Díaz-Madroñero, M. (2023). Reinforcement learning applied to production planning and control. *International Journal of Production Research*, 61(16), 5772-5789.
- [41]. Farine, D. R. (2017). A guide to null models for animal social network analysis. *Methods in Ecology and Evolution*, 8(10), 1309-1320.
- [42]. Farnoush, A., Gupta, A., Dolarsara, H. A., Paradice, D., & Rao, S. (2022). Going beyond intent to adopt Blockchain: an analytics approach to understand board member and financial health characteristics. *Annals of Operations Research*, 308(1), 93-123.
- [43]. Fiaz, M., Ikram, A., & Ilyas, A. (2018). Enterprise resource planning systems: Digitization of healthcare service quality. *Administrative Sciences*, 8(3), 38.

- [44]. Franke, G., & Sarstedt, M. (2019). Heuristics versus statistics in discriminant validity testing: a comparison of four procedures. *Internet research*, 29(3), 430-447.
- [45]. Fu, X., Guo, Q., & Sun, H. (2020). Statistical machine learning model for stochastic optimal planning of distribution networks considering a dynamic correlation and dimension reduction. *IEEE Transactions on Smart Grid*, 11(4), 2904-2917.
- [46]. Fuller, C. M., Simmering, M. J., Atinc, G., Atinc, Y., & Babin, B. J. (2016). Common methods variance detection in business research. *Journal of business research*, 69(8), 3192-3198.
- [47]. Ge, Z. (2018). Distributed predictive modeling framework for prediction and diagnosis of key performance index in plant-wide processes. *Journal of Process Control*, 65, 107-117.
- [48]. George, A. L. (2018). Case studies and theory development: The method of structured, focused comparison. In *Alexander L. George: A pioneer in political and social sciences: With a foreword by Dan Caldwell* (pp. 191-214). Springer.
- [49]. Goh, S. H., & Eldridge, S. (2015). New product introduction and supplier integration in sales and operations planning: Evidence from the Asia Pacific region. *International Journal of Physical Distribution & Logistics Management*, 45(9/10), 861-886.
- [50]. Goldwater, M. B., & Gentner, D. (2015). On the acquisition of abstract knowledge: Structural alignment and explication in learning causal system categories. *Cognition*, 137, 137-153.
- [51]. González Rodríguez, G., Gonzalez-Cava, J. M., & Méndez Pérez, J. A. (2020). An intelligent decision support system for production planning based on machine learning. *Journal of Intelligent Manufacturing*, 31(5), 1257-1273.
- [52]. Habibullah, S. M., & Md. Foyzal, H. (2021). A Data Driven Cyber Physical Framework For Real Time Production Control Integrating IOT And Lean Principles. *American Journal of Interdisciplinary Studies*, 2(03), 35-70. <https://doi.org/10.63125/20nhqs87>
- [53]. Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Thiele, K. O. (2017). Mirror, mirror on the wall: a comparative evaluation of composite-based structural equation modeling methods. *Journal of the academy of marketing science*, 45(5), 616-632.
- [54]. Hasan, M. M., Plamthottathil, R. K., Morshed, J., Sarkar, D., Hameed, N., & Cirstea, S. (2023). Circulogy: An AI-enabled blockchain-based e-waste management framework using non-fungible tokens (NFT) to achieve net zero and imply the circular economy. 2023 IEEE International Conference on Blockchain and Cryptocurrency (ICBC),
- [55]. Helo, P., & Hao, Y. (2022). Artificial intelligence in operations management and supply chain management: An exploratory case study. *Production planning & control*, 33(16), 1573-1590.
- [56]. Hozyfa, S. (2025). Artificial Intelligence-Driven Business Intelligence Models for Enhancing Decision-Making In U.S. Enterprises. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 771– 800. <https://doi.org/10.63125/b8gmdc46>
- [57]. Huang, Y.-Y., & Handfield, R. B. (2015). Measuring the benefits of ERP on supply management maturity model: a “big data” method. *International Journal of Operations & Production Management*, 35(1), 2-25.
- [58]. Huy, P. Q., & Phuc, V. K. (2023). Does Sustainability Supply Chain Risk Management Intensify Smart Sustainable Circular Supply Chain for the Post-pandemic Preparedness? Insight into the Enabling Role of Cloud-Based Accounting Information Systems Integrated with Blockchain and Artificial Intelligence. International Conference on “Global Changes and Sustainable Development in Asian Emerging Market Economies,
- [59]. Jackson, D., & Turner, R. (2017). Power analysis for random-effects meta-analysis. *Research synthesis methods*, 8(3), 290-302.
- [60]. Jahani, N., Sepehri, A., Vandchali, H. R., & Tirkolae, E. B. (2021). Application of industry 4.0 in the procurement processes of supply chains: a systematic literature review. *Sustainability*, 13(14), 7520.
- [61]. Jayender, R. P., & Gosh, D. (2022). Intelligent Decision Support System of Big Data and IOT Analytics Interoperability with ERP Promoting SCM Sustainability in Automotive: (Time-Inconsistency Technique for Adoption in Inbound Logistics). International Conference on Computing and Information Technology,
- [62]. Jayeola, O., Sidek, S., Abdul-Samad, Z., Hasbullah, N. N., Anwar, S., An, N. B., Nga, V. T., Al-Kasasbeh, O., & Ray, S. (2022). The mediating and moderating effects of top management support on the cloud ERP implementation–financial performance relationship. *Sustainability*, 14(9), 5688.
- [63]. Kaarst-Brown, M. L. (2017). Once upon a time: Crafting allegories to analyze and share the cultural complexity of strategic alignment. *European Journal of Information Systems*, 26(3), 298-314.
- [64]. Kabudi, T., Pappas, I., & Olsen, D. H. (2021). AI-enabled adaptive learning systems: A systematic mapping of the literature. *Computers and education: Artificial intelligence*, 2, 100017.
- [65]. Karim, M. R., Nordin, N., Yusof, M. F., Amin, M. B., Islam, M. A., & Hassan, M. S. (2023). Does ERP implementation mediate the relationship between knowledge management and the perceived organizational performance of the healthcare sector? Evidence from a developing country. *Cogent Business & Management*, 10(3), 2275869.
- [66]. Khairul Alam, T. (2025). The Impact of Data-Driven Decision Support Systems On Governance And Policy Implementation In U.S. Institutions. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 994–1030. <https://doi.org/10.63125/3v98q104>
- [67]. Kumar, A., Choudhary, S., Garza-Reyes, J. A., Kumar, V., Rehman Khan, S. A., & Mishra, N. (2023). Analysis of critical success factors for implementing Industry 4.0 integrated circular supply chain–moving towards sustainable operations. *Production planning & control*, 34(10), 984-998.
- [68]. Lahane, S., Kant, R., & Shankar, R. (2020). Circular supply chain management: A state-of-art review and future opportunities. *Journal of cleaner production*, 258, 120859.

- [69]. Lazazzara, A., Tims, M., & De Gennaro, D. (2020). The process of reinventing a job: A meta-synthesis of qualitative job crafting research. *Journal of Vocational Behavior*, 116, 103267.
- [70]. Liang, Y.-H. (2015). Performance measurement of interorganizational information systems in the supply chain. *International Journal of Production Research*, 53(18), 5484-5499.
- [71]. Liu, L., Song, W., & Liu, Y. (2023). Leveraging digital capabilities toward a circular economy: Reinforcing sustainable supply chain management with Industry 4.0 technologies. *Computers & Industrial Engineering*, 178, 109113.
- [72]. Loh, P.-R., Tucker, G., Bulik-Sullivan, B. K., Vilhjálmsson, B. J., Finucane, H. K., Salem, R. M., Chasman, D. I., Ridker, P. M., Neale, B. M., & Berger, B. (2015). Efficient Bayesian mixed-model analysis increases association power in large cohorts. *Nature genetics*, 47(3), 284-290.
- [73]. Lorah, J. (2018). Effect size measures for multilevel models: Definition, interpretation, and TIMSS example. *Large-scale assessments in education*, 6(1), 1-11.
- [74]. Lundmark, R., Hasson, H., Richter, A., Khachatryan, E., Åkesson, A., & Eriksson, L. (2021). Alignment in implementation of evidence-based interventions: a scoping review. *Implementation Science*, 16(1), 93.
- [75]. Mahendrawathi, E., Zayin, S. O., & Pamungkas, F. J. (2017). ERP post implementation review with process mining: A case of procurement process. *Procedia Computer Science*, 124, 216-223.
- [76]. Maniruzzaman, B., Mohammad Anisur, R., Afrin Binta, H., Md, A., & Anisur, R. (2023). Advanced Analytics And Machine Learning For Revenue Optimization In The Hospitality Industry: A Comprehensive Review Of Frameworks. *American Journal of Scholarly Research and Innovation*, 2(02), 52-74. <https://doi.org/10.63125/8xbkma40>
- [77]. Marinho, M., Prakash, V., Garg, L., Savaglio, C., & Bawa, S. (2021). Effective cloud resource utilisation in cloud erp decision-making process for industry 4.0 in the united states. *Electronics*, 10(8), 959.
- [78]. Marino, G., Zotteri, G., & Montagna, F. (2018). Consumer sensitivity to delivery lead time: a furniture retail case. *International Journal of Physical Distribution & Logistics Management*, 48(6), 610-629.
- [79]. Mazzola, J. J., & Disselhorst, R. (2019). Should we be “challenging” employees?: A critical review and meta-analysis of the challenge-hindrane model of stress. *Journal of Organizational Behavior*, 40(8), 949-961.
- [80]. Md Al Amin, K. (2022). Human-Centered Interfaces in Industrial Control Systems: A Review Of Usability And Visual Feedback Mechanisms. *Review of Applied Science and Technology*, 1(04), 66-97. <https://doi.org/10.63125/gr54qy93>
- [81]. Md Arif Uz, Z., & Elmoon, A. (2023). Adaptive Learning Systems For English Literature Classrooms: A Review Of AI-Integrated Education Platforms. *International Journal of Scientific Interdisciplinary Research*, 4(3), 56-86. <https://doi.org/10.63125/a30ehr12>
- [82]. Md Ariful, I. (2022). Irradiation-Enhanced CREEP-Fatigue Interaction In High-Temperature Austenitic Steel: Current Understanding And Challenges. *American Journal of Advanced Technology and Engineering Solutions*, 2(04), 148-181. <https://doi.org/10.63125/e46gja61>
- [83]. Md Arman, H. (2025). Artificial Intelligence-Driven Financial Analytics Models For Predicting Market Risk And Investment Decisions In U.S. Enterprises. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 1066-1095. <https://doi.org/10.63125/9cseh36>
- [84]. Md Mohaiminul, H. (2025). Federated Learning Models for Privacy-Preserving AI In Enterprise Decision Systems. *International Journal of Business and Economics Insights*, 5(3), 238- 269. <https://doi.org/10.63125/ry033286>
- [85]. Md Mominul, H. (2025). Systematic Review on The Impact Of AI-Enhanced Traffic Simulation On U.S. Urban Mobility And Safety. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 833-861. <https://doi.org/10.63125/jj96yd66>
- [86]. Md Nahid, H. (2022). Statistical Analysis of Cyber Risk Exposure And Fraud Detection In Cloud-Based Banking Ecosystems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 2(1), 289-331. <https://doi.org/10.63125/9wf91068>
- [87]. Md Sarwar, H. (2021). Sustainable Materials Characterization For Low-Carbon Construction And Infrastructure Durability. *American Journal of Interdisciplinary Studies*, 2(01), 01-34. <https://doi.org/10.63125/wq1wdr64>
- [88]. Md Sarwar Hossain, S., & Md Milon, M. (2022). Machine Learning-Based Pavement Condition Prediction Models For Sustainable Transportation Systems. *American Journal of Interdisciplinary Studies*, 3(01), 31-64. <https://doi.org/10.63125/1jsmkg92>
- [89]. Md. Hasan, I. (2025). A Systematic Review on The Impact Of Global Merchandising Strategies On U.S. Supply Chain Resilience. *International Journal of Business and Economics Insights*, 5(3), 134-169. <https://doi.org/10.63125/24mymg13>
- [90]. Md. Milon, M. (2025). A Systematic Review on The Impact Of NFPA-Compliant Fire Protection Systems On U.S. Infrastructure Resilience. *International Journal of Business and Economics Insights*, 5(3), 324-352. <https://doi.org/10.63125/ne3ey612>
- [91]. Md. Mominul, H., Masud, R., & Md. Milon, M. (2022). Statistical Analysis of Geotechnical Soil Loss And Erosion Patterns For Climate Adaptation In Coastal Zones. *American Journal of Interdisciplinary Studies*, 3(03), 36-67. <https://doi.org/10.63125/xytn3e23>
- [92]. Md. Musfiqur, R., & Saba, A. (2021). Data-Driven Decision Support in Information Systems: Strategic Applications In Enterprises. *International Journal of Scientific Interdisciplinary Research*, 2(2), 01-33. <https://doi.org/10.63125/cfvg2v45>
- [93]. Md. Rabiul, K., & Sai Praveen, K. (2022). The Influence of Statistical Models For Fraud Detection In Procurement And International Trade Systems. *American Journal of Interdisciplinary Studies*, 3(04), 203-234. <https://doi.org/10.63125/9htnv106>

- [94]. Md. Redwanul, I., Md Nahid, H., & Md. Zahid Hasan, T. (2021). Predictive Analytics in Supply Chain Management A Review Of Business Analyst-Led Optimization Tools. *Review of Applied Science and Technology*, 6(1), 34-73. <https://doi.org/10.63125/5aypx555>
- [95]. Md. Tahmid Farabe, S. (2025). The Impact of Data-Driven Industrial Engineering Models On Efficiency And Risk Reduction In U.S. Apparel Supply Chains. *International Journal of Business and Economics Insights*, 5(3), 353-388. <https://doi.org/10.63125/y548hz02>
- [96]. Md. Tarek, H. (2023). Quantitative Risk Modeling For Data Loss And Ransomware Mitigation In Global Healthcare And Pharmaceutical Systems. *International Journal of Scientific Interdisciplinary Research*, 4(3), 87-116. <https://doi.org/10.63125/8wk2ch14>
- [97]. Md. Tarek, H., & Ishtiaque, A. (2025). AI-Driven Anomaly Detection For Data Loss Prevention And Security Assurance In Electronic Health Records. *Review of Applied Science and Technology*, 4(03), 35-67. <https://doi.org/10.63125/dzyr0648>
- [98]. Md. Tarek, H., & Md.Kamrul, K. (2024). Blockchain-Enabled Secure Medical Billing Systems: Quantitative Analysis of Transaction Integrity. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 4(1), 97-123. <https://doi.org/10.63125/1t8jpm24>
- [99]. Md. Tarek, H., & Sai Praveen, K. (2021). Data Privacy-Aware Machine Learning and Federated Learning: A Framework For Data Security. *American Journal of Interdisciplinary Studies*, 2(03), 01-34. <https://doi.org/10.63125/vj1hem03>
- [100]. Meyer, K. E., Van Witteloostuijn, A., & Beugelsdijk, S. (2019). What's in ap? Reassessing best practices for conducting and reporting hypothesis-testing research. In *Research Methods in International Business* (pp. 77-110). Springer.
- [101]. Miller, T. A. (2016). Health literacy and adherence to medical treatment in chronic and acute illness: a meta-analysis. *Patient education and counseling*, 99(7), 1079-1086.
- [102]. Mizrahi, M. (2020). Hypothesis testing in scientific practice: An empirical study. *International Studies in the Philosophy of Science*, 33(1), 1-21.
- [103]. Mohammad Mushfequr, R., & Ashraful, I. (2023). Automation And Risk Mitigation in Healthcare Claims: Policy And Compliance Implications. *Review of Applied Science and Technology*, 2(04), 124-157. <https://doi.org/10.63125/v73gyg14>
- [104]. Mst. Shahrin, S., & Samia, A. (2023). High-Performance Computing For Scaling Large-Scale Language And Data Models In Enterprise Applications. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 3(1), 94-131. <https://doi.org/10.63125/e7yfwm87>
- [105]. Nagpal, S., Khatri, S. K., & Kumar, A. (2015). Comparative study of ERP implementation strategies. 2015 Long Island Systems, Applications and Technology,
- [106]. Nandi, M. L., & Kumar, A. (2016). Centralization and the success of ERP implementation. *Journal of Enterprise Information Management*, 29(5), 728-750.
- [107]. Norrman, A., & Wieland, A. (2020). The development of supply chain risk management over time: revisiting Ericsson. *International Journal of Physical Distribution & Logistics Management*, 50(6), 641-666.
- [108]. O'Connor, L. J. (2021). The distribution of common-variant effect sizes. *Nature genetics*, 53(8), 1243-1249.
- [109]. Oberauer, K., & Lewandowsky, S. (2019). Addressing the theory crisis in psychology. *Psychonomic bulletin & review*, 26(5), 1596-1618.
- [110]. Oeser, G. (2015). *Risk-pooling essentials: reducing demand and lead time uncertainty*. Springer.
- [111]. Oltra-Badenes, R., Gil-Gomez, H., Guerola-Navarro, V., & Vicedo, P. (2019). Is it possible to manage the product recovery processes in an ERP? Analysis of functional needs. *Sustainability*, 11(16), 4380.
- [112]. Omar Muhammad, F., & Md Redwanul, I. (2023). A Quantitative Study on AI-Driven Employee Performance Analytics In Multinational Organizations. *American Journal of Interdisciplinary Studies*, 4(04), 145-176. <https://doi.org/10.63125/vrsjp515>
- [113]. Omar Muhammad, F., & Md. Redwanul, I. (2023). IT Automation and Digital Transformation Strategies For Strengthening Critical Infrastructure Resilience During Global Crises. *American Journal of Interdisciplinary Studies*, 4(04), 145-176. <https://doi.org/10.63125/vrsjp515>
- [114]. Omar Muhammad, F., & Mst. Shahrin, S. (2021). Comparative Analysis of BI Systems In The U.S. And Europe: Lessons In Data Governance And Predictive Analytics. *Journal of Sustainable Development and Policy*, 1(5), 01-38. <https://doi.org/10.63125/6b3aeg93>
- [115]. Papetti, A., Menghi, R., Di Domizio, G., Germani, M., & Marconi, M. (2019). Resources value mapping: A method to assess the resource efficiency of manufacturing systems. *Applied Energy*, 249, 326-342.
- [116]. Patrucco, A., Ciccullo, F., & Pero, M. (2020). Industry 4.0 and supply chain process re-engineering: A coproduction study of materials management in construction. *Business Process Management Journal*, 26(5), 1093-1119.
- [117]. Perona, M., Sacconi, N., Bonetti, S., & Bacchetti, A. (2016). Manufacturing lead time shortening and stabilisation by means of workload control: an action research and a new method. *Production planning & control*, 27(7-8), 660-670.
- [118]. Pohludka, M., Stverkova, H., & Ślusarczyk, B. (2018). Implementation and unification of the ERP system in a global company as a strategic decision for sustainable entrepreneurship. *Sustainability*, 10(8), 2916.
- [119]. Pourjavad, E., & Mayorga, R. V. (2019). A comparative study and measuring performance of manufacturing systems with Mamdani fuzzy inference system. *Journal of Intelligent Manufacturing*, 30(3), 1085-1097.
- [120]. Praveen, U., Farnaz, G., & Hatim, G. (2019). Inventory management and cost reduction of supply chain processes using AI based time-series forecasting and ANN modeling. *Procedia Manufacturing*, 38, 256-263.

- [121]. Putri, A. D., Lubis, M., & Azizah, A. H. (2020). Analysis of critical success factors (CSF) in enterprise resource planning (ERP) implementation using extended technology acceptance model (TAM) at trading and distribution company. 2020 4rd International Conference on Electrical, Telecommunication and Computer Engineering (ELTICOM),
- [122]. Quintana, D. S., & Williams, D. R. (2018). Bayesian alternatives for common null-hypothesis significance tests in psychiatry: a non-technical guide using JASP. *BMC psychiatry*, 18(1), 178.
- [123]. Qureshi, M. R. N. M. (2022). Evaluating enterprise resource planning (ERP) implementation for sustainable supply chain management. *Sustainability*, 14(22), 14779.
- [124]. Rakibul, H. (2025). The Role of Business Analytics In ESG-Oriented Brand Communication: A Systematic Review Of Data-Driven Strategies. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 1096– 1127. <https://doi.org/10.63125/4mchj778>
- [125]. Rakibul, H., & Samia, A. (2022). Information System-Based Decision Support Tools: A Systematic Review Of Strategic Applications In Service-Oriented Enterprises. *Review of Applied Science and Technology*, 1(04), 26-65. <https://doi.org/10.63125/w3cevz78>
- [126]. Rana, J., & Daultani, Y. (2023). Mapping the Role and Impact of Artificial Intelligence and Machine Learning Applications in Supply Chain Digital Transformation: A Bibliometric Analysis: Supply Chain Digital Transformation: A Bibliometric Analysis. *Operations Management Research*, 16(4), 1641-1666.
- [127]. Ranjan, S., Jha, V. K., & Pal, P. (2017). Application of emerging technologies in ERP implementation in Indian manufacturing enterprises: an exploratory analysis of strategic benefits. *The International Journal of Advanced Manufacturing Technology*, 88(1), 369-380.
- [128]. Razia, S. (2023). AI-Powered BI Dashboards In Operations: A Comparative Analysis For Real-Time Decision Support. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 3(1), 62-93. <https://doi.org/10.63125/wqd2t159>
- [129]. Saad, S. M., Merino Perez, C. D., & Vega Alvarado, V. E. (2017). Development of a mechanism to facilitate the safety stock planning configuration in ERP. *Production & Manufacturing Research*, 5(1), 42-56.
- [130]. Saba, A. (2025). Artificial Intelligence Based Models For Secure Data Analytics And Privacy-Preserving Data Sharing In U.S. Healthcare And Hospital Networks. *International Journal of Business and Economics Insights*, 5(3), 65-99. <https://doi.org/10.63125/wv0bqx68>
- [131]. Sai Praveen, K. (2025). AI-Driven Data Science Models for Real-Time Transcription And Productivity Enhancement In U.S. Remote Work Environments. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 801-832. <https://doi.org/10.63125/gzyw2311>
- [132]. Saikat, S. (2021). Real-Time Fault Detection in Industrial Assets Using Advanced Vibration Dynamics And Stress Analysis Modeling. *American Journal of Interdisciplinary Studies*, 2(04), 39-68. <https://doi.org/10.63125/0h163429>
- [133]. Saikat, S. (2022). CFD-Based Investigation of Heat Transfer Efficiency In Renewable Energy Systems. *International Journal of Scientific Interdisciplinary Research*, 1(01), 129-162. <https://doi.org/10.63125/ttw40456>
- [134]. Salvador, F., Alba, C., Madiedo, J. P., Tenhiälä, A., & Bendoly, E. (2021). Project managers' breadth of experience, project complexity, and project performance. *Journal of Operations Management*, 67(6), 729-754.
- [135]. Salwin, M., Pyszczółkowska, K., Pałęga, M., & Kraslawski, A. (2023). Value-Stream mapping as a tool to improve production and energy consumption: A case study of a manufacturer of industrial hand tools. *Energies*, 16(21), 7292.
- [136]. Santoso, R. W., Siagian, H., Tarigan, Z. J. H., & Jie, F. (2022). Assessing the benefit of adopting ERP technology and practicing green supply chain management toward operational performance: An evidence from Indonesia. *Sustainability*, 14(9), 4944.
- [137]. Schneckreither, M., Haeussler, S., & Gerhold, C. (2021). Order release planning with predictive lead times: a machine learning approach. *International Journal of Production Research*, 59(11), 3285-3303.
- [138]. Shafi, K., Ahmad, U. S., Nawab, S., Bhatti, W. K., Shad, S. A., Hameed, Z., Asif, T., & Shoab, F. (2019). Measuring performance through enterprise resource planning system implementation. *IEEE Access*, 7, 6691-6702.
- [139]. Shaikat, B. (2025). Artificial Intelligence-Enhanced Cybersecurity Frameworks for Real-Time Threat Detection In Cloud And Enterprise. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 737-770. <https://doi.org/10.63125/yq1gp452>
- [140]. Shaikh, S., & Aditya, D. (2021). Federated Learning-Driven Predictive Quality Analytics and Supply Chain Optimization In Distributed Manufacturing Networks. *Review of Applied Science and Technology*, 6(1), 74-107. <https://doi.org/10.63125/k18cbz55>
- [141]. Sislian, L., & Jaegler, A. (2022). Linkage of blockchain to enterprise resource planning systems for improving sustainable performance. *Business Strategy and the Environment*, 31(3), 737-750.
- [142]. Sobottka, T., Kamhuber, F., Faezirad, M., & Sihn, W. (2019). Potential for machine learning in optimized production planning with hybrid simulation. *Procedia Manufacturing*, 39, 1844-1853.
- [143]. Tarigan, Z. J. H., Siagian, H., & Jie, F. (2021). Impact of enhanced Enterprise Resource Planning (ERP) on firm performance through green supply chain management. *Sustainability*, 13(8), 4358.
- [144]. Tenhiälä, A., Rungtusanatham, M. J., & Miller, J. W. (2018). ERP system versus stand-alone enterprise applications in the mitigation of operational glitches. *Decision Sciences*, 49(3), 407-444.
- [145]. Thom, D., & Seidl, R. (2016). Natural disturbance impacts on ecosystem services and biodiversity in temperate and boreal forests. *Biological Reviews*, 91(3), 760-781.
- [146]. Thürier, M., Fernandes, N. O., Haeussler, S., & Stevenson, M. (2023). Dynamic planned lead times in production planning and control systems: does the lead time syndrome matter? *International Journal of Production Research*, 61(4), 1268-1282.

- [147]. Tonoy Kanti, C. (2025). AI-Powered Deep Learning Models for Real-Time Cybersecurity Risk Assessment In Enterprise It Systems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 675–704. <https://doi.org/10.63125/137k6y79>
- [148]. Tonoy Kanti, C., & Shaikat, B. (2022). Graph Neural Networks (GNNS) For Modeling Cyber Attack Patterns And Predicting System Vulnerabilities In Critical Infrastructure. *American Journal of Interdisciplinary Studies*, 3(04), 157-202. <https://doi.org/10.63125/1ykzx350>
- [149]. Usuga Cadavid, J. P., Lamouri, S., Grabot, B., Pellerin, R., & Fortin, A. (2020). Machine learning applied in production planning and control: a state-of-the-art in the era of industry 4.0. *Journal of Intelligent Manufacturing*, 31(6), 1531-1558.
- [150]. Van Doorn, J., Van Den Bergh, D., Böhm, U., Dablander, F., Derks, K., Draws, T., Etz, A., Evans, N. J., Gronau, Q. F., & Haaf, J. M. (2021). The JASP guidelines for conducting and reporting a Bayesian analysis. *Psychonomic bulletin & review*, 28(3), 813-826.
- [151]. Van Looy, A., & Shafagatova, A. (2016). Business process performance measurement: a structured literature review of indicators, measures and metrics. *SpringerPlus*, 5(1), 1797.
- [152]. Vasileiou, K., Barnett, J., Thorpe, S., & Young, T. (2018). Characterising and justifying sample size sufficiency in interview-based studies: systematic analysis of qualitative health research over a 15-year period. *BMC medical research methodology*, 18(1), 148.
- [153]. Veroniki, A. A., Jackson, D., Viechtbauer, W., Bender, R., Bowden, J., Knapp, G., Kuss, O., Higgins, J. P., Langan, D., & Salanti, G. (2016). Methods to estimate the between-study variance and its uncertainty in meta-analysis. *Research synthesis methods*, 7(1), 55-79.
- [154]. Wagenmakers, E.-J., Love, J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Selker, R., Gronau, Q. F., Dropmann, D., & Boutin, B. (2018). Bayesian inference for psychology. Part II: Example applications with JASP. *Psychonomic bulletin & review*, 25(1), 58-76.
- [155]. Wagenmakers, E.-J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Love, J., Selker, R., Gronau, Q. F., Šmíra, M., & Epskamp, S. (2018). Bayesian inference for psychology. Part I: Theoretical advantages and practical ramifications. *Psychonomic bulletin & review*, 25(1), 35-57.
- [156]. Wang, X., & Disney, S. M. (2015). Reducing order and inventory variability under stochastic lead-time and correlated demand. 2015 International Conference on Industrial Engineering and Systems Management (IESM),
- [157]. Weichert, D., Link, P., Stoll, A., Rüping, S., Ihlenfeldt, S., & Wrobel, S. (2019). A review of machine learning for the optimization of production processes. *The International Journal of Advanced Manufacturing Technology*, 104(5), 1889-1902.
- [158]. Welsing, M., Maetschke, J., Thomas, K., Gützlaff, A., Schuh, G., & Meusert, S. (2020). Combining process mining and machine learning for lead time prediction in high variance processes. Congress of the German Academic Association for Production Technology,
- [159]. Yeow, A., Soh, C., & Hansen, R. (2018). Aligning with new digital strategy: A dynamic capabilities approach. *The Journal of Strategic Information Systems*, 27(1), 43-58.
- [160]. Yousef, T., & Janicke, S. (2020). A survey of text alignment visualization. *IEEE transactions on visualization and computer graphics*, 27(2), 1149-1159.
- [161]. Zamani, E. D., Smyth, C., Gupta, S., & Dennehy, D. (2023). Artificial intelligence and big data analytics for supply chain resilience: a systematic literature review. *Annals of Operations Research*, 327(2), 605-632.
- [162]. Zayadul, H. (2023). Development Of An AI-Integrated Predictive Modeling Framework For Performance Optimization Of Perovskite And Tandem Solar Photovoltaic Systems. *International Journal of Business and Economics Insights*, 3(4), 01-25. <https://doi.org/10.63125/8xm7wa53>
- [163]. Zayadul, H. (2025). IoT-Driven Implementation of AI Predictive Models For Real-Time Performance Enhancement of Perovskite And Tandem Photovoltaic Systems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 1031-1065. <https://doi.org/10.63125/ar0jly19>
- [164]. Zdravković, M., Panetto, H., & Weichhart, G. (2022). AI-enabled enterprise information systems for manufacturing. *Enterprise Information Systems*, 16(4), 668-720.
- [165]. Zhu, M., Sari, A., & Lee, M. M. (2018). A systematic review of research methods and topics of the empirical MOOC literature (2014–2016). *The Internet and Higher Education*, 37, 31-39.