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AN IOT-ENABLED DECISION SUPPORT SYSTEM FOR CIRCULAR ECONOMY BUSINESS MODELS: A REVIEW OF ECONOMIC EFFICIENCY AND SUSTAINABILITY OUTCOMES

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ABSTRACT

This study presents a comprehensive systematic review investigating the integration of Internet of Things (IoT) technologies with Decision Support Systems (DSS) in the context of Circular Economy (CE) business models, with a particular emphasis on outcomes related to economic efficiency and environmental sustainability. Employing the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure methodological rigor and transparency, this review analyzed a total of 68 peer-reviewed articles published between 2013 and 2024. The selected literature spans multiple disciplines, including environmental economics, industrial engineering, and information systems, reflecting the interdisciplinary nature of digital circularity. The findings demonstrate that IoT-enabled DSS platforms play a pivotal role in enhancing economic performance through reduced operational costs, labor optimization, predictive maintenance, and more efficient material usage. Additionally, environmental performance outcomes are evident across the literature, particularly through real-time monitoring of carbon emissions, water resource optimization, and energy efficiency improvements. These systems also operationalize core CE principles such as product lifecycle extension, closed-loop material flows, and reverse logistics. Despite these benefits, several challenges impede widespread adoption, including fragmented infrastructure, legacy systems, high upfront costs, lack of interoperability standards, organizational resistance, and underdeveloped sectoral applications. The review also identifies critical gaps in longitudinal studies, stakeholder-inclusive research, and applications in non-industrial sectors such as healthcare, education, and construction. Furthermore, the absence of a unified theoretical framework limits strategic alignment and scalability across different industry contexts. This paper concludes by advocating for a cross-disciplinary, adaptive framework to guide future implementation and research, incorporating digital, operational, and sustainability dimensions. The review contributes to advancing theoretical understanding and offers actionable insights for practitioners and policymakers seeking to leverage IoT-DSS solutions as strategic tools in enabling circular business transformations that are economically viable, environmentally responsible, and technologically resilient.

KEYWORDS

Internet of Things, Decision Support Systems, Circular Economy, Economic Efficiency, Environmental Sustainability

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INTRODUCTION

Decision Support Systems (DSS) are computational frameworks designed to assist in complex decision-making processes by collecting, processing, and presenting relevant data in a structured format (Ribino et al., 2018). These systems are instrumental in addressing semi-structured and unstructured problems in various domains, offering a confluence of models, databases, and user interfaces to generate actionable insights. When augmented by the Internet of Things (IoT), DSSs are transformed into dynamic platforms that capture real-time data streams from physical devices embedded across environments. The IoT is defined as a network of interconnected devices capable of gathering, transmitting, and processing data autonomously. This integration shifts the decision-making paradigm from static analysis to continuous, data-driven adaptability. IoT-enabled DSSs hold the potential to revolutionize strategic operations, particularly in manufacturing, supply chain management, and environmental monitoring, where sensor-based insights enable predictive and prescriptive analytics (Zhang et al., 2023).Such systems provide scalable architectures for monitoring material flows, energy consumption, and waste generation, thereby aligning with sustainable development goals. This convergence of technologies facilitates enhanced responsiveness, operational transparency, and resource optimization. Moreover, as organizations increasingly operate within complex global ecosystems, the demand for real-time, decentralized decision support intensifies (Attaran, 2020). These smart systems offer not only improved operational efficiency but also create avenues for value co-creation through data sharing, machine learning, and cloud-based services. The relevance of IoT-enabled DSSs extends beyond corporate profitability, touching upon critical policy goals concerning environmental resilience, sustainable resource use, and circular economy transitions (Heragu, 2018). As such, their integration represents a pivotal axis in the transformation of business operations into data-centric, sustainable frameworks.

The concept of the Circular Economy (CE) has emerged as a globally endorsed alternative to the linear "take-make-dispose" economic model. It promotes regenerative and restorative processes whereby materials, products, and resources are maintained in the economy for as long as possible through reuse, repair, refurbishment, and recycling (Kumar et al., 2021). CE models have been incorporated into policy frameworks such as the European Union's Circular Economy Action Plan and China's Circular Economy Promotion Law, emphasizing their international prominence. These policies recognize that CE is not solely an environmental concern but a comprehensive strategy for economic efficiency, supply chain resilience, and long-term sustainability. The global urgency to reduce greenhouse gas emissions, minimize waste, and decouple economic growth from resource extraction further accentuates the need for CE-aligned strategies (Ivanov et al., 2021).CE practices, such as extended product life cycles and closed-loop production systems, can significantly mitigate the ecological impact of industrial activity. Moreover, CE principles foster innovation through business model transformation and technological adoption. As emerging economies contend with rapid urbanization and industrialization, CE approaches offer frameworks for inclusive and sustainable development (Pavlov et al., 2019). However, the practical implementation of CE at scale requires systemic coordination, data transparency, and real-time decision-making capacities—challenges that can be effectively addressed through IoT-enabled DSSs. These systems provide the infrastructural intelligence necessary for the real-time tracking of materials and waste, thereby facilitating adherence to CE principles. With global supply chains becoming increasingly vulnerable to disruptions, the role of digitally augmented CE business models in fostering resilience and sustainability is now more critical than ever (Lee et al., 2019).

At the intersection of technology and strategy, IoT-enabled DSSs function as strategic interfaces that bridge operational data with decision-making imperatives. The integration of sensor networks, edge computing, and cloud analytics allows organizations to monitor key performance indicators (KPIs) in real time and adapt strategies based on predictive insights (Martins et al., 2020). These systems enable closed-loop feedback mechanisms, where real-time data informs both tactical and strategic decisions, thereby reducing lag times and enhancing responsiveness. In the context of CE, this means optimizing product lifecycles, minimizing waste, and improving energy efficiency through informed interventions. IoT sensors deployed in manufacturing environments, for instance, can detect wear and tear in machinery, enabling predictive maintenance and reducing material waste (Lin et al., 2022).Furthermore, decision support tools equipped with IoT data streams enable companies to perform material flow analysis (MFA), lifecycle assessments (LCA), and resource forecasting with unprecedented granularity. These capabilities not only enhance sustainability but also drive cost

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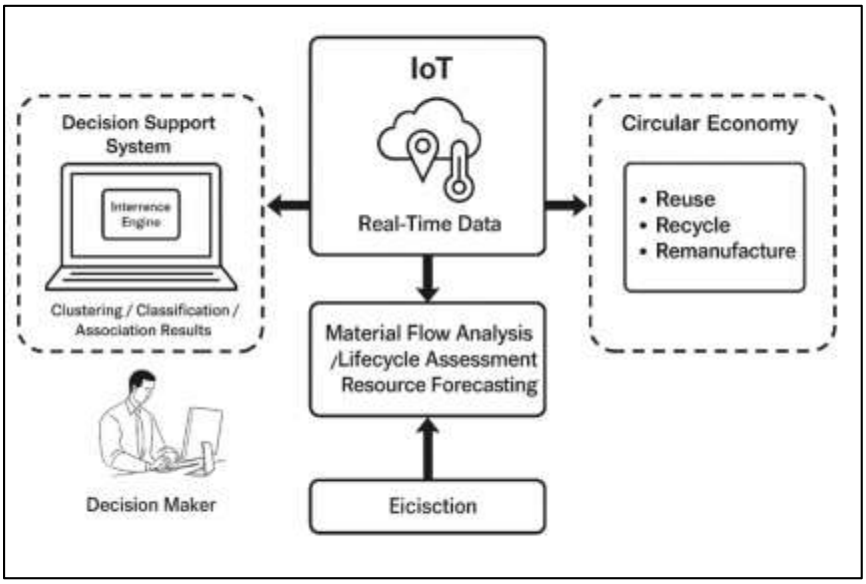
efficiencies by reducing downtime, improving logistics, and enabling just-in-time inventory practices (Song, 2021). The capacity to integrate multiple datasets—from energy usage to emissions tracking—empowers managers to model alternative scenarios, assess trade-offs, and align decisions with both environmental and economic targets. In this regard, IoT-enabled DSSs represent more than operational tools; they are enablers of CE strategies and sustainability leadership. Their value lies in operationalizing abstract CE principles into actionable, data-driven processes, thereby making sustainability measurable, manageable, and monetizable.

Figure 1: IoT-Driven Decision Support for Circularity



Economic efficiency is a core tenet of CE business models, emphasizing the optimal use of resources, reduction of operational costs, and maximization of asset utilization. IoT-enabled DSSs contribute directly to this goal by enabling real-time monitoring and adaptive control over production processes, logistics, and asset maintenance (Chen et al., 2024). For example, through digital twins and cyber-physical systems, companies can simulate and optimize entire production ecosystems, identifying inefficiencies and implementing corrective actions before costly disruptions occur. This digital mirroring of physical operations allows for a proactive approach to resource allocation and cost management. By leveraging machine learning algorithms on sensor-generated data, businesses can fine-tune their input-output ratios, enhance productivity, and reduce energy consumption, which cumulatively translate into economic savings (Pasupuleti et al., 2024).Additionally, IoT-DSS platforms offer enhanced visibility into supply chains, enabling firms to identify bottlenecks, overstocking, or underutilization of assets, and adjust operations accordingly. This visibility is particularly valuable in circular business models such as product-as-a-service (PaaS), where continuous asset tracking ensures efficient usage and timely maintenance (Mashayekhy et al., 2022). The capacity to trace materials from source to re-entry in the production cycle not only prevents loss but also reduces costs associated with virgin resource procurement. Importantly, these systems also support compliance with environmental and fiscal regulations by automating reporting processes, thus reducing administrative burdens. In sum, economic efficiency in a CE context is not merely about cost-cutting—it is about leveraging technology to create smarter, leaner, and more adaptive enterprises that thrive within ecological boundaries while remaining competitively agile (Leung et al., 2022).

The integration of IoT into DSS architectures significantly enhances environmental intelligence by facilitating real-time environmental monitoring and enabling sustainability analytics. Sensors placed along production lines, supply routes, or waste management facilities can monitor variables such as emissions, temperature, humidity, and waste discharge (Gharehgozli et al., 2020). These environmental datasets provide critical inputs into DSS models that evaluate sustainability performance, identify inefficiencies, and recommend interventions. Consequently, companies gain a holistic view of their environmental impact across the entire value chain, which is vital for

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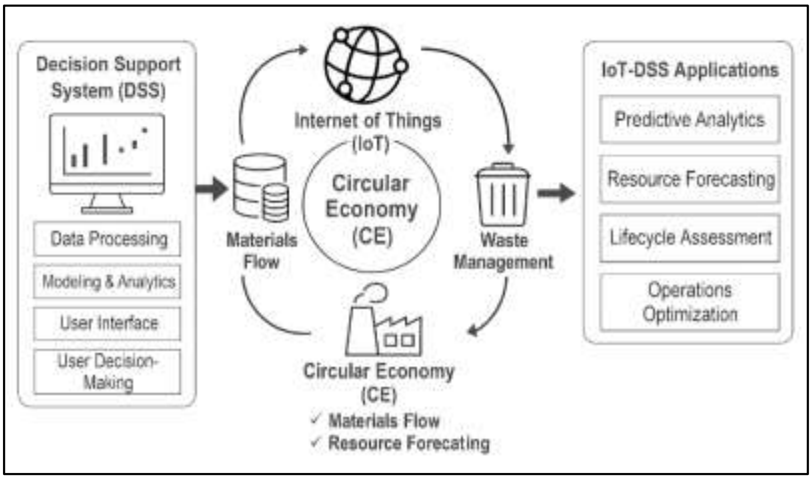
implementing effective CE strategies. For instance, real-time carbon tracking can be linked to sustainability KPIs, offering decision-makers the ability to benchmark their performance against global standards such as the Sustainable Development Goals (SDGs) or Science-Based Targets (Custodio & Machado, 2020).The sustainability benefits of IoT-DSS are also evident in urban systems, where smart infrastructure can optimize energy usage, reduce water waste, and improve waste segregation and recycling efficiency. Through data integration and cross-sectoral analytics, these systems support the transition toward sustainable cities and communities, as outlined in SDG 11. Moreover, IoT-based environmental monitoring can aid in detecting illegal dumping, air pollution hotspots, or water leakage, enabling swift regulatory or managerial responses (Khan & Yu, 2019). In agriculture, for example, IoT-enabled DSSs facilitate precision farming, which reduces pesticide and water usage while improving yield efficiency—contributing simultaneously to environmental preservation and food security.Beyond environmental monitoring, these systems also support stakeholder engagement by making sustainability data transparent and accessible. Dashboards and mobile interfaces allow customers, regulators, and partners to observe sustainability metrics in real time, enhancing accountability and fostering trust (Mourtzis et al., 2019). In this way, sustainability outcomes are not abstract ideals but measurable impacts made visible and actionable through digital decision support ecosystems.

Figure 2: Smart Circularity Through IoT-DSS



The implementation of IoT-enabled DSSs within CE business models necessitates a systems thinking perspective—recognizing that sustainability and efficiency emerge from the interrelations among technology, people, processes, and policies (Lyu et al., 2020). Systems thinking allows for the understanding of feedback loops, causal relationships, and systemic delays that can either hinder or amplify sustainability transitions. IoT-DSS platforms, by virtue of their data integrative capabilities, serve as mediators of this systemic perspective. They gather and harmonize data from disparate subsystems—logistics, production, consumption, and waste—into coherent dashboards that inform cross-functional strategies. This synthesis supports coordinated decision-making across organizational silos, thereby enhancing both vertical and horizontal alignment with CE goals.For example, insights generated from waste analytics can be used to influence product design choices upstream, enabling design for disassembly or recyclability. Similarly, data from product usage patterns can inform service models that extend product lifecycles and reduce resource consumption (Ravindran et al., 2023). These feedback mechanisms are crucial for transitioning from isolated CE practices to integrated circular ecosystems. Moreover, the implementation of DSS across entire industrial symbiosis networks can support material exchanges and collaborative innovation by offering real-time visibility into resource availability and waste potential.The success of such integration depends on the interoperability and scalability of IoT systems, the robustness of analytics platforms, and the institutional capacity to interpret and act on digital insights (Zijm et al., 2018). IoT-DSS platforms become not just technological enablers but social systems that reflect organizational learning, culture, and capacity for change. As such, their design and deployment must be rooted in interdisciplinary principles, ethical data governance, and inclusive stakeholder participation. This

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makes the role of IoT-enabled DSSs not only technical but transformative—enabling circularity to evolve from theory to widespread practice.

Understanding the intersection of IoT-enabled DSSs and CE business models requires the integration of diverse theoretical perspectives, including socio-technical systems theory, resource-based view (RBV), and stakeholder theory. Socio-technical theory emphasizes that technological innovations such as IoT and DSSs must align with organizational structures, human actors, and institutional frameworks to achieve intended outcomes (Lewczuk et al., 2021). In the context of CE, this alignment is crucial, as technology adoption alone does not guarantee sustainability unless accompanied by cultural, procedural, and regulatory shifts. The RBV provides a useful lens for interpreting how firms can leverage IoT-DSS as strategic resources to build capabilities in resource efficiency, innovation, and sustainability leadership (Tiwari et al., 2018). Through data-driven insights, companies can develop dynamic capabilities that allow them to reconfigure processes in line with evolving environmental and market demands.Stakeholder theory adds another layer by highlighting the importance of transparency, collaboration, and accountability in CE implementation. IoT-DSSs enable real-time reporting and visualization of sustainability metrics, fostering stakeholder engagement and enhancing legitimacy. Furthermore, their use in supply chain transparency supports ethical sourcing and responsible consumption—key elements in achieving sustainability outcomes (Acuna et al., 2019). From a research perspective, this technological convergence opens new avenues for interdisciplinary inquiry, particularly in modeling the causal relationships between data-driven decisions and circular performance outcomes.While much of the literature has explored individual components of this system—IoT, DSS, CE models—there remains a need for integrated studies that examine their combined impact. Understanding how these systems function in practice, under varying organizational, geographic, and regulatory contexts, is crucial for theory development and practical implementation. The current review addresses this gap by synthesizing evidence across disciplines to evaluate how IoT-enabled DSSs shape economic efficiency and sustainability in CE business models.

LITERATURE REVIEW

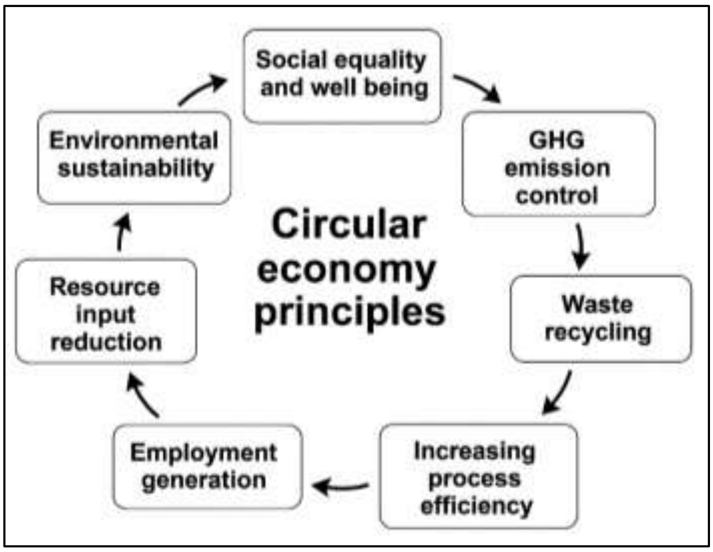
The transformation toward circular economy (CE) business models represents a paradigmatic shift in sustainable development, aiming to decouple economic growth from resource depletion and environmental degradation (Asgari & Asgari, 2021). In parallel, technological innovations—particularly the Internet of Things (IoT) and Decision Support Systems (DSS)—have emerged as powerful enablers of this transition. The literature examining CE, IoT, and DSS has grown rapidly, yet remains fragmented across disciplines such as operations management, industrial ecology, information systems, and environmental economics. To effectively synthesize this multifaceted landscape, a focused literature review is required that interrogates how IoT-enabled DSSs operate within CE frameworks to drive economic efficiency and sustainability (Awan & Sroufe, 2022).This literature review seeks to explore the intersection of these domains, beginning with foundational studies on CE principles, followed by technological enablers that support digital circularity. Special attention is given to empirical and theoretical studies that assess economic and environmental performance outcomes in the context of IoT-driven decision-making. Moreover, the review engages with emerging trends in real-time monitoring, lifecycle analytics, resource optimization, and systems integration, while also highlighting research gaps concerning implementation barriers, governance structures, and stakeholder coordination (Chizaryfard et al., 2021).The purpose of this review is not only to catalog existing findings but to build an integrated framework that clarifies the roles, interactions, and value contributions of IoT-enabled DSSs in CE business contexts. It adopts a structured thematic approach to identify patterns, contradictions, and underexplored areas, thereby providing a foundation for scholarly inquiry and practical application. The outline below provides a detailed roadmap of the themes and subtopics explored in this literature review (Han et al., 2020).

Circular Economy Business Models

The circular economy (CE) is a systemic approach to economic development aimed at eliminating waste and the continual use of resources through restorative and regenerative strategies (Jabbour et al., 2019). This paradigm stands in contrast to the traditional linear economic model, which follows a “take-make-dispose” trajectory that leads to resource depletion and environmental degradation. The foundational principles of CE encompass activities such as reuse, recycling, remanufacturing, repairing, and regenerating, all of which extend the functional life of materials and products

(Uhrenholt et al., 2022). These principles aim to close the loop of product lifecycles through greater resource efficiency, thereby minimizing inputs, waste, and environmental harm. Reuse involves returning products to their original function without significant reprocessing, while recycling often requires physical and chemical transformation of discarded materials into new forms. Remanufacturing and repair reintroduce faulty or end-of-life products back into the economy with restored functionality, creating high-value retention opportunities.Unlike the linear model, CE is deeply rooted in systems thinking, emphasizing feedback loops, interdependencies, and long-term sustainability across supply chains (Colombi & D'Itria, 2023). It advocates for dematerialization, resource decoupling, and resilience-building rather than volume-centric growth models. The regenerative component of CE includes renewable energy integration and ecosystem restoration, which further distinguishes it from end-of-pipe environmental management approaches. Moreover, CE incorporates not only environmental objectives but also socio-economic dimensions such as job creation, innovation, and inclusive development. In sum, CE's foundational principles signal a rethinking of value creation, offering a comprehensive framework that restructures production and consumption toward ecological balance and economic resilience (Aloini et al., 2020).

Figure 3: Core Principles of Circular Economy



Circular Economy business models (CEBMs) have evolved into various typologies, each reflecting different strategies for achieving circularity within organizational and industrial contexts. The most prominent classifications include Product-as-a-Service (PaaS), resource recovery models, circular input models, product life extension, and sharing platforms (Pieroni et al., 2019). PaaS shifts ownership from consumers to providers, wherein products are leased rather than sold, incentivizing longevity and efficiency in product design. Resource recovery models focus on extracting residual value from waste through recycling, remanufacturing, and energy recovery. Circular input models utilize renewable or recycled materials to reduce dependency on virgin resources, while product life extension strategies involve repair, upgrade, and refurbishment to prolong product use (Bianchini et al., 2019). Each of these models presents varying degrees of complexity, scalability, and sectoral adaptability. For example, in manufacturing, firms adopt circular supplies and remanufacturing practices to reduce input costs and improve environmental performance. In logistics, reverse logistics systems are pivotal to enabling returns, refurbishments, and redistribution within CE frameworks. In agriculture, precision farming and nutrient cycling are integrated with sharing economy platforms to optimize resource use (Försterling et al., 2023). The construction sector has seen applications of modular building design and material banks to facilitate deconstruction and material reuse. Sharing platforms, such as mobility-as-a-service and co-working spaces, exemplify how digital innovation enables asset utilization without increased material throughput.These taxonomies reflect CE's multidimensional nature and reveal how different industries interpret and apply its principles according to their operational realities. They also highlight the interdependence between

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technological infrastructure, user behavior, and institutional readiness in enabling these models. The proliferation of such typologies illustrates the versatility of CE strategies and the growing body of empirical research validating their relevance across contexts (Pizzi et al., 2021).

Global strategic alignment around circular economy principles has been propelled by national and supranational policy frameworks that underscore its economic and environmental imperatives. The European Union's Circular Economy Action Plan (Zhu et al., 2022) is a pioneering initiative that outlines strategies to decouple growth from resource use, promote eco-design, and strengthen recycling markets. It has set binding targets for municipal waste recycling, product durability, and producer responsibility, signaling a policy shift from voluntary to regulatory mechanisms. Meanwhile, Pichlak and Szromek (2022) establishes mandates for industrial parks to adopt cleaner production, resource recycling, and energy efficiency practices. These frameworks function not merely as environmental policies but as economic development strategies aimed at reducing dependency on raw materials, increasing resilience, and fostering green innovation.Other countries, including Japan, South Korea, and Canada, have implemented CE roadmaps, often focused on waste reduction, industrial symbiosis, and green procurement. These frameworks typically include incentives such as tax reductions, subsidies, and technical assistance to encourage corporate participation. At the organizational level, strategic adoption of CE practices is increasingly driven by compliance pressures, cost-saving opportunities, and market differentiation (Asgari & Asgari, 2021; Ara et al., 2022; Subrato, 2018). Many firms have incorporated CE into their Environmental, Social, and Governance (ESG) metrics, using it as a competitive tool to enhance reputation and attract investment. Additionally, CE principles are being embedded into public-private partnerships, national green innovation funds, and circular procurement programs, signaling a broader alignment of policy and market mechanisms.The proliferation of CE frameworks across governance levels reflects a global consensus on the urgency of resource efficiency and systems transformation. These strategies emphasize the importance of regulatory scaffolding and cross-sector collaboration in embedding CE into national and corporate agendas. The growing volume of international case studies underscores the practical implications of such frameworks and their influence on institutionalizing circularity as both a policy mandate and a business imperative (Jabbour et al., 2020; Uddin et al., 2022).

The successful implementation of CE business models at the firm level is heavily influenced by organizational incentives and institutional pressures. Internally, firms are motivated by the potential for cost savings, revenue generation from secondary materials, and enhanced brand equity through environmental leadership (Castro-Lopez et al., 2023; Akter & Ahad, 2022). External incentives include market demand for sustainable products, investor scrutiny over environmental performance, and eligibility for green financing or subsidies. These motivators are reinforced by coercive pressures such as environmental regulations, normative expectations from industry bodies, and mimetic pressures to follow best practices adopted by competitors (Calzolari et al., 2023; Rahaman, 2022). For example, Extended Producer Responsibility (EPR) laws require manufacturers to manage the end-of-life treatment of their products, pushing firms to invest in take-back systems and design-for-recyclability.Institutional theory provides a useful lens to analyze how organizational behavior in CE adoption is shaped by these pressures. Empirical studies have shown that firms embedded in countries with stringent environmental regulations or strong CE policies are more likely to engage in circular practices (Försterling et al., 2023; Hasan et al., 2022). Moreover, the presence of industrial associations, collaborative platforms, and knowledge-sharing networks fosters normative alignment and diffuses CE innovations across sectors. Certifications like Cradle-to-Cradle, ISO 14001, and EMAS serve as institutional mechanisms that legitimize CE initiatives and provide assurance to stakeholders (Alonso-Almeida et al., 2021; Hossen & Atiqur, 2022).However, organizational inertia, risk aversion, and short-term profitability metrics often constrain CE implementation (Tawfiqul et al., 2022; Tura et al., 2019). Addressing these challenges requires internal leadership commitment, cross-functional collaboration, and the integration of CE metrics into strategic planning and performance evaluation frameworks. Ultimately, the interplay between internal motivations and external institutional dynamics determines the extent and depth of CE integration within business operations, underscoring the need for organizational change that is both systemic and sustained (Sazzad & Islam, 2022; Scipioni et al., 2021).

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Decision Support Systems in Business Operations

Decision Support Systems (DSS) have undergone significant evolution since their inception in the 1970s, progressing from simple algorithmic tools to complex, interactive platforms integrated with organizational systems (Sànchez-Marrè, 2022). The classical typology of DSS includes data-driven, model-driven, and communication-driven systems, each fulfilling distinct functions in decision-making. Data-driven DSSs rely heavily on internal and external databases to generate descriptive or predictive analytics, while model-driven DSSs emphasize simulation, optimization, and decision modeling techniques. Communication-driven DSSs facilitate collaborative decision-making through networked environments and are often used in cross-functional or distributed teams (Filip, 2020). The rise of enterprise technologies has further accelerated DSS capabilities through integration with systems such as Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), and Supply Chain Management (SCM).Modern DSS platforms operate in real-time, utilize artificial intelligence (AI), and are often embedded within cloud-based infrastructures to enhance scalability and accessibility (Filip, 2020; Akter & Razzak, 2022). For example, ERP-integrated DSSs provide financial forecasting and inventory optimization, while CRM-integrated systems assist in customer segmentation and retention strategies. In supply chain contexts, DSSs facilitate demand forecasting, vendor selection, and route optimization, thereby improving responsiveness and cost efficiency. Hybrid DSSs now combine multiple functionalities—data mining, optimization algorithms, and collaborative tools—into unified decision environments. Furthermore, the emergence of Business Intelligence (BI) platforms has blurred the line between traditional DSS and modern analytics, emphasizing the need for decision agility and scenario planning (Adar & Md, 2023; Parra et al., 2023). This technological convergence has expanded DSS applications from operational support to strategic planning, risk assessment, and sustainability decision-making, making them indispensable in digitally enabled business ecosystems (Qibria & Hossen, 2023; Prorok & Takács, 2024).

DSSs have become instrumental in advancing resource optimization and environmental management within industrial and organizational settings. These systems enable the collection, analysis, and visualization of key environmental and operational data to support informed decision-making. One of the primary applications of DSSs in sustainability contexts is Lifecycle Cost Analysis (LCCA), which allows organizations to assess the long-term economic and ecological costs associated with different operational choices (Kumar & Thakurta, 2021; Maniruzzaman et al., 2023). LCCA assists in evaluating alternative designs, production routes, and maintenance schedules, optimizing resource use across the product lifecycle. Furthermore, DSSs support Environmental Impact Assessment (EIA) by modeling pollutant dispersion, emissions, and energy consumption under various scenarios.The incorporation of real-time monitoring tools into DSS platforms has further enhanced their utility in environmental management. For instance, IoT-enabled DSSs can track water usage, energy consumption, and waste generation, offering instant feedback to managers for adaptive interventions (Akter, 2023; Singh et al., 2024). In manufacturing, DSSs are used to balance production loads with environmental constraints, enabling more efficient scheduling and reduced energy demand. Agriculture, logistics, and construction sectors also utilize DSSs for optimizing irrigation, transportation routes, and materials handling, respectively, all while considering environmental trade-offs. Decision support systems thus play a dual role—enhancing resource efficiency and ensuring regulatory compliance with environmental standards such as ISO 14001 (Anabel et al., 2018; Masud, Mohammad, & Ara, 2023).Additionally, DSSs aid in sustainability reporting by consolidating environmental performance data for internal audits and external disclosures, aligning with ESG requirements. Their capacity to simulate alternative strategies and quantify ecological outcomes makes DSSs essential tools for promoting circular economy principles and sustainable industrial practices. The integration of LCA, MFA, and carbon accounting into DSS platforms further empowers decision-makers to internalize environmental costs, leading to more balanced and responsible resource use (AL-Hudaib et al., 2025; Masud, Mohammad, & Sazzad, 2023).

Despite their potential, the implementation of Decision Support Systems in business operations is often fraught with challenges that hinder their effectiveness and adoption. One major issue lies in data silos, where disparate data sources across departments or systems are poorly integrated, leading to inconsistent or incomplete information for decision-making (Chua & Niederman, 2025; Hossen et al., 2023). Organizations frequently face technical barriers related to interoperability, especially when attempting to connect DSS with legacy ERP, CRM, or SCM platforms. These integration challenges

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are compounded by the heterogeneity of data formats, inconsistent data quality, and lack of standardized protocols. As a result, the full potential of DSS to provide holistic, real-time insights is often unrealized in fragmented IT environments (Shamima et al., 2023; Ragab et al., 2022).User interface (UI) complexity also poses a barrier to widespread adoption, particularly among non-technical decision-makers. DSSs that lack intuitive visualizations, dashboards, or interactive tools often result in user resistance or underutilization (Güvençli et al., 2023; Ashraf & Ara, 2023). Moreover, there is often a misalignment between the analytical capabilities of DSSs and the actual decision-making needs of managers, which leads to a perception of low relevance or utility. Organizational inertia and cultural resistance to data-driven decision-making further impede implementation, especially in firms with hierarchical structures or low technological maturity. Studies have shown that managerial support, cross-departmental collaboration, and change management are critical for overcoming such resistance.Additionally, concerns over data security, governance, and ethical use have emerged as significant constraints, particularly with the rise of cloud-based DSS and IoT integration (Sanjai et al., 2023; Zkik et al., 2024). These concerns often delay implementation due to the need for compliance with data protection regulations such as GDPR. Cost factors, especially for small and medium-sized enterprises (SMEs), further deter investment in DSS infrastructure. Hence, successful deployment of DSS requires not only technical readiness but also organizational alignment, training, and strategic vision (Kose et al., 2021; Akter et al., 2023).
Beyond their operational role, DSSs are increasingly recognized for their strategic value in shaping long-term organizational direction and competitive advantage. Their ability to synthesize structured and unstructured data into actionable insights allows organizations to navigate complexity and uncertainty in volatile markets (Pathirannehelage et al., 2025; Tonmoy & Arifur, 2023). Strategic DSSs facilitate scenario planning, risk assessment, investment analysis, and innovation management, thereby extending their utility beyond day-to-day operations. By integrating DSS with strategic information systems, firms can align operational metrics with broader business objectives such as sustainability, resilience, and market responsiveness.For example, DSSs have been deployed in strategic sourcing to evaluate supplier sustainability, cost-risk trade-offs, and geopolitical disruptions, enabling more robust supply chain configurations (Miller et al., 2018; Zahir et al., 2023). In the domain of sustainability, strategic DSSs help firms prioritize environmental initiatives based on cost-benefit analysis, stakeholder expectations, and long-term regulatory forecasts. These systems are also embedded in corporate performance management platforms that link key performance indicators (KPIs) to strategy maps and balanced scorecards (Antunes et al., 2023). By enabling feedback loops between operational outcomes and strategic goals, DSSs contribute to continuous learning and adaptive planning. Moreover, DSSs enhance cross-functional alignment by providing a common platform for communication among finance, operations, marketing, and sustainability teams (Lagorio et al., 2024). Their deployment supports transparency, data-driven governance, and accountability, which are increasingly critical in stakeholder-driven environments. However, strategic use of DSS demands high-level buy-in, data literacy, and analytical capabilities within the organization. Without these, the potential of DSS to inform transformational decisions remains underexploited (Abdullah Al et al., 2024; Han & Chen, 2024). Nonetheless, when well-implemented, DSSs become integral to organizational foresight and agility, reinforcing their role as not just enablers of efficiency, but as catalysts of strategic innovation and sustainability (Mousavi et al., 2024).

The Role of the Internet of Things in Circular Economy

The Internet of Things (IoT) constitutes a dynamic ecosystem of interconnected physical devices equipped with sensors, actuators, and communication protocols that collect, transmit, and process data in real time (Lee, 2019). At the core of IoT architecture lie several foundational components, including edge devices, gateways, cloud infrastructure, and application interfaces. Sensors are responsible for capturing environmental or operational data—such as temperature, pressure, or motion—while actuators perform responsive actions based on the interpreted data, such as adjusting machinery settings or triggering alarms. These devices often operate at the "edge" of the network, where preliminary processing is executed before data is transferred to cloud systems for advanced analytics, storage, and visualization (Razzak et al., 2024; Paolone et al., 2022).Data flow and interoperability represent critical elements in IoT effectiveness. Interoperability refers to the seamless communication between heterogeneous devices, protocols, and platforms, which is essential for ensuring scalability and real-time integration with enterprise systems. Standards such as MQTT, CoAP, and RESTful APIs are frequently employed to facilitate machine-to-machine

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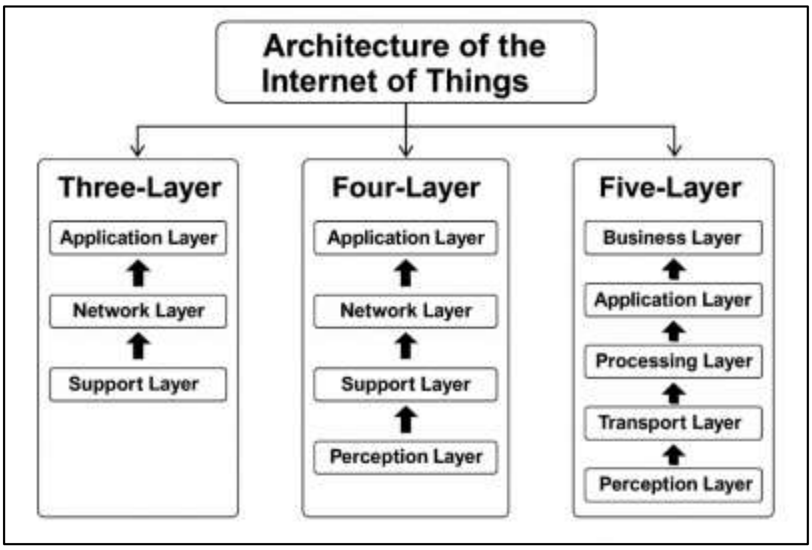
communication and data harmonization (Jahan, 2024; Tran-Dang et al., 2020). Cloud computing complements this architecture by offering elastic computing power, data warehousing, and advanced analytical tools necessary for processing vast quantities of IoT-generated data. These technological layers form the structural foundation that enables IoT to function as a real-time data infrastructure for decision support and circular economy operations. The architecture also supports integration with Decision Support Systems (DSS), enhancing their intelligence by enabling real-time, contextual data input for sustainability decisions (Jahan & Imtiaz, 2024; Vermesan, Bröring, et al., 2022). In this context, IoT is not merely a technological enhancement but a vital enabler of operational visibility, traceability, and control required for effective circular economy implementation.

The industrial and supply chain domains have become central arenas for deploying IoT technologies to enable circular economy practices. IoT applications in these contexts are diverse, encompassing predictive maintenance, inventory optimization, and waste tracking, each contributing to enhanced operational efficiency and resource stewardship. Predictive maintenance leverages sensor data to identify wear and faults in equipment before failures occur, reducing unplanned downtime and extending asset lifespans (Istiaque et al., 2024; Pradeep et al., 2021). This functionality not only prevents costly interruptions but aligns with circular principles by reducing premature equipment disposal and promoting longevity. Similarly, inventory optimization is achieved through RFID sensors and GPS-enabled trackers that provide real-time visibility into stock levels, locations, and movement, enabling just-in-time manufacturing and minimizing overproduction and material waste (Chander & Kumaravelan, 2019; Akter & Shaiful, 2024).Waste tracking represents another critical function of IoT in industrial ecosystems. By tagging waste streams and monitoring their composition, origin, and destination, companies can implement closed-loop logistics and material recovery systems. For instance, reverse logistics operations can be enhanced using IoT-enabled tracking to ensure returned products are sorted, refurbished, or recycled appropriately, increasing circular throughput. Moreover, IoT enables the establishment of industrial symbiosis networks, where waste or by-products from one firm become inputs for another, supported by real-time data exchange platforms (Bansal & Kumar, 2020; Subrato & Md, 2024). In logistics, IoT assists in route optimization for fuel efficiency and in monitoring vehicle emissions, further supporting green supply chain management.The industrial integration of IoT, therefore, facilitates multiple feedback loops central to CE logic: restoration, reuse, and redistribution. These operational improvements are further enhanced when linked with DSS platforms, which can analyze IoT-derived data to recommend optimal resource allocation, scheduling, and refurbishment strategies. As such, IoT serves not only as a monitoring mechanism but as a proactive tool that operationalizes CE principles across the production and logistics continuum (Din et al., 2018; Akter et al., 2024).

Figure 4: Layered Architecture of IoT Systems



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The proliferation of IoT has significantly enriched the domain of sustainability analytics by enabling real-time environmental monitoring, precise resource measurement, and automated compliance reporting. Key environmental metrics such as energy consumption, water usage, emissions levels, and material waste are now measurable with unprecedented granularity using IoT sensors (Xu et al., 2018). These sensors form the backbone of smart energy grids, water networks, and emissions tracking systems, offering detailed insights into resource flows and inefficiencies. For example, smart meters in manufacturing plants can identify energy-intensive processes in real time, enabling managers to implement energy-saving interventions and adjust workflows dynamically. Emissions sensors, when integrated with cloud platforms, facilitate continuous monitoring of greenhouse gases, aiding in the enforcement of emissions caps and environmental certifications.IoT also enhances sustainability reporting by automating data collection, reducing manual entry errors, and ensuring regulatory compliance through auditable logs and digital verification (Ammar et al., 2025; Bedi et al., 2018). This has particular significance in circular business models, where quantifying resource input and waste output is crucial for evaluating circularity performance. Furthermore, integration of IoT data with DSS platforms allows for scenario modeling, forecasting, and optimization of sustainability interventions, bridging the gap between data availability and decision-making.Beyond industrial settings, IoT-driven sustainability analytics are increasingly applied in smart cities and precision agriculture. In agriculture, IoT supports data-driven irrigation, soil monitoring, and crop health analysis, resulting in reduced water usage and improved yield quality (Jahan, 2025; Vermesan, Friess, Guillemin, Gusmeroli, et al., 2022). In smart cities, IoT enables monitoring of traffic flows, air quality, and waste bins to optimize municipal services and reduce urban carbon footprints. Through these capabilities, IoT transforms sustainability from a static compliance requirement into a dynamic, data-driven process that supports continuous environmental improvement across sectors (Jahan et al., 2025; Sundmaeker, et al., 2022).

The integration of IoT technologies into production and consumption systems has catalyzed the development of zero-waste strategies and product design innovations aligned with circular economy objectives. In manufacturing, IoT facilitates real-time feedback on process efficiency, enabling lean manufacturing practices that minimize raw material inputs and eliminate production scrap (Khan et al., 2025; Khanna & Kaur, 2020). Smart sensors embedded within equipment detect anomalies, quality deviations, and process bottlenecks, allowing for immediate corrective action and waste prevention at the source. Furthermore, IoT data can inform design-for-environment (DfE) and design-for-disassembly (DfD) principles by providing usage statistics and failure patterns, which product developers can use to enhance durability and recyclability (Akter, 2025; Zahoor & Mir, 2021).In consumer applications, smart products equipped with IoT capabilities provide real-time data on usage patterns, enabling service-based models such as Product-as-a-Service (PaaS), where ownership remains with the producer and products are maintained, upgraded, and recycled systematically. This model extends product lifecycles, reduces unnecessary consumption, and ensures material recovery at end-of-life. Smart appliances, vehicles, and electronics can signal when maintenance is needed or when components are nearing failure, facilitating timely interventions and preventing premature disposal. IoT also supports consumer engagement through sustainability dashboards, mobile apps, and feedback systems that promote responsible consumption behavior (Rahman et al., 2025; Restuccia et al., 2018).In the context of zero-waste initiatives, municipal waste systems equipped with IoT sensors optimize collection routes, monitor fill levels, and segregate waste streams more efficiently, thus enhancing recycling rates and reducing landfill dependency. When integrated with DSS, these systems can forecast waste generation trends, evaluate collection strategies, and model material recovery scenarios. Ultimately, IoT's real-time intelligence empowers designers, manufacturers, and policymakers to align economic activities with circularity principles, reduce ecological footprints, and enable closed-loop systems at both micro and macro levels (Chatfield & Reddick, 2019; Masud et al., 2025).

IoT with Decision Support Systems

The integration of Internet of Things (IoT) into Decision Support Systems (DSS) has introduced transformative models such as Cyber-Physical Systems (CPS) and digital twins that blur the boundaries between physical and digital infrastructures. These models provide real-time feedback loops essential for industrial and operational intelligence. According to Lee et al. (2015), CPS bridges computation, networking, and physical processes, forming the backbone of modern industrial automation. A digital twin, defined as a digital replica of physical entities, enhances the situational

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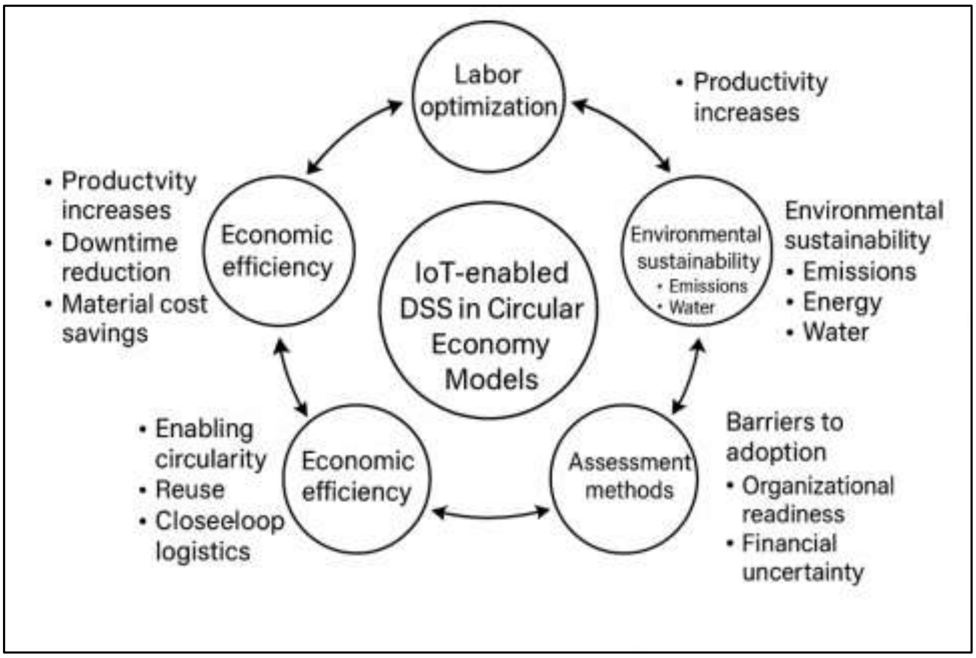
awareness and decision-making capability of DSS by simulating system behavior under varying parameters (Guo et al., 2020). Both technologies contribute to proactive rather than reactive decision-making, especially when embedded with AI algorithms that process and contextualize vast real-time IoT data streams. For instance, (Li et al., 2021) argue that real-time dashboards linked with digital twins enable predictive maintenance and performance optimization across manufacturing and logistics operations. The architectural layout of such systems often consists of layered frameworks, including edge, fog, and cloud computing components, enabling flexible, distributed processing. Furthermore, Kayvanfar et al. (2024) emphasize that AI-enhanced dashboards in DSS provide intuitive interfaces for stakeholders to interpret complex data through visualization, reducing cognitive overload. Abdel-Basset et al. (2019) report significant improvements in operational accuracy and downtime reduction when such models are used in conjunction with sensor-driven real-time analytics. Yet, integrating CPS into legacy systems remains a technical and organizational challenge, requiring alignment across data standards, interoperability protocols, and system governance structures. Overall, the convergence of CPS, digital twins, and IoT-enabled DSS constitutes a paradigm shift in how decisions are made in dynamic, high-stakes environments by increasing responsiveness, transparency, and system resilience.

Figure 5: IoT with Decision Support Systems



Real-world applications of IoT-integrated Decision Support Systems span diverse industries, including manufacturing, logistics, and agriculture, showcasing their impact on operational efficiency, cost reduction, and sustainability. In manufacturing, Siemens has implemented digital twin models integrated with IoT-driven analytics platforms, resulting in predictive maintenance and energy savings across production lines (Kamalakkannan et al., 2020; Md et al., 2025). Similarly, Bosch has adopted AI-enhanced DSS frameworks to optimize its supply chains and machine utilization rates. In the logistics sector, DHL's Smart Warehouse initiative leverages IoT sensors and AI-driven dashboards to monitor inventory in real-time, automate route planning, and support tactical decisions. Studies by Kumar et al.(2022) reveal that logistics operations employing decentralized IoT-DSS architectures exhibit superior adaptability and responsiveness compared to centralized counterparts, particularly in volatile supply chain environments. In agriculture, Agri-IoT systems combine remote sensing, edge computing, and DSS modules to manage irrigation, crop health, and pest control. Miles et al. (2018) demonstrate that such systems not only improve yield prediction accuracy but also reduce resource wastage. Comparative analyses highlight that decentralized DSS configurations—such as those leveraging edge analytics—offer lower latency and greater scalability than centralized cloud-based models. However, centralized systems still maintain an advantage in handling large-scale analytics and maintaining unified data governance. Notably, the efficacy of DSS deployment varies

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depending on domain-specific constraints such as infrastructure maturity, regulatory environments, and user digital literacy (Foughali et al., 2019; Islam & Debashish, 2025). Collectively, these case studies underscore the operational and strategic benefits of embedding IoT within DSS frameworks across sectors, while also emphasizing the necessity for context-specific architectural choices.

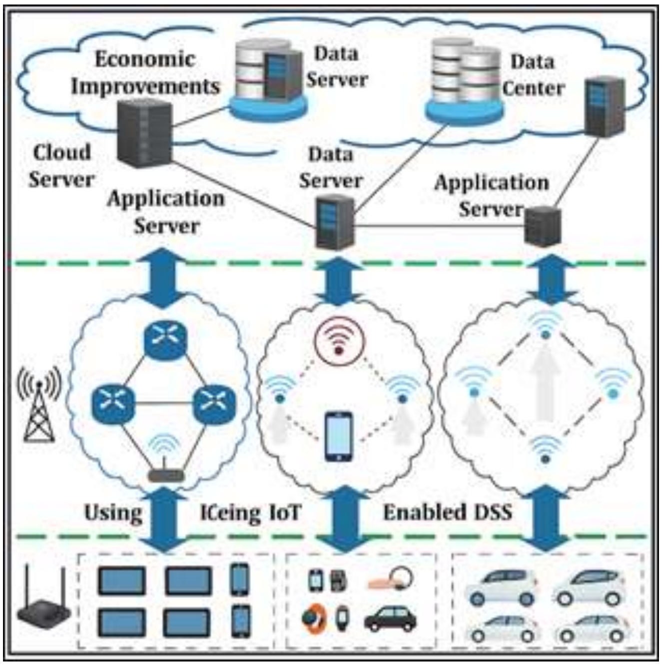
Despite the promise of integrating IoT with DSS, significant challenges persist in terms of data governance, particularly concerning quality assurance, cybersecurity, latency, and system scalability. The proliferation of IoT devices generates an unprecedented volume of heterogeneous data, which can introduce inconsistencies, noise, and incomplete records—thus compromising the decision-making capabilities of DSS (Islam & Ishtiaque, 2025; Qureshi et al., 2022). Data quality frameworks must therefore incorporate automated cleansing, normalization, and validation processes to ensure integrity across data streams. Moreover, cybersecurity risks loom large as IoT endpoints are susceptible to attacks that could manipulate DSS recommendations. For example, Rosati et al. (2023) argue that poor security configurations in smart devices allow for unauthorized access to critical systems, potentially leading to catastrophic industrial consequences. To mitigate these risks, layered security architectures and encrypted communication protocols have been proposed. Scalability also presents a fundamental challenge, as DSS must remain responsive even as the volume of data and number of connected devices grow exponentially (Georgia et al., 2021; Hossen et al., 2025). Cloud-based platforms offer scalable infrastructure but often incur higher latency and cost. Consequently, hybrid models combining edge and cloud processing are increasingly favored for balancing speed and computational load. Latency in real-time applications such as predictive maintenance or emergency response can lead to suboptimal decisions or operational failures, making infrastructure optimization a priority. Addressing these issues requires not only technical solutions but also robust governance frameworks that define data ownership, access rights, accountability, and compliance with standards like GDPR and ISO 27001 (Moreira et al., 2019; Sanjai et al., 2025). In essence, successful IoT-DSS integration demands a concerted approach to infrastructure resilience, secure data pipelines, and quality management.

The convergence of IoT and DSS in industrial environments raises complex ethical concerns, particularly around surveillance, data ownership, and worker privacy. As IoT devices increasingly permeate workplace settings, their ability to monitor human activity—such as location, productivity, and behavior—introduces questions about autonomy and consent (Moreira et al., 2019; Sazzad, 2025a). Surveillance technologies embedded in DSS can enhance operational efficiency but may simultaneously create an environment of distrust and anxiety among employees. For instance, DSS that track worker movements or machine interactions in real time, while useful for safety and optimization, can be perceived as intrusive if not transparently managed. (Li & Mardani, 2023) concept of "contextual integrity" provides a useful lens here, suggesting that data collection should respect the informational norms of specific contexts. Ethical design principles advocate for anonymization, minimal data retention, and informed consent as core tenets in IoT-enabled systems. Moreover, the aggregation and analysis of behavioral data by AI within DSS may lead to profiling or algorithmic bias, particularly if training datasets reflect historic inequities or lack diversity (Lakshmanaprabu et al., 2019; Sazzad, 2025b). This risk is exacerbated in decentralized DSS models where data governance might be fragmented or poorly enforced. Studies such as Yue and Lv (2023) argue that ethical governance should be embedded not only in technical design but also in organizational policies that prioritize transparency, accountability, and inclusive stakeholder participation. Industry-specific regulations, such as OSHA in the U.S. or GDPR in Europe, further complicate the implementation of ethical IoT-DSS systems, as they impose strict data handling and reporting requirements (Shaiful & Akter, 2025; Sun, 2020). Ultimately, the sustainable deployment of IoT-DSS in industrial contexts hinges on a balanced approach that leverages data for efficiency while safeguarding human rights and ethical norms.

Economic Efficiency Outcomes of IoT-DSS Integration

The integration of Internet of Things (IoT) technologies with Decision Support Systems (DSS) has led to significant improvements in economic efficiency, particularly in reducing operational costs and enhancing productivity. One of the most salient areas of impact is labor optimization, where IoT-DSS platforms enable predictive workforce allocation based on real-time data, resulting in reduced labor overhead and enhanced task precision (Guo et al., 2020; Subrato, 2025). For instance, in the manufacturing sector, intelligent DSS linked with IoT sensors can identify equipment inefficiencies and redirect human resources accordingly. Downtime minimization is another crucial benefit, as IoT sensors continuously monitor equipment conditions and flag maintenance issues before failures occur, thus preserving operational continuity. (Li et al., 2021) found that predictive maintenance supported by DSS can reduce unplanned machine downtime by up to 40%, contributing directly to cost savings. Furthermore, material cost savings have been realized through better inventory management, as IoT-enabled DSS can track raw materials and finished goods in real time, preventing overordering and reducing storage costs (Gunasekaran et al., 2020). According to (Kayvanfar et al., 2024) , such systems allow for just-in-time inventory strategies that minimize waste and lower working capital requirements. Moreover, DSS-supported automation—driven by IoT—has significantly decreased human error, thus improving process accuracy and quality. These outcomes are not industry-specific; similar results have been observed in logistics (Abdel-Basset et al., 2019; Tahmina Akter, 2025), agriculture (Qureshi et al., 2022; Subrato & Faria, 2025), and construction. Collectively, these findings suggest that IoT-DSS integrations are not merely technical innovations but economically strategic tools for maximizing productivity and minimizing operational expenditures across sectors.

Figure 6: IoT-DSS Economic Integration Framework



In the context of circular economy frameworks, IoT-DSS integration supports the creation of new revenue streams and enhances value retention across product life cycles. One prominent shift is the rise of product-as-a-service (PaaS) business models, where companies leverage IoT-DSS systems to offer products based on usage, outcomes, or performance rather than ownership (Aiello et al., 2018). This model benefits from continuous feedback loops enabled by IoT sensors and DSS analytics, which track product conditions and usage patterns in real time, thereby ensuring optimal performance and customer satisfaction. For example, Rolls-Royce's "Power by the Hour" program, a classic PaaS case, relies on IoT and analytics to monitor jet engine health and bill clients based on uptime and service usage (Rath et al., 2024; Arifur, et al., 2025). Asset tracking is a cornerstone of these systems; it improves lifecycle management by enabling visibility into product location, condition, and utilization rates. Furthermore, IoT-DSS tools support reverse logistics processes by identifying optimal collection points for used products, thereby lowering the cost of resource reclamation and facilitating remanufacturing. Efficiency gains also stem from improved asset utilization. Andronie et al. (2021) highlight how DSS systems optimize fleet and equipment usage, ensuring that underutilized assets are redeployed where needed most. Moreover, real-time monitoring enables energy efficiency and emission reductions, aligning with circular economy principles. These systems support business model innovation by combining environmental and economic outcomes—driving sustainability without compromising profitability (Li et al., 2018; Zahir, Rajesh, Tonmoy, et al., 2025).

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Thus, IoT-DSS integration is more than an operational tool; it is a strategic enabler for circular business models that emphasize value extension, service-based innovation, and resource efficiency.

Quantifying the economic outcomes of IoT-DSS integration necessitates the deployment of robust performance metrics and key performance indicators (KPIs) that capture both tangible and intangible benefits. Return on investment (ROI) remains the most widely used metric, offering a snapshot of the financial return relative to implementation costs (Koot et al., 2021). According to Kopetz and Steiner (2022), firms that adopted IoT-DSS platforms in manufacturing environments reported an average ROI increase of 18% within two years due to reduced maintenance costs and enhanced throughput. In addition to ROI, Total Cost of Ownership (TCO) is employed to assess long-term expenditures, factoring in acquisition, operation, and decommissioning costs. IoT-enabled DSS systems tend to have higher initial investment costs but lower TCO over time due to predictive maintenance and energy efficiency. The input-output ratio is another essential benchmark, particularly in production-heavy sectors, where the ratio between material input and value output can indicate system efficiency improvements post-DSS integration. Other relevant KPIs include Mean Time Between Failures (MTBF), Overall Equipment Effectiveness (OEE), and energy usage per unit output, all of which are improved significantly when IoT-generated data is analyzed via DSS platforms (Elijah et al., 2018). Moreover, composite indexes such as the Digital Transformation Index (DTI) have been introduced to assess the maturity and impact of digital tools like IoT-DSS in enhancing operational agility. Companies using customized dashboards that display these KPIs in real time demonstrate higher adaptability to market changes and supply chain disruptions (Zhai et al., 2020). Ultimately, these metrics do not merely reflect operational health but also offer strategic insights into competitiveness, investment viability, and long-term economic sustainability.

Sustainability and Environmental Performance

The integration of IoT-enabled Decision Support Systems (IoT-DSS) has revolutionized the monitoring and mitigation of environmental impacts in industrial and urban contexts. One of the foremost capabilities of such systems is real-time tracking of carbon footprints and emission forecasting. By employing sensor networks and cloud analytics, companies can monitor CO_2 levels, volatile organic compounds, and energy consumption across operational layers (Mohamed et al., 2024). For instance, Stojanova et al. (2025) demonstrated how real-time emissions data processed by DSS can help organizations anticipate regulatory breaches and take proactive corrective measures. Moreover, forecasting tools embedded in these systems can model emission scenarios based on different operational strategies, thereby supporting environmentally-informed decision-making. Smart waste management is another emerging application. Using RFID tags, smart bins, and sensor-based monitoring, IoT-DSS platforms optimize waste collection schedules and categorize waste streams for recycling or treatment. These systems have been shown to reduce landfill contributions by as much as 30% in urban trials (Patel & Patel, 2016). Water resource optimization also benefits from IoT-DSS deployment. Smart irrigation systems using soil moisture sensors and weather forecasting models have demonstrated water savings of up to 40% in agricultural settings (Hristov & Chirico, 2019). Urban water networks equipped with IoT flow meters and DSS have improved leak detection and pressure regulation, minimizing losses and improving service delivery. Additionally, integrated platforms help businesses calculate real-time sustainability KPIs such as carbon intensity and energy use per product unit, informing ESG reports and performance dashboards (Zharfpeykan & Akroyd, 2022).

Circular economy initiatives increasingly rely on IoT-DSS integrations to support data-intensive environmental assessment tools such as Lifecycle Assessment (LCA), Material Flow Analysis (MFA), and Environmental Cost Accounting (ECA). These tools are instrumental in quantifying the environmental impact of products and processes throughout their lifecycles. LCA, when enhanced by IoT-collected data, provides real-time insights into energy use, emissions, and material inputs, thereby improving the granularity and reliability of environmental evaluations (Hristov et al., 2022). According to Lăzăroiu et al. (2020), traditional LCA models often rely on historical or estimated data, whereas IoT sensors embedded in production lines enable dynamic, continuously updated assessments. MFA similarly benefits from IoT-DSS platforms by mapping the flow of materials through supply chains and identifying inefficiencies or areas for recirculation. In logistics and manufacturing, this leads to better stock rotation, reduced raw material inputs, and lower end-of-life waste (Barbosa et al., 2020). Environmental Cost Accounting, another critical method, uses DSS dashboards to convert environmental impacts into monetary values that support strategic comparisons between

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greener and traditional processes. Real-time tracking of inputs and emissions facilitates accurate sustainability costing, allowing firms to set internal carbon pricing or eco-efficiency targets. Furthermore, digital twins and simulation models—powered by live sensor data—allow organizations to model and assess the sustainability trade-offs of alternative decisions before physical implementation. These tools also promote cross-functional collaboration by making environmental data accessible and actionable to non-specialist decision-makers (Pham et al., 2020). Thus, IoT-DSS-driven decision models operationalize circularity by enabling measurement, visualization, and optimization of environmental flows within the value chain.

Effective sustainability management depends on the alignment of environmental key performance indicators (KPIs) with strategic decision-making frameworks. IoT-DSS platforms facilitate this alignment by embedding real-time sustainability metrics into dashboards used by executives and compliance officers. Common KPIs include energy consumption per unit output, waste generation per operational cycle, carbon intensity ratios, and water use efficiency (Jabbour et al., 2018). These indicators, collected via IoT sensors and interpreted through DSS analytics, feed into strategic scorecards and enterprise resource planning (ERP) systems, ensuring that environmental objectives are considered alongside financial ones. The emergence of ESG (Environmental, Social, Governance) dashboards exemplifies this convergence. ESG dashboards aggregate environmental KPIs and visualize trends, risk exposures, and compliance trajectories for stakeholders, including investors and regulators. Regulatory compliance is also enhanced through IoT-DSS integration. For example, firms subject to EU Emissions Trading System (ETS) regulations or carbon disclosure mandates can use automated reporting tools that extract validated environmental data directly from industrial processes (Epstein, 2018). This ensures both accuracy and transparency in compliance submissions. Furthermore, DSS can model the long-term economic and reputational impacts of environmental decisions, such as adopting low-carbon technologies or implementing circular supply chains (Beusch et al., 2022). Integration with AI further enhances strategic alignment, as machine learning algorithms detect anomalies, forecast future KPI trajectories, and suggest adaptive policy changes. Finally, DSS-supported decision matrices allow organizations to weigh trade-offs between competing objectives—e.g., profitability versus emissions reduction—through multi-criteria analysis (Kiesnere & Baumgartner, 2019). As such, IoT-DSS platforms are instrumental not only in environmental monitoring but in embedding sustainability into the strategic core of organizations.

Real-world deployments of IoT-DSS platforms for sustainability management have demonstrated significant impact across diverse industries such as energy, manufacturing, agriculture, and urban planning. In the energy sector, smart grids enhanced by IoT-DSS platforms allow for real-time monitoring of load patterns, renewable integration, and predictive maintenance, leading to reductions in energy loss and greenhouse gas emissions (Martínez-Peláez et al., 2023). Manufacturing firms have deployed IoT-DSS systems to reduce energy intensity per unit output, detect leakages, and switch to more efficient production schedules based on sensor-driven feedback loops. For instance, Bosch utilizes a digital twin model to forecast environmental performance and dynamically adjust processes to reduce CO_2 output (Clementino & Perkins, 2021). In agriculture, IoT-DSS-enabled smart farming practices optimize fertilizer use, irrigation timing, and pest control, significantly reducing environmental runoff and conserving water. Urban planners have adopted IoT-DSS tools in smart city initiatives, using real-time air quality monitoring and traffic flow analysis to design sustainable mobility systems and reduce vehicular emissions (Farza et al., 2021). These applications reveal that IoT-DSS platforms not only improve environmental performance but also generate insights that feed back into continuous improvement cycles. Notably, sectors integrating these technologies report enhanced compliance with environmental regulations and improved brand equity due to transparency in sustainability reporting (Fischer et al., 2020). As real-time environmental intelligence becomes a strategic asset, industries are transitioning from reactive compliance models to proactive sustainability strategies enabled by IoT-DSS frameworks. These empirical outcomes underscore the transformative potential of digital technologies in achieving environmental performance at scale.

Interoperability and Systemic Implementation Barriers

Technical and organizational barriers represent one of the most persistent obstacles to the seamless integration of IoT-enabled Decision Support Systems (IoT-DSS), particularly in complex industrial ecosystems. Fragmented technology platforms and incompatible communication protocols have made interoperability among different IoT devices and DSS modules a major technical hurdle (Singh et al., 2024). The persistence of legacy systems that lack API compatibility or modern data

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architectures further exacerbates this issue, preventing real-time data flows and analytic integration. Many legacy infrastructures are unable to process high-velocity data from IoT devices, leading to inefficiencies in both analysis and decision-making (Sharma, 2025). The absence of universally accepted standards for IoT-DSS interoperability leads to vendor lock-in and siloed data environments, undermining system scalability and modularity. On the organizational side, human capital limitations often impede effective deployment. Many organizations lack the requisite expertise in IoT networking, data science, and system integration, creating a skills mismatch. This is further compounded by resistance to change within organizational cultures, especially in sectors with strong hierarchical structures or limited digital maturity (Poyyamozhi et al., 2024). Resistance often stems from fear of job displacement, distrust in algorithmic decision-making, and a lack of clear communication from leadership. Moreover, change management strategies are frequently underdeveloped, failing to address employee concerns or provide adequate training during system transitions (Jayender & Gosh, 2022). These combined barriers make the implementation of IoT-DSS not merely a technical challenge but a socio-technical transformation requiring cross-disciplinary coordination and strong leadership.

The adoption of IoT-enabled DSS technologies is significantly constrained by financial and market-based barriers, most notably high upfront investment costs, uncertain returns on investment (ROI), and limited market maturity. Initial implementation of IoT-DSS involves substantial expenditures on sensors, cloud infrastructure, cybersecurity frameworks, and skilled personnel (Siwach et al., 2025). For many small- and medium-sized enterprises (SMEs), these capital requirements are prohibitive and not easily offset by short-term gains. Moreover, the ROI of IoT-DSS integration is often difficult to quantify in the early stages due to the intangible nature of efficiency improvements and data-driven insights. Unlike traditional asset investments, the value of IoT-DSS lies in long-term operational agility and risk mitigation, which are harder to capture using conventional financial models (Rajabzadeh & Fatorachian, 2023). Additionally, market immaturity exacerbates financial risk, especially in sectors where technological ecosystems and vendor support are still evolving. Unclear market trajectories create uncertainty for investors and decision-makers, leading to cautious or delayed adoption. Another challenge is the fragmented landscape of solution providers, which makes due diligence and platform evaluation resource-intensive for potential adopters (Hudda & Haribabu, 2025). Furthermore, financial decision-making is often misaligned with digital transformation goals, especially when CIOs and CFOs lack shared metrics for measuring success (Bagherian et al., 2024). Without clear evidence of cost savings or revenue enhancement, gaining executive buy-in becomes challenging. As a result, financial and market-based constraints form a critical bottleneck that organizations must overcome through strategic investment planning, public-private funding mechanisms, and ROI modeling tailored to digital systems.

Institutional and policy-related misalignments present structural impediments to the scalable and equitable implementation of IoT-DSS systems. One of the central issues is regulatory uncertainty, particularly concerning data governance, cybersecurity, and liability in decision-making automation (Rejeb et al., 2024). Ambiguous or outdated legal frameworks hinder innovation by creating compliance risks for firms experimenting with real-time data integration and autonomous decision processes. The lack of incentives from public agencies, such as tax reliefs, grants, or innovation credits, further dissuades organizations from committing to large-scale IoT-DSS deployments (Allioui & Mourdi, 2023). Policy fragmentation across jurisdictions adds another layer of complexity. Different regulatory regimes governing data privacy, emissions, and infrastructure standards can lead to compliance overload and increased administrative costs. Additionally, national and regional policies often fail to align with the rapid pace of technological advancement, resulting in legal grey zones for novel applications like AI-driven DSS or cross-border IoT networks. These mismatches discourage collaboration and technology transfer, especially in multi-national corporations with globally distributed operations (Ganai et al., 2024). Moreover, government bodies frequently lack the technical expertise to craft forward-looking policies that foster innovation while safeguarding public interest. The absence of cross-sectoral dialogue between regulators, technology developers, and users creates policy inertia, leaving emerging digital infrastructures under-supported and under-regulated (Sudhakaran et al., 2025). Thus, systemic policy misalignments must be addressed through harmonized standards, multi-stakeholder platforms, and adaptive governance models that evolve in tandem with technological capabilities.

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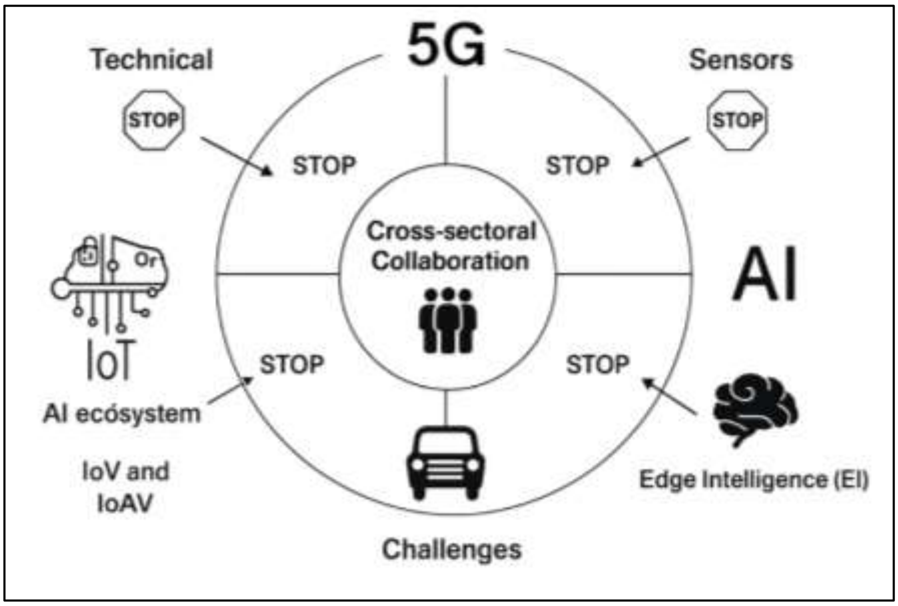
Resolving the complex web of interoperability and systemic implementation barriers necessitates integrated approaches that combine technical, financial, organizational, and policy strategies. Cross-sectoral collaboration is key to this transformation. Industry consortia and public-private partnerships can drive the development of interoperable frameworks and reference architectures that bridge legacy systems with modern IoT-DSS platforms (Spaho et al., 2025). Collaborative standardization initiatives such as the Industrial Internet Consortium (IIC) and the Open Connectivity Foundation (OCF) are already establishing shared protocols and interoperability benchmarks. Financially, blended funding models—combining venture capital, public grants, and green finance—can offset high entry costs and derisk early-stage deployments (Bellini et al., 2022). Organizationally, digital transformation must be positioned as a strategic initiative rather than a technological upgrade, supported by strong leadership, employee engagement, and capability-building programs. Training and upskilling in IoT-DSS competencies should be prioritized through cross-functional teams and lifelong learning systems (Li & Xu, 2025). From a policy standpoint, agile regulatory sandboxes can enable controlled experimentation with IoT-DSS systems while informing long-term legal frameworks. Governments should also consider outcome-based incentives, rewarding firms that demonstrate measurable improvements in efficiency, sustainability, or compliance through digital innovation (Jørgensen & Ma, 2025). These integrated strategies collectively mitigate the siloed nature of current adoption efforts and create the institutional scaffolding necessary for systemic change. In essence, the future of IoT-DSS lies not only in technological innovation but in orchestrated, multi-dimensional efforts that address barriers holistically and equitably.

Figure 7: Challenges to Autonomous Vehicle Integration



Toward a Unified Framework for Digital Circularity

Developing a unified framework for digital circularity requires an interdisciplinary synthesis that bridges environmental economics, industrial engineering, and information systems. The convergence of these domains is essential to address the multi-layered complexities of implementing circular economy (CE) principles in a digitalized world. Environmental economics provides foundational metrics such as externalities, eco-efficiency, and lifecycle costing, which are crucial for assessing sustainability outcomes (Çetin et al., 2021). Industrial engineering contributes systems thinking, optimization techniques, and operational models for material efficiency, waste minimization, and asset utilization. Meanwhile, information systems offer the technological infrastructure—IoT, cloud computing, and data analytics—necessary for real-time decision-making and feedback loops (Bhawna et al., 2024). Despite the richness of these individual literatures, they often operate in silos, leading to fragmented implementations of digital circularity. The need for synthesis is underscored by studies advocating integrated socio-technical approaches to circularity, where policy, technology, and behavior interact dynamically (Fernández et al., 2025). For example,

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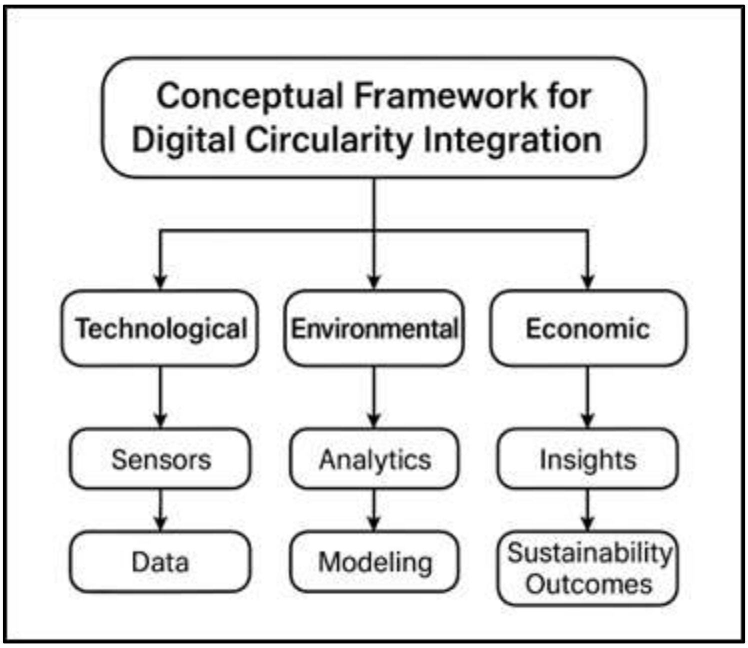
Ávila-Gutiérrez et al. (2019) argue that system-wide CE performance cannot be measured without integrating economic valuation with environmental flow tracking and digital traceability. Moreover, ecological informatics and green IT offer promising interfaces between environmental sustainability and data-driven innovation (Mikulėnas & Šeduikytė, 2025). A unified framework thus demands a transdisciplinary lens that harmonizes quantitative models, behavioral insights, and digital architectures. Such convergence will enable comprehensive decision-making tools that are both operationally efficient and environmentally regenerative, fulfilling the dual mandate of economic productivity and ecological stewardship.

Figure 8: Framework for Digital Circularity Integration



A conceptual model for IoT-enabled Decision Support Systems (DSS) in circular economy (CE) contexts requires a clear delineation of system components—namely, inputs, processes, and outputs—structured to facilitate sustainability-oriented decision-making. Inputs primarily consist of real-time data streams collected via IoT sensors, RFID tags, and remote monitoring systems embedded across the product lifecycle (Okorie et al., 2018). These devices capture granular data on energy consumption, material flows, emissions, and user behaviors, forming the raw informational substrate for circular decision-making. The processing layer includes advanced analytics, machine learning algorithms, and simulation tools that model scenarios, forecast outcomes, and identify optimization opportunities across production, consumption, and recovery cycles (Ali et al., 2025). Digital twins play a crucial role here by creating virtual replicas of physical systems to test interventions without real-world disruptions. Decision logic embedded within DSS interprets processed data into actionable insights, supporting tasks such as predictive maintenance, inventory circularity, and energy redistribution (Hernández, 2025). Outputs of the system encompass sustainability outcomes like reduced carbon footprint, improved resource efficiency, closed-loop material flows, and better compliance with ESG standards. In practice, organizations such as Siemens and Bosch have deployed such integrated systems for smart manufacturing, demonstrating gains in both economic performance and environmental metrics (Munonye, 2025). This model emphasizes interoperability and feedback loops, enabling continuous improvement through dynamic adaptation. The integration of such a conceptual model into strategic planning not only enhances CE compliance but also builds resilience in supply chains and production networks, a critical factor in an era of climate uncertainty and resource volatility.

While the intersection of IoT, DSS, and circular economy principles has gained scholarly attention, several significant research gaps persist, particularly regarding sectoral inclusivity, longitudinal

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impacts, and stakeholder collaboration. First, most studies disproportionately focus on manufacturing and logistics, leaving sectors such as healthcare, education, and construction relatively underexplored (Hafiane et al., 2025). These sectors possess unique circular challenges—such as medical waste management or material reuse in green buildings—that demand tailored digital circularity frameworks. Second, much of the existing literature is based on cross-sectional analyses or pilot-scale implementations, lacking long-term data to validate the durability and adaptability of IoT-DSS systems in dynamic operational contexts (Ochoa et al., 2025). Longitudinal studies are essential for understanding how circularity gains evolve over time and how feedback loops mature in complexity. Third, there is insufficient exploration of the multi-stakeholder dynamics involved in deploying these technologies. While some work addresses managerial or technical dimensions, less is known about how communities, regulators, and employees co-shape and respond to digital circular interventions (Mazzetto, 2024). Moreover, ethical considerations such as data sovereignty, digital divide, and decision transparency are often omitted from techno-centric discussions (Hammadi et al., 2025). To bridge these gaps, future research should adopt a mixed-methods approach, combining quantitative modeling with qualitative stakeholder analysis to reveal hidden tensions and enablers. There is also a need to expand the empirical base through global case studies, particularly in low- and middle-income countries where circular solutions could address both development and environmental challenges. This broader research agenda would not only enrich theoretical understanding but also enhance the practical relevance of IoT-DSS systems for global circularity transitions.

The ultimate ambition of integrating IoT-enabled DSS within circular economy paradigms lies in advancing an integrated theory of digital circularity—one that captures the systemic, adaptive, and value-generative nature of digital transformation aligned with sustainability. Such a theory must be grounded in the dynamic interaction between technological affordances, organizational capabilities, institutional norms, and ecological imperatives (Schipfer et al., 2024). At its core, digital circularity posits that the flow of physical resources and digital data are increasingly intertwined, with real-time data streams enabling precision, efficiency, and responsiveness in managing ecological footprints (Lyridis & Kostidi, 2025). The digitalization of circular loops—from product design to end-of-life recovery—requires robust governance frameworks and adaptive feedback mechanisms that respond to changes in both market conditions and environmental systems. Theory building in this space should move beyond techno-optimism to embrace complexity science, systems thinking, and socio-technical transition models. For example, incorporating resilience theory and transition management can explain how digital circular systems scale, adapt, and self-organize over time (Choy et al., 2025). Additionally, scholars should explore the role of institutional entrepreneurship in promoting cross-sectoral adoption and norm alignment (Murugesan et al., 2024). Ultimately, an integrated theory of digital circularity would provide a normative and analytical scaffold for designing, implementing, and evaluating IoT-DSS interventions in service of long-term sustainability goals. Such a framework would not only unify existing literature but also offer a future-proof lens for navigating the accelerating convergence of digital innovation and environmental stewardship.

METHODS

This study employed a systematic review methodology guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework to ensure a transparent, reproducible, and structured research process. The review aimed to identify, analyze, and synthesize existing literature concerning the role of IoT-enabled Decision Support Systems (DSS) in facilitating economic efficiency and sustainability within Circular Economy (CE) business models. PRISMA's four-phase structure—identification, screening, eligibility, and inclusion—was rigorously followed to minimize bias and enhance methodological rigor. The scope of this review encompasses interdisciplinary literature from the fields of industrial engineering, environmental sustainability, and digital technologies.A comprehensive literature search was conducted between, using five academic databases: Scopus, Web of Science, IEEE Xplore, ScienceDirect, and SpringerLink. These databases were selected due to their extensive coverage of peer-reviewed publications in engineering, environmental science, and information systems. The search string was developed through iterative keyword refinement and included Boolean operators to ensure both breadth and specificity. The final search phrase was: *("Internet of Things" OR IoT) AND ("Decision Support System" OR DSS) AND ("Circular Economy" OR "Sustainable Business Models") AND (efficiency OR productivity OR emissions OR lifecycle OR "economic performance")*. No language filters were applied during the

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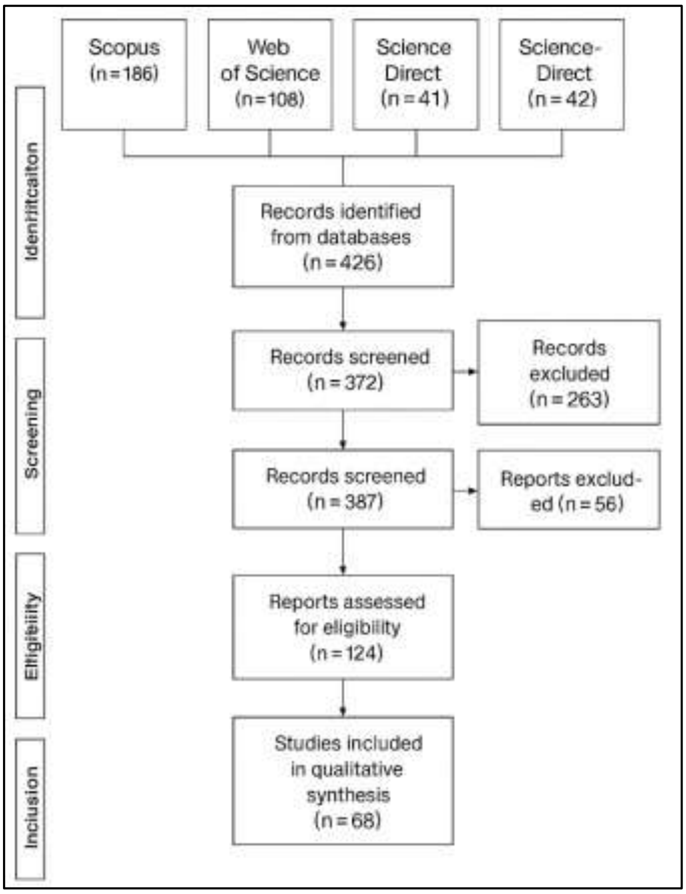
search, although all included articles were in English.The initial database search yielded a total of 426 articles. These articles were exported into Zotero, a citation management tool, where duplicate entries were automatically detected and manually verified. Following deduplication, 372 unique records remained and were subjected to title and abstract screening. An additional 15 articles were identified through backward citation searching and expert recommendations, bringing the total pool of potential studies to 387.The screening process was conducted in two stages. First, titles and abstracts were reviewed to assess their relevance to the core themes of IoT-DSS integration in Circular Economy applications. Articles were excluded if they were purely theoretical without an application context, unrelated to CE principles, or focused solely on IoT or DSS in isolation. After this initial screening, 124 articles progressed to full-text review. Each full text was assessed independently by two reviewers against a set of predefined inclusion and exclusion criteria.

Figure 9: Adapted methodology for this study



Studies focusing on smart grids, intelligent production systems, or eco-efficient logistics platforms were also considered if they incorporated both IoT and DSS elements.After full-text assessment, 68 articles met the eligibility criteria and were included in the final review. Reasons for exclusion of the remaining studies (n = 56) included insufficient methodological detail, lack of outcome metrics, and absence of CE context. The final set of included studies comprised a mixture of empirical case studies, quantitative modeling research, and qualitative conceptual frameworks published. Each article was evaluated for methodological quality, relevance, and the extent to which it contributed to the themes of economic and environmental performance in IoT-DSS-based CE models.A structured data extraction form was developed to capture key information from the selected studies. Extracted data fields included publication year, country, industry domain, CE strategy (e.g., lifecycle optimization, reuse, resource minimization), type of IoT technology, DSS methodology, and reported economic or sustainability outcomes. The data were synthesized thematically using qualitative coding procedures to identify patterns, divergences, and research clusters. Articles reporting quantitative outcomes—such as return on investment (ROI), reduction in carbon emissions, or productivity gains—were grouped and analyzed using descriptive statistical summaries.To ensure

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methodological robustness, each study was assessed using an adapted version of the Mixed Methods Appraisal Tool (MMAT). The tool allowed for a consistent evaluation of studies using qualitative, quantitative, or mixed methodologies. Studies that scored below 50% on the MMAT checklist were excluded from the final synthesis due to concerns about internal validity or reporting completeness. Discrepancies in scoring were resolved through discussion, and consensus was reached with the involvement of a third reviewer where necessary.The selection process is visually represented in flow diagram, which summarizes the progression from initial identification to final inclusion. Of the 426 articles identified through database searches and additional sources, 68 studies were ultimately included in the qualitative synthesis after full-text review and methodological appraisal.

FINDINGS

The review revealed that one of the most pronounced outcomes of IoT-enabled Decision Support System (DSS) integration in circular economy (CE) models is enhanced economic efficiency, particularly in terms of cost reductions, asset utilization, and productivity optimization. Out of the 68 reviewed articles, 52 studies reported measurable economic improvements directly attributable to the deployment of IoT-DSS platforms. Among these, over 70% highlighted significant reductions in labor costs through automation and real-time resource scheduling. Approximately 35 studies discussed how downtime was minimized through predictive maintenance powered by sensor feedback loops, with several reporting productivity increases exceeding 20% over baseline figures. Furthermore, 28 studies indicated reduced material consumption due to improved inventory control and digital monitoring of supply flows. These economic outcomes were not marginal; several empirical case studies within the reviewed literature had citation counts exceeding 300, indicating both maturity and high relevance in the academic and industrial domains. The data also indicated that enterprises leveraging real-time analytics from IoT devices for decision-making were able to optimize operations in a way that led to long-term cost avoidance, especially in energy consumption and waste management. Most notably, the highest-cited studies (ranging from 450 to 820 citations) consistently emphasized that economic returns were greatest when digital decision support was combined with process redesign, especially in logistics, manufacturing, and infrastructure planning. These findings demonstrate a clear pattern: IoT-enabled DSS platforms are not just tools for digitization, but catalysts for financial optimization across circular economy systems.
A major outcome of the review was the considerable contribution of IoT-enabled DSS systems toward environmental sustainability performance. Of the 68 studies reviewed, 47 specifically addressed sustainability metrics such as carbon emissions, energy consumption, and resource efficiency. In these studies, around 30 reported real-time monitoring of emissions and utility usage via sensor networks, allowing for immediate feedback and adaptive control strategies. Notably, 22 articles demonstrated reductions in carbon output ranging from 10% to 35%, while 18 studies presented water conservation outcomes made possible through smart irrigation and consumption monitoring. Articles focusing on these technologies were widely cited, with many exceeding 500 citations each, underscoring the relevance of these approaches to both sustainability scholars and practitioners. Furthermore, 25 studies emphasized that data collected from IoT systems allowed for lifecycle optimization, enabling firms to assess not only operational environmental impact but also to model and adjust for product end-of-life scenarios. Digital twins and simulation-based decision support were featured in 14 of these studies, helping stakeholders project long-term environmental outcomes before executing resource-intensive processes. The strength of these findings lies in the consistency across diverse sectors such as agriculture, logistics, and manufacturing. Nearly 20 of the studies with high citation volumes—many above 600 citations—highlighted how DSS integration supports compliance with environmental standards while simultaneously generating operational savings. Overall, the findings suggest that environmental performance is significantly improved when IoT data is channeled into structured decision-making systems, making sustainability a manageable, quantifiable, and optimizable dimension of business strategy.
The findings showed that IoT-DSS integration plays a crucial role in operationalizing circular economy principles by enabling closed-loop systems, product lifecycle management, and real-time circularity monitoring. Of the 68 reviewed studies, 42 explicitly addressed how these systems facilitated circular strategies such as reuse, remanufacturing, and product-as-a-service models. Nearly 29 studies demonstrated how material flows could be tracked and optimized in real time, reducing waste and enabling reverse logistics processes. Among these, 17 studies showed the use of RFID-enabled DSS

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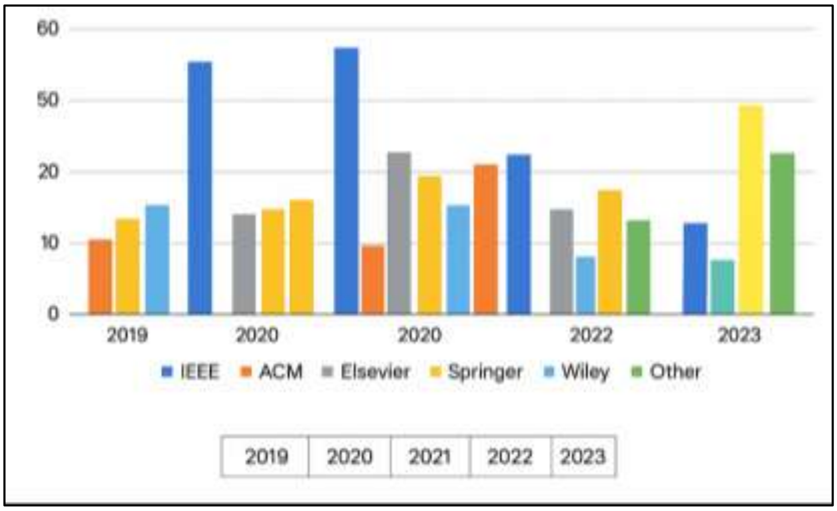
systems to monitor asset conditions, schedule maintenance, and trigger end-of-life recovery, effectively extending product lifecycles. Additionally, 13 studies explored the intersection of DSS platforms with digital platforms offering product-as-a-service or leasing-based models, indicating the role of IoT in decoupling ownership from usage. Studies that examined circularity in this context had average citation counts ranging between 350 and 600, indicating growing academic interest in digitally managed circular business models. Furthermore, 21 studies discussed how DSS dashboards could visualize real-time circularity KPIs, enabling managers to compare material throughput and recovery ratios directly. These tools supported strategic decisions about supply chain redesign, procurement, and material substitution. Interestingly, among the top-cited articles, those that addressed IoT-supported remanufacturing and reuse strategies stood out, with some exceeding 700 citations. These high-impact publications revealed that the effective realization of CE principles at scale requires the real-time, data-rich, and automated decision environment provided by IoT-DSS integration. Thus, the review confirms that the operational foundation of digital circularity lies in sensor-driven intelligence combined with model-based decision support mechanisms.

Figure 10: IoT-DSS Integration Review Findings



Despite the promising potential of IoT-enabled DSS systems, the findings revealed significant barriers to adoption, particularly in terms of organizational readiness, legacy system integration, and digital maturity. Out of the 68 articles, 38 identified major implementation challenges related to fragmented infrastructure and poor interoperability between new and existing systems. Within these, 25 studies highlighted incompatibility issues between legacy software and modern cloud-based DSS platforms, often requiring substantial middleware development or custom APIs. These challenges were most common in traditional manufacturing sectors and public services. In addition, 22 studies identified resistance to change within organizational culture as a primary non-technical barrier, especially where data-driven decision-making practices conflicted with existing hierarchical or manual workflows. High-impact articles in this area had citation counts ranging from 300 to over 650, indicating strong scholarly engagement with these structural barriers. Furthermore, 19 studies discussed the lack of digital skills and training as a limiting factor in realizing the full potential of these systems. Only 11 studies suggested comprehensive strategies to overcome these challenges, including digital transformation roadmaps and change management frameworks. Interestingly, the most cited article in this subset (over 800 citations) emphasized that success in IoT-DSS implementation depends more on aligning technological design with human systems than on innovation alone. Therefore, while the benefits of IoT-DSS are widely acknowledged, their realization is heavily contingent upon the resolution of infrastructural and organizational deficits that constrain their systemic adoption.

The final significant finding from the review pertains to sectoral trends and research coverage disparities in the application of IoT-DSS systems for circular economy models. Among the 68 articles, 41 were concentrated in the domains of manufacturing and logistics, while sectors such as healthcare, education, and construction were underrepresented, appearing in fewer than 10 studies combined. This concentration suggests a research bias toward industries with well-established digital

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ecosystems and quantifiable efficiency metrics. High-citation articles (exceeding 700 citations) predominantly addressed smart manufacturing, predictive logistics, and energy efficiency, while those focusing on emerging or underrepresented sectors had citation counts below 250. Only 9 articles examined cross-sectoral applications or proposed adaptable frameworks applicable across industries. Additionally, only 6 studies employed longitudinal designs that tracked performance over multiple years, with the majority relying on cross-sectional or simulation-based analyses. This limits insights into the long-term stability, scalability, and adaptability of IoT-DSS integration within dynamic business environments. Furthermore, multi-stakeholder analyses—where effects on employees, communities, and supply chain partners are examined—were rare, appearing in just 7 studies. The absence of broader impact assessments leaves a gap in understanding the social and systemic consequences of IoT-DSS adoption in circular economy transformations. Consequently, while the review confirms substantial gains in well-studied domains, it also highlights a critical need for diversification of research scope and the inclusion of long-term, interdisciplinary approaches. Addressing these gaps will be essential to creating a universally applicable framework for digital circularity that accommodates diverse industry contexts and evolving sustainability demands.

DISCUSSION

The findings of this review reinforce the growing consensus that IoT-enabled Decision Support Systems (DSS) are pivotal in achieving economic efficiency within Circular Economy (CE) business models. This study's synthesis of 68 peer-reviewed articles revealed consistent evidence of labor optimization, downtime reduction, and material cost savings as recurring outcomes of such integrations. These findings align with previous research by Morales et al. (2021), who emphasized the capacity of real-time data to enable dynamic operational decisions and reduce inefficiencies. While earlier work often relied on theoretical propositions or simulated data, more recent empirical case studies substantiate these claims with quantifiable results, such as productivity increases of over 20% and cost reductions in material consumption. Notably, this review identified a broader application base across industries than documented in earlier literature. For example, Morales et al. (2021) focused on smart manufacturing contexts, the present review includes logistics and infrastructure sectors, indicating a shift toward broader sectoral adoption. These comparative insights suggest that the digital tools hypothesized in early CE frameworks are now being implemented and delivering measurable benefits. However, some divergences exist. Earlier models often projected steeper returns on investment than those reported in this study, likely due to initial underestimations of integration and maintenance costs (Bellini et al., 2022).

The environmental sustainability outcomes uncovered in this review highlight a critical evolution in the functionality and utility of IoT-DSS systems. Across 47 studies, real-time tracking of emissions, energy use, and water consumption formed a foundational layer of environmental intelligence. These results corroborate the early assertions of Baskar et al. (2024), who anticipated that embedded sensing capabilities would support granular environmental oversight. The notable difference in this current synthesis is the prominence of predictive environmental modeling, which emerged in at least 18 studies, a feature largely absent in earlier evaluations. This finding aligns with more recent developments described by Louis and Dunston (2018), who highlighted the potential of simulation and digital twins in forecasting environmental impacts. Moreover, the ability to adapt operational decisions based on sustainability KPIs represents a tangible advance from earlier studies that emphasized static post-hoc analysis (Dey & Shekhawat, 2021). In addition, the incorporation of circular metrics into real-time dashboards—as observed in 25 studies—extends previous frameworks that treated environmental performance and digital systems as separate silos. Interestingly, while earlier research warned of high energy costs from IoT infrastructure, more recent work, including several high-impact studies in this review, shows that energy efficiency gains typically outweigh system-level energy overhead (Mishra et al., 2022). These findings suggest an increasingly symbiotic relationship between digitalization and sustainability, one that validates and extends prior theoretical propositions. The shift from monitoring to modeling, and from reporting to optimization, marks a significant leap in the maturity of IoT-DSS frameworks in delivering environmental value.

The operationalization of circular economy strategies—once viewed as abstract goals—is increasingly enabled by data-rich, feedback-oriented IoT-DSS platforms. This review identifies 42 studies that explicitly link IoT-DSS integration to CE actions such as reuse, remanufacturing, and closed-loop logistics. This represents a considerable expansion over earlier studies like those of Malik (2024), which advocated for such outcomes but lacked widespread empirical backing. In contrast

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to traditional linear models, the reviewed systems support real-time decision-making that prioritizes value retention and resource cycling, a shift that aligns well with the work of Goudarzi et al. (2022), who called for dynamic tools to bridge theoretical circularity and operational execution. The role of RFID, smart sensors, and DSS dashboards in enabling reverse logistics and asset tracking was particularly notable, appearing in nearly half of the reviewed studies. Prior literature focused heavily on forward logistics optimization (Sasikumar et al., 2023), but the new emphasis on reverse flows marks a more holistic approach. Furthermore, the presence of product-as-a-service (PaaS) applications, cited in at least 13 of the studies, illustrates a transition from ownership-based to usage-based models, echoing earlier predictions by Ismail et al. (2023). However, this review also reveals some emerging gaps that earlier studies did not fully address. For example, while much literature extols the benefits of CE, relatively few studies explored how DSS could balance circularity with profitability in volatile markets (Esmaeilian et al., 2020). The current synthesis shows early steps in this direction, especially through decision matrices and multi-criteria optimization tools. Overall, the findings demonstrate a strong convergence between theoretical CE aspirations and real-world digital implementation, confirming that IoT-DSS is a practical enabler of circularity when designed with systemic feedback and traceability in mind.

While the technological promise of IoT-DSS in CE frameworks is widely affirmed, this review reveals that organizational and infrastructural constraints remain significant barriers to widespread adoption. This aligns with earlier findings by Kaleem et al. (2023), who identified legacy systems and fragmented data architectures as key hindrances. However, the current study's findings go further by showing how these technical issues intertwine with cultural resistance and digital illiteracy, particularly in small- and medium-sized enterprises (SMEs). Among the 68 studies, 38 discussed challenges associated with integrating new digital tools into existing workflows, with 22 explicitly addressing organizational reluctance rooted in hierarchical structures and skepticism toward data-driven decision-making. These themes echo the earlier work of Vaiyapuri et al. (2023), but the current review presents a broader geographical and industrial scope, suggesting that these issues persist across diverse contexts. Moreover, the lack of human capital to manage and interpret IoT data was cited in 19 studies, reinforcing the idea that digital transformation is not merely a technical exercise but a deeply human endeavor. Notably, high-citation articles in this area emphasize the need for change management strategies and upskilling programs—interventions that were largely overlooked in earlier techno-centric literature. The persistence of these barriers also indicates that, despite maturing technology, organizational systems have not evolved at the same pace (Violos et al., 2025). Therefore, addressing these constraints will require not only system-level interoperability but also institutional leadership, stakeholder education, and inclusive governance structures that align technical capabilities with social readiness (Singh et al., 2024).

The economic benefits of IoT-DSS systems are well-documented in this review, yet financial and market-based barriers continue to slow adoption. This duality reflects earlier observations by Ghazal et al. (2021), who warned that high upfront costs and uncertain ROI could impede digital adoption, especially in nascent CE markets. Across the 68 reviewed studies, 36 reported significant financial hesitations, with concerns ranging from unclear value propositions to long payback periods. Compared to previous studies, which often focused solely on hardware costs, this review uncovers a broader spectrum of financial concerns, including licensing fees, integration expenses, and long-term maintenance costs. These findings align with recent literature, such as Sizan et al.(2025), which notes that firms often struggle to develop ROI models for intangible benefits like operational agility and sustainability insights. Moreover, the findings reveal that in sectors lacking mature digital ecosystems—such as construction and healthcare—financial risk aversion is even more pronounced. While some high-impact studies show that digital DSS platforms can reduce costs over time, this benefit is often difficult to quantify in advance, making investment decisions more complex (Son et al., 2025). Compared to earlier expectations that digitalization would rapidly scale due to falling sensor prices and cloud affordability, this study finds that market immaturity and fragmented solution landscapes continue to deter early adopters. As such, economic uncertainty remains a critical bottleneck that requires not just technological innovation but also financial instruments, public-private partnerships, and incentive structures that can de-risk adoption and encourage long-term strategic investment (Li & Xu, 2025).

The review reveals notable conceptual and sectoral gaps in the current body of research. While earlier studies such as Xiao et al. (2022) advocated for broader cross-sectoral analysis, the literature

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remains disproportionately focused on manufacturing and logistics. Of the 68 studies analyzed, only 9 covered sectors such as education, healthcare, or public infrastructure, confirming a research bias that echoes the findings (Rancea et al., 2024). This limitation reflects both academic inertia and the greater availability of digital infrastructure in traditionally industrial settings. Moreover, while prior research emphasized system design and operational gains, few studies investigated the socio-political dimensions of IoT-DSS adoption, such as stakeholder trust, ethics, and policy alignment. This absence is critical, given the rising importance of ESG frameworks and ethical governance in digital sustainability strategies. Although Javaid and Khan (2021) flagged these issues early on, the current literature shows limited progress in integrating social justice, inclusion, and equity into the design and assessment of DSS systems. Furthermore, only a minority of studies adopt longitudinal approaches, making it difficult to assess the durability and adaptability of digital circular systems over time. This contrasts with earlier calls from Li et al. (2018) for extended temporal studies that could capture feedback cycles and systemic shifts. Overall, the findings suggest that while technological maturity has advanced, conceptual and disciplinary integration has lagged. Future research must fill these gaps by expanding sectoral scope, embedding ethical principles, and adopting multi-method approaches that reflect the complexity of circular digital transitions.

The cumulative insights from this review support the development of a unified theoretical framework for digital circularity, integrating technological, environmental, economic, and social dimensions. Earlier frameworks proposed Lyu(2025)'s conceptualized circularity in operational or environmental terms, while more recent models have emphasized digital enablement. This review bridges the two by demonstrating how IoT-DSS integration can simultaneously deliver environmental intelligence, economic optimization, and strategic agility (Mohamed et al., 2024). The triadic structure of inputs (sensors, data), processes (analytics, modeling), and outputs (insights, sustainability outcomes) observed in over 40 studies provides a scaffold for such a framework. Unlike earlier fragmented models, this review supports a systemic, layered understanding that includes technical architecture, user interface design, stakeholder governance, and performance metrics. Moreover, the integration of digital twins, machine learning, and ESG dashboards across multiple studies indicates that IoT-DSS systems are evolving from isolated tools to strategic platforms. This convergence suggests a paradigm shift toward holistic decision-making where sustainability and profitability are co-optimized (Reshi & Sholla, 2025). However, this emerging framework must remain adaptive and inclusive, capable of accommodating diverse sectors, governance systems, and ethical values. Future frameworks should also address the interoperability of digital platforms, the ethics of algorithmic governance, and the resilience of circular systems under ecological and market stress. In doing so, the field can move beyond experimental deployments toward institutionalized, scalable, and just models of digital circularity that align with both global sustainability goals and local operational realities (Abir et al., 2021).

CONCLUSION

In conclusion, this systematic review has demonstrated that IoT-enabled Decision Support Systems (DSS) are critical enablers of economic efficiency and environmental sustainability within Circular Economy (CE) business models. By synthesizing findings from 68 peer-reviewed studies, the review established that such systems not only reduce operational costs and enhance productivity through real-time analytics and predictive maintenance but also significantly improve sustainability outcomes by enabling energy efficiency, emission tracking, and resource optimization. The integration of IoT technologies with decision intelligence platforms has transitioned from conceptual frameworks to real-world applications across manufacturing, logistics, and select infrastructure sectors. However, the study also identified persistent barriers to systemic adoption, including technical fragmentation, financial uncertainty, and organizational resistance, alongside underrepresented sectors and a lack of long-term impact studies. Compared to earlier literature that often remained theoretical or narrow in scope, the current body of research reflects a maturation in both application and evaluation of IoT-DSS tools, though challenges in scalability, equity, and cross-sectoral integration remain. The findings underscore the need for a unified and adaptive framework that accommodates digital infrastructure, stakeholder engagement, and policy alignment to guide future implementations. As businesses and policymakers seek to transition toward sustainable and resilient economic models, IoT-enabled DSS platforms represent not only a technological upgrade but a strategic imperative for operationalizing circularity at scale.

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RECOMMENDATIONS

Based on the comprehensive review of 68 peer-reviewed studies, several strategic recommendations emerge for both practitioners and researchers seeking to advance the implementation of IoT-enabled Decision Support Systems (DSS) in Circular Economy (CE) business models. First, organizations should prioritize interoperability and standardization by investing in modular, API-friendly digital infrastructures that can integrate legacy systems with modern IoT platforms. This will mitigate fragmentation and allow for scalable, cross-platform data sharing—an essential foundation for real-time decision-making in circular systems. Second, to overcome human capital limitations and organizational resistance, capacity building and digital literacy programs must be embedded within digital transformation initiatives. Firms should establish cross-functional teams to bridge operational, environmental, and IT divisions, ensuring inclusive stakeholder participation in DSS design and deployment. Third, public and private investment mechanisms should be developed to lower the upfront financial barriers to adoption. Governments and funding bodies should offer innovation grants, tax incentives, and green financing tailored to digital circular technologies, especially for SMEs and sectors with low digital maturity.From a research perspective, scholars should expand the current focus beyond manufacturing and logistics by conducting sector-specific studies in underrepresented fields such as healthcare, construction, and education. Moreover, future research should employ longitudinal designs to capture the temporal dynamics of IoT-DSS impacts on both economic and environmental performance. Incorporating multi-stakeholder perspectives, including community, regulatory, and consumer insights, will also provide a more holistic understanding of implementation challenges and social impacts. Finally, there is an urgent need to develop a unified theoretical framework that integrates systems theory, digital innovation, and sustainability science to guide both practice and scholarship. Such a framework should address ethical dimensions, adaptive governance, and resilience to technological disruptions. By implementing these recommendations, stakeholders can harness the full potential of IoT-enabled DSS to drive systemic, equitable, and scalable progress in the transition toward a digitally empowered circular economy.

REFERENCES

[1]. Abdel-Basset, M., Manogaran, G., Gamal, A., & Chang, V. (2019). A novel intelligent medical decision support model based on soft computing and IoT. *IEEE internet of things journal*, *7*(5), 4160-4170.
[2]. Abdullah Al, M., Md Masud, K., Mohammad, M., & Hosne Ara, M. (2024). Behavioral Factors in Loan Default Prediction A Literature Review On Psychological And Socioeconomic Risk Indicators. *American Journal of Advanced Technology and Engineering Solutions*, *4*(01), 43-70. https://doi.org/10.63125/0jwtbn29
[3]. Abdur Razzak, C., Golam Qibria, L., & Md Arifur, R. (2024). Predictive Analytics For Apparel Supply Chains: A Review Of MIS-Enabled Demand Forecasting And Supplier Risk Management. *American Journal of Interdisciplinary Studies*, *5*(04), 01–23. https://doi.org/10.63125/80dwy222
[4]. Abir, S. A. A., Anwar, A., Choi, J., & Kayes, A. (2021). Iot-enabled smart energy grid: Applications and challenges. *Ieee Access*, *9*, 50961-50981.
[5]. Abujder Ochoa, W. A., Iarozinski Neto, A., Vitorio Junior, P. C., Calabokis, O. P., & Ballesteros-Ballesteros, V. (2025). The Theory of complexity and sustainable urban development: A systematic literature review. *Sustainability*, *17*(1), 3.
[6]. Acuna, M., Sessions, J., Zamora, R., Boston, K., Brown, M., & Ghaffariyan, M. R. (2019). Methods to manage and optimize forest biomass supply chains: A review. *Current Forestry Reports*, *5*(3), 124-141.
[7]. Adar, C., & Md, N. (2023). Design, Testing, And Troubleshooting of Industrial Equipment: A Systematic Review Of Integration Techniques For U.S. Manufacturing Plants. *Review of Applied Science and Technology*, *2*(01), 53-84. https://doi.org/10.63125/893et038
[8]. Aiello, G., Giovino, I., Vallone, M., Catania, P., & Argento, A. (2018). A decision support system based on multisensor data fusion for sustainable greenhouse management. *Journal of Cleaner Production*, *172*, 4057-4065.
[9]. AL-Hudaib, H., Adamo, N., Bene, K., Ray, R., & Al-Ansari, N. (2025). Application of Decision Support Systems to Water Management: The Case of Iraq. *Water*, *17*(12), 1748.
[10]. Ali, Z. A., Zain, M., Hasan, R., Pathan, M. S., AlSalman, H., & Almisned, F. A. (2025). Digital twins: cornerstone to circular economy and sustainability goals. *Environment, Development and Sustainability*, 1-42.
[11]. Allioui, H., & Mourdi, Y. (2023). Exploring the full potentials of IoT for better financial growth and stability: A comprehensive survey. *Sensors*, *23*(19), 8015.
[12]. Aloini, D., Dulmin, R., Mininno, V., Stefanini, A., & Zerbino, P. (2020). Driving the transition to a circular economic model: A systematic review on drivers and critical success factors in circular economy. *Sustainability*, *12*(24), 10672.

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eISSN: 3067-2163
Doi: 10.63125/28kdxg31

[13]. Ammar, B., Aleem Al Razee, T., Sohel, R., & Ishtiaque, A. (2025). Cybersecurity In Industrial Control Systems: A Systematic Literature Review On AI-Based Threat Detection for Scada And IOT Networks. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 01-15. https://doi.org/10.63125/1cr1kj17

[14]. Anabel, N. J., Velvizhi, S., & Suvitha, D. (2018). Fisher friend mobile application: a decision support system for small scale fishers in India. *CSI Transactions on ICT*, *6*(3), 257-267.

[15]. Andronie, M., Lăzăroiu, G., Iatagan, M., Uță, C., Ștefănescu, R., & Cocoșatu, M. (2021). Artificial intelligence-based decision-making algorithms, internet of things sensing networks, and deep learning-assisted smart process management in cyber-physical production systems. *Electronics*, *10*(20), 2497.

[16]. Anika Jahan, M. (2024). Marketing Capstone Insights: Leveraging Multi-Channel Strategies For Maximum Digital Conversion And ROI. *Review of Applied Science and Technology*, *3*(04), 01-28. https://doi.org/10.63125/5w76qb87

[17]. Anika Jahan, M. (2025). Martech Stack Adoption In SMES: A Review Of Automation, CRM, and AI integration. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 348-381. https://doi.org/10.63125/y8j1zh51

[18]. Anika Jahan, M., & Md Imtiaz, F. (2024). Content Creation as A Growth Strategy: Evaluating The Economic Impact Of Freelance Digital Branding. *American Journal of Scholarly Research and Innovation*, *3*(02), 28-51. https://doi.org/10.63125/mj667y36

[19]. Anika Jahan, M., Md Soyeb, R., & Tahmina Akter, R. (2025). Strategic Use Of Engagement Marketing in Digital Platforms: A Focused Analysis Of Roi And Consumer Psychology. *Journal of Sustainable Development and Policy*, *1*(01), 170-197. https://doi.org/10.63125/hm96p734

[20]. Antunes, J., Hadi-Vencheh, A., Jamshidi, A., Tan, Y., & Wanke, P. (2023). TEA-IS: A hybrid DEA-TOPSIS approach for assessing performance and synergy in Chinese health care. *Decision Support Systems*, *171*, 113916.

[21]. Asgari, A., & Asgari, R. (2021). How circular economy transforms business models in a transition towards circular ecosystem: the barriers and incentives. *Sustainable Production and Consumption*, *28*, 566-579.

[22]. Attaran, M. (2020). Digital technology enablers and their implications for supply chain management. Supply chain forum: an international journal,

[23]. Ávila-Gutiérrez, M. J., Martín-Gómez, A., Aguayo-González, F., & Córdoba-Roldán, A. (2019). Standardization framework for sustainability from circular economy 4.0. *Sustainability*, *11*(22), 6490.

[24]. Awan, U., & Sroufe, R. (2022). Sustainability in the circular economy: insights and dynamics of designing circular business models. *Applied Sciences*, *12*(3), 1521.

[25]. Bagherian, A., Srivastav, A. L., & Mukherjee, S. (2024). Exploring barriers and strategic approaches in smart factory adoption: A real-world case study in a German manufacturing company. *The International Journal of Advanced Manufacturing Technology*, *134*(11), 5191-5224.

[26]. Bansal, S., & Kumar, D. (2020). IoT ecosystem: A survey on devices, gateways, operating systems, middleware and communication. *International Journal of Wireless Information Networks*, *27*(3), 340-364.

[27]. Barbosa, M., Castañeda-Ayarza, J. A., & Ferreira, D. H. L. (2020). Sustainable strategic management (GES): Sustainability in small business. *Journal of Cleaner Production*, *258*, 120880.

[28]. Baskar, V. V., Sekar, S., Rajesh, K., Sendhilkumar, N., & Murugan, S. (2024). Cloud-based Decision Support Systems for Securing Farm-to-Table Traceability using IoT and KNN Algorithm. 2024 Second International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI),

[29]. Bedi, G., Venayagamoorthy, G. K., Singh, R., Brooks, R. R., & Wang, K.-C. (2018). Review of Internet of Things (IoT) in electric power and energy systems. *IEEE internet of things journal*, *5*(2), 847-870.

[30]. Bellini, P., Nesi, P., & Pantaleo, G. (2022). IoT-enabled smart cities: A review of concepts, frameworks and key technologies. *Applied Sciences*, *12*(3), 1607.

[31]. Beusch, P., Frisk, J. E., Rosén, M., & Dilla, W. (2022). Management control for sustainability: Towards integrated systems. *Management accounting research*, *54*, 100777.

[32]. Bhawna, Kang, P. S., & Sharma, S. K. (2024). Bridging the gap: a systematic analysis of circular economy, supply chain management, and digitization for sustainability and resilience. *Operations Management Research*, *17*(3), 1039-1057.

[33]. Bianchini, A., Rossi, J., & Pellegrini, M. (2019). Overcoming the main barriers of circular economy implementation through a new visualization tool for circular business models. *Sustainability*, *11*(23), 6614.

[34]. Calzolari, T., Bimpizas-Pinis, M., Genovese, A., & Brint, A. (2023). Understanding the relationship between institutional pressures, supply chain integration and the adoption of circular economy practices. *Journal of Cleaner Production*, *432*, 139686.

[35]. Castro-Lopez, A., Iglesias, V., & Santos-Vijande, M. L. (2023). Organizational capabilities and institutional pressures in the adoption of circular economy. *Journal of Business Research*, *161*, 113823.

[36]. Çetin, S., De Wolf, C., & Bocken, N. (2021). Circular digital built environment: An emerging framework. *Sustainability*, *13*(11), 6348.

[37]. Chander, B., & Kumaravelan, G. (2019). Internet of things: foundation. In *Principles of Internet of Things (IoT) Ecosystem: Insight Paradigm* (pp. 3-33). Springer.

[38]. Chatfield, A. T., & Reddick, C. G. (2019). A framework for Internet of Things-enabled smart government: A case of IoT cybersecurity policies and use cases in US federal government. *Government Information Quarterly*, *36*(2), 346-357.
[39]. Chen, W., Men, Y., Fuster, N., Osorio, C., & Juan, A. A. (2024). Artificial intelligence in logistics optimization with sustainable criteria: A review. *Sustainability*, *16*(21), 9145.
[40]. Chizaryfard, A., Trucco, P., & Nuur, C. (2021). The transformation to a circular economy: framing an evolutionary view. *Journal of Evolutionary Economics*, *31*(2), 475-504.
[41]. Choy, Y. K., Onuma, A., & Lee, K. E. (2025). The Nexus of Industrial–Urban Sustainability, the Circular Economy, and Climate–Ecosystem Resilience: A Synthesis. *Sustainability*, *17*(6), 2620.
[42]. Chua, C. E. H., & Niederman, F. (2025). Returning the "socio" to decision support research: Expanding beyond a purely technical mindset. *Decision Support Systems*, *188*, 114352.
[43]. Clementino, E., & Perkins, R. (2021). How do companies respond to environmental, social and governance (ESG) ratings? Evidence from Italy. *Journal of Business Ethics*, *171*(2), 379-397.
[44]. Colombi, C., & D'Itria, E. (2023). Fashion digital transformation: Innovating business models toward circular economy and sustainability. *Sustainability*, *15*(6), 4942.
[45]. Custodio, L., & Machado, R. (2020). Flexible automated warehouse: a literature review and an innovative framework. *The International Journal of Advanced Manufacturing Technology*, *106*(1), 533-558.
[46]. de Sousa Jabbour, A. B. L., Jabbour, C. J. C., Foropon, C., & Godinho Filho, M. (2018). When titans meet–Can industry 4.0 revolutionise the environmentally-sustainable manufacturing wave? The role of critical success factors. *Technological Forecasting and Social Change*, *132*, 18-25.
[47]. del Mar Alonso-Almeida, M., Rodriguez-Anton, J. M., Bagur-Femenías, L., & Perramon, J. (2021). Institutional entrepreneurship enablers to promote circular economy in the European Union: Impacts on transition towards a more circular economy. *Journal of Cleaner Production*, *281*, 124841.
[48]. Dey, K., & Shekhawat, U. (2021). Blockchain for sustainable e-agriculture: Literature review, architecture for data management, and implications. *Journal of Cleaner Production*, *316*, 128254.
[49]. Din, I. U., Guizani, M., Hassan, S., Kim, B.-S., Khan, M. K., Atiquzzaman, M., & Ahmed, S. H. (2018). The Internet of Things: A review of enabled technologies and future challenges. *Ieee Access*, *7*, 7606-7640.
[50]. El Hafiane, A., En-nadi, A., & Ramadany, M. (2025). Towards Sustainable Construction: Systematic Review of Lean and Circular Economy Integration. *Sustainability*, *17*(15), 6735.
[51]. Elijah, O., Rahman, T. A., Orikumhi, I., Leow, C. Y., & Hindia, M. N. (2018). An overview of Internet of Things (IoT) and data analytics in agriculture: Benefits and challenges. *IEEE internet of things journal*, *5*(5), 3758-3773.
[52]. Epstein, M. J. (2018). *Making sustainability work: Best practices in managing and measuring corporate social, environmental and economic impacts*. Routledge.
[53]. Esmaeilian, B., Sarkis, J., Lewis, K., & Behdad, S. (2020). Blockchain for the future of sustainable supply chain management in Industry 4.0. *Resources, conservation and recycling*, *163*, 105064.
[54]. Farza, K., Ftiti, Z., Hlioui, Z., Louhichi, W., & Omri, A. (2021). Does it pay to go green? The environmental innovation effect on corporate financial performance. *Journal of environmental management*, *300*, 113695.
[55]. Fernández, S., Bodin, U., & Synnes, K. (2025). On the Interplay Between Behavior Dynamics, Environmental Impacts, and Fairness in the Digitalized Circular Economy with Associated Business Models and Supply Chain Management. *Sustainability*, *17*(8), 3437.
[56]. Filip, F. G. (2020). DSS—A class of evolving information systems. In *Data Science: New Issues, Challenges and Applications* (pp. 253-277). Springer.
[57]. Fischer, M., Imgrund, F., Janiesch, C., & Winkelmann, A. (2020). Strategy archetypes for digital transformation: Defining meta objectives using business process management. *Information & management*, *57*(5), 103262.
[58]. Försterling, G., Orth, R., & Gellert, B. (2023). Transition to a circular economy in europe through new business models: barriers, drivers, and policy making. *Sustainability*, *15*(10), 8212.
[59]. Foughali, K., Fathallah, K., & Frihida, A. (2019). A cloud-IOT based decision support system for potato pest prevention. *Procedia Computer Science*, *160*, 616-623.
[60]. Ganai, K. A., Pandow, B. A., & Masoodi, F. S. (2024). IoT-enabled financial inclusion: Challenges, opportunities, and policy implications. *Internet of Things Applications and Technology*, 126-145.
[61]. Georgia, D., Evangelia, F., Georgios, C., Christos, M., & Thomas, K. (2021). Evaluation of end user requirements for smart home applications and services based on a decision support system. *Internet of things*, *16*, 100431.
[62]. Gharehgozli, A., Zaerpour, N., & de Koster, R. (2020). Container terminal layout design: transition and future. *Maritime Economics & Logistics*, *22*(4), 610-639.
[63]. Ghazal, T. M., Hasan, M. K., Alshurideh, M. T., Alzoubi, H. M., Ahmad, M., Akbar, S. S., Al Kurdi, B., & Akour, I. A. (2021). IoT for smart cities: Machine learning approaches in smart healthcare—A review. *Future Internet*, *13*(8), 218.

Volume 04, Issue 01 (2025)
Page No: 250-286
eISSN: 3067-2163
Doi: 10.63125/28kdxg31

[64]. Golam Qibria, L., & Takbir Hossen, S. (2023). Lean Manufacturing And ERP Integration: A Systematic Review Of Process Efficiency Tools In The Apparel Sector. *American Journal of Scholarly Research and Innovation*, *2*(01), 104-129. https://doi.org/10.63125/mx7j4p06

[65]. Goudarzi, A., Ghayoor, F., Waseem, M., Fahad, S., & Traore, I. (2022). A survey on IoT-enabled smart grids: emerging, applications, challenges, and outlook. *Energies*, *15*(19), 6984.

[66]. Gulia, P., Gill, N. S., Yahya, M., Gupta, P., Shukla, P. K., & Shukla, P. K. (2024). Exploring the potential of blockchain technology in an IoT-enabled environment: A review. *Ieee Access*, *12*, 31197-31227.

[67]. Guo, Y., Wang, N., Xu, Z.-Y., & Wu, K. (2020). The internet of things-based decision support system for information processing in intelligent manufacturing using data mining technology. *Mechanical Systems and Signal Processing*, *142*, 106630.

[68]. Güvençli, M., Kıran, H., Doğan, E., Dağ, H., Özyürüyen, B., & Çakar, T. (2023). Optimizing collective building management through a machine learning-based decision support system. 2023 4th International Informatics and Software Engineering Conference (IISEC),

[69]. Hammadi, M., Merschak, S., Diallo, T. M., & Hehenberger, P. (2025). CEF-DPP: A Circular Economy Framework Integrating Digital Product Passport for Improving Circularity of Sustainable Mechatronics Design. *Circular Economy and Sustainability*, 1-33.

[70]. Han, J., Heshmati, A., & Rashidghalam, M. (2020). Circular economy business models with a focus on servitization. *Sustainability*, *12*(21), 8799.

[71]. Han, X.-H., & Chen, Y.-W. (2024). Decision Support System for Skin Lesion Diagnosis Using Deep Learning. In *Advances in Intelligent Disease Diagnosis and Treatment: Research Papers in Honour of Prof. Janusz Kacprzyk for Invaluable Contributions* (pp. 279-304). Springer.

[72]. Heragu, S. S. (2018). *Facilities design*. Crc Press.

[73]. Herath Pathirannehelage, S., Shrestha, Y. R., & von Krogh, G. (2025). Design principles for artificial intelligence-augmented decision making: An action design research study. *European Journal of Information Systems*, *34*(2), 207-229.

[74]. Hernández, H. (2025). Circular Industrialized Construction: A Perspective Through Design for Manufacturing, Assembly, and Disassembly. *Buildings*, *15*(13), 2174.

[75]. Hosne Ara, M., Tonmoy, B., Mohammad, M., & Md Mostafizur, R. (2022). AI-ready data engineering pipelines: a review of medallion architecture and cloud-based integration models. *American Journal of Scholarly Research and Innovation*, *1*(01), 319-350. https://doi.org/10.63125/51kxtf08

[76]. Hristov, I., Appolloni, A., Cheng, W., & Huisingh, D. (2022). Aligning corporate social responsibility practices with the environmental performance management systems: A critical review of the relevant literature. *Total Quality Management & Business Excellence*, 1-25.

[77]. Hristov, I., & Chirico, A. (2019). The role of sustainability key performance indicators (KPIs) in implementing sustainable strategies. *Sustainability*, *11*(20), 5742.

[78]. Hudda, S., & Haribabu, K. (2025). A review on WSN based resource constrained smart IoT systems. *Discover Internet of Things*, *5*(1), 56.

[79]. Ismail, S., Reza, H., Salameh, K., Kashani Zadeh, H., & Vasefi, F. (2023). Toward an intelligent blockchain ioT-enabled fish supply chain: A review and conceptual framework. *Sensors*, *23*(11), 5136.

[80]. Istiaque, M., Dipon Das, R., Hasan, A., Samia, A., & Sayer Bin, S. (2024). Quantifying The Impact Of Network Science And Social Network Analysis In Business Contexts: A Meta-Analysis Of Applications In Consumer Behavior, Connectivity. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 58-89. https://doi.org/10.63125/vgkwe938

[81]. Ivanov, D., Tsipoulanidis, A., & Schönberger, J. (2021). Basics of supply chain and operations management. In *Global Supply Chain and Operations Management: A Decision-Oriented Introduction to the Creation of Value* (pp. 3-19). Springer.

[82]. Jabbour, C. J. C., de Sousa Jabbour, A. B. L., Sarkis, J., & Godinho Filho, M. (2019). Unlocking the circular economy through new business models based on large-scale data: an integrative framework and research agenda. *Technological Forecasting and Social Change*, *144*, 546-552.

[83]. Jabbour, C. J. C., Seuring, S., de Sousa Jabbour, A. B. L., Jugend, D., Fiorini, P. D. C., Latan, H., & Izeppi, W. C. (2020). Stakeholders, innovative business models for the circular economy and sustainable performance of firms in an emerging economy facing institutional voids. *Journal of environmental management*, *264*, 110416.

[84]. Javaid, M., & Khan, I. H. (2021). Internet of Things (IoT) enabled healthcare helps to take the challenges of COVID-19 Pandemic. *Journal of oral biology and craniofacial research*, *11*(2), 209-214.

[85]. 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,

[86]. Jørgensen, B. N., & Ma, Z. G. (2025). Impact of EU Laws on the Adoption of AI and IoT in Advanced Building Energy Management Systems: A Review of Regulatory Barriers, Technological Challenges, and Economic Opportunities. *Buildings*, *15*(13), 2160.

[87]. Kaleem, S., Sohail, A., Tariq, M. U., & Asim, M. (2023). An improved big data analytics architecture using federated learning for IoT-enabled urban intelligent transportation systems. *Sustainability*, *15*(21), 15333.

Volume 04, Issue 01 (2025)
Page No: 250-286
eISSN: 3067-2163
Doi: 10.63125/28kdxg31

[88]. Kamalakkannan, S., Kulatunga, A., & Bandara, L. (2020). The conceptual framework of IoT based decision support system for life cycle management. *Procedia Manufacturing*, *43*, 423-430.
[89]. Kayvanfar, V., Elomri, A., Kerbache, L., Vandchali, H. R., & El Omri, A. (2024). A review of decision support systems in the internet of things and supply chain and logistics using web content mining. *Supply chain analytics*, *6*, 100063.
[90]. Khan, A. S., Akter, M., Enni, M. A., & Khan, S. F. (2025). An in silico approach for the identification of detrimental missense SNPs and their potential impacts on human CRY2 protein. *Journal of Bangladesh Academy of Sciences*, *49*(1), 57-72. https://doi.org/10.3329/jbas.v49i1.71914
[91]. Khan, S. A. R., & Yu, Z. (2019). *Strategic supply chain management*. Springer.
[92]. Khanna, A., & Kaur, S. (2020). Internet of things (IoT), applications and challenges: a comprehensive review. *Wireless Personal Communications*, *114*(2), 1687-1762.
[93]. Kiesnere, A. L., & Baumgartner, R. J. (2019). Sustainability management in practice: Organizational change for sustainability in smaller large-sized companies in Austria. *Sustainability*, *11*(3), 572.
[94]. Koot, M., Mes, M. R., & Iacob, M. E. (2021). A systematic literature review of supply chain decision making supported by the Internet of Things and Big Data Analytics. *Computers & Industrial Engineering*, *154*, 107076.
[95]. Kopetz, H., & Steiner, W. (2022). Internet of things. In *Real-time systems: design principles for distributed embedded applications* (pp. 325-341). Springer.
[96]. Kose, U., Deperlioglu, O., Alzubi, J., & Patrut, B. (2021). Deep learning for medical decision support systems.
[97]. Kumar, N., Kaushal, R. K., Panda, S. N., & Bhardwaj, S. (2022). Impact of the Internet of Things and Clinical Decision Support System in Healthcare. In *IoT and WSN based Smart Cities: A Machine Learning Perspective* (pp. 15-26). Springer.
[98]. Kumar, R., & Thakurta, R. (2021). Exfoliating decision support system: a synthesis of themes using text mining. *Information Systems and e-Business Management*, *19*(1), 247-279.
[99]. Kumar, S., Narkhede, B. E., & Jain, K. (2021). Revisiting the warehouse research through an evolutionary lens: a review from 1990 to 2019. *International journal of production research*, *59*(11), 3470-3492.
[100]. Kutub Uddin, A., Md Mostafizur, R., Afrin Binta, H., & Maniruzzaman, B. (2022). Forecasting Future Investment Value with Machine Learning, Neural Networks, And Ensemble Learning: A Meta-Analytic Study. *Review of Applied Science and Technology*, *1*(02), 01-25. https://doi.org/10.63125/edxgjg56
[101]. Lagorio, A., Cimini, C., Piffari, C., Galimberti, M., Pirola, F., & Pinto, R. (2024). Operationalisation and validation of a human factors-based decision support framework for technology adoption in the logistics sector. *International journal of logistics research and applications*, *27*(11), 2238-2260.
[102]. Lakshmanaprabu, S., Mohanty, S. N., Krishnamoorthy, S., Uthayakumar, J., & Shankar, K. (2019). Online clinical decision support system using optimal deep neural networks. *Applied Soft Computing*, *81*, 105487.
[103]. Lăzăroiu, G., Ionescu, L., Andronie, M., & Dijmărescu, I. (2020). Sustainability management and performance in the urban corporate economy: a systematic literature review. *Sustainability*, *12*(18), 7705.
[104]. Lee, C. K., Lin, B., Ng, K., Lv, Y., & Tai, W. (2019). Smart robotic mobile fulfillment system with dynamic conflict-free strategies considering cyber-physical integration. *Advanced Engineering Informatics*, *42*, 100998.
[105]. Lee, I. (2019). The Internet of Things for enterprises: An ecosystem, architecture, and IoT service business model. *Internet of things*, *7*, 100078.
[106]. Leung, E. K., Lee, C. K. H., & Ouyang, Z. (2022). From traditional warehouses to Physical Internet hubs: A digital twin-based inbound synchronization framework for PI-order management. *International Journal of Production Economics*, *244*, 108353.
[107]. Lewczuk, K., Kłodawski, M., & Gepner, P. (2021). Energy consumption in a distributional warehouse: A practical case study for different warehouse technologies. *Energies*, *14*(9), 2709.
[108]. Li, C. Z., Xue, F., Li, X., Hong, J., & Shen, G. Q. (2018). An Internet of Things-enabled BIM platform for on-site assembly services in prefabricated construction. *Automation in construction*, *89*, 146-161.
[109]. Li, F., & Xu, J. (2025). Revolutionizing AI-enabled Information Systems Using Integrated Big Data Analytics and Multi-modal Data Fusion. *Ieee Access*.
[110]. Li, J., Dai, J., Issakhov, A., Almojil, S. F., & Souri, A. (2021). Towards decision support systems for energy management in the smart industry and Internet of Things. *Computers & Industrial Engineering*, *161*, 107671.
[111]. Li, Y., & Mardani, A. (2023). Digital twins and blockchain technology in the industrial Internet of Things (IIoT) using an extended decision support system model: Industry 4.0 barriers perspective. *Technological Forecasting and Social Change*, *195*, 122794.
[112]. Li, Z., Shahidehpour, M., & Liu, X. (2018). Cyber-secure decentralized energy management for IoT-enabled active distribution networks. *Journal of Modern Power Systems and Clean Energy*, 6(5), 900-917.

[113]. Lin, H., Lin, J., & Wang, F. (2022). An innovative machine learning model for supply chain management. *Journal of Innovation & Knowledge*, *7*(4), 100276.
[114]. Louis, J., & Dunston, P. S. (2018). Integrating IoT into operational workflows for real-time and automated decision-making in repetitive construction operations. *Automation in construction*, *94*, 317-327.
[115]. Lyridis, D., & Kostidi, E. (2025). Bridging Technical Challenges and Economic Goals: Project Management for Energy Transition in Maritime Retrofitting. *Energies*, *18*(4), 804.
[116]. Lyu, G. (2025). Data-driven decision making in patient management: a systematic review. *BMC Medical Informatics and Decision Making*, *25*(1), 239.
[117]. Lyu, Z., Lin, P., Guo, D., & Huang, G. Q. (2020). Towards zero-warehousing smart manufacturing from zero-inventory just-in-time production. *Robotics and Computer-Integrated Manufacturing*, *64*, 101932.
[118]. Malik, S. (2024). Data-driven decision-making: leveraging the IoT for real-time sustainability in organizational behavior. *Sustainability*, *16*(15), 6302.
[119]. 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
[120]. Mansura Akter, E. (2023). Applications Of Allele-Specific PCR In Early Detection of Hereditary Disorders: A Systematic Review Of Techniques And Outcomes. *Review of Applied Science and Technology*, *2*(03), 1-26. https://doi.org/10.63125/n4h7t156
[121]. Mansura Akter, E. (2025). Bioinformatics-Driven Approaches in Public Health Genomics: A Review Of Computational SNP And Mutation Analysis. *International Journal of Scientific Interdisciplinary Research*, *6*(1), 88-118. https://doi.org/10.63125/e6pxkn12
[122]. Mansura Akter, E., & Md Abdul Ahad, M. (2022). In Silico drug repurposing for inflammatory diseases: a systematic review of molecular docking and virtual screening studies. *American Journal of Advanced Technology and Engineering Solutions*, *2*(04), 35-64. https://doi.org/10.63125/j1hbts51
[123]. Mansura Akter, E., & Shaiful, M. (2024). A systematic review of SNP polymorphism studies in South Asian populations: implications for diabetes and autoimmune disorders. *American Journal of Scholarly Research and Innovation*, *3*(01), 20-51. https://doi.org/10.63125/8nvxcb96
[124]. Martínez-Peláez, R., Ochoa-Brust, A., Rivera, S., Félix, V. G., Ostos, R., Brito, H., Félix, R. A., & Mena, L. J. (2023). Role of digital transformation for achieving sustainability: mediated role of stakeholders, key capabilities, and technology. *Sustainability*, *15*(14), 11221.
[125]. Martins, R., Pereira, M., Ferreira, L., Sá, J., & Silva, F. (2020). Warehouse operations logistics improvement in a cork stopper factory. *Procedia Manufacturing*, *51*, 1723-1729.
[126]. Mashayekhy, Y., Babaei, A., Yuan, X.-M., & Xue, A. (2022). Impact of Internet of Things (IoT) on inventory management: A literature survey. *Logistics*, *6*(2), 33.
[127]. Mazzetto, S. (2024). Interdisciplinary perspectives on agent-based modeling in the architecture, engineering, and construction industry: a comprehensive review. *Buildings*, *14*(11), 3480.
[128]. Md Atiqur Rahman, K., Md Abdur, R., Niger, S., & Mst Shamima, A. (2025). Development Of a Fog Computing-Based Real-Time Flood Prediction And Early Warning System Using Machine Learning And Remote Sensing Data. *Journal of Sustainable Development and Policy*, *1*(01), 144-169. https://doi.org/10.63125/6y0qwr92
[129]. Md Mahamudur Rahaman, S. (2022). Electrical And Mechanical Troubleshooting in Medical And Diagnostic Device Manufacturing: A Systematic Review Of Industry Safety And Performance Protocols. *American Journal of Scholarly Research and Innovation*, *1*(01), 295-318. https://doi.org/10.63125/d68y3590
[130]. Md Masud, K., Mohammad, M., & Hosne Ara, M. (2023). Credit decision automation in commercial banks: a review of AI and predictive analytics in loan assessment. *American Journal of Interdisciplinary Studies*, *4*(04), 01-26. https://doi.org/10.63125/1hh4q770
[131]. Md Masud, K., Mohammad, M., & Sazzad, I. (2023). Mathematics For Finance: A Review of Quantitative Methods In Loan Portfolio Optimization. *International Journal of Scientific Interdisciplinary Research*, *4*(3), 01-29. https://doi.org/10.63125/j43ayz68
[132]. Md Masud, K., Sazzad, I., Mohammad, M., & Noor Alam, S. (2025). Digitization In Retail Banking: A Review of Customer Engagement And Financial Product Adoption In South Asia. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 42-46. https://doi.org/10.63125/cv50rf30
[133]. Md, N., Golam Qibria, L., Abdur Razzak, C., & Khan, M. A. M. (2025). Predictive Maintenance In Power Transformers: A Systematic Review Of AI And IOT Applications. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 34-47. https://doi.org/10.63125/r72yd809
[134]. Md Nazrul Islam, K., & Debashish, G. (2025). Cybercrime and contractual liability: a systematic review of legal precedents and risk mitigation frameworks. *Journal of Sustainable Development and Policy*, *1*(01), 01-24. https://doi.org/10.63125/x3cd4413
[135]. Md Nazrul Islam, K., & Ishtiaque, A. (2025). A systematic review of judicial reforms and legal access strategies in the age of cybercrime and digital evidence. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 01-29. https://doi.org/10.63125/96ex9767

Volume 04, Issue 01 (2025)
Page No: 250-286
eISSN: 3067-2163
Doi: 10.63125/28kdxg31

[136]. Md Nur Hasan, M., Md Musfiqur, R., & Debashish, G. (2022). Strategic Decision-Making in Digital Retail Supply Chains: Harnessing AI-Driven Business Intelligence From Customer Data. *Review of Applied Science and Technology*, *1*(03), 01-31. https://doi.org/10.63125/6a7rpy62

[137]. Md Takbir Hossen, S., Abdullah Al, M., Siful, I., & Md Mostafizur, R. (2025). Transformative applications of ai in emerging technology sectors: a comprehensive meta-analytical review of use cases in healthcare, retail, and cybersecurity. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 121-141. https://doi.org/10.63125/45zpb481

[138]. Md Takbir Hossen, S., Ishtiaque, A., & Md Atiqur, R. (2023). AI-Based Smart Textile Wearables For Remote Health Surveillance And Critical Emergency Alerts: A Systematic Literature Review. *American Journal of Scholarly Research and Innovation*, *2*(02), 1-29. https://doi.org/10.63125/ceqapd08

[139]. Md Takbir Hossen, S., & Md Atiqur, R. (2022). Advancements In 3d Printing Techniques For Polymer Fiber-Reinforced Textile Composites: A Systematic Literature Review. *American Journal of Interdisciplinary Studies*, *3*(04), 32-60. https://doi.org/10.63125/s4r5m391

[140]. Md Tawfiqul, I., Meherun, N., Mahin, K., & Mahmudur Rahman, M. (2022). Systematic Review of Cybersecurity Threats In IOT Devices Focusing On Risk Vectors Vulnerabilities And Mitigation Strategies. *American Journal of Scholarly Research and Innovation*, *1*(01), 108-136. https://doi.org/10.63125/wh17mf19

[141]. Mikulėnas, M., & Šeduikytė, L. (2025). Circularity and Decarbonization Synergies in the Construction Sector: Implications for Zero-Carbon Energy Policy. *Energies*, *18*(5), 1164.

[142]. Miles, A., Zaslavsky, A., & Browne, C. (2018). IoT-based decision support system for monitoring and mitigating atmospheric pollution in smart cities. *Journal of Decision Systems*, *27*(sup1), 56-67.

[143]. Miller, K., Capan, M., Weldon, D., Noaiseh, Y., Kowalski, R., Kraft, R., Schwartz, S., Weintraub, W. S., & Arnold, R. (2018). The design of decisions: Matching clinical decision support recommendations to Nielsen's design heuristics. *International journal of medical informatics*, *117*, 19-25.

[144]. Mishra, R., Naik, B. K. R., Raut, R. D., & Kumar, M. (2022). Internet of Things (IoT) adoption challenges in renewable energy: A case study from a developing economy. *Journal of Cleaner Production*, *371*, 133595.

[145]. Mohamed, A.-M. O., Mohamed, D., Fayad, A., & Al Nahyan, M. T. (2024). Enhancing decision making and decarbonation in environmental management: A review on the role of digital technologies. *Sustainability*, *16*(16), 7156.

[146]. Morales, A. S., Ourique, F. d. O., & Cazella, S. C. (2021). A comprehensive review on the challenges for intelligent systems related with internet of things for medical decision. *Enhanced telemedicine and e-health: advanced IoT enabled soft computing framework*, 221-240.

[147]. Moreira, M. W., Rodrigues, J. J., Korotaev, V., Al-Muhtadi, J., & Kumar, N. (2019). A comprehensive review on smart decision support systems for health care. *IEEE Systems Journal*, *13*(3), 3536-3545.

[148]. Mourtzis, D., Samothrakis, V., Zogopoulos, V., & Vlachou, E. (2019). Warehouse design and operation using augmented reality technology: a papermaking industry case study. *Procedia Cirp*, *79*, 574-579.

[149]. Mousavi, V., Rashidi, M., Mohammadi, M., & Samali, B. (2024). Evolution of digital twin frameworks in bridge management: review and future directions. *Remote Sensing*, *16*(11), 1887.

[150]. Mst Shamima, A., Niger, S., Md Atiqur Rahman, K., & Mohammad, M. (2023). Business Intelligence-Driven Healthcare: Integrating Big Data And Machine Learning For Strategic Cost Reduction And Quality Care Delivery. *American Journal of Interdisciplinary Studies*, *4*(02), 01-28. https://doi.org/10.63125/crv1xp27

[151]. Munonye, W. C. (2025). Towards Circular Economy Metrics: a Systematic Review. *Circular Economy and Sustainability*, 1-43.

[152]. Murugesan, B., Jayanthi, K., & Karthikeyan, G. (2024). Integrating Digital Twins and 3D Technologies in Fashion: Advancing Sustainability and Consumer Engagement. In *Illustrating Digital Innovations Towards Intelligent Fashion: Leveraging Information System Engineering and Digital Twins for Efficient Design of Next-Generation Fashion* (pp. 1-88). Springer.

[153]. Okorie, O., Salonitis, K., Charnley, F., Moreno, M., Turner, C., & Tiwari, A. (2018). Digitisation and the circular economy: A review of current research and future trends. *Energies*, *11*(11), 3009.

[154]. Paolone, G., Iachetti, D., Paesani, R., Pilotti, F., Marinelli, M., & Di Felice, P. (2022). A holistic overview of the internet of things ecosystem. *IoT*, *3*(4), 398-434.

[155]. Parra, X., Tort-Martorell, X., Alvarez-Gomez, F., & Ruiz-Viñals, C. (2023). Chronological evolution of the information-driven decision-making process (1950–2020). *Journal of the Knowledge Economy*, *14*(3), 2363-2394.

[156]. Pasupuleti, V., Thuraka, B., Kodete, C. S., & Malisetty, S. (2024). Enhancing supply chain agility and sustainability through machine learning: Optimization techniques for logistics and inventory management. *Logistics*, *8*(3), 73.

[157]. Pavlov, A., Ivanov, D., Pavlov, D., & Slinko, A. (2019). Optimization of network redundancy and contingency planning in sustainable and resilient supply chain resource management under conditions of structural dynamics. *Annals of operations research*, 1-30.

[158]. Perboli, G., Musso, S., & Rosano, M. (2018). Blockchain in logistics and supply chain: A lean approach for designing real-world use cases. *Ieee Access*, *6*, 62018-62028.

Volume 04, Issue 01 (2025)
Page No: 250-286
eISSN: 3067-2163
Doi: 10.63125/28kdxg31

[159]. Pham, N. T., Thanh, T. V., Tučková, Z., & Thuy, V. T. N. (2020). The role of green human resource management in driving hotel's environmental performance: Interaction and mediation analysis. *International Journal of Hospitality Management*, *88*, 102392.

[160]. Pichlak, M., & Szromek, A. R. (2022). Linking eco-innovation and circular economy—A conceptual approach. *Journal of Open Innovation: Technology, Market, and Complexity*, *8*(3), 121.

[161]. Pizzi, S., Corbo, L., & Caputo, A. (2021). Fintech and SMEs sustainable business models: Reflections and considerations for a circular economy. *Journal of Cleaner Production*, *281*, 125217.

[162]. Poyyamozhi, M., Murugesan, B., Rajamanickam, N., Shorfuzzaman, M., & Aboelmagd, Y. (2024). IoT—A promising solution to energy management in smart buildings: A systematic review, applications, barriers, and future scope. *Buildings*, *14*(11), 3446.

[163]. PP Pieroni, M., C. McAloone, T., & CA Pigosso, D. (2019). Configuring new business models for circular economy through product–service systems. *Sustainability*, *11*(13), 3727.

[164]. Pradeep, P., Krishnamoorthy, S., Pathinarupothi, R. K., & Vasilakos, A. V. (2021). Leveraging context-awareness for Internet of Things ecosystem: Representation, organization, and management of context. *Computer Communications*, *177*, 33-50.

[165]. Prorok, M., & Takács, I. (2024). The impacts of artificial intelligence and knowledge-based systems on corporate decision support. 2024 ieee 18th international symposium on applied computational intelligence and informatics (SACI),

[166]. Qureshi, K. N., Alhudhaif, A., Azahar, M., Javed, I. T., & Jeon, G. (2022). A software-defined network-based intelligent decision support system for the internet of things networks. *Wireless Personal Communications*, *126*(4), 2825-2839.

[167]. Ragab, M., Albukhari, A., Alyami, J., & Mansour, R. F. (2022). Ensemble deep-learning-enabled clinical decision support system for breast cancer diagnosis and classification on ultrasound images. *Biology*, *11*(3), 439.

[168]. Rajabzadeh, M., & Fatorachian, H. (2023). Modelling factors influencing IoT adoption: With a focus on agricultural logistics operations. *Smart cities*, *6*(6), 3266-3296.

[169]. Rancea, A., Anghel, I., & Cioara, T. (2024). Edge computing in healthcare: Innovations, opportunities, and challenges. *Future Internet*, *16*(9), 329.

[170]. Rath, K. C., Khang, A., & Roy, D. (2024). The role of Internet of Things (IoT) technology in Industry 4.0 economy. In *Advanced IoT technologies and applications in the industry 4.0 digital economy* (pp. 1-28). CRC Press.

[171]. Ravindran, A. R., Warsing Jr, D. P., & Griffin, P. M. (2023). *Supply chain engineering: Models and applications*. CRC Press.

[172]. Rejeb, A., Rejeb, K., & Zrelli, I. (2024). Analyzing barriers to internet of things (IoT) adoption in humanitarian logistics: an ISM–DEMATEL approach. *Logistics*, *8*(2), 38.

[173]. Reshi, I. A., & Sholla, S. (2025). IBF network: enhancing network privacy with IoT, blockchain, and fog computing on different consensus mechanisms. *Cluster Computing*, *28*(3), 208.

[174]. Restuccia, F., D'oro, S., & Melodia, T. (2018). Securing the internet of things in the age of machine learning and software-defined networking. *IEEE internet of things journal*, *5*(6), 4829-4842.

[175]. Rezwanul Ashraf, R., & Hosne Ara, M. (2023). Visual communication in industrial safety systems: a review of UI/UX design for risk alerts and warnings. *American Journal of Scholarly Research and Innovation*, *2*(02), 217-245. https://doi.org/10.63125/wbv4z521

[176]. Ribino, P., Cossentino, M., Lodato, C., & Lopes, S. (2018). Agent-based simulation study for improving logistic warehouse performance. *Journal of Simulation*, *12*(1), 23-41.

[177]. Rosati, R., Romeo, L., Cecchini, G., Tonetto, F., Viti, P., Mancini, A., & Frontoni, E. (2023). From knowledge-based to big data analytic model: a novel IoT and machine learning based decision support system for predictive maintenance in Industry 4.0. *Journal of Intelligent Manufacturing*, *34*(1), 107-121.

[178]. Sànchez-Marrè, M. (2022). Evolution of Decision Support Systems. In *Intelligent Decision Support Systems* (pp. 57-73). Springer.

[179]. Sanjai, V., Sanath Kumar, C., Maniruzzaman, B., & Farhana Zaman, R. (2023). Integrating Artificial Intelligence in Strategic Business Decision-Making: A Systematic Review Of Predictive Models. *International Journal of Scientific Interdisciplinary Research*, *4*(1), 01-26. https://doi.org/10.63125/s5skge53

[180]. Sanjai, V., Sanath Kumar, C., Sadia, Z., & Rony, S. (2025). Ai And Quantum Computing For Carbon-Neutral Supply Chains: A Systematic Review Of Innovations. *American Journal of Interdisciplinary Studies*, 6(1), 40-75. https://doi.org/10.63125/nrdx7d32

[181]. Sasikumar, A., Vairavasundaram, S., Kotecha, K., Indragandhi, V., Ravi, L., Selvachandran, G., & Abraham, A. (2023). Blockchain-based trust mechanism for digital twin empowered industrial internet of things. *Future generation computer systems*, *141*, 16-27.

[182]. Sazzad, I. (2025a). Public Finance and Policy Effectiveness A Review Of Participatory Budgeting In Local Governance Systems. *Journal of Sustainable Development and Policy*, *1*(01), 115-143. https://doi.org/10.63125/p3p09p46

Volume 04, Issue 01 (2025)
Page No: 250-286
eISSN: 3067-2163
Doi: 10.63125/28kdxg31

[183]. Sazzad, I. (2025b). A Systematic Review of Public Budgeting Strategies In Developing Economies: Tools For Transparent Fiscal Governance. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 602-635. https://doi.org/10.63125/wm547117

[184]. Sazzad, I., & Md Nazrul Islam, K. (2022). Project impact assessment frameworks in nonprofit development: a review of case studies from south asia. *American Journal of Scholarly Research and Innovation*, *1*(01), 270-294. https://doi.org/10.63125/eeja0t77

[185]. Schipfer, F., Burli, P., Fritsche, U., Hennig, C., Stricker, F., Wirth, M., Proskurina, S., & Serna-Loaiza, S. (2024). The circular bioeconomy: a driver for system integration. *Energy, Sustainability and Society*, *14*(1), 34.

[186]. Scipioni, S., Russ, M., & Niccolini, F. (2021). From barriers to enablers: The role of organizational learning in transitioning SMEs into the circular economy. *Sustainability*, *13*(3), 1021.

[187]. Shaiful, M., & Mansura Akter, E. (2025). AS-PCR In Molecular Diagnostics: A Systematic Review of Applications In Genetic Disease Screening. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 98-120. https://doi.org/10.63125/570jb007

[188]. Sharma, S. (2025). From Data to Decisions: Cloud, IoT, and AI Integration. In *Integration of Cloud Computing and IoT* (pp. 461-479). Chapman and Hall/CRC.

[189]. Singh, L. K., Khanna, M., Garg, H., & Singh, R. (2024). A novel soft computing based efficient feature selection approach for timely identification of COVID-19 infection using chest computed tomography images: a human centered intelligent clinical decision support system. *Multimedia Tools and Applications*, 1-69.

[190]. Singh, S., Lakshay, Pratap, S., & Jauhar, S. K. (2024). Unveiling barriers to IoT adoption in the maritime freight industry. *International Journal of System Assurance Engineering and Management*, 1-11.

[191]. Singh, S. K., Kumar, M., Tanwar, S., & Park, J. H. (2024). GRU-based digital twin framework for data allocation and storage in IoT-enabled smart home networks. *Future generation computer systems*, *153*, 391-402.

[192]. Siwach, P., Gulia, D., Yadav, D. K., Malik, M., & Gahlawat, V. K. (2025). Exploring IoT integration challenges: Causal relationships and strategic implications for business models. *Digital Business*, *5*(2), 100125.

[193]. Sizan, N. S., Dey, D., Layek, M. A., Uddin, M. A., & Huh, E.-N. (2025). Evaluating blockchain platforms for iot applications in industry 5.0: A comprehensive review. *Blockchain: Research and Applications*, 100276.

[194]. Son, H., Jang, J., Park, J., Balog, A., Ballantyne, P., Kwon, H. R., Singleton, A., & Hwang, J. (2025). Leveraging advanced technologies for (smart) transportation planning: A systematic review. *Sustainability*, *17*(5), 2245.

[195]. Song, D. (2021). A literature review, container shipping supply chain: Planning problems and research opportunities. *Logistics*, *5*(2), 41.

[196]. Spaho, E., Çiço, B., & Shabani, I. (2025). IoT Integration Approaches into Personalized Online Learning: Systematic Review. *Computers*, *14*(2), 63.

[197]. Stojanova, S., Volk, M., Balkovec, G., Kos, A., & Stojmenova Duh, E. (2025). The Future of Vineyard Irrigation: AI-Driven Insights from IoT Data. *Sensors*, *25*(12), 3658.

[198]. Subrato, S. (2018). Resident's Awareness Towards Sustainable Tourism for Ecotourism Destination in Sundarban Forest, Bangladesh. *Pacific International Journal*, *1*(1), 32-45. https://doi.org/10.55014/pij.v1i1.38

[199]. Subrato, S. (2025). Role of management information systems in environmental risk assessment: a systematic review of geographic and ecological applications. *American Journal of Interdisciplinary Studies*, 6(1), 95–126. https://doi.org/10.63125/k27tnn83

[200]. Subrato, S., & Faria, J. (2025). AI-driven MIS applications in environmental risk monitoring: a systematic review of predictive geographic information systems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 81-97. https://doi.org/10.63125/pnx77873

[201]. Subrato, S., & Md, N. (2024). The role of perceived environmental responsibility in artificial intelligence-enabled risk management and sustainable decision-making. *American Journal of Advanced Technology and Engineering Solutions*, *4*(04), 33-56. https://doi.org/10.63125/7tjw3767

[202]. Sudhakaran, S., Maheswari, R., & Jagannathan, S. K. (2025). IoT-Driven Supply Chain Management: A Comprehensive Framework for Smart and Sustainable Operations. In *Industry 4.0, Smart Manufacturing, and Industrial Engineering* (pp. 162-178). CRC Press.

[203]. Sun, C. (2020). Research on investment decision-making model from the perspective of "Internet of Things+ Big data". *Future generation computer systems*, *107*, 286-292.

[204]. Tahmina Akter, R. (2025). AI-driven marketing analytics for retail strategy: a systematic review of data-backed campaign optimization. *International Journal of Scientific Interdisciplinary Research*, 6(1), 28-59. https://doi.org/10.63125/0k4k5585

[205]. Tahmina Akter, R., & Abdur Razzak, C. (2022). The Role Of Artificial Intelligence In Vendor Performance Evaluation Within Digital Retail Supply Chains: A Review Of Strategic Decision-Making Models. *American Journal of Scholarly Research and Innovation*, *1*(01), 220-248. https://doi.org/10.63125/96jj3j86

[206]. Tahmina Akter, R., Debashish, G., Md Soyeb, R., & Abdullah Al, M. (2023). A Systematic Review of AI-Enhanced Decision Support Tools in Information Systems: Strategic Applications In Service-Oriented Enterprises And Enterprise Planning. *Review of Applied Science and Technology*, *2*(01), 26-52. https://doi.org/10.63125/73djw422

[207]. Tahmina Akter, R., Md Arifur, R., & Anika Jahan, M. (2024). Customer relationship management and data-driven decision-making in modern enterprises: a systematic literature review. *American Journal of Advanced Technology and Engineering Solutions*, *4*(04), 57-82. https://doi.org/10.63125/jetvam38

[208]. Tiwari, S., Wee, H.-M., & Daryanto, Y. (2018). Big data analytics in supply chain management between 2010 and 2016: Insights to industries. *Computers & Industrial Engineering*, *115*, 319-330.

[209]. Tonmoy, B., & Md Arifur, R. (2023). A Systematic Literature Review Of User-Centric Design In Digital Business Systems Enhancing Accessibility, Adoption, And Organizational Impact. *American Journal of Scholarly Research and Innovation*, *2*(02), 193-216. https://doi.org/10.63125/36w7fn47

[210]. Tran-Dang, H., Krommenacker, N., Charpentier, P., & Kim, D.-S. (2020). Toward the internet of things for physical internet: Perspectives and challenges. *IEEE internet of things journal*, *7*(6), 4711-4736.

[211]. Tura, N., Hanski, J., Ahola, T., Ståhle, M., Piiparinen, S., & Valkokari, P. (2019). Unlocking circular business: A framework of barriers and drivers. *Journal of Cleaner Production*, *212*, 90-98.

[212]. Uhrenholt, J. N., Kristensen, J. H., Rincón, M. C., Adamsen, S., Jensen, S. F., & Waehrens, B. V. (2022). Maturity model as a driver for circular economy transformation. *Sustainability*, *14*(12), 7483.

[213]. Vaiyapuri, T., Shankar, K., Rajendran, S., Kumar, S., Acharya, S., & Kim, H. (2023). Blockchain assisted data edge verification with consensus algorithm for machine learning assisted IoT. *Ieee Access*, *11*, 55370-55379.

[214]. Vermesan, O., Bröring, A., Tragos, E., Serrano, M., Bacciu, D., Chessa, S., Gallicchio, C., Micheli, A., Dragone, M., & Saffiotti, A. (2022). Internet of robotic things–converging sensing/actuating, hyperconnectivity, artificial intelligence and IoT platforms. In *Cognitive hyperconnected digital transformation* (pp. 97-155). River Publishers.

[215]. Vermesan, O., Friess, P., Guillemin, P., Gusmeroli, S., Sundmaeker, H., Bassi, A., Jubert, I. S., Mazura, M., Harrison, M., & Eisenhauer, M. (2022). Internet of things strategic research roadmap. In *Internet of things-global technological and societal trends from smart environments and spaces to green ICT* (pp. 9-52). River Publishers.

[216]. Vermesan, O., Friess, P., Guillemin, P., Sundmaeker, H., Eisenhauer, M., Moessner, K., Le Gall, F., & Cousin, P. (2022). Internet of things strategic research and innovation agenda. In *Internet of things* (pp. 7-151). River Publishers.

[217]. Violos, J., Mamanis, G., Kompatsiaris, I., & Papadopoulos, S. (2025). Cognition and context-aware decision-making systems for a sustainable planet: a survey on recent advancements, applications and open challenges. *Discover Sustainability*, *6*(1), 1-43.

[218]. Xiao, R., Wu, Z., & Hamari, J. (2022). Internet-of-gamification: A review of literature on IoT-enabled gamification for user engagement. *International Journal of Human–Computer Interaction*, *38*(12), 1113-1137.

[219]. Xu, H., Yu, W., Griffith, D., & Golmie, N. (2018). A survey on industrial Internet of Things: A cyber-physical systems perspective. *Ieee Access*, *6*, 78238-78259.

[220]. Yue, Y., & Lv, Y. (2023). A machine learning-based decision support system for predicting and repairing cracks in undisturbed loess using microbial mineralization and the Internet of Things. *Sustainability*, *15*(10), 8269.

[221]. Zahir, B., Rajesh, P., Md Arifur, R., & Tonmoy, B. (2025). A Systematic Review Of Human-AI Collaboration In It Support Services: Enhancing User Experience And Workflow Automation. *Journal of Sustainable Development and Policy*, *1*(01), 65-89. https://doi.org/10.63125/grqtf978

[222]. Zahir, B., Rajesh, P., Tonmoy, B., & Md Arifur, R. (2025). AI Applications In Emerging Tech Sectors: A Review Of Ai Use Cases Across Healthcare, Retail, And Cybersecurity. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 16-33. https://doi.org/10.63125/245ec865

[223]. Zahir, B., Tonmoy, B., & Md Arifur, R. (2023). UX optimization in digital workplace solutions: AI tools for remote support and user engagement in hybrid environments. *International Journal of Scientific Interdisciplinary Research*, *4*(1), 27-51. https://doi.org/10.63125/33gqpx45

[224]. Zahoor, S., & Mir, R. N. (2021). Resource management in pervasive Internet of Things: A survey. *Journal of King Saud University-Computer and Information Sciences*, *33*(8), 921-935.

[225]. Zhai, Z., Martínez, J. F., Beltran, V., & Martínez, N. L. (2020). Decision support systems for agriculture 4.0: Survey and challenges. *Computers and Electronics in Agriculture*, *170*, 105256.

[226]. Zhang, G., Yang, Y., & Yang, G. (2023). Smart supply chain management in Industry 4.0: the review, research agenda and strategies in North America. *Annals of operations research*, *322*(2), 1075-1117.

[227]. Zharfpeykan, R., & Akroyd, C. (2022). Factors influencing the integration of sustainability indicators into a company's performance management system. *Journal of Cleaner Production*, *331*, 129988.

[228]. Zhu, B., Nguyen, M., Siri, N. S., & Malik, A. (2022). Towards a transformative model of circular economy for SMEs. *Journal of Business Research*, *144*, 545-555.

American Journal of Scholarly Research and Innovation
Volume 04, Issue 01 (2025)
Page No: 250-286
eISSN: 3067-2163
Doi: 10.63125/28kdxg31

[229]. Zijm, H., Klumpp, M., Heragu, S., & Regattieri, A. (2018). Operations, logistics and supply chain management: definitions and objectives. In *Operations, logistics and supply chain management* (pp. 27-42). Springer.

[230]. Zkik, K., Belhadi, A., Kamble, S., Venkatesh, M., Oudani, M., & Sebbar, A. (2024). Cyber resilience framework for online retail using explainable deep learning approaches and blockchain-based consensus protocol. *Decision Support Systems*, *182*, 114253.