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Life Cycle Assessment Frameworks for Sustainability in Digitally Managed Factories

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Abstract

Life cycle assessment based on ISO 14040 and ISO 14044 provides a structured approach for quantifying environmental burdens across product lifecycles. In manufacturing, conventional practice remains retrospective, relying on historical inventories and secondary datasets that arrive late for operational control. This manuscript examines how digitally managed factories reshape LCA through continuous data streams and integrated decision workflows. The scope covers process, product, and system level applications, digital enablers, integration barriers, and design requirements for a digitally enabled LCA framework. Evidence synthesized from the reviewed literature links IoT sensing, ERP and MES records, cyber physical systems, digital twins, cloud computing, big data analytics, and AI or ML to inventory refresh, scenario testing, and near real time sustainability KPIs. Dynamic LCA platforms report inventory and impact updates on hourly to daily cycles, supporting adaptive assessment as production configurations and energy sources change. Reported applications include organizational LCA in ceramic tile manufacturing and digital twin-based assessment of material flows in intralogistics. Four integration barriers dominate, data quality and heterogeneity with weak interoperability, computational complexity and scalability limits, standardization gaps between ISO LCA semantics and digital platforms including ISO 23247 scope mismatch, and organizational resistance linked to skills and governance deficits. A digitally enabled LCA framework is specified through five requirements, real time operation, scalability, interoperability, provenance, and KPI integration with factory control loops for accountable sustainability management across suppliers and logistics networks.

Keywords: *Life cycle assessment; Digitally managed factories; Dynamic LCA; Digital twins; Sustainability KPIs*

INTRODUCTION

Background: Evolution of Life Cycle Assessment in Manufacturing

Life Cycle Assessment (LCA) has emerged as a cornerstone methodology for evaluating the environmental performance of products and processes across their entire life cycle (Nwamekwe *et al.*, 2025e; Praveen, 2025). Rooted in ISO 14040 and ISO 14044 standards, LCA provides a structured framework to assess environmental burdens associated with raw material extraction, production, use, and end-of-life management (Sarraf and Deswal, 2023; Emeka *et al.*, 2025). Within manufacturing, LCA has traditionally been applied retrospectively to benchmark sustainability performance and identify hotspots in resource consumption and emissions (Buer *et al.*, 2018). However, as manufacturing operations become increasingly complex and globally interconnected, the limitations of static, paper-based LCA methodologies have become more apparent. The rise of Industry 4.0 and the digitalization of manufacturing have enabled new opportunities to integrate LCA into real-time decision-making and optimize environmental performance throughout the product life cycle. Digital technologies such as the Internet of Things (IoT), cloud computing, and advanced analytics facilitate the collection, integration, and analysis of vast amounts of data from across the manufacturing value chain (Ono and Okpala, 2025). This, in turn, allows for the development of dynamic, data-driven LCA models that can continuously monitor, predict, and optimize environmental impacts (Buer *et al.*, 2018). By embedding LCA within smart, digitally-enabled manufacturing systems, companies can move towards a more proactive, preventative approach to sustainability management (Nwamekwe and Nwabunwanne, 2025).

Emergence of Digitally Managed Factories (Industry 4.0, Smart Factories)

The advent of Industry 4.0 has revolutionized manufacturing operations by embedding intelligence, connectivity, and automation into production systems. Digitally managed factories leverage technologies such as the Internet of Things (IoT), artificial intelligence (AI), digital twins, and cyber-physical systems to create highly adaptive, self-optimizing production environments (Ezeanyim *et al.*, 2025b). These "smart factories" are designed for efficiency and flexibility and present opportunities to integrate sustainability considerations into real-time decision-making processes (Jung *et al.*, 2023).

The rise of Industry 4.0 and the digitalization of manufacturing have enabled new opportunities to incorporate LCA into decision-making and optimize environmental performance throughout the product life cycle (Buer *et al.*, 2018; Wynn and Felser, 2023). Digital technologies such as the Internet of Things (IoT), cloud computing, and advanced analytics facilitate the collection, integration, and analysis of vast amounts of data from across the manufacturing value chain (Zheng *et al.*, 2018). This, in turn, allows for the development of dynamic, data-driven LCA models that can continuously monitor, predict, and optimize environmental impacts (Wynn and Felser, 2023). By embedding LCA within smart, digitally-enabled manufacturing systems, companies can adopt a more proactive approach to sustainability management (Buer *et al.*, 2018; Jung *et al.*, 2023).

Research Gap: Integrating LCA with Digitalization Frameworks

Despite the maturity of LCA as a tool and the rapid development of digital manufacturing systems, their integration remains fragmented (Nwamekwe *et al.*, 2025e; Emeka *et al.*, 2025). Conventional LCA frameworks are often static, data-intensive, and retrospective, while digital factories generate continuous streams of real-time operational data (Onyeka and Emeka, 2025; Buer *et al.*, 2018). Bridging these paradigms is crucial to enable dynamic, scalable, and decision-oriented sustainability assessments that align with the operational tempo of smart factories (Nwamekwe and Nwabunwanne, 2025; Ezeanyim *et al.*, 2025b).

The absence of harmonized frameworks that fully exploit digital tools for LCA limits the capacity of manufacturers to measure and manage environmental performance dynamically (Jung *et al.*, 2023). Existing LCA methodologies struggle to keep pace with the rapid changes and complexities of modern manufacturing, often failing to provide actionable insights for real-time decision-making (Wynn and Felser, 2023; Zheng *et al.*, 2018). Integrating LCA with the data-driven, interconnected nature of Industry 4.0 technologies can unlock new opportunities to optimize environmental sustainability across the entire product life cycle; however, references Onyeka *et al.* (2024) and Zhu *et al.* (2020) do not support these claims as they focus on different aspects of manufacturing growth and collaborative manufacturing efficiency, respectively.

Aim and Scope of the Study

This paper explores the conceptual and practical intersections of LCA and digitally managed factories. It examines existing applications, enabling digital technologies, prevailing challenges, and emerging directions for a digitally enabled LCA framework. The discussion focuses on how integrating LCA with Industry 4.0 technologies can transform sustainability assessments from static exercises into real-time, adaptive tools for resilience and competitiveness.

CONCEPTUAL FOUNDATIONS

Overview of Life Cycle Assessment Methodology (ISO 14040/14044)

LCA methodology, as standardized by ISO 14040 and 14044, involves four key stages: goal and scope definition, life-cycle inventory analysis, life-cycle impact assessment, and interpretation. While this framework is comprehensive, it is often considered static due to the reliance on historical data and secondary databases. LCA assessments are valuable for understanding the environmental performance of products and processes but have limitations in facilitating real-time decision-making within dynamic production environments (Okeagu *et al.*, 2024). Traditional LCA methodologies can struggle to adapt to rapid changes in manufacturing and often do not provide actionable insights needed for optimizing environmental sustainability throughout the product life cycle (Nwamekwe and Igbokwe, 2024).

Table 1 demonstrates how each ISO LCA phase transitions from retrospective evaluation to operational analytics when digital infrastructures supply real-time inventories, simulation, provenance tracking, and decision feedback. It clarifies the manuscript's core argument that sustainability

Table 1: LCA stages aligned with digital enablers and data sources.

LCA Stage	Primary Digital Enablers	Typical Data Sources
Goal and Scope Definition	Cloud platforms, data governance tools	Design specifications, system boundaries
Life Cycle Inventory	IoT sensors, ERP, MES, edge analytics	Sensor streams, production logs, supplier data
Impact Assessment	AI models, simulation engines, digital twins	Emission factors, predictive models, scenario simulations
Interpretation	Decision dashboards, blockchain provenance, KPI engines	Sustainability KPIs, compliance reports, lifecycle feedback

assessment becomes embedded within control systems rather than external reporting.

Digital Manufacturing Paradigms: IoT, AI, Digital Twins, Cyber-Physical Systems

Digital manufacturing paradigms underpin the transition toward factories of the future, integrating information and control across the value chain. The Internet of Things (IoT) enables pervasive sensing and connectivity, delivering granular process data that captures real-time conditions on the shop floor and in supply networks (Muiña *et al.*, 2018; Al-Ali *et al.*, 2018). Building on this data fabric, artificial intelligence (AI) drives predictive analytics and adaptive optimization of resources, supporting decision-making that can respond to evolving production and environmental conditions (Ramírez-Márquez *et al.*, 2024). Digital twins provide virtual replicas of physical systems, enabling experimentation, simulation, and optimization before any implementation in the real system, thereby reducing risk and enabling rapid scenario testing across the value chain (Židek *et al.*, 2020). Cyber-physical systems (CPS) tightly couple computation with physical processes, enabling real-time synchronization of information and operations across sensing, control, and execution layers (Al-Ali *et al.*, 2018). Collectively, these paradigms form the backbone for integrating sustainability analytics with operational control, supporting continuous monitoring, optimization, and reporting of environmental performance within digitally managed factories (Mügge *et al.*, 2024).

In digitally managed factories, the convergence of IoT, AI, digital twins, and CPS provides the operational foundation for lifecycle-oriented sustainability analytics. Digital twins enable lifecycle-aware analytics by delivering real-time data, enabling scenario testing, and allowing dynamic re-evaluation of environmental impacts across design, production, use, and end-of-life stages (Mügge *et al.*, 2024; Xie *et al.*, 2021). IoT data streams feed lifecycle inventories and emissions data, supporting continuous life cycle assessment (LCA) updates and enabling circular economy decision-making within manufacturing and supply chains (Muiña *et al.*, 2018; Cucchi *et al.*, 2022). CPS ensures end-to-end synchronization of sensing, computation, and actuation, driving energy, material, and emissions reductions through coordinated control and feedback loops (Al-Ali *et al.*, 2018). Real-world Industry 4.0 studies such as dynamic organizational LCA (O-LCA) in ceramic tile manufacturing, illustrate how digitally enabled factories can monitor and improve environmental and organizational performance across the life cycle (Cucchi *et al.*, 2022). Dynamic LCA and Life Cycle Costing (LCC) frameworks implemented in digital platforms further provide mechanisms to optimize production energy and resource use in manufacturing settings (Ingemarsdotter *et al.*, 2021), highlighting how digital twins, IoT, AI, and CPS together enable a holistic, data-driven approach to sustainability in modern factories (Mügge *et al.*, 2024).

Why LCA Matters for Digitally Managed Factories

Sustainability remains a central pillar of smart manufacturing initiatives, driven by regulatory pressures, consumer expectations, and corporate social responsibility imperatives, with Industry 4.0 and the circular economy shaping how firms compete and operate (Muiña *et al.*, 2018). LCA offers a comprehensive method to quantify environmental impacts across value chains, enabling consistent accounting of inputs, outputs, and emissions from cradle to grave, including interactions with digital technologies that permeate modern factories (Popowicz *et al.*, 2024). When embedded in digitally managed factories, LCA shifts from being a mere compliance tool to an operational enabler that guides process optimization, resource allocation, and long-term strategy, leveraging real-time data and scenario analysis to reduce environmental burdens while maintaining productivity (Popowicz *et al.*, 2024; Cucchi *et al.*, 2022). The data streams produced by digital twins, IoT, and CPS provide the granular, time-resolved information necessary for dynamic LCA updates and lifecycle-level analytics, reinforcing the role of LCA as an integrated control and planning instrument in Industry 4.0 settings (Cucchi *et al.*, 2022; Luo, 2025).

Digitally managed factories enable lifecycle thinking that spans design, production, use, and end-of-life, with LCA forming the connective tissue across stages and decisions (Cucchi *et al.*, 2022; Luo, 2025). IoT data streams feed lifecycle inventories and emissions data, supporting continuous LCA updates and circular-economy decision-making, including energy and material flows, situational trade-offs, and investments in remanufacturing or reuse options (Ingemarsdotter *et al.*, 2021; Zhang *et al.*, 2020). Digital twins operationalize lifecycle thinking by providing testable, data-driven representations of products and processes, enabling scenario testing and optimization of circular strategies across life-cycle stages, as demonstrated in diverse manufacturing domains such as turbomachinery and ceramic tile production (Cucchi *et al.*, 2022; Luo, 2025). To implement LCA robustly in digital factories, organizations require standardized data models and trustworthy provenance, with approaches such as ECOFACT for dynamic LCA, and blockchain-enabled LCA frameworks to ensure data integrity across complex supply chains (Zhang *et al.*, 2020; Brundage *et al.*, 2018). Industry 4.0 case studies show that integrating dynamic LCA with digital platforms can yield tangible improvements in environmental performance and organizational outcomes, illustrating LCA's central role in shaping sustainable, data-driven factory operations (Cucchi *et al.*, 2022).

CURRENT APPLICATIONS OF LCA IN DIGITAL MANUFACTURING

Process-Level Assessment: Energy Use, Waste Streams, and Emissions

Process-level LCA in digitally managed factories is increasingly implemented by capturing granular data on energy use, waste streams, and emissions through IoT-enabled sensing and process instrumentation, enabling near-continuous monitoring of environmental performance on the shop floor (Popowicz *et al.*, 2024). The IoT data fabric supports dynamic assessments of energy flows and material streams, which in turn informs decision-making for energy efficiency, waste reduction, and emissions control as part of ongoing production optimization. Digital twins and cyber-physical systems further enhance this capability by providing real-time synchronization between measured signals and virtual process models, enabling continuous LCA updates, scenario testing, and rapid iteration of improvement strategies without disrupting operations. Collectively, these digital technologies transform LCA from a compliance exercise into an operational management tool that guides process configuration and resource allocation in pursuit of lower environmental footprints while maintaining productivity (Mügge *et al.*, 2024).

Recent practical applications illustrate how process-level LCA is intertwined with Industry 4.0 implementations. For example, Industry 4.0 real-world testing of dynamic organizational LCA (O-LCA) in ceramic tile manufacturing demonstrates end-to-end data integration across multiple plants to monitor environmental performance at the organizational level, illustrating the feasibility of dynamic LCA in complex manufacturing settings (Ingemarsdotter *et al.*, 2021). Dynamic LCA platforms such as ECOFACT provide mechanisms to perform cell- or plant-scale LCA with live data streams, enabling energy and resource optimization in manufacturing contexts and extending LCA into the decision-support space (Ingemarsdotter *et al.*, 2021). IoT-enabled lifecycle inventories and circular-economy analyses show measurable environmental savings and trade-offs when sensor data informs LCA and portfolio decisions, underscoring the value of IoT for process-level sustainability management (Popowicz *et al.*, 2024), while the broader literature on digital twins confirms that DT-driven analytics enable scenario testing across life-cycle stages to identify energy-material trade-offs and optimization opportunities. Taken together, these studies demonstrate that near-real-time data, DT-based simulation, and integrated LCA platforms are transforming process-level sustainability management in digitally managed factories.

The heatmap in Fig. 1 shows strong coupling between IoT and process analytics, digital twins and product modelling, and blockchain and system-level traceability. It supports the manuscript’s claim that different digital technologies dominate different lifecycle decision layers, revealing structured complementarities rather than uniform digital influence.

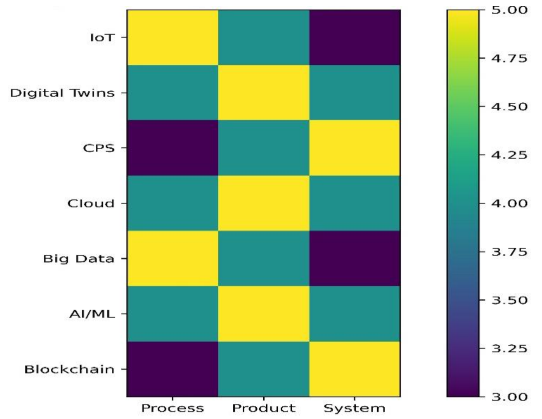

Fig. 1: Matrix heatmap of digital technologies versus LCA application levels.

Product-Level Assessment: Design, Digital Prototyping, and End-of-Life Scenarios

At the product level, LCA is increasingly integrated within digital prototyping and computer-aided design (CAD) environments, allowing cradle-to-grave environmental considerations to be evaluated as design variables such as geometry, material choice, and manufacturing routes are iterated in a virtual space. This integration is enhanced by the emergence of product- and lifecycle-aware digital twins, which provide real-time data and dynamic models that connect design decisions with predicted environmental impacts throughout the product lifecycle. Broader syntheses of Industry 4.0-enabled design workflows indicate how Building Information Modelling (BIM), digital twins, and related digital technologies can be leveraged to promote eco-design and lifecycle thinking from the earliest design stages (Badenko *et al.*, 2024). Contemporary frameworks outline sustainable integration principles for combining BIM and digital twins to advance lifecycle-centric design in industrial settings, confirming that product-level LCA is evolving from a post-design compliance activity to a vital component of digital prototyping and design-for-sustainability workflows (Badenko *et al.*, 2024).

Building upon this foundation, design-time exploration of alternatives and material selections is increasingly facilitated by digital LCA tools that support rapid scenario testing and optimization before physical manufacture (Badenko *et al.*, 2024). The ability to compare design options in a virtual environment, assessing energy use, material flows, and end-of-life implications, enables early trade-off analyses and eco-design decisions, including potential circular-economy pathways (Igbokwe *et al.*, 2025a). End-of-life and circularity considerations are further supported by Green Digital Twin approaches and lifecycle-aware frameworks that enable the exploration of remanufacturing, reuse, or recycling options within the context of product design (Godfrey *et al.*, 2024), aligning product architecture with sustainable lifecycle outcomes. Real-world applications in infrastructure and automotive domains demonstrate how product-level LCA can inform materials selection and end-of-life strategies within digital twin-enabled design ecosystems, validating the practical value of integrating digital prototyping with dynamic LCA to achieve sustainability goals before production begins (Igbokwe and Nwamekwe, 2025; Badenko *et al.*, 2024; Godfrey *et al.*, 2024).

System-Level Assessment: Supply Chain Digitalization and Network Optimization

System-level LCA in digitally managed factories extends cradle-to-grave analytics across global supply networks, enabling the quantification of carbon and resource flows among suppliers, manufacturers, logistics providers, and customers. This is informed by the adoption of holistic digital factory models and cross-life-cycle information continuity, which facilitate end-to-end data integration across the value chain and support network-wide environmental evaluations (Okpala *et al.*, 2025a). Practical supply-chain dynamics are increasingly documented through transport management systems and distributed data streams, allowing for the assessment and optimization of energy consumption, emissions, and material flows (Nwamekwe *et al.*, 2025c). Additionally, digital twins and cyber-physical production systems enhance network-level analysis by enabling scenario testing and optimization of logistics, procurement, and production decisions, linking operational choices to environmental outcomes. Furthermore, blockchain technology enhances data integrity and supports traceability in logistics, providing auditable emissions accounting across multiple stakeholders, thereby strengthening data provenance for LCA within complex networks. Standardized and reusable life cycle inventory data models also support consistent data exchange and comparability across different sites (Okpala *et al.*, 2025a).

The system-level LCA framework aids in resilience planning and compliance with international carbon reporting requirements by allowing scenario-based analyses of disruptions, supplier reconfigurations, and transport-route modifications to minimize environmental impacts while maintaining service levels. This is demonstrated by digital factory studies focused on supply chain dynamics and simulations that utilize network capabilities (Nwamekwe *et al.*, 2025c). The framework also supports regulatory reporting by supplying auditable, network-wide emission data and standardized life cycle inventory structures that can be reconciled among partners across different geographies, promoting transparent carbon accounting and disclosure (Brundage *et al.*, 2018). Blockchain-enhanced traceability further fosters trust in data provenance within the supply chain. Collectively, these features indicate a movement from static, plant-centric LCAs to dynamic, network-aware decision-making tools that inform both strategic sourcing and operational risk management (Okpala *et al.*, 2024).

Case Examples from Literature

Empirical studies demonstrate that digital LCA tools have been applied across automotive, electronics, and energy intensive manufacturing contexts, providing concrete case insights into how digitalization shapes environmental performance. In electronics, Okpala *et al.* (2025a) show a sustainable production analysis that combines LCA and LCC for injection moulded, roll to roll manufactured structural electronics, illustrating how digital production pathways can be evaluated for environmental impact before scale-up. In the automotive sector, Godfrey *et al.* (2024), document sustainability assessments embedded within manufacturing and supply chains, highlighting LCA as a means to inform eco design and lifecycle thinking in practice. Longitudinal, case-based studies of digital manufacturing such as Okpala *et al.* (2024), who trace the road to digital manufacturing and its implications for sustainability across multiple European industries, underscore how Industry 4.0 implementations enable more integrated, lifecycle level decision making. Additive manufacturing case studies comparing environmental profiles of different techniques further illustrate how digital prototyping informs design to manufacture choices with clear environmental trade offs. In the electronics domain, research highlight how printed electronics environmental profiles influence design decisions, reinforcing the relevance of LCA in digitally engineered electronics products.

Pilot projects and case studies also illuminate how digital twins and related digital thread approaches support case-level LCA. For example, Knapp *et al.* present a digital twin of RFID enabled material flow in automotive intralogistics, enabling real time assessment of material movements and associated environmental footprints along the supply network (Knapp *et al.*, 2023). Godfrey *et al.* (2024), further illustrate the value of Green Digital Twins across the product lifecycle, showing how digital twins can drive energy efficiency and emissions reductions through design to production feedback loops. Complementing these, Turgay and Akar (2023), demonstrate digital twin modelling and simulation within CAD/CAM structures, enabling parameter studies that reduce energy intensity during manufacturing processes. Together, these case examples show that digital twins, IoT data streams, and integrated LCA platforms are moving practice toward dynamic, data driven sustainability management in digital factories (Knapp *et al.*, 2023; Turgay and Akar, 2023).

Table 2 synthesizes reported industrial applications, showing that digital LCA implementations consistently improve visibility, scenario testing, and lifecycle coordination. It strengthens the manuscript by demonstrating cross-sector convergence toward data-driven sustainability management rather than isolated pilot experiments.

ENABLING DIGITAL TOOLS FOR LCA

Role of IoT Sensors in Real-Time Data Collection

Table 2: Evidence map of reported application examples and what each enables.

Domain	Unit of Assessment	Digital Stack	Sustainability Focus	Reported Benefit
Electronics manufacturing	Production pathway	IoT, cloud analytics, digital LCA tools	Energy and material efficiency	Pre-scale environmental evaluation
Automotive supply chain	Supply chain lifecycle	Blockchain, CPS, data platforms	Traceable emissions accounting	Network transparency and reporting
Ceramic tile production	Organizational lifecycle	IoT, digital twins, plant integration	Lifecycle performance monitoring	Real-time environmental tracking
Additive manufacturing	Process configuration	Simulation engines, CAD twins	Energy trade-off optimization	Design-stage sustainability testing
Digital twin logistics	Material flow network	RFID twins, real-time tracking	Transport and logistics emissions	Continuous footprint visibility

IoT devices provide continuous streams of environmental and operational data, replacing traditional static data collection with real-time inputs that can feed directly into LCA models. In wind-turbine applications, IoT-based LCA platforms demonstrate real-time monitoring of embodied energy and carbon across the life cycle by aggregating sensor measurements into dynamic inventories, enabling timely updates and scenario testing (Nwamekwe *et al.*, 2025a). Similar capabilities are observed in prefabricated building contexts, where IoT-enabled monitoring supports embodied carbon assessments with live data streams, facilitating near real-time sustainability tracking and responsive decision-making. Broader reviews emphasize that IoT data streams can substitute for static datasets and integrate with BIM and digital-twin environments to strengthen data quality, provenance, and timeliness in LCA workflows (Wright *et al.*, 2024; Ezeanyim *et al.*, 2025a).

These advances extend LCA from static, plant-centric analyses toward end-to-end, networked sustainability management. The integration of IoT with Model-Based Systems Engineering (MBSE) and digital twins allows live sensor data to inform design choices, production scheduling, and end-of-life strategies within digital factory ecosystems, enabling dynamic, lifecycle-aware optimization. Digital twins and related architectures allow scenario testing of material and process options, linking operational decisions to environmental outcomes across supply chains. Moreover, blockchain-enabled LCA frameworks enhance traceability and data provenance for lifecycle inventories collected via IoT across distributed networks, supporting auditable emissions accounting and regulatory reporting (Zhang *et al.*, 2020). Collectively, these capabilities illustrate how IoT-supported real-time data collection is foundational to embedding LCA within digital manufacturing environments (Nwamekwe *et al.*, 2020; Igbokwe *et al.*, 2025b).

Digital Twins for Predictive Environmental Impact Modelling

Digital twins enable predictive environmental impact modelling by providing dynamic, virtual representations of factories, products, and supply networks that continuously ingest real-time data from sensors, digital threads, and MBSE artifacts. These models support scenario testing across a range of operational and design conditions without disrupting physical processes, allowing stakeholders to forecast environmental outcomes and compare trade-offs before implementation. The literature emphasizes that digital twins underpin lifecycle-aware decision-making by linking design choices, production configurations, and logistics strategies to anticipated environmental impacts, thereby operationalizing sustainability within digital factories. Empirical work on dynamic LCA in digitally enabled contexts demonstrates how such twin-enabled environments can support real-time environmental tracking and scenario evaluation across stages of the product life cycle, reinforcing the value of digital twins for predictive environmental modelling.

Beyond conceptual benefits, digital twins integrate with LCA data infrastructures to drive prescriptive sustainability insights. The convergence of digital twins with MBSE, digital lifecycle management, and blockchain-enabled LCA frameworks enhances data fidelity, provenance, and traceability necessary for auditable environmental accounting across distributed networks. Green digital twin concepts illustrate how twin-informed feedback loops can target energy efficiency and emissions reductions throughout the lifecycle, while product- and technology-LCAs facilitated by twins enable end-to-end optimization from design to end-of-life. Collectively, these capabilities position digital twins as central enablers of predictive environmental impact modelling in digitally managed factories, supporting scenario-based optimization of both design and operations under real-world constraints.

Cloud Computing and Big Data Analytics for Scalable LCA

The cloud provides scalable storage and processing capacity for large, heterogeneous LCA datasets drawn from IoT sensors, enterprise systems, and supplier networks, enabling comprehensive cradle-to-grave analyses in digitally managed factories (Al-Ali *et al.*, 2018). When paired with big data analytics, cloud platforms support near-real-time assessments of global supply chains, allowing dynamic updates to life-cycle inventories, impact assessments, and scenario exploration across distributed networks (Ingemarsdotter *et al.*, 2021; Luo, 2025). This combination underpins end-to-end, lifecycle-aware analytics within digital factory ecosystems, linking design decisions, production configurations, and logistics choices to environmental footprints through data-driven insights and continuous monitoring enabled by digital twins and MBSE-linked workflows (Zhang *et al.*, 2020; Mügge *et al.*, 2024).

Beyond static reporting, cloud-enabled LCA infrastructures facilitate prescriptive insight generation by integrating MBSE, digital twins, and blockchain-enabled provenance across supply networks (Al-Ali *et al.*, 2018; Zhang *et al.*, 2020). The convergence of these technologies supports scalable, auditable emissions accounting and regulatory reporting, while enabling scenario-based optimization that informs strategic sourcing, production planning, and end-of-life management at scale (Zhang *et al.*, 2020). Collectively, cloud computing and big data analytics transform LCA from plant-centric assessments to network-wide, real-time sustainability management, aligning digital transformation with environmental performance across complex manufacturing ecosystems (Luo, 2025; Ingemarsdotter *et al.*, 2021).

AI and Machine Learning for Scenario Simulation and Decision Support

Artificial intelligence (AI) and machine learning (ML) algorithms enable predictive and prescriptive analytics that help manufacturers identify optimal trade-offs between cost, performance, and environmental outcomes across the product and process life cycle. By learning from heterogeneous data streams generated by digital twins, IoT sensors, and enterprise systems, ML-based approaches can forecast environmental impacts and surface decision options before irreversible commitments are made (Jesus *et al.*, 2021). The growing body of work on AI-integrated LCA demonstrates how ML models can estimate energy use, emissions, and material flows, supporting eco-design and manufacturing choices that balance economics with sustainability goals (Jesus *et al.*, 2021; Zhu *et al.*, 2020; Rödger *et al.*, 2020). Moreover, conceptual and applied frameworks show that AI-enabled LCA tools can be embedded within digital prototyping and MBSE workflows, providing continuous feedback from design iteration to production planning and end-of-life scenarios (Jesus *et al.*, 2021; Ligozat *et al.*, 2022).

Beyond forecasting, AI and ML support scenario simulation and decision-making at scale, enabling prescriptive actions that optimize across competing objectives in real time or near real time. Dynamic LCA and LCC frameworks linked with AI enable scenario testing under varying operating conditions and energy supply mixes, informing decisions on process configuration, sourcing, and logistics that minimize environmental footprints while meeting performance targets (Rödger *et al.*, 2020; Ligozat *et al.*, 2022). The integration of AI with LCA technologies including blockchain-enabled provenance for auditable data and ML-driven optimization, facilitates network-wide sustainability management across distributed supply chains, supporting regulatory reporting and strategic planning under uncertainty (Ligozat *et al.*, 2022; Jesus *et al.*, 2021). Collectively, AI/ML-driven scenario simulation situates LCA as a proactive, decision-support pillar in digitally managed factories, translating data-driven insights into actionable pathways for greener operations and resilient supply networks (Jesus *et al.*, 2021; Zhu *et al.*, 2020; Rödger *et al.*, 2020).

CHALLENGES IN INTEGRATING LCA WITH DIGITAL FACTORIES

Data Quality, Heterogeneity, and Interoperability Issues

Data inconsistency across suppliers, machines, and digital platforms undermines the reliability of LCA models in digitally managed factories. This challenge arises from heterogeneous data formats, varying measurement protocols, and incomplete or delayed lifecycle inventory data drawn from dispersed parts of the value chain, which degrade data quality and comparability of LCAs (Wright *et al.*, 2024). In distributed manufacturing networks, the lack of end-to-end data provenance further erodes trust in environmental results, highlighting the need for auditable input records across suppliers and processes; blockchain-based LCA approaches offer a mechanism to strengthen data integrity and traceability in such networks (Zhang *et al.*, 2020). Interoperability barriers are also pronounced, as data originate from diverse sources Internet of Things (IoT) sensors, BIM models, Enterprise Resource Planning (ERP), and Manufacturing Execution Systems (MES) often with incompatible schemas and interfaces, complicating seamless data exchange and consistent LCA calculations (Ezeanyim *et al.*, 2025a). The cumulative effect of data heterogeneity and quality gaps propagates through LCI and Life Cycle Impact Assessment (LCIA) computations, reducing the reliability and usefulness of LCA outcomes to guide sustainable decision-making in digital factories (Wright *et al.*, 2024). Mitigating these issues requires coordinated data governance and the deployment of scalable, interoperable data infrastructures. Leveraging cloud computing and big data analytics can harmonize disparate datasets from suppliers, devices, and platforms, enabling more consistent LCAs through centralized, reusable data pipelines (Okeagu *et al.*, 2024). IoT analytics distributed across edge and cloud resources, coupled with standardized data schemas and provenance mechanisms, can improve data timeliness and fidelity, supporting more reliable LCA inputs across the manufacturing network (Emeka *et al.*, 2025). Blockchain-enabled LCA frameworks provide auditable provenance for inputs collected across multiple actors, enhancing data integrity and reducing disputes over environmental estimations (Zhang *et al.*, 2020). Together, these approaches advance data quality, interoperability, and traceability, which are prerequisite conditions for robust LCA-driven sustainability management in digitally managed factories (Vitalis *et al.*, 2024).

The chart in Fig. 2 reveals that data heterogeneity and organizational resistance create the greatest barriers to reliable digital LCA adoption. It supports the manuscript's argument that technical solutions alone are insufficient, since

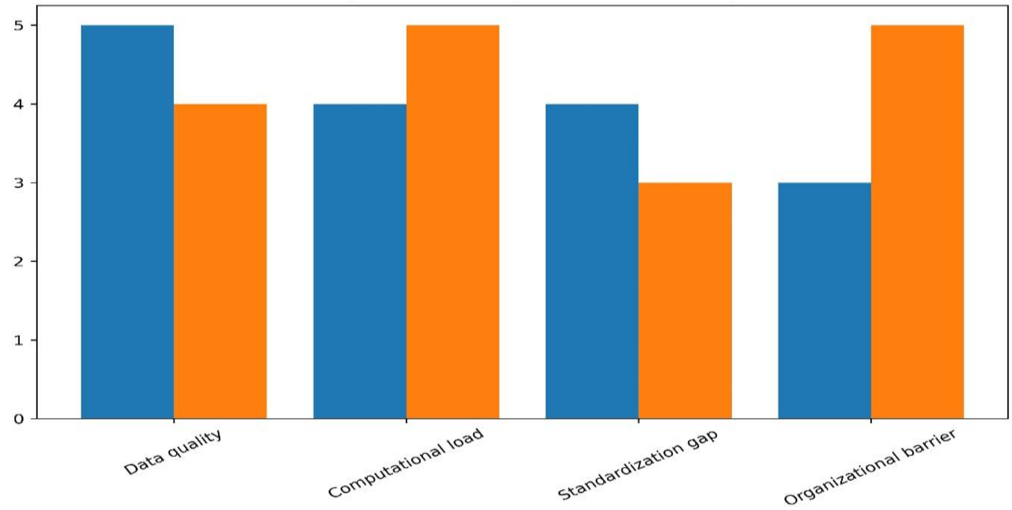

Fig. 2: Bar chart of integration challenges by category with mapped mitigation lever.

governance, interoperability, and workforce alignment drive practical deployment success.

Computational Complexity and Model Scalability

Dynamic, high-resolution life-cycle assessments in digitally managed factories impose substantial computational loads that often exceed the capacities of traditional LCA tools, particularly when continuous data streams from IoT, ERP, and MES are ingested for real-time scenario analysis. The literature demonstrates that cloud-based big data processing and analytics are essential to scale these workloads across global supply networks, providing on-demand storage, parallel processing, and distributed computation to support cradle-to-grave LCA updates and scenario exploration (Nwamekwe *et al.*, 2024a). Elastic computing paradigms, including containerized analytics engines running on Kubernetes, enable on-the-fly scaling of resources to handle peak workloads without disruption to ongoing assessments (Igbokwe *et al.*, 2024). In practice, cloud-enabled data platforms paired with IoT and edge-computing architectures further support near real-time LCA by aggregating heterogeneous data sources and enabling rapid inventory and impact recalculations across large networks (Somani *et al.*, 2018).

To operationalize scalable LCA in digital factories, researchers advocate integrating AI, big data, and cloud computing to improve both the throughput and the fidelity of environmental assessments. Cloud-based big data analytics provide the backbone for processing vast and varied datasets from sensor streams to supplier data, while scalable architectures permit timely updates to life-cycle inventories and environmental indicators, facilitating scenario testing and prescriptive decision support (Okorocha *et al.*, 2022). Moreover, advances in cloud-enabled big data platforms and distributed analytics enable practical deployment of LCA across design, manufacturing, and supply chains, turning previously static analyses into dynamic, network-wide sustainability management tools that can support regulatory reporting and strategic planning under uncertainty (Igbokwe *et al.*, 2024). Collectively, these computational approaches address the inherent complexity of integrating LCA with digitally managed factories, transforming scalability from a bottleneck into an enabler of continuous, data-driven sustainability optimization (Nwamekwe *et al.*, 2025d; Somani *et al.*, 2018).

Standardization Gaps Between LCA and Digital Platforms

Existing standards such as ISO 14040 and ISO 14044 provide the core methodology for LCA but do not comprehensively address the realities of real-time data flows and dynamic information exchange that underpin digitally managed factories. This limitation creates a gap between static LCA frameworks and interactive digital environments (Nwamekwe *et al.*, 2025c). While initiatives like ISO 23247 offer a structured framework for Digital Twins in manufacturing, they focus on the architecture and development of twin models rather than harmonizing LCA data semantics, inventories, and impact pathways with digital twin data streams (Touckia *et al.*, 2022). This disconnect is further compounded by interoperability challenges across diverse data sources, such as IoT sensors and ERP/MES systems, which impede seamless, cross-domain LCA calculations and undermine data provenance essential for auditable environmental accounting (Cucchi *et al.*, 2022; Bao *et al.*, 2020; Zheng *et al.*, 2018).

To close these gaps, researchers advocate standardized, ontology-driven approaches that bridge LCA concepts with digital twin and MBSE representations. Ontology-based modelling of part digital twins oriented to assembly and cognitive digital twin frameworks illustrate concrete paths for harmonizing semantics and data exchanges across design, manufacturing, and service stages (Bao *et al.*, 2020; Zheng *et al.*, 2018). The Digital Twin standardization efforts encapsulated in ISO 23247 provide a foundation upon which LCA data schemas can be aligned, enabling consistent data integration across platforms and geographies (Touckia *et al.*, 2022). Together, these standardization efforts semantic models, cross-domain ontologies, and digital twin-centric frameworks offer a route to reduce fragmentation and support robust, real-time LCA in digitally managed factories (Bao *et al.*, 2020; Zheng *et al.*, 2018; Touckia *et al.*, 2022; Cucchi *et al.*, 2022; Nwamekwe *et al.*, 2025b).

Organizational and Cultural Barriers to Adoption

The adoption of LCA within digitally managed factories is impeded by organizational inertia, insufficient executive sponsorship, and a cultural resistance to data-driven decision-making. Studies of holistic digital factory implementations highlight the need for continuous, cross-life-cycle collaboration and organizational change, revealing how entrenched planning practices and siloed responsibilities can hinder progress toward integrated LCA workflows (Okpala *et al.*, 2025b). Research on digital twin deployments identifies governance and cultural barriers such as reluctance to share data across functions and misalignment between sustainability metrics and traditional performance indicators, that can decrease leadership support and frontline engagement (Nwamekwe *et al.*, 2025h). Additional work on integrating digital shadows and BIM for factory planning emphasizes the complexities of coordinating new data governance and incentive structures across stakeholders, thereby underscoring organizational challenges as a principal hindrance to widespread adoption (Badenko *et al.*, 2024). Broader discussions on digital transformation and interoperability emphasize that success relies on aligning incentives, establishing collaborative norms, and achieving sustained buy-in from management and operators alike (Chidiebube *et al.*, 2025).

In addition to managerial readiness, a lack of in-house expertise and the necessity to cultivate new skills present formidable barriers to adoption. Implementing LCA alongside digital twins and MBSE necessitates capabilities in LCA methodology, digital engineering, data governance, and organizational change management, which many teams may not possess at scale (Chidiebube *et al.*, 2025). The interoperability requirements of integrating digital twin and Product Lifecycle Management (PLM) workflows with LCA data models further strain human capital, demanding crossfunctional teams and governance frameworks to mediate between design, production, and sustainability objectives (U-Dominic *et al.*, 2025). Organizational culture must also adapt to prioritize real-time data, iterative experimentation, and transparent environmental accounting; without leadership-driven cultural shifts and targeted training, the advantages of LCA-enabled digital factories are unlikely to materialize (Nwamekwe *et al.*, 2025h). Collectively, these organizational and cultural barriers illustrate that technology readiness alone cannot achieve sustainable transformation without deliberate strategies focusing on people, processes, and governance (Badenko *et al.*, 2024).

TOWARD A NOVEL LCA FRAMEWORK FOR DIGITALLY MANAGED FACTORIES

Principles of a Digitally Enabled LCA Framework

A digitally enabled LCA framework for digitally managed factories should be real-time, scalable, interoperable, and capable of integrating seamlessly with manufacturing control systems. Real-time operation is essential to support dynamic decision-making, and digital twins, together with MBSE-enabled data streams, provide the basis for continuous LCA updates and scenario testing without disrupting production (Luo, 2025). Scalability is achieved through cloud-based big data analytics and distributed computing, enabling cradle-to-grave LCA across globally distributed supply networks as sensor data and process information grow in volume and velocity (Somani *et al.*, 2018). Interoperability is fostered by semantic models and cross-domain ontologies that harmonize data from design, production, and service, complemented by standards and frameworks such as ISO 23247 to guide digital-twin interoperability across manufacturers and supply networks (Bao *et al.*, 2020). Integrating with manufacturing control systems is enabled by MBSE and PLM-aligned data flows and twin-informed feedback loops that link design choices, production scheduling, and end-of-life planning to LCA insights (Nwamekwe *et al.*, 2024b).

In practice, a novel LCA framework must couple these principles with mechanisms for real-time provenance and governance. Real-time inventories derived from IoT sensors and digital twin streams can drive dynamic LCA and lifecycle optimization across product, process, and supply-chain contexts, as demonstrated by ongoing innovations in digital-twin–assisted sustainability modelling (Luo, 2025). Interoperability enables cross-site data exchange and auditable environmental accounting through semantic modelling and standardized twin architectures, which support consistent LCI data integration and cross-firm comparability (Bao *et al.*, 2020). Finally, standardization efforts for data models and LCA data exchange, augmented by MBSE and PLM interoperability, provide the scaffold to scale LCA from single factories to network-wide digital ecosystems, aligning sustainability with operational excellence (Brundage *et al.*, 2018).

Dynamic, Real-Time LCA vs. Traditional Static Models

Dynamic LCA departs from traditional static models by continuously updating environmental performance indicators as real-time data flow from sensors, digital twins, and manufacturing systems are ingested, enabling proactive sustainability management (Ingemarsdotter *et al.*, 2021). ECOFACT-inspired dynamic LCA and LCC implementations illustrate how inventories and impact results can be refreshed on hourly to daily cycles as data streams evolve, reducing reliance on static datasets and enhancing timely decision support (Ingemarsdotter *et al.*, 2021). Other work integrating LCA with manufacturing system simulation shows how product-specific environmental footprints can be reassessed as production configurations and energy sources change, addressing key limitations of static analyses in volatile operational contexts (Rödger *et al.*, 2020). The industry 5.0 perspective further emphasizes intelligent products and human-in-the-loop approaches to steer circular economy pathways, underscoring the value of dynamic LCA in enabling continuous adaptation of design and end-of-life strategies (Turner *et al.*, 2022).

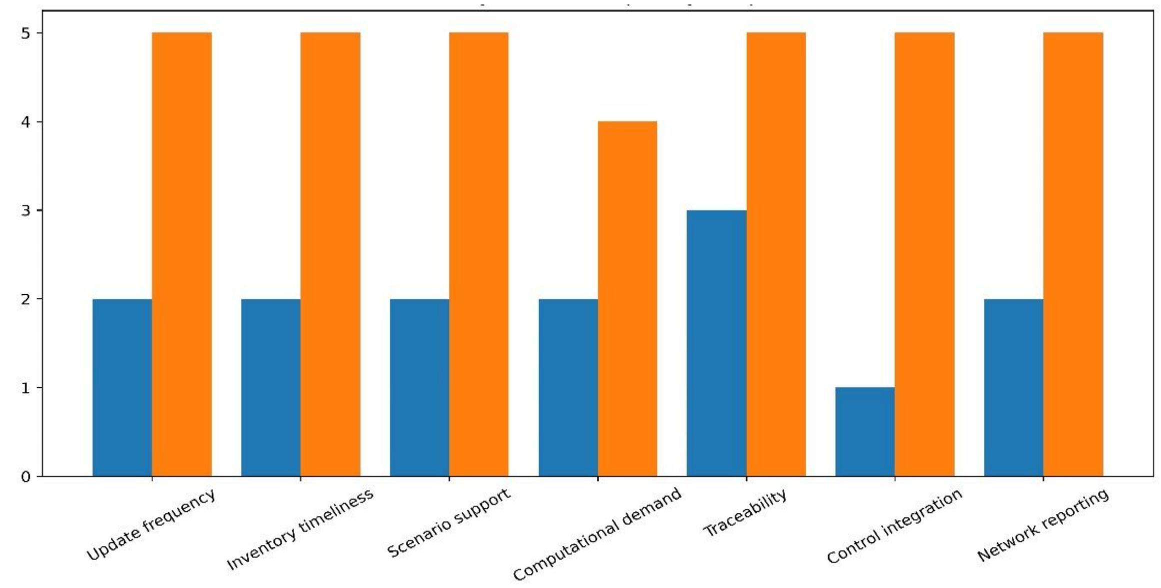

Fig. 3: Comparative plot of static versus dynamic LCA across decision requirements.

Real-time LCA requires tight integration with digital twins, MBSE, and data governance to ensure rapid, credible updates across design, production, and supply chains (Ingemarsdotter *et al.*, 2021). As dynamic LCA scales, cloud- and edge-computing architectures become essential to manage data velocity, variety, and volume while maintaining data provenance and auditable results (Rödger *et al.*, 2020). The combination of dynamic LCA with intelligent product concepts and cross-domain interoperability frameworks also supports scenario testing and prescriptive guidance that align environmental outcomes with cost and performance targets in near real time (Turner *et al.*, 2022). Together, these advances position dynamic, real-time LCA as a core capability for moving life-cycle thinking from episodic reporting toward ongoing, network-aware sustainability management in digitally managed factories (Ingemarsdotter *et al.*, 2021; Rödger *et al.*, 2020; Turner *et al.*, 2022).

The comparative plot in Fig. 3 demonstrates that dynamic LCA consistently outperforms static approaches in timeliness, decision support, and network visibility, while increasing computational demand. It visually reinforces the manuscript's central thesis that sustainability assessment must operate at the tempo of digitally managed factories.

Integrating Sustainability KPIs with Digital Control Loops

Embedding LCA-driven sustainability KPIs directly into factory control loops requires a digitally enabled framework where KPIs are defined, measured in real time, and acted upon alongside productivity and cost objectives. Real-time, KPI-driven feedback supports proactive management of environmental performance, enabled by dynamic LCA that continuously updates inventories and impacts as operations evolve, rather than relying on static snapshots (Nwamekwe *et al.*, 2025g). Integrating LCA into design-for-sustainability workflows, illustrated in additive manufacturing contexts and other production sectors, provides a blueprint for translating life cycle considerations into actionable control signals that guide material choices, process settings, and end-of-life planning from the earliest stages. Achieving seamless KPI integration also rests on harmonized data semantics and interoperable data models that span design, manufacturing, and service, aided by ontology-based digital twin representations and cross-domain standards to ensure consistent KPI calculations across domains (Brundage *et al.*, 2018).

Beyond data models, realizing KPI-driven control requires governance mechanisms and standardized data exchange to achieve auditable, network-wide environmental accounting. Ontology-based modelling and digital-twin architectures can bridge LCA data streams with MBSE and PLM workflows, enabling KPI-informed decision-making that respects both environmental and operational constraints (Brundage *et al.*, 2018). Standards-oriented LCI data models support cross-site comparability and reuse of LCAs within digital factories, reducing fragmentation as KPIs move from single-facility assessments to network-level performance dashboards (Brundage *et al.*, 2018). Empirical work on KPI frameworks for sustainability monitoring in manufacturing further demonstrates how well-defined indicators can drive performance improvements when embedded in daily operations and continuous improvement cycles (Nwamekwe *et al.*, 2025f), while additive manufacturing (AM)- and LCA-focused studies illustrate the economic and environmental benefits of integrating lifecycle insights into ongoing production decisions (Igbokwe *et al.*, 2024). Collectively, these elements chart a path toward a practical, scalable LCA-enabled control loop that aligns environmental outcomes with production efficiency and cost-effectiveness (Nwamekwe *et al.*, 2025f; Brundage *et al.*, 2018).

Multi-Stakeholder Considerations

Any digital LCA framework must account for diverse stakeholders, including suppliers, regulators, and consumers, ensuring transparency and accountability across the value chain (Greif *et al.*, 2024). The integration of knowledge-graph–based data architectures enable the federation of heterogeneous data sources from multiple actors, supporting transparent, evidence-based sustainability decisions across organizational boundaries (Greif *et al.*, 2024). Blockchain-enabled LCA approaches further enhance trust by providing auditable provenance of inputs, transformations, and emissions throughout the supply network, addressing governance and compliance concerns raised by regulators and stakeholders alike (Nwamekwe *et al.*, 2025i). In parallel, multi-echelon supply chains benefit from distributed, verifiable LCA data and governance mechanisms that promote consistent environmental accounting across levels of the network, thereby strengthening the credibility of sustainability reports and stakeholder dialogues (Asif and Gill, 2022). Empirical work on Industry 4.0 deployments such as dynamic organizational LCA across multiple plants, demonstrates the necessity of cross-organizational data-sharing and coordinated stewardship to realize network-wide environmental insights (Cucchi *et al.*, 2022), underscoring the role of governance in multi-stakeholder LCA adoption (Truant *et al.*, 2024).

To operationalize these multi-stakeholder aspirations, standardization and semantic interoperability are essential. Ontology-driven models and cognitive digital-twin frameworks offer concrete pathways to harmonize data semantics across design, manufacturing, and service domains, enabling cross-domain KPI calculations and auditable data exchanges (Truant *et al.*, 2024). Standards-based LCI data models provide reusable foundations for multi-site data exchange, supporting comparability and rapid scaling from single facilities to network-wide ecosystems (Truant *et al.*, 2024). Aligning governance with MBSE/PLM workflows ensures that sustainability KPIs are integrated into decision-making processes that involve suppliers, regulators, and end-users, fulfilling Industry 5.0 objectives that couple human-centric oversight with digital transparency (Truant *et al.*, 2024). Collectively, these approaches pave a practical route toward a truly multi-stakeholder LCA framework that maintains transparency, accountability, and cross-domain interoperability as digitally managed factories expand across value chains (Greif *et al.*, 2024).

FUTURE DIRECTIONS AND RESEARCH OPPORTUNITIES

Autonomous LCA: AI-Driven Continuous Impact Monitoring

Future frameworks could leverage AI to autonomously track and optimize environmental performance without human intervention, drawing on AI-enabled diagnostic signals and intelligent modelling. AI-driven LCA would ingest real-time data streams from sensors and digital twins, enabling ongoing updates to inventories and impact indicators and supporting proactive sustainability management rather than periodic reporting. Early demonstrations of dynamic, network-spanning LCA within Industry 4.0 settings show how autonomous monitoring and scenario analysis can be executed across multiple plants with minimal manual input, highlighting a clear pathway toward near-real-time, AI-assisted decision making in manufacturing ecosystems.

Realizing autonomous LCA requires robust data governance, interoperable data exchanges, and trustworthy provenance across supply chains. Ontology- and semantic-enabled data integration, facilitated by real-time linked data and cross-domain LCI data infrastructures remains essential to scale AI-driven LCA across design, production, and distribution networks (Nwamekwe and Chikwendu, 2025). Blockchain-enabled LCA approaches further strengthen trust by providing auditable input and transformation records across heterogeneous actors, addressing governance and compliance concerns for regulators and stakeholders. Collectively, these capabilities point to a future where AI not only forecasts environmental impacts but also autonomously prescribes actions at the system level, linking design choices, process configurations, and supply-chain decisions to sustainable outcomes in digitally managed factories (Nwamekwe and Chikwendu, 2025).

Blockchain for Transparent and Verifiable Life-Cycle Data

Blockchain technology offers secure, tamper-proof data exchange that addresses trust and transparency issues across supply chains, making it a foundational enabler for transparent LCA data in digitally managed factories. When combined with LCA in industrial networks, blockchain provides auditable provenance of inputs, transformations, and emissions, strengthening governance and compliance for cross-organizational reporting (Nwamekwe *et al.*, 2025i). Furthermore, multi-echelon supply chains can benefit from distributed, verifiable LCA data and governance mechanisms that promote consistent environmental accounting across levels, thereby supporting credible sustainability claims and stakeholder dialogue (Asif and Gill, 2022; Truant *et al.*, 2024). Beyond data integrity, knowledge-graph–based data federation can be used to harmonize disparate data sources and facilitate cross-domain KPI calculations, enabling scalable, cross-firm LCA that still preserves data provenance (Greif *et al.*, 2024). Collectively, these approaches point toward a future where blockchain-enabled LCA underpins trust, traceability, and collaborative decision-making across manufacturing ecosystems (Asif and Gill, 2022; Cucchi *et al.*, 2022).

To operationalize blockchain-enabled transparency, standardization and interoperability are essential. Ontology-driven data models and semantic interoperability can align LCA data semantics with digital twin and MBSE representations, enabling auditable exchanges across design, production, and service domains (Greif *et al.*, 2024; Cucchi *et al.*, 2022). Blockchain-enabled LCA thus benefits from standardized data schemas and governance frameworks that support regulatory reporting while maintaining flexibility to accommodate diverse business models and geographies (Truant *et al.*, 2024). As Industry 4.0 deployments expand, collaborative governance, encompassing suppliers, regulators, and customers will be critical to realize the full potential of blockchain for verifiable life-cycle data, ensuring that network-wide LCA remains credible, comparable, and actionably integrated into decision-making (Nwamekwe *et al.*, 2025i; Asif and Gill, 2022; Truant *et al.*, 2024).

Circular Economy Integration in Digitally Managed Factories

Digital factories provide an effective platform to operationalize circular economy principles, enabling closed-loop material flows supported by real-time LCA. The integration of digital twins and dynamic LCA facilitates continuous monitoring and flexible reconfiguration of product lifecycles, promoting strategies for reuse, remanufacturing, and recycling as conditions evolve on the production floor and within supply chains (Onyeka *et al.*, 2024). Conceptual and empirical research suggests that multiscale digital twin architectures can support real-time representation of material streams, energy flows, and end-of-life options, thereby advancing circular decision-making across design, manufacturing, and service stages (Luo, 2025). The data framework for such closed-loop operations is bolstered by cloud-enabled, real-time data pipelines and Internet of Things (IoT) ecosystems that provide the necessary end-to-end traceability and inventory updates for circularity assessments, production planning, and supplier collaboration in Industry 4.0 environments (Chidiebube *et al.*, 2025).

To further advance circular economy integration in digitally managed factories, future research should focus on translating circularity objectives into operational controls and governance that encompass multiple locations and partners. This includes developing standardized data models and interoperable LCI data infrastructures that enable cross-firm, network-wide circularity KPIs, supported by digital twin-informed feedback loops and MBSE and PLM integration (Vitalis *et al.*, 2024). Empirical studies and conceptual frameworks suggest that scalable circular strategies such as remanufacturing, material reuse, and modular design can be effectively implemented when LCA insights are incorporated into production scheduling, procurement, and end-of-life planning within a digitally interconnected ecosystem (Onyeka *et al.*, 2024; Luo, 2025). As Industry 4.0 technologies continue to grow, achieving synergy between circular economy goals and real-time LCA, shared data governance, and cross-domain interoperability will be crucial for realizing resilient and sustainable manufacturing networks (Vitalis *et al.*, 2024).

Policy and Standards Development for Digital LCA Adoption

Policy frameworks and international standards must evolve to accommodate the integration of digital data flows into LCA methodologies, enabling consistent, auditable, and scalable lifecycle analyses across factories and networks (Muiña *et al.*, 2018; Židek *et al.*, 2020; Mügge *et al.*, 2024). While foundational standards such as ISO 14040/44 remain essential for guiding LCA practice, they do not fully address real-time data exchange, data provenance, or cross-domain interoperability inherent in digitally enabled manufacturing ecosystems, highlighting a clear need for updated guidance and harmonization with digital twin architectures and MBSE/PLM workflows (Al-Ali *et al.*, 2018; Xie *et al.*, 2021; Ramírez-Márquez *et al.*, 2024). Initiatives that embed blockchain-based provenance and knowledge-graph data federation demonstrate how governance, traceability, and multi-actor accountability can be achieved in practice, informing policy developments and compliance requirements across global supply chains (Mügge *et al.*, 2024; Muiña *et al.*, 2018). Empirical work on dynamic organizational LCA and cross-enterprise data-sharing further illustrates the policy-relevant challenges and opportunities of scaling LCA from single facilities to networked ecosystems (Židek *et al.*, 2020; Ramírez-Márquez *et al.*, 2024).

To translate these insights into action, policy and standards development should advance ontologies, semantic interoperability, and standardized LCI data models that span design, manufacturing, and service domains. Ontology-based modelling for digital twins and cognitive DTs offers concrete pathways to harmonize data semantics and enable cross-domain KPI calculations, while standards-backed LCI data schemas support reusable, cross-site data exchange and comparability across firms and geographies (Cucchi *et al.*, 2022; Xie *et al.*, 2021; Ramírez-Márquez *et al.*, 2024). Governance structures integrating MBSE/PLM with LCA data streams can align sustainability KPIs with everyday decision-making, reflecting Industry 5.0 principles that couple human oversight with digital transparency (Xie *et al.*, 2021). Collectively, these directions point toward a policy and standards landscape that sustains transparency, accountability, and interoperability as digital LCA becomes embedded in multi-factory manufacturing networks (Židek *et al.*, 2020; Mügge *et al.*, 2024; Cucchi *et al.*, 2022).

CONCLUSION

Summary of Key Insights

Life-Cycle Assessment in manufacturing remains anchored in ISO 14040 and ISO 14044, with four stages, goal and scope definition, life cycle inventory, impact assessment, and interpretation. Traditional practice relies on historical and secondary datasets, so outputs arrive late for operational control. Digitally managed factories generate continuous data streams through IoT, enterprise systems, cyber-physical systems, and digital twins. This evidence base positions LCA as an operational analytics layer within production and supply networks. The manuscript shows three consistent application levels. Process-level assessment targets energy use, waste streams, and emissions using sensor-driven inventories. Product-level assessment embeds LCA into digital prototyping and design iteration, including end-of-life scenario evaluation. System-level assessment extends lifecycle accounting across suppliers, logistics, and customers, strengthened by traceable data exchange. Dynamic LCA updates align with factory tempo, with inventory and impact refresh cycles reported on hourly to daily windows in digital platforms described in the cited literature.

Contributions to Sustainable Manufacturing Research

The manuscript consolidates a structured linkage between LCA stages and the digital stack required for each stage. Cloud platforms and data governance structures strengthen goal and scope control and boundary management. IoT sensing, ERP, and MES streams improve life cycle inventory granularity and timeliness. Digital twins and simulation engines strengthen impact scenario evaluation. Decision dashboards and provenance mechanisms strengthen interpretation and accountability across stakeholders. The work also clarifies the main barriers that limit credible deployment. Data quality, heterogeneity, and interoperability risks weaken inventory credibility across suppliers and machines. Computational load grows when high-resolution dynamic inventories run continuously across networks. Standardization gaps persist because ISO 14040 and ISO 14044 do not specify real-time data semantics for digital flows, while ISO 23247 focuses on digital twin architecture without harmonizing LCA inventory semantics. Adoption barriers remain rooted in governance, skills, and cultural readiness, so technical integration alone does not deliver sustained practice. These contributions strengthen sustainable manufacturing research by setting clear design requirements for real-time, scalable, interoperable, and auditable LCA operations in digitally managed factories.

Final Reflections

Net-zero strategies in digital factories require lifecycle thinking embedded in daily decisions and long-horizon planning. Dynamic LCA linked to IoT, digital twins, and cloud analytics shifts sustainability from periodic reporting toward continuous management. Auditable provenance strengthens trust across multi-stakeholder networks, including suppliers and regulators, and improves emissions accounting and disclosure. Standardized data models, semantic interoperability, and governance rules should anchor implementation so results remain comparable across sites and over time. The manuscript positions digitally enabled LCA as a practical pathway for transparent sustainability control, resilient operations, and accountable decision-making across process, product, and system levels.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

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