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From Data to Impact: Automating Product Carbon Footprint Assessment through Integrated AI-ERP-LCA Systems

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Abstract

The growing demand for transparent and auditable environmental reporting, driven by regulatory frameworks like the Corporate Sustainability Reporting Directive (CSRD) and mounting market pressure poses a critical challenge for manufacturers: how to perform rigorous Life Cycle Assessments (LCA) efficiently, accurately, and at scale. Traditional LCA methods remain largely manual, disconnected from day-to-day operations, and unfit for organizations managing extensive product portfolios. This paper presents an innovative framework that transforms LCA into a dynamic, automated, and scalable process by integrating four key pillars: internal ERP data streams, scientific databases (e.g., Ecoinvent), ISO standards (14040, 14067), and Product Category Rules (PCRs). At the core of this system lies an artificial intelligence engine that orchestrates data processing, harmonization, and interpretation. The engine leverages AI for: (1) Intelligent data mapping, using NLP to translate unstructured ERP product data into standardized LCA inputs; (2) Data quality assurance, detecting anomalies and inconsistencies in real-time production data; (3) Predictive analytics, forecasting the environmental footprint of new product designs, enabling proactive eco-design strategies. Implemented in the plastic packaging sector, this AI-enhanced model enables cradle-to-gate Product Carbon Footprint (PCF) assessments with minimal manual intervention, aligning with both ISO and GHG Protocol standards. Results demonstrate how automation not only accelerates analysis but also improves data reliability and transparency, empowering organizations to integrate LCA into operational and strategic workflows. The proposed solution marks a paradigm shift: from static, expert-driven assessments to a self-adaptive system capable of supporting autonomous sustainability reporting and real-time decision-making. This approach paves the way toward embedding cognitive environmental intelligence into the digital backbone of manufacturing enterprises.

Keywords: "AI-enhanced LCA; ERP integration; Product Carbon Footprint"

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1. Introduction

Manufacturers face increasing regulatory and market pressures for transparent, auditable environmental reporting on a scale. The Corporate Sustainability Reporting Directive (CSRD) [1] and similar frameworks demand comprehensive product footprint data, while consumers and stakeholders expect verifiable sustainability claims. Life Cycle Assessment (LCA), standardized by ISO 14040 [2] and ISO 14067 [3] provides the methodological foundation for quantifying environmental impacts. However, traditional LCA workflows remain largely manual, time-intensive, and disconnected from operational data systems, limiting their integration into strategic decision-making processes [4].

Current LCA practice faces three barriers: (i) inefficient data collection requiring manual extraction from multiple

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sources; (ii) static assessment approaches that prevent real-time performance optimization; (iii) scalability constraints that limit portfolio-wide analysis and systematic hotspot identification [5].

Digital transformation in manufacturing creates new opportunities to address these constraints through Industry 4.0 technologies. Ferrari et al. [6] demonstrate that integrating Enterprise Resource Planning (ERP) systems with LCA tools enables dynamic environmental monitoring through real-time data streams. Their ceramic tile case study shows how automated LCI updates from production systems eliminate manual data entry while maintaining methodological rigor. Similarly, Piron et al. [7] identify Industry 4.0 technologies as "assets for the life cycle inventory," enabling continuous environmental assessment through IoT sensors and digital manufacturing systems.

Artificial intelligence applications in sustainability assessment are emerging as a transformative approach. Recent advances in natural language processing enable automated mapping between unstructured corporate data and standardized LCA databases. Balaji [8] demonstrates AI-assisted emission factor selection for LCA with 86.9% precision in fully automated mode, significantly reducing expert time requirements. Machine learning algorithms show promise for supporting LCA decision-making through predictive analytics and scenario optimization [9]. However, current AI applications focus primarily on data processing rather than end-to-end workflow automation. While digital LCA, AI for sustainability, and ERP integration are active research areas, they remain largely parallel development streams. Missing is a holistic framework that synergistically combines these approaches into a standards-compliant, fully automated LCA pipeline. Existing automation efforts concentrate on Life Cycle Inventory (LCI) data collection but neglect interpretation, quality assurance, and predictive capabilities that AI enables [10].

This paper addresses these gaps by presenting an AI-enhanced framework that automates end-to-end Product Carbon Footprint (PCF) calculation through integration of four data pillars: ERP streams, scientific LCI databases, ISO methodological rules, and Product Category Rules (PCRs). The framework embeds standards compliance into intelligent algorithms for data mapping, quality assurance, and scenario analytics.

The main contributions are: (i) a cognitive architecture for automated, traceable LCA workflows; (ii) intelligent data mapping from corporate to standardized inputs; (iii) validation in rigid plastic packaging showing major efficiency gains with ISO compliance; and (iv) demonstration of LCA's evolution toward continuous decision support.

2. Literature background

Digitalization is transforming LCA into a dynamic, integrated process, and automation accelerates evaluations, improves accuracy, and reduces human error [11][12].

Main innovation areas include: (i) automated data collection through integration of LCA with ERP and Manufacturing Execution System - MES; (ii) access to real-time primary data via sensors and cloud platforms; (iii) design tools that generate eco-design alternatives with preliminary impact data.

AI enables real-time optimization of manufacturing by reducing energy use, minimizing waste, optimizing supply chains, and supporting predictive maintenance [13]. It also facilitates ESG data analysis for sustainability reporting and CSRD compliance. Within this domain, Natural Language Processing (NLP) [14] can analyze unstructured documents to extract ESG insights and ensure data quality, demonstrating AI's ability to optimize both processes and data interpretation.

Integrating ERP and MES data makes LCA analyses more accurate and representative by using primary data on materials, energy, and logistics. APIs enable continuous data flows [15], but implementations remain partial and rarely support dynamic or real-time decision-making.

A significant gap emerges: LCA digitalization, AI for sustainability, and ERP integration are often treated as separate research streams, lacking a holistic operational framework [16]. Current automation focuses on the LCI phase, while AI targets isolated optimizations and ERP integration is often limited to simple data extraction instead of dynamic analysis.

The framework developed in this work addresses this gap by going beyond data collection automation and combining the three identified pillars: it automates the entire LCA workflow from product identification via a simple code to the generation of graphical and numerical reports including the interpretation phase; it employs intelligent logic, akin to an AI engine, to automatically map heterogeneous corporate data sources (BOMs, process parameters, logistics data from SAP and internal systems) into consistent LCA model inputs; it implements a backward modeling approach that reconstructs the entire life cycle retrospectively from the finished product, enabling advanced automation; and it provides a dynamic "what-if" scenario simulation tool, transforming LCA from a post-hoc reporting instrument into a strategic decision-support system for eco-design and product innovation [17].

3. The proposed AI-enhanced framework

To address the gaps identified in the state of the art, we propose an AI-enhanced framework designed to automate the end-to-end process of Product Carbon Footprint (PCF) calculation. By integrating real-time corporate data, scientific databases, and regulatory standards through an intelligent engine, the framework transforms the traditional, static LCA into a dynamic, strategic decision-support tool. Its architecture is built around a central AI Engine that processes and synthesizes information from four foundational data pillars: ERP data streams, providing live inputs from corporate systems such as SAP and MES; scientific databases, supplying curated LCI datasets such as Ecoinvent; ISO standards, embedding methodological rules from ISO 14040 and ISO 14067; and Product Category Rules (PCRs), offering sector-specific LCA guidelines. These inputs converge in the AI Engine, which performs data mapping, quality assurance, calculation, and predictive analysis, producing actionable outputs including detailed PCF calculations, automated numerical and graphical reports, and comparative "what-if" scenario analyses. The framework connects directly to corporate information systems to extract primary, activity-specific data in real time, eliminating manual entry and ensuring that analyses reflect current operational conditions. Key extracted data include the Bill of Materials (BOM) with product code, weight, and precise composition (e.g., resin type such as HDPE or PET, masterbatches, and virgin/recycled content percentages); work cycles and process data detailing the manufacturing plant, production technology (e.g., Extrusion Blow Molding – EBM, Injection Stretch Blow Molding – ISBM), and energy consumption coefficients (kWh per kg of processed resin) for each line; and logistics and purchasing data covering supplier locations, transport modes (truck, ship, rail), and packaging formats (e.g., big bags, 25 kg sacks) to calculate upstream transport and packaging impacts. For materials and energy flows lacking primary data, the framework integrates internationally recognized LCI databases, with Ecoinvent selected for its comprehensive scope, high granularity, and global acceptance, enabling the selection of geographically and technologically specific emission factors (e.g., electricity mix of a supplier's country). Methodological rigor and compliance are ensured by encoding ISO standards and PCRs directly into the calculation logic. At its core, the AI Engine addresses the challenge of bridging unstructured corporate data and the structured format required for LCA modeling through an intelligent mapping system akin to a domain-specific NLP model: upon receiving a product code, it retrieves the associated BOM and logistics data from the ERP, translates unstructured or semi-structured fields into standardized LCA flows, and cross-references contextual information, such as supplier country, to select the most appropriate datasets from Ecoinvent.

This process automates the traditionally manual and error-prone task of interpreting and classifying thousands of data points, ensuring standardized, replicable, and traceable process flows. A Data Quality Assurance module further safeguards the reliability of PCF results. The framework's primary objective is to shift LCA from a retrospective reporting tool to a predictive design instrument, currently achieved through deterministic scenario modeling that allows users to instantly assess the environmental impact of design changes, such as increasing recycled content from 25% to 75% or relocating production to a plant powered entirely by renewable energy, with real-time recalculation of the PCF. Future developments include a predictive analytics module leveraging historical calculations and scenario simulations to train regression models capable of estimating the environmental impact of novel materials or processes lacking LCI data, based on their technical characteristics, thereby providing valuable guidance in the earliest stages of R&D. Figure 1 provides a schematical representation of the proposed methodology.

The proposed AI-enhanced LCA system features a modular architecture comprising interconnected blocks that manage data acquisition, processing, and analysis across the workflow.

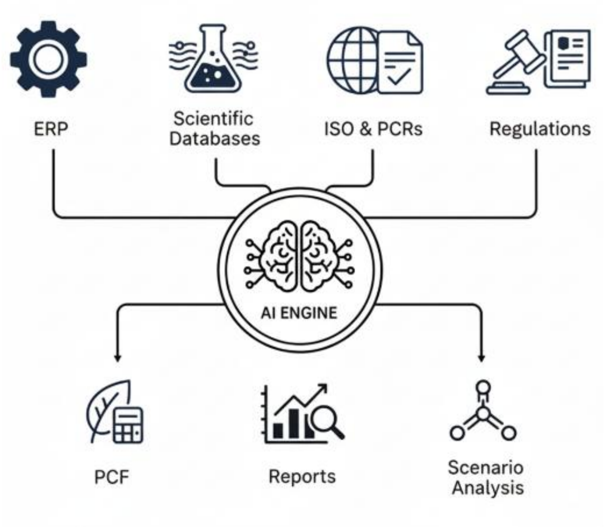

Figure 1: Conceptual diagram of architecture.

(i) Data Ingestion Module acquires product, process, and logistics information from ERP and external sources via standardized APIs, extracting Bills of Materials (BOM), manufacturing parameters, and logistics data according to a unified schema. (ii) Normalization and Preprocessing harmonize inputs by resolving inconsistencies in units, nomenclature, and structure, enabling automated downstream mapping. (iii) AI Engine (NLP/LLM Mapping) interprets normalized ERP data using tailored natural language and large language model algorithms, classifying items and linking them to the most relevant LCI datasets (e.g., Ecoinvent). (iv) Data Quality Assurance applies rule-based logic to validate mappings, detect anomalies, and flag uncertain items for manual review, ensuring reliability and traceability. (v) LCA Calculation Engine aggregates verified data and performs ISO 14040/14067-compliant impact calculations (e.g., GWP), either through integration with LCA tools (SimaPro, GaBi, openLCA) or via native computation modules. (vi) Reporting and Traceability generate standardized outputs with complete data provenance, linking results to their original ERP records and LCI mappings for use in sustainability reporting, decision-making, and audits.

4. Case study

For validation of the proposed methodology, the rigid plastic packaging sector for Fast-Moving Consumer Goods (FMCG) was selected, characterized by high product variety (hundreds to thousands of Stock Keeping Units - SKUs), multiple polymers (HDPE, PET, r-HDPE, r-PET), heterogeneous process technologies (Extrusion Blow Molding - EBM, Injection Stretch Blow Molding - ISBM) across internationally distributed plants, and upstream variability in supplier geography, logistics modes, and inbound packaging formats, with BOM-level differences in recycled content and masterbatch composition. In line with current PCF practice for polymers and packaging, the declared scope focuses on cradle-to-gate (Modules A1–A3, as indicated in the PCR

2019:13, Version: 1.1.3), covering raw material acquisition and production, inbound transport, and manufacturing at the factory gate, while excluding downstream use and end-of-life, as commonly applied in polymer and packaging PCFs and templates (e.g., plastic bottle cradle-to-gate process maps). The sector's methodological heterogeneity in LCAs further underscores the need for automated, standards-aligned data handling to ensure comparability and manage complexity at scale.

The framework was deployed to compute cradle-to-gate PCFs conformant with ISO 14067, consistent with the ISO 14040/44 structure, and aligned with GHG Protocol Product Standard conventions, adopting PCR guidance for packaging (declared unit, A1–A3 scope) to ensure comparability and completeness in upstream and core stages (resins, masterbatch, secondary packaging, inbound logistics, electricity, and process operations). Methodological implementation followed the standard LCA phases: goal and scope definition (declared unit per bottle and per kg resin, A1–A3), LCI compilation (ERP-sourced BOM, energy, transport, packaging mapped to LCI datasets), LCIA (GWP100), and interpretation (hotspots, sensitivity, data quality, uncertainty), in line with ISO/PCF exemplars for polymer and bottle footprints and guidance for cradle-to-gate inventories. The ruleset codified system boundaries, functional/declared unit, allocation, data quality, and cut-offs consistent with packaging PCR logic, aligning with mainstream PCF frameworks for supplier-facing cradle-to-gate inventories.

End-to-end LCA lead time per product fell from about three weeks, previously requiring manual data collection, spreadsheet assembly, and review, to roughly four hours through automated ERP data ingestion, dataset matching, and standardized reporting. This time compression mirrors results observed in large-scale polymer and bottle studies adopting automated cradle-to-gate PCFs with pre-encoded rules and inventories. The full portfolio (~1,500 SKUs) completed in approximately 72 hours of unattended batch processing, enabling portfolio-level analysis previously infeasible with manual workflows, consistent with throughput gains reported in standardized cradle-to-gate pipelines across polymer and packaging sectors. Automated validation and dataset mapping reduced manual entry errors by about 95%, replacing spreadsheet hand-offs with ERP-driven inventories, structured transport and packaging logic, and consistent LCI dataset selection (e.g., electricity mix, supplier-region resin production), aligning with quality improvements seen in system-integrated PCF data flows.

An internal benchmarking analysis demonstrated that the implementation of automated validations and dataset mapping reduced manual data entry errors by approximately 95%. By comparing PCF studies conducted using manual, spreadsheet-based workflows with those processed through an automated, ERP-integrated system across a portfolio of 1,500 SKUs, audit trails revealed a substantial decline in recorded errors. To ensure the reliability of the automated procedures, a multi-layered validation framework was established: a Data Quality Assurance module performs systematic cross-checks between ERP/BOM data and LCI datasets, verifying consistency in material types, geographic origins, and process steps; all data transformations and mapping results remain fully traceable; and any anomalies detected during the mapping phase are flagged for manual review. This hybrid approach, combining NLP-based automated mapping with rule-based validation and human oversight, minimizes the risk of factual errors and ensures high-fidelity alignment between BOM records and the corresponding LCI datasets.

To address the challenge of mapping LCI datasets to BOM entries, particularly in cases requiring proxy datasets, a quality and confidence reporting mechanism was integrated into the framework. Each automated mapping is assigned a confidence rating based on the degree of correspondence between BOM attributes and candidate LCI dataset characteristics: direct matches are classified as "high confidence", whereas mappings involving assumptions, proxies, or incomplete data are labelled "low confidence" or "ambiguous". Confidence ratings are aggregated across products and portfolios to quantify the proportion of robust versus uncertain mappings, while all ambiguous cases are tracked, reported, and manually reviewed prior to inclusion in final results. To prevent factual inaccuracies or "hallucinated" outputs from LLMs, the system combines automated mapping with rule-based verification and expert oversight, ensuring that low-confidence results undergo additional validation. This multi-tiered safeguard preserves methodological rigor and transparency in automated LCA reporting.

The AI-enhanced LCA framework was implemented using an open-source, transformer-based large language model fine-tuned for manufacturing and LCA applications. This model was further adapted with a custom dataset comprising anonymized ERP records, Ecoinvent LCI process descriptions, ISO standards, and historical mapping logs, enabling precise classification and mapping of technical product data and seamless integration with manufacturing datasets. The data pipeline interfaced directly with SAP ERP systems through secure APIs to access real-time product and process data, while LCI datasets from Ecoinvent were retrieved using standardized queries and AI-encoded mapping rules. All data exchanges were managed through controlled middleware to ensure synchronization and traceable provenance. The workflow was structured into five distinct stages: (1) ERP data extraction and normalization, (2) AI-based LCI mapping, (3) automated quality and confidence checks, (4) life cycle impact calculation per ISO 14067, and (5) aggregation, auditing, and reporting, allowing transparent, stepwise validation and targeted human oversight in cases of ambiguity. Designed for replicability and interoperability, the framework's workflow and prompt templates are available upon request and can be readily extended to other sectors and data sources.

The workflow for deriving and analyzing the case study scenario is predominantly automated. All data extraction from ERP systems, normalization, and mapping of BOM entries to LCI datasets are performed by the AI engine using trained natural language processing and rule-based routines. Quality checks, dataset mappings, life cycle impact calculations, and initial report generation also proceed without human intervention. However, human decision-making is incorporated at specific control points: any BOM-LCI mappings flagged as ambiguous or low-confidence by the AI or quality assurance module are reviewed and validated manually by a domain expert before final results are approved. Additionally, scenario interpretation and the configuration of methodological parameters (such as system boundaries, allocation logic, or scenario simulations) may require expert input. This hybrid approach ensures the completeness, reliability, and auditability of both automated and human-overseen steps in the assessment process.

All results were generated under an ISO 14067-compatible workflow (Goal/Scope–LCI–LCIA–Interpretation), with cradle-to-gate boundaries and GWP100 as per polymer/bottle PCF exemplars, aligning with specifications for product-level cradle-to-gate footprints and inventory inclusions.

Traceability was ensured by enabling each impact contribution to be traced back to its originating record (e.g., resin line in BOM with supplier country, packaging type and mass per inbound unit, transport distance and mode, plant electricity factor by location), allowing one-click provenance checks to ERP fields and mapped LCI datasets. This mirrors best-practice polymer/bottle PCF templates that document data lineage per stage, ensuring audit-readiness and transparency for external requests. Results were structured by stage (A1 raw materials, A2 inbound logistics, A3 manufacturing), with sensitivity assessments comparing dataset selections (e.g., Ecoinvent vs alternative baselines), consistent with comparative guideline reviews in plastic packaging LCAs that emphasize harmonized disclosures and stage-wise clarity.

Upstream material production dominated GWP (>70% typical for polymers), with process energy and logistics varying by geography and transport mode. The system identified key drivers, virgin vs. recycled content, supplier region, and secondary packaging format, consistent with polymer PCF case patterns. Replacing virgin HDPE with r-HDPE reduced cradle-to-gate PCF by ~15% for low substitution levels, with larger gains at higher recycled shares. Plant energy mix further amplified reductions, confirming that combining recycled content with renewable electricity significantly lowers GWP. Parametric "what-if" models (e.g., weight reduction, masterbatch change, transport shift, renewable energy use [18]) quantified product- and portfolio-level impacts, enabling eco-design trade-offs aligned with comparative packaging LCA guidance.

For a 1,000 ml HDPE bottle (declared per bottle), Stage A1 covers resin inputs, virgin and recycled, sourced from the BOM and linked to regional LCI datasets. Masterbatch emissions are applied by mass fraction, and secondary packaging for inbound materials (e.g., big bags vs. 25 kg sacks) is included. All data reference ERP item records and purchasing fields. Stage A2 includes inbound transport, modeled by distance and mode (truck, ship, rail) from supplier to plant using t·km factors, in line with cradle-to-gate transport conventions. Distances and modes are derived from ERP supplier locations and logistics master data. Stage A3 accounts for plant energy use by technology (kWh/kg), applying the national electricity mix. Energy coefficients come from metering dashboards and production logs, with records linked to plant and period per cradle-to-gate manufacturing scope.

The framework generates per-stage results and totals, including dataset IDs, key assumptions (allocation, cut-offs), and the declared unit, structured according to ISO sections (Goal & Scope, LCI, LCIA, Interpretation) and PCR-aligned boundary definitions. Outputs are ready for internal or external review and for standardized data exchange (e.g., supplier or customer PCF requests), consistent with current cradle-to-gate PCF guidance for chemicals and packaging. Overall, the results show that an AI-enabled, standards-based, ERP-integrated cradle-to-gate PCF pipeline can significantly improve efficiency and data quality while preserving the transparency and comparability expected in polymer and packaging applications, in full alignment with sectoral methods and supplier PCF templates.

5. Discussion

The results mark a major shift in how product Footprints are generated and used, with dramatic improvements in speed and reliability. LCA evolves from a periodic, retrospective report into a continuous, embedded decision-support tool within engineering and procurement workflows. Efficiency gains, cutting study times from weeks to hours, and reduced manual errors allow frequent recalculations as inputs change (e.g., supplier, plant, energy mix), enabling agile decision-making. Teams can now compare options in near real time, quantify trade-offs, and implement eco-design gates without the high costs of traditional portfolio-wide analyses.

This framework goes beyond data automation, establishing a "cognitive" LCA system that learns and adapts by linking data, models, and decisions. It transforms static models into living inventories through real-time connections to product structures and operations, ensuring data remain current. Encoded standards and intelligent mapping replace expert bottlenecks with guided intelligence, automating routine tasks. Batch processing and integrated quality checks shift the focus from one-off studies to portfolio-level orchestration, enabling consistent footprint metrics across functions. Finally, scenario modeling evolves descriptive analytics into prescriptive design, supporting proactive eco-design and supplier engagement.

LCA becomes an active system for decarbonization, continuously ingesting data, enforcing standards, detecting anomalies, and delivering actionable insights at both product and portfolio levels. Decision latency shrinks, engineering changes, sourcing events, and plant transfers can be assessed within hours, allowing environmental criteria to influence decisions in real time. Transparent, repeatable pipelines accelerate learning across products, sites, and suppliers. Compliance and risk resilience improve through traceability and rapid updates to reflect changing emission factors and supplier mixes.

However, current limitations exist. The framework has been tested in rigid plastic packaging with specific process families; applying it to other sectors (e.g., metals, electronics) will require adapting templates and datasets. It focuses on cradle-to-gate, excluding downstream phase, which would need additional data models to avoid bias. Dataset gaps remain where supplier-specific data are unavailable, and automated rules cannot fully replace expert judgment in complex cases.

Future enhancements include downstream integration for cradle-to-grave studies, scalable supplier data onboarding, embedded uncertainty and sensitivity analytics, prescriptive multi-objective optimization, and cross-sector template generalization. These will strengthen robustness and broaden applicability across industries and materials. Finally, the method can be integrated with AI-powered patent analysis to support technological forecasting, making LCA more forward-looking, [19], and to identify eco-design solutions that address the environmental challenges revealed by the assessment [20].

6. Conclusion

This work addresses a persistent bottleneck in product sustainability assessments: traditional LCA is slow, manual, error-prone, and backward-looking, which limits its use to occasional reporting rather than continuous decision support. The proposed solution, an AI-enhanced, standards-encoded, ERP-integrated framework, transforms cradle-to-gate PCF computation into an automated, transparent, and scalable pipeline that aligns with ISO 14040/44 and ISO 14067 while operationalizing PCR logic for packaging.

Empirically, the framework delivered step-change improvements: study time compressed from weeks to hours; portfolio-scale analysis executed in days; and manual data entry errors nearly eliminated through automated mapping, validation, and provenance to ERP records; all while preserving auditability and methodological rigor via codified scope, units, boundaries, and dataset selection rules. Strategically, it elevated LCA from a static disclosure to a living decision system that supports eco-design, supplier engagement, and plant operations through rapid “what-if” simulations on levers such as recycled content, energy sourcing, weight reduction, and logistics.

The core contribution is not mere automation but the embedding of compliant methodology into a cognitive pipeline that learns from operational data, maintains up-to-date inventories, enforces data quality, and returns decision-ready insights at product and portfolio levels, turning environmental performance into a controllable, routinely optimized parameter alongside cost, quality, and delivery.

Looking ahead, extending downstream modules (A4–C4, D), scaling supplier-specific primary data onboarding, and adding uncertainty propagation and prescriptive optimization will further strengthen completeness, comparability, and impact, enabling cradle-to-grave decisions and circularity road-mapping under real-world constraints.

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