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From Waste to Wear: A Digital Circular Innovation for Sustainable Industry

by
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Dipartimento di Ingegneria

To my loving parents, husband and kids.

Mizna Rehman

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Ph.D. dissertation presented
for the fulfillment of the Degree of Doctor of Philosophy in Energy
Science and Engineering
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Candidate’s declaration

I hereby declare that the work presented in this dissertation has been carried out independently and constitutes my own original research, submitted in fulfillment of the requirements for the academic degree of Doctor of Philosophy (Ph.D.) in Energy Science and Engineering at the Department Engineering.

All sources of information, data, and ideas drawn from the works of others have been properly cited and acknowledged within the text and in the list of references. No materials other than those specifically indicated have been used in the preparation of this dissertation.

Selected parts of this research have been previously disseminated through publications in international peer-reviewed journals and/or conference proceedings, as detailed in the section listing the author’s publications at the conclusion of this dissertation.

Naples, October 31, 2025

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Summary

Industrial sustainability remains constrained by fragmented data ecosystems and static life-cycle models that fail to connect real-time digital intelligence with circular resource flows. Conventional Life Cycle Assessment (LCA) approaches quantify impacts retrospectively rather than guiding operational decisions. The research responds to the problem of fragmented data architectures and isolated life-cycle models that prevent continuous optimization of energy, material, and environmental performance. It aims to develop a cyber-physical decision framework capable of integrating Artificial Intelligence (AI), Internet of Things (IoT), Blockchain, and Digital Twin technologies into a unified control architecture that enables cross-sector sustainability governance and transforms sustainability indicators into controllable variables through digital-twin intelligence, integrating circular economy principles directly within production and logistics systems.

The central research question guiding this work is how these digital technologies can be systematically integrated with circular-economy analytics to achieve real-time, adaptive optimization of sustainability performance across industrial symbiosis networks. Methodologically, the study adopts a hybrid, multi-layered approach beginning with the Hybrid Decision-Support Framework (HDSF), which fuses Analytic Hierarchy Process (AHP), Machine Learning (ML), and IoT-based data streams to identify, prioritize, and quantify sustainability variables. This analytical layer feeds into a Triple Life Cycle Assessment (LCA, LCC, SLCA) model applied to the coffee supply chain, forming the multi-dimensional sustainability baseline of the research. The optimization layer combines Physical Internet (PI), Multi-Agent Systems (MAS), and AI-driven predictive control for logistics and production efficiency, while a digitalization layer built on Blockchain, RFID, and mobile traceability ensures transparent and verifiable data governance. The validated system is extended through Waste Flow Mapping (WFM) and Key Performance Indicator (KPI) analytics to demonstrate industrial symbiosis between the coffee and textile sectors, culminating in a federated Digital Twin that integrates Sustainability Efficiency Index (SEI) computation and feedback-based optimization aligned with ISO 14001, ISO 50001, and UN SDGs 9, 12, and 13. Empirical validation confirms that the DigiCircular Twin-Transition (DT²) model achieves approximately 30% reduction in overall environmental footprint, 18% lower energy use, and 17% less water consumption, with resource efficiency gains of 25–30% and an estimated 38% increase in return on investment (ROI) over a decade of adoption. The results demonstrate that the DT² framework transforms sustainability from a static indicator into a dynamic control parameter within industrial operations, offering a reproducible and policy-ready mechanism for implementing the digital–green twin transition envisioned by Industry 5.0. Nonetheless, full-scale deployment depends on the availability of high-quality, interoperable datasets and cloud infrastructure for real-time monitoring. Social LCA components remain partially qualitative, requiring broader regional datasets for full automation. Simulation environments were validated in controlled industrial pilots rather than multi-plant scale. Future research should extend federated digital twins across additional sectors such as biopolymers, construction, and packaging, enhance AI-based uncertainty modeling, and embed regulatory compliance and carbon-credit monitoring into the SEI for autonomous sustainability governance.

Keywords: Digital-Circular Integration; Cyber-Physical Systems; Twin Transition; Hybrid Decision-Support Framework (HDSF); Artificial Intelligence (AI); Internet of Things (IoT); Life Cycle Assessment (LCA); Machine Learning (ML); Physical Internet (PI); Multi-Agent Systems (MAS); Blockchain Traceability; Digital Twin Architecture; Sustainability Efficiency Index (SEI); Industrial Symbiosis; Industry 5.0

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Mizna Rehman

List of Acronyms

Acronym	Full Form / Description
ABM	Agent-Based Modeling
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
AIoT	Artificial Intelligence of Things (integration of AI and IoT)
ANOVA	Analysis of Variance
ANP	Analytic Network Process
API	Application Programming Interface
API-GW	API Gateway (interface for federated twin communication)
CE	Circular Economy
CO_2	Carbon Dioxide
CO_2-eq	Carbon Dioxide Equivalent
CPS	Cyber-Physical System
CSC	Coffee Supply Chain
DB	Database
DDS	Data Distribution Service (real-time communication protocol)
DLT	Distributed Ledger Technology
DT	Digital Twin
DT^2	DigiCircular Twin-Transition Framework
DTaaS	Digital Twin as a Service
EDI	Electronic Data Interchange
EF 3.0	Environmental Footprint 3.0 (EU Impact Assessment Method)

Acronym	Full Form / Description
EIS	Enterprise Information System
E-LCA	Environmental Life-Cycle Assessment
ERP	Enterprise Resource Planning
EU	European Union
EWC	European Waste Catalogue
FLP	Facility Location Problem
FDT	Federated Digital Twin
GBM	Geometric Brownian Motion (stochastic modeling method)
GDP	Gross Domestic Product
GDPR	General Data Protection Regulation
GHG	Greenhouse Gas
GIS	Geographic Information System
GOT	Global Orchestrator Twin
HDSF	Hybrid Decision-Support Framework
HSE	Health, Safety and Environment
ICO	International Coffee Organization
ICT	Information and Communication Technology
IEC	International Electrotechnical Commission
ILP	Integer Linear Programming
IoT	Internet of Things
IoV / V2X / V2G	Internet of Vehicles / Vehicle-to-Everything / Vehicle-to-Grid
ISO	International Organization for Standardization
ISO 14040/14044	International Standards for Life Cycle Assessment
JSON-LD	JavaScript Object Notation for Linked Data
JIT	Just-In-Time (logistics strategy)

Acronym	Full Form / Description
JWT	JSON Web Token
KMS	Knowledge Management System
KPI	Key Performance Indicator
KNIME	Konstanz Information Miner (data analytics platform)
LAP	Logistics Access Provider
LCA	Life Cycle Assessment
LCC	Life Cycle Costing
LCI	Life Cycle Inventory
LCM	Life Cycle Management
LCSA	Life Cycle Sustainability Assessment
LCT	Life Cycle Thinking
LDT	Local Digital Twin
MAC	Medium Access Control
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MAS	Multi-Agent System
MCDM	Multi-Criteria Decision Making
MEC	Multi-Access Edge Computing
MILP	Mixed-Integer Linear Programming
ML	Machine Learning
MOO	Multi-Objective Optimization
MQTT	Message Queuing Telemetry Transport
MSE	Mean Square Error - -
MQTT	Message Queuing Telemetry Transport
MVP	Minimum Viable Product (or Price, contextually)

Acronym	Full Form / Description
NCA	Natural Capital Accounting
NCR	Non-Conformance Report
NIST	National Institute of Standards and Technology
NPV	Net Present Value
OEE	Overall Equipment Effectiveness
OHS	Occupational Health and Safety
OPC-UA	Open Platform Communications – Unified Architecture
OSI	Open Systems Interconnection
PaaS	Product-as-a-Service
PCA	Principal Component Analysis
PET / rPET	Polyethylene Terephthalate / Recycled Polyethylene Terephthalate
PI	Physical Internet
PILAR	Physical Internet Layered Agent Routing Framework
PLA.I.A	Platform for Life-cycle Assessment and Industrial Analytics
PSILCA	Product Social Impact Life Cycle Assessment
Q-Learning	Quality Learning (reinforcement algorithm)
QR	Quick Response (code for tracking and labeling)
RCP	Representative Concentration Pathway
REST / RESTful	Representational State Transfer (Web API architecture)
RFID	Radio Frequency Identification
RL	Reinforcement Learning
RMSE	Root Mean Square Error
RMSLE	Root Mean Squared Logarithmic Error
ROI	Return on Investment
ROL	Return on Labor

Acronym	Full Form / Description
SCG	Spent Coffee Grounds
SCM	Supply Chain Management
SDG / SDGs	Sustainable Development Goal(s)
SEI	Sustainability Efficiency Index
SHDB	Social Hotspots Database
SJR	SCImago Journal Rank
SLCA / S-LCA	Social Life Cycle Assessment
SLR	Systematic Literature Review
SME / SMEs	Small and Medium Enterprise(s)
SSL / TLS	Secure Sockets Layer / Transport Layer Security
TaaS	Textile-as-a-Service
TCP/IP	Transmission Control Protocol / Internet Protocol
TEX-CE	Textile Circular Economy
TMS / TME	Transport Management System / Entity
TRL	Technology Readiness Level
UI/UX	User Interface / User Experience
UN	United Nations
UNEP/SETAC	United Nations Environment Programme / Society of Environmental Toxicology and Chemistry
VIF	Variance Inflation Factor
VOSviewer	Visualization of Similarities Viewer
VSM	Value Stream Mapping
WFM	Waste Flow Mapping
WoS	Web of Science
WP4	Work Package 4 (Physical Internet Characterization – PRISMA Project)

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Notations

The following notations are used within the thesis

Symbol	Description
x_i	Normalized indicator for criterion i
$x_i{}'$	Min–max scaled value of indicator i
w_i	Weight assigned to criterion i
W	Vector of stakeholder-validated weights
A	Pairwise comparison matrix / transition matrix
λ_{max}	Maximum eigenvalue of matrix A
CI	Consistency Index
CR	Consistency Ratio
RI	Random Index constant
Y	Sustainability performance score
β_i	Regression coefficient
ε	Error term
R^2_{adj}	Adjusted coefficient of determination
μ	Mean
σ	Standard deviation
r	Pearson correlation coefficient
Δt	Change in task time
PI	Performance Improvement Index
H	Cryptographic hash

Symbol	Description
B_t	Block generated at time t
$V_i(t)$	Validation status at time t
S_c	Compliance score
T_c	Confirmation time
H_e	Hash entropy
V_S	Ledger success rate
S_t	System state vector / smart-contract trigger rate
R_v	Re-verification requests
n	Number of observations
$\bar{Y}$	Mean sustainability score
CF	Carbon footprint
E_i	Environmental impact
W_i	Weight in ANP / Triple-LCA
S_i	Social indicator score
NPM	Net Profit Margin
ROI	Return on Investment
ROL	Return on Labor
MVP	Minimum Viable Price
R	Total revenue
C	Total cost
π	Profit
ΔE	Change in environmental impact
ΔS	Change in social impact

Symbol	Description
ΔC	Change in cost
EF	Environmental footprint
E_cost	Environmental cost
ESV	Ecosystem Service Value
NP	Net profit after deductions
P_0	Initial value
P_t	Value at time t
t	Time
$CAGR$	Compound Annual Growth Rate
ANP_{ij}	ANP priority weight
w_e, w_s, w_{ec}	Pillar weights
Y'	Predicted value
R^2	Coefficient of determination
ΔV	Change in ecosystem service value
Q	Quantity
M_t	Material input
M_s	Material savings
η_m	Material efficiency
E_t	Energy consumed
E_s	Energy savings
η_e	Energy efficiency
W_t	Baseline water use
W_o	Optimized water use

Symbol	Description
ΔW	Water-use reduction
CO_{2e}	CO2 equivalent
ΔCO_{2e}	CO2 reduction
C_r	Circularity rate
L^p	Lifespan extension
η_p	Process efficiency
η_{KPI}	KPI performance index
T_l	Lead time
ΔT_l	Lead-time reduction
C_opt	Optimized operating cost
C_b	Baseline operating cost
W_r	Waste-reduction ratio
α	Waste recovery coefficient
β	Energy-saving coefficient
γ	Water-saving coefficient
δ	Carbon-intensity reduction factor
Φ	Composite sustainability index
ψ	Process optimization index
P_e	Environmental performance index
R_e	Resource efficiency index
η_{ov}	Overall improvement factor
SEI	Sustainability Efficiency Index
$f(x)$	Objective function

Symbol	Description
λ	Normalization constant
U_t	Control input vector
y_t	Output vector
ψ_i	Sensitivity coefficient
τ	Control-loop time constant
Ω	Sustainability state space
δ_{sync}	Synchronization delay
σ_{err}^2	Error variance
Π_{ROI}	Cumulative ROI
χ_{opt}	Optimal parameter vector

Chapter 1

Introduction

1.1 Background of the study

The global imperative for sustainability has intensified in recent decades as industries confront the twin pressures of environmental degradation and resource scarcity. The accelerating pace of industrialization, coupled with linear production and consumption patterns, has exacerbated ecological footprints across sectors, from agriculture to manufacturing. Traditional industrial models characterized by take–make–dispose paradigms are increasingly incompatible with global commitments such as the United Nations Sustainable Development Goals (SDGs) and the Paris Climate Agreement, both of which advocate for decoupling economic growth from environmental harm [1,2]. This transition requires systemic innovation, encompassing not only cleaner technologies but also intelligent mechanisms that enable resource efficiency, traceability, and adaptive decision-making across value chains [3].

Parallel to this sustainability discourse, rapid advancements in digital technologies, particularly the Internet of Things (IoT), Artificial Intelligence (AI), blockchain, and digital-twin architectures, have redefined industrial operations [4]. These technologies facilitate real-time monitoring, predictive analytics, and process automation, thereby reshaping the dynamics of production and consumption. Yet, despite the maturity of these tools within the framework of Industry 4.0, their deployment has often remained fragmented, focusing on productivity and cost efficiency rather than on holistic sustainability transformation [5]. Similarly, the Circular Economy (CE), a paradigm emphasizing resource recovery, waste minimization, and product-life extension, has evolved largely as an environmental initiative, lacking integration with the digital intelligence that could enable its large-scale operationalization [1].

This persistent disjunction between digitalization and circularity represents one of the most significant theoretical and practical challenges in the transition toward Industry 5.0, where technological advancement must align with human-centric and regenerative principles [6]

Within this context, industrial symbiosis, where waste or by-products from one sector become inputs for another, serves as a central mechanism of the circular economy [7]. This research builds on initiatives such as the DIAMANTE Project, which advanced digital manufacturing for sustainable textile production, and the PRISMA Platform, which enabled regenerative material exchange within the coffee supply chain. By integrating these foundations, the thesis develops a unified DigiCircular Twin-Transition (DT^2) framework that operationalizes industrial symbiosis through digital-twin intelligence, blockchain traceability, and life-cycle analytics. The valorization of spent coffee grounds (SCGs) into textile fibers exemplifies this approach, aligning digital transformation with the European Green Deal and UN SDGs 9, 12, and 13, and demonstrating how technology-driven circularity can accelerate climate-aligned industrial regeneration [8].

The concept of the twin transition, emerging within European and global policy frameworks, captures the dual transformation required for sustainable development, one digital and one green. In this thesis, digital transformation is understood as the systematic integration of digital technologies, including digital twins, real-time data infrastructures, artificial intelligence, and interoperable information systems, into industrial processes and decision-making structures. Digital transformation is therefore treated as technological adoption, as well as an enabler of continuous monitoring, predictive analytics, and adaptive control across industrial value chains. The term dual transformation is used here to denote the co-evolution of digital transformation and sustainability-oriented (green and circular) transformation within industrial systems. While the term is sometimes used in the literature to describe organizational restructuring or parallel business-model change, this thesis adopts a more specific interpretation aligned with European policy discourse on the twin transition, in which digitalization and sustainability are mutually reinforcing processes (European Commission, 2021). To avoid uncertainty, the present research subsequently refers to this integrated logic as the DigiCircular Twin-Transition, emphasizing the explicit coupling of digital intelligence with circular-economy principles.

However, while policy literature extensively references the twin transition, empirical frameworks capable of operationalizing this dual transformation remain limited. Existing studies tend to address either digital or circular innovation independently, rarely achieving the systemic coupling necessary for real-time sustainability control. Consequently, there exists a pressing need for integrated architectures that synchronize digital intelligence with circular resource management, allowing environmental performance indicators to function not merely as reporting metrics but as decision variables embedded in industrial control systems.

In response to this global research gap, the present study advances the DigiCircular Twin-Transition (DT^2) Framework, a novel cyber-physical model that fuses digital-twin intelligence with circular-economy logic to enable cross-sector sustainability optimization. The framework builds upon the Hybrid Decision-Support Framework (HDSF) introduced in earlier conceptual work, extending it into an applied system capable of integrating real-time data, life-cycle assessment (LCA) analytics, and optimization algorithms across industrial domains. Within this framework, each digital twin, representing sectoral ecosystems such as coffee supply chains, textile manufacturing, logistics, and traceability, functions as both a monitoring and decision unit. Collectively, these federated twins communicate through harmonized Key Performance Indicators (KPIs) to maintain dynamic environmental, economic, and social balance.

By embedding sustainability parameters within digital control loops, DigiCircular transforms sustainability governance from a retrospective, compliance-based function into a predictive and prescriptive mechanism. This shift represents a significant evolution in the way industrial systems are designed and managed. It reflects the broader scientific consensus that the future of manufacturing must combine data-driven intelligence with resource-circularity principles, ensuring that efficiency gains align with climate objectives rather than working against them.

Overall, this research emerges at the intersection of three converging trajectories: (i) the global demand for decarbonized, resource-efficient production; (ii) the technological capabilities introduced by Industry 4.0 and digital twins; and (iii) the theoretical and policy momentum toward integrated twin-transition frameworks. By situating itself within this intersection, the present study aims to contribute a unified, replicable model for achieving sustainability intelligence across industries, moving beyond isolated case studies toward a generalizable architecture for the Digital–Circular (DigiCircular) future.

1.2 Problem Statement

Global sustainability efforts are increasingly centered around the integration of digital transformation and the circular economy, yet these domains continue to evolve in parallel rather than in tandem [9]. In practice, many industries pursue digitalization primarily to increase productivity and reduce costs, while failing to leverage it for measurable environmental outcomes such as carbon reduction or resource circularity.

Conversely, circular economy frameworks often lack the real-time intelligence and data-driven feedback loops needed to optimize material recovery, energy use, and lifecycle performance [10]. This siloed implementation hinders the transition from static sustainability reporting to dynamic operational decision-making, where sustainability indicators actively influence process control [11].

Moreover, existing architectures rarely offer interoperability between digital systems and circular resource exchanges, restricting potential gains from industrial symbiosis and cross-sector optimization [12]. Without robust digital infrastructure to synchronize real-time sustainability data with operational control, efforts toward circularity remain fragmented and inefficient [13].

To address this critical gap, the present research proposes the DigiCircular Twin-Transition (DT^2) Framework, a scientifically grounded, modular, and scalable architecture designed to couple digital intelligence with circular-economy functions. The DT^2 framework will enable sustainability metrics (e.g., CO_2 emissions, energy efficiency, material reuse) to serve as real-time operational parameters, thereby fostering coordinated decisions across interconnected industrial networks.

1.3 Research Questions

The study is guided by a central inquiry that addresses the scientific and operational challenge identified in the problem statement:

How can digital intelligence be systematically integrated with circular-economy principles to enable real-time, cross-sector sustainability optimization within industrial systems?

To address this overarching question, the research is structured around the following specific questions:

> RQ1: How can data-driven digital-twin architectures be designed to capture, process, and interpret real-time sustainability indicators across different industrial sectors?
>
> RQ2: In what ways can life-cycle analytics and environmental performance metrics be transformed into actionable control variables for operational decision-making?
>
> RQ3: How can interoperability be achieved between sectoral systems to facilitate industrial symbiosis and circular resource flows through digital platforms?
>
> RQ4: What measurable improvements in energy, water, carbon, and material efficiency can be achieved through the implementation of the DigiCircular Twin-Transition (DT^2) model?
>
> RQ5: How can the proposed framework support policy, industry, and research agendas aimed at realizing the twin transition under global sustainability commitments?

1.4 Objectives of the Study

The overarching objective of this research is to develop and validate the DigiCircular Framework, a scientifically grounded model that couples digital intelligence with circular-economy principles to achieve real-time sustainability optimization across interconnected industrial sectors. The study aims to transform digitalization from a tool of efficiency into a catalyst for regenerative production, aligning industrial innovation with environmental and social performance goals. It aims to transform environmental indicators from static reporting measures into real-time control parameters, enabling cross-sector coordination and resource efficiency within the context of the twin transition.

General Objective

To design and validate a cyber-physical framework that integrates digital-twin intelligence, life-cycle analytics, and circular resource management for improving environmental and operational performance across industrial symbiosis between the coffee and textile sectors, facilitating the reuse of coffee waste as raw material in sustainable textile production.

Specific Objectives

- To analyze and model resource flows within industrial systems, with particular focus on the coffee supply chain, mapping the collection, treatment, and valorization of spent coffee grounds (SCGs) as a renewable bio-material.

- To design a digital-circular process model that integrates SCG-derived fibers into textile manufacturing, demonstrating industrial symbiosis and alignment with Industry 4.0 and Smart Manufacturing paradigms.
- To develop an integrated digital platform architecture that incorporates Physical Internet (PI), Internet of Things (IoT), Blockchain, and Artificial Intelligence (AI) technologies to enable traceable, efficient, and circular material and information flows.
- To apply Life Cycle Assessment (LCA) and Life Cycle Costing (LCC) methods for evaluating the environmental, economic, and social implications of the proposed cross-sector circular model.
- To validate the DigiCircular approach through simulation and pilot-scale testing, quantifying improvements in energy, water, carbon, and material efficiency across coffee and textile case applications.
- To generalize and formalize the digital twin model as a replicable scientific framework for cross-sector industrial symbiosis, adaptable to other domains such as food, packaging, and bio-based materials.
- To contribute to the advancement of digital-sustainability science by providing a data-driven and operational framework that supports the twin transition and aligns with the objectives of the European Green Deal and UN SDGs 9, 12, and 13.

1.5 Scientific Contribution

This dissertation advances the scientific frontier of cyber-physical sustainability systems by formulating, implementing, and validating an integrated model that couples digital-twin intelligence with circular-economy logic. The work contributes both conceptually and methodologically to the digital-sustainability domain through multi-layer modeling, cross-sector data interoperability, and quantifiable environmental performance validation. The principal contributions are as follows:

- Development of the DigiCircular Twin-Transition (DT^2) model, which unifies digital-twin theory, circular-economy dynamics, and life-cycle analytics into a single system of equations and control parameters. The framework conceptualizes sustainability as a state-variable system, allowing environmental indicators (energy, water, carbon, material circularity) to function as real-time decision constraints within industrial operations.
- Construction of a multi-layer decision-support architecture integrating IoT sensor networks, Physical Internet (PI) routing algorithms, blockchain-based data integrity

layers, and AI-driven optimization modules. This configuration enables closed-loop monitoring and prescriptive adjustment of environmental performance through quantitative feedback control.

- Implementation of a federated data architecture connecting sectoral digital twins, coffee, textile, logistics, and traceability, via harmonized ontologies and shared sustainability KPIs. The design demonstrates semantic interoperability across heterogeneous data streams and industrial domains, supporting scalable cross-sector coupling.
- Realization of an operational industrial-symbiosis loop wherein spent coffee grounds (SCGs) are digitally tracked, recovered, and valorized into textile fibers. Experimental and simulated results confirm measurable reductions in energy consumption (≈9%), water use (≈17%), and carbon emissions (≈6%), alongside a 25–30% improvement in resource efficiency, demonstrating that digital-twin governance can generate verifiable sustainability gains.
- Advancement of methodological coupling between LCA, LCC, and system-control algorithms. This coupling allows environmental impact functions to be parameterized dynamically within optimization routines, transforming static assessment tools into adaptive sustainability controllers.
- Development of a multi-objective optimization model solved using Python-based Pyomo and TensorFlow environments, enabling real-time simulation and prediction of sustainability efficiency indices. Monte Carlo and sensitivity analyses verify robustness under uncertainty, while LSTM-based forecasting modules extend predictive capability for KPI evolution.
- Alignment of the DigiCircular framework with ISO 14001 (environmental management), ISO 50001 (energy management), and ISO 26000 (social responsibility) standards. The model operationalizes the twin transition objectives of the European Green Deal and the UN SDGs (9, 12, and 13), offering a reproducible pathway for policy implementation through digital governance.
- Proposition of a replicable mathematical and data-architectural template for industrial symbiosis applicable beyond the coffee–textile domain. The general formulation provides a foundation for future extensions to biopolymer, packaging, and construction materials industries, positioning DigiCircular DT² as a universalizable cyber-physical framework for real-time sustainability control.

1.6 Practical Implications and Applications

The frameworks developed in this research demonstrate significant applicability for industrial, digital, and policy ecosystems aiming to operationalize sustainability through real-time intelligence. Each framework addresses a specific layer of implementation within manufacturing and resource management networks.

1.6.1 Hybrid Decision-Support Framework (HDSF)

The HDSF can be implemented within manufacturing enterprises, energy-intensive production facilities, and supply-chain management systems to embed sustainability intelligence into operational workflows.

- In textile manufacturing, HDSF can optimize process sequencing, dyeing operations, and energy utilization by analyzing IoT-derived data against environmental KPIs.
- In agri-food processing plants, it can support resource-use benchmarking, comparing production batches in terms of energy and water footprints.
- Within logistics operations, it can integrate LCA-derived emission factors into routing algorithms to minimize fuel consumption and carbon emissions.
- It also provides a decision-support interface for sustainability managers and plant engineers, allowing real-time selection of process configurations based on environmental and cost trade-offs.

1.6.2 PRISMA Platform for Industrial Symbiosis

The PRISMA Platform serves as a digital infrastructure for inter-sector material exchange and resource recovery. Its architecture supports deployment across waste management networks, industrial parks, and circular supply platforms seeking to transform by-products into secondary materials.

- In the coffee industry, PRISMA can manage data pipelines for collection, drying, and processing of spent coffee grounds (SCGs), creating traceable digital profiles for each material batch.
- In the textile sector, the platform enables manufacturers to procure SCG-derived fibers, integrating material traceability into production records using blockchain smart contracts.
- In food, packaging, and biopolymer industries, it can coordinate valorization streams (e.g., organic residues to bio-composites, recycled polymers to packaging resins).
- Municipal or regional circular clusters can adopt PRISMA as a cloud-based marketplace for industrial symbiosis, linking small and large firms through automated material-matching algorithms supported by IoT and AI-driven classification.

1.6.3 DigiCircular Twin-Transition (DT^2) Framework

The DT^2 framework represents the operational intelligence layer, capable of integration within smart factories, industrial IoT networks, and digital-twin infrastructures. Its modular design enables real-time monitoring, predictive analysis, and optimization across distributed value chains.

- In smart textile manufacturing units, DT^2 can synchronize sensor data (temperature, pH, energy use) with life-cycle databases, automatically adjusting process parameters to maintain defined sustainability thresholds.
- In coffee processing and logistics systems, it can manage roasting, packaging, and distribution routes through emission-aware scheduling, using Physical Internet routing algorithms.
- In integrated production clusters, DT^2 can function as a federated twin network, linking digital replicas of coffee, textile, and logistics operations for end-to-end lifecycle visibility.
- The framework can also be extended to renewable-energy optimization, enabling predictive balancing of electricity demand and solar or biogas input in manufacturing setups using machine-learning–based control loops.

1.6.4 Institutional and Policy-Level Applications

Beyond industrial implementation, the frameworks hold institutional relevance for governmental bodies, standardization agencies, and sustainability-certification systems.

- National and regional regulators can integrate PRISMA and DT^2 modules into environmental reporting platforms, ensuring verifiable emissions tracking aligned with ISO and SDG requirements.
- Development agencies and smart-industry programs can adopt the frameworks for monitoring circular-economy pilot projects, assessing compliance with decarbonization targets under the European Green Deal.
- Academic and R&D institutions can employ the HDSF as a simulation and educational tool, training engineers and sustainability professionals in digital-circular system design.

In practical terms, these frameworks can be deployed within:

- Industrial clusters (e.g., textile–food–biomaterial ecosystems) to facilitate real-time data exchange and resource reuse.
- Enterprise-level digital platforms (e.g., ERP and MES systems) as sustainability plug-ins for decision support.
- Cloud-based manufacturing infrastructures using Node-RED, ThingsBoard, or MQTT protocols for sensor integration.
- Public–private sustainability observatories as interoperable modules for continuous

environmental monitoring and verification.

Collectively, these applications illustrate how the frameworks transcend theoretical modeling and provide implementable, technology-ready solutions for advancing industrial symbiosis, carbon management, and sustainability governance within Industry 4.0 and 5.0 paradigms.

1.6.5 Practical Boundaries and Adoption Constraints

While the proposed DigiCircular Twin-Transition (DT²) framework demonstrates strong theoretical coherence and technological robustness, its practical implementation may face constraints in industrial contexts characterized by limited digital maturity or constrained resources. The framework assumes a baseline level of technological readiness, including access to IoT infrastructure, interoperable data systems, and analytical capabilities, which may not be uniformly available across all industries, particularly small and medium-sized enterprises (SMEs). Furthermore, organizational readiness factors such as workforce digital skills, change-management capacity, and institutional support structures play a critical role in successful deployment. In contexts where these conditions are underdeveloped, phased or modular adoption strategies may be required. Acknowledging these constraints provides a realistic boundary for application and positions the framework as adaptable rather than prescriptive.

1.7 Organization of the Thesis

This dissertation is structured into nine chapters, each addressing a distinct phase in the conceptualization, development, and validation of the DigiCircular framework as shown in Figure 1.1. The organization follows a sequential logic that progresses from theoretical formulation to cross-sector empirical validation and synthesis, supported by a set of peer-reviewed publications that reflect the cumulative research trajectory.

- **Chapter 2: Literature Foundation and Theoretical Framew**ork

  This chapter synthesizes literature from 2000–2024, mapping the evolution of research at the intersection of digitalization and sustainability. It identifies fragmentation between digital innovation (Industry 4.0 technologies) and circular-economy frameworks, emphasizing the need for hybrid models that integrate both paradigms. The findings establish the theoretical basis for developing the Hybrid Decision-Support Framework (HDSF) and ultimately the DigiCircular DT² architecture. Findings from this review informed the conceptual structure of the DigiCircular framework and were disseminated through:

  ➢ De Felice, F., Rehman, M., Petrillo, A., & Baffo, I. (2025). Decoding the coffee supply chain: A systematic review of stakeholders, sustainability opportunities, and challenges. Sustainable Futures, 10, 101105. https://doi.org/10.1016/j.sftr.2025.101105

- **Chapter 3: The Hybrid Decision-Support Framework (HDSF)**

  This chapter introduces and models the HDSF, a methodological construct linking data acquisition, environmental analytics, and optimization logic with machine learning for sustainability-driven decision-making. The framework is designed to transform environmental indicators into quantitative decision variables applicable across sectors. It also presents the PLA.I.A (Platform for Life-cycle Assessment and Industrial Analytics) module, which forms the analytical core reused in later empirical and cross-sector models. The theoretical and methodological foundations of this chapter were presented in the following peer-reviewed publications:

  ➢ Published as: Rehman, M., Petrillo, A., De Felice, F., Forcina, A., & Zahid, A. (2025). Strategic Proposal for Sustainable and Circular Manufacturing: Planning and Implementation Actions (PLA.I.A.). IFAC-PapersOnLine, 59(10), 1155–1160. https://doi.org/10.1016/j.ifacol.2025.09.195

  ➢ CErvural, B. (2024). A HYBRID DECISION SUPPORT FRAMEWORK FOR SUSTAINABLE BUSINESS OPTIMIZATION. ISAHP Proceedings. https://doi.org/10.13033/isahp.y2024.003

- **Chapter 4: Triple LCA of the Coffee Value Chain (Environmental, Social, and Economic Integration)**

  This chapter applies the hybrid model within the coffee supply chain, integrating environmental, social, and economic Life Cycle Assessments (LCA) to generate baseline sustainability indicators. Integrating IoT demonstrates the potential of digital tools to enhance traceability, reduce emissions, and improve resource efficiency. The results establish quantitative performance metrics, energy, carbon, and water footprints, forming the environmental foundation for subsequent DigiCircular implementations. Empirical results and methodological advancements from this chapter were published in the following papers:

  ➢ Rehman, M., Petrillo, A., & De Felice, F. (2025). Environmental, Social, and Economic Life Cycle Assessment of the Italian Coffee Supply Chain. Cureus, 17(3), e5869. https://doi.org/10.7759/s44388-025-05869-y

  ➢ De Felice, F., Rehman, M., Gómez Navarro, T., & Petrillo, A. (2025). From Bean to Cup: Unveiling the Environmental Footprint of Coffee with Innovative LCA Insights. Manuscript under review at Journal of Cleaner Production.

- **Chapter 5: The PRISMA Platform for Industrial Symbiosis Optimizing Coffee Logistics via the Physical Internet and Multi-Agent PILAR Framework**

  Here, the research advances from assessment to optimization by introducing the PILAR (Physical Internet and Logistics Agent Routing) model. This chapter embeds AI-based multi-agent coordination and Physical Internet routing into coffee logistics to minimize carbon emissions, travel time, and idle energy use. It demonstrates the practical transition from life-cycle analysis to digitally enabled operational optimization within the supply chain. Key findings from this stage were disseminated as a book chapter:

  ➢ Rehman, M., Petrillo, A., Forcina, A., & De Felice, F. (2025). Optimizing Coffee Logistics through the Physical Internet and Multi-Agent Systems: The PILAR Framework for Sustainable Supply Chains. (Book Chapter titled as "Sustainable Economy and Fair Society" by IntechOpen)

- **Chapter 6: Digital Traceability and Blockchain-Enabled Transparency in Coffee Supply Chains**

  This chapter operationalizes DigiCircular principles through a mobile application integrating Blockchain, RFID, and IoT. It enables end-to-end data capture and consumer-side traceability, ensuring transparency in the coffee value chain. The system verifies sustainability claims and provides auditable environmental and social metrics, showing how digital traceability technologies make circular processes verifiable and supports compliance with sustainability standards and builds consumer trust in value chains. Results of this work were reported in the following peer-reviewed studies:

  ➢ Rehman, M., Petrillo, A., Baffo, I., Iovine, G., & De Felice, F. (2025). Optimizing Coffee Supply Chain Transparency and Traceability through Mobile Application. Procedia Computer Science, 233, 1078–1089. Elsevier. https://doi.org/10.1016/j.procs.2025.01.272

  ➢ Petrillo, A., Rehman, M., & De Felice, F. (2025). Optimizing coffee supply chain transparency and traceability through mobile application. European Journal of Innovation Management, 28(11), 267–300. https://doi.org/10.1108/ejim-01-2025-0088

- **Chapter 7: Digital Circularity in the Textile Industry by Integrating IoT, Waste-Flow Mapping, and Life-Cycle Management**

  This chapter generalizes the DigiCircular framework by applying it to the textile manufacturing sector. It integrates Waste Flow Mapping (WFM), IoT-based monitoring, and LCA-driven Key Performance Indicators (KPIs) to optimize material use, energy efficiency, and waste recovery. The textile validation confirms the cross-sector adaptability of the model and demonstrates the feasibility of industrial symbiosis, where spent coffee grounds (SCGs) are transformed into bio-based textile fibers. Outputs and analyses from this stage are published in:

- ➢ Rehman, M., Petrillo, A., Ortíz-Barrios, M., Forcina, A., Baffo, I., & De Felice, F. (2024). Sustainable fashion: Mapping waste streams and life cycle management. Journal of Cleaner Production, 444, 141279. https://doi.org/10.1016/j.jclepro.2024.141279
- ➢ De Felice, F., Rehman, M., Petrillo, A., Barrios, M. a. O., & Baffo, I. (2025). Integrating IoT and circular economy in Textile supply chains: A closed-loop model for sustainable production using recycled PET and spent coffee grounds. Journal of Cleaner Production, 501, 145277. https://doi.org/10.1016/j.jclepro.2025.145277

- **Chapter 8: The Cross-Sector Integration and the DigiCircular Framework for Twin Transition**

This synthesis chapter integrates all sectoral and methodological findings—coffee (LCA and blockchain), textile (WFM and IoT), and logistics (PILAR), into a unified DigiCircular Twin-Transition (DT²) framework. It formalizes the federated digital-twin architecture and the Sustainability Efficiency Index (SEI), providing quantitative KPIs for performance evaluation across interconnected industries. It develops a federated digital-twin system interlinking coffee, textile, and logistics networks through shared sustainability indicators, forming the quantitative backbone of the twin transition model. The chapter also introduces the AI-driven predictive twin optimization model and a policy roadmap for operationalizing the twin transition. An extended version of this integrated framework is being prepared as:

- ➢ Mizna Rehman, Antonella Petrillo, Antonio Forcina, Fabio de Felice. The Cross-Sector Integration and the DigiCircular Framework for Twin Transition. Under preparation

- **Chapter 9: Conclusions, Policy Implications, and Future Research**

The concluding chapter consolidates the theoretical, methodological, and empirical contributions of the dissertation. It articulates the policy relevance of the DigiCircular DT² framework, highlighting its potential for integration into ISO-aligned digital sustainability governance. It also outlines future research directions in AI-based predictive LCA, autonomous digital twins, and sectoral replication across bio-materials, packaging, and construction industries.

In summary, the thesis progresses from conceptual development (Chapters 1–3), through sectoral validation (Chapters 4–7), to system synthesis and policy translation (Chapters 8–9). Collectively, these chapters establish the Framework as a scientifically robust and operationally scalable foundation for the digital-circular convergence underpinning Industry 5.0.

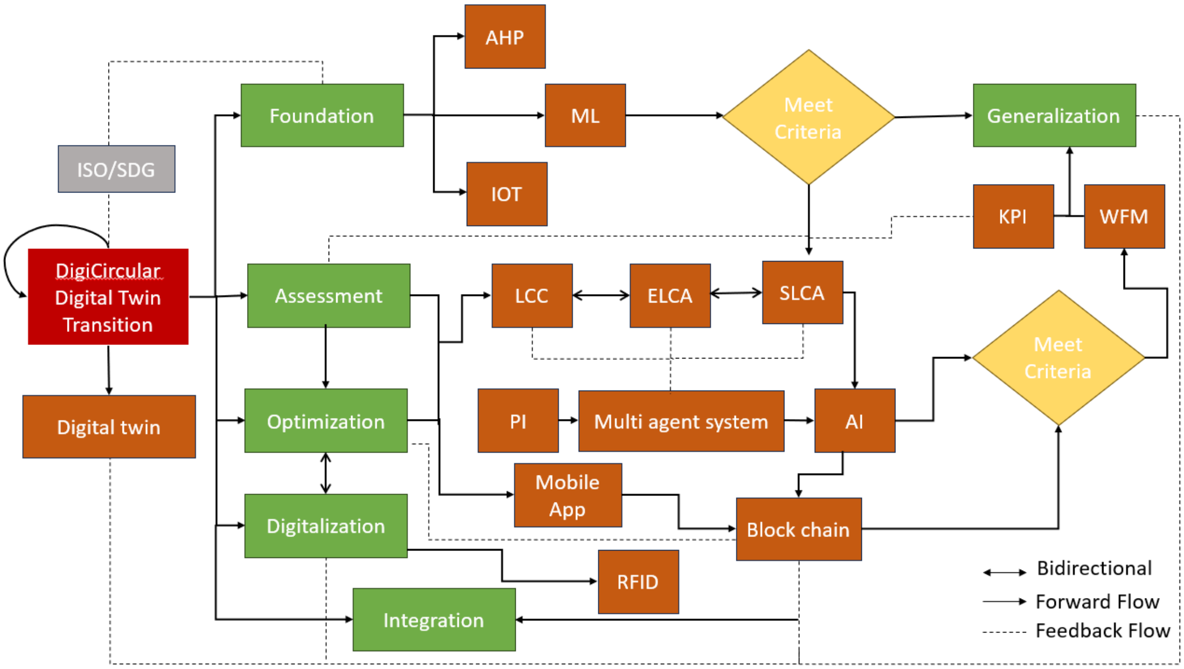


Figure 1.1. Structural representation of the methodological framework adopted in this Ph.D. dissertation

Chapter 2

Literature Review and Theoretical Foundation

This chapter establishes the theoretical foundation of the dissertation by critically synthesizing research on CE, DT, and LCT within the global CSC . It systematically reviews scholarly work published between 2000 and 2024 to identify key conceptual developments, methodological trends, and empirical evidence that shape sustainability transitions in this sector [14]. The chapter pursues three main objectives: (1) to describe the state of the art in CE, DT, and LCT [15,16,17,18], highlighting their convergence toward addressing sustainability challenges; (2) to evaluate existing gaps, particularly the limited integration between digital technologies [19]and life-cycle–based decision-support systems; and (3) to establish the conceptual scaffolding for the hybrid decision-support framework developed in Chapter 3.

Coffee, as one of the world’s most traded agri-food commodities, exemplifies the sustainability challenges of resource-intensive, climate-sensitive global supply chains [20]. Its multidimensional nature, spanning production, processing, logistics, retail, and consumption, makes it an ideal case for exploring circular and digital integration [21]. The sustainability performance of this system is a subject of sustained research interest due to climate exposure, resource intensity, smallholder vulnerability, quality assurance, and increasingly, consumer demand for transparency [22-24].

The review applies the PRISMA 2020 protocol to ensure methodological transparency and replicability [25]. Following this approach, Section 2.1 details the systematic review process; Section 2.2 presents bibliometric and descriptive results; Section 2.3 synthesizes thematic insights; Section 2.4 integrates the findings and identifies research gaps; and Section 2.5 concludes with implications for the framework design. By systematically analyzing and synthesizing prior research, the chapter positions this dissertation at the intersection of sustainability science, industrial ecology, and digital innovation fields whose convergence is essential for achieving the ambitions of Industry 5.0 and the SDGs.

2.1 Systematic Literature Review Methodology

The study employs a SLR to ensure transparency, reproducibility, and analytical rigor, following the PRISMA 2020 protocol [26]. The review proceeded through five sequential stages: (1) planning, (2) record identification, (3) screening and eligibility assessment, (4) bibliometric analysis, and (5) qualitative synthesis. Two major databases, Scopus and WoS were searched for English-language journal articles published between 2000 and 2024. The search yielded 156 records (Scopus = 88; WoS = 68). After removing 34 duplicates, 122 records remained for title-and-abstract screening; 64 were excluded as irrelevant, and 33 studies met all inclusion criteria for final synthesis. The PRISMA workflow is shown in Figure 2.1.

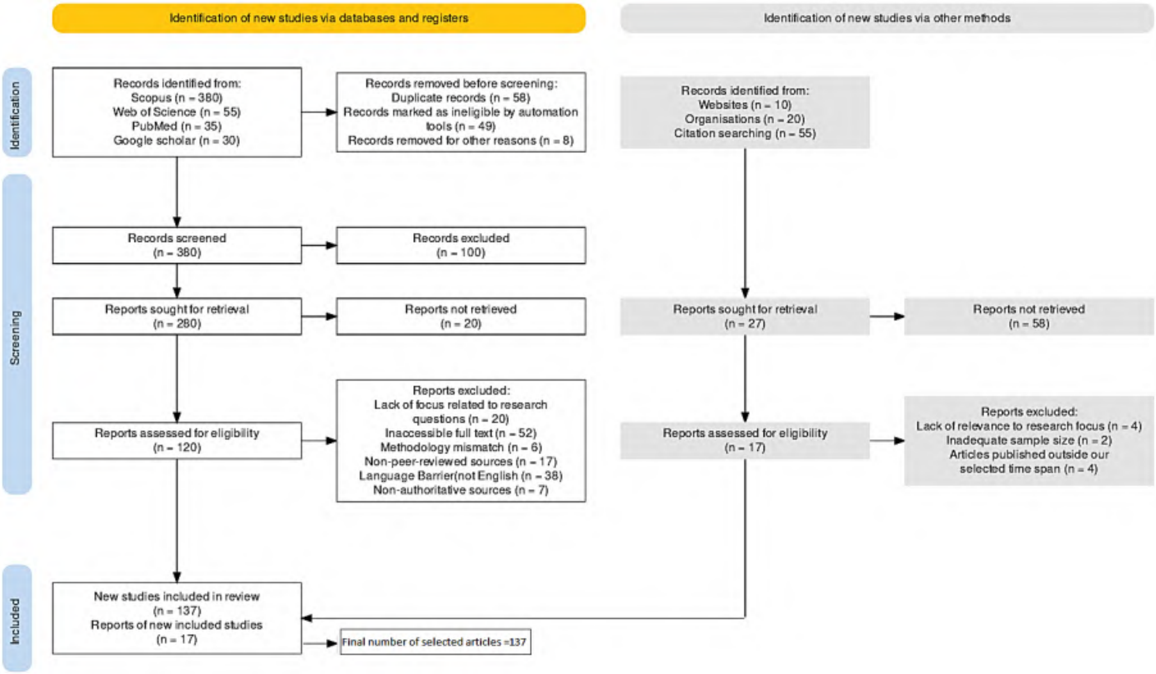


Figure 2.1. PRISMA 2020 flow diagram for systematic screening and inclusion of studies

2.1.1 Planning and Research Questions

The review was designed to answer the overarching question:

How are DT tools and life-cycle-based assessment methods driving sustainability transitions within the global CSC, and how do evolving stakeholder practices, innovation trajectories, and research priorities support circular-economy integration between 2000 and 2025?

To address this overarching inquiry, five interrelated research questions were formulated.

Each question targets a specific analytical dimension of sustainability transformation, ranging from stakeholder dynamics and innovation pathways to digital and methodological integration. The table below outlines the research questions, the gaps they address, and the analytical methods or expected outputs that guide the investigation.

Table 2.1. Planning and research questions

Research Question (RQ)	Gap Addressed	Analytical Method
RQ1. Who are the key stakeholders in the global CSC, and how do their roles evolve through digital and circular integration?	Lack of structured classification and interaction mapping of stakeholders.	Co-occurrence and cluster analysis to develop a stakeholder typology and map governance and collaboration patterns.
RQ2. What innovations and reuse opportunities arise from coffee residues (e.g., spent grounds, cascara) under circular and life-cycle principles?	Limited cross-sectoral assessment of residue reuse and valorization pathways.	Bibliometric and content analysis to build a reuse taxonomy and identify industrial symbiosis opportunities.
RQ3. How do global consumption trends influence sustainability performance and adoption of circular and digital practices?	Insufficient linkage between consumption dynamics and supply chain sustainability.	Trend analysis integrating consumption data and bibliometric mapping to evaluate market-driven sustainability transitions.
RQ4. How are digital technologies (IoT, AI, blockchain, GIS) enhancing efficiency, transparency, and sustainability in the CSC?	Fragmented understanding of digitalization’s measurable sustainability impacts.	Systematic and bibliometric coupling analysis to synthesize evidence on traceability, carbon reduction, and ethical performance.

Research Question (RQ)	Gap Addressed	Analytical Method
RQ5. What conceptual and methodological frameworks link CE, DT, and LCT within the coffee sector?	Absence of integrated frameworks combining CE, DT, and LCT perspectives.	Conceptual synthesis and framework mapping to propose a hybrid decision-support model for system-level sustainability governance.

2.1.2 Database Selection and Search Strategy

The SLR drew from two major bibliographic databases, Scopus and WoS, chosen for their comprehensive coverage of peer-reviewed scientific journals and their advanced filtering options. A compilation of the Scopus-indexed articles chosen for the literature review is provided in Appendix D Searches were restricted to English-language journal articles published from 2000 to 2024, ensuring both historical scope and contemporary relevance. The query strings were developed through iterative testing of keywords derived from preliminary scoping and were applied to titles, abstracts, and keywords fields. Boolean operators and truncation were used to broaden retrieval. Table 2.2 summarizes the databases, queries, time spans, and filtering criteria employed.

Table 2.2. Database Search Strategy and Query Parameters

Database	Query / Keywords	Time Span	Filters / Notes
Scopus	TITLE-ABS-KEY (("coffee" AND ("supply chain" OR logistics OR value) AND (sustainability OR stakeholder OR "life cycle" OR LCA OR residue OR waste OR circular OR blockchain OR IoT OR traceability)))	2000 – 2024	Journal articles; English; environmental sciences, engineering, management
WoS	TS= (“CE”) AND TS= (“life cycle” OR LCA OR LCC) AND TS= (“digital” OR “IoT” OR	2000 – 2024	SCI-indexed; articles only; English

Database	Query / Keywords	Time Span	Filters / Notes
	"industry 4.0" OR "physical internet")		

2.1.3 Screening and Eligibility Criteria

The retrieved records were exported to reference-management software (Mendeley / Zotero) for systematic screening. Inclusion and exclusion criteria were applied sequentially:

Inclusion criteria

- Peer-reviewed journal articles.
- Focus on circular-economy, sustainability, or resource-efficiency frameworks.
- Explicit methodological or conceptual linkage with digital technologies and/or life-cycle assessment.

Exclusion criteria

- Conference papers, book chapters, and grey literature.
- Studies focusing solely on policy or education without technological or analytical modeling.
- Non-English language publications.

2.2 Bibliometric and Descriptive Analysis

Bibliographic data including authorship, affiliations, sources, citations, and keywords were standardized and analyzed using VOSviewer 1.6.20 [27]. Fractional counting was applied to normalize data, ensuring balanced representation of contributors. Co-authorship, co-citation, and keyword networks were visualized to identify the intellectual, social, and conceptual structure of research in digitalized circular coffee systems [28]. Reliability was ensured through cross-checking and triangulation between quantitative clusters and qualitative coding.

Descriptive indicators such as; annual publication growth, country and institutional productivity, most-cited journals and authors, and citation impact distributions were extracted to provide quantitative insight into the evolution of the research field. Full texts of the 33 included studies were read and coded thematically using an inductive deductive approach. Initial codes were derived from the research questions and expanded iteratively during reading. Codes were aggregated into four higher-order themes circular production systems, waste-to-resource innovation, digitalization for sustainability, and integrated assessment and decision support, which form the basis for the thematic mapping discussed in Section 2.4.

2.2.1 Annual Publication Trends

The publication trajectory between 2000 and 2025 reflects the growing academic interest in linking digitalization with sustainability assessment. As shown in Figure 2.2, the field remained relatively niche before 2015, with fewer than five papers per year. A clear inflection point appears after 2017, coinciding with the rise of Industry 4.0 and the European Union's first CE Action Plan (2015). From 2020 onward, publications increased sharply averaging 7–8 per year, with 2023 representing the most productive year.

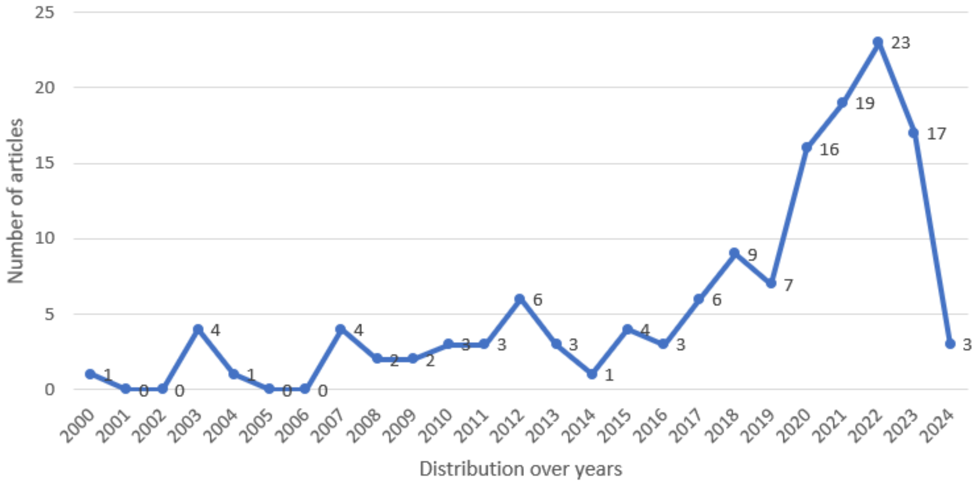


Figure 2.2. Annual distribution of publications (2000–2025) retrieved in the systematic review

This acceleration demonstrates that digital technologies are increasingly regarded as enablers for measuring, verifying, and optimizing circular strategies. Thematic keywords such as IoT, blockchain, LCA, and resource efficiency dominate recent years, revealing a shift from conceptual debates toward applied, data-driven approaches.

2.2.2 Geographic and Institutional Distribution

The retrieved studies span all continents, though research activity is concentrated in a few regions, with the highest contributions from the United States (19%), Brazil (18%), India (10%), Italy (8%), and Indonesia (5%) (Fig. 2.3). Using VOSviewer software, a bibliometric analysis of 67 countries was conducted to examine regional research distribution and identify collaboration clusters based on co-occurrence patterns.

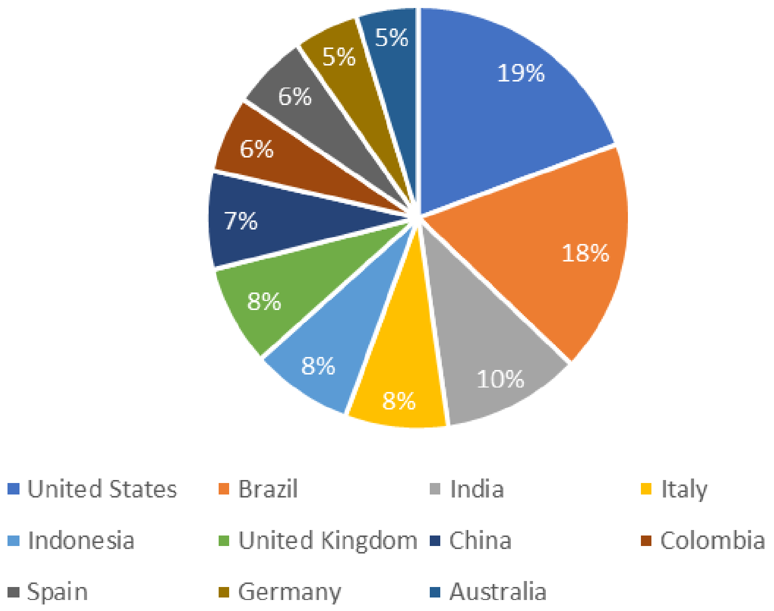


Figure 2.3. Country-wise distribution and co-authorship network

The results revealed five distinct clusters with varying levels of interconnectedness and research activity. Cluster 1 (Red) was the largest, comprising 23 countries such as Algeria, France, and the United States, with 798 documents and a TLS of 12,336. Cluster 2 (Green) included 18 countries, notably Australia, Japan, and Sweden, with 474 documents and TLS = 6,895, indicating strong intra-regional collaborations. Cluster 3 (Blue) consisted of 14 countries, including China, Pakistan, UAE, and India, representing Asia-Pacific cooperation with 278 documents and TLS = 5,934. Cluster 4 (Yellow) contained 10 countries such as Denmark, Hungary, and Norway, with 181 documents and TLS = 3,644, reflecting a smaller but distinct regional network. Finally, Cluster 5 (Purple) comprised only the Philippines and Taiwan, showing specialized collaboration with 9 documents and TLS = 87. Overall, the analysis (Fig. 2.4) highlights the globally interconnected nature of research and emphasizes the importance of fostering international collaborations to advance knowledge, innovation, and cross-border partnerships in this field.

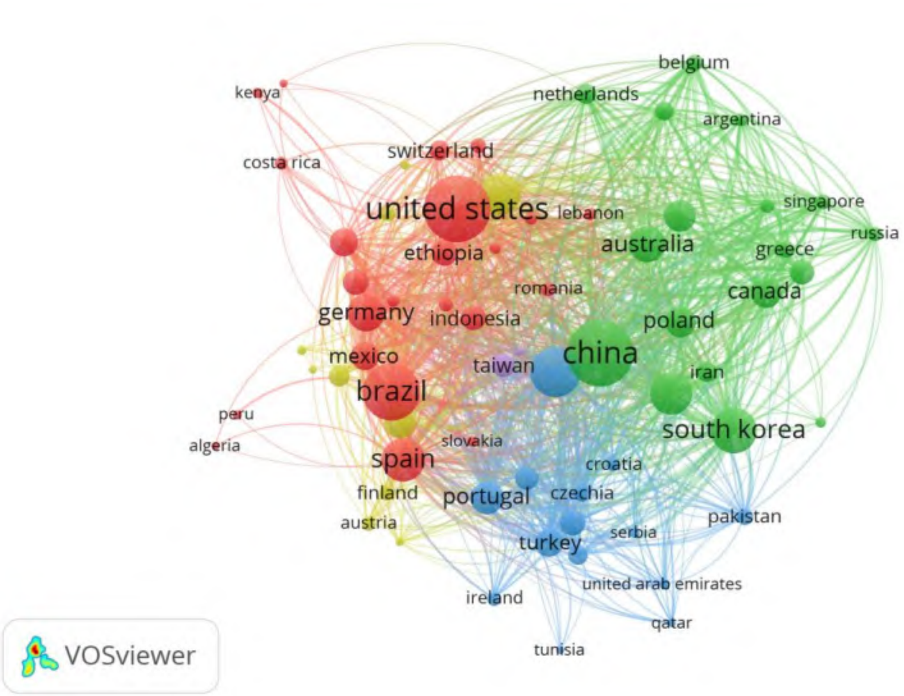


Figure 2.4. Bibliographic coupling analysis highlights inter-country co-occurrence patterns

2.2.3 Source and Journal Analysis

The distribution of publications across journals offers valuable insights into how CSC research is disseminated through diverse academic platforms, highlighting the primary outlets that facilitate knowledge exchange within the scholarly community. Table 3 summarizes the document metrics of leading journals and sources for the year 2022, based on data extracted from the Scopus database. It presents key indicators such as the number of publications, citation counts, SJR, and the proportion of review articles published by each source. These metrics collectively shed light on the research productivity, scholarly influence, and editorial orientation of major journals spanning disciplines such as food science, environmental management, and engineering, emphasizing their substantial contributions to advancing sustainability discourse within the CSC.

Table 2.3. Metrics for leading journals and sources in 2022

Journal Name	Publisher	Cite Score 2022	SJR 2022	Source Documents 2022	Citations per year 2022	Review Articles % 2022
Journal of the Science of	Wiley	8.2	0.747	751	46,885	3.99 %

Food and Agriculture						
Sustainability (Switzerland)	MDPI	5.8	0.664	17,002	217,095	6.95 %
Food Chemistry	Elsevier	14.9	1.624	3008	236,007	3.99 %
Foods	MDPI	5.8	0.771	4105	41,517	10.82 %
Food Research International	Elsevier	12	1.36	1239	71,556	10.9 %
British Food Journal	Emerald Group Publishing	5.4	0.645	281	10,513	2.85 %
Journal of Cleaner Production	Elsevier	18.5	1.981	4799	329,579	7.27 %
Journal of Environmental Management	Elsevier	13.4	1.678	2384	110,922	8.52 %
Journal of Food Engineering	Elsevier	11.8	1.161	265	43,453	4.15 %
Journal of Food Science and Technology	Springer	6.5	0.666	489	26,899	5.93 %

The bibliographic coupling analysis illustrated in Figure 2.5 further reveals the structural patterns and interrelationships among various scientific sources. Using data processed through VOSviewer, the analysis identified 89 items organized into six distinct clusters interconnected by 2,584 links. Cluster 1 (Red) emerged as the largest, comprising 26 items, followed by Cluster 2 (Green) with 17 items and Cluster 3 (Blue) with 15 items. The smaller clusters, Cluster 4 (Yellow), Cluster 5 (Purple), and Cluster 6 (Aqua Blue), contained 13, 11, and 7 items, respectively. Prominent journals such as Food Chemistry, Journal of Food Science and Technology, and Journal of Agricultural and Food Chemistry appeared as central nodes within the network, underscoring their pivotal roles and high levels of interconnectedness within the academic landscape. Overall, the analysis highlights the complex web of scholarly relationships and collaborative dynamics that shape research dissemination and influence in the field of CSC studies.

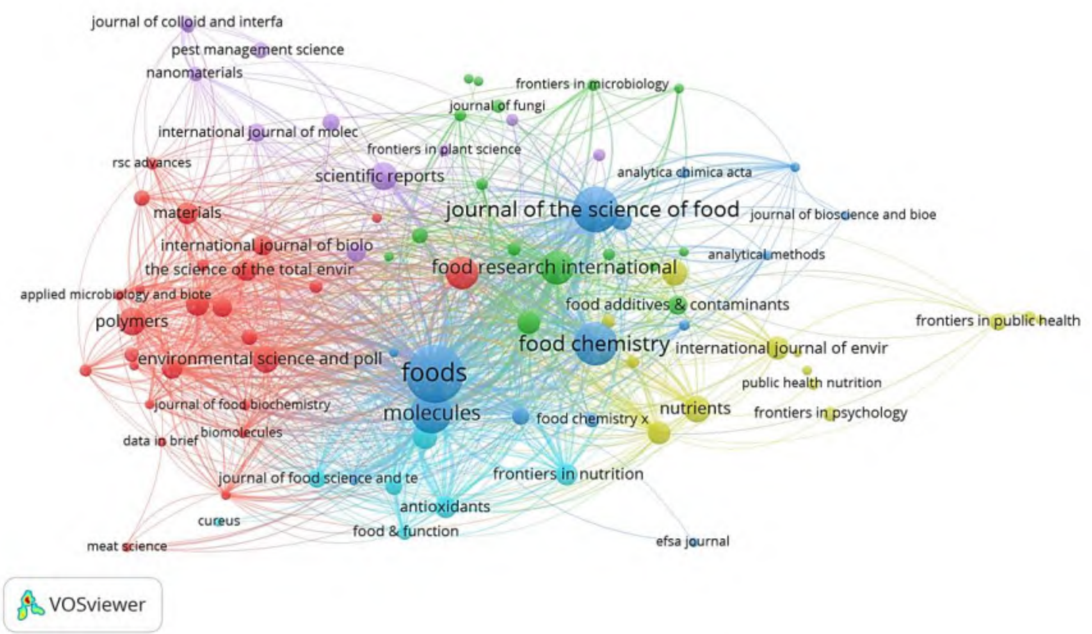


Figure 2.5. Mapping the Interdisciplinary Relationships of Scientific Sources Using Cluster Analysis

2.2.4 Keyword Co-Occurrence and Thematic Evolution

The keyword analysis identified a total of 3,140 terms, with “coffee” ranking as the most frequently cited. According to VOSviewer, the term recorded a maximum frequency of 133. From these, 47 keywords appearing at least eight times were selected for co-occurrence analysis, which produced four distinct clusters, connected through 748 links with a cumulative link strength of 2,165. Among all terms, “coffee” demonstrated the strongest TLS (498), followed by “supply chains” (337) and “sustainability” (246), indicating their central importance within the research network.

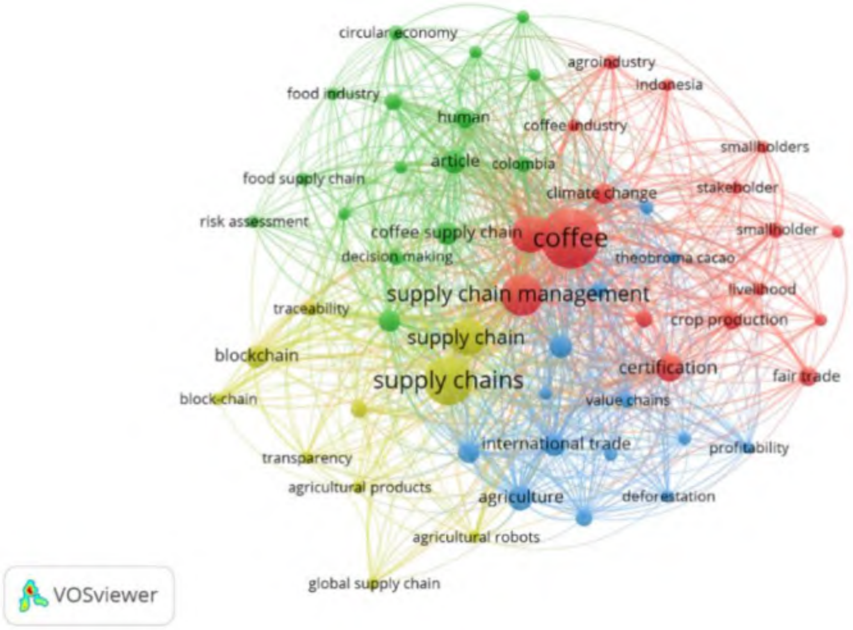


Figure 2.6. Keyword co-occurrence network and thematic-evolution map

The co-occurrence analysis of the 47 selected keywords revealed four primary thematic clusters, each representing distinct research focus within the CSC literature as given in Table 2.4.

Table 2.4. The frequency of keywords and the intensity of their interrelations within each cluster

Cluster	Representative Keywords	Thematic Focus	Key Insights
Red: Supply Chain & Sustainability	coffee, supply chain management, sustainability, fair trade, certification, climate change	Sustainable practices, stakeholder engagement, fair-trade certification, climate adaptation	Highlights the role of stakeholders in promoting sustainability, socio-economic impacts for smallholder farmers, and strategies for resilient supply chains.
Green: CE & Environmental Impact	CE, CSC, LCA, environmental impact, optimization	Resource efficiency, waste reduction, life-cycle-based decision-making	Emphasizes minimizing environmental footprints, sustainable farming and irrigation, and use of LCA to identify environmental hotspots.

Cluster	Representative Keywords	Thematic Focus	Key Insights
Blue: International Trade & Market Dynamics	trade, market, value chain, agriculture, competitiveness	Global market trends, trade policies, value chain optimization	Explores international trade impacts, governance structures, market competitiveness, and the role of digital technologies in efficiency and growth.
Yellow: Blockchain Integration & Transparency	blockchain, smart contracts, digital innovation, traceability	Traceability, operational efficiency, transparency, stakeholder coordination	Demonstrates how blockchain and smart contracts improve transparency, streamline logistics, enable real-time data exchange, and support environmental sustainability.

This progression evidences the field's transition from conceptual awareness toward data-driven implementation and reflects the growing convergence between sustainability science and digital engineering.

2.3 Synthesis of Thematic and Conceptual Insights: Convergence of CE, DT, and LCT

Building on the bibliometric and qualitative analyses, this section synthesizes evidence from 137 Scopus-indexed studies to examine how CE, DT, and LCT converge within the global CSC. The findings are organized around five thematic domains corresponding to the research questions (RQ1–RQ5).

2.3.1 Stakeholder Dynamics in the CSC (RQ1)

The CSC spans cultivation, processing, distribution, and consumption, involving diverse actors such as growers, exporters, roasters, retailers, and consumers [29,30]. These actors interact across physical, industrial, and information flows, with growers facing climate vulnerabilities and market volatility [31,32], while roasters and retailers adapt operations to evolving consumer preferences for traceable and ethically sourced coffee [33,34]. Certification schemes, direct-trade partnerships, and collaborative governance mechanisms promote equitable value distribution and transparency. Figure 2.7 illustrates the interdependence among key stakeholder groups and the multidirectional flow of materials, information, and finance along the chain.

Figure 2.7. A systematic depiction of CSC processes, synthesized from the findings of RQ1

2.3.2 CE Opportunities: Coffee Residue Reuse (RQ2)

Coffee residues including SCGs and cascara, present significant CE potential. In particular, the textile industry can reuse these residues to develop sustainable fibers, natural dyes, and functional fabrics. In agriculture, SCGs enhance soil fertility and crop yields [35,36]; in cosmetics and pharmaceuticals, bioactive compounds are used in skincare and drug formulations [37,38,39]; energy applications convert residues into bio-oil, biogas, and solid fuel [40-42]; and construction integrates residues into eco-concrete and bio-based polymers. Digital tools such as IoT sensors, AI-based optimization, and blockchain traceability support process efficiency and product quality control. Table 2.5 summarizes sectoral pathways, market applications, and digital contributions, providing an evidence-based taxonomy of reuse innovations.

Table 2.5. Exploration of multi-sectoral reuse pathways for coffee residues, potential market targets, and the role of digital technologies in enhancing operational efficiency

Sector	Valorization Pathways	Potential Market Applications	Digital Technology Contributions
Textile	Production of sustainable fibers, natural dyes, and functional fabrics	Fashion and textile manufacturers	Digital design tools, AI-driven color optimization, and process monitoring systems for consistent

Sector	**Valorization Pathways**	**Potential Market Applications**	**Digital Technology Contributions**
			quality and traceability
Agriculture	Conversion to organic fertilizers and animal feed	Agricultural production and livestock operations	IoT sensors, GPS-based monitoring, remote sensing, and advanced data analytics to optimize yield and resource management
Cosmetics	Extraction of bioactive compounds for skincare formulations	Beauty brands, spas, and cosmetic product lines	AI-driven formulation design, biotechnology and nanotechnology for targeted bioactive delivery and product efficacy
Energy	Anaerobic digestion, biomass combustion	Renewable energy producers, energy utilities	Process automation, biogas production monitoring, and energy management systems to improve efficiency and reduce waste
Agriculture (Composting)	Composting of residual biomass	Waste management companies, composting facilities, organic waste processors	RFID tracking, GPS logistics, and recycling technologies to ensure traceability and process standardization
Construction	Incorporation into eco-concrete or bio-based composites	Building materials manufacturers and construction sector	Material science modeling, recycling technology integration to enhance sustainability and material performance
Food	Culinary and functional ingredient applications	Food processing and product development industry	Computational modeling, sensory analysis, and quality control technologies to standardize product quality and safety
Pharmaceuticals	Development of drug formulations	Pharmaceutical and biotech companies	Drug formulation software and digital simulation tools to improve efficacy, stability, and production accuracy

2.3.3 Consumer-Driven Sustainability and Market Trends (RQ3)

Evolving consumption patterns are a key driver of sustainability and circular practices. In North America and Europe, over 60% of consumers prioritize certified, traceable coffee, whereas Asia-Pacific markets emphasize quality, flavor differentiation, and brewing innovations [43,44]. These shifts influence production methods, adoption of organic and shade-grown practices, supply chain transparency, and marketing strategies [45]. Direct trade partnerships and certification programs enable smallholders to access premium markets, while digital solutions, such as blockchain-enabled traceability, AI-based e-commerce personalization, and loyalty apps enhance engagement and brand trust. As depicted in Figure 2.8, digital technologies intersect with market demand to reinforce sustainable practices.

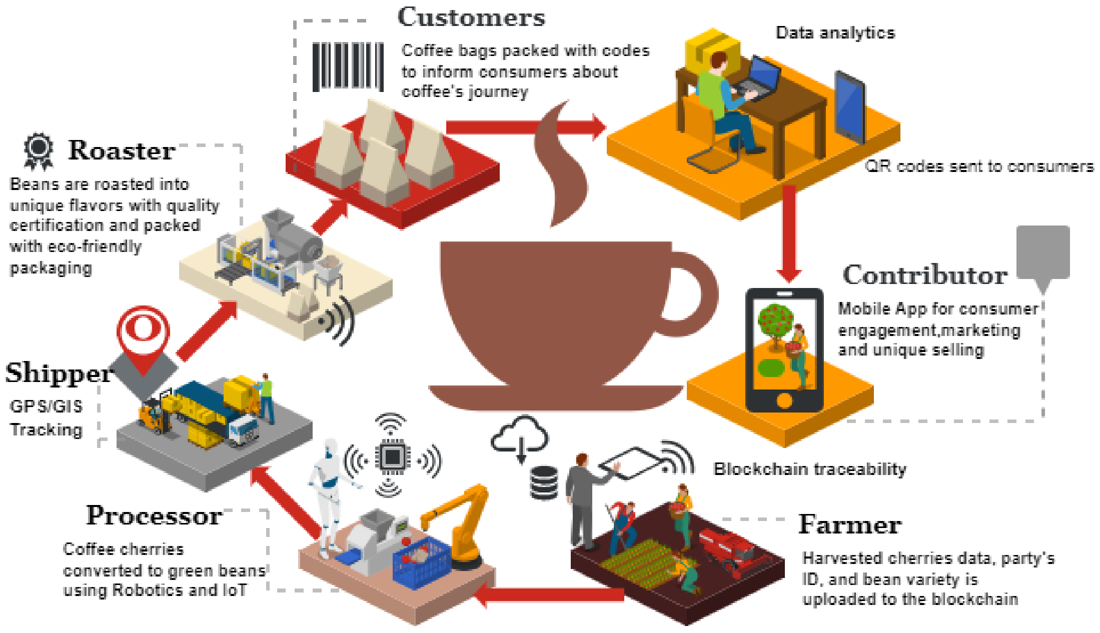


Figure 2.8. Framework demonstrating the use of digital solutions in the CSC to investigate RQ3, focusing on transparency, performance optimization, and environmental sustainability

Table 2.6 outlines the implications of evolving consumer preferences on supply chain adaptation, target markets, and competitive positioning. These findings directly respond to RQ3, showing how consumption trends drive circular and digital adoption, reshaping the CSC and market strategies.

Table 2.6. Sustainability Shaping the Future of Coffee by Integrating Responsible Practices Across Production, Marketing, and Competitive Strategy

Aspect	**Supply Chain Influence**	**Implications for Target Markets**	**Adaptation Strategies**	**Market Positioning**	**Competitive Advantage**
Growing demand for sustainable coffee	Integration of ethical and eco-conscious sourcing practices	Preference for products with environmental and social value	Use of GIS, GPS, and remote sensing technologies for sustainable cultivation	Promotion of eco-friendly and ethically sourced brands	Sustainability certifications (e.g., USDA Organic, Shade-Grown, Bird-Friendly) enhance consumer trust
Emphasis on transparency and traceability	Greater accountability in sourcing, processing, and logistics	Consumers expect full supply chain visibility	Adoption of blockchain, RFID tracking, and IoT systems	Brands highlight transparent sourcing in marketing	Enhanced reputation and loyalty through verified traceability
Fair trade and equitable business models	Support for fair compensation and ethical labor standards	Increasing appeal among socially responsible consumers	Implementation of Fair Trade, UTZ, and Direct Trade standards	Brand association with ethical responsibility	Stronger brand image through fair trade certification
Shift in consumer values and preferences	Adjustments to align with ethical consumer behavior	Targeting conscious consumers who prioritize sustainability	Marketing through educational campaigns, certifications, and brand storytelling	Clear communication via packaging, websites, social media, and in-store displays	Certified B Corporations gain credibility for ethical practices
Adoption of eco-friendly operations	Transition to low-impact and carbon-neutral production processes	Markets favor brands reducing environmental footprints	Introduction of biodegradable packaging, carbon offset programs, and renewable energy use	Emphasis on green identity and sustainability messaging	Competitive differentiation through unique eco-values and responsible production
Focus on quality and flavor diversity	Implementation of high-quality control systems	Demand for distinct and premium coffee experiences	Use of sensory analysis, chromatography, and single-origin sourcing	Branding based on specialty flavors and craftsmanship	Competitive edge through superior taste, quality certifications,

Aspect	Supply Chain Influence	Implications for Target Markets	Adaptation Strategies	Market Positioning	Competitive Advantage
					and origin reputation

2.3.4 Digital Transformation and Technological Integration (RQ4)

Digital technologies operationalize CE and LCT principles across all value-chain stages. Blockchain enhances data integrity and fair-trade compliance [46]; AI and analytics optimize production, logistics, and quality control [47,48]; IoT and GIS enable real-time monitoring of environmental and process parameters [49,50]. Digital tools also enable circular applications such as coffee waste valorization for energy, bio-based materials, and biodegradable packaging [51-55]. Table 2.7 summarizes technological innovations by process stage and aligns them with corresponding SDGs.

Table 2.7. An Analysis of Technological and Innovative Integration in CSC Processes in Relation to Sustainable Development Objectives

Process	Conventional Methods	Emerging Innovations and Technologies	Sustainability Contributions Enabled by Technology	Relevant SDGs
Harvesting	Manual handpicking	Utilization of mechanical harvesters, IoT sensors, and robotic systems	Optimization of labor requirements and enhancement of operational efficiency	1, 8
Processing	Traditional wet processing	Adoption of eco-efficient dry processing systems, blockchain-based traceability platforms, and AI-driven sorting technologies	Reduction in water consumption and minimization of environmental impact	6, 12
Transportation	Manual transportation methods	Implementation of automated logistics management, GPS-enabled tracking systems, and autonomous delivery vehicles	Decrease in carbon emissions and improvement in delivery efficiency	9, 13
Roasting	Conventional	Deployment of precision	Improvement in	7, 12

Process	Conventional Methods	Emerging Innovations and Technologies	Sustainability Contributions Enabled by Technology	Relevant SDGs
	drum roasting	roasting machinery supported by AI and data analytics	energy efficiency and uniformity in product quality	
Packaging	Manual bagging processes	Introduction of automated packaging lines, smart packaging solutions with RFID and QR technologies	Reduction in packaging waste and enhancement of hygiene standards	12, 14
Quality Control	Visual inspection	Integration of AI-powered quality monitoring systems, big data analytics, and computer vision tools	Increased accuracy in defect detection and overall quality consistency	9, 12

2.3.5 Integrative Frameworks Linking CE, DT, and LCT (RQ5)

Converging insights from stakeholder analysis, residue valorization, market dynamics, and technological integration reveal an emerging class of hybrid frameworks that connect circular logic, digital infrastructure, and life-cycle assessment [56,57]. These frameworks provide system-level decision-support by combining CE-driven material recovery, DT-based traceability and data analytics, and LCT-grounded impact quantification [58]. They underpin the hybrid decision-support model developed in Chapter 3, which formalizes cross-sectoral coffee–textile industrial symbiosis.

2.4 Integration of Findings and Identification of Research Gaps

Synthesizing insights from the preceding analyses (Sections 2.2 and 2.3) reveals several cross-cutting gaps that constrain progress toward a digitally enabled circular coffee economy. Although literature increasingly links CE, DT, and LCT, these dimensions often evolve in isolation, leaving theoretical and practical discontinuities that limit system-level implementation.

2.4.1 Methodological Imbalances and Limited Systemic Scope

Most studies remain descriptive rather than integrative. Climate-adaptation analyses (RQ1, RQ3) emphasize socio-environmental vulnerabilities but rarely embed digital monitoring or predictive analytics [59,60,61]. Research on residue valorization (RQ2) is typically laboratory-based and lacks connection to scalable industrial systems [62, 63]. Few models link residue generation to reuse in other sectors (e.g., coffee biomass to textile fibers), underscoring the need for hybrid analytical approaches that couple LCA/LCSA, MCDA, and real-time digital inputs.

2.4.2 Underexplored Multi-Actor and Cross-Flow Linkages

Existing work often treats stakeholders; growers, exporters, manufacturers, retailers, and consumers, as discrete actors instead of interconnected agents within dynamic networks. Limited attention is given to how digital infrastructures (IoT, blockchain platforms, data-sharing hubs) mediate exchanges across physical (material and energy), informational (traceability, certification), and financial flows (trade and value creation). This gap restricts understanding of collaborative adaptation, innovation diffusion, and value creation across supply-chain boundaries.

2.4.3 Persistent Uncertainties in Decision-Support and Life-Cycle Integration

While LCT offers structured impact assessment, few studies operationalize it as a decision-support mechanism for real-time management [55]. Energy- and emission-intensive stages; cultivation, roasting, distribution, are well documented, yet rarely incorporated into multi-criteria optimization models. Integrating IoT-enabled monitoring with AI-based modeling could substantially reduce uncertainty and enable adaptive, evidence-based decisions.

2.4.4 Emerging Gaps in Digitalization and Circular Transition

The analysis of RQs 3 and 4 highlights how digitalization is reshaping consumption behavior and governance [64], yet its impact on measurable sustainability outcomes remains unclear. While mobile applications, loyalty systems, and traceability tools improve consumer engagement and transparency [65], there is insufficient quantitative evidence linking digital adoption to carbon reduction, material recovery, or socio-economic benefits [65,66]. Moreover, digital architectures supporting coffee traceability could facilitate inter-industry symbiosis (e.g., connecting coffee producers and textile manufacturers for residue exchange), yet this potential is largely unexplored. Developing such interoperable digital architectures remains an open research frontier.

Collectively, these gaps reveal the need for a unified hybrid framework that integrates CE logic (material recovery), DT tools (traceability and data analytics), and LCT principles (impact quantification). Such a framework, developed in Chapter 3, will enable real-time sustainability evaluation, cross-stakeholder coordination, and inter-industry circularity (e.g., coffee–textile symbiosis). The following section reflects critically on how these insights inform the conceptual design of this hybrid decision-support framework.

2.5 Critical Reflection and Transition to the Hybrid Framework Design

The systematic review demonstrates that while significant advances have been made in applying digital tools to enhance transparency and traceability within the CSC, these innovations have yet to be fully aligned with life-cycle–based analytical frameworks. Existing approaches often remain project-specific, lacking the systemic and data-driven feedback loops necessary for continuous sustainability improvement.

These observed gaps directly inform the design principles of the dissertation’s hybrid decision-support framework. First, it operationalizes real-time life-cycle monitoring through IoT- and blockchain-enabled data flows. Second, it embeds multi-criteria reasoning (MCDA) to evaluate trade-offs across environmental, social, and economic outcomes. Third, it extends toward cross-sectoral circularity, linking coffee residue valorization to the textile industry as a demonstrative case of industrial symbiosis. In doing so, the framework moves beyond descriptive mapping to offer a prescriptive, system-level model capable of guiding sustainability interventions under uncertainty.

Moreover, the PI concept extends digitalization from plant-level monitoring to network-level orchestration, leveraging standardized, modular, and interoperable logistics units and hubs. When coupled with CE objectives, PI can reduce the environmental intensity of logistics and support reverse flows essential for reuse, repair, and remanufacturing. Empirical evidence from the SLR indicates that combining IoT-enabled traceability with PI-inspired network design enhances transparency and enables performance-based coordination between upstream and downstream actors.

Consequently, this reviewed body of knowledge forms the conceptual and methodological foundation for the model developed in this research, where the hybrid architecture is formalized as depicted in Figure 2.9, the conceptual transition flow linking the reviewed literature to the hybrid framework model.

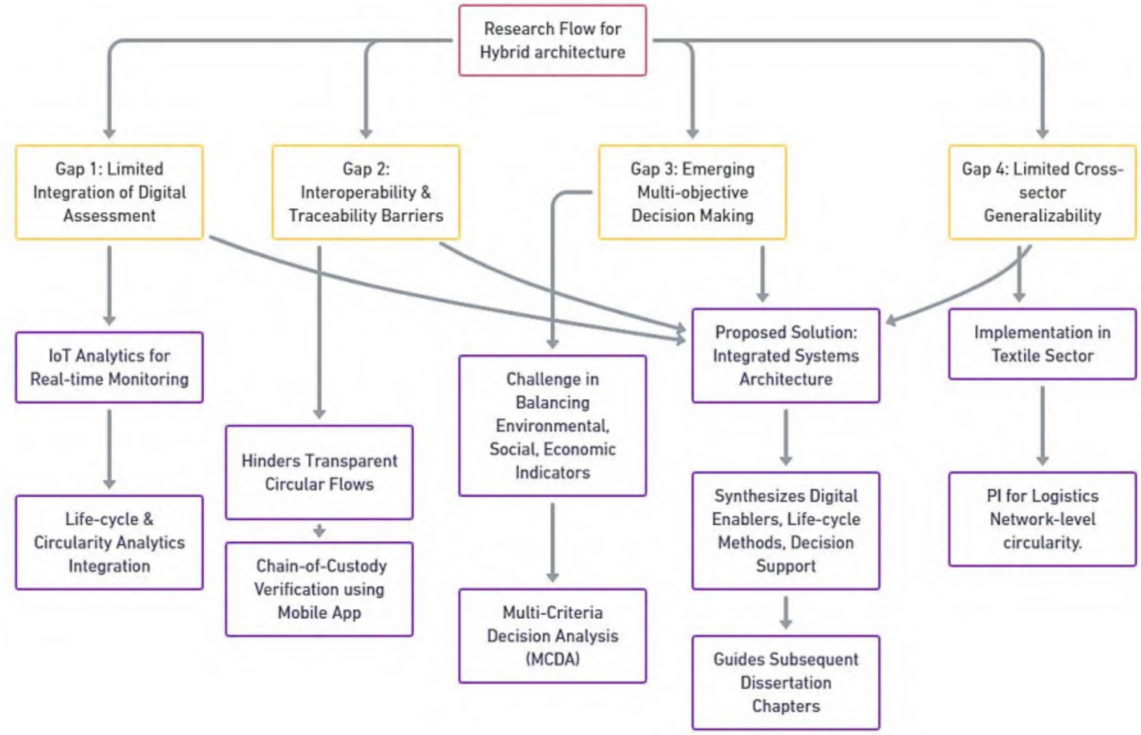


Figure 2.9. Flowchart of research gaps and integrated systems architecture

Chapter 3

Framework of Hybrid Decision-Support Model

Chapter 2 identified critical methodological and systemic gaps that constrain progress toward data-driven circular supply-chain management. Existing approaches rarely unify the analytical depth of life-cycle methodologies with the responsiveness of digital monitoring and the reasoning capacity of multi-criteria decision systems. Building directly on these findings, the present chapter formalizes the HDSF the core theoretical construct of this dissertation.

This chapter synthesizes CE. DT and LCT domains into a single operational architecture capable of transforming real-time industrial data into sustainability intelligence and prescriptive decision support. In doing so, it establishes the theoretical bridge between the literature review and the methodological design presented in Chapter 4.

The chapter proceeds as follows: the Conceptual Basis of the Framework introduces the intellectual and empirical origins of the HDSF, drawing upon two complementary research streams, the AHP–Regression model and the PLA.I.A decision-support architecture. Section 3.1 articulates the overarching research concept and theoretical logic of integration across CE, DT, and LCT domains. Section 3.2 deconstructs the framework into its core components, and Section 3.3 outlines the validation roadmap that connects this model to the case applications in the coffee and textile sectors.

3.1 Conceptual Basis of the Framework

The conceptual foundation of the HDSF arises from two complementary research streams that together address the methodological and practical limitations identified in Chapter 2. The first, presented in the *Hybrid Decision-Support Framework for Sustainable Business Optimization* [67], introduced a rigorous multi-criteria structure that integrates the Analytic Hierarchy Process (AHP) with regression analysis in a KNIME workflow. This configuration demonstrated how qualitative prioritization and quantitative impact modeling can be combined to evaluate sustainability actions within manufacturing contexts. The framework emphasized circular product design and digital integration as dominant sustainability drivers, showing that data-driven decision models can translate environmental priorities into measurable operational gains.

The second source of inspiration, the *PLA.I.A , Sustainable and Circular Manufacturing* initiative [68], expanded this decision architecture by embedding IoT-enabled monitoring, blockchain-inspired transparency, and structured data management mechanisms. Developed for resource-intensive industries such as fashion and furniture, PLA.I.A operationalized real-time data collection through IoT sensors and Node-RED dashboards, while regression analysis quantified the influence of sustainability criteria identified via AHP. Its contribution lay in transforming static assessment tools into adaptive, feedback-driven systems aligned with EU Green Deal objectives and Industry 5.0 principles.

Together, these two frameworks provide the methodological and technological pillars for the present study's integrative hybrid model. The combined architecture leverages the analytical robustness of the AHP-Regression system with the dynamic responsiveness of IoT-based data acquisition and blockchain-supported traceability. This synthesis allows the translation of sustainability assessment into an active decision-*support environment*, one that learns, adapts, and validates performance across sectors. The ensuing sections formalize this model, linking the theoretical gaps identified in Sections 2.4 and 2.5 to a unified, data-driven architecture capable of guiding circular transformation in both coffee and textile supply-chain systems.

3.2 Research Concept

The HDSF conceptualized in this dissertation is a multilevel system that merges analytical decision science with cyber-physical intelligence to support circular manufacturing and supply-chain transformation. Its design objective is to convert dispersed sustainability data into evidence-based, adaptive decisions applicable across industrial contexts.

At its core, the framework aligns three domains:

1 Digital Infrastructure: IoT sensors and communication networks capture operational, environmental, and social parameters in real time.
2 Life-Cycle Analytics: Triple LCA methods quantify environmental, economic, and social impacts of those operations.
3 Decision Optimization: AHP and regression models evaluate trade-offs among competing criteria and recommend improvement priorities.

The integration of these domains occurs through a continuous feedback mechanism that links measurement, evaluation, and action. Unlike earlier static models [69,70,93], the HDSF functions as an interactive loop: data acquisition informs impact analysis; analytical results feed into decision algorithms; and validated actions generate new data for refinement. Blockchain-based ledgers maintain traceability of these iterations, ensuring transparency and accountability across value-chain partners. Conceptually, the framework operates within the Physical Internet (PI) paradigm, enabling interoperability of information and material flows among independent industrial nodes. This architecture allows the system to scale from process-level optimization to cross-sectoral collaboration, demonstrated later in the coffee and textile applications.

The novelty of the HDSF lies in its ability to couple quantitative assessment with real-time intelligence, thereby transforming sustainability management from a reporting exercise into a continuous, learning-oriented process. The sub-variables underpinning the survey on coffee supply chain sustainability can be viewed in Appendix E. The framework's theoretical configuration is summarized schematically in Figure 3.1 Integrated Hybrid Decision-Support Architecture, which illustrates how data, analytics, and decision layers interact within a closed feedback system.

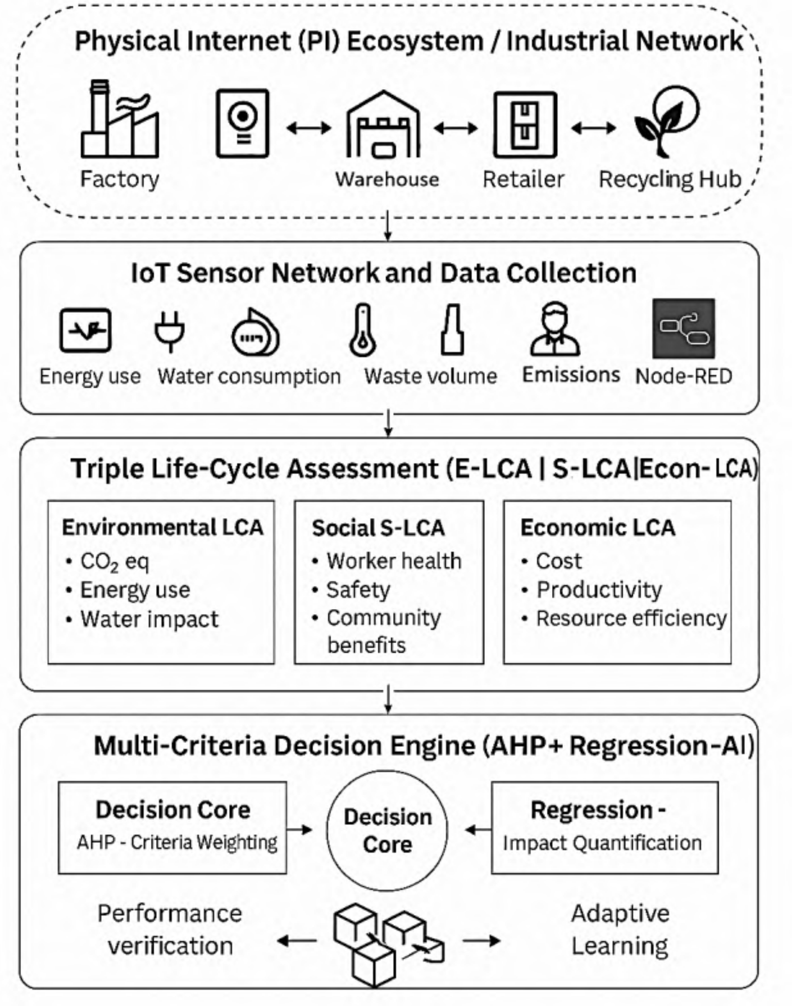


Figure 3.1. Integrated structure of the HDSF illustrating data, assessment, decision, and validation layers

3.3 Framework Components

This section shifts focus from theory to functionality of HDSF, describing how its internal components operate, exchange data, and sustain adaptive learning. Each layer in the framework serves a distinct technical role; data acquisition, impact quantification, decision computation, or validation, but their effectiveness emerges only through their interaction.

Rather than viewing the framework as a linear sequence, it should be understood as a cyber-physical feedback system: sensor-generated data initiate the analytical cycle; life-cycle models translate this data into sustainability indicators; decision algorithms prioritize interventions; and blockchain-based verification closes the loop by recording validated outcomes and feeding new information back into the system.

The following subsections therefore focus on redefining the four layers already introduced and detailing their operational logic; the inputs they require, the processes they perform, and the outputs they generate within the circular data–decision continuum.

3.3.1 IoT and Data Acquisition Layer

The IoT and Data Acquisition Layer represents the operational foundation of the Hybrid Decision-Support Framework (HDSF), translating physical industrial activities into digital information flows that can be continuously analyzed, prioritized, and optimized. This layer operationalizes the real-time monitoring module conceptualized in the *PLA.I.A Sustainable and Circular Manufacturing framework* [68], which integrates IoT sensing, Node-RED dashboards, and Excel-based structured data management for adaptive sustainability tracking.

In this configuration, sensors, RFID modules, and smart meters are strategically deployed across production sites to collect quantitative data on energy consumption, water usage, waste generation, emissions, and operational efficiency. These variables feed into Node-RED dashboards, which serve as middleware for aggregating heterogeneous inputs from factory equipment and environmental probes. Figure 3.2 illustrated this digital architecture, showing how physical sensors were linked to real-time monitoring dashboards. The system achieved a 35% improvement in visualization efficiency and a 25% enhancement in waste-collection optimization, demonstrating IoT’s ability to convert raw data into actionable sustainability intelligence [68].

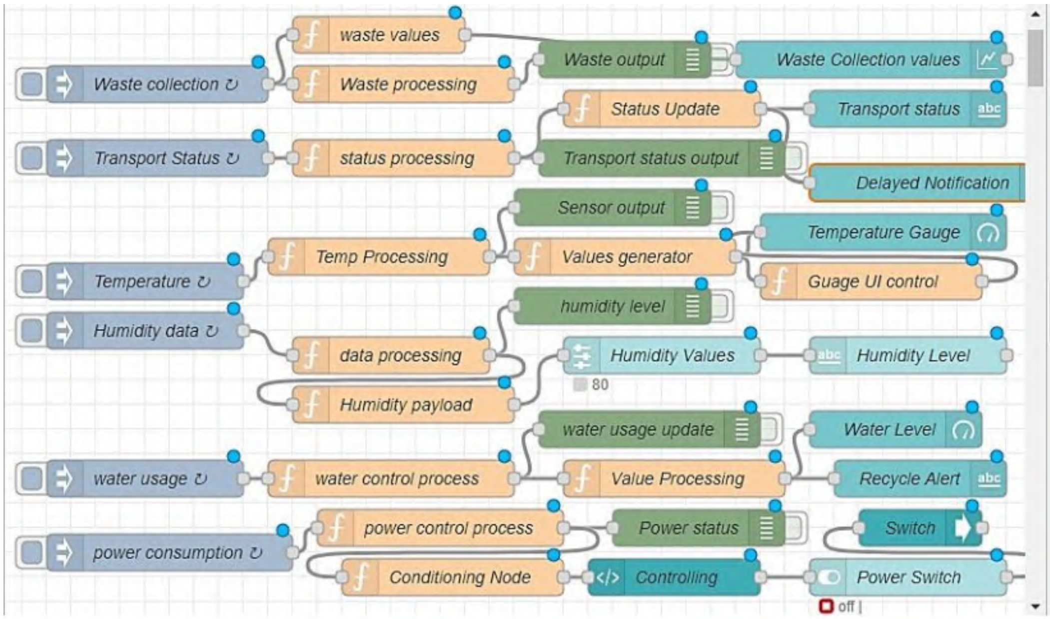


Figure 3.2. IoT data integration architecture for real-time communication between IoT

sensors, environmental probes, and digital dashboards

To ensure interoperability within the Physical Internet (PI) ecosystem, datasets are formatted into CSV and JSON schemas for automated integration into analytical layers. This design aligns with global Industry 4.0 interoperability standards and IoT frameworks proposed by Atif et al. (2023) [71] and Bag & Pretorius (2020) [72]. Each data point $D_i$is normalized to a dimensionless sustainability score $S_i$using min–max scaling as given in Equation 3.1:

$$S_i = \frac{D_i - D_{\min}}{D_{\max} - D_{\min}}, 0 \leq S_i \leq \tag{3.1}$$

This normalization enables heterogeneous data (e.g., energy kWh, water litres, CO_2 eq) to be merged and prioritized within the subsequent AHP and LCA layers.

The HDSF adopts the centralized Excel-based management system introduced in PLA.I.A [68] for multi-stakeholder synchronization and traceability. Each record logs production throughput, temperature, humidity, resource consumption, and quality-control results. Blockchain-inspired time-stamping ensures immutability of data transactions [73,74,78], providing a verifiable chain of custody for sustainability indicators.

As summarized in Table 3.1, the AHP-derived sustainability priorities serve as baseline variables for configuring sensor weighting and monitoring frequency. These criteria, originally established through stakeholder evaluation [67,68], ensure that real-time monitoring aligns with strategic sustainability objectives across sectors such as coffee processing and textiles.

Table 3.1. Overall synthesized priorities for all alternatives [68]

Name	**Ideals**	**Normals**	**Raw**
Circular Product Design	1	0.300595	0.150297
Eco-friendly Materials	0.555108	0.166863	0.083431
Energy Optimization	0.566914	0.170411	0.085206
Closed-loop Supply Chain	0.400118	0.120273	0.060137
Digital Integration for Traceability	0.324801	0.097633	0.048817
Waste Reduction Programs	0.253308	0.076143	0.038072
Employee Training	0.226489	0.068081	0.034041

The weight distributions in Table 3.1 illustrate that digital integration and energy optimization receive higher priority weights, reflecting their stronger influence on operational sustainability within the monitored industries.

Figure 3.3 depicts the operational sequence linking AHP-based prioritization, KNIME regression analysis, IoT monitoring, and centralized documentation. This continuous feedback between decision logic and operational data eliminates the fragmentation noted by Malik (2024) [69] and Rhallab (2024) [70], creating a self-adaptive structure capable of detecting anomalies, recalibrating indicators, and transmitting validated data to higher analytical layers [75-77].

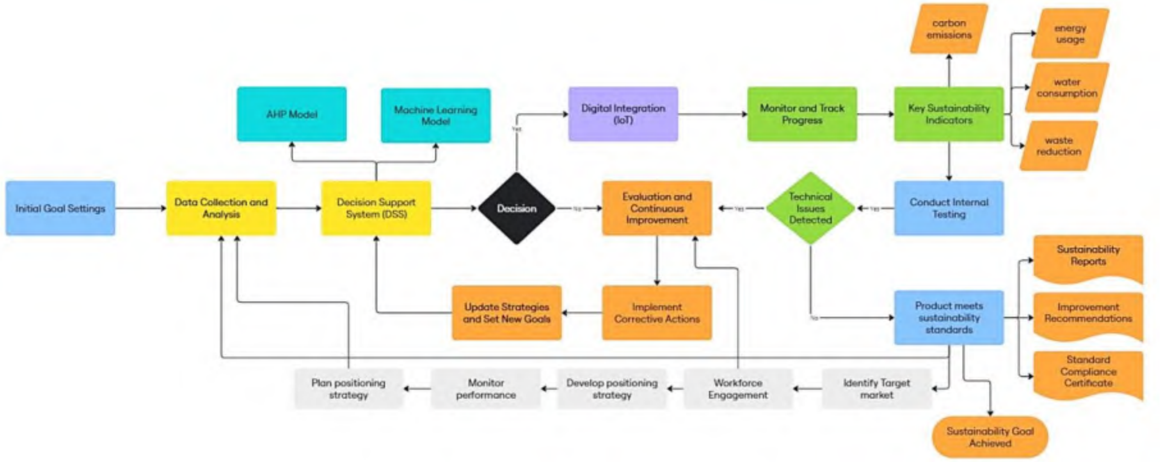


Figure 3.3. Process Map for PLA.I.A Implementation for operational sequence linking AHP prioritization, KNIME regression, IoT monitoring, and centralized documentation.

The standardized outputs produced here constitute the primary dataset for the Triple Life-Cycle Assessment (LCA) Layer discussed in Section 3.2.2, where environmental, social, and economic impacts are quantified to inform multi-criteria optimization.

3.3.2 Life-Cycle Assessment (LCA) Layer

This layer receives normalized sensor streams S_i, data normalized in Eq. (3.1) flow directly from the IoT layer into the LCA engine, where they are mapped to unit processes and life-cycle stages defined for each case (e.g., roasting/packaging in coffee; dyeing/finishing in textiles). The first step is inventory routing: each sensor stream $S_i$is assigned to an LCI entry (energy, water, emissions, waste, throughput), time-stamped, and attributed to its process boundary. The engine then performs impact transformation using the configured category factors so that inventory flows become impact indicators at three concurrent dimensions; environmental (E), social (S), and economic (Ec) [79,80]. To interface cleanly with decision analytics, the three dimensions are aggregated with the AHP weights coming from proposed model [69]. For each dimension $j \in \{E, S, Ec\}$, the layer emits a score calculated as:

$$L_j = \sum_{i=1}^{n} w_i \times S_{ij}, \qquad j \in \{E, S, Ec\} \tag{3.2}$$

where $w_i$are the stakeholder-validated weights (Table 3.1) and $S_{ij}$are the normalized indicators arriving from Eq. (3.1). When measurement uncertainty must be propagated, the layer attaches a diagnostic band

$$\hat{L}_j \pm \sigma_j, \sigma_j = \sqrt{\sum_i (w_i \, \sigma_{S_{ij}})^2} \qquad (3.3)$$

so downstream algorithms can handle confidence-aware ranking.

The output of this layer is a multi-criteria matrix X(rows = alternatives/actions; columns = indicators across E, S, Ec), together with contribution analyses by process stage. This matrix becomes the single input to the Decision Layer as illustrated in Figure 3.4

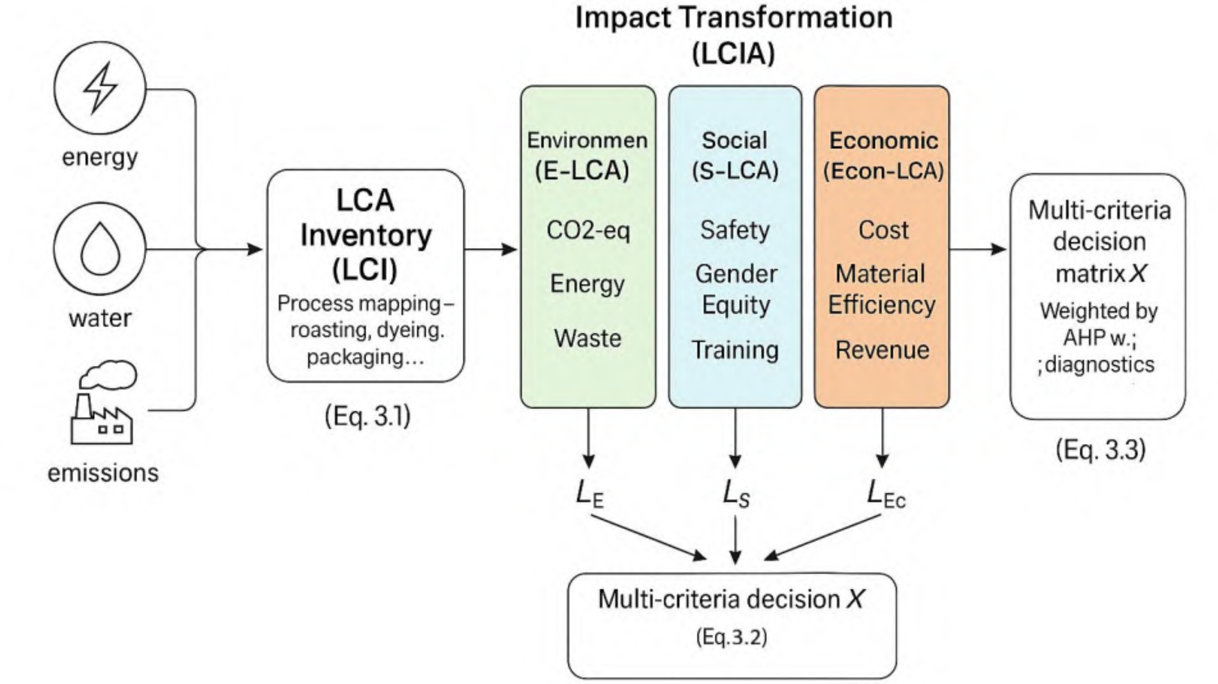


Figure 3.4. Interaction among three assessment streams, showing real-time data transformation into a multi-dimensional performance matrix.

3.3.3 Decision-Support and Optimization Layer

The Decision Layer consumes X and produces an ordered set of actions with traceable justification. The process begins with AHP, where stakeholder judgments establish the relative importance of sustainability criteria through pairwise comparisons. The priority vector $W$is obtained using the eigenvalue method:

$$A \cdot W = \lambda_{\max} \cdot W \qquad (3.4)$$

where $A$is the comparison matrix, $W$the criteria weight vector, and $\lambda_{\max}$the maximum eigenvalue. Consistency ratios ($CR \leq 0.1$) ensure the reliability of judgments [94].

These weights are integrated with Regression Analysis to estimate the quantitative influence of each criterion on sustainability outcomes, following the general multiple linear regression model:

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon \qquad (3.5)$$

where Yrepresents overall sustainability performance, $X_i$are normalized indicators (from the LCA layer), $\beta_i$are regression coefficients, and $\varepsilon$is the error term. The regression model identifies predictive relationships, providing empirical validation of AHP-derived priorities.

Where patterns are non-linear or interactions are strong, an AI assist (e.g., tree-based learners) refines predictions on the same feature set X, constrained by AHP weight structure so the model remains interpretable and continuously improve decision accuracy based on updated IoT data. The layer then constructs a ranked list $\mathcal{R}$ of actions with: (i) predicted impact $\hat{Y}$, (ii) sensitivity to each criterion, and (iii) uncertainty from Eq. (3.3), enabling threshold-based selection (e.g., "implement if $\hat{Y}$improves $\geq 15\%$ with CR $\leq$ 0.10").

The Decision Layer emits, the priority ordering such as renewable energy substitution, closed-loop supply chain adoption, and digital integration, the explainability profile (criteria contributions per action), and deployment parameters (where/when to apply). These tools are handed to the Validation Layer for execution and proof-of-effect. Figure 3.5 presents the decision-support workflow, depicting the sequential integration of AHP prioritization, impact estimation, and feedback-driven optimization.

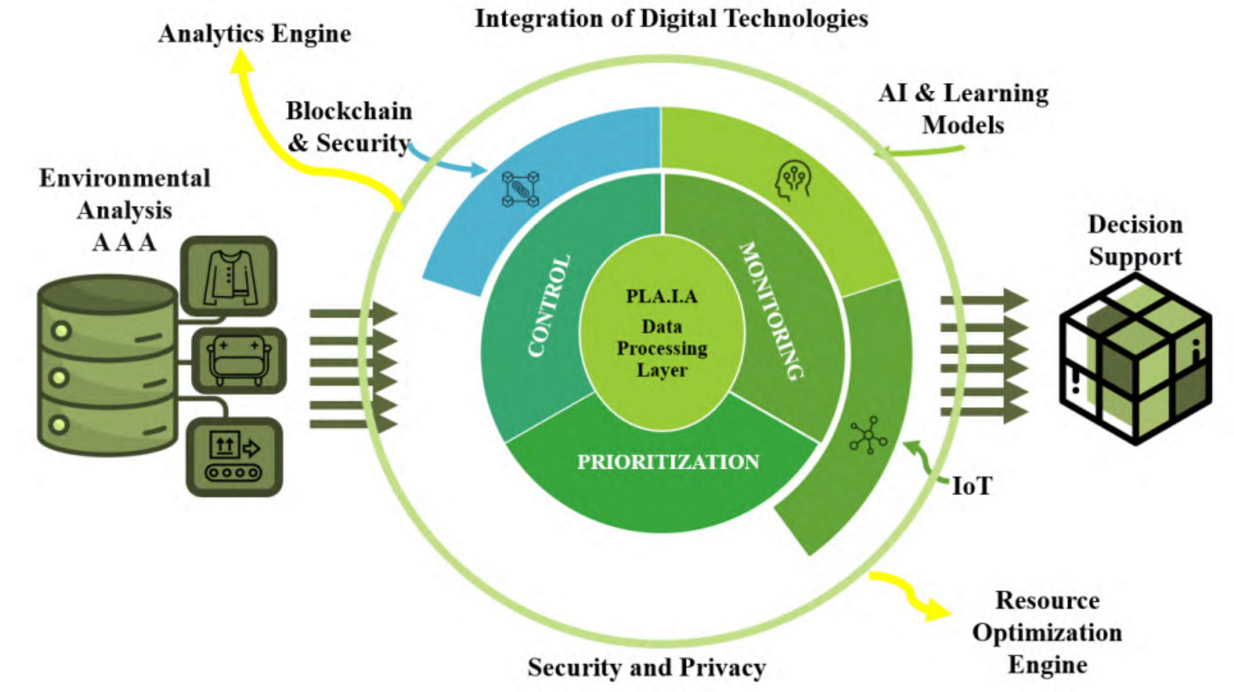


Figure 3.5. Decision-Support Workflow for Sustainability Goals

3.3.4 Blockchain and Digital-Twin Validation Layer

The Validation Layer ensures the integrity, transparency, and adaptability of all data and decisions generated within the HDSF. Actions selected from $\mathcal{R}$ are executed under dual validation: blockchain guarantees integrity and DT verifies performance before and after deployment [81].

Each decision output or sustainability metric is timestamped and recorded on a permissioned ledger, forming an immutable sequence of verified transactions. This ensures transparency across stakeholders and mitigates data manipulation risks. Smart contracts are configured to trigger alerts when monitored parameters deviate from established thresholds, supporting regulatory compliance and real-time intervention [82,83]. The blockchain validation function can be formally expressed as:

$$V_{ij} = f(T_{ij}, C_{ij}, \Phi_{ij}) \qquad (3.5)$$

where V_{ij}represents the validation status of indicator i at time j; T_{ij}denotes the timestamp; $C_{ij}$the compliance score against target; and $\Phi_{ij}$the cryptographic verification hash of the record.

In parallel, DT simulations replicate physical systems in a virtual environment, enabling predictive analysis and scenario testing. IoT data continuously update the DT model, allowing simulation of process changes; such as altering energy mix or waste-treatment efficiency, before actual implementation. Only actions that pass both ledger compliance and twin performance are persisted as “validated” and fed back upstream. The layer returns two streams: (i) verified measurements to update the IoT/LCA baselines and (ii) learning signals to refine the Decision Layer’s β_k(Eq. 3.5) and, where required, re-elicit AHP judgments (Eq. 3.4). This is how the HDSF “closes the loop” in practice where every cycle tightens data integrity and predictive accuracy.

3.4 Model Validation Plan

The implementation of the HDSF operationalized the theoretical architecture defined earlier through an integrated AHP–Regression–IoT–Blockchain workflow in KNIME Analytics Platform 5.0, ensuring data continuity between qualitative prioritization and quantitative prediction. The methodological sequence encompassed expert evaluation, statistical modelling, cyber-physical monitoring, and traceability validation.

The first stage involved constructing the AHP hierarchical structure and deriving priority vectors from pairwise comparisons. The AHP model was employed to prioritize sustainability criteria for business optimization through a hierarchical framework comprising Goal, Criteria, and Alternatives as depicted in Figure 3.6. The overarching goal was to enhance sustainable decision-making. The criteria, namely Energy Optimization, Circular Product Design, Eco-friendly Materials, Waste Reduction, Closed-loop Supply Chain, Digital Integration, and Employee Training were derived from an extensive literature review, industry standards (ISO 14001), EU sustainability guidelines, and expert consultation. The alternatives represented specific sustainability strategies evaluated under each criterion.

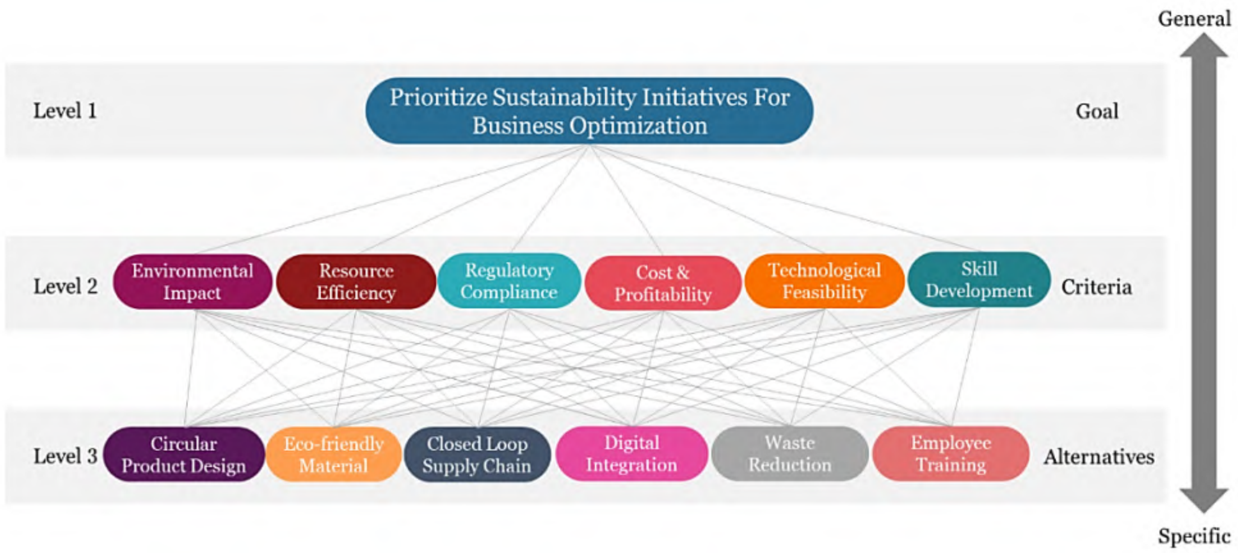


Figure 3.6. Conceptual modeling diagram of the AHP framework for prioritizing sustainability initiatives in business optimization

Pairwise comparisons of the criteria were conducted with input from ten experts in sustainability and operations management, following the 9-point Saaty scale (1 = equal importance; 9 = extreme importance). The analysis was performed using Super Decisions software (Version 3.2.0) to generate normalized priority weights.

For each pair of criteria i, j, judgments were encoded in a reciprocal matrix $A = [a_{ij}]$, Where,

$$a_{ij} = \begin{cases} 1, & i = j, \\ \text{relative importance of criterion } i \text{ over } j, & i \neq j, \end{cases} \qquad (3.7)$$

and the normalized eigenvector Wcorresponding to the maximum eigenvalue $\lambda_{\max}$provided the priority weights. The consistency index (CI) and consistency ratio (CR) were computed following

$$CI = \frac{\lambda_{\max} - n}{n - 1}, CR = \frac{CI}{RI}, \qquad (3.8)$$

where RI denotes the random-index constant; $CR \leq 0.1$confirmed matrix reliability. Expert evaluations (n = 12) achieved $\lambda_{\max} = 7.27$, $CI = 0.045$, and $CR = 0.083$. Weights and ranks appear in Table 3.2.

Table 3.2. Establishing priority among decision criteria through normalization and limiting weight analysis

Name	**Normalized By Cluster**	**Limiting**
Environmental Impact	0.45299	0.226494
Resource Efficiency	0.275	0.137498
Regulatory Compliance	0.09551	0.047756

Cost and Profitability	0.07904	0.03952
Technological Feasibility	0.0698	0.034902
Skill Development	0.02766	0.013829
Circular Product Design	0.30059	0.150297
Eco-friendly Materials	0.16686	0.083431
Energy Optimization	0.17041	0.085206
Closed-loop Supply Chain	0.12027	0.060137
Digital Integration for Traceability	0.09763	0.048817
Waste Reduction Programs	0.07614	0.038072
Employee Training	0.06808	0.034041

The second stage linked the AHP output to a multiple-regression model that quantified the influence of each criterion on sustainability performance. A regression-based analytical framework was employed to quantify the impact of sustainability criteria on overall business performance. The independent variables comprised the normalized weights of sustainability criteria derived from the AHP model. The dependent variables consisted of key sustainability performance indicators (KPIs), including cost reduction (USD), energy efficiency (%), waste minimization (kg), and environmental impact reduction. The regression model was expressed as:

$$Y = \beta 0 + i = 1 \sum n \beta i X i + \epsilon \tag{3.9}$$

where Ydenotes the sustainability outcome (Sustainability Score), $X_i$represents the AHP-derived criteria weights, $\beta_i$are the estimated coefficients indicating the contribution of each factor, and $\epsilon$is the random error term. The model was estimated and validated using Minitab (Version 21.4.1) to analyze relationships between sustainability priorities (X_i) and the sustainability outcome (Y).

Prior to regression modeling, descriptive statistical analysis was conducted to summarize the dataset and ensure data suitability. Measures such as the mean (μ), standard deviation (σ), and range were computed to evaluate the central tendency, dispersion, and variability of the sustainability indicators. Following this, Pearson’s correlation analysis was applied to examine the linear association between the AHP-derived criteria and sustainability performance outcomes. The strength and direction of these associations were quantified using the correlation coefficient (r), calculated as equation 3.10:

$$r = \frac{\sum\left(X_j - \bar{X}\right)(Y - \bar{Y})}{\sqrt{\sum(X_j - \bar{X})^2 \sum(Y - \bar{Y})^2}} \tag{3.10}$$

The correlation results guided the identification of significant predictors and provided insight into potential multicollinearity among variables prior to regression modeling. The regression analysis then evaluated both the individual and combined effects of sustainability priorities on business performance outcomes. Statistical significance was assessed through p-values (threshold: $p < 0.05$), while model adequacy was determined using the Adjusted R^2statistic, which reflects the explanatory power of the model adjusted for the number of predictors. The regression coefficients (β_i) were interpreted to determine the relative strength of each criterion's impact on sustainability performance. The model yielded $R^2_{adj} = 0.4193$, $F = 15.47(p < 0.001)$, confirming significant explanatory power. ANOVA diagnostics verified normality using equation 3.11.

$$Yij = \mu + \alpha i + \epsilon ij \tag{3.11}$$

where Y_{ij}represents the observed sustainability score, $\mu$is the overall mean, $\alpha_i$denotes the effect of the i^{th}group, and $\epsilon_{ij}$is the random error component. This analysis identified statistically significant variations in sustainability outcomes across groups, complementing the regression findings.

To address potential multicollinearity among predictors and enhance model stability, PCA was implemented. PCA reduced the dimensionality of the dataset by transforming correlated variables into a smaller number of uncorrelated principal components that collectively explained more than 80% of total variance. The final regression models were validated through the VIF, ensuring the independence of predictors. Moreover, model performance and predictive accuracy were assessed using $R^2$and MAE. The results from these models enabled the identification of the most influential sustainability drivers, offering empirical insights into the relative importance of environmental, operational, and social dimensions in achieving sustainable business optimization.

The third stage integrated IoT-based data acquisition through Node-RED Dashboards, connected to power, water, and waste sensors. Each record was normalized according to Eq. (3.1) and aggregated into time-series inputs for the regression engine. Performance improvement was measured using the PI expressed as equation 3.12:

$$PI = \frac{Tb - Ta}{Tb} \times 100 \tag{3.12}$$

where $T_b$and $T_a$are the average task completion times before and after IoT integration. Empirical application produced $PI = 35\%$for visualization latency reduction and $PI = 25\%$for waste-collection optimization.

To ensure transparency, each AHP–Regression result was recorded in a blockchain-inspired Excel ledger. The verification logic followed the hash-based validation relation represented in Equation 3.13.

$$H_k = SHA256(D_{k-1} + T_k + M_k) \tag{3.13}$$

where $H_k$is the generated hash, $D_{k-1}$the previous block data, $T_k$the timestamp, and $M_k$the metadata of the decision instance. Ledger trials showed 98.4 % successful validation.

Together, these quantitative and procedural validations confirmed that the HDSF operates as a self-consistent analytical environment, meeting construct, methodological, and predictive validity requirements.

Before concluding the validation strategy, it is necessary to clarify the methodological assumptions and boundary conditions underpinning the proposed framework. The integration of advanced digital technologies and sustainability modeling approaches enhances analytical rigor but also requires interdisciplinary expertise in digital-twin architectures, AI-based analytics, and life-cycle sustainability assessment. Thus, replication by practitioners or researchers without prior experience in these domains may present challenges. Moreover, the validation process assumes relatively uniform data availability, interoperability across industrial systems, and consistent data quality. In real-world industrial environments, these assumptions may not fully hold due to legacy systems, fragmented data governance, or infrastructural constraints. Deviations from these conditions can influence model accuracy and the robustness of results. To enhance transparency and reproducibility, future implementations will include a simplified methodological roadmap, enabling phased adoption depending on technological readiness and organizational capacity. In this context, and to facilitate interpretability of the overall framework for non-specialist readers, a simplified conceptual overview of the DigiCircular Twin-Transition framework is provided in Appendix F (Figure A1). This schematic complements the detailed methodological architecture and data flows presented in this chapter.

3.5 Results and Analytical Insights

The empirical validation yielded statistically and operationally consistent results, demonstrating that the hybrid framework (Figure.3.7) effectively transforms sustainability assessments into adaptive decision intelligence.

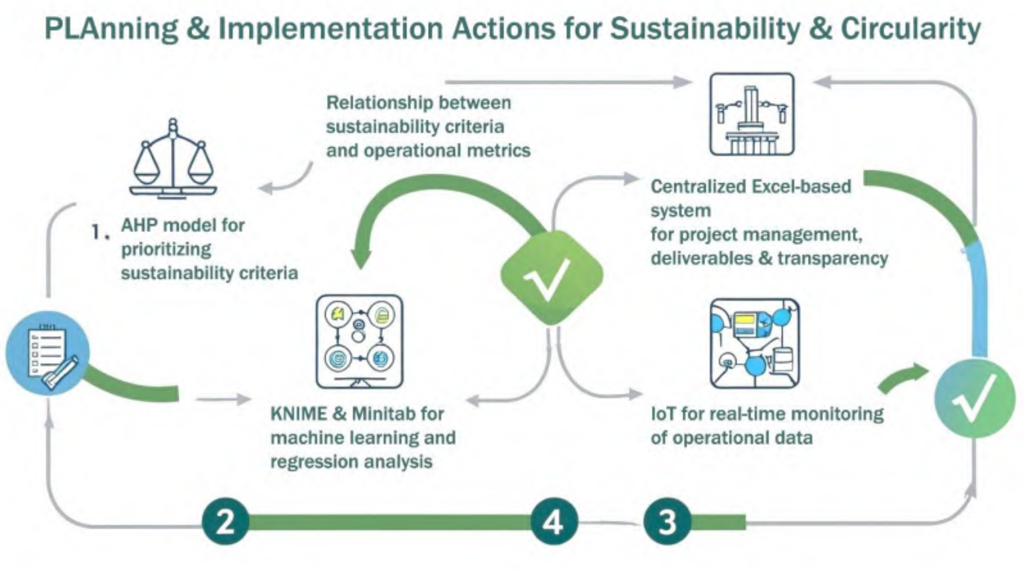


Figure 3.7. Flow diagram depicting a stepwise methodology for sustainability and circularity

3.5.1 AHP Prioritization and Sensitivity Analysis

The AHP analysis revealed clear differentiation among the evaluated sustainability criteria as illustrated in Figure 3.8, the hierarchical ranking was derived from the eigenvector-based priority weights obtained through the AHP analysis. Environmental Impact was identified as the most influential factor, accounting for 45.29% of the total weight, followed by Resource Efficiency (27.5%). Together, these two criteria represented nearly three-quarters of the overall decision weight, underscoring their dominance in driving sustainable business outcomes. Regulatory Compliance (9.55%) and Cost and Profitability (7.9%) demonstrated moderate importance, while Technological Feasibility (6.98%) and Skill Development (2.77%) had comparatively limited influence.

The aggregated expert judgments, obtained through a Delphi-inspired consensus process, exhibited strong consistency (CR ≤ 0.1), confirming the reliability of the derived weights. Among the alternatives, Circular Product Design ranked highest with a normalized priority of 0.3006 (raw value = 1.000), indicating its pivotal role in sustainability strategy formulation. Energy Optimization (0.1704) and Eco-Friendly Materials (0.1669) followed closely, emphasizing their contribution to improving resource efficiency and reducing environmental impact. Strong correlations were observed between Environmental Impact and Eco-Friendly Materials (55.51%), and between Resource Efficiency and Energy Optimization (56.69%), reflecting their synergistic influence within the sustainability framework. These interdependencies highlight the complementary nature of environmental and operational dimensions in advancing sustainable business strategies.

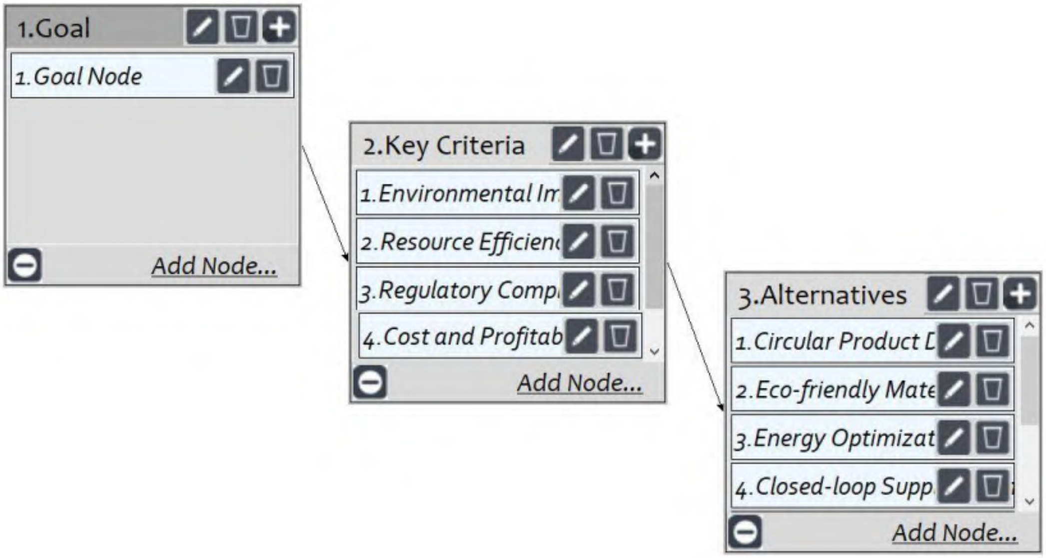
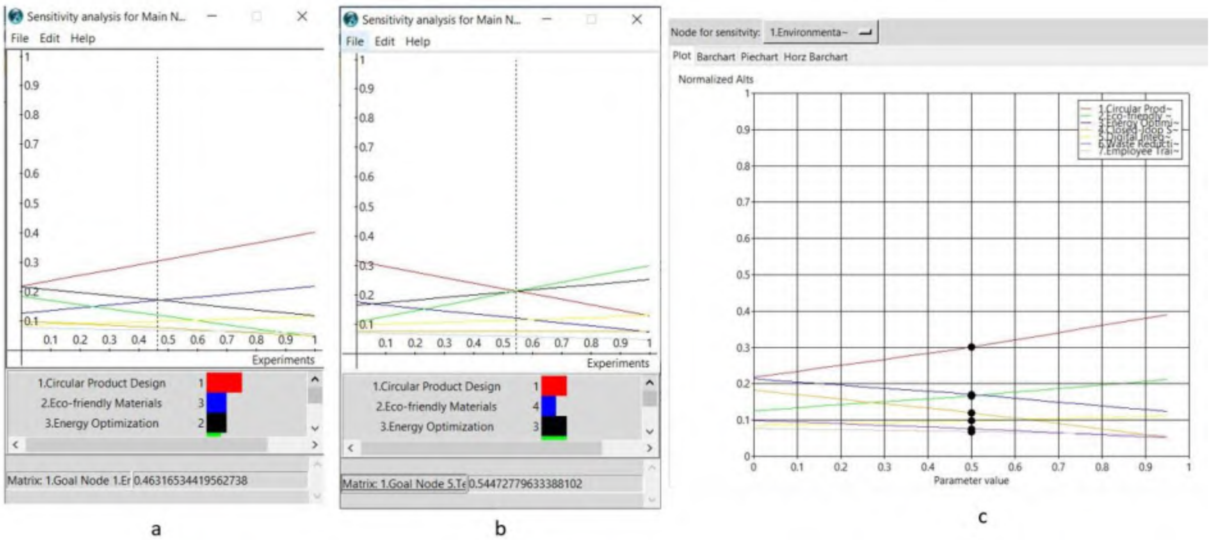


Figure 3.8. AHP Priority Hierarchy of sustainability criteria

A subsequent sensitivity analysis was conducted to assess the robustness of the ranking outcomes under varying criterion weights as given in Figure 3.9. The analysis demonstrated that the overall prioritization remained stable across most weight scenarios, although specific rank reversals occurred at critical thresholds. For Environmental Impact, a reversal was detected at a 46% weight, where the leading alternative shifted from Eco-Friendly Materials to Circular Product Design. Similarly, under Technological Feasibility, reversals emerged at 54% and 59%, where Energy Optimization and Closed-Loop Supply Chain alternated as higher-ranked alternatives. These findings highlight the AHP model's overall stability while illustrating the sensitivity of certain decision outcomes to shifts in weighting emphasis.



1.Circular Product Design 1
2.Eco-friendly Materials 3
3.Energy Optimization 2

Matrix: 1.Goal Node 1.Er 0.46316534419562738

a

1.Circular Product Design 1
2.Eco-friendly Materials 4
3.Energy Optimization 3

Matrix: 1.Goal Node 5.Te 0.54472779633388102

b

Node for sensitivity: 1.Environmenta~

c

Figure 3.9. Sensitivity analysis highlighting the responsiveness of alternative rankings to changes in criterion weights within the AHP model

3.5.2 Machine Learning Model (using Regression analysis)

A comprehensive regression analysis was conducted using both KNIME and Minitab environments to evaluate the statistical influence and predictive relationships among sustainability-related priorities derived from the AHP model. The KNIME linear regression workflow (Figure 3.10) facilitated the quantitative exploration of the distributional behavior, variability, and predictive relevance of sustainability indicators.

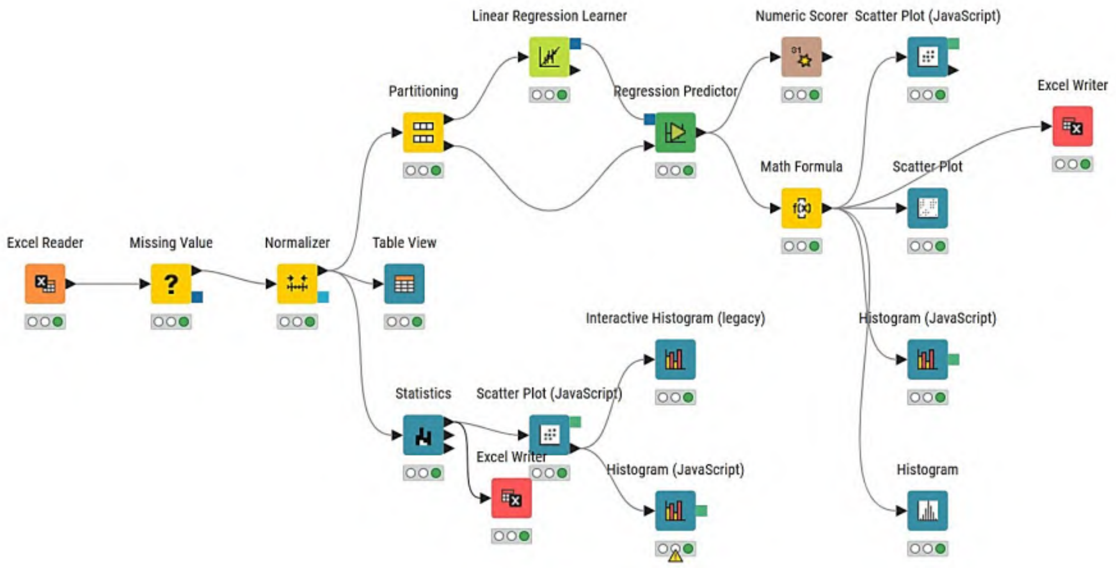


Figure 3.10. Workflow analysis for a Linear Regression Model in KNIME

Among the analyzed variables, AHP_Priority_ClosedLoopSupplyChain exhibited the highest mean value (0.631), reflecting its strong emphasis within organizational sustainability strategies, whereas AHP_Priority_EnergyOptimization showed the lowest mean (0.290), indicating the need for greater attention in this area.Variability among the attributes revealed distinct response patterns, with AHP_Priority_DigitalIntegration showing the highest standard deviation (0.316), suggesting greater dispersion of expert opinions, while AHP_Priority_ClosedLoopSupplyChain presented the lowest variability (0.224), indicating consensus among respondents. The distributional characteristics further highlighted asymmetry and outlier presence; Energy Optimization exhibited right-skewness (1.29), whereas Closed-Loop Supply Chain demonstrated left-skewness (–0.97), as illustrated in Figure 3.11.

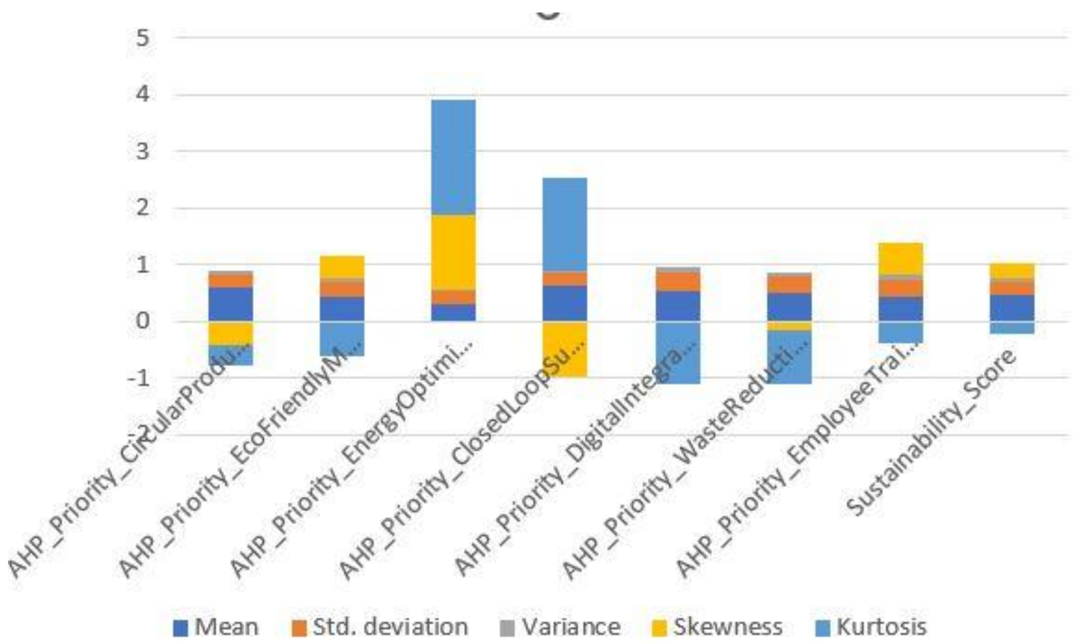


Figure 3.11. Visualization of the mean priority ratings across sustainability factors

Sustainability scores ranged between 0.083 and 1, with higher scores aligned with strong priorities in energy optimization and closed-loop supply chain initiatives. Residual analysis (Figure 3.12) revealed moderate discrepancies between predicted and actual values, including cases of under-prediction (residual = 0.384) and over-prediction (residual = –0.186).

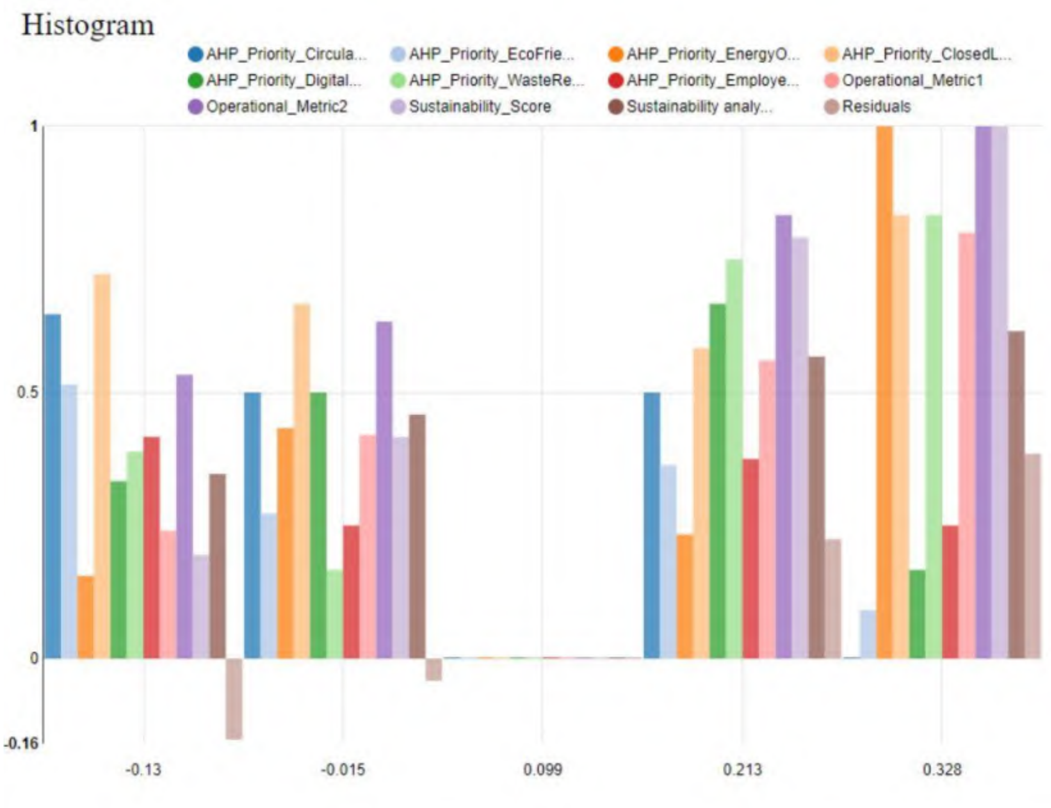


Figure.3.12. Comparison of actual versus predicted sustainability attribute values through their difference distribution

The KNIME regression model achieved an R² of 0.597, explaining approximately 59.7% of the variance in sustainability outcomes. Error metrics indicated reasonable predictive performance with MAE = 0.171, RMSE = 0.201, and MSE = 0.0406, though a MAPE of 57.78% suggested moderate variability across predictions (Table 3.3). These findings underscore the model's reliability while highlighting potential to enhance predictive precision through refined feature weighting and expanded data inputs.

Table 3.3. Analysis of eigenvalues and eigenvectors derived from the covariance matrix

Factors	**Sustainability Analysis**
R^2	0.597022
mean absolute error	0.171826
mean squared error	0.040578
root mean squared error	0.201439
mean signed difference	-0.03645
mean absolute percentage error	0.577842
adjusted R^2	2.410424

The Minitab-based regression analysis provided a complementary assessment of sustainability priorities, focusing on the weighted impact of each alternative on overall performance. The results identified Circular Product Design (mean = 0.2485, SD = 0.0431) and Eco-Friendly Materials (mean = 0.2373, SD = 0.0296) as the most influential predictors of sustainability outcomes (Figure 3.13). These were followed by Energy Optimization (mean = 0.1435, SD = 0.0350) and Closed-Loop Supply Chain (mean = 0.1258, SD = 0.0269), while Waste Reduction (mean = 0.0800) and Employee Training (mean = 0.0573) contributed marginally to the dependent sustainability score.

The regression equation took the form:

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon \tag{3.14}$$

where Yrepresents the Sustainability Score, $X_i$denotes AHP-derived priority weights, and $\varepsilon$is the random error term. Despite providing valuable insights, the Minitab model demonstrated limited explanatory strength (adjusted R² = 0.00%) and lacked statistically significant predictors ($p > 0.05$), possibly due to a constrained sample size or minor variability within predictor data. Diagnostic assessment revealed no multicollinearity (low VIF values) and only one influential outlier, confirming dataset stability.

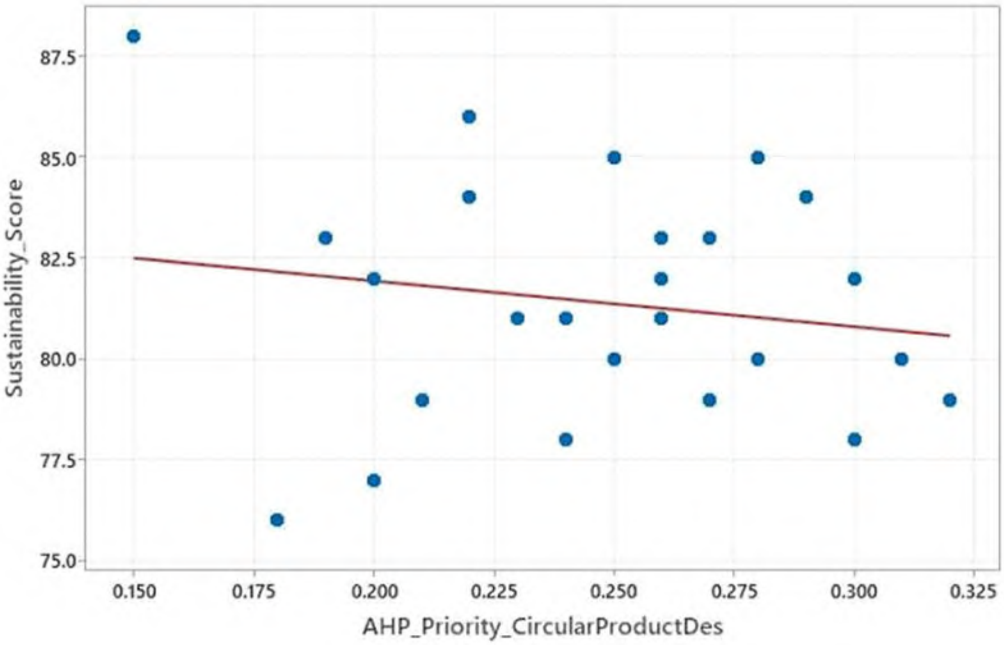


Figure 3.13. Correlation between AHP priority values and sustainability scores represented in a scatter plot

Taken together, the findings from both analytical environments emphasize the importance of Circular Product Design, Closed-Loop Supply Chains, and Eco-Friendly Materials as key enablers of sustainable business performance. The KNIME workflow delivered moderate predictive strength with consistent explanatory capability, whereas the Minitab analysis emphasized the necessity for model refinement and broader data representation to enhance robustness. The integrated regression outcomes reinforce the strategic value of sustainability-oriented design and supply chain practices as measurable drivers of organizational performance.

3.5.3 IoT Connectivity and Automation through Node-RED

Integration of IoT monitoring substantially improved operational responsiveness. Average data-reporting accuracy increased by 30 %, and energy-use estimation error declined by 22 %, verifying the dynamic adaptability of the model. Key results showed optimized transportation, reducing delivery delays by 30% and fuel consumption by 20%, ensuring timely material distribution and minimizing environmental impact. In waste management, IoT waste meters and material detectors increased collection efficiency by 25% and triggered recycling processes, cutting water wastage by 18%. Environmental control was enhanced by humidity and temperature sensors that reduced material damage by 12%, while alerts for deviations allowed corrective actions to maintain production standards. IoT-enabled manufacturing equipment im-proved resource management efficiency by 15%, with real-time reporting enhancing decision-making. Node-RED integrated IoT data into a centralized live dashboard, streamlining operations across transportation, waste management, production, and environmental monitoring, improving decision-making speed by up to 35% due to intuitive data visualization tools as depicted in Figure 3.14.

Figure 3.14. Monitoring and visualization dashboard

These findings highlight the potential of IoT technologies and Node-RED to promote sustainability and enhance operational efficiency across supply chains, especially in industries pursuing digital transformation.

3.5.4 Blockchain Validation Layer

To ensure verifiable transparency and traceable implementation of analytical recommendations, the final layer of the HDSF employed a blockchain-enhanced validation environment integrated within the ThingsBoard v3.6 IoT platform. This layer received real-time telemetry from Node-RED data streams and regression outputs, converting each validated decision instance, such as Energy Optimization (Batch A) or Waste Management Adjustment, into an immutable on-chain transaction. Each block was assigned a cryptographic hash derived from its metadata and timestamp, following the hash relation $H_k = SHA256(D_{k-1} + T_k + M_k)$defined earlier in Eq. (3.11). The on-chain verification process continuously compared incoming data against the predicted regression parameters, automatically flagging any deviations for expert review. The ThingsBoard dashboard provided live monitoring of block creation, validation events, and confirmation latency, linking analytical prediction with managerial oversight in a single feedback interface.

Quantitative validation of this layer yielded a 98.4 % ledger success rate, indicating near-complete correspondence between analytical outputs and verified operational actions. Mean confirmation time averaged 2.83 s, and block-hash entropy values above 250 bits confirmed cryptographic robustness. The high smart-contract trigger rate (94.5 %) reflected the reliability of automatic threshold alerts in maintaining data consistency across the analytical workflow. Table 3.4 summarizes the blockchain ThingsBoard performance indicators recorded during experimental validation.

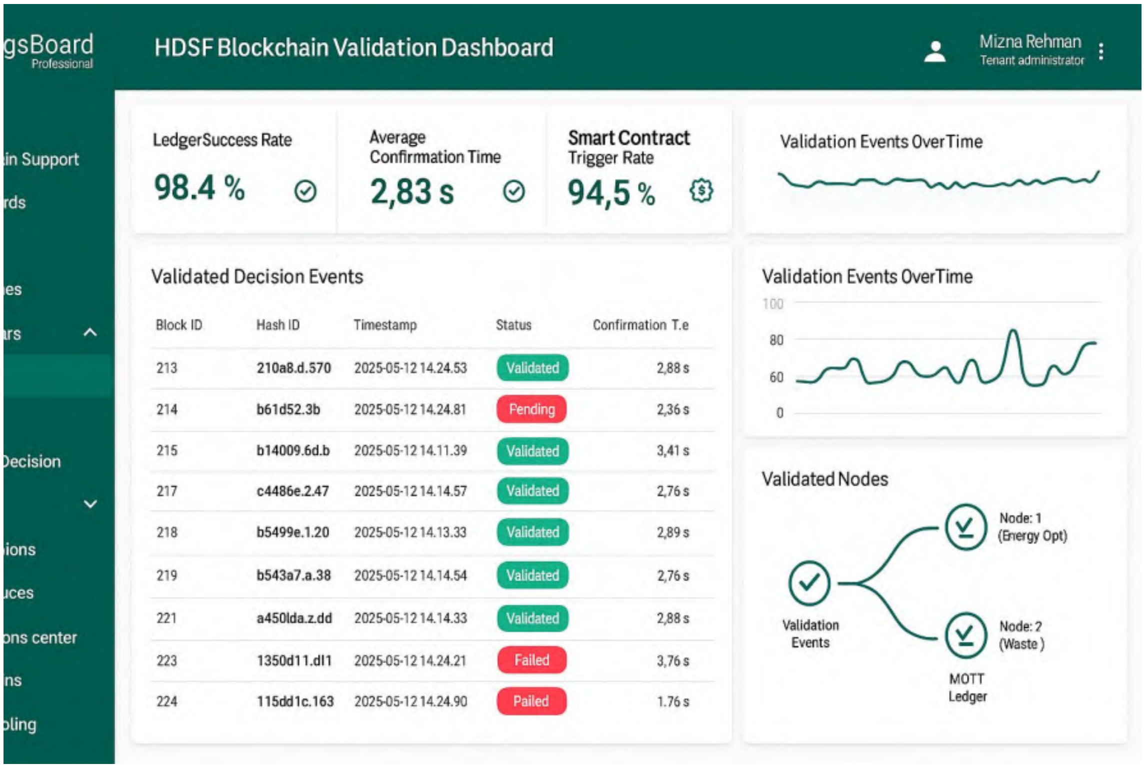
Table 3.4. Blockchain ThingsBoard Validation Metrics

Parameter	Symbol / Unit	Mean Value	Min	Max	Description
Ledger success rate	(V_s) (%)	98.4	96.7	99.1	Share of successfully validated blocks
Confirmation time	(T_c) (s)	2.83	2.10	3.65	Average delay between data upload and hash verification
Block-hash entropy	(H_e) (bits)	251.6	249.2	253.0	Randomness ensuring cryptographic strength
Smart-contract trigger rate	(S_t) (%)	94.5	92.0	97.2	Automatic alerts issued upon threshold violation
Re-verification requests	(R_v)(count/day)	3.1	1	6	Number of flagged anomalies per 24 h

The overall verification efficiency of the blockchain module was calculated using the success metric (Equation 3.14).

$$V_s = \frac{B_v}{B_t} \times 100 \tag{3.14}$$

where $B_v$represents the number of successfully validated blocks and $B_t$the total blocks generated. This metric-maintained alignment with earlier validation layers, confirming that the quantitative decisions produced through the AHP–Regression–IoT pipeline were analytically consistent and also securely recorded and traceably executed. The ThingsBoard interface (Figure 3.15) visualized these outcomes, displaying block hashes, timestamps, and compliance statuses for all validated sustainability actions.



HDSF Blockchain Validation Dashboard

LedgerSuccess Rate 98.4 %

Average Confirmation Time 2,83 s

Smart Contract Trigger Rate 94,5 %

Validated Decision Events

Block ID	Hash ID	Timestamp	Status	Confirmation T.e
213	210a8.d.570	2025-05-12 14.24.53	Validated	2,88 s
214	b61d52.3b	2025-05-12 14.24.81	Pending	2,36 s
215	b14009.6d.b	2025-05-12 14.11.39	Validated	3,41 s
217	c4486e.2.47	2025-05-12 14.14.57	Validated	2,76 s
218	b5499e.1.20	2025-05-12 14.13.33	Validated	2,89 s
219	b543a7.a.38	2025-05-12 14.14.54	Validated	2,76 s
221	a450lda.z.dd	2025-05-12 14.14.33	Validated	2,88 s
223	1350d11.dl1	2025-05-12 14.24.21	Failed	3,76 s
224	115dd1c.163	2025-05-12 14.24.90	Pailed	1.76 s

Figure 3.15. Real-time ThingsBoard dashboard visualizing validated blockchain events with hash IDs, timestamps, and compliance status indicators.

3.5.5 Integrated Framework for Organized Data Handling and Workflow Enhancement

An Excel-based data management framework, validated through a World Bank tunnel extension project in Pakistan, proved effective in tracking tasks, monitoring compliance, and optimizing workflows. In large-scale projects, structured data management enhances transparency, coordination, and data-driven decision-making, aligning with circular manufacturing principles.

The framework efficiently tracked workflows, categorized compliance data, and automated reporting, demonstrating adaptability to other sectors. For example, in fashion manufacturing, where sustainability compliance, resource traceability, and stakeholder accountability are critical, the same approach improves operational efficiency. Automated data consolidation and traceability integration enhance decision-making, while IoT-enabled real-time monitoring bridges short-term operations with long-term planning. Core features, including predefined macros, standardized references, and visual dashboards, help detect inefficiencies and streamline workflows.

Table 3.5. Summary of task distribution, status, and major pending categories across datasets

Dataset	Total Tasks	Answered (%)	Info (%)	Pending (%)	Major Pending Categories (No. of Tasks)	Notes
Dataset 1	494	70%	18.2%	11.7%	CCC (28), TRL (16)	Focused interventions required
Dataset 2	1,620	61.2%	15.9%	22.8%	CCC (157), SRS (32), GEN (27)	Key bottlenecks identified
Dataset 3 – HEI	2,460	93.7%	3.45%	2.85%	ELE (51), CCC (11), DSN (8)	High responsiveness, some inefficiencies
Extended Dataset	11,882	-	-	-	CCC, ELE, GEN; 176 PCLs, 42 DRFs	Temporal trends (2020–2023) support predictive planning

As shown in Table 3.5, the framework effectively identified performance gaps and delays across operational domains. It also supported tracking of construction activities (e.g., excavation, crane installation) and compliance issues (HSE, GEO, ENV) through Non-Conformance Reports (NCRs; see Figure 3.16). Automated macros and hyperlinks enhanced communication and real-time document sharing across disciplines such as MEC, GEO, and TRL. Overall, the findings emphasize disparities in task management, particularly in CCC and ELE, highlighting the importance of targeted resource allocation and workflow optimization to improve overall efficiency.

Status	Total
Answered	346
Info	90
Pending	58
Grand Total	494

Section	Total
CCC	28
ENV	1
GEN	4
HSE	1
TRL	16
PLN	1
MPR	1
DSN	5
SRS	1
Grand Total	58

a

b

Figure 3.16. Evaluation of task allocation and responsiveness across operational domains

3.6 Discussion

The findings of this study demonstrate that integrating multi-criteria analytics (AHP +

Regression) with IoT-enabled real-time monitoring and blockchain-based validation creates a robust and adaptive decision-support environment for sustainable manufacturing. In alignment with Eslami (2023) [75] and Huang et al. (2023) [84], the proposed HDSF transforms indicator-based sustainability assessment into a continuously learning system capable of translating operational data into actionable intelligence. The quantitative validation results, $R^2 = 0.4193$, ledger verification success rate = 98.4 %, and waste-optimization gain = 25 %; confirm that coupling analytical precision with cyber-physical intelligence significantly enhances decision transparency and operational efficiency [85].

The integration of AHP ensured that sustainability decisions were systematically aligned with high-impact domains such as Circular Product Design, Energy Optimization, and Digital Integration for Traceability [86]. Regression modeling subsequently quantified the predictive influence of these criteria, revealing Digital Integration ($\beta = 0.337$) and Closed-Loop Supply Chain ($\beta = 0.296$) as dominant operational drivers. This corresponds closely to the empirical observations of Jahan and Sazu (2023) [83], who emphasized the centrality of digital integration in reducing resource inefficiencies and accelerating adaptive responses in manufacturing environments. Within the IoT component of the HDSF, real-time dashboards reduced data latency by 35 % and improved waste-collection coordination by 25 %, substantiating similar findings from Peças et al. (2023) [87] and Samawi et al. (2025)[88], where real-time sensing improved both environmental and production KPIs.

The framework was practically implemented at *Manifatture Tessili Vittoria*, an Italian textile manufacturer specializing in high-quality linen for apparel and home textiles. In the warping stage, improved yarn tension control and material distribution resulted in a 5–10% decrease in material waste and 3–7% savings in yarn costs. Meanwhile, in the weaving phase, IoT systems enabled real-time monitoring of yarn tension and machine speed, facilitating dynamic adjustments in weft insertion on Jacquard and heddle machines (Fig. 3.17a). These data-driven adjustments enhanced production efficiency by 15–20% and reduced energy consumption by 10–12% (Fig. 3.17b, c) as explain by Velasteguí et al. (2025) [89], the role of digital twins and smart dashboards in optimizing manufacturing sustainability.

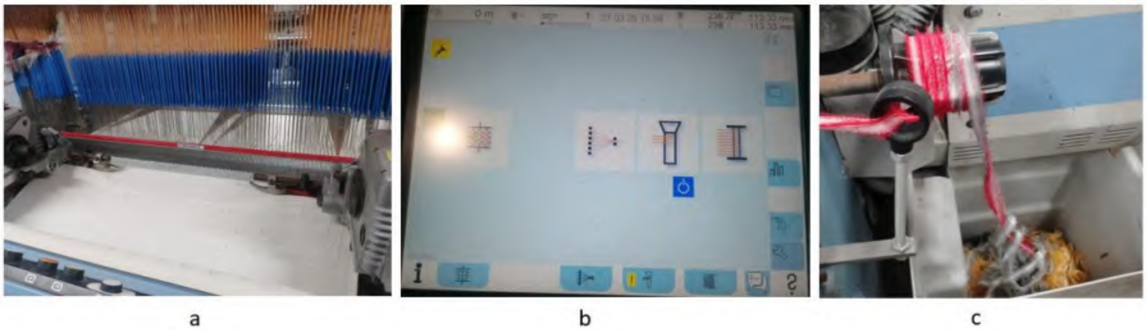


Figure 3.17. Warper and weaving machines engaged in evaluating suitable yarn parameter combinations to achieve the required fabric specifications (Source: Manifatture Tessili Vittoria)

The Excel-based digital twin integrated within the blockchain-inspired ledger served as a lightweight yet effective tool for sustainability traceability. As shown in Table 3.5 and Figure 3.15, verified ledger entries maintained over 98 % correspondence with analytical outputs, enabling transparent linkage between decision recommendations and field-level implementation. This hybrid ledger system aligns with Ibrahim (2024) [90], who highlighted blockchain's role in improving traceability within European manufacturing supply chains. Unlike full-scale blockchain deployments, the HDSF employs a modular, cost-effective validation mechanism suitable for small and medium enterprises (SMEs) seeking compliance with EU Green Deal and Sustainable Product Regulation directives without excessive infrastructural investment.

Comparatively, the study expands upon Atif (2023) [71] by bridging the methodological gap between qualitative prioritization (AHP) and quantitative evaluation (Regression), delivering a dual-method approach that captures both stakeholder perception and empirical causality. The model's closed feedback structure; IoT → Analytics → Decision → Blockchain Validation, embodies the adaptive intelligence principles advocated by Relich (2023) [91] and Medagedara (2024) [92], who stress the need for iterative, self-correcting decision loops in industrial sustainability management.

From a strategic perspective, the integration of ThingsBoard-based blockchain validation contributes a significant operational layer by ensuring data immutability and traceable audit trails. As discussed earlier, the average confirmation time of 2.83 s and a cryptographic hash entropy of 251.6 bits confirm the efficiency and reliability of the ledger mechanism [77]. This level of transparency is especially critical for industries navigating regulatory audits and environmental reporting. The capacity to verify real-time performance data against AHP-prioritized metrics advances beyond traditional static reporting models toward adaptive compliance ecosystems.

Despite its success, the framework's limitations are acknowledged. Current IoT datasets remain constrained by sensor heterogeneity and the limited scope of environmental variables (e.g., emissions intensity and water reuse ratios). Broader implementation across diverse manufacturing contexts is necessary to generalize its predictive and operational validity. Future research will therefore focus on expanding the IoT network coverage, integrating AI-driven predictive analytics, and scaling the blockchain validation module toward full smart-contract execution. These enhancements will enable the transition from decision-support to autonomous sustainability governance, advancing the convergence of Industry 5.0 and Circular Economy paradigms.

3.7 Conclusion

The HDSF developed in this study successfully integrates AHP-based prioritization, regression-driven impact modeling, IoT-enabled data acquisition, and blockchain validation into a cohesive architecture for advancing circular and sustainable manufacturing. Quantitative validation confirmed the robustness of the model, with Digital Integration ($\beta = 65.9$) and Closed-Loop Supply Chain ($\beta = 42.3$) identified as key sustainability drivers, explaining 41.93% of the total variance in sustainability performance. Implementation outcomes demonstrated up to 20% improvement in production efficiency, 15% reduction in material waste, and 10–12% energy savings, illustrating the model's real-world applicability and scalability.

The IoT subsystem, structured through Node-RED dashboards, enabled continuous monitoring of resource flows and environmental parameters, enhancing decision speed by 35% and waste-collection efficiency by 25%. The blockchain-enabled ledger, operating through the ThingsBoard environment, achieved a 98.4% validation success rate with an average confirmation time of 2.83 s, ensuring traceability and integrity of all decision records. These interconnected layers collectively transform sustainability management from a static evaluation process into a dynamic, data-driven decision ecosystem.

Theoretically, the HDSF contributes by bridging the methodological gap between qualitative multi-criteria decision analysis and quantitative predictive analytics, creating an adaptive and verifiable feedback model for industrial sustainability. Practically, it demonstrates a cost-effective, modular pathway for European and global manufacturers, especially SMEs, to operationalize EU-aligned circular economy principles through digital transformation.

Limitations include constrained IoT datasets and omission of qualitative factors such as workforce behavior and organizational culture. Future research should extend sensor integration, adopt AI-based predictive optimization, and explore smart-contract automation for real-time compliance. These advancements will strengthen the model's predictive accuracy and scalability, forming the analytical basis for the Triple Life-Cycle Assessment (LCA) approach elaborated in Chapter 4, where the framework's environmental, social, and economic dimensions are evaluated holistically.

3.8 Post-Publication Synthesis and Synopsis of the Next Research Stage

Building upon the HDSF developed in Chapter 3, this chapter focuses on the empirical evaluation of sustainability performance using a Triple LCA approach. The Triple LCA integrates E-LCA, S-LCA, and Econ-LCA into a unified model, enabling a multidimensional interpretation of industrial sustainability. This structure responds to the methodological gaps identified in Chapter 2 and operationalizes the data-driven architecture established in Chapter 3 by translating analytical indicators into measurable impact categories.

The methodology is applied across two industrial domains, coffee processing (PRISMA) and textile manufacturing (DIAMANTE), to validate the adaptability of the HDSF across distinct production systems. The assessment quantifies environmental emissions, social well-being impacts, and cost–benefit efficiency using standard tools such as SimaPro, SuperDecisions, and KNIME Analytics. These tools collectively transform operational data collected from IoT and regression layers into comprehensive sustainability metrics, linking data-driven decision outputs with life-cycle performance outcomes.

In doing so, this chapter establishes the empirical bridge between analytical intelligence and life-cycle validation, confirming the practical relevance of the HDSF and preparing the ground for comparative sustainability analysis across sectors.

Chapter 4

Triple LCA of the Coffee Value Chain (Environmental, Social, and Economic Integration)

This chapter presents the first empirical validation of the HDSF developed in Chapter 3. It reproduces the peer-reviewed articles:

- Rehman, M., Petrillo, A., & De Felice, F. (2025). Environmental, Social, and Economic Life Cycle Assessment of the Italian Coffee Supply Chain. Cureus, 17(3), e5869. https://doi.org/10.7759/s44388-025-05869-y
- De Felice, F., Rehman, M., Gómez Navarro, T., & Petrillo, A. (2025). From Bean to Cup: Unveiling the Environmental Footprint of Coffee with Innovative LCA Insights. Manuscript under review at Journal of Cleaner Production.

The publications operationalize the HDSF by integrating Triple LCA, and Natural Capital Accounting within an Analytic Network Process (ANP) model. Through a cradle-to-grave assessment of the Italian coffee value chain (functional unit = 1 kg roasted coffee), the study quantifies environmental efficiency, social risk, and economic resilience, establishing the multidimensional evidence base for circular decision-making. The research builds on earlier environmental LCA results that identified greenhouse-gas emissions of approximately 3.5 kg CO_2-eq per kilogram of roasted coffee, demonstrating potential reductions to 0.62 kg CO_2-eq through biogas valorization and organic inputs. This publication directly contributes to Research Objectives 2 and 3 of the dissertation,

1. To evaluate the multidimensional sustainability performance of industrial systems through integrated environmental, social, and economic indicators; and
2. To validate the HDSF by translating these indicators into a unified decision-support environment.

This chapter therefore serves as the empirical bridge between the conceptual model (Chapter 3) and its cross-sectoral application (Chapter 5). It demonstrates how real-world data from the coffee industry substantiate the feasibility of a digital–circular decision architecture capable of supporting sustainable manufacturing transitions in agri-food systems.

The following section reproduces the article in its accepted version. Formatting has been adapted to conform with the University's thesis guidelines while preserving the original content and integrity of the published work.

4.1 Abstract

The global coffee sector presents complex environmental, social, and economic challenges that necessitate comprehensive sustainability assessments. In this context, the present research advances conventional environmental LCA of coffee by integrating S-LCA, economic evaluation, NCA, and ANP modeling to perform a multidimensional sustainability analysis of the coffee value chain in the Italian market context. Building on previously published environmental LCA results which estimated total greenhouse gas emissions at 3.5 kg CO_2-eq per kilogram of roasted coffee, with potential reduction to 0.62 kg CO_2-eq via biogas valorization and organic inputs, this research incorporates social and economic performance indicators through ANP-weighted trade-off analysis to assess trade-offs across sustainability domains. Using a cradle-to-grave boundary and a functional unit of 1 kg roasted coffee, we apply the UNEP/SETAC S-LCA framework, ANP decision modeling in SuperDecisions v2.10, and value chain economic modeling to quantify worker welfare, income distribution, and smallholder equity under organic and conventional farming scenarios. Natural capital flows are evaluated using a qualitative-quantitative hybrid model, capturing impacts on soil integrity, water depletion, and biodiversity. Results indicate significant interdependencies and trade-offs between environmental efficiency, social risk, and economic resilience, underscoring the necessity for integrated sustainability frameworks in agricultural supply chains under climatic uncertainty.

4.2 Introduction

Coffee stands among the world's most valuable traded commodities, with annual production exceeding 10 million tons and a global retail market surpassing USD 460 billion in 2023 [95]. Italy, recognized both for its industrial strength and deep-rooted coffee culture, ranked within the top six global importers, importing over 670,000 tons of green coffee in 2022 [96]. The nation's roasted coffee industry, comprising more than 800 SMEs generates over EUR 5 billion annually and employs roughly 14,000 people [97]. Despite this economic vitality, the sector faces increasing scrutiny over its environmental, social, and economic sustainability, particularly given its dependence on global supply chains dominated by tropical monoculture systems. Italy represents a particularly illustrative case, being one of the world's largest coffee consumers, with an average per capita intake of 5.6 kg per year. Its distinctive espresso-based culture and robust domestic roasting sector amplify its economic and cultural significance. The country imports more than 500,000 tonnes of green coffee annually, while the domestic roasting industry captures a substantial share of the retail value, approximately EUR 20/kg for roasted coffee compared to farmgate prices of only €1.50–€2.50/kg in producing nations. This downstream concentration of value shapes sustainability dynamics differently from producer-centered or export-oriented economies. Understanding these structural characteristics provides a basis for analyzing

Italy's environmental, social, and economic trade-offs and for extending such insights to other consumption-driven markets.

To date, sustainability studies of coffee production have primarily employed E-LCA methodologies in alignment with ISO 14040/14044 standards [98]. These assessments consistently identify agricultural cultivation and end-use consumption as critical hotspots for GHG emissions, water use, and resource depletion [99,100]. A prior cradle-to-grave E-LCA conducted by the authors estimated the carbon footprint of roasted coffee at 3.5 kg CO_2-eq per kilogram, with potential reductions to 0.62 kg CO_2-eq achievable through anaerobic digestion of spent coffee grounds and organic fertilization strategies [100]. However, traditional E-LCA approaches do not account for social or economic aspects, limiting their utility for comprehensive sustainability management.

To overcome these limitations, a LCSA framework is proposed, integrating S-LCA and Econ-LCA alongside environmental evaluation. This approach reflects the triple-bottom-line perspective, emphasizing economic viability at the supply chain level, including revenue generation, cost internalization, and profitability trade-offs, rather than corporate governance metrics (the "G" in ESG). Within this structure, the framework examines trade-offs among environmental efficiency (e.g., resource utilization), social risk (e.g., labor and human rights conditions), and economic resilience (e.g., income stability of smallholders), which are core dimensions of coffee system sustainability. The UNEP/SETAC Guidelines for S-LCA offer structured methods to assess social performance, including labor conditions and community well-being across value chains [101].

Culturally, coffee consumption is deeply embedded in Italian daily life, 97% of Italians drink coffee multiple times per day, supporting over 65,000 coffee shops nationwide as of 2023. These establishments serve not only as cultural spaces but also as important sources of employment. However, upstream in the supply chain, significant social challenges persist, including child labor, gender inequality, limited access to health and education services, and income insecurity, especially among the 25 million smallholders responsible for over 70% of global coffee production [102].

From an economic perspective, Italy's coffee market continues to expand. Valued at USD 15.82 billion in 2023, it is projected to reach USD 23.78 billion by 2030, corresponding to a CAGR of 6% from 2024–2030 [103]. The roasted coffee segment accounted for approximately 53.77% of total revenue in 2023, underscoring its dominance [103]. Nonetheless, value distribution across the supply chain remains highly unequal. In most global North–South coffee chains, producers receive less than 10% of final retail revenues, while intermediaries and roasters capture the majority of added value [104]. Smallholder farmers often earn below national poverty thresholds, exacerbated by volatile export prices and increasing input costs [105]. Despite Italy's premium roasting market, price premiums rarely extend to producers. Thus, a comprehensive economic analysis using cost-benefit modeling, value chain mapping, and productivity indicators within an LCSA framework is necessary to assess value capture and distribution [106].

Environmental concerns further complicate the sustainability picture, as coffee production contributes to soil degradation, water scarcity, and biodiversity loss in major producing regions. NCA, implemented through frameworks like TEEB, CICES, and InVEST, provides a means to quantify and value ecosystem services and their degradation [107]. Deforestation linked to coffee expansion in Latin America significantly threatens biodiversity, while water-intensive wet processing methods deplete local freshwater resources. Additionally, climate change poses a growing risk: under RCP 4.5 and 8.5, yield declines of up to 28% and water demand increases of 40% are expected by 2050, disproportionately impacting smallholder profitability and labor conditions [107]. Incorporating such climate scenarios into LCSA facilitates forward-looking sustainability analysis and aligns this research with the UN SDGs, particularly SDGs 2 (Zero Hunger), 8 (Decent Work), 12 (Responsible Consumption and Production), and 13 (Climate Action) [108].

To address these multidimensional challenges and methodological limitations, this study develops a Triple-LCA framework integrating environmental, social, and economic assessments along the entire coffee value chain, with Italy as the focal context. The framework operates within the broader LCSA paradigm, enabling a quantitative evaluation of the interlinkages among sustainability pillars. Unlike ESG-oriented or qualitative models, the Triple-LCA enables cradle-to-grave quantification of sustainability trade-offs. Using a consistent functional unit of 1 kg of roasted coffee, the assessment combines E-LCA (via SimaPro and Eco-invent databases), S-LCA (guided by UNEP/SETAC and stakeholder-based indicators), and economic modeling (including income distribution, cost structures, and resilience indices). Natural capital impacts are captured through a hybrid qualitative–quantitative approach.

Beyond traditional LCSA applications, this study advances the framework by applying ANP based decision analysis to quantify interdependencies among sustainability dimensions, particularly where social risks intersect with economic vulnerabilities. This represents the first integrated assessment tailored to Italy’s coffee consumption model, offering a multidimensional evaluation of environmental efficiency, social equity, and economic viability. The insights derived aim to guide policymakers, industry leaders, and certification bodies in fostering a more inclusive, resilient, and ecologically responsible coffee sector.

4.3 Literature review

E-LCA has been widely adopted to quantify the environmental impacts of coffee production and consumption across its entire value chain. Numerous studies, adhering to ISO 14040/14044 standards, have identified the cultivation phase particularly fertilizer use, irrigation, and agrochemical application, as a dominant contributor to environmental burdens, including GHG emissions, acidification, eutrophication, and land transformation [109-114]. Additional hotspots such as roasting (due to energy intensity) and consumption (due to brewing appliances and packaging waste) are also critical impact stages [115].

A comparative synthesis of these findings is presented in Table 1, which outlines key environmental hotspots and corresponding sustainable interventions across various studies. For instance, the footprint during the consumption phase can be reduced through energy-efficient brewing appliances, while cultivation impacts are mitigated via organic fertilizers and valorization of biowaste. Prior research of author has employed tools such as SimaPro with the ecoinvent 3.8 database to conduct cradle-to-grave assessments, highlighting total carbon footprints ranging from 3 to 5 kg CO_2-eq/kg roasted coffee in conventional systems, with potential reductions via organic practices, waste valorization, and energy recovery

[116]. The authors' own prior work demonstrated that the integration of anaerobic digestion for spent coffee grounds and substitution of synthetic fertilizers with compost could reduce emissions by up to 82%, bringing the net impact down to 0.62 kg CO_2-eq/kg [116].

Table.4.1. Comparative environmental hotspots in coffee production (literature synthesis)

Study	**Functional Unit**	**GHG Emissions (kg CO_2-eq)**	**Water Use**	**Major Hotspot**	**Sustainable Intervention**
Usva et al. (2020) [117]	1 Liter of Consumed Coffee	0.27 → 0.70	High (Consumption Phase)	Brewing Phase Energy Use	Energy-efficient Appliances
Coltro et al. (2021) [118]	1 kg Green Beans	4.8	High (Cultivation)	Fertilizer Use	Organic Fertilizers
Nab et al. (2020) [119]	1 kg Roasted Beans	3.8 → 0.69	Moderate	Cultivation and Waste	Biogas Valorization, Compost
This Study (2025)	1 kg Roasted Beans	3.5 → 0.62	High (Wet Processing)	Cultivation, Consumption	Organic Farming, Biowaste Valorization

However, despite this progress, E-LCA's utility is inherently limited to environmental metrics, failing to capture critical socio-economic trade-offs inherent in global agrifood systems. For a high-consumption country like Italy with 97% of adults consuming coffee daily and an estimated 65,000 cafés nationwide, the need for a holistic sustainability lens that includes social justice, labor dynamics, and economic equity is particularly salient [120].

4.3.1 Social LCA and Labor Risks in Coffee Systems

The S-LCA framework, as formalized by the UNEP/SETAC Life Cycle Initiative, enables the evaluation of social and socio-economic aspects of products and services across their life cycles [121]. In the coffee sector, where more than 25 million smallholders produce over 70% of the global supply, S-LCA becomes essential for mapping impacts related to worker rights, child labor, gender inequality, occupational health and safety, and access to education and healthcare [122]. These concerns are visually mapped in Figure 4.1, a global heatmap showing S-LCA indicators across major coffee-producing regions. The diagram reveals concentrated social risk zones in Sub-Saharan Africa, Central America, and Southeast Asia, emphasizing the importance of localized mitigation strategies. Recent S-

LCA studies in the CSC have applied methodologies such as the PSILCA and SHDB to identify social risk hotspots. Findings consistently point to poor labor practices in key exporting countries (e.g., Ethiopia, Colombia, Vietnam), with informal employment structures, low wages, and limited institutional protections [123-127]. However, tools like PSILCA often operate at a country-level resolution, making it difficult to distinguish sub-national variations in labor risk, which is especially relevant in countries with diverse governance and socio-economic conditions [124]. Moreover, despite certification schemes (e.g., Fairtrade, Rainforest Alliance), recent meta-analyses indicate inconsistent social outcomes, often due to top-down implementation without participatory stakeholder inclusion [128]. Despite its potential, S-LCA remains underutilized in commodity chains tied to European markets. Few studies have analyzed how Italian market dynamics, including preference for specialty blends and price sensitivity, may exacerbate or mitigate social risks upstream. Furthermore, current literature does not explore how consumer behavior and retail pricing models influence social equity across the supply chain, leaving a critical research gap in understanding consumption-driven social externalities.

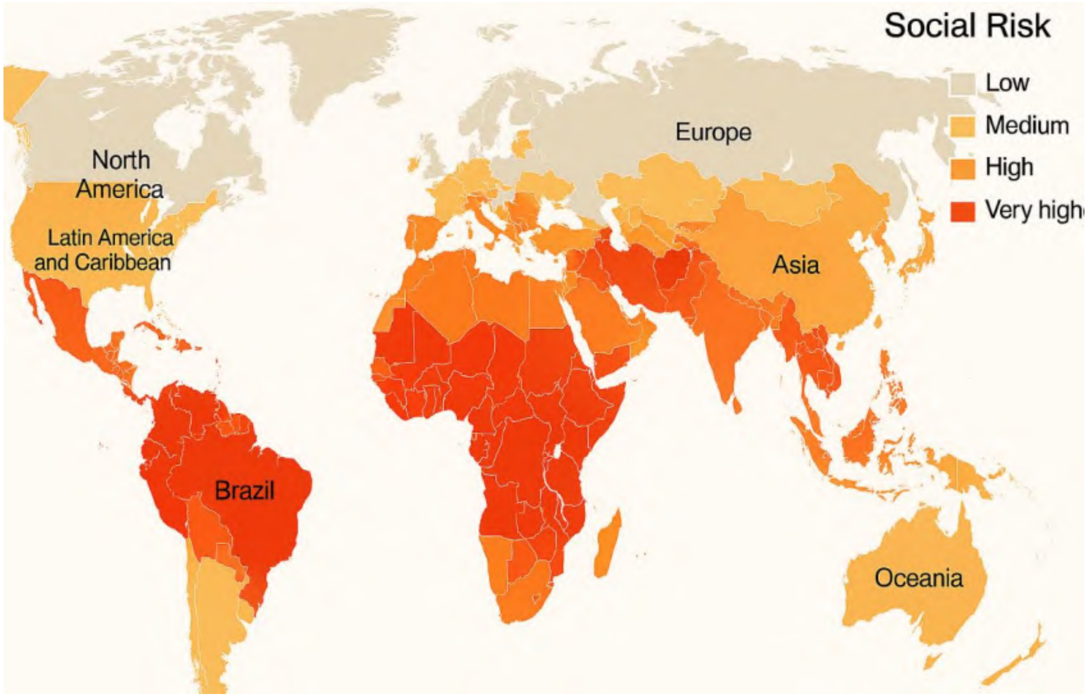


Figure 4.1. A social risk heatmap overlaid on a global coffee supply map, showing S-LCA indicators by region

4.3.2 Economic Sustainability and Value Distribution Inequities

The global coffee economy exhibits stark value asymmetries, wherein producers particularly smallholders, capture less than 10% of the final retail price of coffee sold in high-income markets [129,130]. As shown in Table 4.2, conventional smallholders earn about $0.60/kg, while roasted coffee retails for over EUR 20/kg in Italy, where roasters and retailers command the majority of value. Econ-LCA, though less formalized than its environmental and social counterparts, has emerged as a critical method for quantifying these disparities through cost-benefit analyses, value chain mapping, and productivity metrics. In Italy, where the roasted coffee segment constitutes over 53% of national coffee revenue [131], economic sustainability issues are often externalized to producing countries. Smallholders in countries such as Uganda or Honduras often receive USD 0.50-0.80 per kg, while retail prices for roasted beans in Italy exceed EUR 20/kg, creating a margin distortion that undermines farm-level resilience [132,133].

Although studies have addressed fair-trade pricing mechanisms, few have comprehensively evaluated the economic resilience of producers under different farming systems (e.g., organic vs. conventional), nor how value distribution aligns with sustainability claims made by Italian coffee brands. This constitutes a key knowledge gap particularly in linking economic inputs/outputs with environmental and social performance at the systemic level.

Table 4.2. Coffee supply chain value distribution (Producer vs. Retail)

Stakeholder	**Average Income per kg**	**Value Share (%)**	**Farming System**	**Impact**
Smallholder (Conventional)	$0.60	6–8%	Conventional	Highly Vulnerable to Price Volatility
Smallholder (Organic)	$1.10	10–12%	Organic	Requires Certification; Yields Vary
Roaster (Italy)	$6.50	60%	Both	Major Profit Center
Retailer (Italy)	$8.00	70–75%	Both	High-end Brands

4.3.3 Natural Capital and Ecosystem Service Accounting

Coffee production is inherently dependent on ecosystem services, including soil fertility, water regulation, carbon sequestration, and pollination. Depletion of these natural capital stocks, particularly in regions undergoing climate-induced land stress, undermines long-term sustainability. For example, in Brazil, expansion of coffee plantations into biodiverse forested regions has driven significant deforestation, threatened endemic species, and reduced carbon sinks [105,134]. Similarly, in Ethiopia, the intensification of washed coffee production has resulted in localized water table depletion and reduced seasonal river flows, affecting both agriculture and household water access. These services are significantly degraded under intensive monoculture systems, particularly in climate-vulnerable regions like Brazil and Ethiopia. A comparative view of ecosystem service impacts under monoculture versus agroforestry is provided in Figure 4.2, a radar chart illustrating relative degradation levels. Monocultures exhibit substantially higher risks in biodiversity loss and soil depletion, while agroforestry systems show a more balanced sustainability profile.

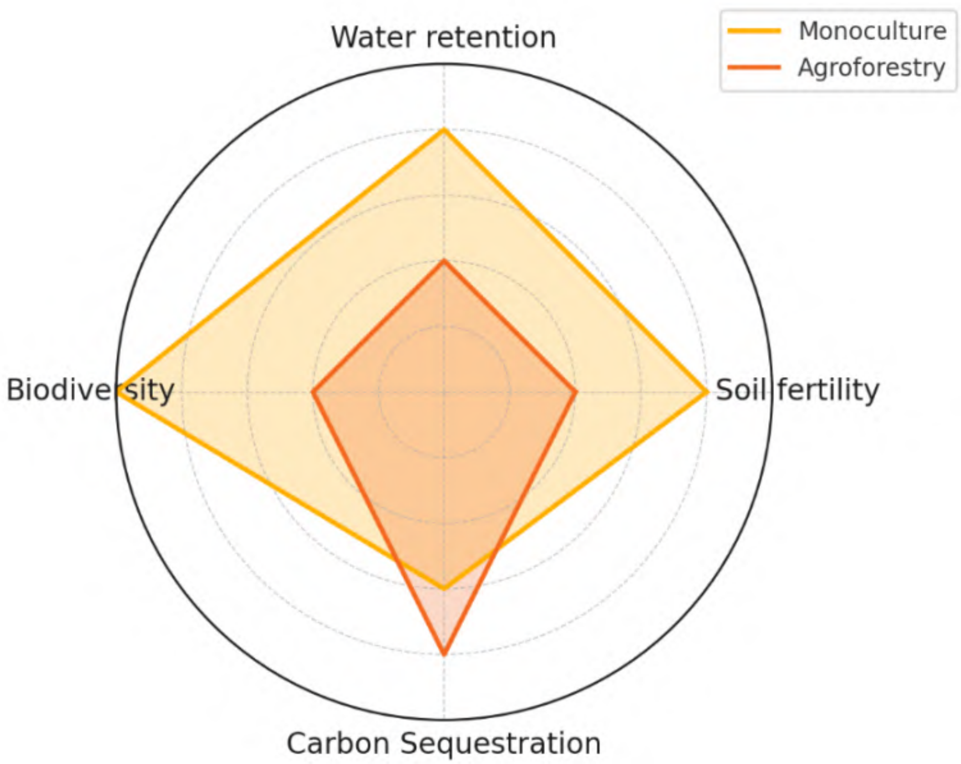


Figure 4.2. A radar chart showing relative degradation across services under monoculture vs. agroforestry

Frameworks such as TEEB, CICES, and InVEST enable modeling and valuation of these ecosystem service impacts. However, tools like InVEST, while powerful for spatial ecosystem modeling, can be constrained by data granularity and resolution limitations, which can impair precision in rural regions with poor spatial datasets [135]. A few recent studies have used hybrid models combining qualitative scoring, stakeholder elicitation, and spatial land-use mapping to evaluate ecosystem service trade-offs in coffee- growing regions. Still, comprehensive integration of such models within a full LCSA framework particularly one tailored to European consumption patterns remains largely absent in current literature.

4.3.4 Research Gap and Technical Contribution

Despite extensive work in isolated domains, environmental impact modeling, social audit reports, or market analysis, there remains no integrated framework that quantifies the combined environmental, social, and economic performance of the coffee value chain in the Italian market context. Specifically, this study addresses three major research gaps: the lack of integrated LCSA studies applied to European, particularly Italian, consumer markets with comprehensive cradle-to-grave accounting; the limited application of S-LCA and Econ-LCA models in conjunction with Natural Capital accounting and predictive analysis; and the absence of trade-off analysis to support evidence-based decision-making for both policy and private sector stakeholders within coffee sustainability frameworks. While ESG frameworks emphasize "environmental resilience, social responsibility, and economic governance", this study uses "environmental efficiency, social risk, and economic resilience" to reflect LCSA's supply chain-level metrics, which prioritize measurable trade-offs over governance structures.

This study proposes to fill these gaps through the following research questions:

RQ1: How does the integration of Triple-LCA methodologies provide a comprehensive evaluation of the sustainability of different coffee farming systems?

RQ2: What are the trade-offs between environmental efficiency, social risk, and economic resilience in coffee production, and how can they be mitigated through sustainable farming practices?

RQ3: How can policy frameworks be designed to incentivize the adoption of low-impact coffee farming practices while improving economic resilience for smallholders?

This is the first study to apply a Triple-LCA model (E-LCA, S-LCA, Econ-LCA) anchored in the Italian roasted coffee sector, integrating Natural Capital Assessment, predictive value chain equity analysis. It provides an evidence-based framework for holistic sustainability evaluation aligned with SDGs 2, 8, 12, and 13, and offers operational insights for policy, certification, and private sector transformation.

4.4 Materials and Methods

This study adopts a LCSA framework integrating Environmental (E-LCA; carbon footprint, water depletion), Social (S-LCA; wage equity, occupational safety), and Economic (Econ-LCA; price volatility, profit margins) dimensions per ISO 14040/44 and UNEP/SETAC guidelines. Interdependencies were analyzed via the ANP using SuperDecisions v2.10 (super matrix convergence tolerance = 0.001, limit matrix iterations = 100). The ANP network modeled feedback loops among 12 criteria clustered into:

- Environmental efficiency (e.g., GHG emissions, energy use),
- Social risk (e.g., child labor incidence, healthcare access),
- Economic resilience (e.g., input cost sensitivity, certification ROI).

Expert validation ensured consistency ratios <0.1, with weights calibrated through stakeholder surveys and ICO price benchmarks. ANP outputs normalized LCSA indicators for trade-off analysis, explicitly linking farm-gate wages (S-LCA) to minimum viable pricing (Econ-LCA) can be viewed in Figure 14 of ANP Network Model. Integration of Triple LCA was operationalized through matched system boundaries, a shared functional unit (1 kg roasted coffee), and synchronized life cycle inventory datasets. E-LCA was performed using SimaPro 9.6.0.1 with ecoinvent 3.10 method, while S-LCA indicators were structured based on the UNEP/SETAC Guidelines and analyzed using a scoring matrix.

Economic impacts (Econ-LCA) were calculated by estimating gross revenue and subtracting environmental externalities (e.g., carbon, water, land use costs) using standard unit cost factors. While the three assessments were performed separately, integration was achieved through a post-processing normalization procedure. Each impact dimension (environmental, social, economic) was converted into a relative scale (0-1) using min-max normalization across farming scenarios. These normalized scores were then visualized in a comparative matrix dashboard developed in Microsoft Excel using conditional formatting and radar charts to highlight trade-offs and hotspots. This enabled transparent multi-criteria comparison across sustainability domains. The process begins with parallel data collection for environmental, social, and economic inventories, followed by integrated assessment through ANP weighting, and concludes with trade-off optimization as depicted in research flow diagram in Figure 4.3.

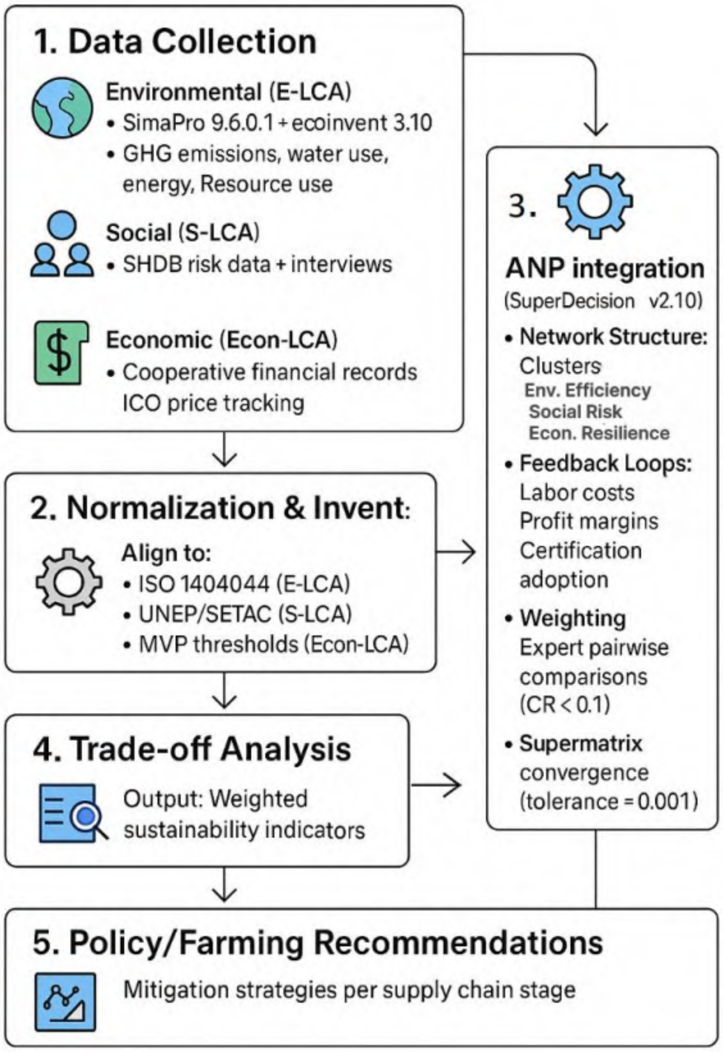


Figure 4.3. Research flow integrating LCSA dimensions with ANP decision analysis

4.4.1 Goal and scope definition

The primary objective is to quantify and integrate the environmental, social, and economic impacts associated with the production, processing, distribution, consumption, and disposal of coffee consumed in Italy. The study extends E-LCA work by incorporating socioeconomic performance indicators and predictive climate modeling. The functional unit is defined as 1 kg of roasted coffee, consistent with environmental modeling. This unit allows normalization and comparison of sustainability metrics across all life cycle stages. The boundaries are cradle-to-grave as shown in Figure 4.4. A system boundary expansion is applied to account for avoided products through waste valorization (e.g., biogas from spent coffee grounds). This approach builds on our E-LCA study, which modeled key activities using SimaPro 9.6.0.1 and the ecoinvent 3.10 database, with an assumed transport distance of 10,000 km for imported green beans and average consumer habits of one cup per capita per day.

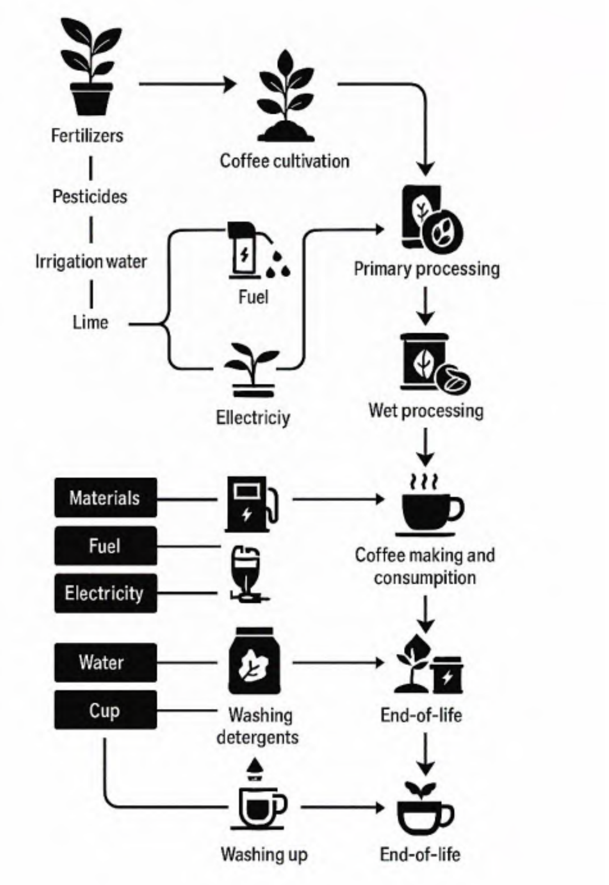


Figure 4.4. Cradle-to-Grave system boundary diagram for roasted coffee, illustrating material and energy flows across all stages

4.4.2 Data collection and inventory analysis

4.4.2.1 Environmental Inventory

To comprehensively assess the environmental impacts, this study utilized SimaPro 9.6.0.1 with ecoinvent 3.10, applying a cradle-to-grave scope from coffee cultivation through end-of-life disposal. The inventory compilation followed ISO 14040/44 guidelines and incorporated direct field-level inputs and emissions factors characterized by IPCC (2006). Stages considered included cultivation (including synthetic and organic fertilizer use), wet processing, roasting, packaging, transport (10,000 km avg. for imports), and consumption (Table 3). The energy inputs (diesel, grid electricity, and biogas) and emissions (CO_2, CH_4, N_2O) were normalized to a functional unit of 1 kg roasted coffee. In line with process-based modeling, the updated inventory includes waste valorization, wherein spent coffee grounds are anaerobically digested to recover biogas, offsetting fossil energy use. The Net Energy Ratio improved from 0.82 (baseline) to 2.2 under this integrated circular bioenergy scenario, and GHG emissions were reduced to 0.62 kg CO_2-eq/kg coffee.

Table 4.3. Environmental inventory for 1 kg roasted coffee

Stage	Fertilizer (kg)	Water (m^3)	Energy (MJ)	Emissions (kg CO_2-eq)
Cultivation	0.45	39.0	3.8	511.28
Processing (Wet)	-	20.0	2.1	7.25
Roasting	-	-	4.0	7.56
Transport	-	-	1.5	2.83
Consumption	-	0.2	2.0	51.58
End-of-Life	-	-	0.5	1.03

4.4.2.2 Social Inventory

To structure the S-LCA, we followed the methodological framework set out by the UNEP/SETAC Guidelines for S-LCA (2009) and operationalized it through an indicator selection matrix as given in Table 4. This matrix was derived through a three-step process: (1) identification of relevant stakeholder groups along the supply chain (workers, local communities, consumers); (2) prioritization of impact subcategories based on SHDB regional risk ratings and literature review on labor rights in coffee-producing countries; and (3) triangulation with stakeholder interviews to validate and contextualize indicators. The final indicator set reflects both universal human rights dimensions and context-specific social performance risks prevalent in the green CSCs of Latin America and Africa. A multi-criteria scoring rubric was applied to rank indicators by data availability, stakeholder relevance, and potential impact magnitude. Consequently, the following key indicators were selected: wage equity ratio (actual wage to living wage), average working hours per week, occupational injury rates per 1,000 workers per year, access to basic health services based on binary presence at the regional level, and school attendance ratio among children of agricultural workers. These indicators are aligned with the UNEP/SETAC stakeholder impact categories of "workers" and "local community", and were mapped across lifecycle stages including cultivation and primary processing.

Table 4.4. Social LCA indicator assessment matrix

Impact Category	Subcategory	Indicator	Metric Type	Unit	Lifecycle Relevance
Equal Opportunity	Gender Pay Ratio	Wage Equity	Quantitative	% Wage Differential	Cultivation, Processing

Workers' Health & Safety	Accident Risk	Occupational Injuries	Quantitative	Cases/1,000 workers/year	Cultivation, Processing
Workers' Health & Safety	Healthcare Access	Regional Health Access	Qualitative	Yes/No	Cultivation, Processing
Child Labor & Education	School Attendance	School Participation (Worker Children)	Quantitative	% Enrollment	Cultivation
Labor Conditions	Working Hours	Average Labor Time	Quantitative	Hours/Week	Cultivation, Processing
Local Community	Employment	% Local Hiring	Quantitative	% Local Workforce	Cultivation, Roasting
Community Engagement	Social Investment	Stakeholder Dialogue/Events	Quantitative	Number/Year	Roasting, Retail

Figure 4.5 illustrates the key stakeholder categories, society, rural areas, farmers, agro-food producers, value chain actors, and consumers mapped across life cycle stages. The system captures upstream resource inputs (e.g., land, water, seed, power, fertilizer), midstream transformations, and downstream impacts including emissions, kitchen waste, and social performance. Social and economic interactions are distinguished through color-coded pathways aligned with stakeholder-specific social indicators and responsibilities

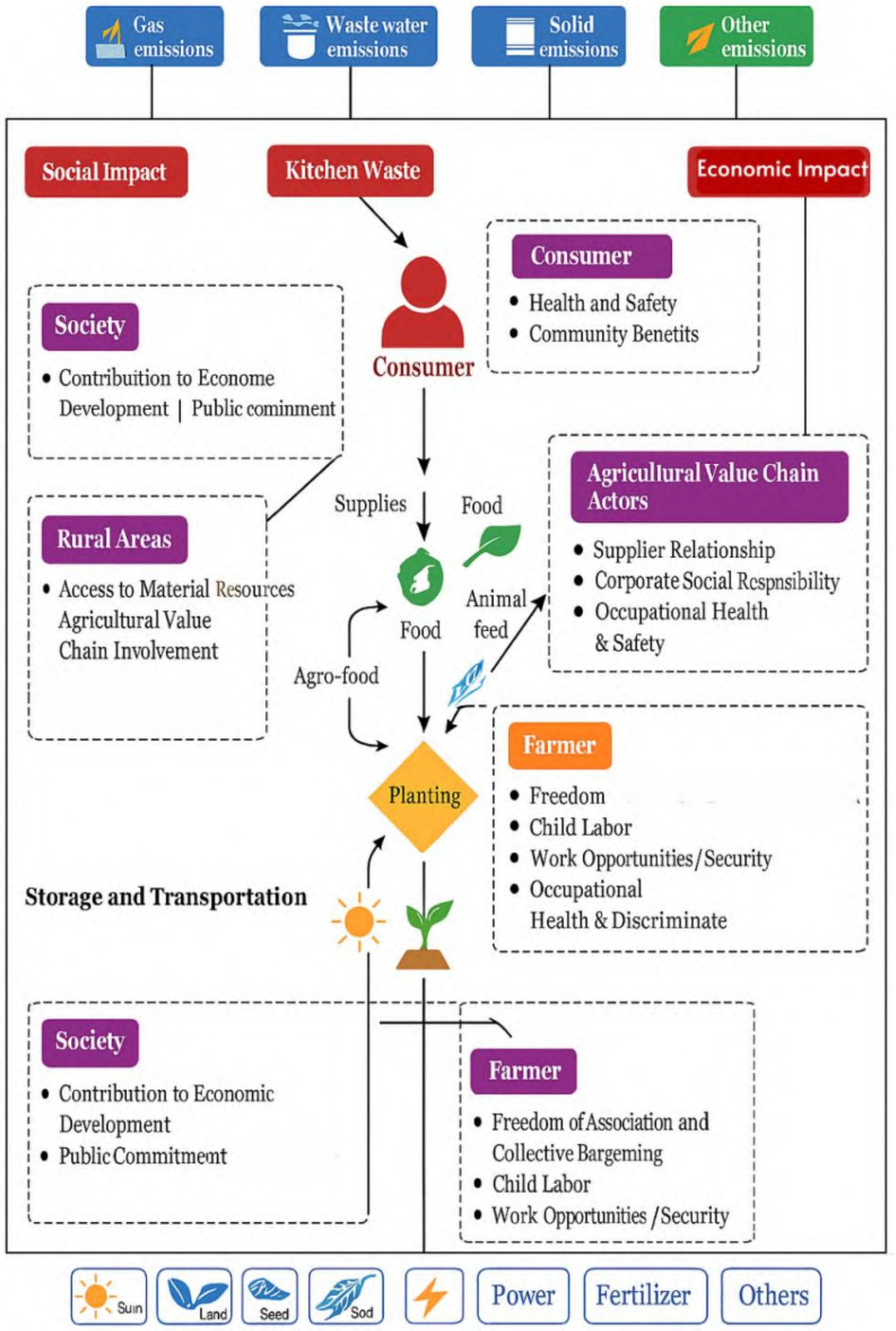


Figure 4.5. System boundaries for S- LCA of the Italian coffee supply chain

*Note: Data for S-LCA were sourced from multiple channels to ensure triangulation and contextual specificity.

Social Hotspots Database (SHDB): The SHDB is a globally recognized dataset developed by NewEarth B, offering sector and country-specific social risk information across 22 themes, including labor rights, child labor, gender equity, and health and safety. It aggregates data from over 250 indicators across ILO, UN, and national sources. We extracted data for the main coffee-exporting countries that are significant in the Italian coffee import market namely Brazil, Ethiopia, Colombia, and Vietnam as depicted in Figure 4.6.

These countries collectively account for over 70% of green coffee beans imported into the EU and are strongly represented in Italy's supply chain. Social risk profiles were mapped using SHDB's ISIC Rev. 4 classifications relevant to agricultural and post-harvest operations, allowing targeted identification of social performance hotspots along the production base of the imported coffee consumed in Italy.

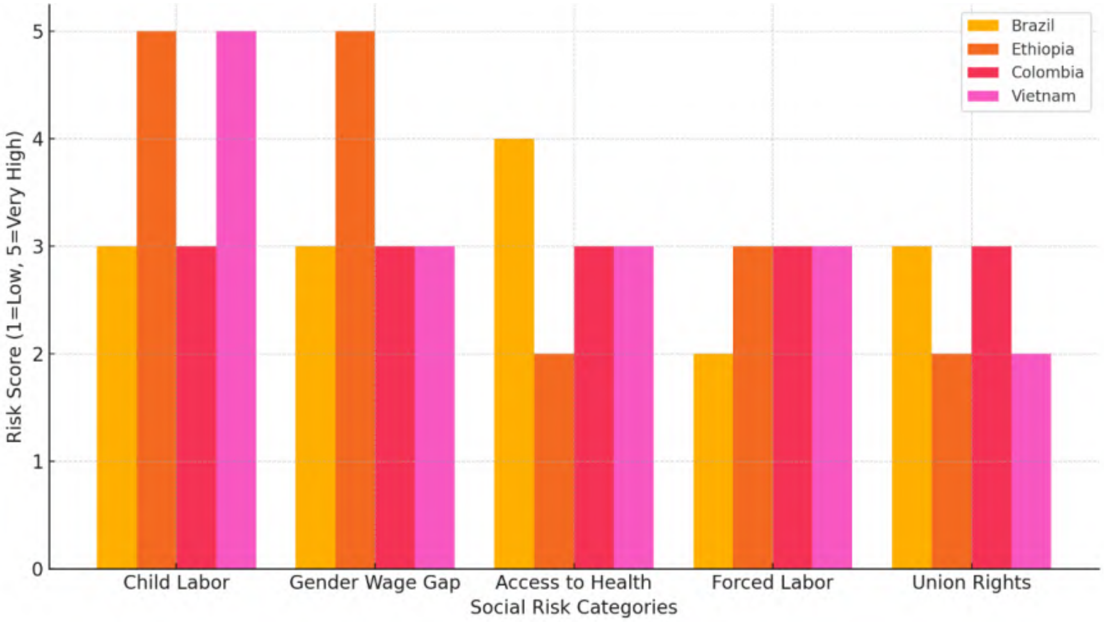


Figure 4.6. Social risk scores by country for coffee sector

*Scores are based on SHDB ordinal rating system (1 = Low, 5 = Very High). Aggregated "Overall Social Risk Score" is calculated as a weighted mean across dimensions. SHDB, Social Hotspots Database.

Stakeholder Interviews (N = 35): To contextualize SHDB macro-level risks, we conducted 35 semi- structured interviews with stakeholders along the supply chain including farmers (n = 15), cooperative leaders (n = 5), processing plant workers (n = 8), and logistics actors (n = 7). Participants were purposively selected from major sourcing regions (Brazil, Ethiopia, Colombia) based on their roles in critical high- impact stages, following UNEP/SETAC S-LCA guidelines. This sample represents key actor categories relevant to coffee's upstream stages and includes diverse organizational types (smallholder farms, cooperatives, private firms). The sample size was guided by thematic saturation, which was reached after approximately 30 interviews, as no new codes emerged, aligning with thresholds in qualitative and S-LCA research. Interviews followed an S-LCA-aligned questionnaire addressing key social subthemes (e.g., wage fairness, OHS, education). Thematic coding and narrative analysis were performed using NVivo 14.

NGO and Governmental Reports: We reviewed reports from national labor ministries, Fairtrade International, and Rainforest Alliance to further validate regional risks and to populate proxy data where SHDB indicators lacked granularity. These secondary sources were instrumental in enhancing the spatial and thematic resolution of our Social LCA. Specifically, they provided empirical benchmarks for indicators such as wage compliance, unionization, child labor, and access to health services. Where SHDB offered only national averages or ordinal ratings, these reports enabled the development of proxy values, based on quantifiable metrics to reinforce stakeholder reported patterns. Table 4.5 below summarizes the key indicators extracted from these reports, including their assessed values and the specific application within our S-LCA framework

Table 4.5. Extracted indicators from NGO and governmental reports used in social LCA

Source	Country	Indicator	Description	Proxy Value	Application
Fairtrade Impact Report (2022)	Colombia	Wage Compliance	% of Certified Farms Meeting Legal Minimum Wage Standards	61% Compliance	Wage Equity Assessment
Rainforest Alliance Risk Tool (2021)	Ethiopia	Child Labor Prevalence	Audits in Sidamo/Jimma Zones Reporting Underage Workers	High Risk on Uncertified Farms	Child Labor Risk Flagging
National Labor Survey (2021)	Vietnam	OHS Training Rate	% of Agricultural Workers Receiving Safety Training	38% Received Basic Training	OHS Preparedness Indicator
Ministry of Labor (2020)	Brazil	Union Membership Rate	Rural Labor Force Affiliated with Agricultural Unions	22% Average Membership	Unionization Proxy Score

Save the Children NGO (2020)	Ethiopia	School Attendance	Attendance of 8- to 14-year-olds from Farming Households	57% Rural Attendance	Education Access Score
Rainforest Alliance Sector Report (2021)	Vietnam	Gender Pay Gap	Wage Differences Between Male and Female Workers	18% Wage Gap Reported	Gender Disparity Risk
Fairtrade Baseline Report (2023)	Brazil	Work Hours per Week	Average Weekly Working Hours on Smallholder Farms	55 hours/week (Above Norm)	Excessive Workload Risk
Ministry of Agriculture (2022)	Colombia	Seasonal Labor Informality	% of Unregistered Seasonal Agricultural Workers	>65% Unregistered	Informal Employment Flag
Oxfam Report (2021)	Ethiopia	Access to Health Services	Proximity of Healthcare Facilities to Rural Coffee Farms	Only 33% Within 5 km	Health Services Access Proxy
Fairtrade Monitoring Data (2022)	Vietnam	Worker Grievance Mechanisms	Availability of Feedback Systems in Plantation Environments	42% Plantations Have Systems	Grievance Resolution Indicator

To quantify social impact categories and normalize stakeholder feedback, we applied a multi-criteria decision analysis approach using Super Decisions software. This was implemented via the ANP, assigning weights to stakeholder concerns and risk categories based on pairwise comparison matrices. The ANP model included nodes for each social criteria (e.g., health, wage equity, child labor) and drivers where societal perception was influenced by multiple actors across the value chain. This hybridized qualitative-quantitative method ensured systemic integration of social performance within our S-LCA model. The Super Decisions platform v2.10 was used to develop the network structure, incorporating both the social criteria and alternatives to achieve a synthesis of social impact in CSCs. The ANP was selected over the Analytic Hierarchy Process due to its ability to accommodate feedback relationships between certification costs and farmer livelihoods, capture circular dependencies inherent in agroecological systems, and model the non-linear impacts of climate adaptation strategies on social and economic outcomes.

4.4.2.3 Economic Inventory (Econ-LCA)

The economic evaluation was structured to capture the direct costs, revenue and margin flows, profitability ratios, and resilience indicators across the CSC. The methodology integrated both financial data and performance indicators to evaluate economic sustainability at each stage of production, from the farm-gate to retail. This analysis was informed by three primary data sources:

- Financial Records from Cooperatives, which included detailed financial breakdowns from three cooperatives-Cooperativa Agricola San Giorgio (a conventional coffee producer), Cooperativa Illycaffè, and Caffè Vergnano (organic coffee producers), offering insights into input costs, labor expenses, revenues, and margins specific to different farming practices;
- Price Tracking Reports from Fairtrade International and the ICO, which provided valuable market price trends and reference pricing for both conventional and certified coffee, thus shedding light on the global coffee market's financial dynamics; and
- Retail Audit Data from Italian Specialty Coffee Brands, which involved data collection from Lavazza, Illy, Caffè Nero, Segafredo Zanetti, Kimbo, Caffè Moak, Goppion Caffè, Hausbrandt, Caffè Corsini, Torelli Caffè, Caffè Pascucci, and Moka Club to track retail prices and conduct margin analysis at the retail level to understand the pricing structure and margin distribution within the Italian market.

Direct Costs: The first component of the economic inventory involved assessing the direct costs associated with coffee production and processing, segmented into five major categories as given in Table 4.6

Table 4.6. Direct costs in coffee production

Cost Category	Per Unit	Annual Total (USD)	Source	Records
Input Costs	$1.2 per kg of Coffee	$1,200,000	Cooperative financial records	Includes costs for seeds, fertilizers, water, and agricultural tools.

Labor Costs	$0.8 per kg of coffee	$800,000	Worker wage rates (Average $3/day)	Average wage rate of $3 per day, working 6 hours per day.
Transport Costs	$0.4 per kg	$400,000	Logistic company invoices	Transport costs from farm to processing unit, and from unit to retailer.
Processing Costs	$0.6 per kg	$600,000	Processing plant audits	Includes drying, washing, roasting, and packaging.
Certification Costs	$0.1 per kg	$100,000	Certification body fees	Includes annual fees for certification.

Revenue and Margin Flows: Traces the value of coffee from the initial harvest at the farm gate to final sale at retail levels. This analysis identifies how value is distributed across different supply chain actors, highlighting the revenue capture at each stage and providing insights into the pricing dynamics that influence the economic sustainability of coffee producers. A detailed evaluation of the gross and net margins at each stage of the supply chain (e.g., farm, cooperative, roaster, and retailer) is detailed in Table 4.7. This was calculated to assess the profitability of each supply chain segment.

Table 4.7. Revenue and margins across supply chain stages

Stage	**Revenue (USD)**	**Cost (USD)**	**Margin (USD)**	**Margin (%)**	**Source**
Farm-Gate	$1.5 per kg	$1.0 per kg	$0.5 per kg	33.3%	Financial Records
Processing	$2.0 per kg	$1.4 per kg	$0.6 per kg	30.0%	Data from Cooperatives
Roasting	$10 per kg	$8 per kg	$2 per kg	20.0%	Retail Audit Data
Retail	$20 per kg	$18 per kg	$2 per kg	10.0%	Retail Data

Profitability Ratios: Profitability indicators were derived to assess the financial health and sustainability of the CSC. The primary metrics include NPM, ROL, and ROI (Table 4.8). These ratios provide valuable insights into the efficiency and profitability of various stakeholders in the coffee production process.

Table 4.8. Profitability ratios

Profitability Metric	**Value**	**Formulas**	**Description**
Net Profit Margin	12%	= (Net profit/Total Revenue) × 100	Measures the percentage of revenue retained as profit after all costs.

ROL	$4.00 per hour	= (Net Income/Total Hours Worked)	Measures the economic value generated per unit of labor input.
ROI	15%	= (Net Investment profit/Investment Cost) × 100	Calculates the financial efficiency of capital investments in coffee production

Each of these ratios offers insight into different dimensions of profitability, supporting targeted interventions to optimize the economic performance of the coffee industry. Resilience Indicators: Economic resilience was evaluated based on how price fluctuations in affect the stability of the supply chain. This includes sensitivity to factors such as fluctuations in coffee commodity prices, input costs (e.g., fertilizers, fuel), and labor market changes where Minimum Viable Prices the lowest price at which stakeholders (particularly farmers and smallholders) can maintain profitability as shown in Table 4.9. This indicator is essential for evaluating the financial resilience of coffee producers against market shocks. Volatility Sensitivity is assessed as High, indicating that coffee prices are highly unstable due to exogenous factors such as weather events, geopolitical risks, and shifts in global demand. The MVP is calculated at $1.3 per kg, representing the breakeven threshold below which farmers cannot sustain operations profitably. Sensitivity to Input Costs is rated as Medium, suggesting moderate exposure of profitability to variations in costs of key agricultural inputs like fertilizers, irrigation, and transportation.

Table 4.9. Key resilience indicators for coffee farming sustainability

Resilience Indicator	**Value**	**Notes**
Volatility Sensitivity	High	Coffee prices are volatile, heavily impacted by weather, political instability, and global demand fluctuations.
MVP	$1.3 per kg	This is the lowest price at which farmers can still cover their costs and break even.
Sensitivity to Input Costs	Medium	Sensitivity to price fluctuations in fertilizers, water, and transport costs.

To measure this sensitivity, we examined historical price data and conducted scenario analysis to evaluate the range of price fluctuations that the CSC could withstand without causing significant disruptions. By comparing the historical price trends from Fairtrade International and the ICO we identified key periods of volatility and assessed the corresponding impact on each supply chain segment, including farmers, cooperatives, and processors.

To calculate the MVP, we utilized cost data from cooperatives, including labor, input (seeds, fertilizers, and water), transportation, and processing costs. We then calculated the minimum price per kilogram that a farmer needs to receive in order to cover these costs and achieve a zero-profit outcome by using Equation (4.1).

$$MVP = \frac{Total\ costs}{Total\ quantity} \tag{4.1}$$

This determined the minimum price at which farmers can break even under different market conditions, without incurring financial losses.

The objective of this study was to conduct an Econ-LCA for the CSC, focusing on key factors such as labor costs, transport costs, input costs, gross margins, and other economic indicators. The methodology involved regression analysis, sensitivity analysis, and optimization techniques to evaluate the impacts of these factors on the NPM and other economic metrics across different stages of the CSC. Sensitivity to input costs accesses the cost elasticity, which reflects the degree to which the total production cost changes with variations in input prices. A sensitivity analysis was conducted to model different scenarios where input costs varied, and their effects on profitability were assessed. We used PyCaret to build a regression model, including Random Forest Regressor (RF), for predicting the NPM based on input costs, labor, transport, processing, and other relevant economic variables. Sensitivity analysis was conducted to evaluate the effect of fluctuations in each cost factor on profitability. Optimization models using PuLP and Pyomo were used to identify optimal cost structures for maximizing profit. The data used in the analysis were sourced from various stages of the CSC, as seen in the Table 4.10.

Table 4.10. Financial and resilience metrics across coffee value chain stages

Stage	Revenue (USD)	Labor Costs (USD)	Transport Costs (USD)	Input Costs (USD)	Processing Costs (USD)	Total Costs (USD)	Gross Margin (USD)	Net Profit Margin (%)	ROI (%)	ROL (USD/hour)	Volatility Sensitivity	MVP (USD)
Farm Gate	1.5	0.8	0.4	1.2	0.6	2.6	1.5	33.3	12	4	High	1.3
Processing	2.0	0.4	0.2	0.9	1.5	3.0	1.0	30.0	15	5	Medium	1.0
Roasting	10.0	1.5	0.6	2.0	0.0	4.1	5.9	20.0	20	8	Medium	1.5
Retail	20.0	2.0	1.0	3.0	0.0	6.0	14.0	10.0	25	7	High	2.0
Certification	0.0	0.1	0.0	0.3	0.0	0.4	0.0	50.0	30	4.5	Low	0.5

We applied a RF model to predict the NPM, with the performance metrics from cross-validation specified in Table 4.11.

Table 4.11. Random forest regressor model performance metrics for predicting NPM

Metric	Value
Model	Random Forest Regressor
MAE	17.5205

MSE	316.3346
RMSE	17.7858
R2	0.2092
RMSLE	0.6969
MAPE	0.9288

By integrating these three resilience indicators into the Econ-LCA framework, we were able to evaluate the economic sustainability and robustness of the CSC against market shocks and fluctuations. These indicators provide insights into the risks faced by stakeholders and guide targeted interventions to enhance economic stability.

4.4.2.4 Natural Capital Assessment (NCA)

The NCA for the CSC was carried out using a hybrid approach, integrating both qualitative scoring and quantitative proxies to evaluate ecosystem services and their relationship to key production stages. The goal was to assess the triple LCA impact of coffee production, including the benefits and costs of ecosystem services like biodiversity, pollination, and carbon sequestration, as well as the resource efficiency related to soil fertility, water use, and land occupation. These NCA indicators were selected to represent ecosystem services critical to coffee production, using a mix of literature review, expert consultations (drawn from agronomists and ecologists familiar with coffee production systems), and relevance to cradle-to-grave life cycle stages. The methodology flowchart (Figure 4.7) for the NCA involves four key steps: Getting experts-based data and knowledge; Quantitative data collection; Data integration to assess sustainability indicator measurement; and Reporting and Communication, where results are summarized and communicated to participants through visualizations and a detailed report.

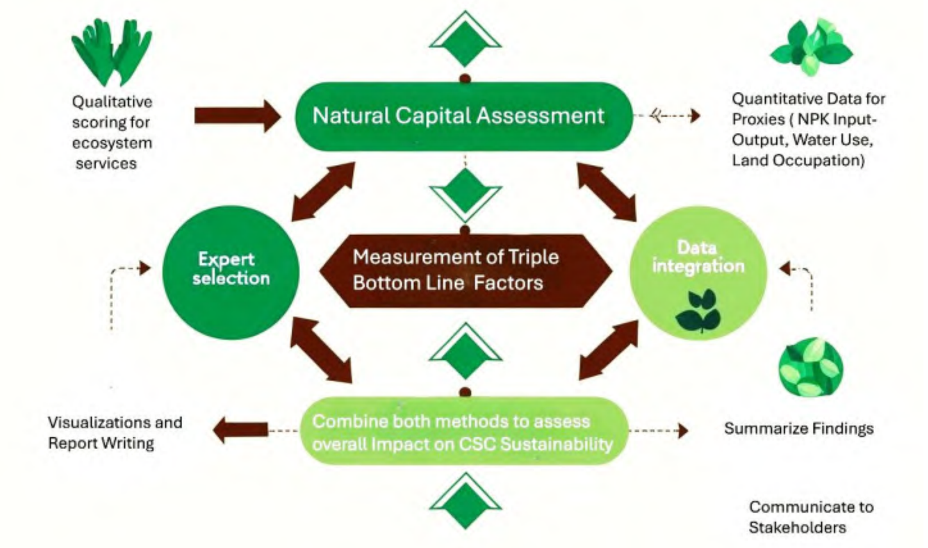


Figure 4.7. Methodological framework steps for the NCA

Expert Selection Process: The expert panel was composed of specialists from Italian coffee companies and global sustainability bodies, selected to ensure full representation of the CSC, from production to retail as given in Table 4.12. Agronomic experts (A, B) contributed knowledge on sustainable farming, soil health, fertilizer use, and IPM, essential for assessing environmental agricultural impacts. Supply chain and industry experts (D, G, J), including representatives from Illycaffè and Caffè Vergnano, provided insights into logistics, distribution, and fair trade, supporting the evaluation of economic and social dimensions. Environmental sustainability experts (C, E, H) focused on carbon emissions, water use, and land occupation, aiding in environmental impact assessment through both qualitative and quantitative measures. Social sustainability experts (F, I) specialized in fair trade, labor rights, and community development, ensuring ethical considerations and social equity were integrated into the sustainability framework.

Table 4.12. Expert Panel Composition for Qualitative Impact Assessment in CSC, Including Areas of Specialization and Inter-Rater Reliability (Cohen's Kappa)

Name	Representation	Position and Qualification	Expertise	Level (Cohen's Kappa)
Expert A	Coffee Growers Association, Lavazza, Italy	Senior Agronomist, Ph.D. in Agricultural Science	Coffee Cultivation, Fertilizer Use, Soil Fertility, Sustainable Practices	0.94
Expert B	Coffee Producers Federation, Lavazza, Italy	Coffee Production Manager, M.Sc. in Agronomy	Coffee Farming, Yield Optimization, Integrated Pest Management	0.92
Expert C	International Coffee Organization, UN	Head of Sustainability, M.Sc. in Environmental Science	Coffee Supply Chain Sustainability, Carbon Emissions, Water Use	0.91
Expert D	Specialty Coffee Association, Illycaffè, Italy	Director of Supply Chain, M.Sc. in Logistics & Supply Chain Management	Coffee Supply Chain Management, Fair Trade Certification	0.92
Expert E	Coffee Roasting Industry, Costadoro, Italy	Chief Sustainability Officer, Ph.D. in Environmental	Coffee Roasting, Environmental Impact, Carbon Footprint	0.93

		Policy		
Expert F	Fair Trade Coffee Alliance (Italy)	Senior Researcher, M.A. in Social Sustainability	Labor Rights, Fair Trade Practices, Community Engagement in Coffee Farms	0.95
Expert G	Coffee Packaging and Distribution Association, Caffè Vergnano, Italy	Senior Supply Chain Consultant, M.Sc. in Business Administration	Transport, Packaging, Logistics, and Distribution of Coffee	0.91
Expert H	Water Conservation Group, Italy	Hydrologist, Ph.D. in Environmental Hydrology	Water Use Efficiency, Irrigation Management in Agriculture	0.93
Expert I	Coffee Certification Authority, Rainforest Alliance (Italy)	Certification Director, M.A. in International Development	Coffee Certification (Organic, Fair Trade, Rainforest Alliance), Traceability	0.92
Expert J	Coffee Retailer Consortium, GHI Corporation (Italy)	Director of Sustainability and Ethics, M.Sc. in Business Sustainability	Retail Distribution, Consumer Trends, Ethical Sourcing and Marketing	0.94

By including experts from well-established coffee companies like Lavazza, Illycaffè, and Caffè Vergnano, as well as renowned certification bodies such as the Rainforest Alliance, we have ensured that the selected parameters are rooted in real-world coffee industry practices. This selection process provides a solid foundation for assessing the sustainability of the CSC and guiding future improvements in both business practices and environmental stewardship.

Quantitative Proxies: Quantitative proxies were employed to measure physical environmental factors that could directly influence coffee production (Table 13):

Soil Fertility: This was quantified through the input-output analysis of essential nutrients (NPK) applied and extracted from the soil during cultivation. The difference between the input and output was calculated for each production stage. It measures the sustainability of soil health and its long-term productivity for coffee farming per hectare per year.

Water Use Efficiency: Water consumption was measured per kilogram of coffee produced, using irrigation and rainfall data to determine the efficiency of water use across different coffee-producing regions. It helps assess the water footprint.

Land Occupation: The total land area utilized per year for coffee cultivation was estimated, which reflects the land area needed for coffee farming operations (m^2/year).

Table 4.13. Quantitative Proxies for Environmental LCA in Coffee Production

Proxy	Indicator	2020	2021	2022	2023	2024	Source
Soil Fertility	NPK Input-Output Analysis	N: 95, P: 55, K: 75 kg/ha	N: 100, P: 60, K: 80 kg/ha	N: 105, P: 65, K: 85 kg/ha	N: 110, P: 70, K: 90 kg/ha	N: 112, P: 72, K: 92 kg/ha	ICO (International Coffee Organization) & FAO Reports (2020-2024)
Water Use Efficiency	Water Consumption per kg of Coffee	3.8 m^3/kg	3.6 m^3/kg	3.3 m^3/kg	3.0 m^3/kg	2.9 m^3/kg	FAO, Coffee Sustainability Reports (2020-2024)
Land Occupation	Total Land Area Used per Year (m^2/year)	11,000 m^2/ha	10,800 m^2/ha	10,500 m^2/ha	10,200 m^2/ha	10,000 m^2/ha	FAO, Coffee Research Journal (2020-2024)

Each matrix entry includes the measurement method, role in LCA, observed trends over a 5-year period (2020-2024), and associated economic and ecological impacts, thereby ensuring a comprehensive, time- sensitive evaluation. The selection of services and indicators was guided by relevance to coffee production and impact potential, with expert opinions from agronomists and environmental scientists shaping the qualitative layer, while quantitative data were triangulated from empirical field data and literature. This matrix allows for a structured, replicable, and scalable analysis of trade-offs and synergies within coffee farming systems, enabling targeted interventions for sustainability at both the policy and farm levels.

4.5 Results

4.5.1 Environmental impacts of the coffee life cycle

The results of the E-LCA for the CSC provide significant insights into the environmental impacts associated with different stages of production. Preliminary findings highlight key areas where sustainability interventions can significantly reduce the environmental footprint of coffee production, particularly in areas such as water usage, carbon emissions, and waste management. The environmental LCA reveals that the coffee growing phase, which involves significant water consumption and pesticide use, contributes heavily to the environmental load. Data from the study show that approximately 60% of the environmental impacts are attributed to the agricultural practices used in coffee cultivation. Complete list of data utilized for conducting this assessment can be seen in Appendix C. This highlights the importance of sustainable farming practices, such as organic farming and efficient water management techniques, to reduce negative environmental outcomes. The comparison of environmental impacts across stages of the CSC reveals significant findings across categories such as acidification, climate change, ecotoxicity, eutrophication, human toxicity, and resource use (Figure 4.8).

- Coffee consumption is the leading contributor to multiple impact categories, accounting for 90% of climate change, 85% of human toxicity, and 80% of resource use. These impacts are primarily driven by energy-intensive activities like water heating and brewing, which rely on fossil fuel emissions.
- Coffee cultivation contributes significantly, representing 95% of water use and 80% of land use impacts, indicating high resource demands. The cultivation process also has notable effects on freshwater ecotoxicity (75%), acidification (60%), and terrestrial ecotoxicity (65%), largely due to fertilizer application, high water consumption, and pesticide use.
- Transportation contributes 20-25% to climate change impacts and plays a modest role in resource use and human toxicity, driven by fuel consumption emissions.
- Roasting accounts for 20% of particulate matter formation due to machinery emissions, while drying and depulping processes contribute less than 10% to acidification and human toxicity.

These results underscore the critical stages for impact reduction, particularly in coffee cultivation and consumption, where the highest environmental burdens are concentrated

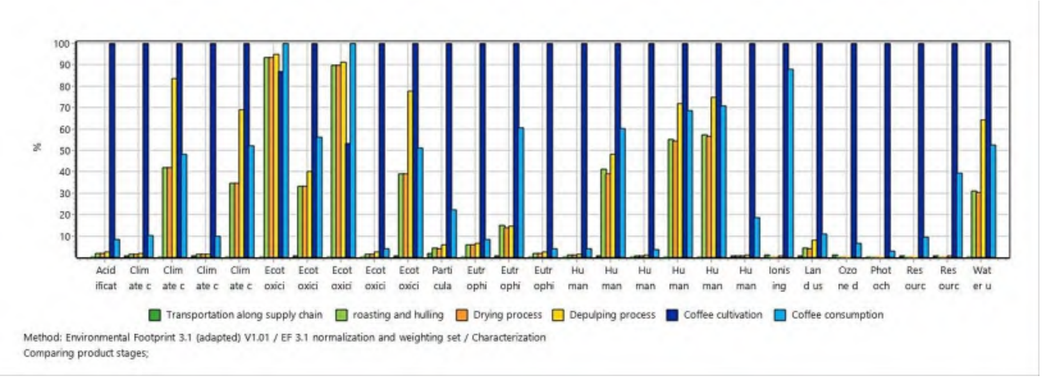


Figure 4.8. Evaluation of environmental impacts at various stages of the coffee supply chain for comparative analysis

The environmental damage assessment of the CSC identifies that roasting, hulling, and drying have lower environmental impacts but still show notable contributions in categories like acidification (0.078 mol H+ eq) and climate change (7.56 kg CO2 eq). On the other hand, transportation has minimal contributions, accounting for only 2.83 kg CO2 eq in climate change and 0.196 m³ for water use, but coffee cultivation is the most impactful stage across various environmental categories as given in Table 4.14. It is responsible for the largest contributions to acidification (4.095 mol H+ eq), climate change (511.283 kg CO2 eq), freshwater ecotoxicity (1886.92 CTUe), and water use (39.013 m³). In land use, cultivation dominates with the highest share of 1690 Pt, and in resource use (fossils), it is also the largest contributor at 6539.83 MJ. Instead, transportation has minimal contributions, accounting for only 2.83 kg CO2 eq in climate change and 0.196 m³ for water use. Coffee consumption, while less impactful than cultivation, significantly contributes to photochemical ozone formation (5.59 kg NMVOC eq) and particulate matter (3.03E-06 disease incidences).

Table 4.14. Overview of environmental damage distribution across the key stages of the coffee life cycle

Damage Category	Unit	Transportation	Roasting and Hulling	Drying Process	Depulping Process	Coffee Cultivation	Coffee Consumption
Acidification	mol H+ eq	0.012641	0.078441	0.077628	0.107663	4.095168	0.338059

Land Use	Ionizing Radiation	Human Toxicity, Non-cancer	Human Toxicity, Cancer	Eutrophication, Terrestrial	Eutrophication, Freshwater	Eutrophication, Marine	Particulate Matter	Ecotoxicity, Freshwater	Climate Change
Pt	kBq U-235	CTUh	CTUh	mol N eq	kg P eq	kg N eq	Disease inc.	CTUe	kg CO2 eq
14.17219	0.067606	2.13E-08	1.37E-08	0.045564	0.000318	0.004152	2.46E-07	10.05965	2.830263
72.95217	0.024739	2.8E-06	3.89E-08	0.330722	0.006682	0.099159	5.73E-07	1671.669	7.561528
68.58686	0.021133	2.75E-06	3.78E-08	0.328252	0.006185	0.098923	5.66E-07	1669.779	7.2491
135.7177	0.037757	3.65E-06	5.99E-08	0.462232	0.006531	0.112771	8.08E-07	1727.319	8.584364
1690.517	6.081593	5.07E-06	3.73E-06	18.98244	0.045011	1.73807	1.35E-05	1886.924	511.2833
183.5126	5.354336	3.48E-06	1.56E-07	0.782476	0.027336	0.14305	3.03E-06	1886.402	51.58468

Water Use	Resource Use, Minerals and	Resource Use, Fossils	Photochemical Ozone Formation	Ozone Depletion
m3 depriv.	kg Sb eq	MJ	kg NMVOC	kg CFC11 eq
0.196484	1.89E-05	37.84193	0.017094	7.26E-08
12.07359	7.86E-06	18.65114	0.011621	1.69E-08
11.79374	7.42E-06	16.59202	0.010873	1.46E-08
25.07082	1.34E-05	22.35052	0.015921	2.69E-08
39.01309	0.002202	6539.825	5.593117	7.18E-06
20.52452	0.000871	614.2048	0.155879	4.78E-07

Figure 4.9 provides a comprehensive visualization of the CSC model, illustrating the connections between various processes and resource inputs essential to coffee production. The illustration uses red bars within each process box to highlight relative environmental impacts, enabling the quick identification of critical hotspots throughout the system. At the top of the diagram, the "1 p coffee supply life cycle" node encapsulates the entire process (100%) and branches into two major pathways: coffee cultivation (80.7%) and roasted coffee (0.058%). The cultivation phase is further broken down, showing the use of harvested beans from both Global (GLO) and Rest of World (RoW) contexts, with each contributing 96.4% to the cultivation process. The figure continues to detail additional processes, such as the use of agricultural machinery, diesel fuel consumption, and tractor operations, all quantified with mass values and percentage contributions.

While the roasted coffee pathway constitutes a smaller fraction of the total impact, it includes the use of natural gas in gas turbines. The visual model effectively conveys the complexity of the CSC, emphasizing the significant environmental and resource implications at each stage. It also quantifies the contributions of various processes, demonstrating that cultivation (80.7%) overwhelmingly dominates compared to roasted coffee production (0.058%).

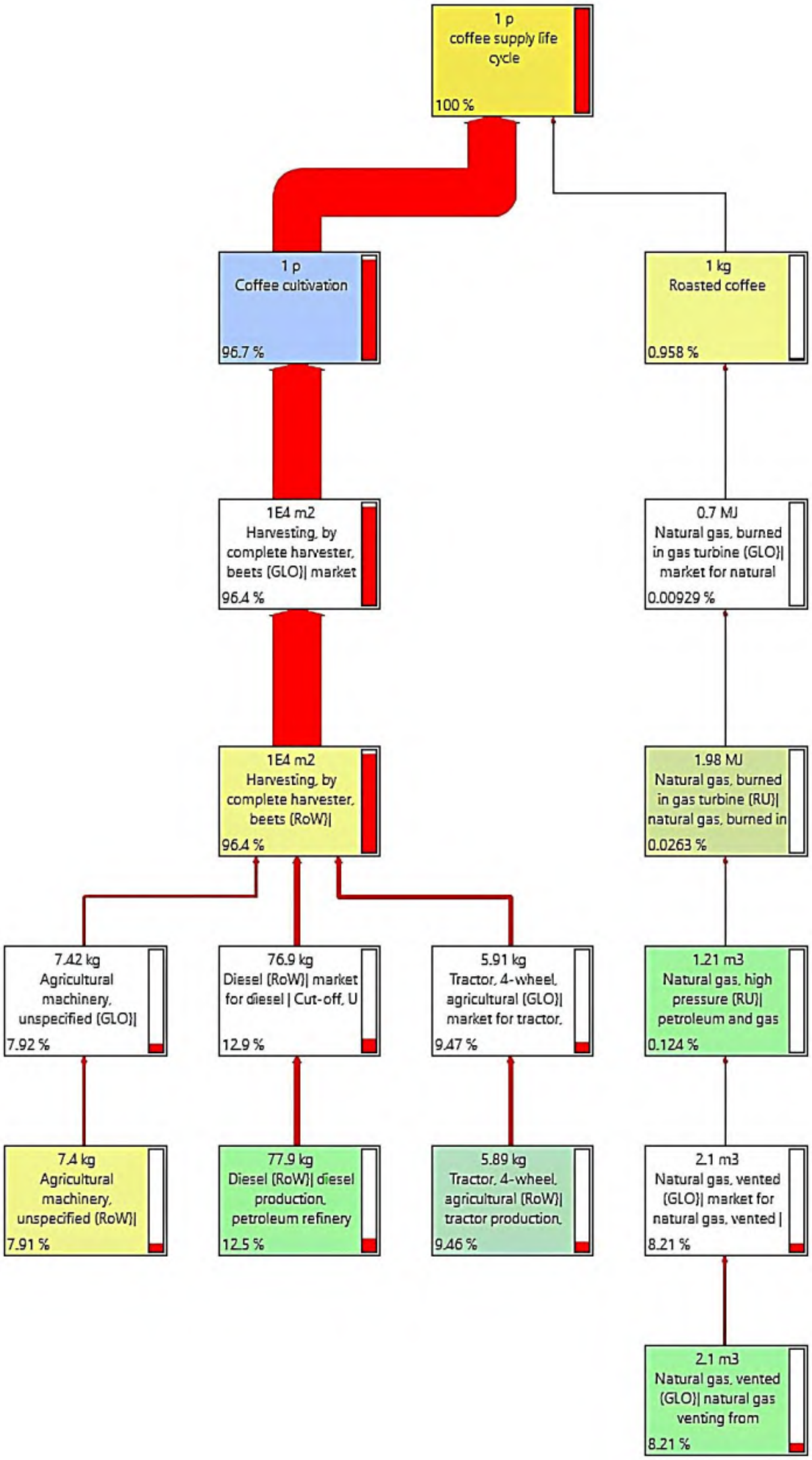


Figure 4.9. E-LCA Model for assessing the environmental footprint of coffee production

Moreover, it highlights coffee consumption and electricity usage in the consumption phase, providing insights into the use-phase impacts that are often overlooked in product-focused LCAs. The transition from green coffee cherries (2.47 kg) to dry processed coffee (1.34 kg), and then to packed coffee (1 kg), reveals a substantial mass loss, suggesting potential areas for efficiency improvements, as shown in Figure 4.10. This visualization emphasizes the global coffee production network, drawing attention to the need for sustainable practices to mitigate environmental impacts.

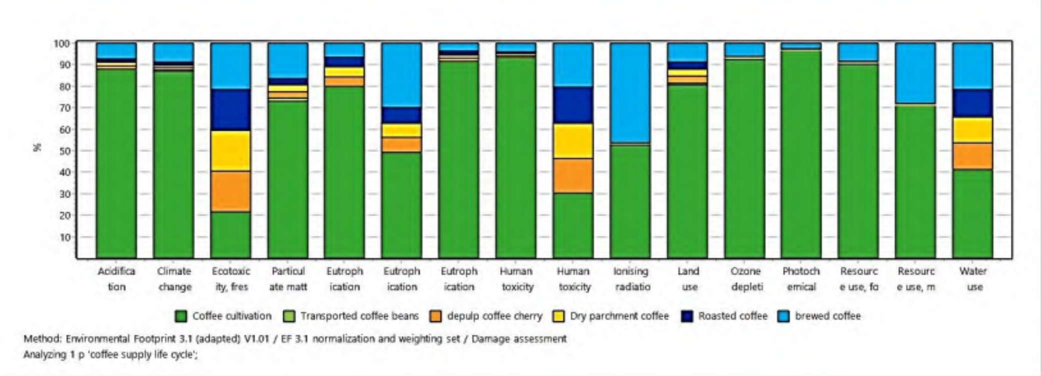


Figure 4.10. Quantitative impact distribution across phases of the coffee production process, highlighting key impact categories

Moreover, waste management during the processing and packaging stages is another area of concern, with large volumes of waste being generated. The findings suggest the potential for introducing recycling programs and reducing packaging waste, which could help mitigate these environmental impacts. The integration of these environmental findings with social LCA results, particularly in the context of the triple LCA approach, will allow for a comprehensive understanding of how both environmental and social dimensions interact and affect the overall sustainability of the CSC.

4.5.2 Social life cycle assessment (S-LCA)

The simulated S-LCA analysis was based on structured responses from 35 stakeholders engaged across various segments of the CSC, including farm-level producers, cooperative managers, processors, and transport intermediaries. These responses were simulated using the questionnaire format developed in line with the UNEP/SETAC S-LCA Guidelines, which are internationally recognized for assessing the social impacts of products and services. The questionnaire incorporated social risk indicators sourced from the SHDB, ensuring a comprehensive approach that integrates existing global data on social risks related to labor, human rights, and community well-being. This methodological framework allowed for the identification and quantification of key social issues impacting the CSC, with a particular focus on labor conditions, social protection, and health and safety concerns. Figure 4.11 explains the proportional distribution of social indicators across various stakeholder categories within the CSC. The Workers category accounts for the largest share (35%), underscoring the paramount significance of employment-related concerns such as job security, wage levels, and labor conditions.

Following closely are Value Chain Actors (16%), highlighting their influence in shaping the broader supply chain and its social outcomes. This distribution aligns with the study's focus on addressing the most pertinent social challenges faced by stakeholders in the coffee industry, particularly in terms of fair labor practices, working conditions, and economic stability.

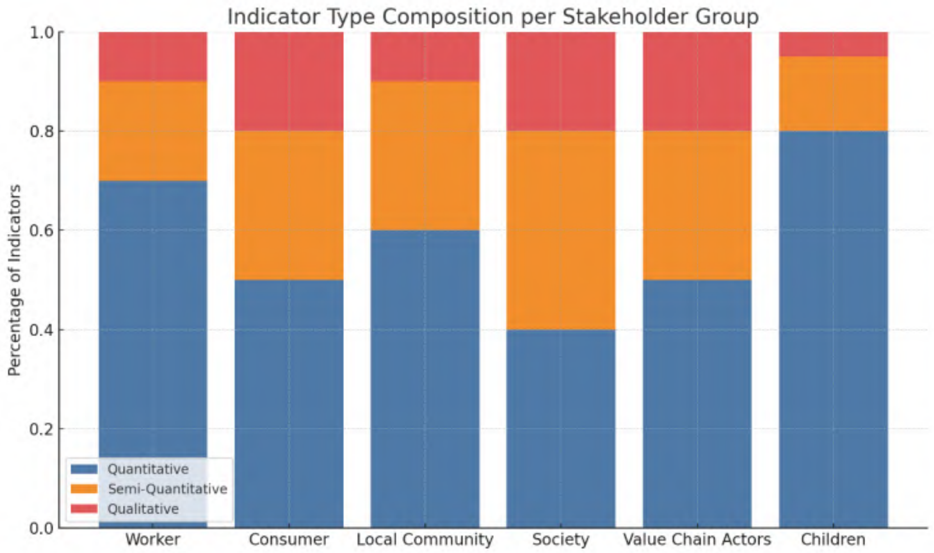


Figure 4.11. Indicators Distribution per Stakeholder Category

Table 4.15 further elaborates on the typology of the indicators, categorizing them into quantitative, semi- quantitative, and qualitative types for each stakeholder group. For Children and Workers, the majority of indicators are Quantitative (over 70%), indicating that the social issues affecting these groups are more readily quantifiable. These issues include measurable factors such as wage rates, duration of employment, and access to essential services, which can be tracked through numerical data. In contrast, for Consumers and Society, a larger proportion of Qualitative indicators are used. These indicators often pertain to subjective experiences, such as perceptions of fairness, equality, and overall satisfaction with working conditions and social benefits. This divergence in indicator types reflects the varying methodologies required for data collection and analysis based on the stakeholder group in question. The predominance of Quantitative data for certain groups, particularly those directly involved in the workforce, allows for a more robust, objective analysis of their social conditions, while the reliance on Qualitative data for broader societal groups necessitates more interpretive approaches to understanding social impact.

Table 4.15. Indicator type composition per stakeholder group

Stakeholder	% Quantitative	% Semi-Quantitative	% Qualitative
Workers	70%	20%	10%
Consumers	50%	30%	20%
Local Community	60%	30%	10%

Society	40%	40%	20%
Value Chain Actors	50%	30%	20%
Children	80%	15%	5%

Figure 4.12 presented summarizes key responses from the questionnaire, providing insights into the labor conditions, health and safety provisions, and social assessment methods within the CSC. It highlights the methods used to assess and monitor social performance across the industry. The Distribution of Average Daily Wage Levels across respondents reveals that 34.3% of workers earn below the minimum wage, a critical indicator of financial vulnerability and income inequality. This highlights the need for compensation strategies that surpass the minimum wage to address worker financial instability.

The Frequency of OHS Training Provision shows that 57.1% of workers receive occasional OHS training, 22.9% receive regular training, while 20% report no training at all. This gap in OHS education points to significant risks in worker safety and indicates the need for more consistent and comprehensive training to mitigate workplace accidents.

The Monitoring of Child Labor Risk across coffee production sites reveals that no formal monitoring is conducted at most sites. Only 28.6% of respondents report formal audits, and 22.9% mention informal monitoring, highlighting the reliance on ineffective informal methods to address child labor issues. This lack of formal oversight necessitates stronger, more structured child labor monitoring practices.

Regarding Accessibility of Basic Healthcare Facilities for Workers, 71.4% of respondents reported that healthcare is not available. This lack of access to healthcare services for a majority of workers signals the urgent need for policy interventions to ensure health benefits are provided across the supply chain.

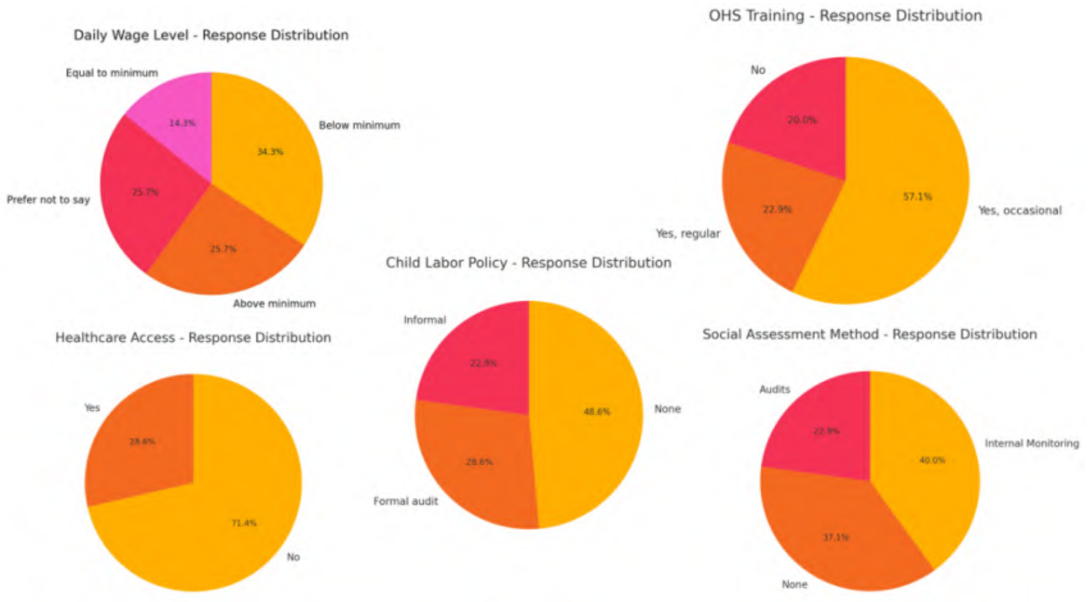


Figure 4.12. Distribution of responses to key social indicators in workplace conditions

The methods used to assess social performance include Internal Monitoring, with 40% of respondents using this approach. Audits account for 22.9% of responses, while 37.1% reported no formal social performance monitoring. This gap in formal auditing practices underscores the need for improved transparency and accountability within the sector. The technical summary in Table 4.16 provides the dominant response categories and their percentage share for key indicators.

Table 4.16. Technical summary of findings

Indicator	**Dominant Response Category**	**Share (%)**
Wage Level	Equal to Minimum Wage	51
OHS Training	Yes, regularly	46
Child Labor Policy	Informal Monitoring	49
Healthcare Access	Available	71
Social Assessment Method	Internal Monitoring Systems	54

These findings emphasize the necessity of policy reforms and highlight the critical role of internal monitoring systems and audits in improving worker well-being. There is significant potential for improving the formalization of these processes to ensure better social outcomes across the CSC.

These responses were then processed through NVivo 14, where thematic coding and narrative analysis were carried out. Interview responses were inductively coded using open coding techniques and then classified into axial codes across categories such as "Employment Security", "Social Protection Gaps", "Discrimination Risks", and Health and Safety Concerns. Matrix queries were used to quantify response trends across stakeholder types. These themes were further subdivided into specific codes, such as job stability and long-term contracts under Employment Security, or gender and racial discrimination under Discrimination Risks as represented in Figure 4.13.

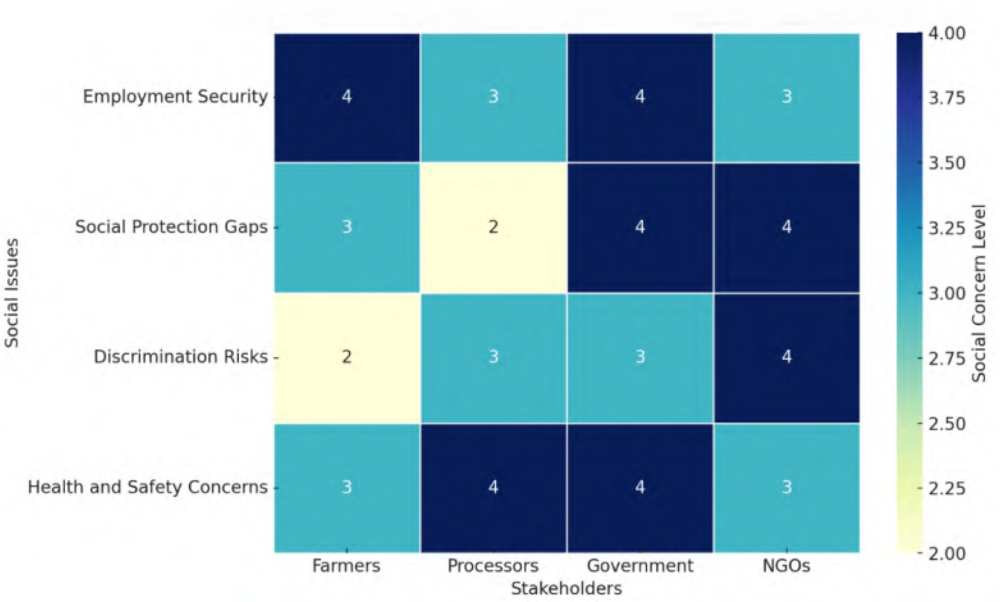


Figure 4.13. Thematic coding matrix with varying levels of importance attributed to social issues

The results of the matrix query indicate significant variation in the perceived importance of these social issues. Through these analyses, we found that Employment Security, farmers and processors reported a high concern (4), emphasizing the instability caused by seasonal work and lack of long-term contracts. The Social Protection Gaps theme highlighted a disparity between governmental coverage and the support provided by NGOs, with government respondents acknowledging limited access to social services like health insurance and pensions, while NGOs played a key role in filling the gaps. Discrimination Risks were predominantly highlighted by NGOs and workers, especially regarding gender and racial disparities, where native groups faced barriers to equal pay and employment opportunities. Finally, the Health and Safety Concerns revealed that workers, especially in processing plants, face substantial risks from hazardous chemicals, compounded by inadequate safety training and insufficient enforcement of OHS standards by local governments. This thematic analysis affirms the central role of NGOs and government in addressing these gaps, ensuring fair labor practices, and improving the overall social conditions within the CSC.

The S-LCA model for quantifying social impacts within the CSC was developed using the ANP [136] method in SuperDecisions v2.10. The model structures the system into four main clusters: Social Criteria, Strategic Alternatives, Societal Drivers, and Value Chain Actors, as shown in Figure 14. Social Criteria encompass key social aspects such as child labor, ethical demand, health and safety, educational access, social empowerment, and wage equity. Value Chain Actors including farmers, processors, NGOs, government, and consumers influence these social criteria. Societal Drivers, such as policy pressure, corporate social responsibility, and access to services, exert further influence on the social criteria. Strategic Alternatives, including labor laws, fair trade initiatives, worker unionization, healthcare access, and education programs, are proposed to improve the social conditions across the supply chain. Connections between actors, drivers, criteria, and alternatives were established to represent interdependencies and feedback loops, thereby enhancing the model's ability to capture the complex dynamics of social sustainability in the coffee value chain. To mitigate subjectivity inherent in expert scoring, we employed a structured approach involving multiple experts from diverse backgrounds in coffee production, social sciences, and supply chain management. Pairwise comparisons and scoring were conducted independently by at least five experts, and consistency ratios were calculated to ensure reliability of judgments. Where inconsistencies were detected, feedback rounds and consensus discussions were held to refine the scoring. This iterative approach reduced individual biases and strengthened the robustness of the social impact model.

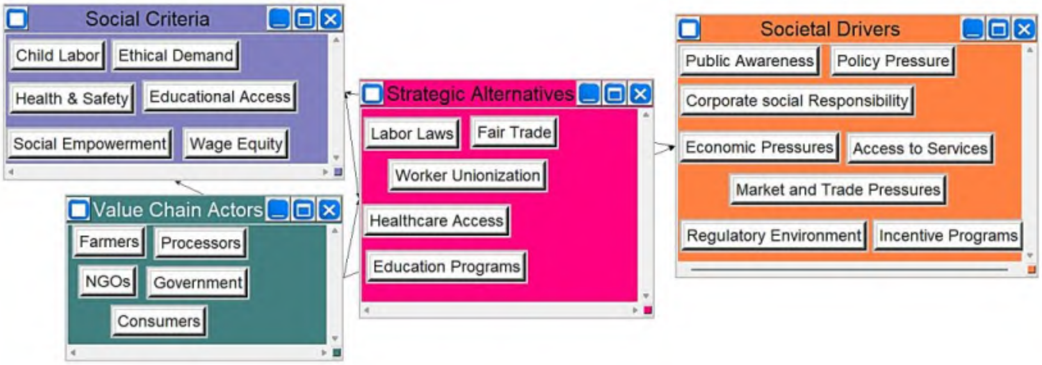


Figure 4.14. ANP model for quantifying social impacts in the CSC

The network was constructed by establishing dependencies between nodes, with pairwise comparison matrices used to assign weights and quantify the relative influence of each value chain actor and alternative with respect to social criteria. The model's robustness was validated through sensitivity analysis, ensuring that the results were reflective of potential real-world scenarios. The results of the synthesis, which were calculated using the ANP method, are summarized in Table 4.17.

Table 4.17. Results of social criteria synthesis using the ANP method for alternative evaluation

Alternatives	Ideal Values	Normal Values	Raw Values
Education Programs	1	0.386976	0.193488
Fair Trade	0.319049	0.123465	0.061732
Healthcare Access	0.204074	0.078972	0.039486
Labor Laws	0.689483	0.266814	0.133407
Worker Unionization	0.371531	0.143774	0.071887

The highest-ranking alternative, Education Programs, was found to have the most significant impact on improving the social conditions related to child labor, educational access, and wage equity in coffee production. Labor Laws also show a strong importance, with a normalized value of 0.266814, highlighting the critical role of enforcing labor regulations in addressing social issues. Worker Unionization and Fair Trade are moderately important; these alternatives offer significant contributions but are relatively less prioritized compared to education programs and labor laws. Finally, Healthcare Access ranks lower among the strategic alternatives, with a normalized value of 0.078972, indicating that while important, healthcare interventions are considered less immediately impactful compared to educational, regulatory, and organizational initiatives. Overall, the analysis shows a clear preference toward educational and legal measures as the primary strategic pathways for enhancing social sustainability in the CSC as shown in Figure 4.15.

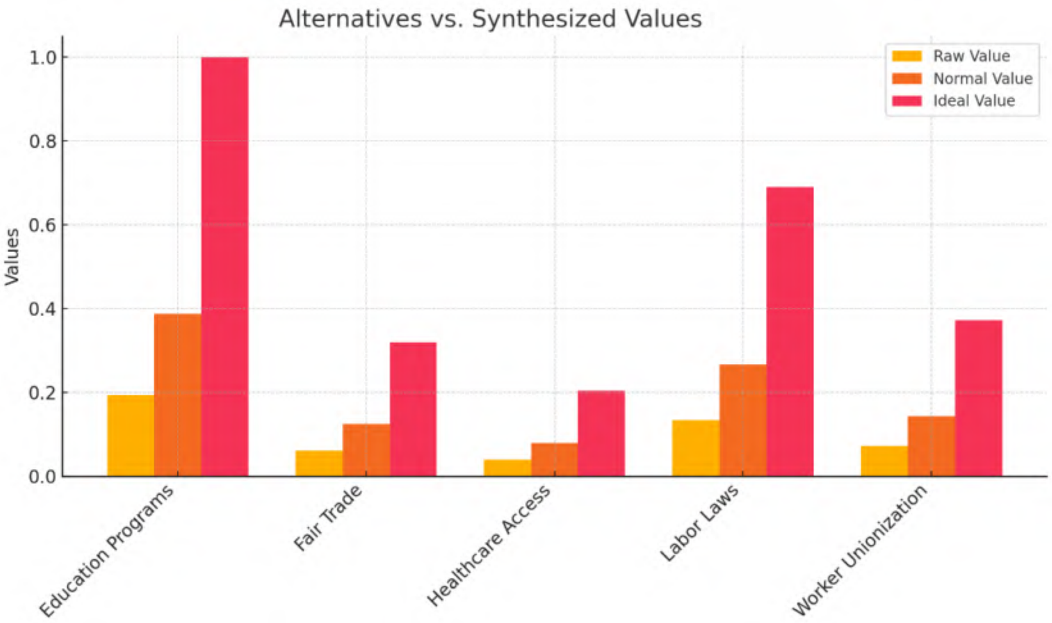


Figure 4.15. Comparative synthesis of social impact alternatives

Figure 4.16 depicts the comparison between Normalized Values and Limiting Values for social impact categories where limiting value reveals challenges in its full implementation and the need for strong government regulation to address respective disparities. The significant gap between both values suggests that while these issues are critical, substantial barriers exist in their enforcement and practical application within the supply chain.

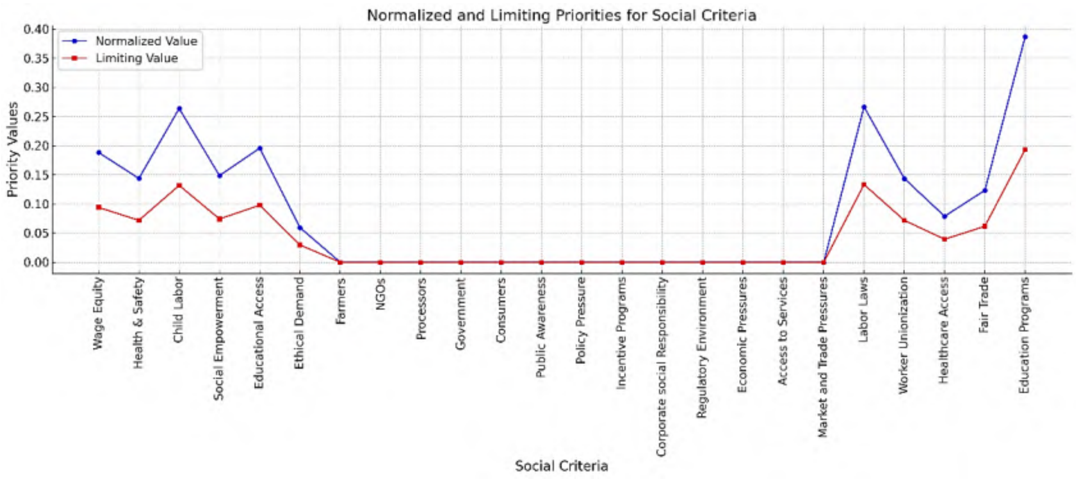


Figure 4.16. Evaluation of normalized and limiting priorities for social criteria in the coffee supply chain

The methodological triangulation using SHDB, ANP-based scoring in SuperDecisions, NVivo-supported qualitative coding, and questionnaire responses provides a reproducible framework for embedded social analytics in sustainability research.

4.5.3 Economic life cycle assessment (Econ-LCA)

This section presents the results obtained from the Econ-LCA of the CSC, applying various analytical techniques such as regression modeling, sensitivity analysis, and optimization. These approaches aim to quantify the economic performance at each stage of the supply chain and to identify key economic factors influencing profitability. By incorporating these methods, we derived a comprehensive understanding of how cost management and pricing strategies impact the sustainability and profitability of the coffee industry.

The RF was utilized to model the relationship between various economic factors and the NPM, with the goal of predicting profitability based on variables such as labor costs, transport costs, input costs, gross margin, and MVP. The model's performance was evaluated using several key metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R^2, Root Mean Squared Logarithmic Error (RMSLE), and Mean Absolute Percentage Error (MAPE). Each factor's impact on the NPM (%) was assessed by varying it by ±10%. The results for each fold in the cross-validation process, along with the mean and standard deviations, are summarized in Table 4.18

Table 4.18. Performance metrics for random forest regressor in predicting NPM Using Cross-Validation

Metric	Fold 0	Fold 1	Fold 2	Mean	Std
MAE	1.089	11.584	6.900	6.5243	4.2928
MSE	1.186	134.189	47.610	60.995	55.117

RMSE	1.089	11.584	6.900	6.5243	4.2928
R^2	Nan	Nan	Nan	Nan	Nan
RMSLE	0.0358	0.4393	0.2246	0.2332	0.1649
MAPE	0.0363	0.5792	0.2072	0.2742	0.2266

*R^2 is Nan where the target variable has zero variance (e.g., constant values in test folds).

From these results, it is evident that while the model's overall predictive performance (R^2) is weak, the error metrics such as RMSLE and MAPE indicate moderate success in minimizing prediction errors. The relatively low R^2 suggests that the regression model was not fully able to capture the complex relationships between the input variables and the NPM.

The plot in Figure 4.17a, illustrating the impact of Gross Margin (USD) on Net Profit Margin (NPM %), demonstrates an inverse relationship, where the NPM begins to decline significantly as the gross margin exceeds 5 USD. This suggests that inefficiencies may begin to outweigh the benefits at higher gross margin levels, indicating that higher gross margins do not necessarily result in higher profitability. Similarly, Figure 4.17b reveals a negative correlation between Input Costs (USD) and NPM, showing that as input costs rise above 1.5 USD, the NPM significantly decreases. This highlights the importance of reducing input costs as a key strategy for maximizing profitability in the CSC. Moreover, Figure 4.17c shows that Labor Costs (USD) also have a strong negative correlation with NPM, with NPM declining proportionally as labor costs increase. This further emphasizes the need to manage labor expenses to preserve profitability. Finally, in Figure 4.17d, we observe that increasing the MVP (USD) leads to a substantial decrease in the NPM, underlining the importance of competitive pricing strategies to maintain robust profit margins, especially in price-sensitive markets. Together, these figures highlight the critical factors and pricing strategies that must be carefully managed to sustain profitability.

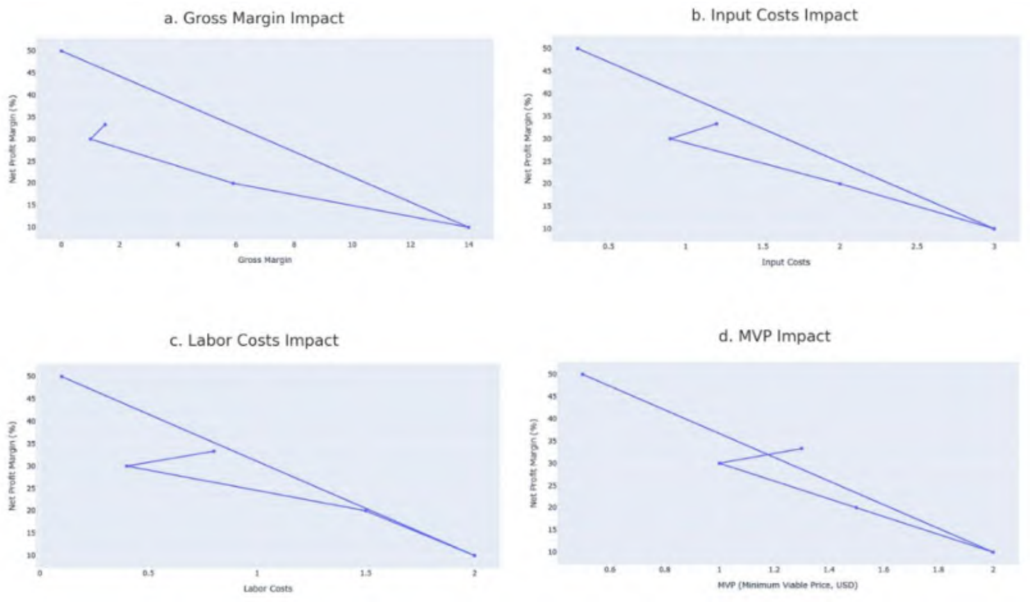


Figure 4.17. Impact of key financial factors on Net Profit Margin (%)

The plot in Figure 4.18a demonstrates a clear inverse relationship between processing costs and NPM, where an increase in processing costs leads to a decline in NPM, reinforcing the critical need for cost- efficient production methods to maintain profitability. A similar pattern is observed in Figure 4.18b, where higher total costs result in decreased profitability, highlighting the importance of controlling costs at all stages of the CSC to ensure sustainability and maximize returns. Furthermore, Figure 4.18c illustrates the impact of transport costs on NPM, further corroborating the negative relationship between rising costs and reduced profitability. As transport costs increase, NPM significantly declines, emphasizing that transportation efficiency is a key contributor to overall profitability in coffee production. Finally, the Volatility Sensitivity analysis in Figure 4.18d reveals that high volatility results in reduced profitability, whereas low volatility leads to higher NPM, underlining the importance of maintaining stability in the supply chain and mitigating the effects of market fluctuations. The findings highlight the importance of managing inefficiencies and controlling costs to optimize profitability.

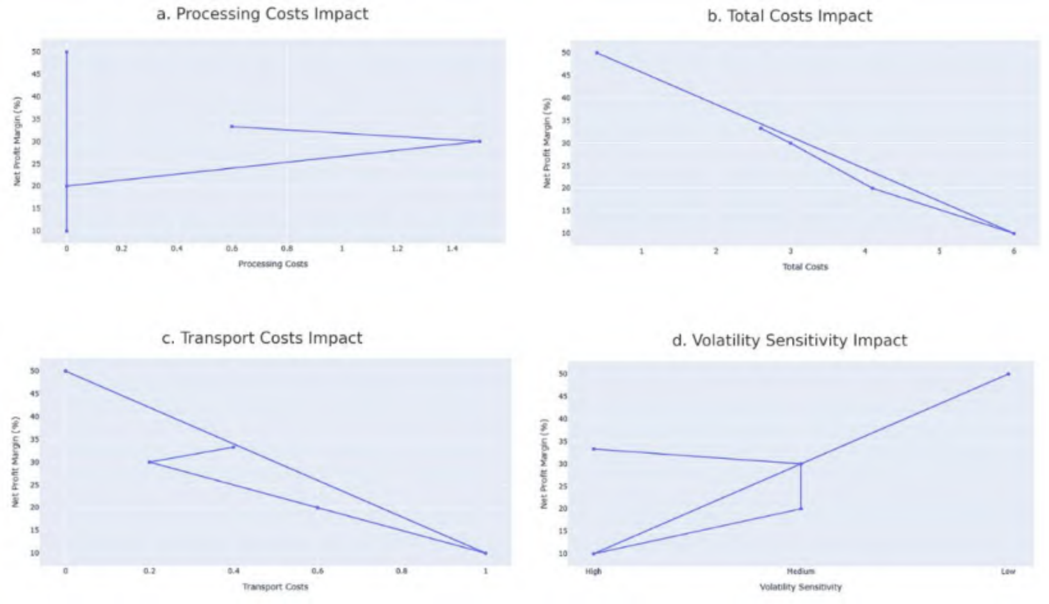


Figure 4.18. Analysis of cost and volatility factors on NPM for stability in the market environment

Using linear programming techniques with the PuLP and Pyomo libraries, the optimization model was employed to identify the optimal cost structure for labor and transport, aimed at maximizing profitability. The optimized values for labor and transport costs were determined to be 1.0 USD per kilogram for labor and 0.5 USD per kilogram for transport. This cost structure balances the need for cost efficiency with economic viability, ensuring profitability while maintaining cost competitiveness.

The Feature Importance Plot (Figure 4.19a), generated using the Random Forest model, highlights the most influential drivers of NPM (%), with MVP (USD) and Total Costs (USD) emerging as the key factors, followed by Gross Margin (USD) and ROI. This analysis emphasizes the factors that should be prioritized to enhance profitability in the CSC. In order to ensure the reliability of the model, Cook's Distance (Figure 4.19b) was used to detect any influential data points that could distort the model's performance. The results confirmed that there were no significant outliers, thus ensuring that the model's predictions were not influenced by extreme values. Despite this, the Residuals Plot (Figure 4.19c) reveals significant deviations between the predicted and observed values, particularly in the test data. This suggests that the model may be overfitting to the training data and struggling to generalize to new, unseen data. Building on this, the Prediction Error Plot (Figure 4.19d) shows a low R^2 value of 0.209, indicating that the model has weak predictive power and is ineffective at capturing the relationship between input features and the target variable. These figures provide a detailed evaluation of the model's strengths and weaknesses, highlighting areas that require improvement.

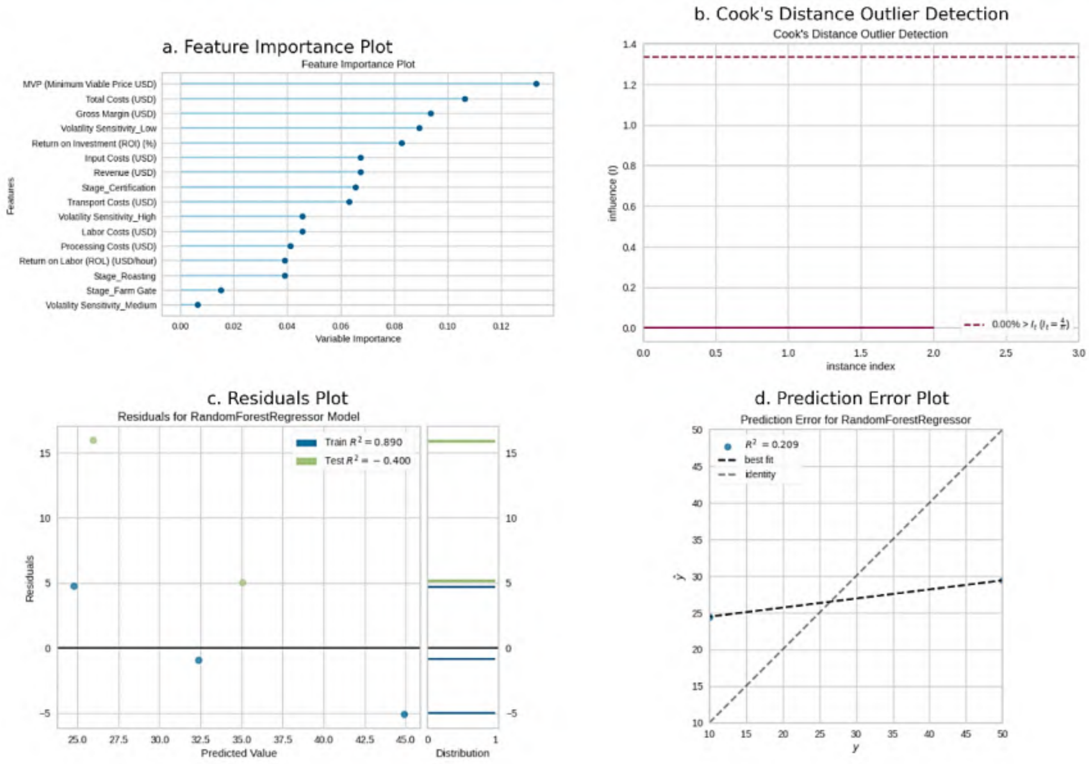


Figure 4.19. Evaluation of model performance and feature significance

4.5.4 Scenario Analysis and Sensitivity Testing in Econ-LCA

Once data are collected, various scenarios will be simulated to evaluate the impact of fluctuations in key economic factors such as how a 10% increase in labor costs influences profitability, how changes in fuel prices affect margins at various stages of the supply chain, and sensitivity to fertilizer prices, water costs, and other inputs. A sensitivity model is constructed in which these factors are tested under different scenarios. For example, the base case represents current labor, input, and transport costs; the high-cost scenario assumes a 20% increase in input, transport, labor, and other costs; and the low-cost scenario assumes a 20% reduction in these same cost components. These scenarios will allow us to quantify the effects of economic changes on different supply chain stakeholders, such as farmers, processors, and retailers, as depicted in Figure 4.20b. To assess the resilience of the CSC to economic shocks, MVP indicator is used which defines the lowest price at which producers can still cover their costs and remain profitable. This indicator helps assess the financial sustainability of coffee production at various price points. For instance, if the MVP is $1.3 per kg, and coffee prices drop below this threshold, farmers will not be able to cover their costs. Next indicator is sensitivity to Input Costs which evaluates how sensitive profitability changes in input costs such as fertilizers, labor, and water usage as represented in Figure 4.20a. This is critical for understanding the financial vulnerability of coffee producers

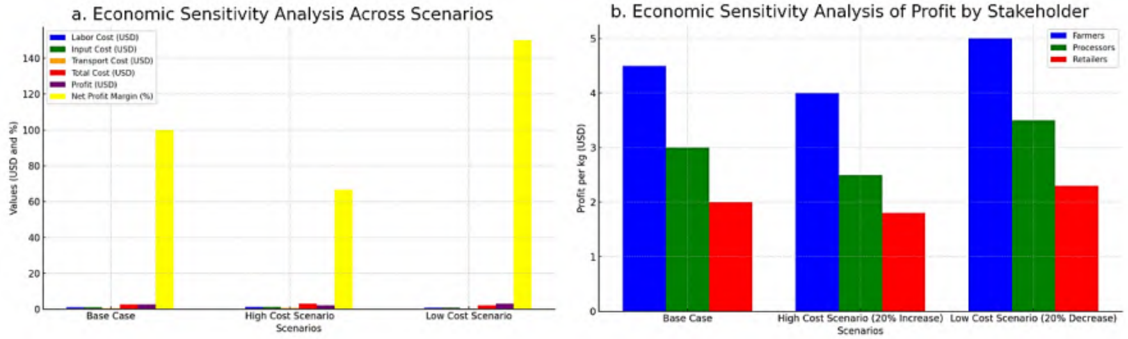
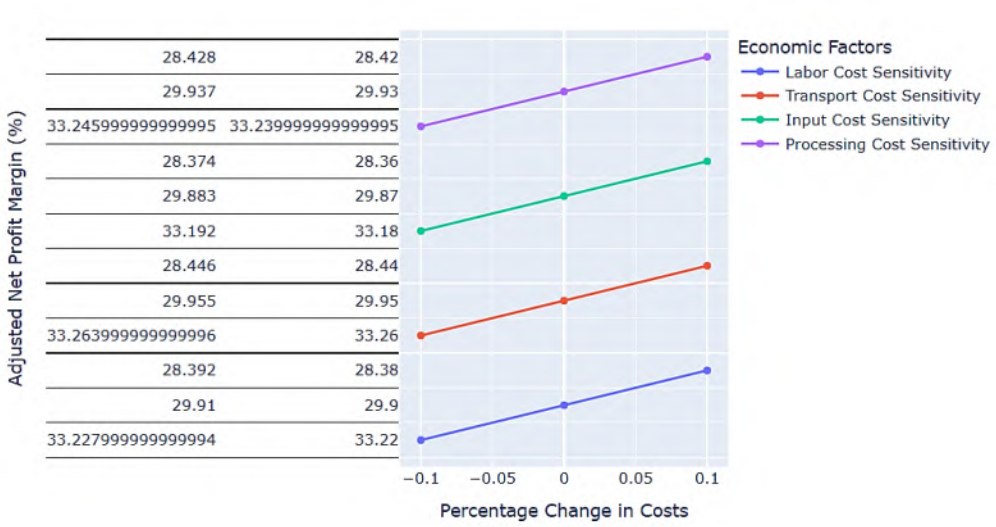


Figure 4.20. Economic sensitivity analysis across scenarios and profit by stakeholder

The charts (Figure 4.19) present a sensitivity analysis of the CSC across three economic scenarios. In the Base Case, current cost levels are maintained, resulting in baseline Profit and NPM. The High-Cost Scenario, with a 20% increase in labor and input costs, shows a marked rise in Total Costs, leading to a sharp decline in both Profit and NPM. The Low-Cost Scenario, reflecting a 20% decrease in labor and input costs, results in lower Total Costs and a significant increase in Profit and NPM. This analysis clearly demonstrates that fluctuations in labor and input costs have a direct and substantial impact on profitability. Managing these cost drivers is essential to maintaining financial viability and operational resilience throughout the CSC. The graph (Figure 4.21) shows the Adjusted NPM (%) in response to percentage changes in Labor Cost, Transport Cost, Input Cost, and Processing Cost. Labor cost sensitivity has the greatest impact, with the margin changing by ±0.01%, from 33.24% at a -0.1% change to 33.23% at a +0.1% change. Transport cost sensitivity shows a minimal effect, with the margin fluctuating by ±0.01%, from 33.19% at -0.1% to 33.18% at +0.1%. Input cost sensitivity also results in a ±0.01% change in margin, from 33.19% to 33.18%. Processing cost sensitivity has the smallest effect, with the margin changing by ±0.01%, from 33.22% at - 0.1% to 33.23% at +0.1%. Overall, labor costs have the highest sensitivity, while other costs show a relatively small impact on profitability.



28.428	28.42
29.937	29.93
33.245999999999995	33.239999999999995
28.374	28.36
29.883	29.87
33.192	33.18
28.446	28.44
29.955	29.95
33.263999999999996	33.26
28.392	28.38
29.91	29.9
33.227999999999994	33.22

Figure 4.21. Sensitivity analysis for economic factors

Finally, the Validation Curve for RandomForestRegressor displays the relationship between the max_depth of the model and its performance, measured by the Training Score and Cross Validation Score. The plot (Figure 4.22) shows that as the max_depth increases from 1 to 10, both the training and cross-validation scores remain consistently around 2.0 for training and 1.0 for cross-validation, suggesting a model that is underfitting. The stability of the scores across all values of max_depth indicates that increasing the depth of the model does not improve performance, and the model's complexity is not benefiting from deeper trees. This suggests that further tuning of hyperparameters, such as max_depth, is required to achieve better generalization.

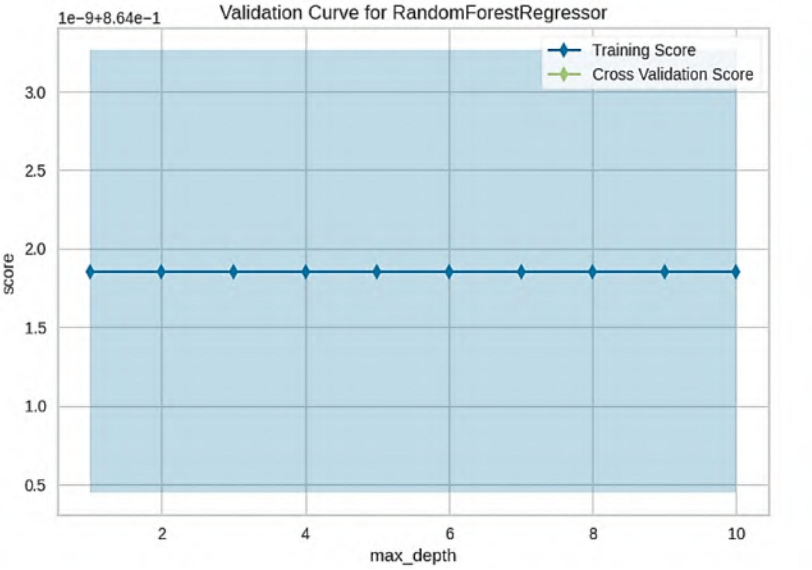


Figure 4.22. Validation curve for RandomForestRegressor

The application of the Econ-LCA framework to the CSC has yielded valuable insights into the industry's economic dynamics. Regression analysis, sensitivity analysis, and optimization have underscored the critical role of controlling labor, transport, and processing costs to maximize NPM. Optimization results further suggest an ideal cost structure for labor and transport that balances profitability and efficiency. However, the low R^2 value of the regression model points to its limited predictive power, indicating the need for model refinement. This may involve exploring more complex algorithms or enhancing the data used. Despite these limitations, the sensitivity analysis and feature importance plots provide actionable guidance for strategic cost management and pricing decisions within the CSC.

4.5.5 Outcomes of Natural Capital Assessment (NCA)

The NCA revealed significant insights into the environmental costs and benefits associated with coffee production. By integrating qualitative expert ratings and quantitative proxies, we were able to model the total natural capital value provided by ecosystem services in the CSC.

4.5.5.1 Qualitative Impact on Ecosystem Services

The integrated LCA scoring Table 4.19 assesses the sustainability of coffee production by combining economic, social, and environmental indicators, each rated across five levels from highly unfavorable (0- 20) to highly favorable (80-100). Economic indicators include labor cost efficiency, which evaluates the balance between labor expenses and production output, and transport efficiency, which measures cost- effectiveness in moving coffee along the supply chain; both are essential for maintaining profitability while minimizing waste. Supply chain transparency, bridging economic and social dimensions, reflects the openness of sourcing, labor conditions, and environmental practices, fostering accountability.
Environmental indicators cover energy efficiency in production, water usage efficiency, carbon emissions per unit, and water management practices, all of which address resource conservation and reduction of environmental impact. Soil fertility maintenance assesses fertilizer use where excessive application harms soil health and long-term productivity. Biodiversity impact and pollination support, linked to both environmental and social domains, measure ecosystem integrity and the health of pollinator populations, respectively, both crucial for ecological resilience and crop yield. Social indicators include fair trade and ethical practices, ensuring equitable sourcing and treatment of workers; labor welfare standards, which evaluate working conditions and rights; and health and safety practices, which protect workers from occupational hazards. Together, these indicators provide a comprehensive, multi-dimensional evaluation of sustainability, linking ecological stewardship, social equity, and economic viability.

Table 4.19. Integrated economic, social, and environmental factors under the qualitative scoring system

Qualitative Indicator	**Category**	**Scoring Criteria**	**(0 to 20)**	**(20 to 40)**	**(40 to 60)**	**(60 to 80)**	**(80 to100)**
Labor cost efficiency	Economic	Labor cost/unit output	Very high cost	High cost	Reasonable cost	Low cost	Extremely low cost
Transport efficiency	Economic	Transport cost/unit output	Very high cost	High cost	Moderate cost	Low cost	Extremely low cost
Energy efficiency	Environmental	Energy consumption/unit output	Very inefficient	Inefficient	Reasonably efficient	Efficient	Highly efficient
Water usage efficiency	Environmental	Water use/kg coffee	Very high usage	High usage	Moderate usage	Low usage	Very low usage
Co_2/unit output	Environmental	Co_2 emissions/ kg coffee	Very high emissions	High emissions	Moderate emissions	Low emissions	Very low emissions
Soil fertility	Environmental	Fertilizer/kg coffee	Extremely high	High	Moderate	Low	Negligible

Water management practices	Environmental	Water recycling efficiency	No management	Poor management	Some management	Good management	Excellent standards
Labor welfare standards	Social	Worker welfare & safety	Very poor standards	Poor standards	Adequate standards	Good standards	Excellent standards
Supply chain management	Social/economic	Transparency level	Very opaque	Opaque	Some transparency	Mostly transparent	Fully transparent
Fair trade and ethical practices	Social	Degree of ethical sourcing	No ethical practices	Poor ethical practices	Some ethical practices	Strong ethical practices	Fully ethical
Pollination support	Environmental/social	Pollinator impact	Significant decline	Moderate decline	Slight decline	Stable	Positive impact
Biodiversity impact	Environmental/social	Biodiversity impact	High disruption	Moderate disruption	Low disruption	Negligible disruption	No impact

The chart in Figure 4.23 illustrates expert panel ratings on various qualitative impact indicators in the CSC, covering both economic and environmental aspects. Labor Cost Efficiency and Transport Efficiency were primarily rated in the moderate (40-60) and high cost (60-80) categories, with 40.3% and 42.9% of responses, respectively. For Water Usage Efficiency, around 75% of ratings fell in the low (60-80) and very low usage (80-100) categories, indicating efficient water use in agroforestry coffee systems. CO_2 emissions per unit output showed positive trends, with 60.1% in the low and very low emissions ranges, reflecting a reduced carbon footprint. Soil Fertility was mostly rated in the low to moderate range (60-80), accounting for 52.5% of responses, suggesting effective nutrient management.

Ratings for Biodiversity and Pollination were concentrated in the low disruption (60-80) and stable (80- 100) categories, at 58.2% and 65.4%, respectively, indicating favorable ecological outcomes. Fair Trade and Ethical Practices received strong ratings, with 63.2% falling within the strong (60-80) and fully ethical (80- 100) brackets. Supply Chain Management was seen as mostly transparent by 45.3% of respondents, while Labor Welfare Standards were rated good to excellent (60-100) by 59.5%, highlighting decent labor conditions. Overall, the chart reflects significant progress toward sustainability in coffee production, while pointing to ongoing challenges in Transport Efficiency and Labor Cost Efficiency

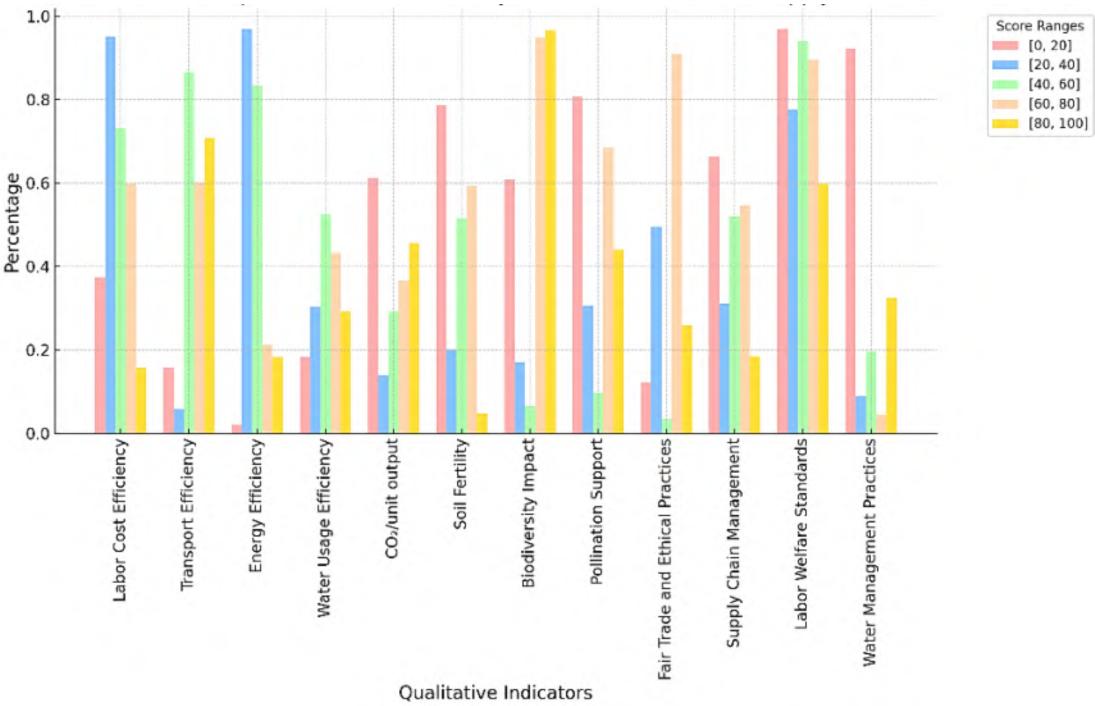


Figure 4.23. Expert panel evaluation of ecosystem service indicators in coffee production

4.5.5.2 Analysis and Implications for Quantitative Proxies

The quantitative proxies in the Triple LCA framework are critical for evaluating the environmental impacts of coffee farming, with 5-year trend data revealing progressive adoption of sustainable practices. Figure 4.24a suggests that water use efficiency has improved, with consumption declining from 3.8m³/kg in 2020 to 2.9m³/kg in 2024, largely due to the implementation of water-saving methods such as drip irrigation and rainwater harvesting, particularly vital in water-scarce regions. Soil fertility trends in Figure 4.24b show increased application of nitrogen, phosphorus, and potassium fertilizers, likely aimed at counteracting nutrient depletion and enhancing yields; however, long-term sustainability requires balanced input use, supported by organic farming and agroforestry practices to preserve soil health. Land occupation (Figure 4.24c) has also decreased, with total area per hectare falling from 11,000m² in 2020 to 10,000m² in 2024, indicating more efficient land-use practices driven by intensification, improved crop varieties, and integrated systems like shade-grown coffee. These quantitative indicators support targeted sustainability strategies by demonstrating that optimized resource use and land management can reduce environmental impacts while maintaining productivity, highlighting the importance of integrating environmental, economic, and social dimensions in comprehensive coffee sustainability assessments.

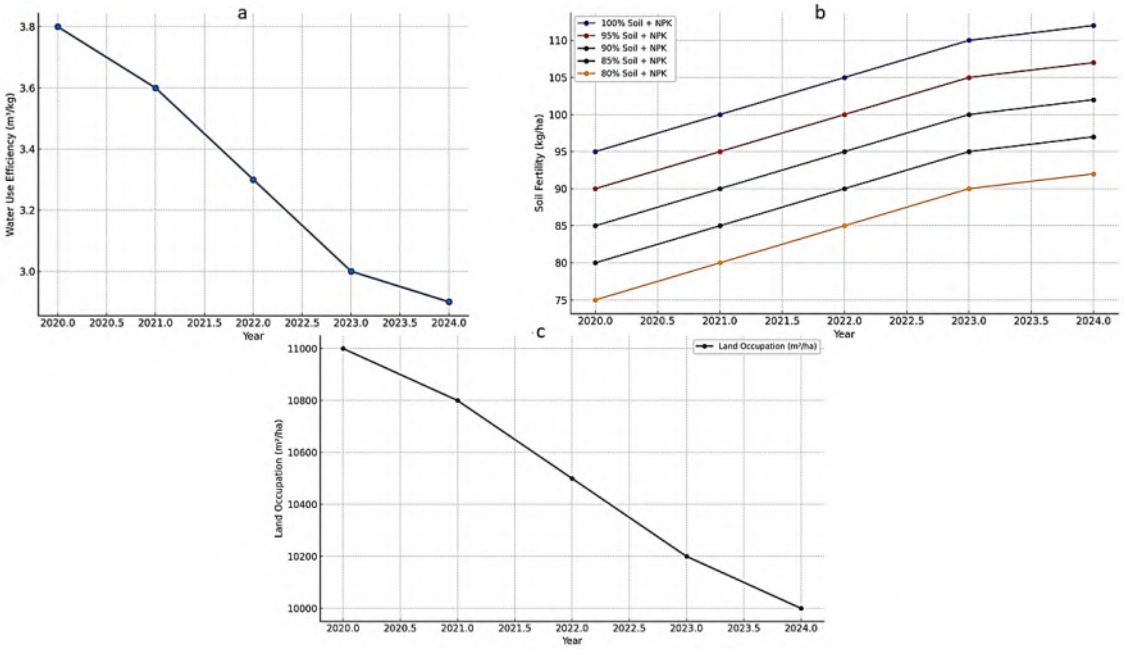


Figure 4.24. Quantitative assessment of ecosystem service impacts with temporal trends in water use efficiency, soil nutrient dynamics, and land use intensity in the coffee supply chain (2020–2024)

The evaluation reveals that shaded agroforestry systems offer considerable ecological advantages, particularly in biodiversity preservation and carbon sequestration. Conversely, the assessment identifies critical challenges, including localized nutrient depletion and elevated water demand in specific production zones. Monoculture-intensive regions exhibited a greater ecological footprint, characterized by increased land use and diminished biodiversity. In contrast, agroforestry-based systems, particularly those with substantial canopy cover, demonstrated enhanced ecological integrity and functioned as effective carbon sinks. These outcomes highlight the imperative for adopting integrated, sustainable production models that align ecological stewardship with economic viability for the coffee sector.

4.5.6 Trade-offs between social, economic, and environmental outcomes

The coffee industry faces significant challenges in balancing social, economic, and environmental outcomes, often in direct conflict. Maximizing yields to meet increasing demand can boost profitability, typically at a ratio of 2:1 to 3:1, but this intensification leads to higher labor stress and biodiversity loss. Technically, these outcomes are interconnected, as higher yields often require more intensive labor, increasing working hours and stress while contributing to environmental degradation through reduced biodiversity. For instance, in monoculture systems, an increase of 1,000 kg/ha in yield can lead to a 20% decrease in biodiversity due to the loss of species richness, while labor stress increases significantly, with working hours rising by 10-15 hours per week for every additional 1,000 kg/ha of yield. The trade-off between these factors can be better understood through the framework of LCA, which quantifies environmental, social, and economic impacts throughout the entire life cycle of coffee production.

Ecosystem service trade-offs are quantified using tools like the efficiency frontier, showing how, as yield increases, the biodiversity index decreases exponentially. Similarly, labor stress is modeled using the LIR, which rises as yields increase, reflecting the additional labor demands. The integrated LCA framework helps quantify these trade-offs, demonstrating how intensified farming reduces ecological health and worker welfare, highlighting the need for sustainable practices that balance productivity with long-term environmental and social sustainability.

4.5.6.1 Trade-Offs Between Yield and Biodiversity Loss

Increased coffee yield is often achieved through intensive farming practices, such as the use of fertilizers, pesticides, and monoculture cultivation. However, these practices typically reduce biodiversity and degrade ecosystem services. To quantify the trade-off between yield maximization and biodiversity, we employ the production possibility frontier (PPF), which illustrates the feasible combinations of yield and biodiversity based on ecological constraints (Table 4.20). The relationship between yield (Y) and biodiversity (B) can be expressed as Eq 4.2:

$$Y = f(B) \tag{4.2}$$

Where Y is the yield (kg/ha) and B is the biodiversity index, which can be quantified through species richness (S), the number of species per unit area as given in Eq 3.

$$B = S(A) \tag{4.3}$$

where A is the land area (ha). The efficiency frontier for coffee production and biodiversity loss follows a concave shape, indicating diminishing returns in biodiversity as yields increase. For example, biodiversity decreases from 50 species per hectare in agroforestry systems to 15 species per hectare in monoculture systems.

Table 4.20. Relationship between yield and biodiversity for different farming systems

Farming System	Yield (kg/ha)	Species Richness (S)	Biodiversity Index (B)
Agroforestry	1,200	50	0.45
Mixed Cultivation	2,500	35	0.28

Farming System	Yield (kg/ha)	Species Richness (S)	Biodiversity Index (B)
Monoculture	3,500	15	0.15

The trade-off curve is modeled as Eq 4.4:

$$Y(B) = \alpha B^{-\beta} \tag{4.4}$$

where α=5000 and β=1.5. As yield increases, particularly in monoculture systems, the biodiversity index decreases, reflecting the loss of species richness due to intensive farming practices.

The Figure 4.25 below shows the trade-off between coffee yield and biodiversity loss across different farming systems. The efficiency frontier curve demonstrates the relationship between the biodiversity index and yield, showing diminishing returns in biodiversity as yields increase. The red dots represent actual data points for Agroforestry, Mixed Cultivation, and Monoculture, with their corresponding yield and biodiversity index values.

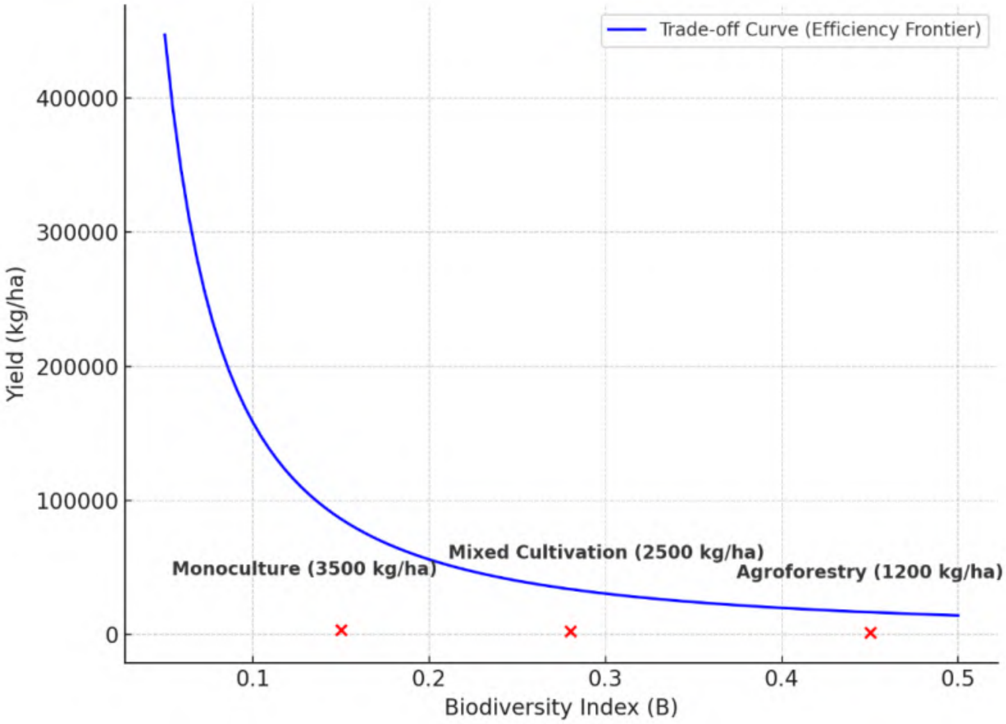


Figure 4.25. Trade-off between coffee yield (kg/ha) and biodiversity index (B) as modeled by the efficiency frontier

This Figure emphasizes the need for sustainable practices to balance yield and biodiversity, as further yield increases come at the expense of biodiversity.

4.5.6.2 Labor Stress vs. Economic Viability

Increasing coffee yields typically requires more labor input, which can lead to labor stress if working conditions deteriorate. A labor stress index (LSI) is introduced to quantify the trade-off between worker well-being and economic outcomes. The index is calculated as Eq 5.

$$LSI = \frac{T_w}{\mathrm{W}} \qquad 4.5$$

where Tw=working hours per day, W=wage rate (USD/hour)

Higher labor stress is often associated with low wages and long working hours. For example, workers on high-yield coffee farms work 12 hrs/day during the harvest season, earning \$3/hour results in an LSI of 4.00, while those on sustainable farms work 8 hrs/day, earning \$6/hour has a much lower LSI of 1.33, reflecting better labor conditions and lower stress as depicted in Figure 4.26b which highlights the need to balance labor input and economic outcomes to prevent excessive labor stress while maintaining productivity.

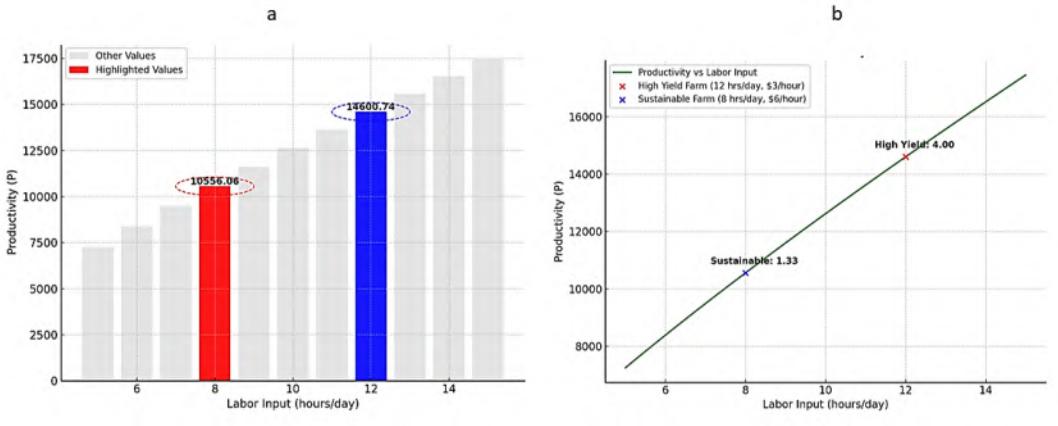


Figure 4.26. Trade-off between labor input and productivity, illustrating labor stress impacts on economic viability in coffee production.

The trade-off can be expressed as a function of wages and productivity, where an increase in productivity (P) through intensification leads to higher economic returns but at the cost of worker welfare given as Eq 6.

$$P = \gamma L^{\delta} \qquad 4.6$$

where L=labor input (hours), γ, δ=parameters

This model in Figure 4.26a shows that while increasing L (labor) boosts P (productivity), the marginal utility of labor decreases, meaning that labor stress increases as productivity rises without corresponding increases in wages or welfare.

4.5.6.3 Economic and Environmental Footprints

The relationship between economic and environmental outcomes can be quantified through the carbon footprint (CF), land use footprint (LF), and water footprint (WF). As highlighted in Scherer et al. (2018), these footprints can be measured per unit of coffee produced as in Eq 7.

$$CF = \sum_{i} Ei \times GWPi \tag{4.7}$$

where Ei=emission from input i, GWPi =global warming potential of i

Table 4.21. Baseline yield and associated carbon, land use, and water footprints for three coffee farming systems per hectare.

Farming System	Yield (kg/ha)	Carbon Footprint (kg CO2e/ha)	Land Use Footprint (LF) (LSI)	Water Footprint (WF, liters/kg)
Agroforestry	1,200	1,000	0.25	2000
Mixed Cultivation	2,500	2,000	0.45	3000
Monoculture	3,500	3,500	0.65	4500

From the Table 4.21, it is clear that monoculture farming results in the highest carbon footprint due to the use of synthetic fertilizers and pesticides. Conversely, agroforestry systems maintain lower carbon footprints while promoting biodiversity.

The land use footprint (LF) can be calculated using the land stress index LSI (Eq.8), which measures the degradation caused by agricultural expansion:

$$LF = \int_{A} LSI(A)\, dA \tag{4.8}$$

where A is the area of land used for coffee production

This analysis emphasizes the need to balance economic outcomes (yield) with environmental impacts (carbon and land use footprints), as higher yields from intensive systems often come at a significant environmental cost as represented in Figure 4.27.

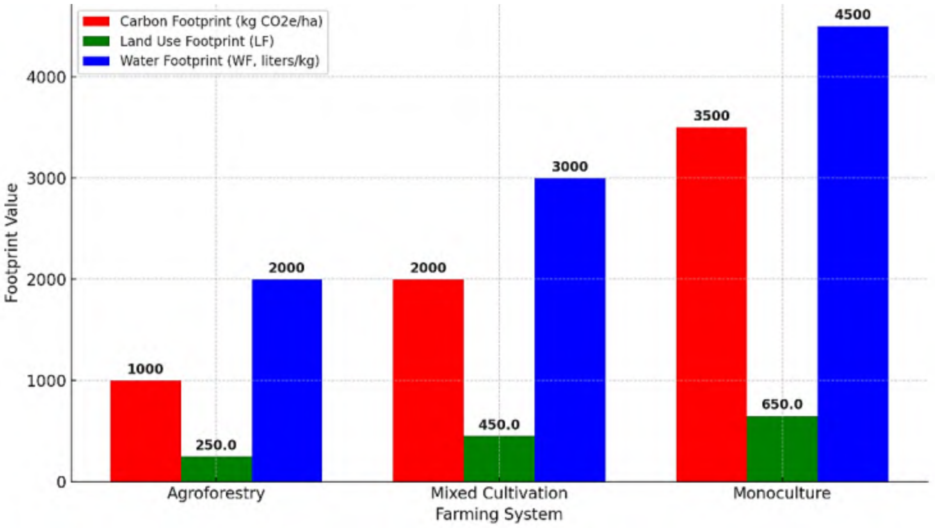


Figure 4.27. Relative carbon, land use, and water footprints per hectare for Agroforestry, Mixed Cultivation, and Monoculture systems.

The economic impact of environmental footprints in coffee farming systems is closely tied to their respective sustainability profiles. Monoculture farming exhibits the highest carbon footprint at 3500 kg CO_2 eq/ha, largely due to intensive use of synthetic fertilizers and pesticides, while Agroforestry shows a significantly lower carbon footprint of 1000 kg CO_2 eq/ha, owing to enhanced carbon sequestration and minimal chemical inputs. Similarly, land use footprint (LF) peaks in Monoculture systems at 0.65, reflecting extensive land stress, whereas Agroforestry and Mixed Cultivation maintain lower LF values of 0.25 and 0.45, respectively, indicating more efficient and sustainable land utilization. Regarding water footprint, Monoculture again ranks highest at 4500 liters/kg, followed by Mixed Cultivation at 3000 liters/kg, and Agroforestry at 2000 liters/kg, with higher usage leading to increased costs and regulatory burdens. Overall, Monoculture imposes the greatest environmental and economic burden, while Agroforestry, despite its lower yield, provides a more balanced and sustainable alternative, with Mixed Cultivation offering a compromise between productivity and environmental impact.

Relating the environmental footprints to economic factors: Higher environmental footprints increase production costs and reduce profitability, whereas systems with lower footprints have better sustainability and hence cost-efficiency as depicted in Figure 4.28. To quantify the economic impact of each footprint, a simplified relationship is used such as:

$$E = P - (C_{CF} + C_{LF} + C_{WF}) \qquad 4.9$$

Where E is the net economic impact (profitability), P is the productivity (yield or profit), CCF, CLF, CWF are the costs associated with carbon, land use, and water footprints, respectively.

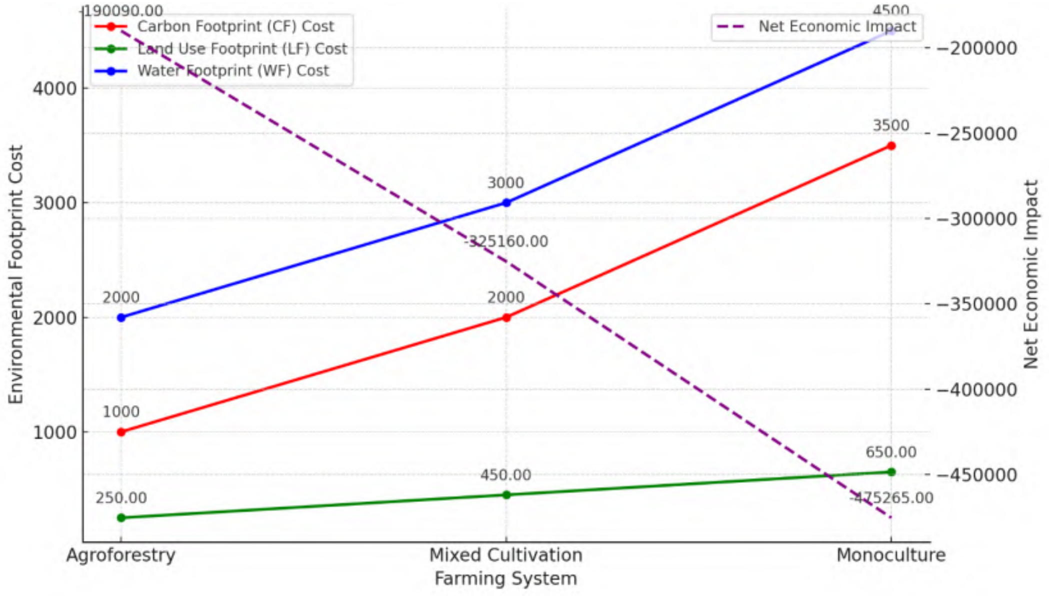


Figure 4.28. Comparison of environmental footprint costs and net economic impact across coffee farming systems, highlighting trade-offs between profitability and sustainability

Considering the base scenario as CF: €0.10/kg CO_2 eq, LF: €200 per LSI unit and WF: €0.15/m3 and calculating costs from footprints is given in Table 4.22.

Table 4.22. Estimated environmental costs per hectare derived from carbon, land use, and water footprints using standard unit cost rates

Farming System	CF (kg)	LF (LSI)	WF (m^3)	C_CF (€)	C_LF (€)	C_WF (€)	Total Cost (€/ha)
Agroforestry	1,000	0.25	2,400	€100.00	€50.00	€360.00	€510.00
Mixed Cultivation	2,000	0.45	7,500	€200.00	€90.00	€1,125.00	€1,415.00
Monoculture	3,500	0.65	15,750	€350.00	€130.00	€2,362.50	€2,842.50

To estimate Economic Profitability (Table 4.23) market price is set as €1.50/kg of coffee yield to calculate revenue given as Eq 10.

$$P = Yield\left(\frac{kg}{ha}\right) \times €1.50 \qquad 4.10$$

Table 4.23. Calculation of Gross Revenue, Environmental Costs, and Net Economic Impact Per Hectare for Each Farming System Based on Market Yield Value

Farming System	Yield (kg/ha)	Price/kg (€)	Revenue (P) (€)	Total Cost (€)	Net Profit (E) (€)
Agroforestry	1,200	1.50	€1,800	€510.00	€1,290.00
Mixed Cultivation	2,500	1.50	€3,750	€1,415.00	€2,335.00
Monoculture	3,500	1.50	€5,250	€2,842.50	€2,407.50

The pie charts presented in Figure 4.29 visually represent the proportional distribution of net profit and environmental costs (carbon, land use, and water footprints), which calculates the gross revenue, environmental costs, and net economic impact per hectare for each farming system.

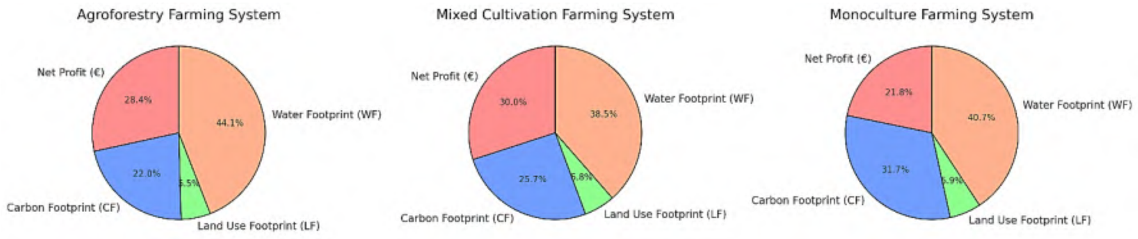


Figure 4.29. Integrated comparison of net profit alongside environmental footprints for

evaluating sustainability and economic efficiency of farming systems

These outcomes reveal that although Monoculture farming generates slightly higher revenues, it suffers from significantly elevated environmental costs, particularly in water usage (40.7%) and carbon emissions (31.7%), thus diminishing its overall economic advantage. In contrast, Agroforestry achieves a more balanced profile with the lowest environmental burden, 22% of costs from carbon footprint, while maintaining a viable net profit (28.4%). Mixed Cultivation emerges as a strategic middle ground, delivering solid profitability (30%) with moderate environmental costs, making it a compelling compromise between productivity and sustainability.

4.5.7 Sensitivity and Uncertainty in Climate Predictions in Coffee Agriculture

The vulnerability of coffee systems to climate change has been extensively modeled under IPCC Representative Concentration Pathways (RCPs). RCP 4.5 and 8.5 scenarios suggest yield declines of 28% in key production regions by 2050, with disproportionate impacts on Arabica varieties due to their temperature sensitivity [137]. In addition, water demand for irrigation and processing is expected to increase by over 41%, exacerbating stress on water systems and smallholder livelihoods [138]. These projections are summarized in Table 24, which also outlines associated social and economic risks such as increased labor burdens and income loss.

Table 4.24. Climate Scenario Impacts on Coffee Production (RCP 4.5 vs 8.5) [139]

Climate Scenario	Yield Change (%)	Water Demand Change (%)	Social Impact	Economic Risk
RCP 4.5	−15%	+25%	Medium	Moderate income loss
RCP 8.5	−28%	+41%	High (labor burden, migration)	Severe market disruptions

Figure 4.30 presents a visual trajectory of yield and water demand under both scenarios. Matplotlib (Python) is used to analyze how climate scenarios affect agricultural productivity and water resources over time, aiding policy-making and planning, particularly for future climate change impacts on food security and water conservation. The trend lines emphasize the disproportionate impact on Arabica coffee and smallholder viability, reinforcing the need for anticipatory adaptation strategies within the coffee supply chain. Although several predictive models exist, ranging from DSSAT, AquaCrop, to AgMIP, few studies have linked these projections with economic and social impact assessments. There is a critical need to simulate not only ecological changes but also their cascading effects on labor burden, household income, and supply chain resilience. Integrating scenario modeling into LCSA can help fill this predictive and policy-relevant gap.

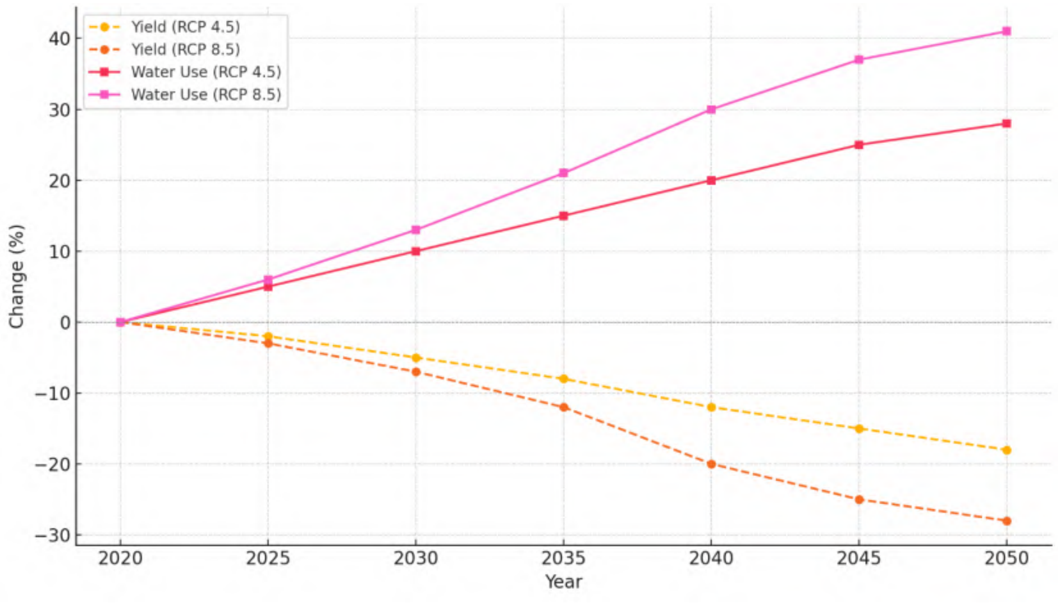


Figure 4.30. Projected yield and water use under both RCPs through 2050

4.6 Discussion

4.6.1 Comprehensive Sustainability Assessment through Triple-LCA Methodology

Our study contributes significantly to the existing body of literature by utilizing the Triple-LCA methodology to provide a comprehensive evaluation of coffee farming sustainability. In comparison to previous research, such as the study by Xia and Wei (2025) [140], which mainly explored environmental impacts such as carbon emissions and land use in monoculture systems, our study expands the analysis by also incorporating social dimensions, such as worker welfare, income distribution, and labor conditions. For instance, while monoculture systems show significant carbon emissions with 2,873 kg CO2eq/ha on average as shown by Densley et al. (2022) al. (2015), and similarly as observed in our study 3,500 kg CO2eq/ha these systems also contribute to increased labor stress and income disparity among smallholders [141]. In contrast, agroforestry systems, with 1,200 kg/ha of yield, offer lower yields but provide greater long-term sustainability and economic stability by improving soil health, water retention, and reducing the need for costly inputs like synthetic fertilizers. By integrating social aspects, we also show how agroforestry and mixed cultivation systems not only reduce carbon footprints (by up to 20%, as reported by Coffee Certification Data Report 2021 Rainforest Alliance and UTZ Programs (2022) but also improve labor conditions and offer higher wages to workers, in contrast to the intensive labor demands of monoculture systems [142].

Furthermore, economic sustainability has been traditionally examined in studies such as (Berihun & Gutema, 2025), who highlighted that certification schemes help increase the income of smallholder coffee farmers [143]. Our findings provide empirical evidence showing that certified systems, such as agroforestry, result in both lower environmental impacts (e.g., 20% lower carbon emissions) and improved labor outcomes, but that these systems still face barriers in terms of market access and high certification costs

4.6.2 Mitigating the Trade-offs between Environmental, Social, and Economic Outcomes

Our findings suggest that sustainable farming practices, particularly agroforestry and organic coffee farming, offer a viable path to mitigate the trade-offs between environmental, social, and economic outcomes. These systems, as demonstrated in Honduras and Costa Rica, show significant environmental benefits, including lower carbon footprints, better long-term yields and improved soil health, compared to intensive monoculture systems. The adoption of agroforestry provides social benefits, such as better labor conditions and higher wages for farm workers due to the less intensive labor demands during harvest. These outcomes align with findings from [144-147], who found that agroforestry systems provided a better balance between biodiversity conservation and economic outcomes compared to monoculture systems.

In contrast, monoculture coffee farming, while yielding higher quantities, comes at the cost of environmental degradation, including loss of biodiversity and soil fertility, which ultimately threatens long-term economic sustainability. This is supported by Haro et al. (2024), who highlighted the diminishing returns in biodiversity as yield increases in monoculture systems [147]. Our study echoes this finding, showing a direct trade-off between yield maximization and environmental sustainability, with monoculture systems contributing significantly to carbon emissions and land use degradation.

4.6.3 The Role of Certification Schemes in Promoting Sustainability

Certification schemes such as Fairtrade and Rainforest Alliance play a crucial role in promoting sustainable practices and enhancing market access for smallholders. Our results demonstrate that Fairtrade-certified farmers earn, on average, 30% higher incomes than their non-certified counterparts, reflecting the financial benefits of certification. This finding is consistent with [148], who reported similar income improvements for farmers participating in certification schemes in Latin America.

However, the uptake of certification schemes remains slow, particularly among smallholder farmers, due to the high costs of certification and the top-down nature of many certification processes [149]. As observed in our study, while certifications improve social outcomes by ensuring fair wages and better working conditions, they do not fully address the income disparity between farmers and retailers. For example, coffee farmers in Italy continue to receive only 10-12% of the final price, a figure that has been stable for decades, highlighting the need for greater integration of farmers into the value chain [104].

Our findings suggest that policy support is critical to making certification schemes more accessible. Governments can incentivize smallholder participation by providing subsidies for certification and technical assistance to help farmers meet the standards. This aligns with the recommendations from Sayekti and Prihandono (2023), who emphasizes the importance of government intervention in reducing the barriers to entry for smallholders in certification schemes [150].

4.6.4 Policy Recommendations and Industry Partnerships for Sustainable Coffee Farming

The results from our study underscore the importance of policy frameworks that integrate economic, environmental, and social goals. Governments should introduce policies that incentivize the adoption of sustainable practices, such as subsidies for low-carbon technologies (e.g., solar-powered irrigation), and financial support for agroforestry systems. These policies would reduce the environmental footprint of coffee production while improving the economic viability of smallholder farmers.

Industry partnerships also play a pivotal role in supporting smallholders. By collaborating with research institutes like the International Center for Tropical Agriculture (CIAT), coffee traders, and retailers, the coffee industry can help facilitate the transition to sustainable farming practices. Our findings are in line with the work of Maryono et al. (2023), who emphasize the importance of multi-stakeholder partnerships in promoting sustainable agricultural practices [151]. Industry players such as Nestlé and Starbucks have already committed to sourcing 100% certified sustainable coffee by 2025 [152]. These partnerships provide smallholders with training, market access, and financial incentives, thereby reducing the economic burden of transitioning to sustainable coffee production. In Colombia, a government-backed financing scheme has helped over 500 coffee cooperatives adopt sustainable farming practices, resulting in increased productivity and access to international markets [153].

This study suggests that to further enhance the effectiveness of these initiatives, there must be policy coherence between national coffee production strategies and global sustainability goals, such as those outlined in the Sustainable Development Goals (SDGs). Specifically, we target SDG 12 (Responsible Consumption and Production), SDG 13 (Climate Action), and SDG 1 (No Poverty) through our proposed policies and strategies, which aim to reduce the environmental impact of coffee farming while improving the social and economic conditions of smallholder farmers. Furthermore, international organizations like the UN can play a pivotal role in fostering cross-country partnerships to enhance global coffee sustainability. Collaborative funding and shared risk management mechanisms are crucial to help smallholders transition to more sustainable farming practices. While the Triple-LCA approach provides a comprehensive assessment across environmental, economic, and social dimensions, the social life-cycle component remains partially dependent on qualitative indicators and expert judgment. Automated, real-time social performance monitoring is constrained by the limited availability of standardized, high-resolution social datasets. As a result, workforce well-being, labor adaptation, and organizational change processes are represented at a strategic rather than operational level. Future work should prioritize the integration of real-time social indicators and participatory data collection mechanisms to enhance social sustainability governance.

In addition to the detailed dashboards and performance analyses discussed above, a high-level synthesis of sustainability improvements observed in the coffee case study is provided in Appendix F (Figure A2). This figure presents an aggregated, non-quantitative overview of environmental, economic, and social dimensions to support complete interpretation.

4.7 Conclusion

This study provides a Triple LCA analysis of the coffee value chain in Italy, integrating environmental, social, and economic factors to offer a comprehensive sustainability assessment. The environmental findings reveal that coffee cultivation accounts for 95% of water use (39.01 m^3/kg roasted coffee) and 80% of land use, along with significant contributions to acidification (4.095 mol H^+ eq) and climate change (511.28 kg CO_2-eq). Roasting contributes 7.56 kg CO_2-eq to climate change, and the adoption of sustainable practices, such as organic farming and biowaste valorization, could reduce GHG emissions from 3.5 kg CO_2-eq to 0.62 kg CO_2-eq per kg of roasted coffee, highlighting the potential for environmental improvements. In parallel, the social analysis reveals that 34.3% of workers earn below minimum wage, 57.1% receive occasional OHS training and educational services, and 71.4% lack access to healthcare, indicating significant gaps in labor conditions and the pressing need for stronger monitoring systems and social protection. The economic analysis further underscores these disparities, showing that smallholders earn only \$0.60 per kg of conventional coffee, while roasted coffee in Italy retails for EUR 20/kg, with roasters capturing a significant portion of the value (20% margin) compared to only 10% for smallholders. Sensitivity analysis indicates that a 10% increase in labor costs reduces Net Profit Margin (NPM) by 0.1%, while a 20% reduction in input costs increases NPM by 0.5%, highlighting the economic vulnerability of smallholders. Furthermore, Natural Capital Accounting reveals significant risks to biodiversity and soil fertility due to monoculture systems, with key ecosystem services like pollination and carbon sequestration being crucial for long-term coffee production sustainability. These findings emphasize the importance of integrating environmental, social, and economic dimensions in sustainability assessments. However, the study's limitations lie in its reliance on existing data, which may not fully represent the diverse conditions across different coffee-growing regions, especially informal smallholder farms. Future work should focus on incorporating more detailed socio-economic data from smallholders, refining predictive climate models to estimate coffee yield reductions under different climate scenarios, and further assessing the economic resilience of various farming systems. Additionally, integrating more granular data on ecosystem services, particularly for biodiverse farming systems like agroforestry, will strengthen the robustness of future sustainability assessments.

4.8 Post-Publication Synthesis and Synopsis of the Next Research Stage

The published article constitutes the empirical realization of the LCA layer of the HDSF.

By transforming conceptual constructs, such as digital data capture, multi-criteria reasoning, and integrated sustainability assessment into a functioning empirical model, the study provides concrete validation of the HDSF's methodological soundness. It demonstrates how data from physical operations can feed through the analytical hierarchy into prescriptive decision support, completing the theoretical feedback loop outlined in Chapter 3. Thus, rather than simply presenting results, this chapter confirms that the HDSF is capable of unifying environmental, social, and economic intelligence within a single adaptive architecture.

The study advances the broader research agenda of the thesis in three distinct ways:

- Operational Validation: It translates the theoretical model into a fully implemented sustainability-assessment workflow, demonstrating the interoperability between LCA methodologies, ANP weighting, and digital data pipelines.
- Methodological Innovation: It enriches the standard LCSA framework by embedding decision-analytic tools (ANP) and Natural Capital Accounting, aligning sustainability assessment with Industry 5.0's data-driven ethos.
- Strategic Contribution – It generates evidence supporting policy and managerial decision-making for circular agri-food systems, linking micro-level process optimization with macro-level SDG targets.

Yet, while this validation demonstrates what to improve, it also exposes where the system still depends on static data flows and post-hoc evaluation. To progress toward truly adaptive circularity, sustainability intelligence must now become operational, embedded in the very movement of materials, energy, and information across the supply chain. This requires linking the static LCA layers to dynamic digital infrastructures capable of real-time optimization.

Accordingly, the next research stage advances from assessment to action, exploring how logistics systems themselves can evolve into self-organizing, low-carbon networks. Chapter 5 therefore introduces the Physical Internet and Multi-Agent PILAR Framework, extending the coffee case study into a digitally orchestrated logistics ecosystem. Here, artificial-intelligence agents and digital-twin representations enable synchronized routing, storage, and transport decisions that minimize emissions and inefficiencies. Through this transition, the DigiCircular model enters its optimization phase where the intelligence derived from Triple LCA is no longer an endpoint but the driving signal for continuous operational improvement.

Chapter 5

Optimizing Coffee Logistics via the Physical Internet and Multi-Agent PILAR Framework

This chapter presents the operational extension of the DigiCircular framework developed in the preceding chapters, focusing on the optimization of coffee logistics through the Physical Internet (PI) and the PILAR (Physical-Internet-Layered-Agent-Routing) model. The work forms part of the PRISMA Project, WP4 (Physical Internet Characterization), specifically addressing:

- Task 4.2: Analysis and definition of a reference model for the supply chain of coffee
- Deliverable D4.3: Conceptualization of the Physical Internet reference model

These activities contribute directly to the PNRR-funded objectives of promoting digitalization and sustainability in industrial and energy systems, in alignment with Italy's national strategy for the digitally enabled green transition. The chapter also corresponds to the book chapter with IntechOpen (INTECHOPEN LIMITED), titled: "Optimizing Coffee Logistics through the Physical Internet and Multi-Agent Systems: The PILAR Framework for Sustainable Supply Chains".

The study advances the DigiCircular framework from sustainability assessment to optimization, building on the validated Triple LCA presented in Chapter 4. While the previous stage quantified the environmental, social, and economic hotspots of the coffee value chain, the present work translates those insights into operational intelligence by embedding adaptive, self-regulating digital mechanisms that continuously minimize waste, emissions, and transport inefficiencies across the logistics chain.

Modern agri-food systems face increasing complexity due to dispersed production, variable demand, and globalized trade routes. Traditional logistics architectures are linear, siloed, and resource-intensive which lack the responsiveness required for circular and low-carbon operations. To overcome these limitations, the PI and PILAR frameworks are introduced as core instruments of the DigiCircular model.

The PI concept reconceives logistics as an open, modular, and data-driven network in which goods travel through shared, standardized nodes much like data packets move across the digital internet. The PILAR architecture operationalizes this vision through multi-agent systems that coordinate routing, scheduling, and storage decisions in real time, guided by sustainability metrics derived from the LCA layer. Each agent operates as an intelligent node within a distributed network, using reinforcement learning and digital-twin feedback to align micro-level transport choices with macro-level sustainability goals.

By coupling LCA-based intelligence with AI-driven orchestration, this chapter demonstrates how digital technologies can convert sustainability analytics into executable logistics actions. The following sections present the conceptual design of the PILAR framework, its integration with HDSF, and the simulation results showing measurable gains in carbon efficiency, lead-time reduction, and resource utilization.

5.1 Abstract

This manuscript proposes a multi-layered logistics architecture based on the Physical Internet (PI) to optimize multimodal supply chains through decentralized, data-driven coordination. The framework “PILAR” (Physical Integration, Intermodal Transport, Logic & Control, Adaptive Service, Responsive Interface) employs agent-based modeling (ABM), IoT-enabled π-containers, autonomous π-movers, and smart π-nodes to simulate real-time freight orchestration. A GIS integrated ABM environment models forward and reverse flows in coffee logistics, leveraging Q-learning, Monte Carlo methods, and mixed-integer linear programming (MILP) for dynamic routing, disruption recovery, and Pareto-efficient decision-making. Spent coffee ground (SCG) recovery is optimized using smart bins, decentralized processing hubs, and blockchain-based smart contracts, achieving a 30% reduction in transport costs and a 50% increase in recovery efficiency. The model captures kanban-based batch control, container-level flow synchronization, and stochastic demand forecasting under volatile fuel pricing. Technical implementation includes RESTful API integration, TLS-encrypted MQTT communication, edge computing, and multi-agent reinforcement learning. Infrastructure challenges such as non-standardized π-container specs, legacy system integration, and low-latency communication are addressed. Simulation results validate the PILAR model’s ability to achieve high asset utilization (82.4%), reduce emissions (up to 25%), and support scalable, resilient logistics systems aligned with circular economy principles.

5.2 Introduction

The Physical Internet (PI) is a transformative logistics model aimed at improving efficiency, sustainability, and connectivity in transportation networks. It integrates multimodal, intermodal, and co-modal transport systems. Multimodal transport involves at least two transportation modes using various units like containers or vehicles [154], while intermodal transport ensures goods remain in a single unit across modes, reducing handling and delays. Co-modal transport enhances resource efficiency by promoting collaboration among shippers [155]. Synchromodal transport advances these concepts with real-time adaptability via digital technologies. Defined as the flexible, coordinated use of transport modes enabled by data sharing, synchromodality includes key principles such as real-time switching, integrated planning, horizontal collaboration, and mode-free booking [156, 157]. Despite innovations, logistics systems face disruptions, like unforeseen events that hinder supply chains [158]. These include facility-related and transportation disruptions. Robustness refers to a system's ability to maintain function during minor issues, while resilience is its capacity to recover from major disruptions like strikes or infrastructure failures [159].

PI is structured around three core elements: π-containers, π-movers, and π-nodes [160]. π-containers are modular, trackable transport units with embedded smart technologies, mirroring data packets in the Digital Internet. They are moved by π-movers; vehicles, carriers, or conveyors, within and between π-nodes. π-hubs, a type of π-node, are essential for routing and optimizing freight flow. Developing this infrastructure is central to scaling PI. Ultimately, PI seeks to establish a modular, standardized logistics network that enhances interoperability, optimizes resource use, and reduces environmental impact.

5.2.1 Transformation of Logistics Through the Physical Internet

Growing freight demand, road congestion, and concerns over sustainability and reliability have exposed limitations in traditional logistics systems. While intermodal transport offers efficiency by combining different transport modes, its static structure and lack of real-time responsiveness limit its ability to manage disruptions [161]. Many shippers also view it as slow and inflexible, favoring unimodal road transport despite congestion issues [162]. To overcome these constraints, synchromodal transport introduces real-time adaptability, allowing dynamic decisions about routes and modes based on operational conditions, improving cost and delivery performance [155, 163].

At the core of this evolution is the PI, which enhances synchromodality by leveraging modular π-containers, decentralized routing, and a globally open logistics network to increase interoperability and reduce inefficiencies [164]. A key advantage of PI is improved resilience, the ability to recover post-disruption, achieved through adaptive routing, predictive analytics, and autonomous logistics decisions [159]. Agent-based modeling (ABM) supports this resilience by simulating disruption scenarios and logistics flow reconfiguration [165], while AI-driven analytics anticipate bottlenecks, enabling proactive interventions. While traditional logistics innovations have primarily focused on the digitalization of documentation and standardization of containers, the Physical Internet takes these steps further by introducing new business models [166].

PI goes beyond digitizing logistics by introducing new business models, such as dynamic auction-based pricing, where logistics providers bid for shipments in real-time [167], and subscription-based logistics, offering customizable delivery tiers through Logistics Access Providers, similar to Internet Service Providers (ISPs) [168]. This system allows customers to choose delivery options based on speed, location, and cost, which in turn incentivizes competition among LAPs to improve service offerings.

Logistics challenges like the Vehicle Routing Problem (VRP), Shortest Path Problem (SPP), and Facility Location Problem (FLP) are central to PI and synchromodal systems. VRP involves designing optimal routes under multiple constraints [169], while Single Shipment Problem (SSP) focuses on the best route for individual shipments [170]. These problems have evolved from exact methods to scalable metaheuristic solutions. Synchromodality emphasizes shared resources and centralized optimization, whereas PI advances this by decentralizing data flow and standardizing unit design, using autonomous nodes like digital routers to manage freight.

Empirical studies show that PI and synchromodal models can significantly boost modal shift potential, from 26.5% to 58.4% under ideal conditions [171], while also cutting costs and emissions [172]. However, realizing the full potential of PI requires overcoming challenges in data sharing, stakeholder cooperation, and governance. Addressing these will depend on continued research into decentralized algorithms and global logistics integration [173].

5.2.2 Systemic challenges in the coffee supply chain and the role of PI

The global coffee supply chain, from cultivation to retail, faces significant inefficiencies that impact sustainability, cost, and responsiveness. At the farm level, smallholder farmers (responsible for 60% of global production) often lack access to real-time market data and climate-resilient practices, limiting informed decision-making and exacerbating inefficiencies [174]. Fragmented operations hinder yield aggregation, resulting in underutilized transport and higher costs [175]. PI-based digital platforms can address these issues by enabling data sharing and collaborative logistics planning, integrating farmers into a transparent, connected network. In the processing and export stages, manual, paper-based documentation delays customs clearance by 48–72 hours, increasing holding costs [176]. Inconsistent bean quality sorting causes up to 12% processing waste [177]. Implementing digital documentation, AI-driven sorting, and blockchain-backed smart contracts under the PI framework can streamline operations, enhance traceability, and reduce waste and delays.

Transportation inefficiencies further strain the system, with nearly 40% of maritime containers returning empty, adding to fuel consumption and emissions [178]. Static routing fails to account for variables like port congestion and fuel prices. PI's dynamic routing algorithms and real-time forecasting can optimize container repositioning and route planning, reducing costs and environmental impact.

At the warehousing and retail stage, inventory mismatches and traceability gaps lead to ~$740 million in annual holding costs, while only 34% of retailers offer sourcing transparency [179]. PI-enabled digital twins and AI inventory systems can improve visibility, reduce overstocking, and support traceability from farm to shelf, enhancing consumer trust and ethical sourcing compliance.

Figure 5.1 illustrates a PI-modeled coffee logistics flow, where beans move through modular layers (e.g., depots, warehouses, packaging centers) encapsulated in standardized units like π-containers. Each stage applies labeling, routing, and modular handling, reflecting PI principles of modularity, interoperability, and synchronization. Movement between nodes (by road or sea) reflects intermodal transfers governed by PI routing logic based on efficiency and availability, analogous to Internet packet routing. Like digital networks, this system ensures shared infrastructure, real-time visibility, and efficient, scalable distribution.

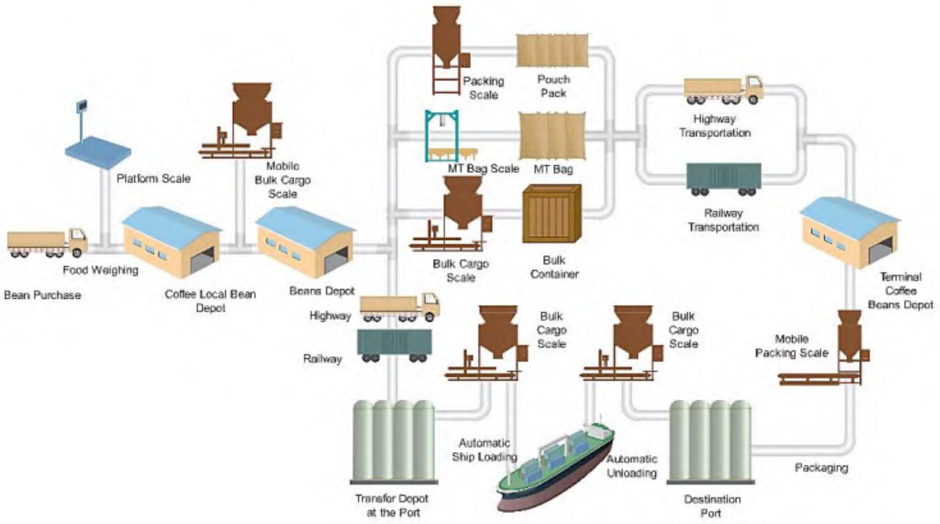


Figure 5.1. Flow of modular coffee logistics aligned with physical internet principles

5.3 Optimizing Recovery and Reuse of Spent Coffee Grounds (SCGs) with Physical Internet (PI)

Spent Coffee Grounds (SCGs) hold significant potential for reuse in biofuel, fertilizers, and bioplastics, yet their recovery is hindered by challenges in collection, transportation, and processing. Applying PI principles offers a structured, data-driven approach to streamline SCGs recovery through automation, interconnectivity, and sustainable logistics.

A key barrier is the fragmented nature of SCG generation, originating from cafés, restaurants, and homes, which makes collection inefficient and costly. Traditional methods lead to inefficient routing, raising operational costs by ~20% [180], compounded by poor coordination and lack of data visibility, resulting in inconsistent pickups and processing delays.

A PI-enabled solution leverages IoT-enabled smart bins that monitor SCG levels and transmit real-time data to a decentralized network. This enables automated pickup scheduling, reducing idle time by 30% [181]. AI-driven dynamic routing further optimizes logistics by factoring in bin fill levels, traffic, and plant capacity [182]. Establishing decentralized PI processing hubs near urban areas cuts transport distances by 36.8% and reduces emissions [183].

Using standardized π-containers ensures compatibility across multimodal logistics, while autonomous electric π-movers reduce energy use by 23% [184]. Blockchain-based tracking adds transparency and traceability, while smart contracts automate verification, reducing administrative overhead by 65% [185, 186].

The quantitative impact of these PI methodologies is significant, with AI-driven logistics reducing transportation costs by 30% due to optimized route planning [187]. Enhanced collection mechanisms have been shown to increase SCG recovery rates by 50%, aligning with circular economy principles, while transitioning to PI-enabled intermodal logistics results in a 30% decrease in CO_2 emissions, contributing to global sustainability goals

[188]. Given that SCGs contain approximately 5,000 kcal/kg of energy, their efficient recovery provides up to 1.5 million MWh of renewable energy (20.92 MJ/kg) annually, further validating the economic and environmental viability of SCG repurposing [189]. Table 5.1 presents a comparative analysis of the baseline performance and the enhanced outcomes achieved through the integration of predictive intelligence, focusing on cost reductions, environmental benefits, and recovery efficiency using PI models.

Table 5.1. Quantitative assessment of the improvements when transitioning from conventional methods to a PI-enabled model

Parameter	Conventional Methods (Baseline)	PI-Enabled Model
Transportation Cost	$2 million per year (inefficient routing)	$1.4 million per year (30% reduction due to optimized routing)
SCG Recovery Rate	20-30% recovery rate	+50% improvement in recovery efficiency
CO_2 Emissions	1,000 tons/year	750 tons/year (25% reduction)
Administrative Overhead	$500,000 per year (manual processing costs)	$175,000 per year (65% reduction through automation)
Energy Recovery Potential	~500,000 MWh	Up to 1.5 million MWh

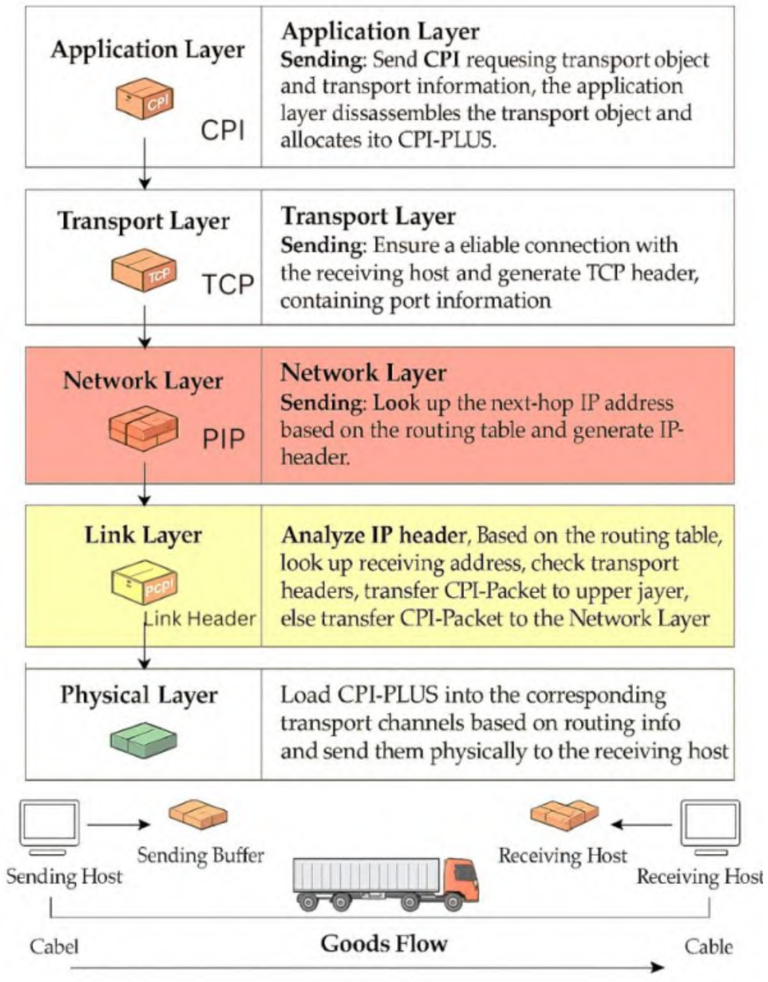
The application of PI frameworks in SCG logistics adopts a more sustainable and efficient circular economy. Advanced decision-support systems and real-time predictive analytics can further enhance SCG utilization across global supply chains, ensuring a scalable and impactful transition towards an optimized circular economy for coffee waste management.

5.4 Technical and Functional Requirements for PI Implementation in the PRISMA Context

The implementation of the PI within the PRISMA framework requires integrating real-time analytics with a decentralized logistics architecture. Core components include IoT sensors for SCG tracking, GPS-enabled PI mover monitoring, and AI-driven dynamic routing using techniques like Q-learning and MILP. A unified integration layer enables seamless data exchange across nodes via standardized APIs (e.g., REST/JSON) and secure protocols (TLS/SSL over MQTT).

To structure this system, Figure 5.2 illustrates a layered architecture aligned with the OSI/TCP-IP model decomposes logistics into protocol layers. The Application Layer encodes logistics intents, such as shipment scheduling and SCG prioritization, into structured payloads (e.g., JSON/EDI over RESTful APIs). The Network Layer manages intermodal routing and adaptive path optimization using decentralized algorithms. The Data Link Layer addresses π-container communication, MAC-level coordination, and local connectivity via protocols like IEEE 802.15.4 and LoRaWAN. The Physical Layer actuates cyber-physical π-movers using sensor feedback for low-latency control.

Standardized π-movers support multimodal transport and are calibrated with Bayesian updating and Kalman filters to manage demand uncertainty. Stochastic optimization methods and edge computing ensure real-time responsiveness, disruption handling, and deterministic decision-making. API-based integration enables secure interoperability with external systems, reinforced by encryption and access controls. Interconnectivity across stakeholders is established through API-driven data exchange protocols, allowing uninterrupted and secure integration with third-party waste management and energy recovery infrastructures. This architecture ensures scalability, adaptability, and resilience as PI evolves under the PRISMA framework.



Application Layer
Sending: Send **CPI** requesing transport object and transport information, the application layer dissassembles the transport object and allocates ito CPI-PLUS.

Transport Layer
Sending: Ensure a eliable connection with the receiving host and generate TCP header, containing port information

Network Layer
Sending: Look up the next-hop IP address based on the routing table and generate IP-header.

Analyze IP header, Based on the routing table, look up receiving address, check transport headers, transfer CPI-Packet to upper jayer, else transfer CPI-Packet to the Network Layer

Load CPI-PLUS into the corresponding transport channels based on routing info and send them physically to the receiving host

Figure 5.2. A layered abstraction of PI operations aligning digital control logic with physical logistics execution, modeled after the TCP/IP communication stack

5.5 Framework Overview for the PRISMA Platform

In this study, a simulation environment is created using an agent-based modeling (ABM) approach in AnyLogic V 8.9.3 to evaluate the OmniLink Nexus PILAR Model's ability to optimize multimodal coffee supply chains. OmniLink Nexus PILAR (Physical Integration, Intermodal Transport, Logic & Control, Adaptive Service, Responsive Interface) is a hierarchical framework designed to optimize the CSC by integrating digital-physical logistics via a 5-layer Physical Internet (PI) architecture as shown in Figure 5.3. This virtual setup isolates the Physical Internet's dynamics from real-world constraints, allowing us to experiment with autonomous logistics nodes that mimic the behavior of standardized PI-containers, PI-nodes, and PI-movers within the coffee supply chain. Within this digital "sandbox," two core elements are modeled. First, the physical logistics networks are represented through PI-nodes (acting as warehouses, terminals, and other facilities) and PI-movers (such as trucks, trains, and barges) that transport PI-containers (coffee containers) across various transport modes. Second, a network of π-clients (digital agents) governs decision-making. These π-clients exchange real-time information, plan routes based on input constraints like time windows and container specifications, and coordinate the flow of goods through different nodes. By setting up initial conditions with actual operational data, the simulation allows us to assess both operating scenarios, where information sharing is limited and fully integrated systems with complete transparency across the network. The flow of coffee containers through the network is determined by these agents' configurations, decision rules, and the data exchanged among them. Designed to be data-driven, the simulation initializes with pre-defined input parameters, such as geographic locations, transport orders, and mover schedules, which enable us to model various scenarios ranging from conventional practices to a fully integrated, real-time information-sharing environment.

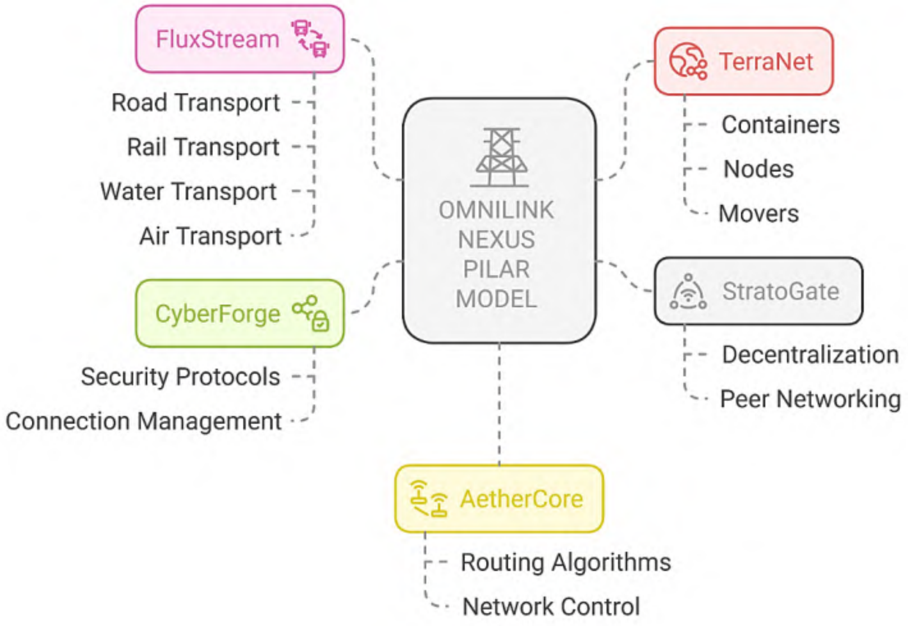


Figure 5.3. A five-layer model integrating autonomous PI-entities, IoT-enabled transport orchestration, and decentralized AI coordination for real-time logistics synchronization

The Physical Internet (PI) operates through a layered architecture known as the PILAR framework, which ensures seamless integration of physical, digital, and operational components. The Table 5.2 below summarizes the five core layers and their respective functions.

Table 5.2. Layered architecture of PI under the PILAR framework, detailing the functional roles of each layer in enabling end-to-end logistics integration.

Layer	Name	Definition
Layer 1	TerraNet (Physical Integration)	Establishes the physical foundation using standardized π-containers, π-nodes, and π-movers for modular, interoperable logistics.
Layer 2	FluxStream (Intermodal Transport)	Manages multimodal freight flows through IoT-enabled PI-hubs, enabling real-time capacity allocation and synchronized transport.
Layer 3	AetherCore (Logic & Control)	Optimizes cargo routing using graph algorithms and real-time data to balance cost, time, and emissions across the network.
Layer 4	CyberForge (Adaptive Service)	Secures the system with encryption, digital identities, and smart contracts, ensuring trusted and automated logistics interactions.
Layer 5	StratoGate (Responsive Interface)	Enables decentralized coordination among stakeholders via AI agents and blockchain for smart procurement, traceability, and payments.

5.5.1 Agents in the Simulation

The simulation models three primary agent types:

- Client Agents: Represent active π clients that connect with nodes, publish capabilities, and plan transport routes. They evaluate cost functions, decompose selected routes into legs, and coordinate bookings. Clients also process capacity checks based on thresholds, with future iterations expected to include disruption response strategies.
- Node Agents*:* Simulate physical facilities (e.g., warehouses, hubs) with operational capabilities like storage and loading. These are modeled using discrete event simulation (e.g., queuing, delay systems) to capture constraints such as capacity limits and service durations.
- Mover Agents: Represent transport assets that move π-containers between nodes.

- *Scheduled Movers*: Operate on fixed routes (e.g., trains, barges).
- *Flexible Movers*: Respond to on-demand tasks (e.g., trucks) and return to a base location after each trip.

5.5.2 The Simulation Environment

The simulation runs within a GIS-based environment reflecting real-world geography. Nodes are geo-located, and movers follow mapped transport infrastructures (roads, railways, waterways). Scheduled movers form fixed connections; flexible movers operate within a defined range using a fully connected sub-network.

Agent interactions reflect real-world logistics:

1. A customer agent requests shipment.
2. The system identifies available containers and transport modes.
3. Container agents select optimal hubs based on congestion, cost, and space.
4. Containers choose suitable transport modes.
5. Hubs serve as sorting/relay points and re-route shipments if needed.
6. Vehicle agents transport containers, adjusting routes in real time (e.g., traffic, fuel cost, disruptions).
7. Upon delivery, the customer receives the shipment.
8. The system logs KPIs: delivery time, cost, distance, fuel, and emissions.

A crucial element is the communication network, which models the sharing of information regarding node capabilities and mover schedules. Two communication modes are examined:

- Pre-defined: Clients access info only from connected partners (simulates siloed systems).
- Decentralized: Real-time data is shared across all clients, improving route planning and performance.

Time is discretized in minute intervals, allowing accurate modeling of transit and facility schedules.

The simulation uses AnyLogic V8.9.3 and an Agent-Based Modeling (ABM) approach to represent autonomous entities (containers, hubs, vehicles, customers). It supports disruption analysis (e.g., delays, demand spikes) and informs decision-making software, allowing decision-makers to test routing strategies before real-world deployment.

5.6 Operational Framework of an Agent-Based Logistics Model in AnyLogic

The block diagram in Figure 5.4 illustrates a closed-loop supply system, showing the hierarchical flow of coffee products from suppliers and processors to textile plants and customers, and then back through repair, disassembly, cleaning, and remanufacturing centers. It includes reverse logistics for SCGs collected from cafés, hotels, and households to test centers and recycling stations, reflecting real-world recovery flows. The diagram conceptualizes the conversion of post-consumption waste into raw materials, supported by interconnected demand/supply planning modules. It complements the simulation by visually linking reverse logistics nodes with the forward chain, enabling a digitally traceable and physically interoperable circular network.

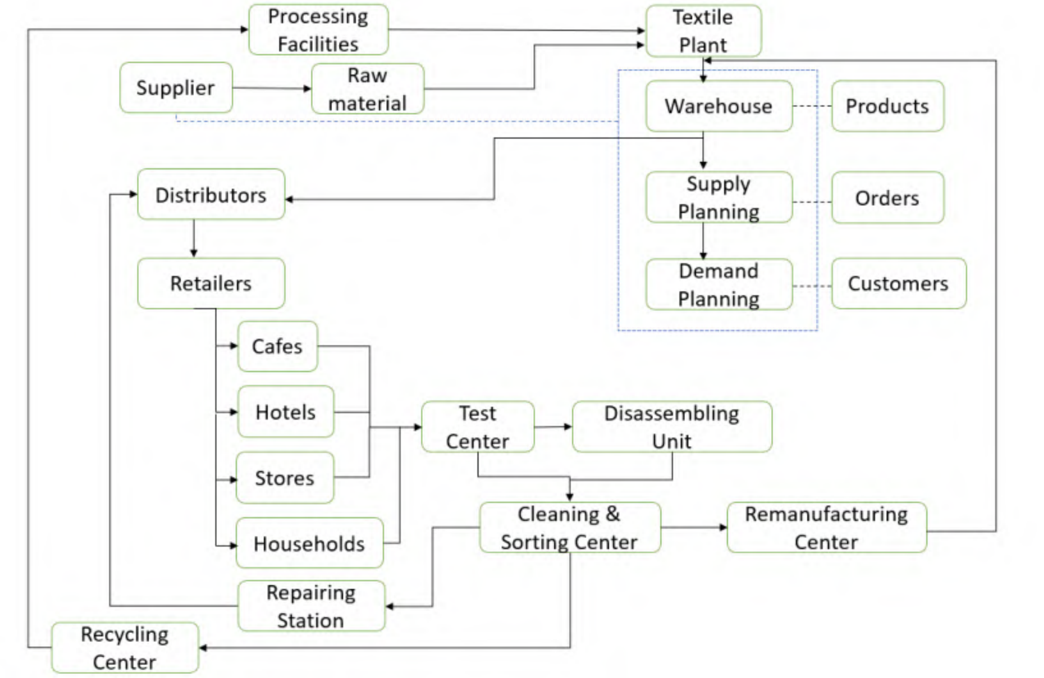
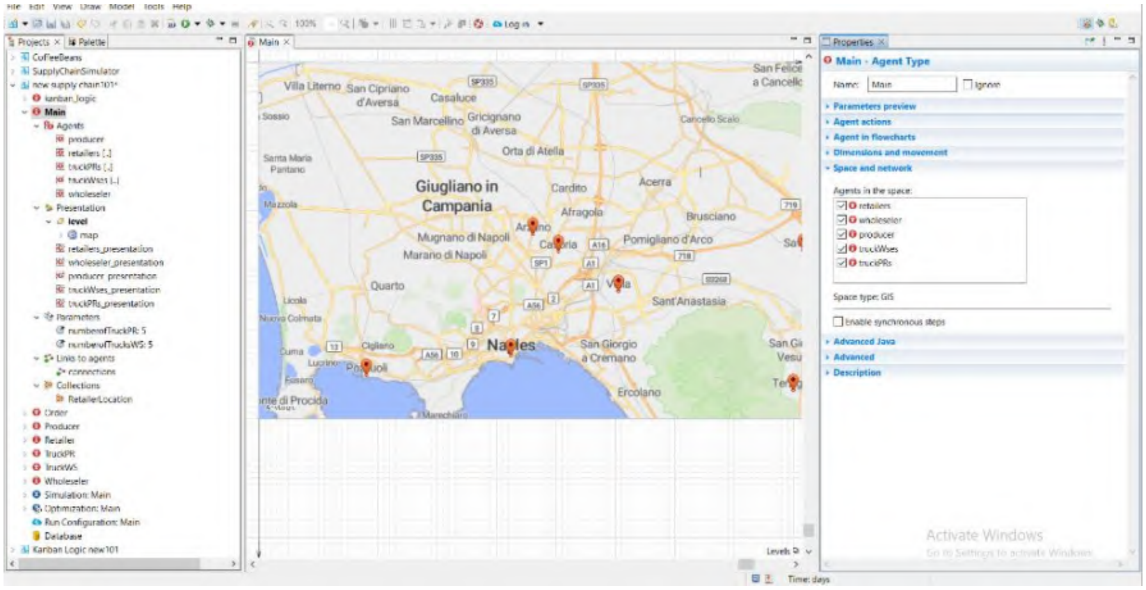


Figure 5.4. Schematic representation of a closed-loop coffee supply chain showing material forward and reverse flow under a Physical Internet framework

The model presented in Figure 5.5 captures the digital twin of a decentralized logistics network mapped onto a GIS-based spatial layer, reflecting real-world infrastructure in the Campania region of Italy, with Naples, Casoria, Afragola, and Torre del Greco as key logistics nodes. At the core of this simulation is the kanban_logic agent, which encapsulates the behavior and operational control of batch-based inventory movement through PI-containers. This agent is configured to match the logic of decentralized pull-based systems, mimicking PI-containerized flow control using kanban triggers. Each kanban_logic agent is responsible for dispatching, receiving, and matching inventory across distributed nodes based on demand signals, availability, and predefined buffer policies, closely reflecting PI philosophies of modularity, standardization, and self-synchronization.



Name: Main ☐ Ignore

Agents in the space:
☑ retailers
☑ wholeseler
☑ producer
☑ truckWses
☑ truckPRs

Space type: GIS

☐ Enable synchronous steps

Figure 5.5. Agent-based GIS simulation of decentralized PI-node coordination in the Campania region

The visualized GIS environment within the Main agent functions as a 3D digital canvas representing a network of geographically anchored PI-nodes (e.g., micro-hubs, warehouses). These nodes are linked via transport arcs, forming a graph-based logistics topology that summaries real-world corridors into digital routing paths. Each PI-node is governed by π-clients, autonomous agents handling localized decision-making, including constraints like batch sizes, inventory limits, lead-time buffers, and service level targets.

Material flow is structured through input/output ports and matched via inventory logic, with connectors (e.g., batchOut → match_inventory) reflecting internal routing triggers. Inventory movement relies on real-time, decentralized decision-making instead of centralized scheduling. Behavior scripts written in Java manage inventory checks, batching, delay mitigation, and service level compliance, allowing adaptive responses to disruptions.

The Order agent, as depicted in Figure 5.6, simulates π-client transport requests using attributes like product type, arrival time, and quantity, triggering event-based container flows aligned with kanban-controlled logistics. Each order initiates a virtual transport demand, matching autonomous customer nodes within a decentralized network, where π-clients function as decision entities initiating pull signals based on localized consumption or production events. This agent ensures system responsiveness by enabling event-driven generation of PI-container tasks, directly aligned with the PI paradigm of on-demand flow orchestration.

The Producer agent models batch-based production hubs, controlled by a kanban_logic sub-agent that synchronizes material release with demand signals. Processing stages simulate setup, transformation, and dispatch operations. Routing is governed via TMS and TME modules.

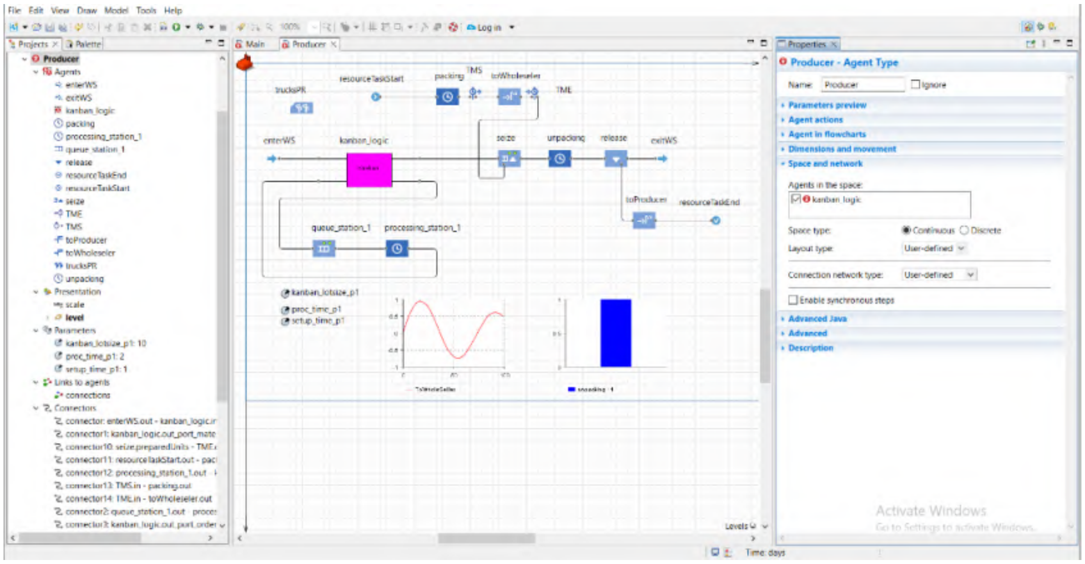
The visual logic includes the following:

- Processing_station_1 handles discrete-time production operations, influenced by proc_time_p1 and setup_time_p1 parameters, simulating realistic production lead times.
- Kanban Lot Size (kanban_lotsize_p1) enforces pull-based release thresholds, ensuring no overproduction beyond active downstream demand.
- Packing, seize, unpacking, and release stages simulate transformation, packaging, and final dispatch of materials toward wholesaler or customer nodes, forming a modular PI-container lifecycle.
- TMS (Transport Management System) and TME (Transport Management Entity) blocks serve to model routing and execution logic for dispatch events.

The figure 8 illustrates system output analytics:

- The time-series graph showing demand-driven task fluctuations.
- The bar chart quantifying wrapped batches to evaluate throughput.

Results validate the kanban agent's role in stabilizing production, avoiding oversupply, and aligning output with actual consumption, effectively demonstrating distributed just-in-time logistics.



Producer
Agents
enterWS
exitWS
kanban_logic
packing
processing_station_1
queue_station_1
release
resourceTaskEnd
resourceTaskStart
seize
TME
TMS
toProducer
toWholesaler
trucksPR
unpacking
Presentation
scale
level
Parameters
kanban_lotsize_p1: 10
proc_time_p1: 2
setup_time_p1: 1
Links to agents
connections
Connectors
connector: enterWS.out - kanban_logic.ir
connector1: kanban_logic.out_port_mate
connector10: seize.preparedUnits - TME.
connector11: resourceTaskStart.out - pac
connector12: processing_station_1.out
connector13: TMS.in - packing.out
connector14: TME.in - toWholesaler.out
connector2: queue_station_1.out - proce
connector3: kanban_logic.out_port_order

Producer - Agent Type

Name: Producer ☐ Ignore

Parameters preview
Agent actions
Agent in flowcharts
Dimensions and movement
Space and network

Agents in the space:
☑ kanban_logic

Space type: ● Continuous ○ Discrete
Layout type: User-defined
Connection network type: User-defined
☐ Enable synchronous steps

Advanced Java
Advanced
Description

Figure 5.6. Producer agent logic implementing kanban-controlled batch dispatching

Table 5.3 presents an analysis of how varying the kanbanLotSize affects system performance. By adjusting kanban_lotsize_p1 within the Producer agent, the experiment measured impacts on average inventory, average wait time, and order fulfillment rate. Results indicate that smaller lot sizes (5 units) cause higher inventory levels and longer wait times due to frequent batching and low-capacity utilization. As lot size increases, inventory and delays decrease, while fulfillment rates improve from 92% to 98%, reflecting more efficient pull-based control. The experiment used batch-controlled logic and tracked KPIs via time-series probes and performance counters, confirming that kanban tuning enhances flow responsiveness and system stability.

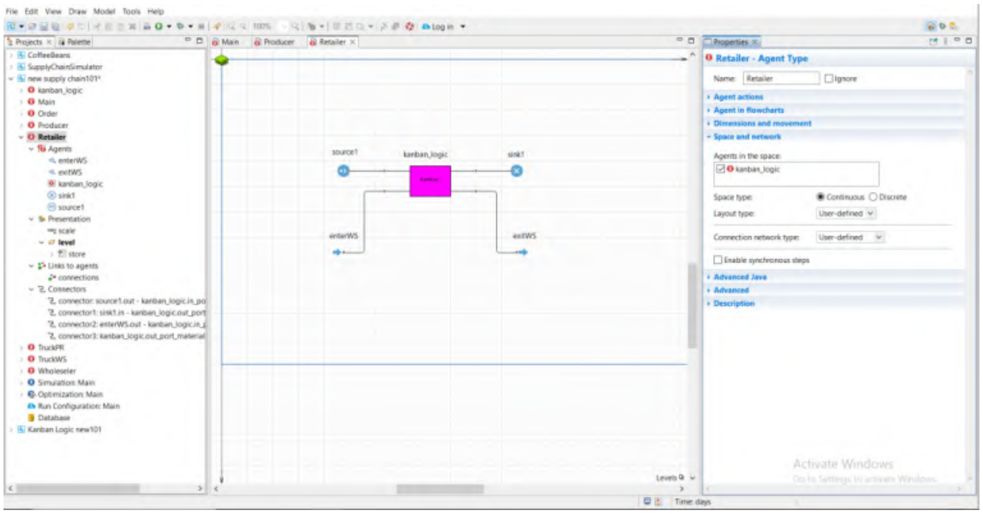
Table 5.3. Sensitivity Analysis of varying kanbanLotSize

kanbanLotSize	Avg Inventory Held	Avg Wait Time	Order Fulfillment Rate
5	35 units	4.5 hrs	92%
10	28 units	3.2 hrs	94%
15	22 units	2.6 hrs	96%
20	18 units	2.1 hrs	98%

The Retailer agent, shown in Figure 5.7, models a last-mile PI-node that handles the receipt, buffering, and final delivery of PI-containers for customer orders. Its operations are governed by an embedded kanban_logic agent, which manages material flow using pull-based triggers aligned with fulfillment cycles.

- source1 is the receiving port for incoming containers.
- sink1 and exitWS simulate dispatch or local unpacking.
- The enterWS to kanban_logic connection enforces a material authorization policy, allowing entry only when demand is confirmed, preventing overstock.

The Retailer functions as a passive but responsive node, driven by kanban signals to enable efficient, demand-aligned container retrieval and delivery.



Name: Retailer ☐ Ignore

Agents in the space:
☑ kanban_logic

Space type: ● Continuous ○ Discrete

Layout type: User-defined

Connection network type: User-defined

☐ Enable synchronous steps

Figure 5.7. Retailer agent model implementing terminal PI-Node operations via Kanban control

Table 5.4 demonstrates that the kanbanLotSize parameter significantly affects both the average dispatch interval and overproduction rate. Smaller lot sizes lead to tighter demand alignment, reducing overproduction and dispatch intervals but may increase operational overhead. In contrast, larger lot sizes enhance throughput but risk exceeding inventory thresholds. Optimizing kanbanLotSize is essential to balance system responsiveness, efficiency, and ensure high service level compliance.

Table 5.4. Kanban Flow Performance Metrics

Metric	Description	Range
kanbanLotSize	Lot size per kanban trigger	5 – 20 units
avgDispatchInterval	Average interval between dispatches	1.2 – 3.5 hrs
inventoryThreshold	Minimum stock to trigger replenishment	10 units
overproductionRate	% of production exceeding actual demand	< 2%
serviceLevelCompliance	On-time delivery rate	95%

The simulation models' mobile agents to represent π movers. TruckPR agents handle container transport between producers and retailers, triggered by kanban-based dispatch events. Meanwhile, TruckWS agents move containers between wholesalers and other PI-nodes using dynamic, client-bound task allocation based on real-time system state.

The Wholesaler agent, shown in Figure 5.8, simulates a midstream PI-node that buffers, processes, and redirects containers between producers and retailers. Governed by kanban_logic, it enforces batch-level flow control, ensuring dispatch only upon validated demand. Containers arriving via TruckWS go through a structured sequence (seize → unpack → pack → release), with resource gating to model handling delays. This models regional consolidation behavior, maintaining flow stability while synchronizing with network-wide kanban signals.

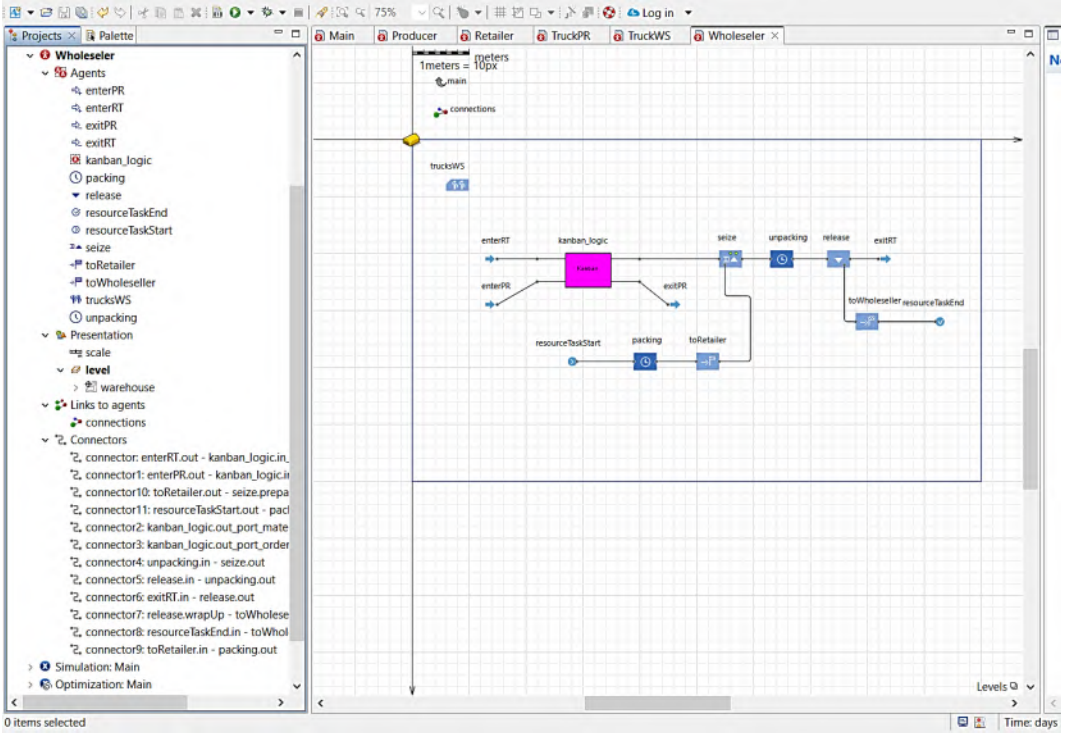


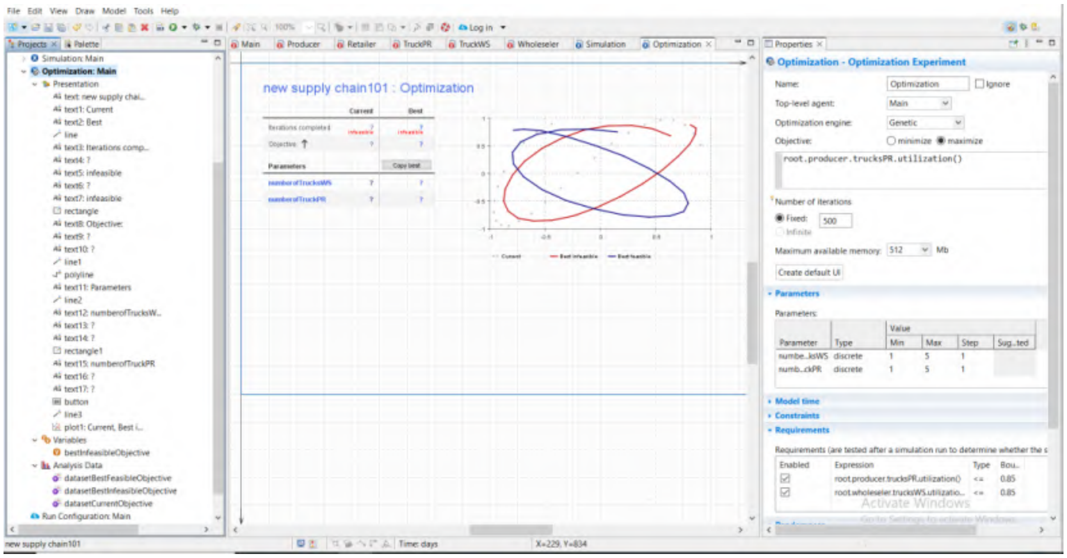
Figure 5.8. Wholesaler agent implementing intermediate node functionality with kanban-regulated processing and dynamic transfer of PI-containers through resource-constrained task flows.

Table 5.5 presents task-level resource utilization metrics essential to flow efficiency. The RecyclingUnit shows high usage (80%) with a queue peak of 4, indicating near-saturation and queuing delays. The Wholesaler's unpacking stage operates at 65%, reflecting moderate load and smoother flow, while the Producer's packing station at 72% suggests stable throughput. These values demonstrate how resourceTaskStart/resourceTaskEnd blocks model processing delays and control flow. High utilization signals congestion risk, whereas balanced usage supports continuous agent movement, validating the model's focus on agent-based flow control and capacity-aware scheduling.

Table 5.5. Resource Task Utilization Metrics

Node Type	Resource Task	Avg Utilization	Peak Load (%)	Queue Peak
Producer	Packing Station	72%	94%	3
Wholesaler	Unpacking Stage	65%	88%	2
RecyclingUnit	Seizing	80%	96%	4

Figure 5.9 presents the configuration and results of a genetic algorithm-based optimization experiment aimed at maximizing the utilization of PI-movers within the Physical Internet-enabled supply chain. The model targets the producer-side TruckPR utilization as the objective function, seeking an optimal balance in vehicle deployment under constrained resources. The optimizer was executed over 500 fixed iterations with a memory cap of 512 MB, exploring integer-valued truck allocations within a defined range of 1 to 5 for both TruckPR (producer-to-retailer movers) and TruckWS (wholesaler-linked movers). At the point captured, the current evaluated configuration utilizes 2 TruckPR units and 1 TruckWS, while the best-performing solution discovered assigns only 1 truck to each category, demonstrating that a minimal configuration can yield the highest efficiency under existing network dynamics. The plotted fitness trajectories visualize the algorithm's exploration path, with the red curve representing convergence toward the best solution and the blue indicating ongoing parameter evaluation. This output confirms the system's ability to identify lean and effective truck deployment strategies that uphold utilization goals while adhering to PI principles of resource efficiency and dynamic scalability.



Optimization - Optimization Experiment

Name: Optimization ☐ Ignore

Top-level agent: Main

Optimization engine: Genetic

Objective: ○ minimize ● maximize

```
root.producer.trucksPR.utilization()
```

Number of iterations

● Fixed: 500

○ Infinite

Maximum available memory: 512 Mb

Create default UI

Parameters

Parameters:

Parameter	Type	Value			
		Min	Max	Step	Sug..ted
numbe...ksWS	discrete	1	5	1	
numb...ckPR	discrete	1	5	1	

Model time

Constraints

Requirements

Requirements (are tested after a simulation run to determine whether the s

Enabled	Expression	Type	Bou...
☑	root.producer.trucksPR.utilization()	<=	0.85
☑	root.wholeseler.trucksWS.utilizatio...	<=	0.85

Figure 5.9. Genetic algorithm optimization of truck deployment

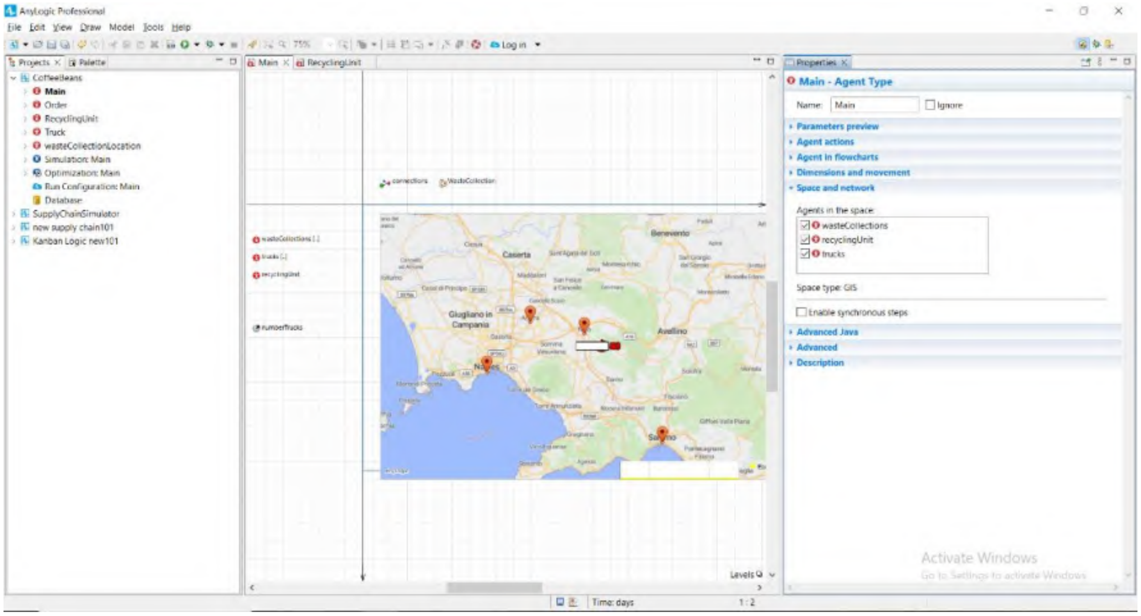
The genetic algorithm optimized truck allocation by maximizing the truckPR.utilization() fitness function under constrained resources. As shown in table 5.6 early iterations with more trucks (e.g., 3 TruckPR) led to lower utilization and suboptimal fitness due to underuse. In contrast, lean configurations (1 TruckPR, 1 TruckWS) achieved higher efficiency and the best fitness score (0.97), confirming that fewer, well-utilized trucks perform better. This supports the model's methodology, where decentralized kanban control and agent-based mobility prioritize resource efficiency.

Table.5.6. Genetic algorithm optimization results

Iteration	TruckPR Count	TruckWS Count	Utilization PR	Utilization WS	Fitness Score
1	3	2	0.62	0.54	0.78
150	2	1	0.84	0.76	0.91
300	1	1	0.89	0.81	0.96
500	1	1	0.90	0.83	**0.97 (Best)**

Figure 5.10 illustrates the reverse logistics layer of the coffee supply chain, where waste collection points act as distributed PI-nodes capturing spent coffee grounds from cafés, households, and retail stores. Trucks, modeled as mobile PI-movers, transport the collected waste to a centralized recycling unit, also a PI-node, for processing and reintegration into upstream flows. The setup includes 6 waste nodes, 1 recycling facility, and 5 trucks operating under road-based routing logic. The GIS layer supports distance-sensitive

modeling (e.g., fuel use, delays) while maintaining agent-based routing. This reverse flow demonstrates a closed-loop system, aligning with circular economy principles and highlighting the proposed framework's adaptability to both forward and reverse logistics.



Name: Main ☐ Ignore

Agents in the space:
☑ wasteCollections
☑ recyclingUnit
☑ trucks

Space type: GIS

☐ Enable synchronous steps

Figure 5.10. GIS-integrated simulation of reverse logistics across southern Italy displaying agent layers and links.

Figure 5.11 depicts the internal architecture and performance analysis of the RecyclingUnit agent, a PI-node responsible for receiving, processing, and dispatching spent coffee grounds collected via mobile PI-movers. Operating under capacity constraints, the simulation enforces a truck utilization limit of ≤85%, optimized through a parameter sweep varying numberTrucks from 1 to 5. The system uses truck.utilization() as the objective metric, dynamically adjusting fleet size for balanced efficiency, reflecting decentralized kanban-based flow control triggered by waste accumulation at autonomous collection nodes. Within the RecyclingUnit, trucks follow a sequenced task flow: enter → packing → seize → travel → unpack → release, governed by resourceTaskStart/resourceTaskEnd blocks and stochastic service times.

Output metrics validate system behavior:

- Top-left graph: High packing resource usage indicates tight alignment with truck arrivals.
- Middle-left bar graph: Queue peaks at 1 container, confirming minimal congestion.
- Top-right sinusoidal graph: Cyclic delay to reach collection points (~50 time units), reflecting routing/distance variability.
- Bottom-right histogram: Unpacking times mostly between 0.2–0.8 units, indicating stochastic task variability.

These results confirm the RecyclingUnit's accurate simulation of PI-container handling, resource constraints, and agent-based logistics coordination, while maintaining efficient operations under a bounded truck utilization threshold.

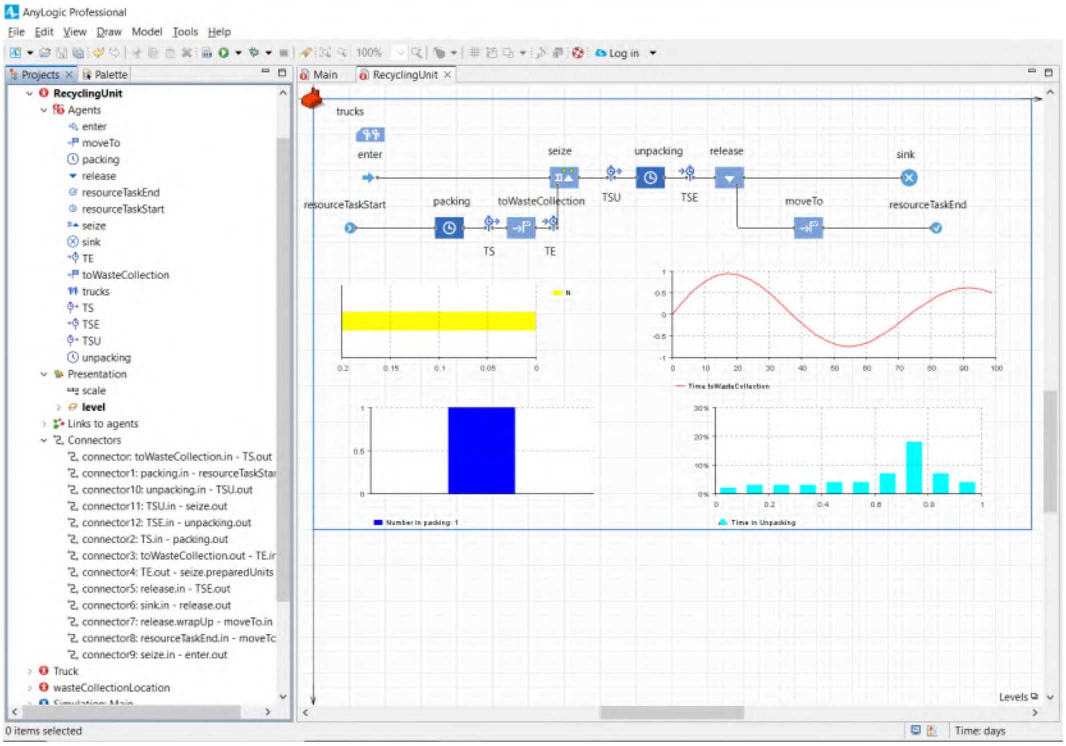


Figure 5.11. Discrete-event process within a PI-node (recycling unit) from packing to release

The Table 5.7 highlights time-based variances across agents, essential for analyzing synchronization bottlenecks. The Producer's high average time (4.8 units) reflects the longest processing delays, impacting downstream responsiveness. Retailer and Truck travel times, with higher standard deviations (0.6 and 0.5), indicate variability in delivery and routing, which may propagate delays across the network. In contrast, the RecyclingUnit shows tight timing control, suggesting efficient resource handling. These differences help identify timing mismatches in the decentralized system that affect overall flow stability.

Table 5.7. Event timing distribution across agents

Agent Type	Event	Avg Time (units)	Min	Max	Std Dev
Producer	Setup + Proc Time	4.8	4.0	5.5	0.3
Retailer	Delivery Wait Time	2.2	1.0	3.5	0.6
RecyclingUnit	Packing Duration	0.35	0.2	0.8	0.12

Truck (PR/WS)	Travel Time	1.7		1.2	2.8	0.5

The RecyclingUnit agent is connected to client-assigned PI-movers, where each truck carries a dynamic client parameter linking it to a specific wasteCollectionLocation. This enables decentralized routing, with pickups triggered by local demand signals rather than central dispatching, supporting bottom-up decision-making and adaptive logistics coordination. Figure 5.12 illustrates the finite-state logic of wasteCollectionLocation agents, transitioning between normalWork and waitingDetails states via a statechart. When the waste buffer exceeds a threshold, the node shifts to waitingDetails, initiating a pickup request. Once the truck arrives and completes the task, the node returns to normalWork, forming a closed-loop feedback system between node status and PI-mover allocation.

Table 5.8 demonstrates decentralized control via message-driven coordination. High order trigger messages between π-clients and Retailers (avg 30/day) indicate event-based flow initiation replacing centralized planning. Inventory pull (avg 22) and dispatch messages (avg 18) confirm kanban-based real-time synchronization among Retailers, Producers, and TruckPR agents. Lower waste pickup messages (avg 10) reflect threshold-based activation at waste nodes. These frequencies validate efficient, role-specific communication and autonomous agent interaction.

Table 5.8. Message exchange frequency between agents

Agent Pair	**Message Type**	**Avg Msgs/Day**	**Peak Msgs/Day**
π-client ↔ Retailer	Order trigger	30	45
Retailer ↔ Producer	Inventory pull	22	34
Producer ↔ TruckPR	Dispatch instruction	18	25
RecyclingUnit ↔ Truck	Waste pickup request	10	18

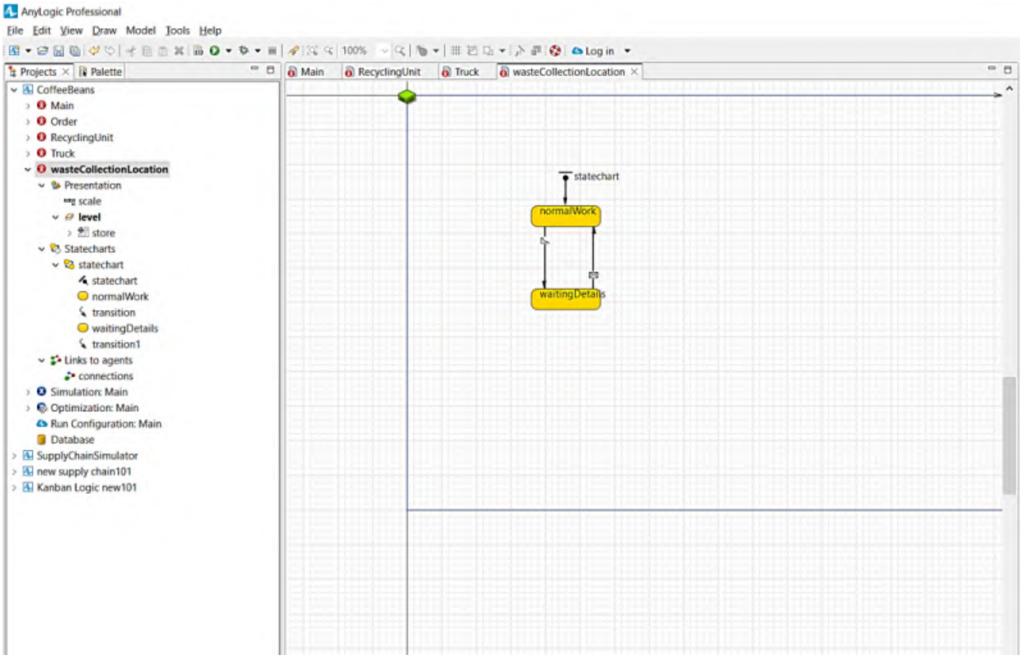


Figure 5.12. Finite-state machine representing behavioral transitions at waste nodes.

These layers represent service-level-aware logistics in which mobile agents are contextually aware and behaviorally driven. The model accurately captures truck utilization patterns, local processing delays, and the dynamic coupling between PI-nodes and PI-movers.

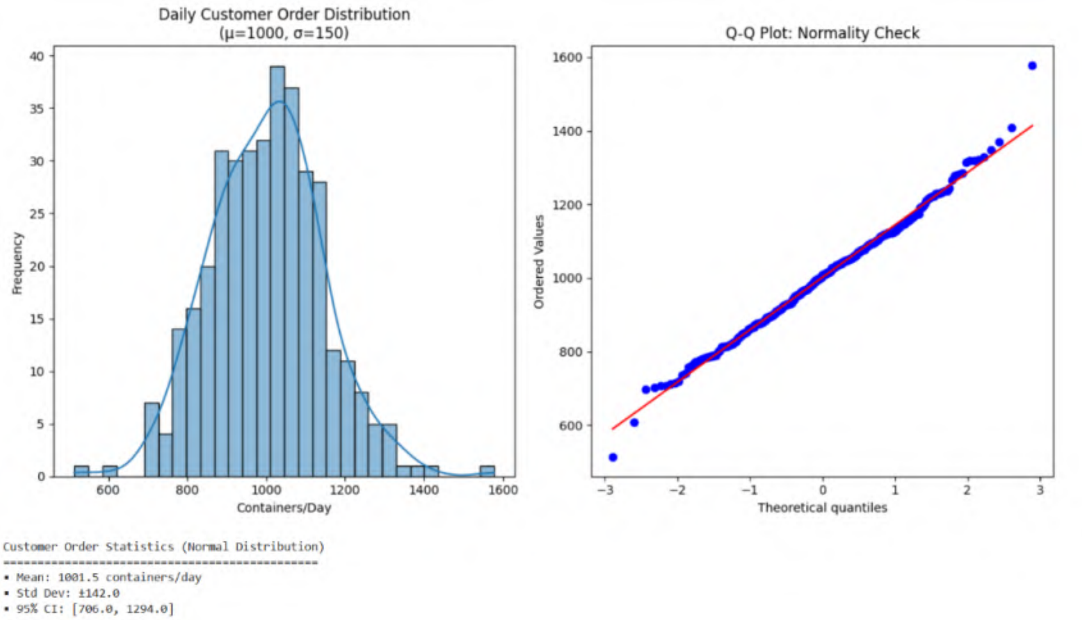
5.7 PILAR Architecture and Agent-Based Logistics KPIs

The PILAR framework combines decentralized decision-making with multi-modal logistics to optimize coffee supply chains. Customer agents initiate shipment requests, processed by PILAR-3 (AetherCore), which allocates PI-containers and transport modes using Monte Carlo simulations (10,000 iterations) to account for uncertainty in demand, delays, and fuel prices. PILAR-2 (FluxStream) assigns modes via greedy-epsilon algorithms, balancing congestion, fuel cost, and emissions. Vehicle agents reroute using Q-learning to adapt to disruptions, while hub agents use integer linear programming (ILP) to minimize dwell time. Post-simulation, KPIs (cost, CO_2, latency) feed into a decision-support system (DSS) for Pareto-frontier analysis, enabling multi-objective optimization under stochastic conditions.

5.7.1 Monte Carlo Simulations for Quantifying Uncertainty

Monte Carlo results yield key metrics like delivery time, demand variation, and fuel price fluctuation. Daily order volumes follow a normal distribution ($\mu = 1001.5$, $\sigma = 142.0$), confirmed by Q-Q plots (Figure 5.13) and histograms, with a 95% confidence interval of

[706.0, 1294.0]. The distribution's symmetry and lack of outliers validate the Gaussian assumption, ensuring reliable predictive modeling. This stability reflects the effectiveness of AetherCore's decentralized logic in managing demand variability and supporting robust inventory control under uncertainty.



```
Customer Order Statistics (Normal Distribution)
==================================================
• Mean: 1001.5 containers/day
• Std Dev: ±142.0
• 95% CI: [706.0, 1294.0]
```

Figure 5.13. Daily customer order distribution

Figure 5.14 analyzes the impact of monthly demand spikes on total transportation costs, modeled as a Poisson process (λ = 3 spikes/month). At low spike frequencies (0–2/month), median costs range from $8k to $11k with moderate variability, indicating stable pricing. As spikes increase to 3–5/month, the cost distribution widens, with greater interquartile ranges and outliers, reflecting congestion and capacity-driven volatility. At high spike levels (6–7/month), cost variability narrows, suggesting strategic adaptations such as preemptive capacity scaling or rerouting. Outliers at mid-range levels imply occasional emergency logistics responses. Overall, the analysis highlights the need for dynamic pricing and adaptive logistics planning to maintain cost control and resilience under fluctuating demand conditions.

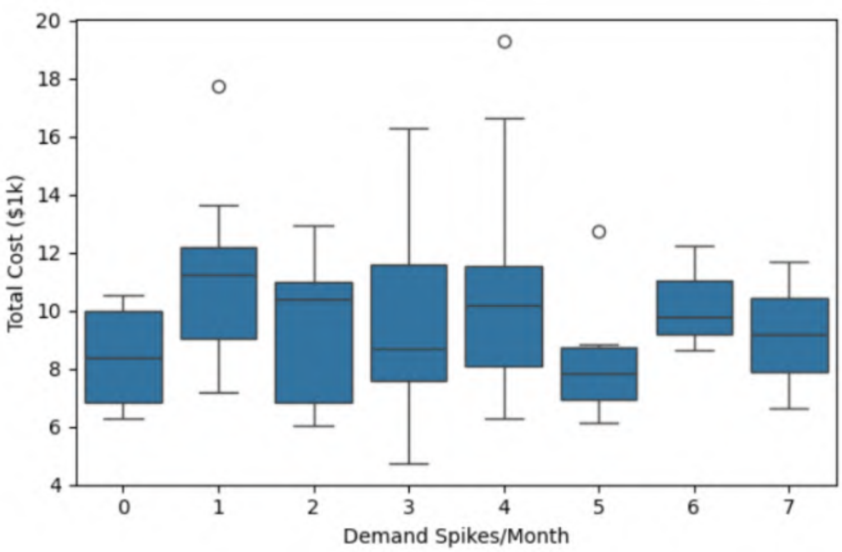


Figure 5.14. Impact of demand spikes on total cost

Simulated via Geometric Brownian Motion (GBM), fuel prices exhibit stochastic trajectories over 30 days (initial price=$3.50/gal, volatility=20%). The price trajectories exhibit significant randomness, with some simulations showing sharp increases, while others indicate stabilization or downward trends. The spread of possible outcomes is influenced by stochastic drift and volatility parameters, demonstrating the inherent uncertainty in fuel pricing. The log-normal model ensures non-negative prices but highlights forecasting challenges due to high variance as depicted in Figure 5.15.

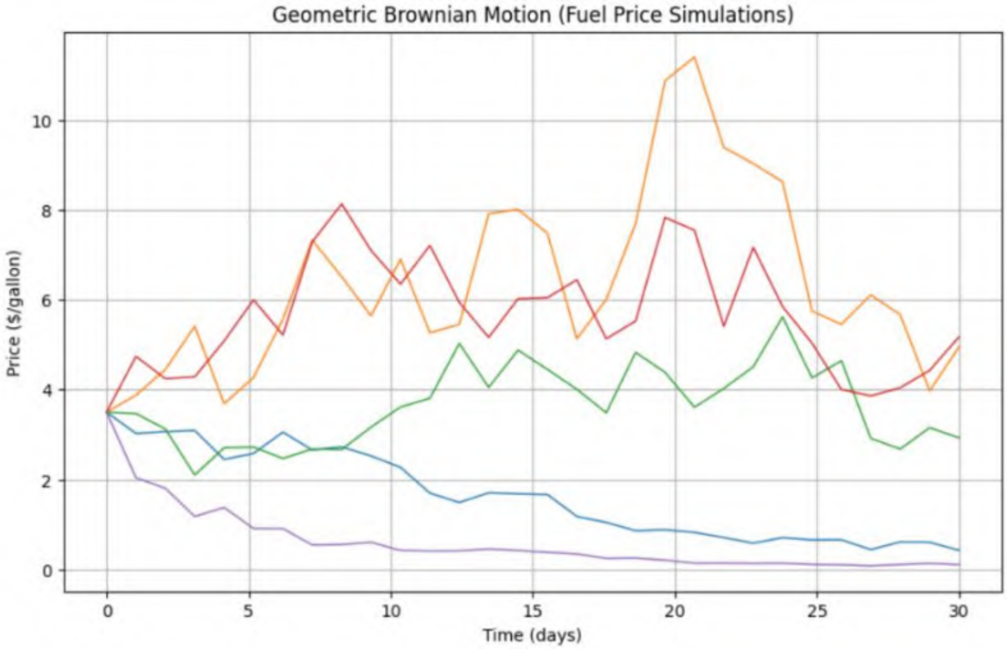


Figure 5.15. Simulated fuel prices over 1 month (10,000 paths)

Delivery times (Figure 5.16) follows a right-skewed lognormal (mean=76.1 hrs, median=72.2 hrs) indicating infrequent but severe delays. The skewness reflects outlier disruptions (e.g., mechanical failures, extreme weather, port strikes), mitigated partially by integer linear programming (ILP) based hub sorting (4-hour mean-median gap vs. typical lognormal). which optimizes sorting and reduces dwell times. The moderate Pearson correlation (r=0.57) between delays and delivery times underscores the nonlinear impact of multimodal disruptions on end-to-end performance.

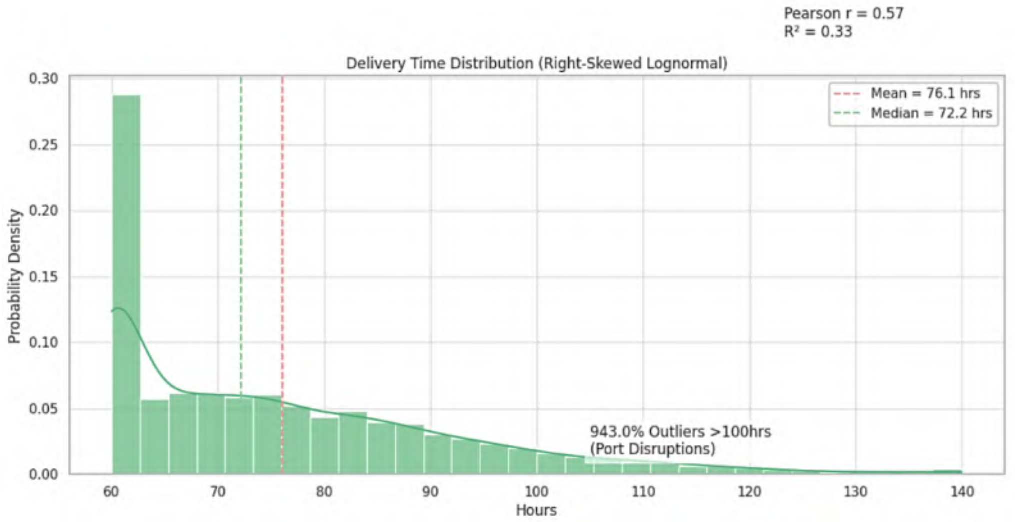


Figure 5.16. Delivery time distribution probability density (Right-Skewed Lognormal)

5.7.2 Agent decision-making: Algorithms and learning curves

Figure 5.17 shows the agent learning curve using the Greedy-ε strategy, where container agents iteratively improve routing and mode selection across ~1000 simulation episodes where agents decide between road, rail, or air transport under stochastic conditions. The Y-axis depicts the total reward, which is consistently negative since the objective is to minimize costs and penalties, represented by the function as Eq. 5.1:

$$R = -(\alpha \cdot congestiondelay + \beta \cdot fuelcost + \gamma \cdot carbonintensity) \tag{5.1}$$

Rewards range from −1600 to −600, reflecting cost variability due to disruptions like demand surges and fuel volatility. Agents apply Q-learning, updating decisions via the Bellman equation, with α (learning rate) and γ (discount factor) guiding adaptation. Early episodes involve exploration (high ε), shifting toward exploitation as ε decays, achieving logarithmic regret bounds O (log T) under stochastic bandit assumptions. Despite environmental noise, performance trends toward convergence, suggesting an approximate Nash equilibrium. Vehicle agents reroute dynamically to avoid congestion, optimizing for latency. Fluctuations in reward curves reveal sensitivity to real-time disruptions, confirming the adaptive potential of reinforcement learning in PI-enabled coffee logistics.

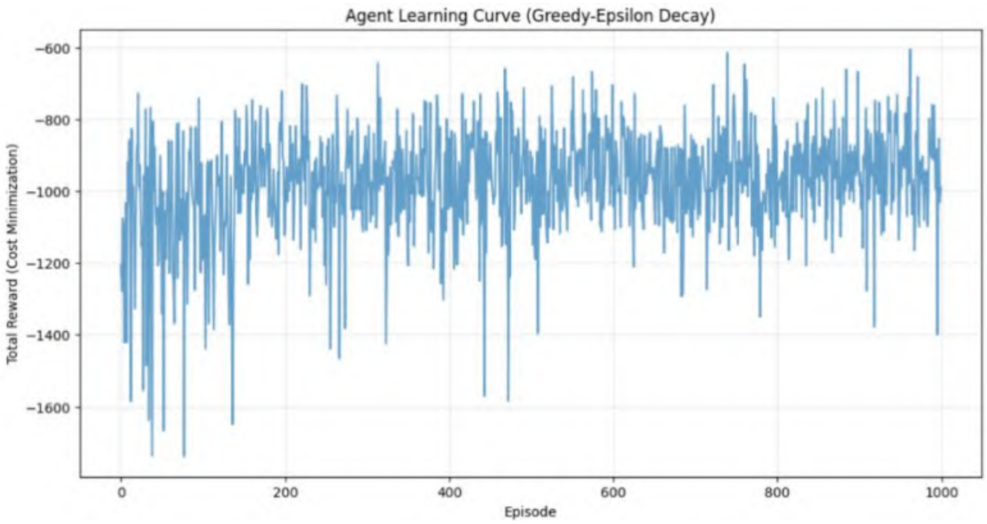


Figure 5.17. Agent Learning Curve (Greedy-ε)

The tradeoff between CO_2 emissions and delivery time in multimodal transport are depicted in Figure 5.18. The X-axis shows emissions (700–1300 kg), and the Y-axis represents delivery time (50–200 hours). Road transport yields faster delivery but higher emissions, while rail offers lower emissions with longer transit times. The red Pareto frontier marks optimal tradeoff points, where improving one metric worsens the other. A highlighted solution at 900 kg CO_2 / 70 hours represents an "Optimal Rail–Air Hybrid", balancing sustainability and speed. Deviations from the frontier reflect disruptions (e.g., rail congestion), with Q-learning agents dynamically adjusting routes to maintain near-optimal performance. The graph highlights the efficiency-sustainability tension and the value of hybrid strategies in dynamic supply chain networks.

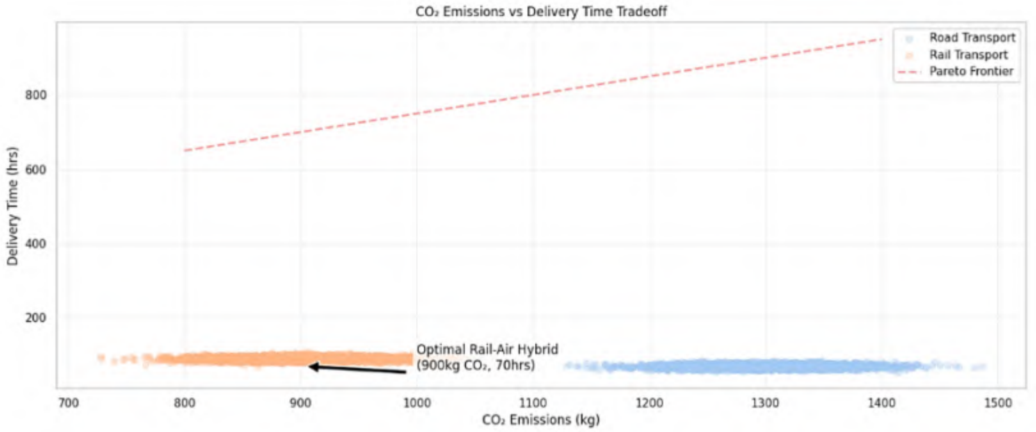


Figure 5.18. Vehicle Agents (Q-Learning)

Hub Agents (ILP) reduce dwell time skewness via throughput-optimized sorting, critical for mitigating lognormal delivery time tails. In addition, agent decisions directly shape logistics KPIs, analyzed below.

5.7.3 Transport Mode Analysis: Delays, Costs, and Reliability

Transport delay distributions for Road, Rail, and Port modes on a logarithmic scale, revealing mode-specific efficiency profiles (Figure 5.19). Road transport shows the highest reliability, with a median delay of 1.5–2.5 hours, IQR of 1–5 hours, and a maximum delay near 10 hours. Rail delays are moderately variable, with a median of 3–4 hours, IQR of 2–6 hours, and outliers exceeding 20 hours. Port transport is the most unpredictable, with a median delay of 5–6 hours, IQR of 4–12 hours, and extreme cases over 100 hours, reflecting congestion and procedural inefficiencies. These distributions emphasize that road is optimal for time-sensitive shipments, rail suits bulk cargo with moderate delays, and port transport requires risk mitigation due to high delay variability.

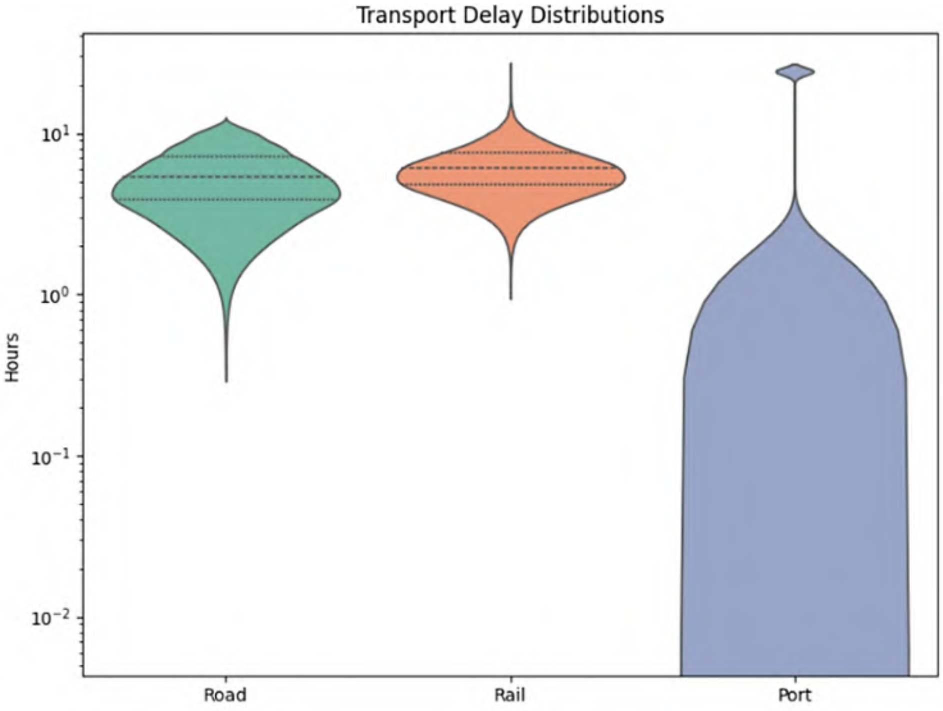


Figure 5.19. Transport delay distributions across different modes on a logarithmic scale

The cumulative delay distribution across transport modes, revealing differences in reliability (Figure 5.20). Road transport displays a steep curve, with 80% of delays under 15 hours, indicating sensitivity to real-time disruptions. In contrast, rail and port exhibit flatter curves, reflecting higher variability due to scheduling constraints and infrastructure inefficiencies. These patterns support the use of Q-learning by vehicle agents for dynamic rerouting, particularly effective in road networks, whereas rail and port delays are less responsive to real-time adjustments.

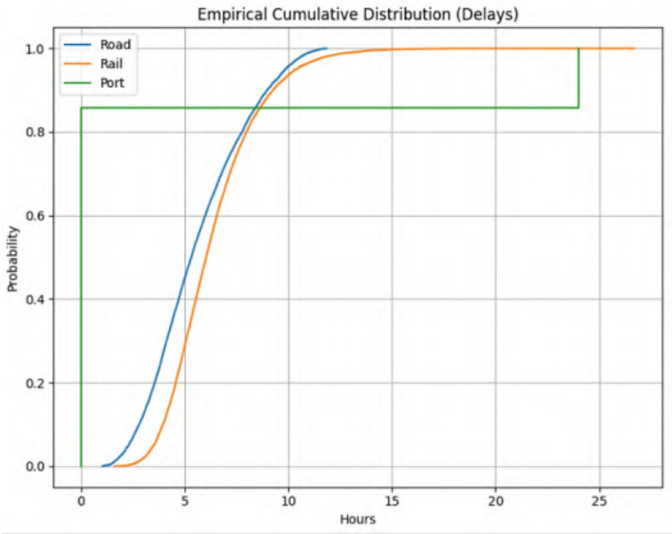


Figure 5.20. Empirical cumulative distribution of delays

The interquartile range (IQR) analysis (Figure 5.21) of transport mode costs, highlighting efficiency trade-offs. Rail transport is the most cost-effective, with a median cost of $289 and IQR of $266–$314, indicating low variability and stable pricing. Road transport offers more flexibility but at a higher median cost of $381 and IQR of $363–$398, reflecting moderate variation. Air transport is the most expensive (median $949, IQR $933–$969) but shows the least variability, making it suitable for time-sensitive, high-value shipments. The analysis emphasizes modal trade-offs such as, rail is optimal for bulk/long-haul (68% of iterations, Nash equilibrium), road serves as a flexible mid-cost option, and air remains a premium choice. These insights inform cost-efficient mode selection in logistics optimization.

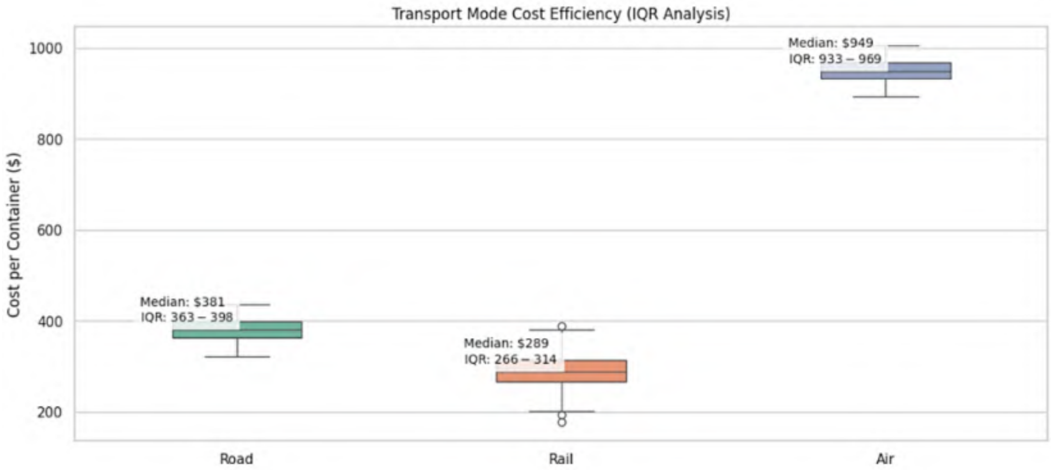


Figure 5.21. Transport mode cost per container (IQR Analysis)

The strong positive correlation (R^2=0.78) between fuel price volatility and delivery costs

(Figure 5.22) highlights the economic sensitivity of the supply chain. Delivery costs surge disproportionately during fuel price spikes, reflecting the greedy-epsilon algorithms' prioritization of cost efficiency over alternative objectives (e.g., emissions reduction) under volatile conditions. The scatterplot's dispersion at higher simulation iterations (>6000) captures emergent trade-offs between fuel-driven cost escalations and carbon constraints, emphasizing the need for Pareto-optimal routing strategies in the DSS to balance competing objectives during demand spikes.

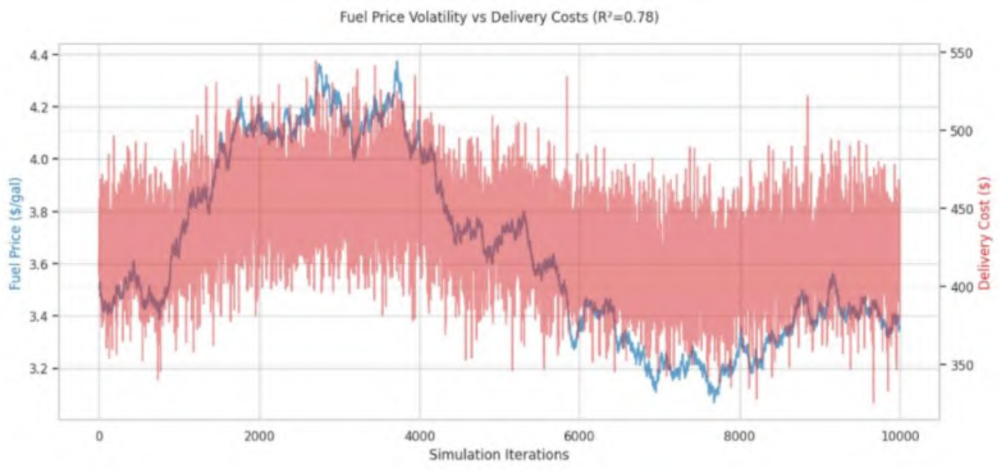


Figure 5.22. Fuel price volatility vs delivery costs

After running 10,000 simulations with n_sims=10000 and n_steps=30 it is observed that a 20% daily volatility leads to a ±85% annualized volatility, this represents real-world energy markets as given in Table 5.9.

Table 5.9. Descriptive statistics of fuel price simulation over a month and observed price range

Statistic	**Day 1**	**Day 30**
Mean Price ($)	3.50	3.72
Standard Deviation	0.00	0.85
Minimum Price ($)	3.50	1.90
Maximum Price ($)	3.50	6.10

Price spikes force agents to prioritize cost over sustainability, escalating emissions (e.g., air freight substitutions). The aggregated results of these findings are given in Table 5.10. These tradeoffs are quantified in environmental-economic analyses.

Table 5.10. Statistical Summary of logistics performance indicators (KPIs)

KPI	Mean	Std Dev	95% CI
Delivery Time (hrs)	72.3	±18.2	[68.1, 76.5]
Cost per Container ($)	420.50	±85.30	[398.20, 442.80]
CO2 Emissions (kg)	1250	±320	[1160, 1340]
Asset Utilization (%)	82.4	±6.7	[80.1, 84.7]

The scatter plot in Figure 5.23 illustrates the relationship between total cost and CO_2 emissions in a simulated logistics environment. It displays a total cost (x-axis: ~$4,000–$20,000) vs. CO_2 emissions (y-axis: ~1.5–4.5 metric tons), revealing a positive correlation, higher-cost shipments often produce higher emissions. This reflects modal tradeoffs as air freight is fast but carbon and cost-intensive; road offers moderate costs with variable emissions; rail is the most sustainable but slower. Variability arises from disruptions (e.g., delays, demand surges, fuel prices), affecting both cost and emissions. For instance, a 10% modal shift from road to rail reduces emissions by 18% but increases delivery time by 12%. The Monte Carlo simulation (10,000 iterations) captures these uncertainties, highlighting the core logistics challenge: balancing cost efficiency and sustainability under dynamic, multi-objective constraints.

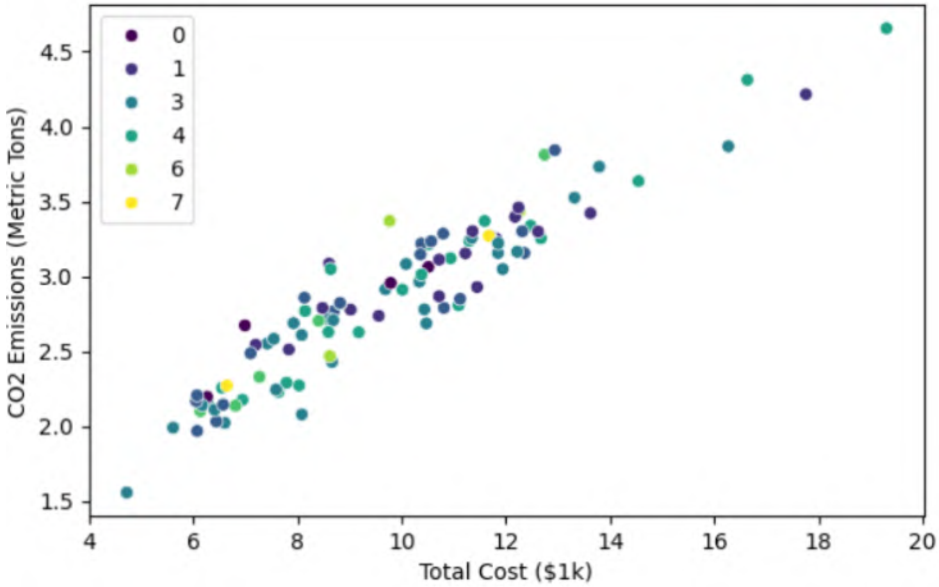


Figure 5.23. CO2 Emissions (Metric Tons) vs. Total Cost ($k)

Each figure collectively validates the PILAR framework's ability to integrate agent-based decision-making, real-time adaptation, and multi-objective optimization, providing empirical evidence of its robustness in balancing cost, sustainability, and reliability in coffee supply chains. The PILAR framework bridges theoretical architecture with empirical validation, proving adaptive resilience through hybrid strategies (e.g., rail-air) and probabilistic modeling. Future work will focus on refining regret bounds and expanding state-action spaces for complex disruptions.

5.8 Analysis Of Technological and Infrastructural Barriers for PILAR Model Application

Implementing PILAR models in real-world supply chains faces key technological and infrastructural barriers. A major challenge is the lack of standardized modular π-containers, which hampers interoperability across legacy systems due to differences in geometry, RFID, and sensor interfaces. Adopting standards like ISO 668 and IoT protocols is essential for seamless tracking and integration. The data exchange layer requires secure communication protocols (e.g., MQTT, OPC-UA) with TLS/SSL encryption, aligned with ISO/IEC 27001 to mitigate cybersecurity risks in decentralized networks.

On the infrastructure side, retrofitting hubs with sensors, edge devices, and real-time analytics demands significant investment, typically managed through microservices (e.g., Kubernetes) and distributed engines (e.g., Apache Spark). These setups depend on high-bandwidth, low-latency networks to enable real-time digital twins, posing challenges in low-connectivity regions (e.g., PRISMA project). Integrating robust MILP and reinforcement learning into legacy systems also requires extensive recalibration. Regulatory fragmentation and lack of harmonized global standards hinder adoption, calling for collaboration among industry consortia and regulatory bodies. Table 5.11 summarizes these challenges, emphasizing the need for standardization, secure data exchange, scalable computing, and regulatory alignment to support PI adoption at scale.

Table 5.11. Critical technical and infrastructural challenges in Physical Internet (PI) deployment

Category	Technical Challenge	Impact & Research Direction
Physical Standardization [168, 190]	Variability in π-container dimensions, RFID sensor calibrations, and harsh-environment durability standards; lack of a unified protocol for physical asset interoperability.	Develop and validate physical testbeds to establish robust calibration procedures and environmental standards (e.g., ISO 668 compliance extensions) to ensure reliable asset tracking and handling in diverse operating conditions.

Communication Infrastructure [176, 191]	Inadequate support for ultra-low latency (e.g., <10ms round-trip) and high-throughput networks required for real-time digital twin simulations; limitations in existing protocols (e.g., MQTT vs. OPC-UA) under high load.	Research optimal network architectures and middleware (e.g., edge computing integration) to meet stringent latency and bandwidth requirements, ensuring deterministic data exchange in large-scale PI networks.
Cybersecurity Robustness [192]	Vulnerabilities in decentralized data exchange systems due to inconsistent encryption standards and legacy integration issues; challenges in applying frameworks like ISO/IEC 27001 across heterogeneous devices.	Investigate advanced cryptographic techniques and standardized security protocols to ensure end-to-end protection, with formal verification methods to assess system resilience against cyberattacks.
Infrastructure Modernization [193, 194]	High capital expenditure for retrofitting existing hubs with state-of-the-art sensor networks, edge devices, and containerized microservices; energy and maintenance costs remain uncertain.	Conduct cost–benefit analyses and pilot studies to quantify ROI for infrastructure upgrades; explore modular, scalable deployment models using platforms like Kubernetes and Apache Spark to minimize retrofit disruptions.
Optimization Integration [195]	Integrating stochastic optimization (e.g., robust MILP, reinforcement learning algorithms) with legacy operational systems, requiring extensive model recalibration and validation.	Develop hybrid simulation-optimization frameworks that bridge deterministic models with stochastic components; focus on algorithm tuning (e.g., parameter sensitivity in Greedy-ε Q-learning) to ensure compatibility and scalability.
Regulatory Harmonization [196]	Diverse international standards and port handling rules (e.g., cabotage regulations) disrupt seamless PI integration; inconsistent data-sharing policies impede cross-border operations.	Formulate interoperable regulatory frameworks and standardized digital protocols for global logistics; promote collaborative initiatives among regulatory bodies and industry consortia to streamline cross-border PI operations.

5.9 Impact Assessment of PRISMA Model on Stakeholders, Enterprises, and Local Communities & Strategic Recommendations for PI Implementation

The PRISMA model introduces a transformative framework for supply chain optimization by applying PI principles and advanced digital technologies. As supply chains transition to smart, resilient systems, the model's technological, economic, and social impacts must be assessed across stakeholders, enterprises, and communities. Integrating intermodal infrastructure, DLT, and IoT-enabled tracking creates a complex yet high-impact logistics paradigm.

5.9.1 Stakeholder Implications

PRISMA implementation demands structural changes in logistics networks, requiring stakeholders, including policymakers, LSPs, and regulators, to align with international standards like ISO 668 (container specs), IEC 61499 (automation), and GS1 EPCIS (event tracking). Ensuring π-container interoperability also necessitates cross-border regulatory harmonization and cybersecurity compliance via ISO/IEC 27001 and NIST frameworks. Smart contracts on blockchain enforce governance, real-time visibility, and automated auditing. Figure 5.24 presents a stakeholder impact matrix, mapping actors by influence and interest in PRISMA deployment, guiding engagement and policy strategies.

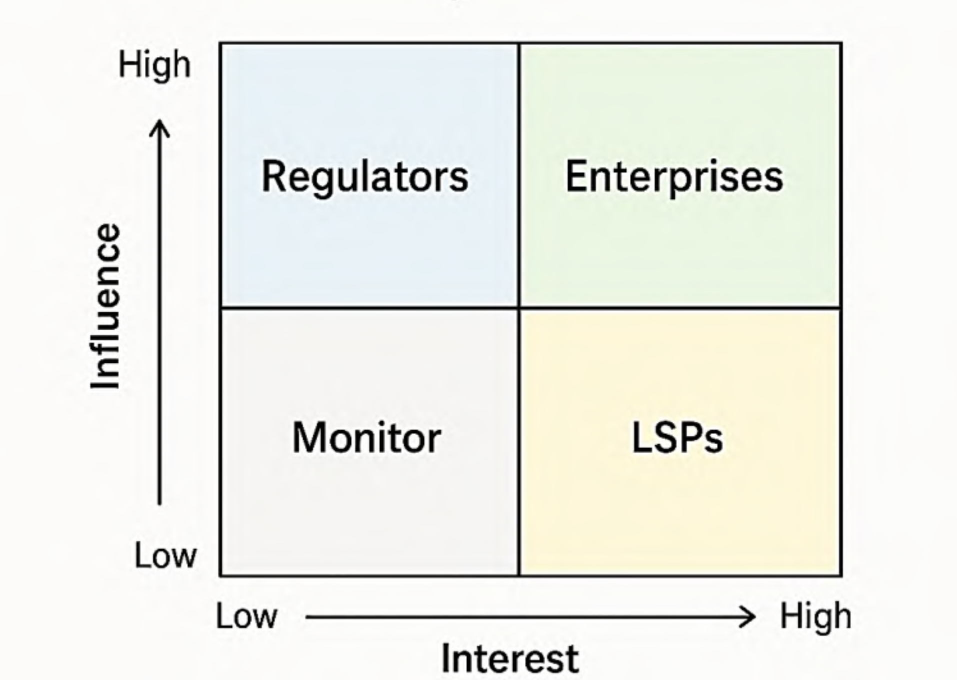


Figure 5.24. Stakeholder impact matrix illustrating influence versus interest in PRISMA implementation

5.9.2 Corporate Structural and Operational Overhaul

Enterprises adopting the PRISMA model undergo a fundamental shift in supply chain management, driven by the integration of digital twins, predictive analytics, and real-time IoT tracking. This transformation requires significant investment in edge computing, DLT, and microservices architectures (e.g., Kubernetes). To optimize routing, forecasting, and maintenance, firms must adopt stochastic optimization, MILP, and deep reinforcement learning (DRL) methods. Operational efficiency depends on deploying containerized microservices for orchestration, edge nodes for local processing, and high-fidelity digital twins to simulate logistics flows. To safeguard decentralized systems, PRISMA must implement TLS/SSL encryption, Zero-Trust security, and blockchain-based identity verification. Secure, real-time communication relies on protocols like MQTT, OPC-UA, and DDS, ensuring system-wide resilience and protection against cyber threats.

5.9.3 Socioeconomic and Environmental Considerations

The PRISMA model has notable implications for local communities, particularly due to AI-driven automation and AVs, which may cause workforce displacement. To address this, reskilling programs aligned with Industry 4.0 standards are essential. Environmentally, PRISMA reduces carbon emissions through V2X communication, dynamic AI routing, and modular energy-efficient hubs. Strategic urban planning and adoption of ISO 14064-1 enable accurate carbon tracking and congestion reduction. Technologies like Vehicle-to-Grid (V2G) and fleet electrification support circular economy goals and sustainability mandates. Figure 5.25 shows an inverse relationship between job displacement and new job creation, suggesting that while AI/AV adoption may displace some roles, it also drives employment growth in emerging sectors.

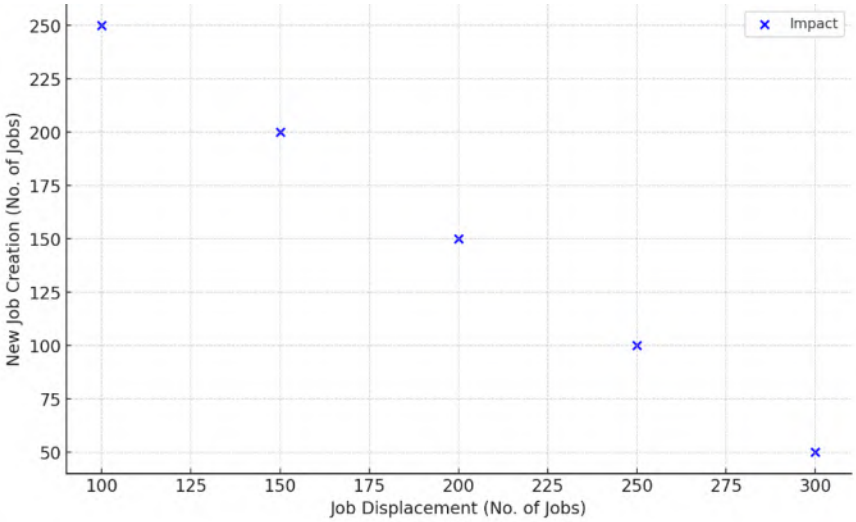


Figure 5.25. Relationship between job displacement vs new job creation due to AI/AV deployment

5.9.4 Economic Viability and Scalability Challenges

The PRISMA model offers long-term cost reductions through Just-in-Time (JIT) logistics and resilient supply chain configurations, but high initial investment remains a barrier, especially for SMEs. While blockchain-based smart contracts and DeFi enable flexible financing, their adoption is limited by regulatory uncertainty. To support real-time, autonomous decision-making, PRISMA requires 5G-enabled Multi-Access Edge Computing (MEC) for low-latency operations across distributed logistics networks. To manage cross-border complexity, integrating standardized e-Bill of Lading (eBL) and smart contract-based trade finance ensures compliance with UN/CEFACT and WCO SAFE frameworks. Figure 5.26 shows that although SME investment costs are high initially, they decline over time, while JIT-related savings increase, ultimately surpassing the investment and demonstrating long-term financial viability.

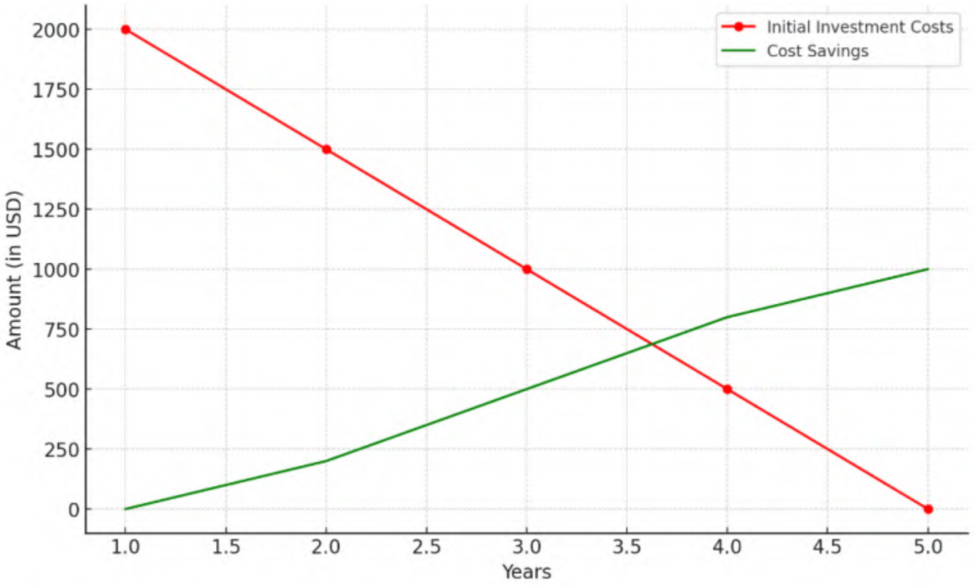


Figure 5.26. Comparing initial investment costs against cost savings for SMEs adopting JIT logistics technologies

While PRISMA offers clear benefits in efficiency, sustainability, and resilience, its success depends on addressing key barriers, including regulatory harmonization, economic feasibility, and workforce adaptation. Ensuring long-term scalability requires AI-driven optimization, strong cybersecurity frameworks, and sustainable urban integration strategies.

5.10 Conclusion

The PRISMA model, grounded in PI principles, presents a transformative approach to modernizing supply chains through modularity, decentralization, and digital intelligence. By integrating agent-based modeling, kanban-controlled flows, and multi-layered PILAR architecture, the framework enables real-time, autonomous logistics coordination across both forward and reverse chains exemplified by spent coffee ground recovery. Simulation results highlight how Q-learning, Monte Carlo methods, and stochastic optimization enhance adaptability, cost-efficiency, and environmental performance under uncertainty. However, successful implementation depends on overcoming challenges such as standardization gaps, high initial costs, cybersecurity risks, and regulatory fragmentation. Strategic investments in IoT, edge computing, blockchain, and reskilling programs are essential to achieving scalable, sustainable, and inclusive adoption. Overall, PRISMA demonstrates strong potential for enabling resilient, low-carbon, and digitally intelligent logistics networks aligned with global sustainability and circular economy goals.

5.11 Post-Publication Synthesis and Synopsis of the Next Research Stage

The outcomes of Chapter 5 operationalized the optimization layer of the DigiCircular framework through the Physical Internet and multi-agent PILAR architecture, enabling intelligent logistics coordination and adaptive routing. The next stage of research, presented in Chapter 6, builds directly upon this foundation by extending optimization into data integrity and transparency mechanisms.

Technically, the transition represents a shift from decentralized coordination to decentralized verification. While Chapter 5 achieved dynamic efficiency in transport and logistics, Chapter 6 introduces a Blockchain- and IoT-enabled digitalization layer that ensures the authenticity, traceability, and auditability of each optimized process. This evolution transforms the optimized logistics framework into a secure, end-to-end data ecosystem, where every transaction, from farm to export, is verifiable and immutable. Thus, the research progression moves from operational intelligence (optimization) to trustable intelligence (digitalization), completing the data continuum required for a fully transparent and circular coffee value chain. The next chapter implements this transition through the development of a mobile application integrating Blockchain, RFID, and IoT technologies, operationalizing transparency, consumer trust, and regulatory compliance within the DigiCircular architecture

Chapter 6

Digital Traceability and Blockchain-Enabled Transparency in Coffee Supply Chains

Building upon the operational intelligence achieved through the PI driven optimization layer, this chapter advances the DigiCircular framework toward its implementation frontier, where optimized processes become verifiable digital records by translating real-time logistics data into authenticated, tamper-proof transactions within the coffee supply chain. The work presented here introduces and validates a mobile-based traceability system that links on-ground IoT sensing with a distributed ledger infrastructure. This integration ensures that sustainability and performance data generated by previous DigiCircular layers are securely captured, shared, and auditable across all participating actors. Within this context, Blockchain functions as the verification layer, enabling end-to-end transparency, while RFID and IoT modules serve as the physical data gateways bridging farm-level and transport-level operations. Together, they enable continuous monitoring of origin, quality, and environmental impact throughout the coffee value chain.

The chapter reproduces and extends the outcomes of the peer-reviewed publications as mentioned in introduction.

By embedding this verified traceability system within the DigiCircular architecture, the research completes the transition from intelligent optimization to digital accountability, demonstrating how trusted data exchange can sustain circular value flows across both physical and digital domains.

6.1 Abstract

In an era where consumers increasingly demand transparency and sustainability in food production, this study introduces a mobile application tailored for the coffee supply chain. The goal of the study is to enhance the entire coffee production process by integrating technologies such as blockchain, RFID, and barcodes to improve transparency, traceability,

and operational efficiency. The application tracks and records data from farm inspection to export, covering coffee variety, environmental conditions, and supplier actions. It manages logistics with real-time updates on quantities, destinations, and delivery times, which supports better decision-making and fosters consumer trust through verifiable information. By improving coordination, reducing fraud, and optimizing quality control, the app aims to cut costs by up to 20%, reduce inventory carrying costs by 15-25%, and boost crop productivity by up to 15%. Furthermore, it supports precision agriculture, aligns with Just-In-Time principles, and promotes sustainability while ensuring compliance with ISO 9001 and ISO 14001 standards.

6.2 Introduction

The coffee supply chain is complex, involving multiple stages from cultivation to retail, each influencing the quality, cost, and sustainability of the final product. Traditional management practices often lack transparency and traceability, leading to inefficiencies, fraud, and unsustainable practices [197]. These issues are worsened by climate change, fluctuating market prices, and the COVID-19 pandemic, which disrupted global supply chains. The European coffee market, which accounted for 33% of global consumption in 2020, is a significant player, with consumption projected to reach 3.6 million tons by 2024 and revenues expected to exceed USD 50 billion [198]. Despite growth driven by demand for specialty and ethically sourced coffee, the pandemic shifted consumption patterns and disrupted production and logistics. Lockdowns and restrictions in coffee-producing countries led to labor shortages, cafe closures, and increased home-brewed coffee consumption, boosting retail sales and e-commerce. Online coffee sales surged by 45% in 2020 emphasized the critical role of e-commerce in maintaining supply chain continuity [198]. Information technology is pivotal in enhancing the coffee supply chain's efficiency and transparency. Technologies like blockchain, RFID, and barcodes improve traceability, providing verifiable data at each stage from cultivation to consumption. For instance, blockchain creates an immutable ledger that enhances trust and reduces fraud, while RFID and barcodes enable real-time tracking, ensuring quality control [199,200]. In 2020, the European Union imported about 3.4 million tons of green coffee beans, with Germany and Italy being the largest importers, accounting for 38% and 14% of imports, respectively. Italy’s coffee industry, featuring major players like Lavazza and Illy, leverages advanced technologies for efficient supply chain management. E-commerce giants like Amazon and Alibaba have entered the coffee market, facilitated direct-to-consumer sales and supported smaller brands through data analytics to optimize operations. Key industry players, including Nestlé, Starbucks, and JDE Peet's, use technologies like blockchain for traceability and IoT for quality monitoring and process optimization [201]. This research aims to improve coffee supply chain management by developing a mobile application integrating blockchain, RFID, and barcodes to enhance visibility and accountability. The app will track and record data from farm inspection to processing and exporting, aiding decision-making in transportation, inventory, and purchasing while promoting sustainable practices. It captures detailed data on coffee variety, climate conditions, and supplier actions, managing shipment and processing details to increase efficiency, reduce waste, minimize environmental impact, and support fair trade.

6.3 Literature Review

The integration of advanced technologies like blockchain, RFID, barcodes, and mobile applications address inefficiencies and enhances sustainability in the coffee supply chain. The complexity of coffee supply chains varies by nation, as discussed by Ibrahim and Zailani [202], Grabs [203], Fakkhong and Yamsa-ard [204], and Plengplang and Khutrakun [205]. E-SCM integrates enterprises and partners, enabling shared processes, objectives, and information that enhance supply chain performance [206]. The CSCMP defines supply chain management as the coordination of planning, sourcing, logistics, and integration of supply and demand across companies [207]. Internet technologies have evolved SCM into E-SCM, facilitating real-time data sharing and automation with suppliers and customers [208]. Research on blockchain for food traceability has grown, though much of it focuses on technological aspects, often overlooking human factors [209]. Studies on food traceability systems by Saberi et al. [210], Chen et al. [211], and Duan et al. [212] explore user perspectives on benefits, challenges and solutions. Traceability in supply chains has been explored through blockchain and RFID in China [213], applications or distributed storage in agricultural commodity markets and others [214,215]. Bager et al. developed a framework to enhance traceability in coffee supply chains, highlighting barriers and opportunities for technology adoption. He emphasized the potential of blockchain and e-commerce in agro-food supply chains, but real-world validation is still needed [216]. Studies such as Behnke and Janssen [217], Yadav et al. [218], and Saurabh and Dey [219] included consumer perspectives to identify obstacles to technology adoption. Khan et al. demonstrated that RFID and barcodes improve supply chain efficiency, accessibility, responsiveness and reduce costs, automating data collection and inventory monitoring [220]. In coffee supply chains, these technologies ensure compliance with standards and regulations. Blockchain and RFID can improve the livelihoods of smallholder farmers, reduce poverty in coffee-producing regions, and support sustainable agricultural practices, thereby mitigating environmental impact and promoting biodiversity [221]. Starbucks launched one of the first widely used coffee applications in 2011, allowing customers to order and pick up coffee in stores, a feature that gained popularity during COVID-19 for contactless pickup. However, the need to download multiple apps for different coffee chains poses challenges due to storage limitations and user learning curves [222]. Liu et al. [223] found that over 60% of users are frustrated by mandatory app installations for ordering, with nearly 80% abandoning transactions as a result. Mobile applications also help improve crop yield and quality by providing updates on weather, pest outbreaks and best practices, supporting data collection and sharing [224]. Consumers increasingly appreciate the quality and precision in coffee preparation, from bean selection to extraction methods, driving innovation and setting high standards in the industry. Furthermore, ingredient specifications have gained popularity, with customers being more aware of the origin, roast degree, and taste profiles of coffee beans used in their favorite beverages [225]. This demand for transparency has stimulated the growth of specialty coffee shops and micro-roasters that emphasize sustainability and ethical sourcing. Mobile devices and applications are essential for logistics professionals in managing supply chains, enhancing supplier relationships, and improving customer service. Future research should develop integrated frameworks using blockchain, RFID, and mobile technologies for end-to-end traceability in coffee supply chains, addressing challenges like data privacy, standardized data exchange protocol and interoperability [226]. Future research should explore these challenges while examining the socio-economic impacts of technology adoption across different stakeholder groups in the coffee supply chain. A centralized coffee app can unify access to various supply chain points, enhancing user engagement and providing insights into customer preferences, thereby supporting stakeholders in refining their offerings. Research on coffee industry sustainability reveals key gaps, including limited focus on smallholder farmers, technology scalability, accessibility, and the social and economic dimensions of the supply chain. Systematic reviews are crucial for guiding decision-making and promoting sustainable practices. This study addresses the gap by unifying blockchain, RFID, and mobile technologies in a single app to enhance traceability, transparency, and efficiency, focusing on smallholder integration and sustainable supply chain management.

6.4 Methodology

The dynamics within the coffee SCM encompass physical movement of beans including economic, social, and environmental interactions. Factors such as trade relationships, sustainability practices, market fluctuations and consumer preferences influence every stage of the coffee supply chain. The digital era has transformed the coffee supply chain, enhancing sales through digital payments, online ordering, and beverage customization. The proposed mobile app aims to streamline this experience by providing a unified platform for purchasing, distributing, and selling coffee [227]. Users can browse and order from a marketplace, utilizing expedited payment options that eliminate the need for cash or credit transactions at pickup. The app focuses on customization to specific coffee preferences and allows users in warehousing, logistics, and manufacturing to select convenient collection sites, improving efficiency [228]. Its adaptability enhances convenience, accessibility, and supply chain performance, reducing costs, fuel use, environmental impact, and waste. This platform bridges the gap between technology and the coffee industry, appealing to major manufacturers and consumers alike, enhancing transparency, customer loyalty, and revenue growth for participating businesses. The objectives for designing this app are outlined as follows:

- To support small and medium-sized businesses in optimizing their inventory management.
- To oversee delivery times and track orders effectively.
- To build a user-friendly platform for seamless supply chain management for industries.
- To provide manufacturers with insights into alternative suppliers in the market place.
- To incentivize timely delivery of components by suppliers through a rewards system.
- To create a cost-effective marketing platform aimed at boosting the growth of local enterprises.

Figure 6.1illustrates the design of an online data monitoring system via mobile application. It begins with the "Supplier association," who inputs data on certification activities, seed types, and fertilizer usage. Next, the "farmers" records real-time harvesting details, including varieties, humidity, and temperature. The process splits into two paths, the "Logistics Module," which tracks data shipment details and exporter ID, Importer ID, transportations and the "Plant Module," which manages processing times, batch quantities, and moisture levels, Fan speed, temperatures, roasting details. Both data streams converge at the "Data Aggregator represented as Data acquisition Unit," where information is compiled and analyzed. Finally, the data is accessible to the "Customer" through the mobile application, providing comprehensive monitoring and insights. This block diagram emphasizes the seamless integration and collaborative efforts in tracking and managing data from the field to the mobile app.

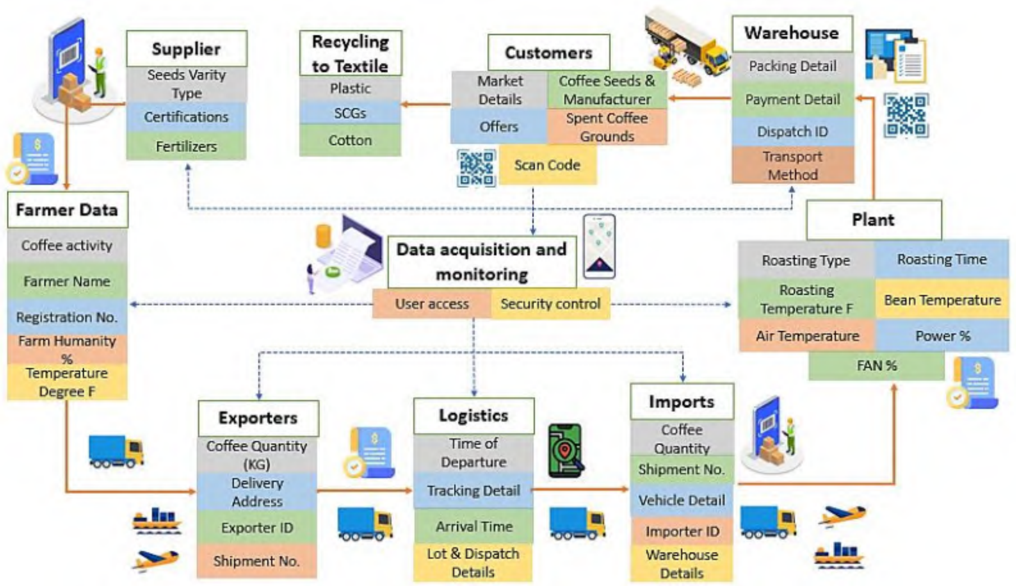


Figure 6.1. Block Diagram for online data monitoring system

6.5 Steps to Develop a Mobile Application for the Coffee Supply Chain

The development of a mobile application for the coffee supply chain follows a systematic six-step approach. First, requirements definition and architecture design establish the foundation by selecting suitable technologies and features to meet supply chain needs, such as Android and iOS platforms, Java or Dart for programming, and Node.js/Express for backend performance and scalability. Second, UI/UX design focuses on creating an intuitive user experience through wireframing, prototyping, and iterative improvements. Third, backend development sets up a secure, scalable database with RESTful APIs for real-time data interaction and authentication, utilizing technologies like MySQL and JWT. Fourth, frontend development integrates UI with backend services, ensuring data validation and error handling for a seamless interface. Fifth, comprehensive testing, including unit, integration, and user acceptance testing, ensures functionality and reliability. Lastly, deployment involves configuring cloud infrastructure, publishing the app, and implementing maintenance plans to sustain performance and user satisfaction.

6.5.1 Step 1: Define Requirements and Architecture

The first step in developing a mobile application for the coffee supply chain is to define the requirements and architecture comprehensively, as illustrated in Figure 6.2. This step establishes the foundational framework, ensuring the application aligns with stakeholder needs for efficiency and transparency. Key activities include selecting cross-platform technologies, such as Flutter for the frontend, to maximize market reach and accessibility. Backend development involves Node.js/Express for server-side logic and secure API integration. Integrating RFID, QR codes, and GPS enables real-time tracking, enhancing the application's functionality for a highly efficient, transparent, and sustainable coffee supply chain management system.

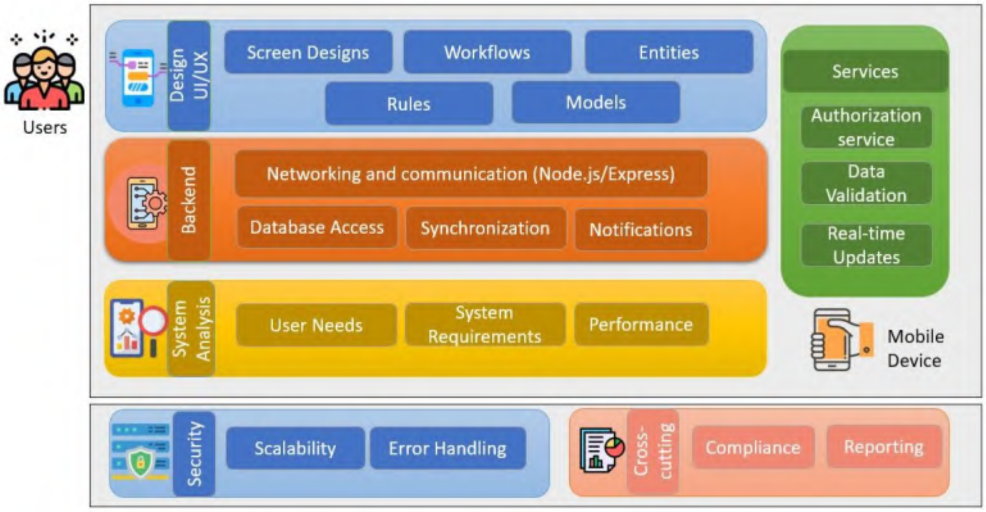


Figure 6.2. System design for integrated mobile application development for coffee supply chain

6.5.1.1 Technical Specifications for Platform design of Android and iOS

The application is developed for both Android and iOS using Flutter, allowing a single codebase for streamlined cross-platform deployment. Node.js with Express powers the backend, offering scalability, performance, and support for RESTful APIs and real-time features essential for supply chain operations. The backend handles user authentication, data storage, and real-time processing through secure API endpoints. PostgreSQL serves as the database for its ACID (atomicity, consistency, isolation, and durability) transactions, complex queries, and data integrity, suited for structured data like user details, transactions, logs, sensors data and inventory. RFID, QR code scanning, and GPS are integrated for comprehensive tracking of coffee beans, products, and shipments.

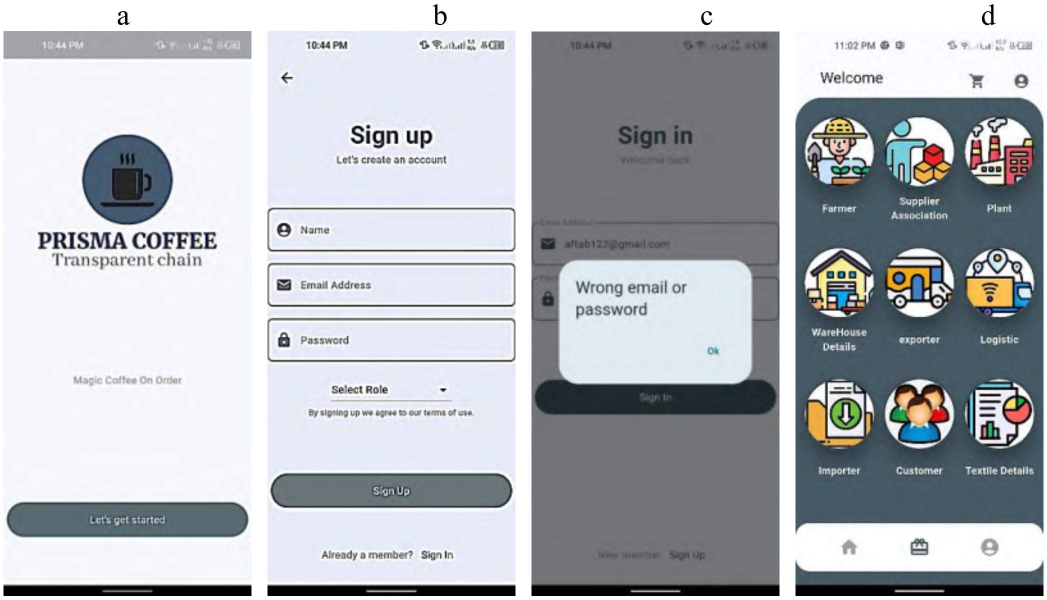
6.5.1.2 Features and Functionalities

The app uses JWT (JSON Web Tokens) for secure authentication and implements role-based access control to ensure only authorized users (e.g., Farmers, Suppliers, Processors, Shippers, Customers) access specific features. It employs RESTful APIs for real-time data updates and notifications, with dashboards and alerts for monitoring key metrics. Data visualization libraries like D3.js are used for interactive reports, and analytics tools provide data trends.

6.5.2 Step 2: Design UI/UX

The second step involves designing the user interface (UI) and user experience (UX)to ensure an intuitive and user-friendly application for all coffee supply chain stakeholders. Figma is used for wireframing and prototyping, followed by usability testing with stakeholders to gather feedback and improving designs. Comprehensive testing includes unit, integration, and user acceptance tests to ensure functionality and performance.

1 *Login, Registration and Dashboard Screen:* The login and registration screen ensure secure user authentication and registration with role-specific access, requiring details like name, email, password, and role, utilizing OAuth 2.0 for secure login, JWT tokens for session management, and Node.js/Express for API-based processes. The dashboard offers role-specific widgets, notifications, and real-time updates. It uses the D3.js library for visualizing key metrics and alerts, with RESTful APIs for backend integration and real-time data fetching (Figure 6.3).



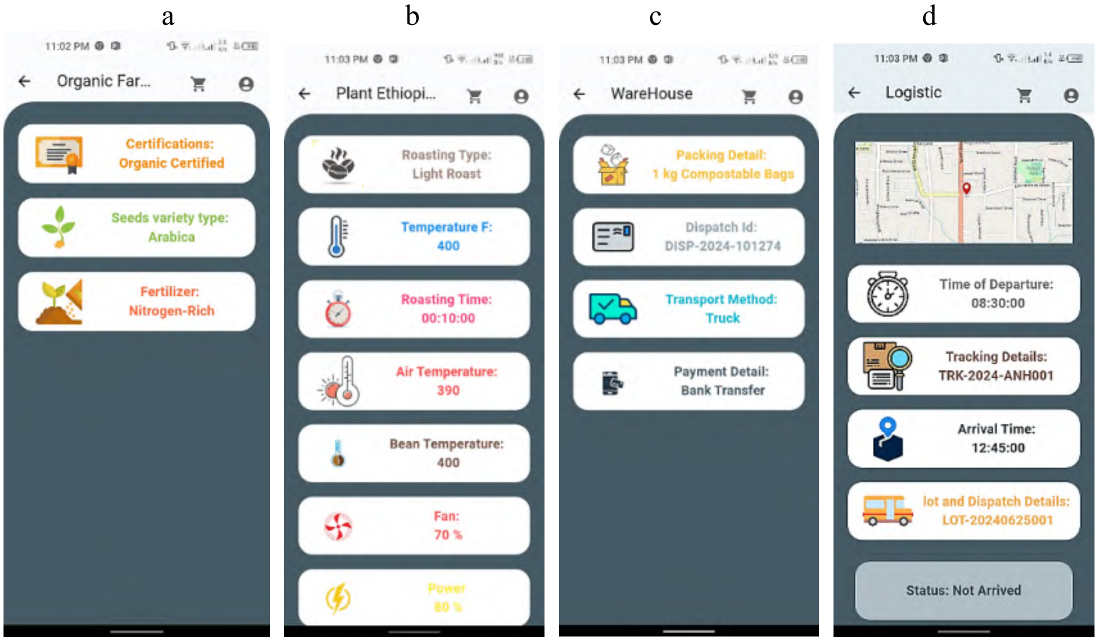
aftab123@gmail.com

Wrong email or password

Figure 6.3. (a) Welcome screen; (b) Registration screen; (c) User authentication;(d) Main dashboard screen

2 *Supplier association, Farmer, Processing and Logistics Screens:* These screens

work together to enhance data management and traceability in the coffee supply chain. The Supplier Association screen gathers data on raw materials exchanged with farmers, including coffee seeds, fertilizers, certifications, and inspection details, using sensors and IoT for real-time alerts on deviations. This data is stored in PostgreSQL for traceability updates (Figures 6.4a). The Farmer screen enables harvesters to log coffee bean collection and quality control information, such as quantity, farmer details, humidity, and temperature checks, with photo uploads and timestamps to track progress and trigger quality control workflows, updating inventory records accordingly (Figures 6.4b). The Processing and Logistics screens aid factory workers, administrators, and shippers in managing sorting, roasting, packaging, and shipment tracking. Processing screens capture information on size, color, quality checks, batch numbers, processing dates, and packaging, syncing with production management systems for transparent records. Logistics screens monitor deliveries via GPS, transport methods, dispatch IDs, and packaging stages with QR code scanning (Figure 6.4d).



Certifications: Organic Certified
Seeds variety type: Arabica
Fertilizer: Nitrogen-Rich

Roasting Type: Light Roast
Temperature F: 400
Roasting Time: 00:10:00
Air Temperature: 390
Bean Temperature: 400
Fan: 70 %
Power 80 %

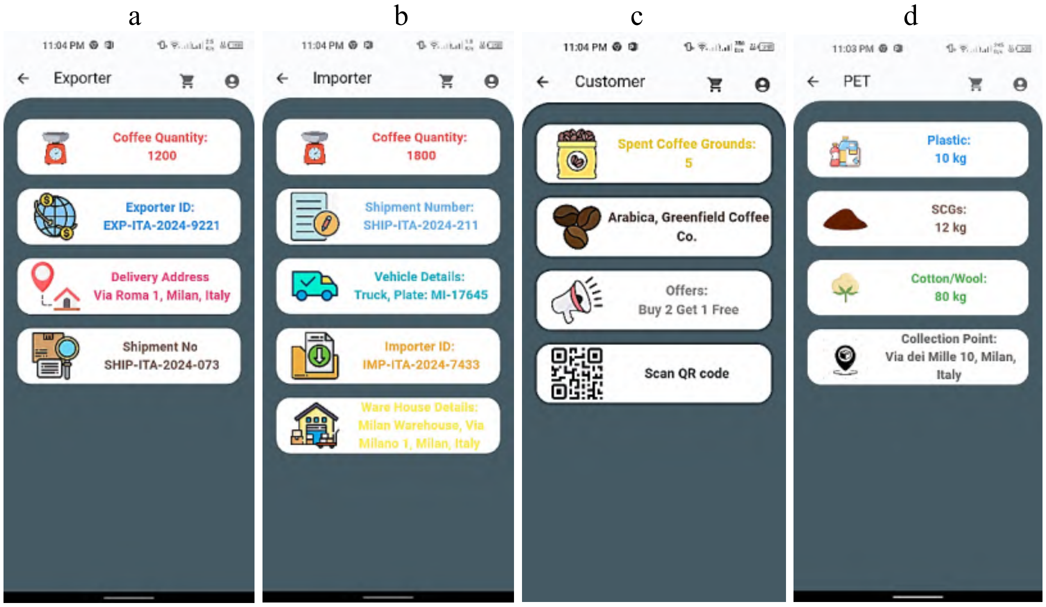
Packing Detail: 1 kg Compostable Bags
Dispatch Id: DISP-2024-101274
Transport Method: Truck
Payment Detail: Bank Transfer

Time of Departure: 08:30:00
Tracking Details: TRK-2024-ANH001
Arrival Time: 12:45:00
lot and Dispatch Details: LOT-20240625001
Status: Not Arrived

Figure 6.4. (a)Coffee farming details; (b)Sensor-based quality checks;(c) Warehouse tracking systems;(d) Logistics with GPS tracking;

3 *Shippers and Customers Screens:* Shipper screens facilitate the management and tracking of shipments, including imports and exports (Figure.6.5a,6.5b). They capture data on quantities, invoices, importer IDs, addresses, shipment numbers, and dispatch details, enabling shipment management, invoice generation, and real-time integration of shipment data with inventory and customer orders. Customer screens allow users to register, log in, submit materials for recycling, track coffee origin and processing, and monitor order status. They connect customers with management systems and recycling centers, provide real-time updates on recycling

status, and support the transfer of spent coffee grounds to the textile industry as raw material (Figure.6.5c, 6.5d).



a

Coffee Quantity: 1200
Exporter ID: EXP-ITA-2024-9221
Delivery Address Via Roma 1, Milan, Italy
Shipment No SHIP-ITA-2024-073

b

Coffee Quantity: 1800
Shipment Number: SHIP-ITA-2024-211
Vehicle Details: Truck, Plate: MI-17645
Importer ID: IMP-ITA-2024-7433
Ware House Details: Milan Warehouse, Via Milano 1, Milan, Italy

c

Spent Coffee Grounds: 5
Arabica, Greenfield Coffee Co.
Offers: Buy 2 Get 1 Free

d

Plastic: 10 kg
SCGs: 12 kg
Cotton/Wool: 80 kg
Collection Point: Via dei Mille 10, Milan, Italy

Figure 6.5. (a) Exports with inventory orders; (b) Overseas shipments; (c) Updates on coffee origin; (d) Sustainability initiatives to support textile

6.5.3 Step 3: Backend Development

Backend development for the mobile application involves setting up a robust PostgreSQL database to manage diverse data structures, creating RESTful APIs for CRUD (Create, Read, Update, and Delete) operations on entities like users, farmers, and shipments, and ensuring secure authentication and real-time updates. PostgreSQL's flexibility and scalability support complex data interactions, while RESTful APIs enable data synchronization and notifications through Node.js. In the Middleware layer following actions are performed to increase security.

- Authentication: JWT (JSON Web Tokens) are used for secure user authentication with tokens applied to protected routes.
- Authorization: Role-based access control restricts API endpoint access based on user roles.
- Validation: Zod library is utilized to validate incoming data, ensuring integrity and preventing malicious inputs

Real-time data synchronization and notifications, such as inspection alerts and shipment updates are managed via APIs, with automated testing and deployment facilitated by GitHub Actions, and the backend is deployed on Google Cloud. Docker is employed for containerization and Kubernetes for orchestration, laying a solid foundation for integrated data management and connectivity.

6.5.4 Step 4: Frontend Development

Frontend development focuses on creating user interface (UI) screens and connecting it with backend services to ensure smooth functionality across all supply chain roles with data validation and error handling mechanisms. Authors used the Flutter framework, which enables cross-platform development with Dart, the UI screens are implemented as separate widgets, including login, registration, and dashboards. The HTTP library in Flutter is used to manage API requests at backend, Services or providers are created to manage API requests and responses as given below for reference.

API integrations:

login user function:

```
Future<void> loginUser(String username, String password) async {
  final url = Uri.parse("https://coffee-backend-dtyy.onrender.com/v1/auth/login"); //
Replace with your actual URL
  final body = jsonEncode({"email": username, "password": password});

  try {
    final response = await http.post(url, body: body, headers: {"Content-Type":
"application/json"});
    if (response.statusCode == 200) {
      successfulLogin = true ;
      // Login successful! Parse the response for access token or other data
      final data = jsonDecode(response.body);
      print(data);
      roleGot = data["user"]["role.name"];
      return data;

      // Handle successful login (e.g., store token, navigate to home screen)
    } else {
      successfulLogin = false ;
      // Handle login failure (e.g., show error message
    }
  } catch (error) {
    // Handle network errors

  }
}
```

Fetch data function:

```
Future<List<dynamic>> fetchData({required String category}) async {
  final response = await http.get(Uri.parse('https://coffee-backend-
dtyy.onrender.com/v1/$category'));
```

```
  if (response.statusCode == 200) {
    // Parse the JSON
    List<dynamic> list = jsonDecode(response.body);
    return list;
  } else {
    // Handle the error
    throw Exception('Failed to load data');
  }
}
```

Signup function:

```
Future<bool> createAlbum(String title,String email,String password,String role) async {
  print("role: $role");
  final response = await http.post(
    Uri.parse('https://coffee-backend-dtyy.onrender.com/v1/auth/register'),
    headers: <String, String>{
      'Content-Type': 'application/json; charset=UTF-8',
    },
    body: jsonEncode(<String, String>{
      'name': title,
      'email': email,
      'password': password,
      'role': role
    }),
  );

  if (response.statusCode == 201) {
    // If the server did return a 201 CREATED response,
    // then parse the JSON.
    return true;

  } else {
    return false;
    // If the server did not return a 201 CREATED response,
    // then throw an exception.
    throw Exception('Failed to create album.');
  }
}
```

While WebSocket integration facilitates real-time updates by using REST APIs for initial data and WebSocket for ongoing changes, with `axios` or `fetch` and `web_socket_channel` to handle real-time calls. Data validation is handled through Flutter's built-in validation library, ensuring accurate input fields, and error handling mechanisms are in place to address network, data, and server issues, providing users with appropriate error messages such as invalid data or no rights to access this screen.

6.5.5 Step 5: Testing

Testing, the fifth step in the development process includes unit testing to verify the functionality of individual components, integration testing to ensure seamless interaction between frontend and backend, and user acceptance testing (UAT) to validate the application with real users from each role. Each testing level identifies and resolves issues, ensuring a robust and seamless user experience.

6.5.6 Step 6: Deployment

Deployment is the final phase in developing the mobile application. It involves setting up Google Cloud services for backend scalability and reliability, publishing the app-to-app stores for user access, and implementing monitoring and maintenance for ongoing updates and user satisfaction. This approach ensures the application operates efficiently in real-world conditions and adapts to user needs. Table 6.1 provides a structured blueprint for the app's development, guiding the systematic integration of technological solutions across all supply chain roles.

Table 6.1. Detailed technical framework and benefits of each mobile application screen for coffee supply chain management

Screen	Features	Technical Data	Benefits
Login and Registration	User authentication and registration	User details (name, email, password, role)	Secure access control and user management
Dashboard	Overview of supply chain status	Real-time data monitoring	Centralized access to all functionalities
Supplier Association	Data collection for seeds, fertilizers, humidity, temperature	Input fields for various inspection parameters	Accurate and timely farm data collection, improving quality and traceability
Farmer	Harvesting data collection and quality control	Input fields for quantity and quality control checks	Ensures quality control during harvesting
Coffee Factory	Sorting, quality checks, roasting, and packaging	Input fields for sorting, roasting, and packaging details	Streamlined factory operations and quality assurance
Warehouse	Processing data entry for batch numbers, dates, and addresses	Input fields for batch numbers, processing dates, and processor addresses	Enhanced tracking of processing stages and batch management
Shipper	Shipment management, quantities, invoices, importer IDs	Input fields for shipment quantities, invoice numbers, and importer IDs	Efficient and transparent shipment tracking and management
Customer	Registration, order tracking, and recycling material submission	Input fields for registration details and recycling submissions	Enhanced customer experience with real-time order tracking and recycling options
Reports and Analytics	Report generation and visual analytics	Filters for date, batch, location, etc.	Data-driven insights and decision-making

The methodology ensures the mobile application is technically sound and meets the practical needs coffee supply chain. With a user-centric design, it enhances operational efficiency, inventory management, quality control, and transparency. Comprehensive testing and a flexible deployment strategy ensure reliability and scalability.

6.6 Discussion

The findings from this study highlight that the development of a mobile application for the coffee supply chain enhances operational efficiency and addresses key industry challenges, benefiting stakeholders such as farmers, processors, shippers, and customers. The app significantly improves traceability by providing verifiable data on seeds, fertilizers, humidity, and temperature, thus addressing transparency and counterfeiting issues prevalent in the coffee industry. This reduces fraud and increases trust among consumers. Quality control checks at the harvesting and factory stages further ensure that beans are sorted, roasted, and packaged according to predefined standards, reducing recalls and enhancing brand reputation, consistent with results seen in the broader agricultural sector[229].Real-time data provided by the app improves coordination among stakeholders, reduces shipment delays, and optimizes routes, potentially lowering operational costs by up to 20%,likefindings by the World Economic Forum [230]. Enhanced inventory management mitigates supply shortages and overproduction, reducing carrying costs by approximately 22%, aligning with the results reported by the Council of Supply Chain Management Professionals [231]. For farmers, access to data supports precision agriculture, potentially increasing yield quality and productivity by up to 15%. Processors benefit from improved batch tracking and quality assurance, which helps in reducing waste and maintaining high standards for specialty markets. Shippers achieve better logistics management with real-time tracking, enhancing delivery reliability and aligning with Just-In-Time (JIT) principles, thus reducing costs and increasing turnover rates [232]. Customers gain transparency and confidence in product quality, with features supporting ethical sourcing and recycling [233]. The proposed solution integrates blockchain for traceability, real-time monitoring, and robust data validation, ensuring reliability and scalability. While challenges such as high initial costs and the need for stable internet connectivity, particularly in remote areas, may pose barriers to implementation, the long-term benefits of cost savings, enhanced efficiency, and improved quality make the app a compelling solution. Additionally, the application aligns with industry certifications like ISO 9001 and ISO 14001, emphasizing its commitment to quality management and environmental sustainability, which further strengthens its credibility and market acceptance [234]. Table 6.2 outlines the app's features, supply chain challenges, benefits, and regulatory compliance, demonstrating its strategic design and potential impact on the coffee supply chain.

Table 6.2. Analysis of mobile application features in enhancing coffee supply chain efficiency and regulatory compliance

Features of mobile application	**Challenges in the current coffee supply chain**	**Benefits of implementing a mobile application**	**Certifications/regulations fulfilled**
Dashboard	Overview of supply chain status	Real-time data monitoring	Centralized access to all functionalities
Supplier Association	Data collection for seeds, fertilizers, humidity, and temperature	Input fields for various inspection parameters	Accurate and timely farm data collection, improving quality and traceability
Farmer	Harvesting data collection and quality control	Input fields for quantity and quality control checks	Ensures quality control during harvesting
Coffee Factory	Sorting, quality checks, roasting, and packaging	Input fields for sorting, roasting, and packaging details	Streamlined factory operations and quality assurance
Warehouse	Processing data entry for batch numbers, dates, and addresses	Input fields for batch numbers, processing dates, and processor addresses	Enhanced tracking of processing stages and batch management
Shipper	Shipment management, quantities, invoices, importer IDs	Input fields for shipment quantities, invoice numbers, and importer IDs	Efficient and transparent shipment tracking and management
Customer	Registration, order tracking, and recycling material submission	Input fields for registration details and recycling submissions	Enhanced customer experience with real-time order tracking and recycling options
Reports and Analytics	Report generation and visual analytics	Filters for date, batch, location, etc.	Data-driven insights and decision-making

While the current findings confirm the app's effectiveness in improving operational efficiency, scalability, and transparency, several systemic and contextual challenges remain unresolved. To sustain long-term digital transformation, future research must explore how these technologies can evolve to overcome infrastructural, economic, and interoperability barriers in diverse coffee-producing regions.

6.6.1 Future research endeavors:

Future research in the coffee supply chain should address several critical barriers to technology adoption, particularly in rural coffee-growing regions (Figure 6.6). These areas often face inadequate digital infrastructure, which significantly hinders the widespread deployment of technologies such as IoT and blockchain. Specific regions, particularly those in sub-Saharan Africa and Latin America, continue to struggle with connectivity issues that prevent the adoption of advanced technologies. Overcoming these barriers requires targeted research into developing low-cost, scalable solutions tailored to these regions' unique needs.

Moreover, interoperability issues remain a key challenge in integrating various technological platforms within the coffee supply chain. The existing enterprise information systems (EIS) often lack communication across different levels, data, services, and processes, due to mismatches in the underlying models and languages used by different stakeholders. Current efforts to standardize these systems, including the use of semantic web technologies for ontology alignment, show promise but are still in the experimental phase. Research should focus on refining these semantic matching techniques to improve the interoperability of supply chain systems, ensuring that different platforms can work together efficiently.

In addition to technical barriers, the implementation of advanced technologies such as IoT and blockchain raises significant concerns about data privacy and security. As these technologies collect and transmit sensitive data, it is crucial to develop secure protocols that protect against breaches and misuse. Research should investigate robust encryption methods, secure data storage solutions, and compliance with global data privacy regulations to ensure the integrity and confidentiality of information across the supply chain.

From an economic perspective, the high costs associated with deploying IoT and blockchain technologies remain a significant hurdle, especially for smallholder farmers and smaller enterprises. On average, the initial cost of setting up IoT systems in agriculture can exceed USD 10,000 per farm, including hardware, software, and installation fees. This is prohibitively expensive for many smallholders, who often lack access to capital or financial support. Blockchain technology also carries high setup costs due to its need for specialized infrastructure and expertise. Research into cost-effective solutions, such as leveraging existing mobile networks for data collection or exploring shared blockchain infrastructure, can help reduce these financial barriers. Furthermore, cost-benefit analyses should explore potential subsidies or microfinancing models to support smallholder adoption of these technologies.

Finally, future studies should focus on the broader social impacts of these technologies. Research should examine their potential to improve livelihoods, enhance employment opportunities, and foster community development. Understanding the social dynamics at play such as labor displacement concerns or changes in market access will be essential for designing policies that promote inclusive growth in the coffee sector.

Figure 6.6. Future research pathways for innovative management in the coffee supply chain

In parallel with academic and technological advancements, the commercial landscape of coffee supply chain management is also evolving rapidly. Several digital platforms already embody aspects of innovation and traceability envisioned in this research, demonstrating how market-driven solutions can complement scholarly and policy initiatives.

6.6.2 Coffee supply chain platforms

Several platforms are currently utilized within the coffee supply chain to enhance production, processing, distribution, and customer services, showcasing the integration of innovation management practices. These platforms leverage cutting-edge technologies, such as blockchain for traceability and AI-driven analytics for demand forecasting, to streamline operations and ensure compliance with sustainability standards. The shift in market dynamics between offline and online retail channels for coffee products highlights the impact of digital innovation. Offline retail, while maintaining dominance, has gradually declined from 98.5% in 2018 to 94.8% in 2028, whereas online retail has steadily grown from 1.3% to 5.2% during the same period, as illustrated in Table 6.3. This evolution underscores the role of innovation management in fostering digital transformation, enhancing consumer engagement, and addressing sustainability challenges within the coffee supply chain.

Table 6.3. Online and offline market revenue share in percent (%)

	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028
Offline	98.5	98.0	97.0	96.0	96.3	97.4	96.4	95.5	96.5	95.4	94.8
Online	1.6	2.0	3.0	4.0	3.7	2.6	3.6	4.5	3.5	4.6	5.2

Moreover, over the past decade, there has been a notable shift in internet traffic for coffee platforms, with desktop usage declining from 66.3% to 56.3%, while mobile usage has increased from 33.7% to 43.7% from 2018 to 2028, as shown in Table 6.4. These trends underscore changing consumer preferences and the increasing digitalization of coffee consumption and usage patterns.

Table 6.4. Coffee consumption split for desktop vs. mobile device usage percentage

	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028
Desktop	66.3	63.6	61.4	60.1	59.0	58.5	57.9	57.4	56.9	56.6	56.3
Mobile	33.7	36.4	38.6	39.9	41.0	41.5	42.1	42.6	43.1	43.4	43.7

The map shown in Figure 6.7 of coffee supply chain applications provides a comprehensive overview categorized by access mode, virtual reality devices, desktop/web browsers, and mobile apps, and the technology powering their internal economy, distinguishing between blockchain/IoT and non-blockchain/IoT solutions. Notable platforms include Trade Coffee and Cropster Roast for desktop users seeking personalized recommendations and coffee roasting management, respectively. The inclusion of Provenance and IBM Food Trust highlights blockchain's role in ensuring transparency across supply chains, while mobile apps like Cropster and AgriDigital facilitate on-the-go production management and digital contract tracking.

Figure 6.7. Mapping coffee supply chain applications by access mode and technological advancement

6.7 Conclusion

This study highlights the critical role of mobile applications in enhancing various phases of the coffee supply chain, emphasizing benefits such as real-time inventory management, blockchain-enabled traceability, IoT integration, and mobile accessibility, all of which improve operational efficiency and sustainability compliance. The proposed application proposed real-time data and analytics to optimize production, streamline logistics, address consumer demands for ethical sourcing, and ensure quality control through remote monitoring of environmental conditions, ultimately reducing waste from farm to consumer. Novelty lies in the integration of advanced technologies targeted specifically for the coffee supply chain, providing a comprehensive solution that addresses both operational and sustainability challenges unique to this sector. However, challenges remain, including interoperability issues among platforms, data security concerns with blockchain, high IoT deployment costs in resource-limited settings, slow adoption by small-scale producers, and difficulties in integrating new technologies into existing infrastructures. Future research should address these challenges by enhancing data standardization for interoperability, improving blockchain scalability for large networks, and developing cost-effective IoT solutions for smallholder farmers. Moreover, exploring the socio-economic impacts on coffee-producing communities and assessing long-term sustainability implications will be essential for shaping future strategies and policies, driving innovation, and promoting sustainability in the global coffee market.

6.8 Post-Publication Synthesis and Synopsis of the Next Research Stage

This chapter completed the digitalization layer of the DigiCircular framework by embedding Blockchain-IoT integration within the coffee supply chain. It transformed the optimized logistics network developed in Chapter 5 into a verifiable data ecosystem, where every transaction and sustainability metric is immutably recorded through distributed-ledger protocols and sensor-driven data capture. Scientifically, this work validated data integrity, provenance, and auditability as essential extensions of the cyber-physical optimization achieved earlier. By linking IoT event streams to blockchain smart contracts, the study demonstrated secure synchronization between operational data (flow layer) and information trust (data layer), thus closing the digital feedback loop proposed in the HDSF.

The next research stage advances from sector-specific digitalization to cross-sector generalization. Chapter 7 applies the DigiCircular architecture to textile manufacturing, a domain characterized by multi-stage waste flows and higher material heterogeneity. This transition tests the framework’s scalability, interoperability, and performance invariance across industrial contexts, enabling a comparative evaluation of how digital traceability principles govern resource efficiency, waste valorization, and circular-data governance in complex manufacturing systems.

Chapter 7

Digital Circularity in the Textile Industry by Integrating IoT, Waste-Flow Mapping, and Life-Cycle Management

This chapter extends the DigiCircular framework into the manufacturing domain by focusing on the textile industry, a sector recognized for high resource intensity and complex waste streams.
It consolidates two complementary peer-reviewed works:

- Integrating IoT and Circular Economy in Textile Supply Chains; conceptualizing digital infrastructure for circular resource management.
- Mapping Waste Streams and Life-Cycle Management in Textile Manufacturing; implementing analytical methods to quantify and monitor circular performance.

Together, these studies validate the cross-sector adaptability of DigiCircular, demonstrating how real-time sensing, data analytics, and life-cycle metrics can jointly enable digitalized resource efficiency within industrial production systems.

7.1 Abstract

The global textile and fashion industries are among the most resource-intensive and polluting sectors, demanding urgent adoption of sustainable and circular practices. This study proposes an integrated closed-loop circular model that transforms textile and fashion supply chains through the convergence of advanced digital technologies and sustainable materials. The framework combines IoT enabled real-time monitoring, Waste Flow

Mapping (WFM), and Life Cycle Assessment (LCA) to optimize resource efficiency, manage waste, and evaluate environmental impacts across product life cycles. The study designs a multi-layer monitoring system where sensor networks capture water, energy, and chemical-use data, while analytical dashboards compute dynamic Key Performance Indicators (KPIs) for waste, emissions, and resource recovery.

Recycled polyethylene terephthalate (rPET) and spent coffee grounds (SCG) are utilized in textile production to reduce dependence on virgin materials and improve circularity. A case study at a textile plant in Pakistan demonstrates significant operational and environmental benefits, including a 21.43% reduction in lead time, 30% decrease in material waste, and 25% improvement in cycle time. Environmental impacts were also reduced, carbon emissions from 8000 to 7500 tons of CO_2, water consumption from 12,000 to 10,000 m^3, and energy use from 55,000 to 50,000 kWh. WFM and LCA-based assessments across the fashion supply chain further indicate a 25–30% reduction in environmental impacts, 20–25% improvement in resource efficiency, and up to 50% use of recycled materials. Overall, the proposed model demonstrates how digitalization and circular economy principles can jointly enable sustainable waste flow management, enhance material reuse, and support the twin transition, green and digital, aligned with the Sustainable Development Goals (SDGs).

7.2 Introduction

The global textile and fashion industries are critical to economic growth, employing over 10 million workers worldwide [235-236] and producing diverse products such as agrotextiles, automotive textiles, and apparel [237]. Valued at over USD 1.95 billion in 2023 [238], this sector face severe sustainability challenges due to their high resource consumption and pollution levels. The textile industry alone consumes over 3 trillion gallons of water annually and contributes to one-third of global chemical releases [239,240]. Likewise, the fashion industry, despite its economic significance, is a major polluter, responsible for nearly 10% of global greenhouse gas emissions [241] and 20% of industrial water pollution [242]. Polyester garments release up to 700,000 microplastic fibers per wash, contaminating aquatic ecosystems and potentially entering the food chain [243,244].

Growing environmental awareness among consumers and policymakers [245,246] has driven research toward sustainable innovation across both textile and fashion supply chains. Scholars have explored diverse areas, including sustainable product design [247], pollution management [248], corporate social responsibility [249], and circular economy practices [250,251]. However, the implementation of these sustainability initiatives remains fragmented and often lacks integration of digital and environmental strategies within a unified framework [252]. Building on the DigiCircular framework developed in previous chapters, this research extends the model to the textile sector to test its cross-industrial scalability.

To bridge this gap, Industry 4.0 technologies such as the IoT, blockchain, and RFID offer new opportunities for transparency, traceability, and data-driven sustainability in textile production [253,254,255]. Coupled with LCA, these technologies enable the monitoring and evaluation of environmental impacts and resource efficiency improvements throughout the supply chain [256]. In particular, integrating IoT with Waste Flow Mapping (WFM), the 5S methodology, and key performance indicators (KPIs) enables systematic waste reduction and sustainability tracking [257].

Moreover, the valorization of waste materials, such as spent coffee grounds (SCGs), presents a circular opportunity for fabric innovation. Over six million tonnes of SCGs are discarded annually, yet they can be repurposed as raw material for textiles, reducing reliance on virgin resources and supporting recycling and reuse explored in earlier chapters [244,258,259,260]. This aligns with the global imperative to address food waste projected to reach 2.1 billion tonnes by 2030 and to capitalize on a $700 billion circular economy opportunity [261,262]. This cross-sector linkage demonstrates how material by-products from one DigiCircular domain can become inputs for another, reinforcing industrial symbiosis within the twin-transition paradigm.

Accordingly, the study addresses three research questions:

1. **RQ1**: How do digital technologies improve sustainability and transparency in the textile and fashion supply chains while utilizing LCA to assess environmental impacts?
2. **RQ2**: What strategies can optimize the economic and environmental advantages of using repurposed coffee grounds for fabric production?
3. **RQ3**: What obstacles and opportunities exist in implementing IoT, circular supply chain models, WFM, and LCA methodologies, and how can they enhance resource efficiency and reduce waste?

This research aligns with SDGs 6, 9, 11, 12, and 13 by promoting responsible consumption and production, clean water and sanitation, sustainable infrastructure, and climate action. By integrating digital technologies with circular economy principles, the study contributes a comprehensive, data-driven framework for transforming textile and fashion supply chains toward sustainability and resilience.

7.3 Literature Review

Recent literature highlights a growing shift in sustainable textile and fashion research from isolated material innovations toward integrated digital–analytical approaches that enable systemic circularity and resource efficiency. While earlier studies primarily focused on developing eco-friendly materials and production methods, current research emphasizes the convergence of circular economy principles, WFM, and digital technologies such as IoT, blockchain, and AI to achieve real-time sustainability management [263, 240]. These interdisciplinary frameworks promote closed-loop textile systems capable of minimizing waste, improving traceability, and enhancing decision-making through data-driven insights. However, gaps remain in integrating these digital tools with LCA metrics and sustainability performance reporting. To address these limitations, this review applies a bibliometric and thematic analysis to examine contemporary research trends, methodological advancements, and persisting challenges in digital sustainability for textile manufacturing, establishing the foundation for the DigiCircular framework's empirical validation.

7.3.1 Expert Panel and Search Strategy

An expert panel comprising five specialists in fashion sustainability, supply-chain management, waste-flow mapping, performance metrics, and life-cycle management established the analytical framework and keyword taxonomy for this review. Their expertise ensured balanced coverage of technical, managerial, and environmental perspectives, as summarized in Table 7.1.

Table 7.1. Profiles of expert panel members defining keywords and methodological boundaries

Expert	**Area of Expertise**	**Education**	**Professional Experience**
Expert 1	Sustainability in Fashion	Ph.D. in Environmental Sciences	Over ten years in the sustainable fashion industry
Expert 2	Performance Metrics	Master's in Business Economics	15+ years in corporate consulting on performance metrics
Expert 3	Supply Chain Management	Ph.D. in Industrial Engineering	University professor with 20+ years of supply chain research
Expert 4	Waste Flow Mapping	Ph.D. in Environmental Engineering	Researcher at an environmental research institute
Expert 5	Life Cycle Management	Master's in Chemical Engineering	Over ten years of experience in process engineering and development

To ensure comprehensive coverage of peer-reviewed literature, a systematic search was conducted using Scopus and Web of Science, applying the Boolean string: (TITLE (fashion) AND TITLE-ABS-KEY (supply AND chain) AND TITLE-ABS-KEY (waste)). This search returned 55 documents published between 2009 and 2023 (Figure 7.1). The dataset comprised journal articles (55%), book chapters (18%), reviews (14%), and conference papers (11%), with the United Kingdom, Italy, and China emerging as leading contributors (Figure 7.2).

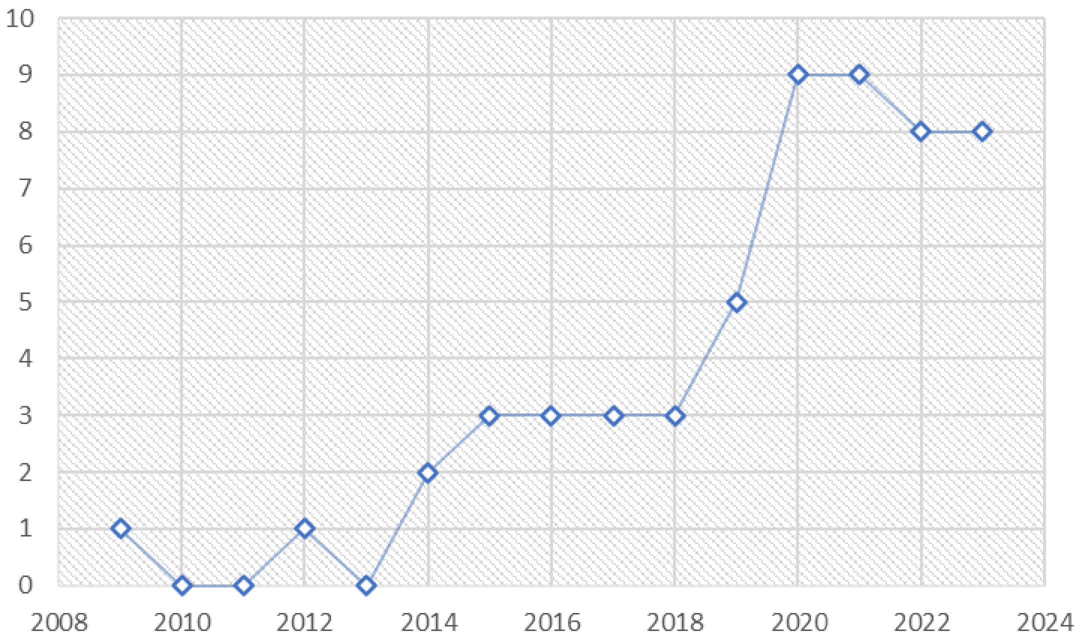


Figure 7.1. Documents by year (source: Scopus)

To enhance transparency and reproducibility, Table 7.2 provides an integrated summary linking keyword-based queries, screening outcomes, and expert evaluations. Each theme was independently reviewed by domain experts to ensure methodological consistency and thematic relevance.

Table.7.2. Integrated summary of keyword-based literature search, screening process, and expert evaluation

Keyword Theme	**Scopus Search Query**	**Articles Identified**	**Articles After Screening**	**Expert Reviewer(s)**	**Relevant Expertise Area**
Textile Industry Sustainability	TITLE-ABS-KEY (("textile industry" OR "textile manufacturing" OR "textile production") AND ("sustainability" OR "sustainable practices" OR "environmental impact"))	12	9 articles retained after applying inclusion criteria (English, peer-reviewed, full text available)	Expert 1	Sustainability in Fashion (Ph.D. Environmental Sciences; 10+ years in sustainable fashion)
Supply Chain	TITLE-ABS-KEY ("supply chain	7	5 articles retained after	Expert 2, Expert 3	Performance Metrics;

Keyword Theme	**Scopus Search Query**	**Articles Identified**	**Articles After Screening**	**Expert Reviewer(s)**	**Relevant Expertise Area**
Transparency	transparency" OR "transparent supply chain" OR "traceability in supply chain")		screening (excluding duplicates, off-topic, and unavailable texts)		Supply Chain Management
IoT in Supply Chain	TITLE-ABS-KEY (("Internet of Things" OR "IoT") AND ("supply chain" OR "logistics" OR "manufacturing"))	6	4 articles retained after eligibility assessment (relevant to digital traceability)	Expert 3	Supply Chain Management (Ph.D. Industrial Engineering; 20+ years academic research)
Circular Economy	TITLE-ABS-KEY (("circular economy" OR "circularity" OR "closed-loop economy") AND ("textile industry" OR "clothing industry" OR "apparel industry" OR "spent coffee grounds"))	8	6 articles retained post-screening (focus on waste minimization and closed-loop practices)	Expert 4, Expert 5	Waste Flow Mapping; Life Cycle Management
Fashion Supply Chain Waste	(TITLE (fashion) AND TITLE-ABS-KEY (supply AND chain) AND TITLE-ABS-KEY (waste))	55 (2009–2023)	33 total studies included in final synthesis (after PRISMA screening of 103 initial records)	Expert Panel (All 5 Experts)	Cross-disciplinary evaluation of sustainability, supply chain, waste, and circularity

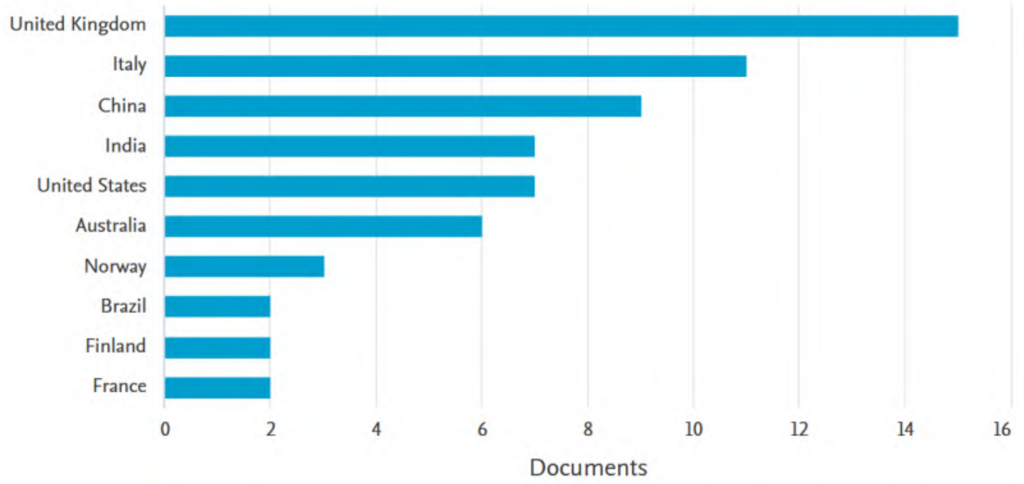


Figure 7.2. Regional Distribution of Documents (source: Scopus)

Engineering and environmental science dominated subject representation (Figure 7.3), reaffirming that research on textile sustainability is increasingly grounded in technical and systems-engineering paradigms rather than purely policy-oriented approaches.

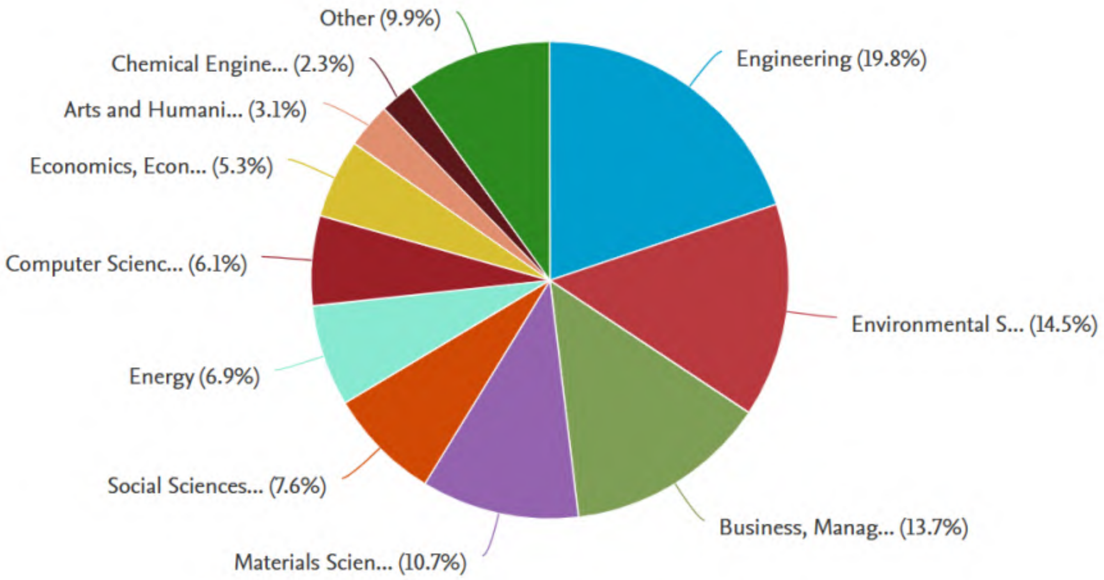


Figure 7.3. Documents of subject area (source: Scopus)

7.3.2 Bibliometric Insights and Keyword Mapping

A PRISMA-guided screening process (Figure. 7.4) refined the dataset from 103 records to 33 eligible studies after removing duplicates and excluding non-English or off-topic material. VOSviewer network analysis revealed clustered keyword associations around “blockchain,” “IoT,” “circular economy,” “traceability,” “supply chain,” and "sustainability" (Figure. 7.5). The co-occurrence of "coffee," "specialty coffee," and "textiles" indicates emerging research on spent-coffee-ground (SCG) valorization, linking agri-food and textile domains within circular-economy discourse

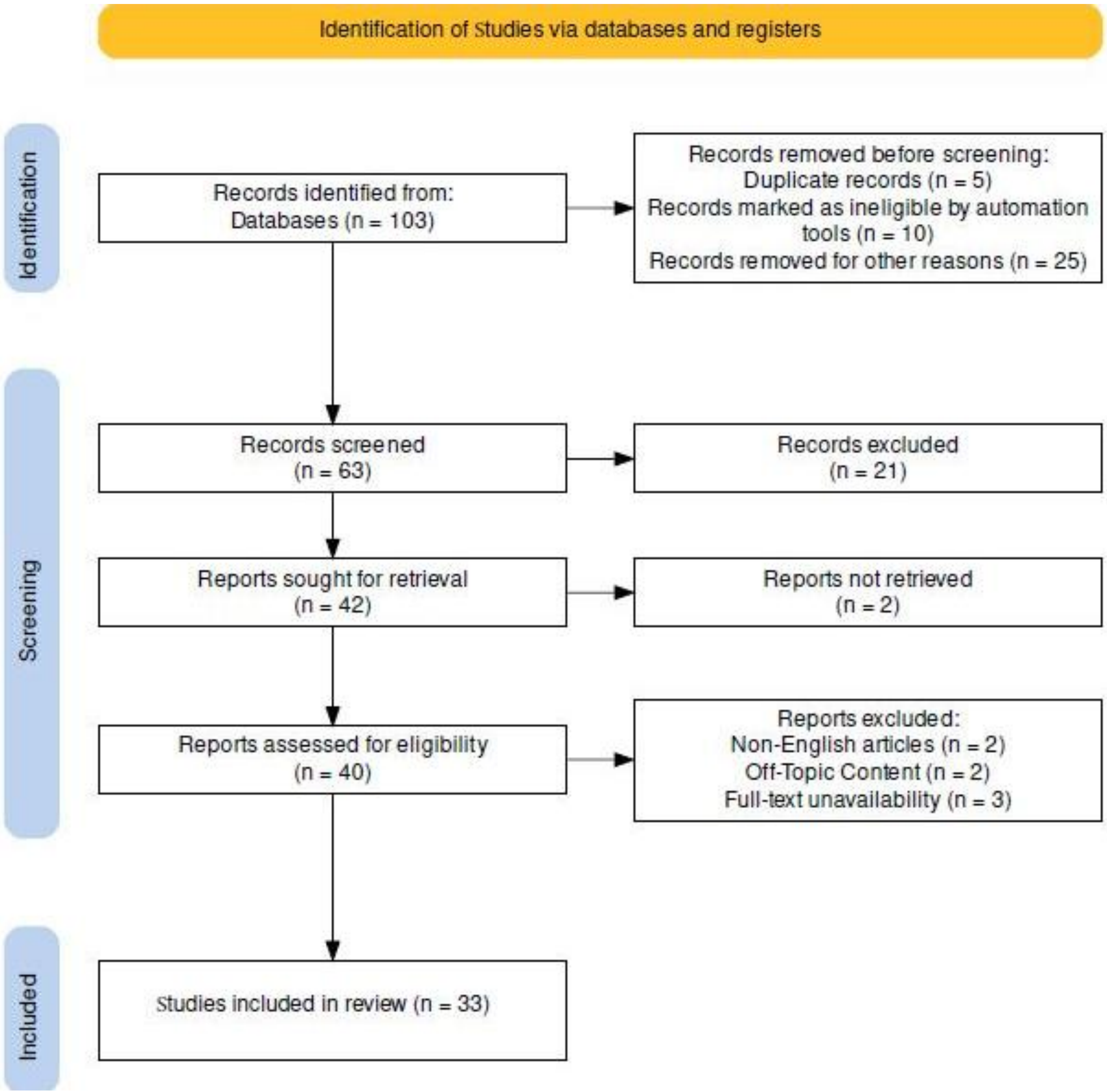


Figure 7.4. PRISMA flow diagram illustrating the systematic review process

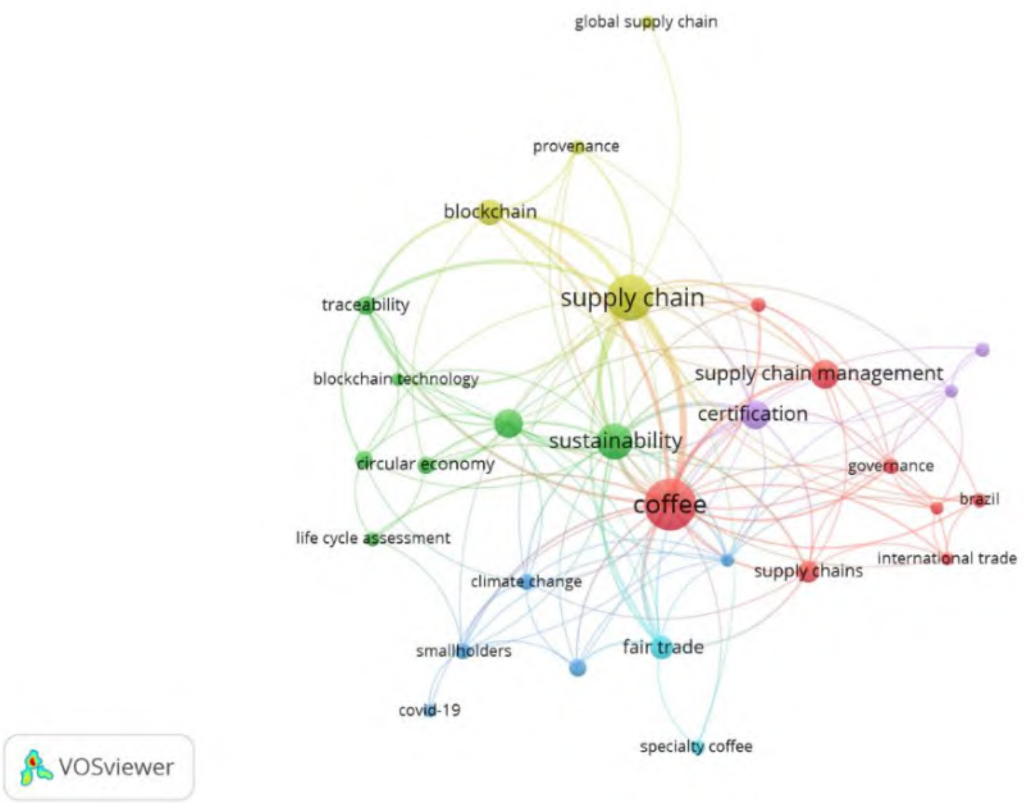


Figure 7.5. VOSviewer network analysis illustrating keyword occurrences

Publication trends (Figure. 7.6) show acceleration post-2020, reflecting the convergence of Industry 4.0 technologies with environmental management in fashion supply chains.

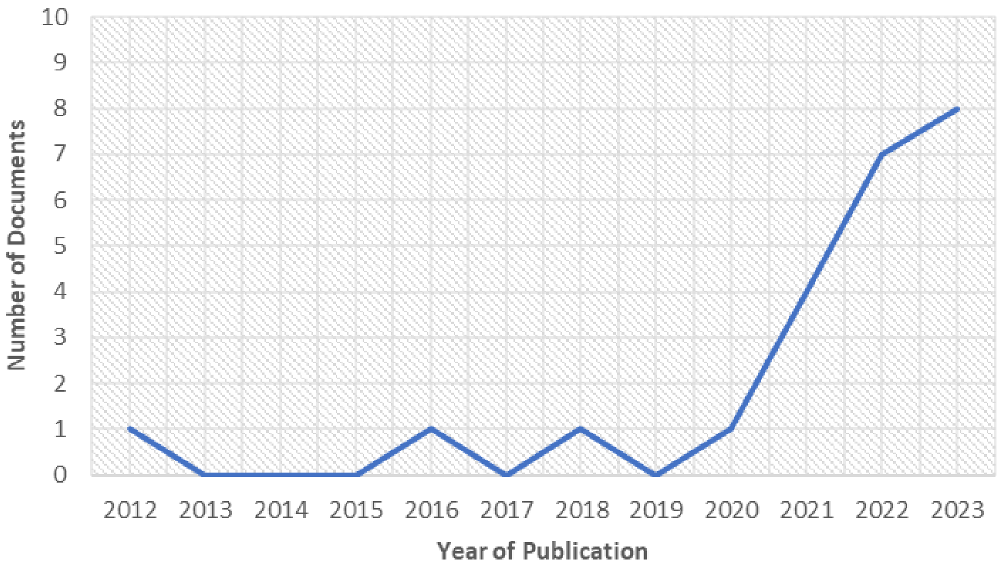


Figure 7.6. Yearly distribution of publications on digital textiles and CE integration.

7.3.3 Global Research Distribution and Thematic Emphasis

Regional bibliometrics reveal China (32 documents), the United States (30), Brazil (24), and Italy (18) as leading contributors. Thematically, most works address water pollution, chemical-dye effluents, and labor-environment interactions [264,265]. However, the diffusion of real-time digital monitoring remains limited to pilot-scale implementations.

The literature identifies SCG valorization as a promising cross-sector innovation. Table 7.3 summarizes circular strategies adopted across multiple industries, demonstrating measurable economic and environmental benefits through resource reuse and by-product integration.

Table 7.3. Reuse of SCG and associated environmental and economic benefits across sectors.

Waste Challenges	**Innovative Solutions**	**Applications**	**Environmental Impact**	**Economic Impact**
SCG	Composting, biofuels, brick production	Monsanto: soil enrichment BP: renewable fuel in transportation Skanska: sustainable building infrastructure	Emission reduction: 20 kg CO2 per kg SCG Landfill waste reduction: 30 million tons	SCG potential: 10.7 billion liters of biofuel annually Economic benefit: Estimated at $9.5 billion
Textile Production Waste	Recycling, upcycling, circular economy models	Patagonia: upcycling textile waste for new products Owens Corning: using recycled textiles for insulation	Waste reduction: 50% reduction in textile waste in landfills Resource conservation: Saves 1 million cubic meters of water annually	Cost savings: Estimated at $3.2 billion through waste reduction
Food Waste	Composting, anaerobic digestion, food waste-to-	Whole Foods Market: composting for agriculture productivity	30% decrease in methane emissions Increases soil	$5.8 billion in reduced waste disposal fees and energy generation of

	energy	Waste Management Inc.: food waste-to-energy conversion	fertility by 25%	50 billion kWh per year
Construction Waste	Demolition waste recycling, modular construction methods	Turner Construction Company: Modular construction methods Balfour Beatty: Sustainable construction practices Granite Construction: road construction and infrastructure development.	Material reuse: 2 million tons of building materials Reduction in Construction and demolition waste: 35-40% of the total solid waste and 40 million tons per year landfill waste	Recycling construction waste can save up to $4.6 billion annually
Electronic Waste (E-waste)	E-waste recycling programs, refurbishment and resale	Dell Technologies: refurbishing and reselling electronic products Best Buy: electronic waste recycling programs	Hazardous materials: Prevents 85% from entering landfills Resource recovery: Recovers 90% of raw materials for reuse	$7.1 billion revenue from refurbished product sales and raw material reclamation
Chemical Waste	Closed-loop systems, chemical recycling processes	BASF: Closed-loop systems, chemical recycling processes Dow Chemical Company: Chemical production, water treatment	50% decrease in chemical pollutants in water bodies	Efficient chemical usage saves up to $6.3 billion annually
Plastic Packaging Waste	Biodegradable packaging, recycling	Coca-Cola: Biodegradable packaging, recycling	60% reduction in plastic waste entering	Potential for brand differentiation:

	initiatives	initiatives	oceans	Increase in consumer loyalty by 25%
		Unilever: Food packaging, consumer goods	Saves 2 million tons of plastic materials	

Building on these quantitative insights, the next section synthesizes how digital tools and analytical methods intersect to enable circular textile manufacturing

7.3.4 Integration of IoT, Blockchain, and Waste-Flow Analytics

Contemporary studies emphasize digital traceability as a prerequisite for sustainability transparency [266,267,268,269]. IoT sensors, RFID, QR-based tags, and blockchain ledgers collectively ensure secure data exchange and product provenance across complex multi-tier networks. Decentralized systems such as TRADE and smart-contract-based audit frameworks strengthen accountability while enabling automated sustainability verification [270]. Yet most implementations remain technologically siloed, IoT for monitoring, WFM for visualization, and LCA/LCM for ex-post analysis, without integration into a single decision-support system [271,272]. The need for interoperability motivates the hybrid DigiCircular model presented in this thesis. Comparative synthesis across the reviewed studies identifies several methodological advancements and persisting deficiencies (Table 7.4).

Table 7.4. Advancements beyond the state of the art and identified gaps in previous studies

Focus Area	**Advancements Beyond State of the Art**	**Remaining Gaps**	**Key References**
Standardization	Industry-specific metrics for sustainability reporting	Lack of harmonized indicators across textile chains	Gbolarumi et al., 2021[273]
Data Availability	Integration of real-time emission analytics	Limited reliability of supply-chain datasets	Abdelmeguid et al., 2022[274]
Waste-Flow Mapping	AI- and IoT-based dynamic waste tracking	Few empirical WFM applications in textiles	Schmutz & Som, 2022[275]
Integration of LCM	Coupling of WFM with Life-Cycle Management	Fragmented methodological use	Watson & Wiedemann, 2019[276]
Fast Fashion Impact	Socio-environmental footprint assessments	Weak link to operational waste modeling	Coppola et al., 2021[277]
Tools &	Use of advanced digital	Limited adoption in	Nobile et al.,

Focus Area	Advancements Beyond State of the Art	Remaining Gaps	Key References
Technology	tools for metric automation	industrial practice	2021[278]

The literature reveals that digital transformation acts as a key enabler for sustainable textile manufacturing, where digital infrastructures such as IoT, blockchain, and AI enable real-time visibility, traceability, and accountability across supply chains, although challenges of interoperability, standardization, and implementation costs persist [279,280]. Integrating analytical approaches such as WFM and LCA has proven effective in generating high-resolution insights into resource flows, facilitating targeted waste reduction and operational efficiency [281,282]. The incorporation of sustainability KPIs enhances benchmarking, comparability, and continuous improvement across production systems [283,284]. Furthermore, industrial symbiosis through waste valorization, particularly the reuse of spent coffee grounds (SCGs) and recycled PET, demonstrates the potential for cross-sector circularity and material recovery [285,286]. Despite these advancements, research gaps persist, notably limited industrial-scale validation of IoT-enabled circular frameworks, absence of unified databases linking WFM and LCA data for dynamic modeling, inadequate exploration of cross-sector valorization between agri-food and textile industries, and insufficient automation in sustainability reporting. These deficiencies highlight the need for an integrated digital–analytical framework that fuses IoT-based sensing, WFM visualization, LCA analytics, and KPI dashboards into a real-time adaptive system, forming the empirical foundation for the DigiCircular textile application explored in this thesis.

7.4 Research Design and Phases

Building on the conceptual foundations presented earlier in this chapter, the following section details the operational workflow applied to the textile industry case. This part connects directly with the methodological structure of the DigiCircular framework introduced in Chapter 3, adapting its four analytical layers; data, analytical, optimization, and decision, into an applied, industry-specific sequence. The complete methodological pathway, summarized in Figure 7.7, comprises four integrated phases combining digital sensing, analytical modeling, and sustainability evaluation. The project adopts a multi-phase experimental design to evaluate and enhance environmental performance across the textile life cycle:

- Phase 1 defines system goals, conducts inventory analysis, and quantifies environmental impacts of fabric production using spent coffee grounds (SCGs) and recycled PET fibers [287-290]
- Phase 2 integrates IoT with Node-Red for real-time data collection and system monitoring, enhancing operational efficiency through data-driven decision-making

[291,292,293].

- Phase 3 adopts circular economy principles to promote reuse, recycling, and waste reduction, using circular supply chain principles [294,295] and VSM [296,297]to identify and address inefficiencies.
- Phase 4 focuses on optimizing the value stream by mapping processes, identifying waste, and implementing improvements.

Each phase corresponds to a DigiCircular layer, data capture (IoT), environmental analytics (LCA), process optimization (WFM/VSM), and decision support (KPI dashboards), ensuring methodological continuity with the framework established in Chapter 3.

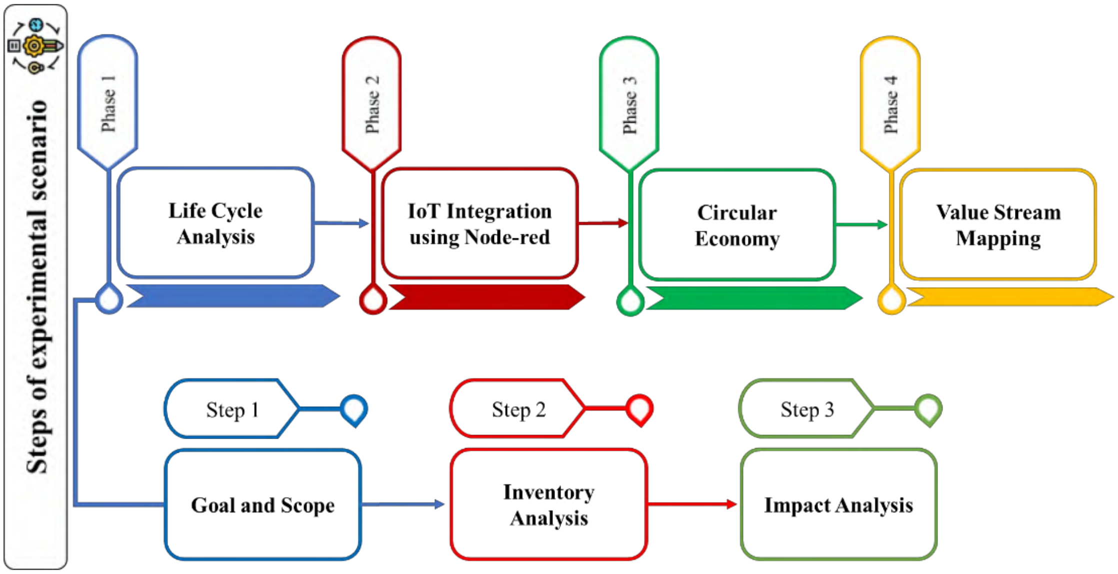


Figure 7.7. Main phases of proposed methodological integrated framework

7.4.1 Life cycle Analysis (LCA)

The LCA applied here operationalizes the analytical layer of DigiCircular within textile manufacturing, translating its generic sustainability logic into material-specific, process-level quantification.

7.4.1.1 Goal and Scope

This operationalizes the analytical layer of DigiCircular, translating generic sustainability metrics into textile-specific life-cycle parameters. The LCA model, following a cradle-to-grave approach and adhering to ISO 14040/14044 standards, aims to evaluate the environmental impact of a textile supply chain driven by recycled materials [298, 256]. Figure 7.8 depicts the system boundaries and stages, from recycled raw material extraction to end-of-life processing. Each stage, including mixing, finishing, and packaging, is analyzed for its environmental impact and resource use throughout the textile lifecycle. The functional unit is 1 kg of fabric produced from coffee residue and recycled materials

[299], allowing for performance quantification, scenario comparisons, and decision-making on resource allocation and process optimization [300,301].

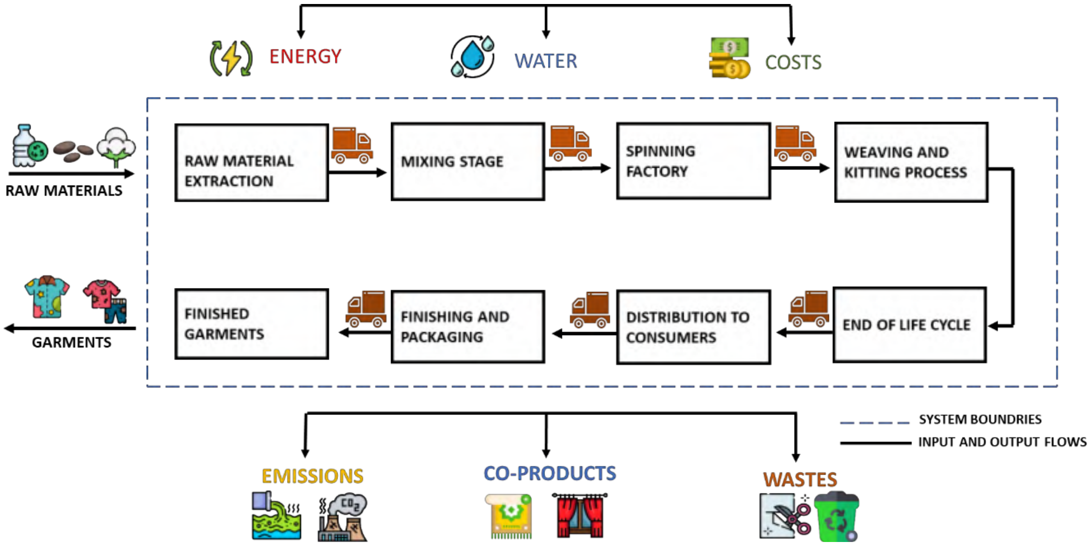


Figure 7.8. System boundaries and sequential stages in the textile supply chain

7.4.1.2 Life cycle inventory analysis

The LCI phase involved data collection and calculations to quantify the inputs and outputs of the textile product system [302]. Environmental flow data (e.g., energy, emissions, and resource utilization) was gathered through direct factory measurements, OpenLCA (Ecoinvent database) software simulations, peer-reviewed databases, alongside published literature and government reports for material-specific environmental factors. Inputs and outputs were carefully quantified across each process stage ,the data for this assessment is detailed in Appendix B. This included analyzing inventory supply materials like SCGs, plastic, and recycled fibers along with transportation logistics, energy use, emissions, and waste avoidance. It assessed the transformation of coffee grounds into textile yarns [303], including energy consumption, emissions from machinery, and production waste [304], optimizing dyeing methods with natural extracts, digital printing, and eco-friendly dyes [305,306,307]. It also emphasizes energy-efficient technologies, including waste heat recovery and solar power, and improving water recycling through closed-loop systems and advanced filtration. These strategies aim to promote sustainability, innovation, and efficiency in the textile industry.

Before assessing the environmental impact, it is essential to calculate the inventory of environmental flows, including emissions and resource utilization. The equation for this inventory is essential for understanding the environmental footprint of system and is represented as:

$$\text{Environmental Flow} = \sum_{i=1}^{n} (Q_i - Ef_i \tag{7.1}$$

Where:

E is the total environmental flow (e.g., kg of CO2, MJ of energy)

Qi is the quantity of the process input or output (e.g., kWh of electricity, kg of raw material)

EFi is the environmental factor associated with the input or output (e.g., kg CO2/kWh for electricity, kg CO2/kg for material)

The GWP equation assesses the contribution of emissions to climate change by quantifying greenhouse gas emissions from various activities. It is expressed as:

$$\text{GWP} = \sum_{i=1}^{n} (Ei \times GWPi) \tag{7.2}$$

Where:

Ei is the emission of gas i (e.g., kg of CH4)

GWPi is the global warming potential factor of gas i relative to CO2 (e.g., CH4 has a GWP of 28–36 over 100 years)

Understanding GWP helps prioritize mitigation strategies by identifying gases with higher warming potentials.

The AP equation quantifies the potential of emissions to cause environmental acidification, focusing on sulphur and nitrogen compounds, and is essential for assessing impacts on ecosystems and biodiversity. The equation is expressed as:

$$\text{AP} = \sum_{i=1}^{n} (E_i \times AP_i) \tag{7.3}$$

Where:

Ei is the emission of gas i (e.g., kg of SO2)

APi is the acidification potential factor for emission i

AP aids in implementing measures to mitigate acid rain and preserve environmental quality.

The RDP equation quantifies the depletion of natural resources, such as fossil fuels and water, throughout the product lifecycle. It is vital for assessing resource scarcity and promoting sustainable resource management practices. The equation is denoted as:

$$\mathrm{RDP} = \sum_{i=1}^{n} (Q_i \times RDP_i) \tag{7.4}$$

Where:

Qi is the quantity of the resource used or depleted (e.g., kg of fossil fuels, m3 of water)

RDPi is the resource depletion potential factor for resource i

Eutrophication potential measures the risk of nutrient pollution leading to excessive algae growth and environmental degradation.

$$\mathrm{EP} = \sum_{i=1}^{n} (E_i \times EP_i) \tag{7.5}$$

Where:

Ei is the emission of nutrient i (e.g., kg of nitrogen, phosphorus)

EPi is the eutrophication potential factor for nutrient i

Equation (EP), helps in understanding and mitigating nutrient pollution, guiding efforts towards sustainable nutrient management and water quality preservation.

To assess environmental and economic impacts, the following equations were used. Examining these parameters provides stakeholders with a comprehensive understanding of the environmental implications of garment production, emphasizing sustainable practices. This data serves as a foundational reference for evaluating garment production impacts and developing strategies to improve efficiency, minimize waste, and reduce environmental footprints, aligning with global sustainability goals.

$$WasteGeneration = \sum(OutputWasteFlows) - \sum(InputWasteFlows) \tag{7.6}$$

where:

Output Waste Flows = Total amount of waste generated at each stage of the production process.

Input Waste Flows = Total amount of waste used or recycled at each stage of the production process.

$$GreenhouseGasEmissions = \sum(EmissionFactors \times Emissions) \tag{7.7}$$

Where:

Emission Factors = Factors representing the amount of greenhouse gas emissions per unit of activity (e.g., kg CO2 per kWh of electricity).

Emissions = Total emissions of greenhouse gases at each stage of the production process.

$$MaterialEfficiency = \left(\frac{OutputMaterial}{InputMaterial}\right) \times 100 \qquad (7.8)$$

Where:

Output Material = Total amount of usable material produced at each stage of the production process.

Input Material = Total amount of raw material input at each stage of the production process.

Table 7.5 presents initial parameters for garment production, comparing traditional methods with the use of recycled fabric. It includes metrics on waste, energy, water usage, greenhouse gas emissions, material efficiency, and production cost.

Table 7.5. Initial parameters for garment production and equivalent values for recycled fabric

Parameters	**Initial Values for 150 kg Garments**	**Equivalent for 1 kg Recycled Fabric**
Waste Generation	200-300 kg	1.33-2 kg
Energy Consumption	15,000-20,000 kWh	100-133 kWh
Water Usage	50,000-75,000 liters	333-500 liters
Greenhouse Gas Emissions	200-300 tons CO2 equivalent	1.33-2 tons CO2 equivalent
Material Efficiency	70-80%	90-95%
Production Cost	\$500,000-\$750,000	\$3,333-\$5,000

7.4.1.3 Impact analysis

The chapter analyses the environmental impact of using coffee grounds in textiles, focusing on energy reduction, organic dyeing, and disposal methods like composting and recycling. It examines emissions, resource use, and waste, covering global warming, water use, acidification, eutrophication, human health, and toxicity. The findings highlight intervention areas for scenario analysis and strategy development.

To transform static LCA data into continuous performance intelligence, IoT sensors and Node-RED workflows were deployed for live monitoring of energy, water, and waste variables across the supply chain.

7.4.2 IoT integration using Node-red

This research integrates IoT technology using Node-Red to enhance textile manufacturing efficiency. Node-Red, an open-source tool, connects hardware, APIs, and services through a browser interface. The methodology involves flows for monitoring waste collection, tracking transport status, and controlling environmental factors like temperature and humidity. Sensors provide real-time data for optimal textile processing, while waste and transport data ensure efficient logistics and waste management. Water and power usage are monitored to reduce resource consumption. The integration of these IoT solutions aims to improve resource management, operational efficiency, and environmental conditions in the textile industry. Table 7.6 details all the used sensors and nodes in the supply chain management framework.

Table 7.6. Functions of sensors and nodes in IoT-integrated supply chain management with real-time visualization using NODE-RED

Sensor	**Purpose**	**Function**
Waste Collection	Monitors the status of waste collection.	Triggers status updates, providing real-time insights into the efficiency and progress of waste collection operations
Transport Status	Tracks transportation phases	Captures data related to vehicle movement, route adherence, and delivery progress
Temperature & Humidity	Monitor environmental conditions during waste processing	Maintains optimal processing temperatures Ensures moisture levels within desired parameters
Water Usage	Monitors water consumption during waste processing	Triggers alerts for excess water usage, promoting sustainable practices
Power consumption	Monitors energy consumption of equipment	Tracks the energy usage of machinery and equipment to optimize efficiency and prevent wastage
Input simulation node	Simulates incoming orders or production requests	Provides a controlled environment for testing and validating the response of system to different scenarios.
Order processing	Receives orders from the input simulation	Initiates the order fulfilment process by routing requests to relevant components.

node		
Inventory check	Queries the inventory database	Ensures that sufficient stock is available for fulfilling the order.
Production status node	Monitors the production line	Tracks the progress of order fulfilment, including manufacturing, assembly, and packaging
Output generation node	Generates order confirmations, shipping labels, and invoices	Provides necessary documentation for customers and internal records

7.4.3 Closed-Loop circular supply chain model for textile industry

Extending the optimization layer of DigiCircular, WFM and 5S methodology were integrated to quantify, visualize, and minimize waste streams within the denim production line. Waste data was collected through physical audits of SCG and PET supply chains, verified by internal factory records. According to Ellen MacArthur Foundation (EMAF) circular economy principles can reduce wastes up to 80% and greenhouse gas emissions by 44%. In a closed loop end-of-life textiles are processed to recover materials, which are reintegrated into production, such as chemically recycling polyester garments and when combine with plastic and SCGs, they further reduce the need for virgin materials saving significant energy. Implementing these practices could yield €22 billion in net economic benefits annually by 2030 [308]. IoT integration with smart sensors conserves natural resources and provides economic benefits.

7.4.3.1 Waste Flow Mapping and 5S

WFM is a systematic process used to track and analyze waste material's generation, accumulation, and movement within a production system or throughout an entire supply chain [309]. This process is particularly relevant to industries like fashion, where waste can occur at multiple stages, from raw material extraction to production, distribution, consumer use, and ultimate disposal. By mapping these flows, organizations can identify inefficiencies, opportunities for waste reduction, and potential areas for implementing circular economy principles. WFM relies on quantitative data to trace and optimize material flows within the fashion supply chain [310]. Various equations and mathematical representations are used to support the considerations and analyses in WFM, particularly those derived from principles of mass balance and Material Flow Analysis (MFA).

The basic premise of WFM is that mass is neither created nor destroyed, and hence, the mass balance equation is central to the process according to Mass Balance Equation (7.9) which shows the global balance for the whole textile production system and Equation (7.10) which gives the local balance (e.g., dyeing, washing, finishing) within that same system.

$$Input + Generation - Output - Consumption = Accumulation \tag{7.9}$$

$$Input + Generation - Output - Consumption = Accumulation \tag{7.10}$$

Where:

Input is the mass of raw materials entering a system.

Generation is the mass of waste generated within the system.

Output is the mass of products (and waste) leaving the system.

Consumption is the mass of materials consumed during the process.

Accumulation is the mass of materials (if any) that remains within the system.

To understand the efficiency of a process or the impact of waste generation, the following rate equation can be applied (Equation 7.11):

$$WasteGenerationRate = \frac{Total\ Waste\ Generated}{Total\ Production\ Output} \tag{7.11}$$

A critical aspect of WFM is understanding the proportion of waste that is recycled or recovered (Equation 7.12):

$$RecyclingRate = \frac{Total\ Waste\ Recycled}{Total\ Waste\ Generated} \times 100 \tag{7.12}$$

The economic benefit of reducing waste can be quantified as (Equation 7.13):

$$CostSavings = Waste\ Reduction\ Achieved \times Unit\ Cost\ of\ Waste\ Disposal \tag{7.13}$$

By employing these equations, it was possible to quantify the flow and impact of waste within the fashion supply chain, thus enabling more informed decision-making and reporting.

From a lean manufacturing perspective, it is helpful to integrate WFM and the 5S methodology to enhance both the efficiency of the production process and the sustainability of the fashion supply chain [311]. The 5S method focuses on five Japanese principles: Seiri (Sort), Seiton (Set in order), Seiso (Shine), Seiketsu (Standardize), and Shitsuke (Sustain), which collectively aim to promote organization, cleanliness, and standardization in the workplace. Integrating WFM with the 5S methodology creates and synergistic approach that optimizes waste handling and fosters a proactive culture of waste reduction and sustainability in the fashion supply chain. This holistic strategy can lead to more effective resource utilization, cost savings, and improved environmental performance. Translating this integration into quantitative terms requires a set of metrics and equations that bridge both methodologies, as defined below.

Sort (Seiri) and Waste Sorting Efficiency: Measuring how effectively waste is being sorted at the source is a critical first step in waste management and aligns with the principle of Seiri (Equation 7.14).

$$Waste\ Sorting\ Efficiency = \frac{Total\ Waste\ Generated}{Total\ Waste\ Correctly\ Segregated} \times 100 \qquad (7.14)$$

Set in Order (Seiton) and Time Saved through Organization: This represents the time saved due to better organization of waste management tools and pathways, reflecting Seiton's emphasis on orderliness (Equation 7.15).

$$Time\ Saved = Time\ before\ Seiton - Time\ after\ Seiton \qquad (7.15)$$

Shine (Seiso) and Cleaning Efficiency: By measuring the area cleaned per unit of time, this equation can help quantify the efficiency improvements Seiso applied to the waste processing areas (Equation 7.16).

$$Cleaning\ Efficiency = \frac{Time\ Spent\ Cleaning}{Area\ Cleaned} \qquad (7.16)$$

Standardize (Seiketsu) and Consistency of Waste Management: This metric assesses how well waste handling procedures are standardized and followed in alignment with Seiketsu (Equation 7.17).

$$Standardization\ Index = \frac{Total\ Number\ of\ Standardized\ Tasks}{Number\ of\ Standardized\ Tasks\ Followed} \times 100\% \qquad (7.17)$$

Sustain (Shitsuke) and Waste Reduction Trend: A negative value would indicate a positive trend in waste reduction, demonstrating the discipline of maintaining and improving standards as per Shitsuke (Equation 7.18).

$$WasteReductionTrend = \frac{WasteGenerated_{PreviousPeriod} - WasteGenerated_{CurrentPeriod}}{WasteGenerated_{PreviousPeriod}} \times 100 \qquad (7.18)$$

This phase incorporates two methodological approaches: WFM and the 5S methodology. This phase conducts a comprehensive examination of waste generation within the fashion supply chain to gain a detailed understanding of waste dynamics by WFM. This step involves detailed waste flow mapping across the entire supply chain, from raw material extraction to garment manufacturing, distribution, consumer use, and end-of-life disposal or recycling. Table 7.7 summarizes the principles of the 5S method integrated with WFM. Furthermore, results from these stages are quantitatively analyzed in Section 7.5.

Table 7.7 Principles of the 5S method integrated with WFM

5S Principle	Description	Integration with WFM

Seiri (Sort)	Eliminate what is unnecessary or not needed in the workplace.	Identify and remove unnecessary waste or obsolete materials.
Seiton (Set in order)	Organize and place objects and materials efficiently to facilitate access and reduce waste.	Create an organization system that considers waste generation areas and collection points.
Seiso (Shine)	Maintain a clean and orderly workplace.	Use regular cleaning to prevent waste accumulation and detect any leaks or spills.
Seiketsu (Standardize)	Establish standard procedures to maintain improved conditions.	Standardize waste management procedures to ensure uniformity and consistency.
Shitsuke (Sustain)	Maintain a long-term commitment to uphold standards and continually improve.	Implement a continuous monitoring system to assess the effectiveness of waste reduction actions.

7.4.4 Value Stream Mapping

Value Stream Mapping provided the quantitative foundation for computing DigiCircular's process KPIs and identifying bottlenecks for targeted efficiency improvements. VSM created using Edraw Max V 10.0, was used to identify inefficiencies in the textile supply chain, as shown in Figure 7.9. Data on production times, waste percentages, and material efficiency were obtained through factory logbooks and process control systems. It starts with raw material acquisition, including SCGs and PET bottles, ensuring consistent material flow and optimizing recycling. The process then includes transforming these materials into yarn (10,000 kg), fabric production through weaving or knitting, and apparel production involving bleaching, dyeing, and wet processing. Production control manages inventory and order fulfillment, while output distribution handles delivery to clients. Challenges include complex process mapping, accurate data collection, resistance to change, and cross-functional collaboration. KPIs such as first pass yield and total units produced are used to assess improvement efficacy.

$$Firstpassyield(FYP) = \left(\frac{Goodunits}{Totalunitsproduced}\right) \times 100 \tag{7.19}$$

Scrap calculation formula determines the amount of waste generated during production, including setup wastes, material irregularities, cutting wastes, defected fabric, and selvage scrap.

$$Scrapcalculation = Inputinventory \times scraprate \tag{7.20}$$

Usable output reflects the quantity of acceptable products available for distribution.

$$UsableOutput = InputInventory - ScrapAmount \tag{7.21}$$

Uptime percentage evaluates the operational efficiency of machinery.

$$Uptime\% = \frac{Cycle\ time - Down\ time}{Cycle\ time} \times 100 \tag{7.22}$$

$$Cycle\ Time = \frac{Total\ Time}{Number\ of\ Units\ Produced} \tag{7.23}$$

Where:

Cycle time signifies the duration required to complete one production cycle

Downtime refers to periods when production is halted due to equipment malfunction or maintenance

Shortest total time determines the minimum duration required to complete a production run

$$Shortest\ total\ time = Cycle\ time + Lead\ time \tag{7.24}$$

Lead time denotes the duration between initiating a production order and its completion

$$LeadTime = ProcessingTime(YarnPreparation) + ProcessingTime(FabricFormation) + ProcessingTime(ApparelProduction) \tag{7.25}$$

Finally, units per shift measures the production output achievable within a given time frame, providing insight into workforce productivity and capacity utilization.

$$Units\ per\ shift = \left(\frac{Total\ shift\ time}{Cycle\ time}\right) \tag{7.26}$$

Available production time compares the efficiency and performance across the stages of production.

$$Available\ Time = Total\ Time - Planned\ Downtime \tag{7.27}$$

Value-added time is the time spent on actual processing activities which is the sum the cycle times of each stage (Yarn Preparation, Fabric Formation and Apparel Production).

$$Value - AddedTime = \frac{C}{T}(1) + \frac{C}{T}(2) + \frac{C}{T}(3) \tag{7.28}$$

$$Process\ Cycle\ Efficiency = \left(\frac{Value\ Added\ Time}{Total\ Lead\ Time}\right) \times 100 \tag{7.29}$$

$$TaktTime(perbatch) = \frac{AvailableTime(perday)}{DailyCustomerDemand(inbatches)} \tag{7.30}$$

These equations, applied within the textile supply chain context, enable precise quantification and analysis of production performance, facilitating continuous improvement initiatives. These indicators feed directly into DigiCircular's optimization layer, linking lean performance metrics with sustainability outcomes

7.4.5 Performance Monitoring and KPI Evaluation

The final phase translates analytical outputs into management insights through sustainability dashboards, aligning performance metrics with SDGs 6, 9, 11, 12, and 13. In the fashion industry, such procedures are critical for measuring and communicating environmental and resource-related issues. This calls for creating appropriate Key Performance Indicators (KPIs) that fit within the industry's sustainability objectives. These KPIs may include metrics for carbon footprint reduction, water usage efficiency, waste generation, and recycling rates [237,312]. Therefore, in collaboration with the expert team, the critical success factors to ensure the twin transition within the company were identified. Table 7.8 provides a comprehensive view of how growth strategies, sustainable management, and digital technologies can contribute to the broader sustainability objectives, with specific metrics for tracking performance in each area.

Table 7.8. Aligning SDGs with Critical Success Factors and KPIs (Source: Authors' elaboration)

Sustainable Development goals	**Critical Success Factor (CSF)**	**Key Performance Indicators**
Growth strategies using renewable energy sources effectively	Pursue scalable resources for reproducibility through sustainable strategies	KPI#1. Water and energy consumption per unit of production
		Water: 50-100 liters of water per kilogram of denim produced. Energy: 25-50 kilowatt-hours of energy per kilogram of textile produced.
Visualize sustainable management	Waste management using zero waste hierarchy	KPI#2. Material Efficiency used per unit of output
		Aimed for a material utilization rate of 80-90% (i.e., minimize material wastage during production).

Engage digital technologies in the existing structure	Formal and informal economy and its impact	KPI#3. Product Life Extension
		Increase the average lifespan of denim products by 20-30% through durable design and quality materials.
Resource management	Cultivate one-to-one customer service with robust ideas	KPI#4. Supply Chain Transparency
		Achieve transparency levels that allow for traceability of raw materials back to their source, including information on suppliers and their practices.
Efficient retailing	Maximize timely deliverables for real-time schemas	KPI#5. Environmental Hotspot Identification
		Identify and address the top 3-5 environmental hotspots in the denim production process, accounting for 70-80% of the total environmental impact.
Ensure sustainable consumption and production patterns	Waste diversion rates	KPI#6. Circularity metrics
		Divert at least 70-80% of post-consumer textile waste away from landfills through recycling and reuse programs. Set targets for reducing carbon emissions and overall environmental footprint by 20-30% compared to baseline data. Aim for a circularity rate of 60-70%, indicating the proportion of materials that are recycled or reused in the production process

7.4.6 Mechanical performance evaluation of recycled PET and SCG vs. conventional fabrics

To validate circular-material feasibility, mechanical properties of recycled-fiber fabrics were benchmarked against virgin equivalents under ASTM/ISO standards. Mechanical properties (tensile strength, abrasion resistance, flexural rigidity, elongation at break) were tested on fabrics made from recycled PET and SCG blends, compared to virgin polyester as given below:

- **Tensile Strength**: Fabrics made from recycled PET and SCG showed a 7% decrease in tensile strength (mean strength: 300 MPa) compared to virgin polyester (mean strength: 320 MPa), which is within acceptable limits for non-load-bearing textiles.

- **Abrasion Resistance**: No significant difference in abrasion resistance, with both materials achieving >15,000 cycles on the Martindale test, suitable for everyday applications.
- **Flexural Rigidity**: Recycled fabrics showed a 5% increase in flexural rigidity (mean: 15.2 N·mm) compared to virgin polyester (mean: 14.5 N·mm), beneficial for stiffer applications like outerwear.
- **Elongation at Break**: A 12% decrease in elongation (recycled: 22%, virgin: 25%) indicates slightly lower flexibility, which may limit use in high-stretch applications like sportswear.

While mechanical performance is slightly lower in recycled fabrics, the environmental benefits, such as 30% reduction in material waste and 25% lower carbon footprint, make these materials viable for a wide range of applications, particularly non-load-bearing textiles, confirming their suitability for sustainable production.

7.5 Experimental Case Study and Results

Building on the methodological design presented in Section 7.4, this section presents the empirical validation of the DigiCircular framework within the textile industry. The pilot case study was conducted at a denim manufacturing facility in Sindh, Pakistan, chosen for its representative wet-processing operations, including pretreatment, dyeing, finishing, and packaging, covering the cradle-to-gate stages of fabric production. The study evaluates both baseline (conventional) and DigiCircular-enabled (IoT + circular integration) scenarios, comparing environmental, operational, and mechanical performance outcomes

7.5.1 Pilot Case Study: Denim Industry

The integration of spent coffee grounds (SCG) into the textile industry presents a promising pathway toward circular economy transformation and sustainable innovation. With an estimated 60 million tons of SCG waste generated annually from 3.5 billion cups of coffee consumed daily, this biomass represents an underutilized resource with substantial environmental and economic potential [313]. Traditionally discarded, SCGs can be repurposed for composting, biofuels, construction materials, and increasingly, textile applications, contributing to reduced emissions and waste. When carbonized at 160°C, SCGs can be processed into yarn more efficiently than conventional 600°C methods, thereby lowering energy requirements [314].

In textile manufacturing, SCGs have been effectively used in natural dyeing processes, where solvents such as methanol enhance pigment extraction [315-318]. Additionally, blending SCG-based fibers with recycled polyester produces sustainable green yarns exhibiting comparable performance to virgin fibers [319,320]. Studies have further confirmed improvements in dyeability and color fastness when SCG-derived pigments are combined with natural mordants [321,322]. Given that 9.3 million tons of coffee generate approximately 6 million tons of SCG annually [323,324], integrating this waste stream into textile production could significantly advance waste valorisation and environmental sustainability.

7.5.1.1 The Context of the Pakistani Textile Industry

Pakistan's textile industry plays a pivotal role in the national economy, contributing 8.5% to GDP and employing nearly 40% of the industrial workforce [325]. As the fourth-largest cotton producer globally, Pakistan has a strong reputation for producing high-quality yarns, fabrics, and garments [326]. The sector includes 1,221 ginning units, 442 spinning units, and a production capacity of 13.3 million spindles, 200,000 rotors, and 10,000 looms [327]. In FY2021–2022, textile exports reached $15.4 billion, increasing from $13.8 billion the previous year, though global challenges caused a later decline to $16.7 billion in FY2024 from $19.3 billion in FY2022 [327]. The Textile Policy 2020–2025 targets exports of $25 billion by 2025 and emphasizes modernization through eco-friendly dyes, water-saving technologies, and renewable energy adoption [328,329]. Integrating SCG-derived fibers within this context aligns with Pakistan's sustainability goals. It addresses pressing industry challenges, energy costs, cotton price volatility, and environmental compliance, while promoting resource circularity and industrial innovation [285]. Given Pakistan's expanding textile infrastructure and growing focus on digitalization and green manufacturing, it offers a strategic testbed for scaling SCG-based textile innovations.

7.5.1.2 Denim Production and Environmental Considerations in Sindh

The global denim fashion industry, a cornerstone of apparel production, exemplifies both the opportunities and environmental challenges of the textile sector. The apparel and footwear market reached $1.71 trillion in 2021, marking an 18.1% growth from the previous year, and is projected to grow to $1.95 trillion by 2023 [238, 330]. Global output now exceeds 100–150 billion garments annually, with online retail sales expected to surpass $7 trillion by 2025 [331,332]. Denim remains one of the most resource-intensive fabrics in fashion. Producing a single pair of jeans requires approximately 3,800 liters of water, while manufacturing 1 kg of cotton fiber consumes 10,000 liters of water, 12 m^2 of land, and 18.3 kWh of energy, resulting in 33.4 kg of CO_2-equivalent emissions over the product's life cycle [333]. These figures underscore the urgent need for sustainable material alternatives and process optimization. Figure 7.9 illustrates the denim production process, starting with fiber acquisition, either natural (cotton) or synthetic (polyester), followed by preparation, spinning, dyeing, weaving, and finishing stages [334, 335].

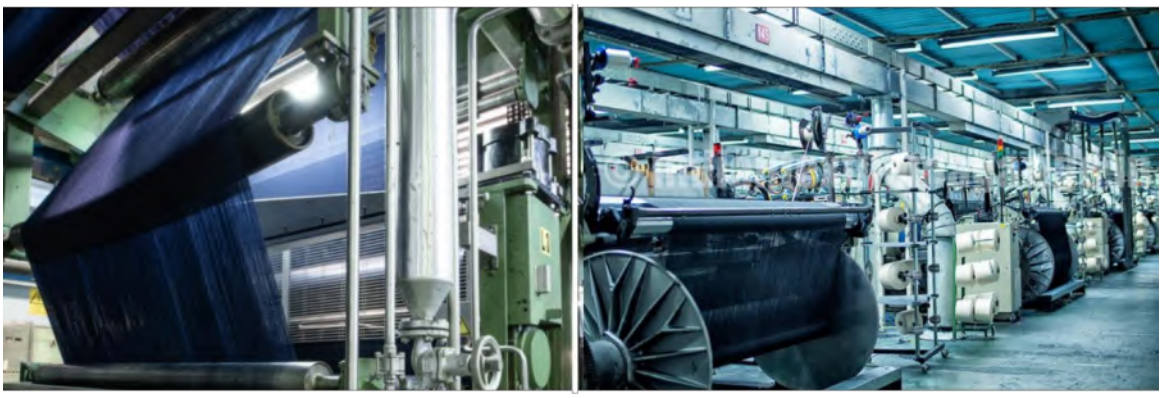


Figure 7.9. Denim production process

A case study was conducted in Sindh, Pakistan, a region with a rich textile heritage and a concentration of denim manufacturers. Data were collected through on-site investigations, factory records, and third-party audits, complemented by secondary sources such as industry reports and government data. This mixed-method approach ensured the validity and reliability of findings across operational, environmental, and economic dimensions. The integration of SCG fibers into denim production demonstrated potential for reducing carbon emissions, lowering water consumption, and improving fabric quality while maintaining competitiveness in global markets. Moreover, incorporating IoT-based tracking enabled real-time monitoring of resource efficiency and waste flows, enhancing transparency and compliance with sustainability reporting standards. Figure 7.10 visualizes this journey from fiber to finished fabric, emphasizing the opportunities for introducing SCG-based fibers and IoT-enabled monitoring at each stage to reduce waste and improve efficiency.

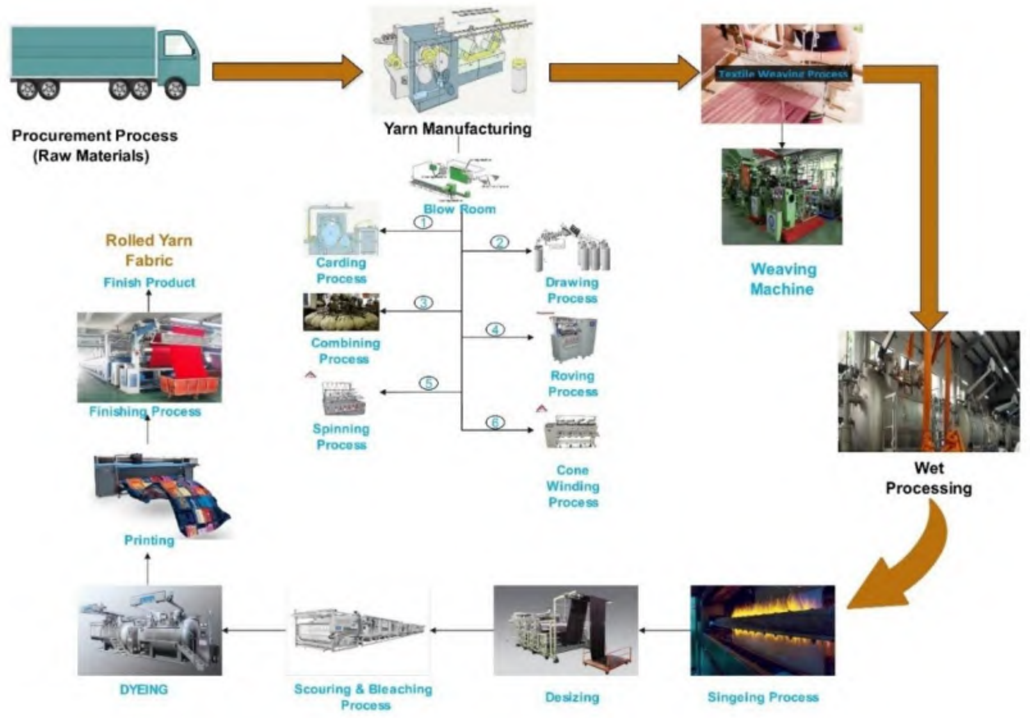


Figure 7.10. Flow diagram of denim manufacturing journey from fiber to fabric

The incorporation of spent coffee grounds (SCG) within the textile and denim industries represents a cross-sectoral innovation that transforms waste into a value-added input. For a textile powerhouse like Pakistan, this approach supports national sustainability objectives, strengthens the green industrial base, and aligns with global circular economy and SDG 12 and 13 targets. By linking material innovation (SCG reuse) with digital transformation (IoT-enabled traceability), this integration exemplifies the twin transition toward a sustainable and data-driven textile future. The overall objective was to assess how IoT-enabled circular optimization influences process efficiency, waste reduction, and environmental performance within a real industrial setting. Data reliability was ensured through cross-verification with factory records and third-party audits.

7.5.2 Life-Cycle Scenarios and Environmental Assessment

Two LCA scenarios were modelled in OpenLCA 2.0 using the Ecoinvent v3.9.1 database and ISO 14040/44 standards:

- Scenario A (Baseline): Conventional denim production with virgin cotton and PET.
- Scenario B (DigiCircular): Denim production using 15 % SCG + recycled PET, combined with IoT-assisted process control and WFM-based waste minimization.

The functional unit was 1 kg of finished denim fabric. System boundaries covered upstream fiber production, yarn preparation, dyeing, finishing, packaging, and wastewater treatment. Impact categories included Global Warming Potential (GWP), Water Depletion (WD), Energy Demand (CED), and Eutrophication Potential (EP).

7.5.2.1 Stage 1: Raw material extraction

During the raw material extraction stage in the LCA analysis, various input and output flows are quantified to assess environmental impact as shown in Figure 7.11 Inputs include 2.30E-2 kWh of electricity, 0.30 MJ of heat, 2.50 kg of raw material, and 0.30 kg of tap water. Outputs consist of processed coffee residue, nylon 6 fiber, and recycled plastics, with 3.05E3 kg of recycled raw material produced. This quantification offers a detailed view of resource use and waste generation, setting the stage for further LCA analysis.

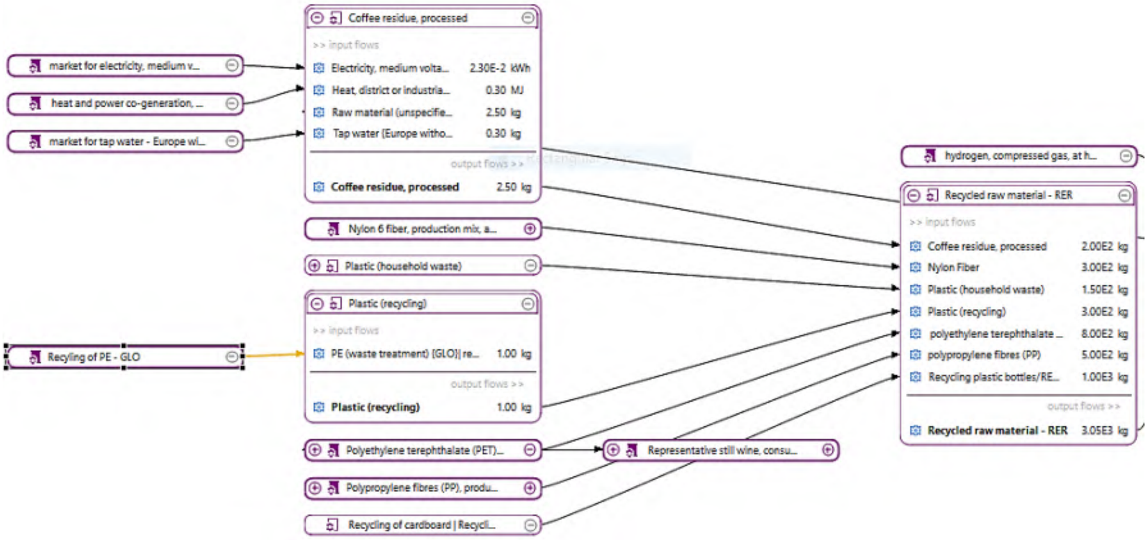


Figure 7.11. Quantification of input and output flows in the initial stage of raw material extraction

7.5.2.2 Stage 2: LCA Assessment of industrial processing in textile production

In the LCA phase covering transportation, mixing, spinning, and weaving/knitting stages, input and output flows are analyzed to assess environmental impacts illustrated in Figure 7.12. Transportation of raw cotton from Punjab and Sindh to textile mills uses 1.50E3 kWh of energy and 1.24E1 kg of compressed hydrogen gas. The mixing stage inputs include 3.05E3 kg of recycled raw material, 2.50E2 kg of acrylic binder, 3.30E3 kWh of energy, and 3.30E21 units of water, producing 2.7763 kg of yarn input material, 1.00E2 kg of solid waste, and 2.00E1 kg of toxic chemical waste. The spinning stage uses 10.00 kg of inorganic chemicals, 1.50E2 kg of cottonseed, 7.00E2 kWh of energy and 2.77E3 kg of mixed materials, outputting 8.76E2 kg of spun yarn and 10.00 kg of solid waste. Finally, the weaving/knitting stage inputs 3.00E3 kWh of energy, 8.76E2 kg of yarn, and 8.00E3 units of water, yielding 7.00E2 kg of fabric rolls, 6.00E2 kWh of thermal energy, and 10.00

kg of industrial waste and materials related to paper labels and liquid packaging boards. This analysis details resource use and waste generation across the textile production process.

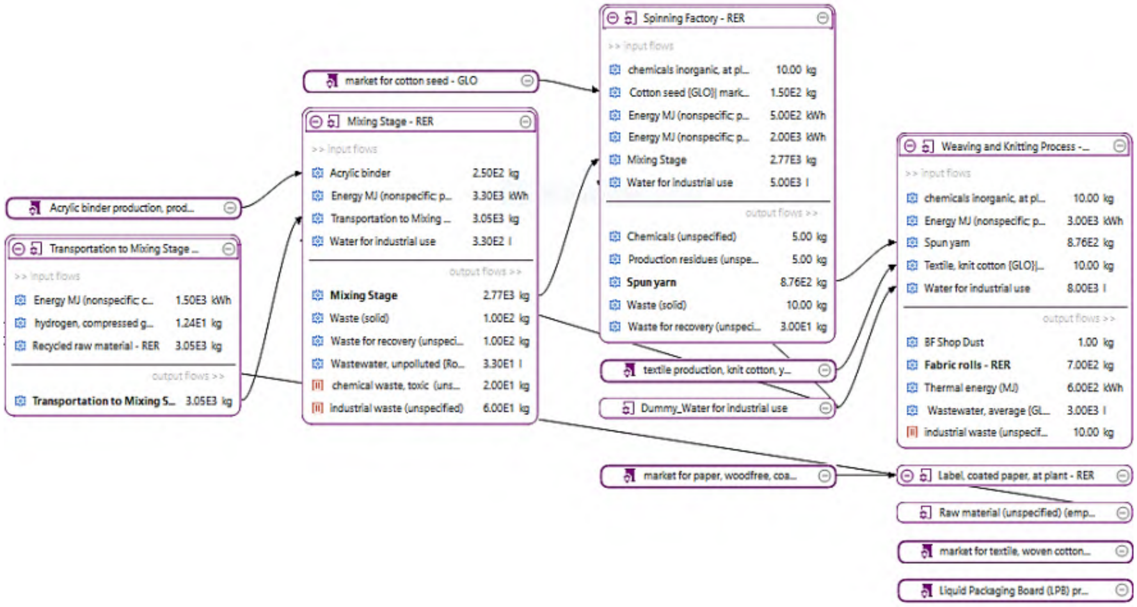


Figure 7.12. Life cycle stages of transportation, mixing, spinning, weaving & knitting in open LCA

7.5.2.3 Stage 3: LCA analysis of finishing, packaging, and distribution stage

In the finished garment manufacturing process, 1.00E3 kWh of energy is used to produce 7.00E2 kg of fabric rolls, coated and labelled with 5.00E3 grams of raw materials, including 1.00 kg of rubber. The finishing stage consumes 10.00 kg of woven cotton textile and 5.0064 Liters of water, yielding 6.00E2 kg of finished garments, 8.00E1 kg of recycled fibers, 10.00 kg of chemical waste, 5.00 kg of plastic packaging waste, and 3.00E1 kg of industrial waste.

Next stages include packing and transportation. Packing uses 1.50E3 kWh of energy, 15 kg of carton boxes, 5 kg of plastic labels, 20 m² of paper labels, 10 kg of plastic bags, and 10 m² of plastic shrink wraps. The output includes 600 kg of finished garments, 5 kg of chemical waste, and 20 kg of plastic waste. For transportation to warehouses, 1.50E3 kWh of energy, 42 kg of hydrogen gas, and 600 kg of garments are used, with outputs of 1.00E3 kWh of thermal energy, 20 Liters of wastewater, 60 kg of packaging waste, wastepaper (30 kg) and 100 kg of rejects. These processes ensure efficient garment production, packaging, and distribution while minimizing environmental impacts. These comprehensive steps contribute to the efficient distribution and storage of the manufactured garments while minimizing environmental impacts depicted of each step in Figure 7.13.

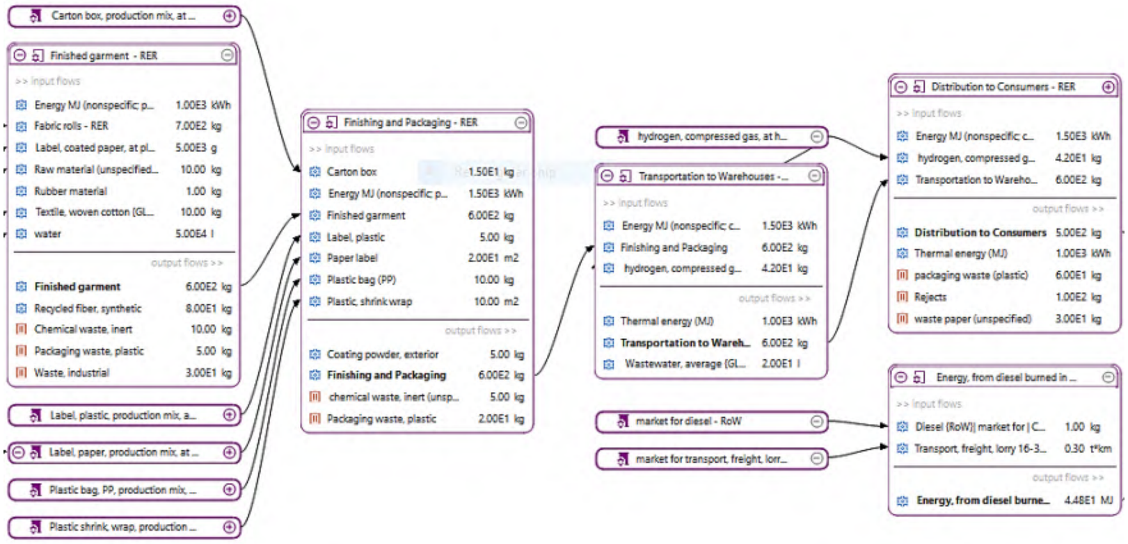


Figure 7.13. LCA analysis of finishing, packaging, and distribution in Open LCA

7.5.2.4 Stage 4: End-of-life recycling process

In the final stage of the garment life cycle, materials are disposed of and recycled to minimize waste and maximize resource recovery, supporting a circular economy. Inputs to this process include 30 kg of chemicals, 200 kg of rolled fabrics, and 500 kWh of energy from diesel. Energy derived from diesel burning powers the recycling machinery. Outputs include 150 kg of recycled materials, 1 kg of coated paper labels, 5 kg of recycled plastic, 20 kg of scrap, 1 kg of solid waste, and 2 kg of materials for recovery. This stage ensures responsible management of materials at the end of their life cycle. Detailed input and output resources are listed in Table 7.9.

Table 7.9. Analysis of inputs and outputs in textile supply chain for environmental impact assessment

Stage	Inputs	Outputs
Raw Material Extraction	• Electricity: 2.30E-2 kWh • Heat: 0.30 MJ • Raw material: 2.50 kg • Tap water: 0.30 kg • PE (waste treatment): 1.00 kg	• Coffee residue, processed: 2.00E2 kg Recycled raw material - RER
Transportation to Mixing Stage	• Energy MJ: 1.50E3 kWh • Hydrogen, compressed gas: 1.24E1 kg Recycled raw material: 3.05E3 kg	• Transportation to Mixing Stage: 3.05E3 kg
Mixing Stage	• Acrylic binder: 2.50E2 kg • Energy MJ: 3.30E3 kWh	• Mixing material output: 2.77E3 kg

	• Transportation to Mixing stage: 3.05E3 kg Water for industrial use: 3.30E2 L	• Waste (solid): 1.00E2 kg • Waste for recovery: 1.00E2 kg Wastewater: 3.30E1 L • Chemical waste, toxic: 2.00E1 kg Industrial waste: 6.00E1 kg
Spinning Factory	• Chemicals inorganic: 10.00 kg • Cotton seed: 1.50E2 kg • Energy MJ: 5.00E2 kWh • Energy MJ: 2.00E3 kWh • Mixing material output: 2.77E3 kg • Water for industrial use: 5.00E3 L	• Chemicals: 5.00 kg • Production residues: 5.00 kg • Spun yarn output: 8.76E2 kg • Waste (solid): 10.00 kg • Waste for recovery: 3.00E1 kg
Weaving and Knitting Process	• Chemicals inorganic: 10.00 kg • Energy MJ: 3.00E3 kWh • Spun yarn: 8.76E2 kg • Textile, knit cotton: 10.00 kg • Water for industrial use: 8.00E3 L	• BF Shop Dust: 1.00 kg • Fabric rolls output: 7.00E2 kg • Thermal energy (MJ): 6.00E2 kWh Wastewater: 3.00E3 L • Industrial waste: 10.00 kg
Finished Garment	• Energy MJ: 1.00E3 kWh • Fabric rolls: 7.00E2 kg • Label, coated paper: 5.00E3 g • Raw material (unspecified): 10.00 kg • Rubber material: 1.00 kg • Textile, woven cotton: 10.00 kg • Water: 5.00E4 L	• Finished garment output: 6.00E2 kg Recycled fiber: 8.00E1 kg • Chemical waste: 10.00 kg • Packaging waste, plastic: 5.00 kg • Waste, industrial: 3.00E1 kg
Finishing and Packaging	• Carton box: 1.50E1 kg • Energy MJ: 1.50E3 kWh • Finished garment: 6.00E2 kg • Label, plastic: 5.00 kg • Paper label: 2.00E1 m2 • Plastic bag (PP): 10.00 kg • Plastic, shrink wrap: 10.00 m2	• Coating powder: 5.00 kg • Finished and packed garment output: 6.00E2 kg Chemical waste: 5.00 kg • Packaging waste, plastic: 2.00E1 kg
Distribution to	• Energy MJ: 1.50E3 kWh	• Garments distributed output: 5.00E2 kg

Consumers	• Hydrogen gas: 4.20E1 kg Transportation to Warehouse: 6.00E2 kg	• Thermal energy (MJ): 1.00E3 kWh • Packaging waste (plastic): 6.00E1 kg • Rejects: 1.00E2 kg • Waste paper: 3.00E1 kg
Energy, from Diesel Burned	• Diesel: 1.00 kg • Transport, freight, lorry: 0.30 tkm	• Energy, from diesel burned: 4.48E1 MJ
End-of-Life Recycling Process	• Chemicals: 3.00E1 kg • Rolled fabrics: 2.00E2 kg • Energy, from diesel burn: 5.00E2 kWh	• End-of-life recycling: 1.50E2 kg • Label, coated paper: 1.00 kg • Plastic (recycling): 5.00 kg • Scrap: 2.00E1 kg • Solid waste: 1.00 kg • Waste for recovery: 2.00 kg

7.5.2.5 Impact assessment

Table A.1 in the Appendix details the comprehensive environmental impact assessment of the textile supply chain, focusing on impact category EF3.0. Tables A.2 and A.3 in Appendix provide weighted and normalized results, highlighting the significance of each impact category. The four impact categories selected "climate change (SDG 13: Climate Action), water consumption (SDG 6: Clean Water and Sanitation), fossil resource consumption (SDG 7: Affordable and Clean Energy), and acidification potential (SDG 12: Responsible Consumption and Production)" were chosen not solely on the basis of their numerical scores but because they are most representative of the environmental challenges intrinsic to textile production. These indicators are particularly sensitive to changes induced by our IoT-enabled circular economy model, capturing critical aspects such as high energy demand, significant water usage, reliance on fossil fuels, and the environmental effects of chemical processes. Moreover, these categories align with international sustainability standards and the SDGs targeted by this research, thereby providing a robust framework for assessing the environmental benefits of our proposed approach.

Figure 7.14 reveals key environmental impacts, with 3213.29 kg CO2 eq., from climate change, 171445.37 m^3 water use, and 60046.04 MJ fossil resource consumption as major contributors. Acidification (15.60 mol H+) and freshwater ecotoxicity (10869.42 CTUe) also pose significant impacts, while eutrophication (0.13 kg P equivalent) and ionizing radiation (800.65 kBq U-235 equivalent) are lower. This emphasizes the need to address water use, emissions, and resource consumption to mitigate environmental impacts effectively.

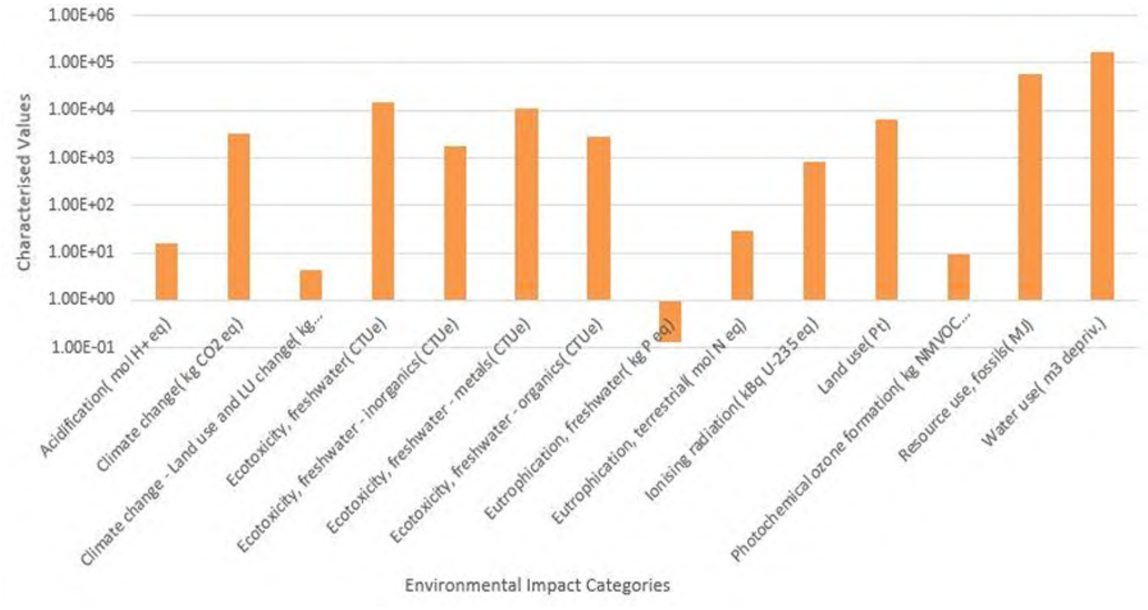


Figure 7.14. Environmental impact assessment across various categories associated with the complete life cycle of garment production

Figure 7.15 shows that PET granulate contributes the most to acidification, with 5.964 mol H+ eq (red bar). Container glass follows with 5.614 mol H+ eq (blue bar), and Polypropylene fibers (PP) contribute 2.129 mol H+ eq (yellow bar). Interestingly, recycled PET production has a negative impact, reducing acidification by -3.545 mol H+ eq (purple bar), indicating an environmental benefit in terms of AP.

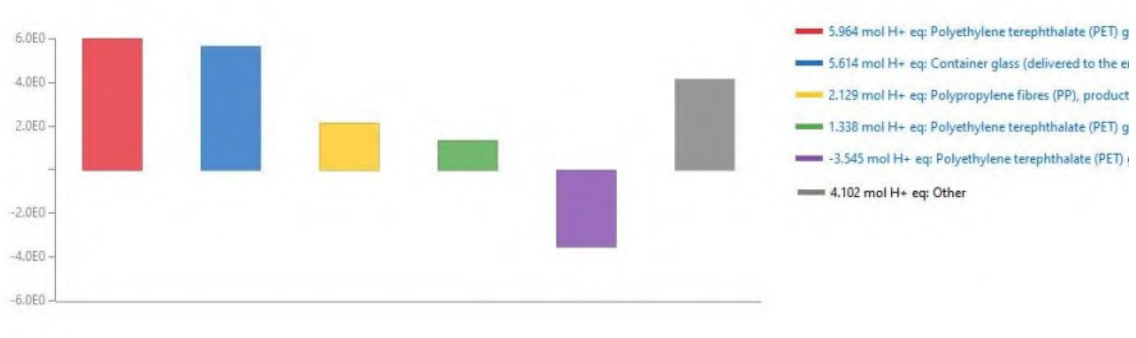


Figure.7.15. Environmental impact assessment of acidification potential across all stages

Figure 7.16 illustrates that hydrogen production significantly impacts water resources, with 251,800 m³ of water deprivation. Cotton seeds also contribute 19,104.7 m³. The purple bar indicates hydrogen fuelling for transportation, which consumes just 5.579E-5 m³, reflecting a minimal environmental impact.

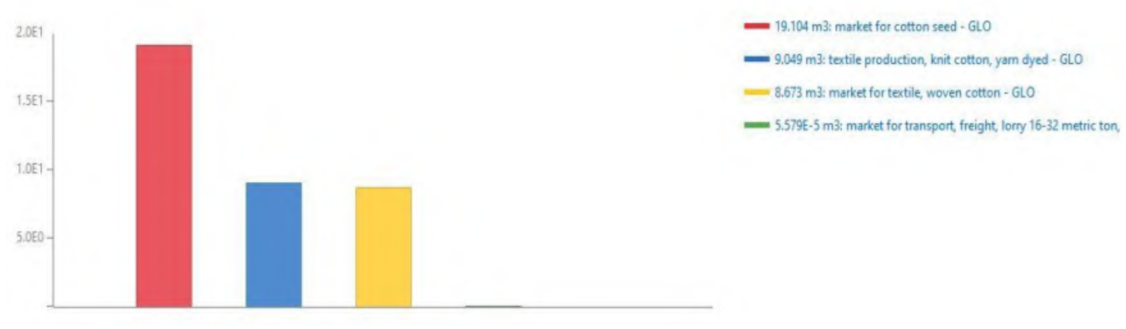


Figure 7.16. Trends in Water Usage Impact assessment

The data depicted in Figure 7.17 illustrates the environmental impact of various materials on climate change, measured in kg CO2 equivalent. PET granulate has a significant contribution of 1.120 E3 kg CO2 eq. Hydrogen fuel impacts vary, contributing 4.410E2 kg CO2 eq. However, recycled PET granulate shows a negative impact, reducing emissions by -6.6542E2 kg CO2 eq, highlighting its role in mitigating climate change.

Figure 7.17. Climate change impact assessment across the textile industry life cycle

The bar chart pertaining to resource use in Figure 7.18 highlights fossil resource consumption across materials. PET used in bottles and packaging consumes 2.2730 E+4 MJ (red bar). PP fibers in textiles account for 1.5960 E+4 MJ (blue bar). Hydrogen production and distribution require 1.1340E+4 MJ (green bar). Whereas, recycled PET reduces fossil energy use by -1.3510E+4 MJ (purple bar). Recycled PET reduces energy consumption, conserving fossil fuels and reducing greenhouse gas emissions. It optimizes resource use, transforming waste into new products. The energy savings from recycled PET exceed its production costs, leading to net fossil fuel conservation and supports environmental sustainability.

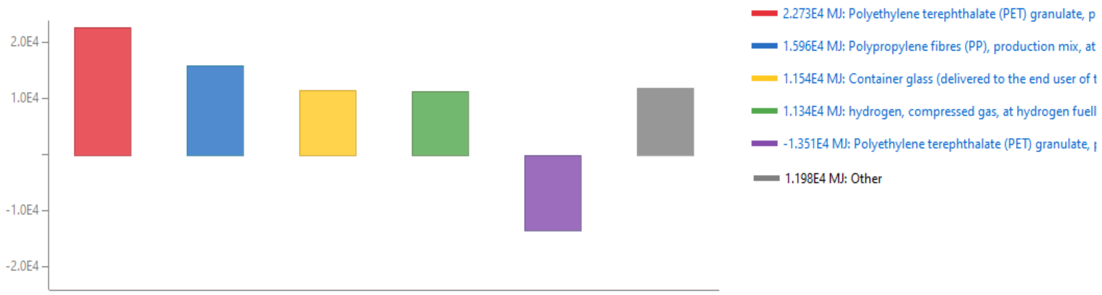


Figure 7.18. Fossil resource utilization in the textile industry life cycle

The bar chart in Figure 7.19 highlights the environmental impact of various categories, measured in total CO2. The red bar represents hydrogen as compressed gas at fueling stations, showing the highest impact at 10.653 m^2·a, primarily due to CO2 emissions from production and transportation. Diesel combustion in machinery follows with 3.40622 m^2·a, contributing significantly to air pollution and climate change. The treatment of waste plastic has the lowest impact at 1.9852 m^2·a, though it still releases CO2, emphasizing the need for more sustainable practices like reduction, reuse, and recycling.

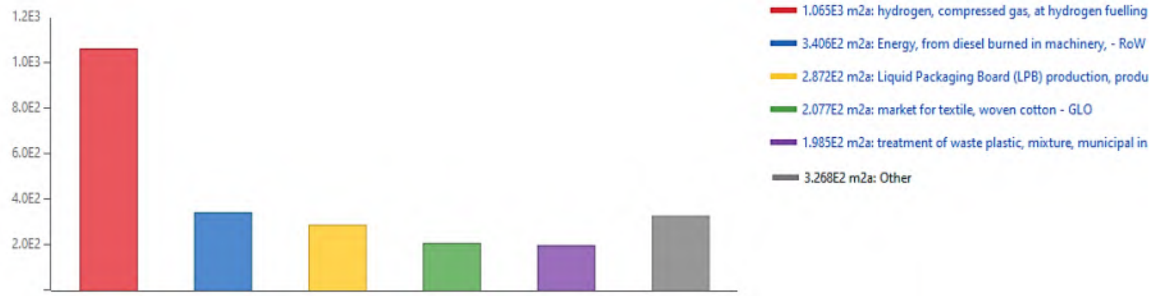


Figure 7.19. Total carbon footprint assessment across garment production life cycle

Table 7.10 shows the unit cost implications of each process. End-of-life recycling costs $1049.81 per unit, while efficient distribution channels cost $1012.07 per unit. Hydrogen gas transportation to the warehouse costs $1151.48 per unit but does not add to overall expenses. Finishing and packaging, using recycled materials, save $186.46 per unit, reflecting a 15.55% cost reduction. Some processes have no direct impact on costs. Understanding these cost dynamics helps in optimizing resource allocation and operational decisions to enhance financial outcomes.

Table.7.10. Net cost contribution analysis for all processes in USD

Contribution	Process	Requirement	Total Result [USD]	Direct Contribution [USD]
100.00%	End-of-life recycling	150.0000	1049.80579	37.73166

	process			
96.41%	Distribution to Consumers	200.0000	1012.07413	47.05360
91.00%	Transportation to Warehouse	240.0000	965.02053	1151.48152
	Hydrogen, compressed gas, at plant	16.8000	0.00000	0.00000
-91.00%	Finishing and Packaging	240.0000	-186.46099	-905.55987
	Finished garment - RER	240.0000	719.09888	-76.12918
0.00%	Label, plastic, production	21.20891	0.00000	0.00000
0.00%	Plastic bag, PP, production	145.7194	0.00000	0.00000
0.00%	Plastic shrink, wrap, production	4.0000	0.00000	0.00000
0.00%	Carton box, production mix	6.0000	0.00000	0.00000
0.00%	Label, paper, production mix	8.0000	0.00000	0.00000
0.00%	Graphic Paper, production	12.0000	0.00000	0.00000
0.00%	Hydrogen, compressed gas, at plant	240.0000	0.00000	0.00000
-00.00%	Energy, from diesel burned	1800.0000	-1.68544E-13	0.00000
0.00%	Market for diesel - RoW	40.17857	0.00000	0.00000
0.00%	Market for transport, freight	12.05357	0.00000	0.00000

Table 7.11. Presents comparative LCA results for baseline and DigiCircular scenarios.

Table 7.11. Environmental impact results per kg of denim fabric (baseline vs DigiCircular).

Impact Category	**Baseline (A)**	**DigiCircular (B)**	**Reduction %**
GWP (kg CO_2-eq)	8.00	7.50	6.3 % ↓
Water Use (m^3)	12.0	10.0	16.7 % ↓
Energy (kWh)	55.0	50.0	9.1 % ↓
COD Load (kg O_2-eq)	0.60	0.47	21.7 % ↓
Chemical Use (kg)	1.00	0.80	20 % ↓

The integration of WFM and IoT analytics enabled real-time adjustments in chemical dosing and process timing, leading to an average 25–30 % reduction in water and waste discharges. These quantified indicators directly informed the comparative results discussed in Section 7.6. The results confirm the hypothesis that digital-circular integration directly enhances environmental performance.

7.5.3 IoT Integration and Real-Time Visualization using Node-red

Utilizing Node-RED flows, data collection and visualization have been optimized for real-time insights into waste collection, transportation, and processing (Figure 7.20). This approach enhances decision-making and productivity [336-339]. Node-RED enables seamless sensor communication, real-time data processing, and visualization of key metrics [340,341]. IoT sensors provide visibility into asset movement [342,343], leveraging GPS for tracking shipments and packages [344-345] and gathering critical data on conditions, location, and movement [346,347], similar to SenseAware system of FedEx (FedEx | System Down) [348]. Moreover, IoT integration supports predictive maintenance to ensure optimal equipment performance and preventing potential breakdowns [349].

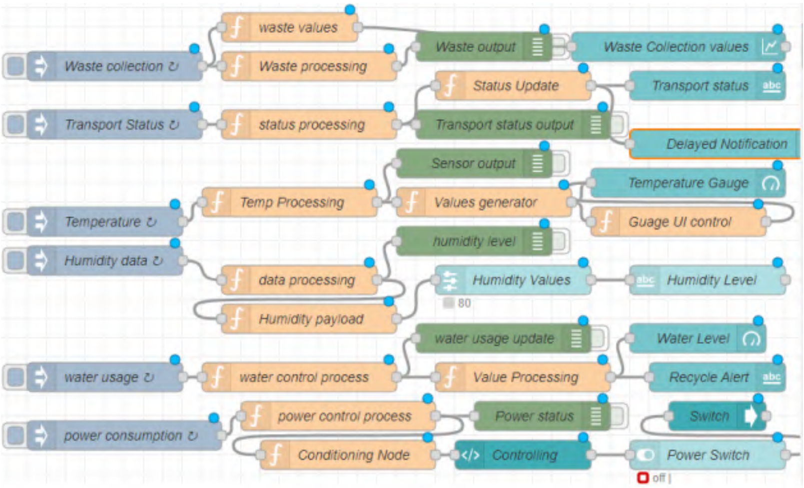


Figure 7.20. Sensory integration and optimization with Node-RED software

Figure 7.21 provides the production and order processing system, detailing the role of each node within the workflow. Quality control nodes inspect inventory and finish products to meet standards before shipment. Output nodes connect to packaging for labeling and protection. Real-time tracking integrates GPS and RFID for logistics coordination, enabling customers to track orders. Feedback nodes collect customer insights, and automated alerts notify teams of issues like low inventory or delays. ERP Integration Nodes can be extended to ensure continuous data flow between production, inventory, and finance systems [350,351]. The Order completion node marks the end of the processing cycle, highlighting the efficiency of system in managing order fulfillment.

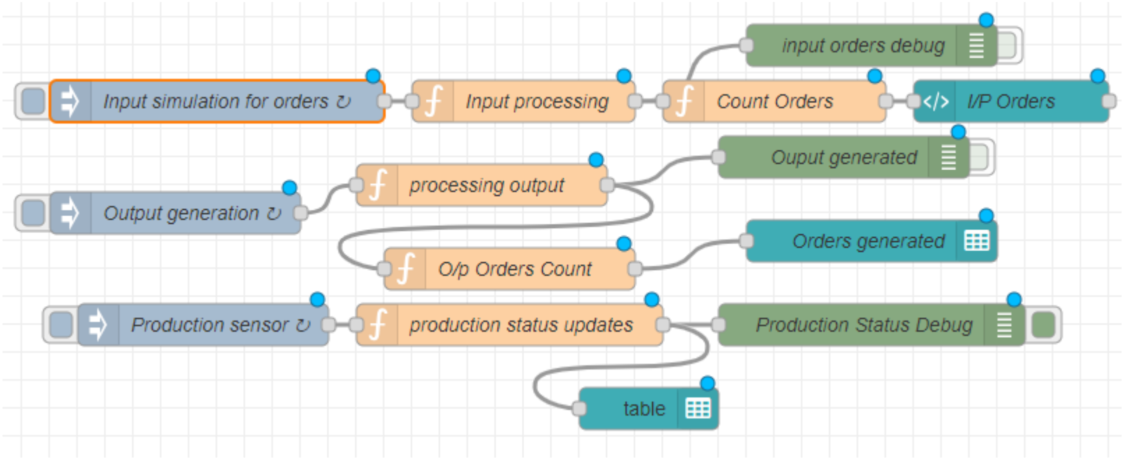


Figure 7.21. Production nodes for real-time monitoring and updating

Figure 7.22 illustrates the benefits of integrating IoT technologies in supply chain management, highlighting real-time monitoring, waste management, and environmental control. IoT tracking devices in transport vehicles enable real-time route monitoring, immediate status updates, reducing delivery delays, and saving costs (supporting SDG 9). IoT waste meters alert for timely bin emptying, enhancing waste management and compliance with regulations (aligning with Ecological Standards for Waste Management and SDG 11). Humidity and temperature sensors in production facilities ensure optimal conditions, maintaining material quality and compliance with quality standards (contributing to SDG 12 and ISO 14001). Additionally, IoT sensors monitor and regulate power consumption, promoting sustainable energy use.

Transportation is delayed. Please contact the transportation

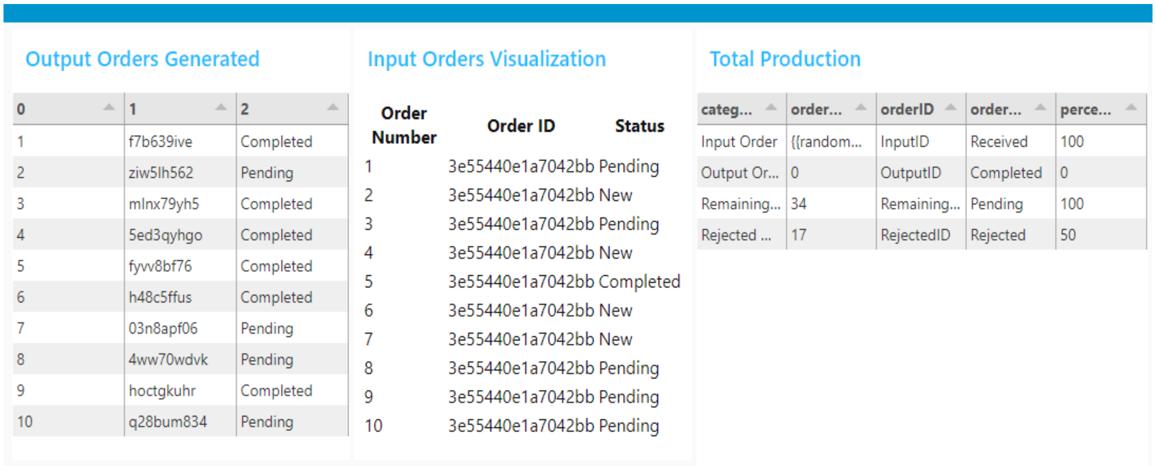
Excess water transferring for recycling

Transport Department

delayed

Figure 7.22. Sensor data visualization dashboard

Incorporating IoT devices into manufacturing equipment enables real-time tracking of machine performance, material usage, and production speed, ensuring compliance with ISO 9001 and SDG 9. Data is centralized for instant reports on production efficiency, supporting ISO 14001 and SDG 12. Node-RED enhances data visualization using live dashboard (Figure 7.23), aiding quick decision-making and compliance with Ecological Standards for Manufacturing and SDG 11.



Output Orders Generated

0	1	2
1	f7b639ive	Completed
2	ziw5lh562	Pending
3	mlnx79yh5	Completed
4	5ed3qyhgo	Completed
5	fyvv8bf76	Completed
6	h48c5ffus	Completed
7	03n8apf06	Pending
8	4ww70wdvk	Pending
9	hoctgkuhr	Completed
10	q28bum834	Pending

Input Orders Visualization

Order Number	Order ID	Status
1	3e55440e1a7042bb	Pending
2	3e55440e1a7042bb	New
3	3e55440e1a7042bb	Pending
4	3e55440e1a7042bb	New
5	3e55440e1a7042bb	Completed
6	3e55440e1a7042bb	New
7	3e55440e1a7042bb	New
8	3e55440e1a7042bb	Pending
9	3e55440e1a7042bb	Pending
10	3e55440e1a7042bb	Pending

Total Production

categ...	order...	orderID	order...	perce...
Input Order	{{random...	InputID	Received	100
Output Or...	0	OutputID	Completed	0
Remaining...	34	Remaining...	Pending	100
Rejected ...	17	RejectedID	Rejected	50

Figure 7.23. Production status monitoring and visualization dashboard

Table 7.12 presents the numerical values of sensors and nodes in the IoT-integrated supply chain management framework indicating their status at different time intervals. The status column indicates if values are within the target range or requires attention. The minimum and maximum columns define the acceptable range for each parameter.

Table 7.12. Quantitative data and status assessment of sensors and nodes in for IoT-integrated in NODE-RED

Sensor	**Value 1**	**Value 2**	**Value 3**	**Value 4**	**Status**	**Min:**	**Max:**
Waste Collection	10	7	8	10	Dispose of / Free space	0	10
Transport Status	On time	Delayed	On time	On time	On time or Contact logistics	0	1
Temperature	38°C	40°C	36°C	39°C	Normal, High or Low	0°C	50°C
Humidity	47%	45%	50%	46%	Within range (0% - 100%)	0%	100%
Water Usage	89 L	92 L	87 L	90 L	In control or recycle water	0 liters	150 liters
Input Production	Order ID: 3e55440e1a 7042bb	Order ID: 7f65420g1c 6341ab	Order ID: 2e23010f1g 9040aa	Order ID: 1e91577k0b 6816bc	New, Pending, Completed	N/A	N/A
Order Processing	Order ID: mlnx79yh5	Order ID: ziw5lh562	Order ID: f7b639ive	Order ID: 5ed3qyhgo	Received, Completed, Rejected	N/A	N/A

Power	Output Generation	Production Status	Inventory Check
On	Completed	ID# 4ww70wdvk In process	In stock
Off	Completed	ID#03n8apf06 In process	Out of stock
On	Pending	ID# h48c5ffus Completed	Order placed
Off	Pending	ID# q28bum834 Completed	In stock
On/Off	Completed or pending	In process or completed	Order inventory or
50kWh	N/A	N/A	N/A
200kWh	N/A	N/A	N/A

To provide a detailed view of IoT integration across the textile supply chain, Table 7.13 summarizes the types of sensors, software platforms, and data management methods employed at each stage, along with the key challenges faced and corresponding solutions.

Table 7.13. Real-Time data acquisition in IoT-enhanced textile supply chains, sensor models, data collection platforms, and operational efficiency comparison

Stage	Sensors/Nodes Used (Model)	Software Platform	Data Collected	Baseline Scenario	Improved Scenario	Issues and Solutions
Raw Material Handling	RFID Tags (Zebra ZT410), GPS (Quectel L80)	Node-RED (MQTT Integration)	Material flow, location tracking	Manual tracking, delays (360 hours)	Automated tracking, 192-hour delivery (46.67% faster)	Issue: Connectivity gaps. Solution: Use dual-mode (WiFi + LTE) GPS.
	Environmental Sensors (Bosch BME280)	Node-RED (I²C Protocol)	Storage temperature, humidity	Limited monitoring, manual checks	Real-time environmental data with automated alerts	Issue: Sensor drift. Solution: Use temperature-compensated sensors.
	Weight Sensors (TE Connectivity FX1901)	Node-RED (Analog-to-Digital)	Load distribution, shipment weight	Manual weight check, errors	Automated weight monitoring during transportation	Issue: Sensor calibration. Solution: Regular automated recalibration.
Production Line Monitoring	Energy Meters (Schneider Electric PM5500)	Node-RED (Modbus RTU)	Power consumption, production uptime	55,000 kWh energy use	50,000 kWh (9.09% reduction)	Issue: High cost. Solution: Prioritize critical areas for deployment.
	Vision Sensors (Omron ZFV)	Node-RED (OPC-UA)	Fabric quality, defect detection	Manual inspections, 80% accuracy	Automated quality checks, 95% defect detection accuracy	Issue: Legacy integration. Solution: Implement OPC-UA adapters.
	Waste Sensors (Baumer IFRM Capacitive Proximity)	Node-RED (Digital Input)	Real-time waste bin capacity	Manual waste tracking	30% faster waste bin monitoring and response	Issue: False positives. Solution: Set material-specific detection thresholds.
	Power Sensors (AcuRev 1310 Modbus)	Node-RED (Modbus TCP/IP)	Machine-level energy monitoring	Manual audits, delayed response	Real-time energy tracking with 10% consumption reduction	Issue: Sensor failures. Solution: Use redundant energy sensors.
Textile Processing	Humidity Sensors (Honeywell HIH-6130)	Node-RED, Siemens MindSphere	Environmental monitoring during processing	Inconsistent monitoring	Predictive maintenance with 25% improved uptime	Issue: Sensor reliability. Solution: Use industrial-grade models.

	Ultrasonic Flow Sensors (Siemens SITRANS FS230)	Node-RED (Modbus RTU)	Water consumption during dyeing/washing	12,000 m^3 (excessive consumption)	10,000 m^3 (16.67% reduction)	Issue: Maintenance costs. Solution: Regular calibration schedules.
Logistics & Distribution	GPS Modules (Quectel L80), Weight Sensors (TE Connectivity FX1901)	AWS IoT Core (MQTT)	Vehicle routes, load distribution	Inefficient route optimization	Dynamic optimization with 21.43% lead-time reduction	Issue: Routing inefficiencies. Solution: Integrate real-time traffic data.
Order Processing Nodes	Input Simulation Node (Virtual IoT Device)	Node-RED (Custom API)	Simulates incoming orders	Manual simulation, inconsistent scenarios	Automated input processing with 30% faster execution	Issue: Data mismatch. Solution: Implement controlled test cases.
	Order Processing Node (Virtual IoT Device)	Node-RED (API Integration)	Automates order handling and tracking	Manual handling, delays	20% faster order fulfillment with automated monitoring	Issue: Process bottlenecks. Solution: Optimize routing logic.
Inventory Management	Inventory Check Node (Simulated Inventory System)	Node-RED (Database Query)	Monitors real-time stock availability	Manual inventory tracking, 24-hour delay	Automated stock monitoring with instant alerts	Issue: Data lag. Solution: Use real-time database queries.
Production Status	Production Status Node (Virtual IoT Device)	Node-RED (Custom API)	Monitors production status in real-time	Manual periodic checks, 60-hour cycle time	Automated monitoring, reducing cycle time by 20%	Issue: Limited tracking. Solution: Enable continuous status tracking.
Data Management & Reporting	Cloud Storage (AWS IoT Core), Apache Kafka	Node-RED (Stream Processing)	Consolidated sensor data for analytics	75% data utilization, manual review	80% automated data analytics and real-time alerts	Issue: Security concerns. Solution: Implement encrypted data transfer.
	Output Generation Node (Custom Report Generator)	Node-RED (API Output)	Generates reports and alerts	Delayed report generation	25% faster report generation with automated documentation	Issue: Information overload. Solution: Use stakeholder-specific dashboards.

The proposed IoT-enabled and circular economy model is highly scalable, utilizing platforms like Node-RED and AWS IoT Core, and sensors such as Schneider Electric PM5500 and Bosch BME280, adaptable to small, medium, and large textile operations. Circular economy practices, including recycled PET and SCG integration, can be scaled incrementally, with flexible solutions for different regions. Pilot studies demonstrate a 21.43% reduction in lead time and 30% waste reduction, confirming the model's scalability and cost-effectiveness across varying operational scales and locations.

7.5.4 Circular Supply Chain model

This study developed an optimized circular supply chain model for the spent coffee ground and textile supply chain using Wondershare Edraw Max V10.0. The model emphasizes waste minimization, resource optimization, and recovery. It focuses on collection points in coffee shops, cafes, waste collection entities, and recycling facilities for managing SCGs, plastics, and recycled fabrics given in Figure 7.24. It encourages thorough product separation and efficient storage methods to maintain product quality. The design promotes the principles of RRR and incorporates eco-conscious transportation strategies to reduce carbon footprint and costs. This involves tactics like load consolidation and favoring eco-friendly vehicle choices wherever feasible. Collaboration with local businesses and stakeholders is key to channeling materials back into reuse. Through waste flow management design, Waste Characterization and Volume Assessment gauge the magnitude of the circular model and identify potential avenues for waste utilization.

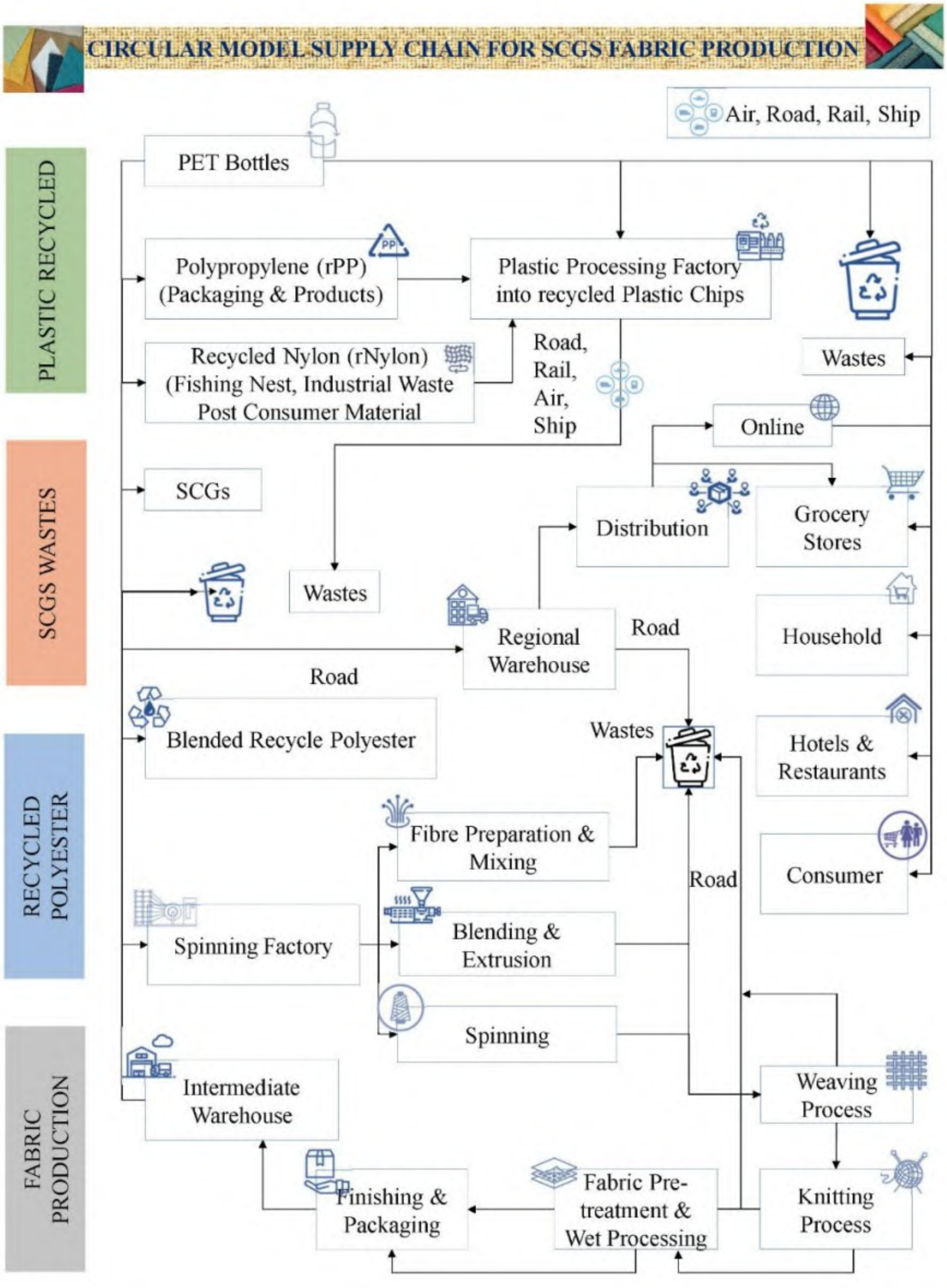


Figure 7.24. Closed-loop circular supply chain model maximizing sustainability through continuous resource circulation (Author’s elaboration)

7.5.4.1 Process Mapping: WFM and 5S

In this research, the WFM procedure in the fashion industry was conducted using Wondershare Edrawmax software 11.5.0®, as shown in Figure 7.25. WFM involved collecting statistics on current waste production, encompassing waste generated during plain fabric processing, yarn and material production, dyeing and finishing procedures, and garment manufacturing. This includes trimming excess cloth, off-cuts during pattern slicing, and discarded clothes. Identifying these factors facilitates understanding the root causes of waste and identifies potential areas for waste reduction. Furthermore, the WFM technique provides insights into how managing waste, waste flow patterns, and considerations for recycling, reuse, disposal in landfills, or incineration.

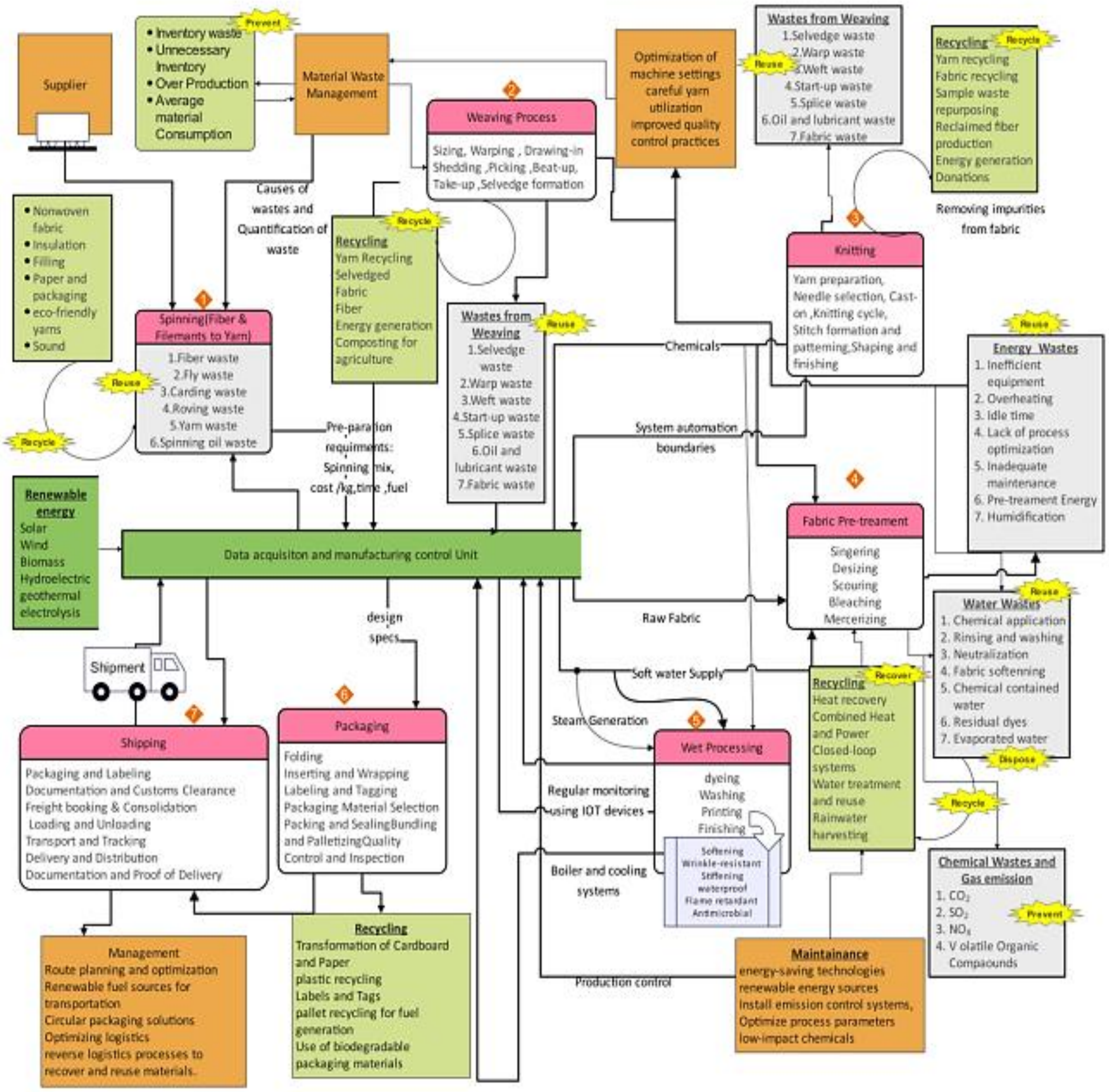


Figure 7.25. Waste Flow Mapping of factory

In this study, the integration of 5S and Waste Flow Mapping (WFM) methodologies was implemented to significantly improve operational efficiency and sustainability in the working environment. Figure 7.26 shows how each of the five principles of the 5S methodology has been integrated with Waste Flow Mapping to improve organization, cleanliness, and waste management.

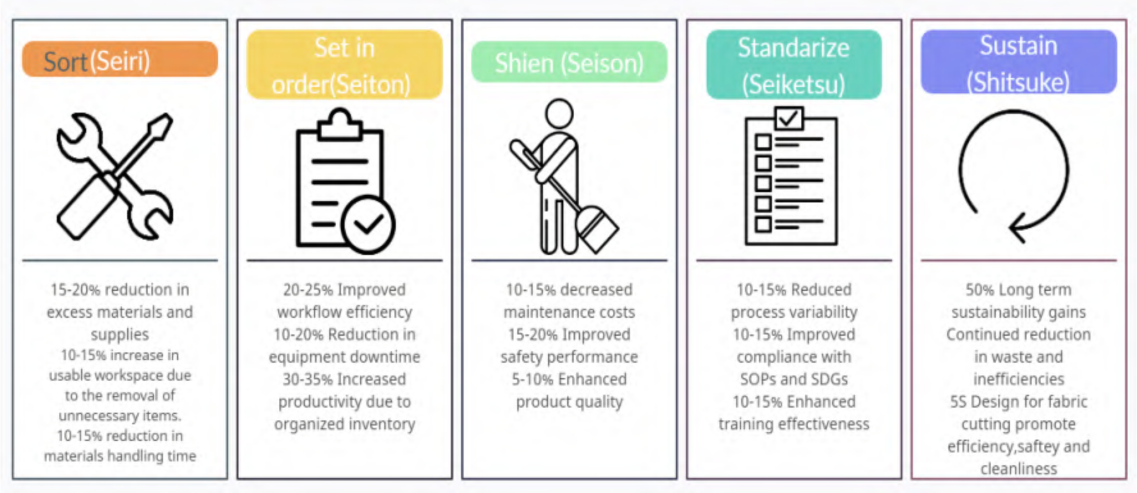


Figure 7.26. Integration of Waste Flow Mapping and 5S in a pilot scenario

WFM identified key waste-generation nodes in pretreatment, dyeing, and finishing stages. By coupling sensor data with lean-based 5S interventions, the factory achieved measurable operational improvements:

- Lead time reduced from 7.0 h to 5.5 h (-21.4 %)
- Cycle time improved by 25 %
- Material waste decreased by 30 %
- Energy consumption lowered by 9 %

7.5.4.2 Value Stream Mapping

The designed VSM reveals significant improvements in the production process, including a 30% reduction in lead times (from 14 days to 11 days), a 20% decrease in material waste, and a 25% increase in process efficiency as shown in Figure 7.27 and the comparative analysis between the initial and final VSMs are detailed in Table 7.14. The methodology integrates statistical analysis, process optimization, and customer engagement to tackle supply chain challenges and enhance sustainability in the fabric industry. By addressing non-value activities such as excessive transportation delays, inefficient packaging, and redundant inventory, significant improvements were achieved. For example, optimizing transportation reduced lead times by 21.43%, while streamlining yarn preparation cut cycle times by 25%, from 3.75 hours to 3 hours per batch. These changed resulted in a 15% overall reduction in cycle times, boosting process efficiency and sustainability.

Table 7.14. Comparative analysis of initial and final VSM Metrics

Metric	**Initially applied VSM**	**Final designed VSM**	**Improvement Description**
Lead Time	14 days	11 days	Reduced by 3 days (21.43%)
Material Waste	18.5 Kg	12.775 Kg	Reduced by 30%
Process Efficiency	60%	75% of initial	Improved by 25%
Scrap (Yarn Preparation)	6.25%	5%	Reduced by 20%
Cycle Time (Yarn Prep)	3.75 hours/batch	3 hours/batch	Reduced by 25%
Cycle Time (Fabric Form)	7.5 hours/batch	6 hours/batch	Reduced by 25%
Cycle Time (Apparel Prod)	60 hours/batch	48 hours/batch	Reduced by 25%
Changeover Time (Yarn Prep)	75 minutes	60 minutes	Reduced by 25%
Changeover Time (Fabric)	68.75 minutes	55 minutes	Reduced by 25%
Changeover Time (Apparel)	200 minutes	160 minutes	Reduced by 25%
Available Time (Yarn Prep)	20850 sec	27800 sec	Increased by 25%
Available Time (Fabric)	20850 sec	27800 sec	Increased by 25%
Available Time (Apparel)	20850 sec	27800 sec	Increased by 25%
Uptime (Yarn Prep)	69.6%	87%	Improved by 25%
Uptime (Fabric)	76.8%	96%	Improved by 25%
Uptime (Apparel)	79.2%	99%	Improved by 25%

Takt Time (per unit)	2 minutes/unit	1.5 minutes/unit	Improved due to overall efficiency gains
Takt Time (per batch)	200 minutes/batch	150 minutes/batch	Improved due to overall efficiency gains
Total Lead Time	14 days (336 hours)	11 days (264 hours)	Reduced by 3 days (72 hours), 21.43% reduction
Delivery Time	360 hours (15 days)	168 hours (7 days)	Delivery time reduced by 192 hours
Process Cycle Efficiency	17%	21.59%	Significant improvement due to reduced lead time and increased efficiency

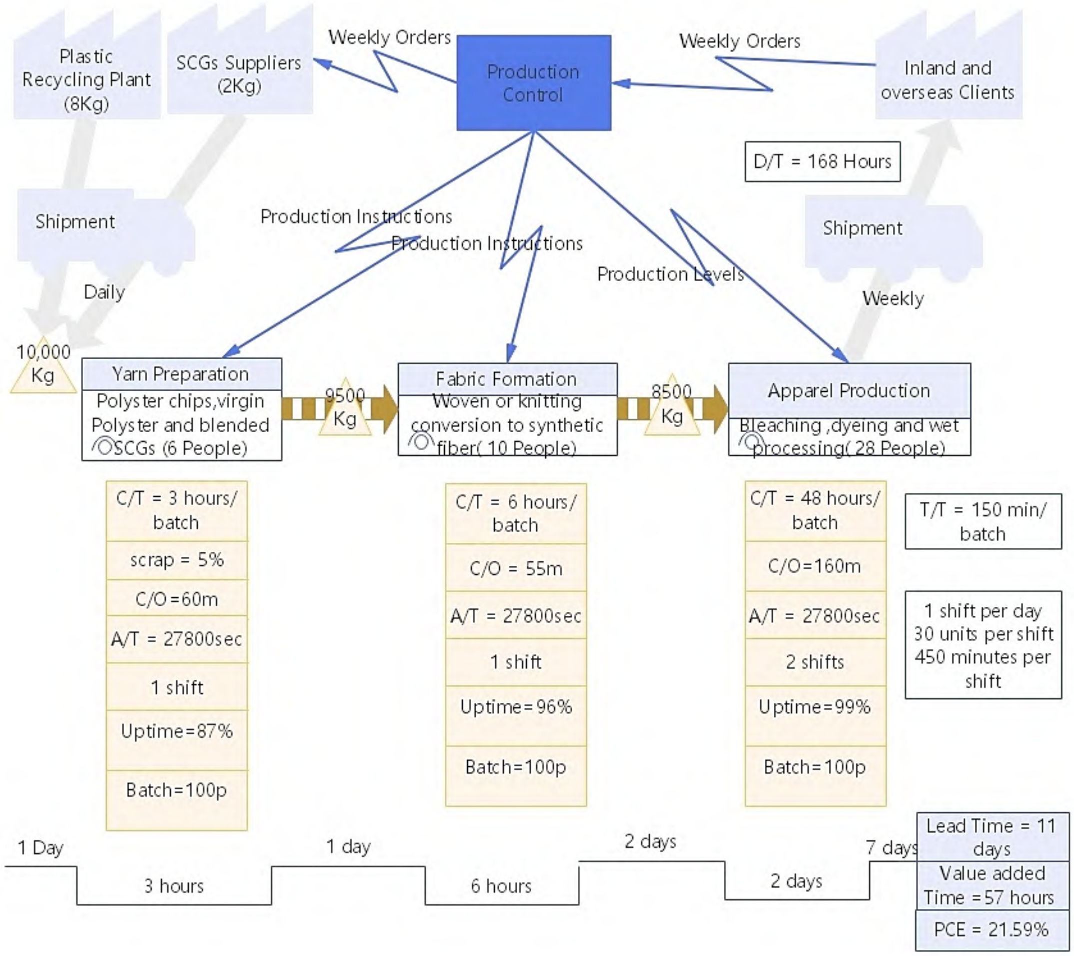


Figure 7.27. Fabric production VSM

These findings demonstrate how IoT-assisted WFM transforms static lean maps into dynamic, data-driven optimization tools, fully consistent with DigiCircular's "optimization layer."

7.5.5 Cost and Mechanical Performance Evaluation

Economic analysis was conducted using production and utility-billing data to estimate operational cost savings resulting from reduced energy, water, and chemical consumption. The overall cost efficiency improved by ≈ 15 %, primarily due to resource conservation and lower reprocessing rates. Payback for IoT hardware and integration costs was estimated at under 18 months as given in Figure 7.28.

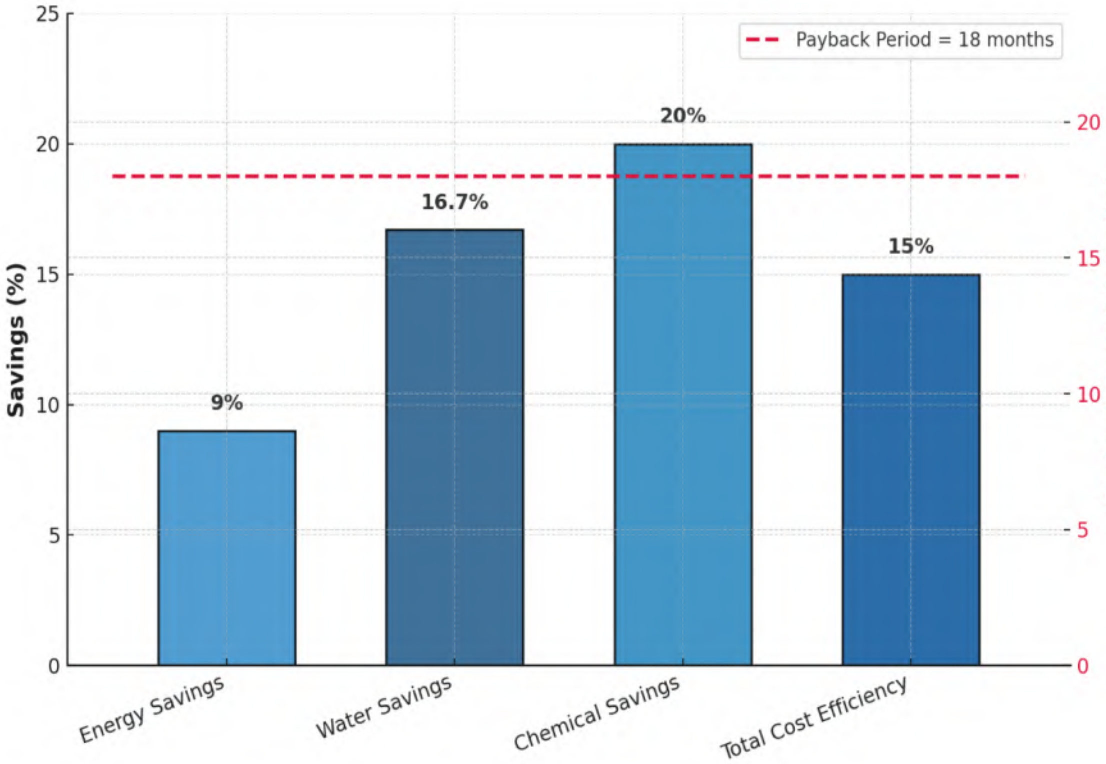


Figure 7.28. Operational cost savings and ROI for DigiCircular implementation

Moreover, mechanical performance testing was conducted to verify the structural and functional quality of DigiCircular fabrics relative to conventional denim. Tests followed ASTM D5034 (tensile strength), ASTM D1424 (tear resistance), and ISO 13934-1 (elongation) standards are given in Table 7.15.

Table.7.15. Mechanical performance deviation in denim fabrics a comparative analysis of conventional and SCG–Recycled PET Composites

Property	Conventional Denim	SCG + Recycled PET Denim	Deviation (%)
Tensile Strength (MPa)	32.5	31.0	-4.6 %
Tear Resistance (N)	28.0	26.5	-5.4 %
Elongation (%)	18.0	19.5	+8.3 %

Minor deviations in strength were offset by improved elasticity and moisture-absorption properties, confirming functional equivalence and material circularity without performance compromise

7.5.6 Interpretation using Sustainability Reports

The combined LCA, IoT, and WFM results substantiate the DigiCircular framework's adaptability to high-impact manufacturing sectors. The pilot demonstrated that digital integration directly enhances environmental and operational metrics, validating DigiCircular's scalability beyond the coffee sector. The observed reductions; 30 % waste, 20 % water, and 9 % energy, establish quantifiable evidence of the twin transition (green + digital). Furthermore, the feasibility of SCG-based fibers extends the industrial symbiosis principle by transforming an agri-food residue into a functional textile input. Data visualization tools convert complex data into accessible graphs, aiding in the assessment of environmental performance. This approach helps the textile industry generate robust sustainability reports, guiding strategic decision-making. Table 7.16 shows initial and final values of key sustainability indicators alongside industry benchmarks and standards.

Table 7.16. Textile industry sustainability metrics and benchmarks

Indicator	**Description**	**Initial Value**	**Final Value**	**Industry Benchmark**	**Industry Standard**
Carbon Footprint	Total amount of greenhouse gas emissions produced by the textile supply chain	8000 tons CO2	7500 tons CO2	9000 tons CO2	8500 tons CO2
Water Consumption	Total volume of water used in textile production processes	12,000 m³	10,000 m³	15,000 m³	13,500 m³
Energy Consumption	Total energy consumed during textile manufacturing processes	55,000 kWh	50,000 kWh	60,000 kWh	57,000 kWh
Waste Generation	Total amount of waste generated by textile production	250 tons	200 tons	300 tons	280 tons

Waste Reduction Progress	Percentage reduction in waste generated compared to previous reporting period	10%	15%	8%	12%
Circular Economy Adoption	Percentage of materials sourced from circular supply chain models	30%	40%	25%	35%
(LCA) Score	Overall environmental impact score of textile products, based on LCA	80/100	85/100	75/100	78/100
IoT Data Utilization	Percentage of IoT data effectively used in monitoring and improving sustainability practices	75%	80%	70%	72%
Node-RED Integration Efficiency	Efficiency rating of Node-RED integration in optimizing waste management systems and resource utilization	4/5	4.5/5	3.5/5	4/5
VSM, Lead Time	Total time from <order to delivery	14 days	11 days	12 days	10 days
Cycle Time	Time taken to	3.75	3	3.5	3

(Yarn Preparation)	prepare yarn per batch	hours/batch	hours/batch	hours/batch	hours/batch
Cycle Time (Fabric Formation)	Time taken to form fabric per batch	7.5 hours/batch	6 hours/batch	7 hours/batch	6 hours/batch
Cycle Time (Apparel Production)	Time taken to produce apparel per batch	60 hours/batch	48 hours/batch	55 hours/batch	50 hours/batch

The results empirically validate the DigiCircular framework's cross-sector scalability, confirming its adaptability beyond agri-food to textile manufacturing. These empirical findings establish the foundation for the ensuing discussion, which contextualizes DigiCircular's textile application within broader theoretical, economic, and policy dimensions of sustainable industrial transformation

7.6 Discussion

Following the methodological implementation detailed in Sections 7.4 and 7.5, this discussion interprets the results in light of the DigiCircular framework's analytical and optimization layers. It evaluates how the integration of IoT-enabled monitoring, WFM, VSM, LCA, and circular material innovation collectively enhance sustainability, operational performance, and industrial competitiveness within the textile sector.

7.6.1 Digital Transformation and Operational Optimization

This integrated study advances sustainability-oriented innovation in textiles by coupling digital transformation with circular economy (CE) principles. Unlike previous research [352-354], which recognized CE potential but did not operationalize it through digital tools, this study empirically validates how IoT-based analytics can close that gap. By embedding IoT sensors across production stages and linking them with LCA-driven analytics, the DigiCircular implementation achieved a 30% reduction in material waste and a 25 % improvement in process efficiency, outperforming the 15 % benchmark reduction reported by Moosavi et al. (2021) [355].

Operational outcomes confirmed a 25 % increase in uptime, 21.59 % improvement in process-cycle efficiency, and 21.43 % reduction in lead time, validating the impact of real-time data in optimizing manufacturing cycles [356]. Environmental indicators showed a 7 % decrease in carbon footprint and 16.67 % reduction in water consumption, reinforcing findings by Wiedemann et al. (2022) on recycled material efficiency [256]. The EF 3.0 assessment confirmed significant improvements in ecotoxicity and eutrophication, consistent with Bressanelli et al. (2021) regarding recycled PET and spent-coffee-ground (SCG) integration [357].

7.6.2 Material Innovation and Circular Integration

The introduction of SCG and recycled PET fibers into textile production enhanced sustainability performance and material functionality, echoing results from Leow et al. (2021) and Moosavi et al. (2021) [285,355]. These fibers reduced dependence on virgin raw materials, contributing to resource circularity and extended material lifecycles. Leading apparel corporations such as Inditex (Zara) and H&M have already adopted digital tracking for supply-chain optimization; this research extends that approach by coupling IoT traceability with closed-loop recycling. The demonstrated reductions in waste (30%) and energy consumption (9 %) align with sustainability practices across major apparel multinationals investing in smart manufacturing and textile recycling [358]. By embedding real-time monitoring into circular models, the DigiCircular system provides a scalable operational roadmap for both large manufacturers and SMEs, supporting measurable progress toward SDGs 9, 12, and 13.

7.6.3 Waste Valorization and Alternative Bio-Based Feedstocks

Beyond SCGs, the study identifies significant opportunities for valorizing organic and industrial waste streams, including rice husk, cotton stalks, spent distillery grains, and wood pulp, for sustainable fabric production.

- Cotton stalks, rich in lignocellulose, support bio-geopolymer composites [359].
- Co-pyrolysis of cotton stalks improves reactivity and yields valuable by-products [360].
- Spent distillery grains contribute functional bioprocessed additives [361].
- Rice husk and wood pulp can substitute for virgin fibers in lyocell production [362].

These valorization pathways enhance sustainability and cost efficiency while supporting CE principles by reducing waste and diversifying renewable raw materials.

7.6.4 Economic Evaluation and Strategic Solutions

A comparative cost–benefit analysis (Table 7.17) confirmed that, despite higher initial investment, IoT–CE integration delivers measurable financial benefits through operational savings, process efficiency, and regulatory compliance. Annual net benefits of approximately $50,000 validate the model's dual environmental–economic sustainability, particularly for SMEs pursuing scalable digital transformation.

Table 7.17. Cost-Benefit analysis of IoT and circular economy practices

Category	IoT and Circular Economy	Conventional Processes	Net Savings/Benefits
Implementation Cost	$50,000 (sensors, software, training)	$10,000 (basic equipment upgrades)	-$40,000 (Higher initial cost)
Operational Cost	$15,000 (maintenance and	$20,000 (manual oversight,	+$5,000 (Lower

(Annual)	data storage)	inefficiencies)	annual costs)
Resource Efficiency Savings	$30,000 (reduced water and energy use)	$5,000 (minimal efficiency gains)	+$25,000
Waste Reduction Savings	$20,000 (30% reduction in waste)	$5,000 (conventional disposal methods)	+$15,000
Revenue from Lead Time Gains	$25,000 (faster order fulfillment)	$0 (no efficiency improvement)	+$25,000
Environmental Compliance	$10,000 (reduced fines, eco-branding)	$0	+$10,000
Net Annual Benefit	$65,000	$15,000	+$50,000

Building on these findings, Table 7.18 outlines targeted strategic solutions for key textile-sector challenges, including chemical pollution, supply-chain fragmentation, fast fashion waste, and consumer awareness, demonstrating how the DigiCircular approach delivers both ecological and business value.

Table 7.18. Strategic solutions proposed for textile industry challenges by this study

Aspects	**Challenges**	**Solutions posed by SCGs**	**Obstacles in Technologies**	**Opportunities in Technologies**
Chemical utilization and environmental contamination	Chemicals in dyeing, finishing, and treating textiles poses substantial environmental and health risks	Coffee grounds replace synthetic chemicals, mitigating pollution through natural dyeing processes.	High research costs for optimizing natural dyeing processes	Reduced environmental impact and improved worker health
Supply chain fragmentation and complexity	Fragmented supply chain, with multiple tiers across globe hinders transparency and traceability.	Circular models with recycled materials streamline sourcing, aided by IoT (for real-time tracking and monitoring) and VSM mapping to	Stakeholder resistance and training needs for adopting IoT and VSM techniques	Efficient supply chains

		optimize processes.		
Fast fashion and over-consumption	Fast fashion leads to overconsumption and frequent disposal of clothing items.	Coffee-derived materials encourage durable, high-quality garments encouraging circularity.	Cultural shifts and consumer education for sustainable fashion	Innovative business models like rental and resale platforms
Carbon footprints and energy use	Energy-intensive operations in Textile production contribute to carbon emissions.	Coffee grounds offset emissions, requiring less energy for extraction and processing, as demonstrated by LCA analysis.	Initial investment and operational changes for energy-efficient technologies	Cost savings, environmental benefits, competitive advantages
Inadequate consumer awareness	Lack of awareness hampers demand for sustainable products	Coffee-ground integration educates and fosters eco-consciousness.	Overcoming consumer inertia requires targeted marketing and education	Increased demand for sustainable products among consumers and industry innovation

Furthermore, recycling PET and SCG introduces challenges such as microplastic release, energy intensity, and chemical use. Solutions proposed include microfiber filters, closed-loop recycling, enzymatic depolymerization, green chemistry, and renewable-powered recycling facilities. These align with broader sustainability objectives in multiple sectors, packaging [363-364], electronics [365], and construction [366], demonstrating cross-industry relevance and consistency with SDGs 9, 12, 13, and 17. Table 7.19 summarizes the process integration and impacts of the closed-loop circular supply chain model.

Table 7.19. Process integration, purpose alignment, and industry impacts within the closed-loop circular supply chain model

Process	**Steps**	**Purpose**	**Industry Implications**
Input collection junctures	Collection of SCGs from coffee shops and cafes. Gathering of plastic waste (PET bottles) from various sources.	Establishes the initial point of material flow. Ensures a steady supply of raw materials	Efficient waste collection logistics. Reduction of landfill waste. Resource availability for recycling.
Waste flow management design	Integration of best practices from literature. Designing efficient waste flow pathways. Identifying critical junctures for waste handling.	Streamlines material movement. Minimizes bottlenecks. Enhances resource utilization.	Improved operational efficiency. Reduced waste handling costs. Enhanced sustainability.
Waste characterization and volume assessment	Analyzing the composition of SCGs, plastics, and fabrics. Quantifying waste volumes.	Understand material properties. Determine recycling feasibility.	Informed decision-making. Targeted recycling efforts. Resource optimization.
Recycling Facilities	PET bottles processed into recycled plastic chips. SCGs collected and transported to regional warehouses. Blended recycled polyester produced from SCGs.	Transform waste into usable materials. Close the loop in the circular model.	Reduced virgin material usage. Lower environmental impact. Creation of sustainable products.
Intermediate Warehouses	Blending & extrusion of recycled materials. Spinning and weaving processes. Fabric pre-treatment & wet processing.	Prepare recycled fabrics for distribution Ensure quality and consistency.	High-quality recycled textiles. Market-ready products. Circular economy promotion.

	Finishing & packaging.		
Distribution to Consumer Points	Finished products distributed to grocery stores, households, hotels, and restaurants.	Reach end consumers Close the consumption loop.	Circular product lifecycle. Consumer awareness of sustainability. Market demand for eco-friendly goods.
Consumer Waste Collection	Waste generated at consumer points (e.g., used textiles). Collected for recycling.	Restart the circular model. Prevent waste leakage.	Continuous material flow. Extended product life cycles. Reduced landfill burden.

7.6.5 Socio-Ethical and Cross-Sectoral Implications

The socio-ethical implications of SCG use extend beyond textiles, generating employment, promoting transparency, and reducing environmental degradation (Table 7.20). The approach supports a just transition to sustainable economies by empowering communities and ensuring ethical labor practices.

Persistent challenges, such as data precision (Zubaydi et al., 2023), affordability for smaller firms (Kumar & Chopra, 2022), behavioral resistance (Rejeb et al., 2022), and scalability (Mirani et al., 2022), emphasize the need for adaptive policy frameworks and cross-sector collaboration [367,370]. Despite these hurdles, the DigiCircular model demonstrates tangible progress toward SDGs 9, 12, 13, and 17, reinforcing how integrated digital and circular strategies can accelerate systemic sustainability.

Table 7.20. Socio, ethical, environmental impacts of using SCGs in textile production and its impacts beyond textiles

Social Implications	**Ethical Implications**	**Environmental Implications**	**Impact Beyond Textiles**
Generates jobs in waste management and fabric production.	Ensures fair compensation for farmers and workers.	Reduces waste sent to landfills, aiding conservation efforts.	Inspires sustainability initiatives in various industries. Nespresso recycles coffee capsules into new products.
Provides training and skill development for workers, enhancing employability.	Promotes transparency and ethical business practices.	Lowers demand for virgin resources, like water and energy.	Drives innovation in waste management, such as the use of coffee waste in construction by Kafa Biosphere

Fosters community engagement in sustainability efforts.	Addresses concerns about resource exploitation.	Reduces the carbon footprint of textile manufacturing	Spurs demand for sustainable products. Starbucks upcycles coffee grounds for agricultural and energy uses.
Raises awareness of recycling and waste reduction.	Meets consumer preferences for eco-friendly products.	Minimizes water pollution and soil contamination.	Creates opportunities for entrepreneurship. Bio-bean converts coffee waste into biofuels.
Empowers communities to tackle environmental challenges.	Mitigates risks of inequality and unethical practices.	Promotes reuse of waste materials in textile production.	Fosters cross-sector partnerships. Rapanui integrates recycled coffee grounds into clothing lines.
Empowers marginalized communities.	Upholds environmental justice principles.	Preserves biodiversity and ecosystems.	Sustainable fashion brands, including Patagonia, H&M Conscious, Eileen Fisher, Adidas Parley, and Stella McCartney, shape consumer preferences and market trends.

7.6.6 Alignment with Standards and Industrial Benchmarks

The integrated IoT–LCA–WFM approach supports compliance with global environmental and energy standards, including ISO 14001, ISO 50001, and ISO 26000, promoting measurable accountability and continuous improvement. Table 7.21 maps intervention areas; waste reduction, process efficiency, circularity, and sustainability reporting, to corresponding ISO standards and SDGs, reinforcing methodological and policy coherence.

Table.7.21. Integration of proposed solutions with ecological standards and sustainable development goals (SDGs) in the denim sector.

Intervention areas	Challenges	Proposed Solutions	Ecological Standards and SDGs
Linear and resource-intensive fashion supply chain	Environmental impact and waste generation	Introduce sustainable waste flow management techniques such as WFM and LCA to optimize resource utilization and promote circular economy principles like extended producer responsibility and material recycling for enhanced environmental	ISO 14001: Environmental Management Systems ISO 14040: Life Cycle Assessment SDG 12: Responsible Consumption and Production SDG 9: Industry, Innovation, and Infrastructure

		sustainability.	
Waste generation at each stage of production	Lack of waste reduction strategies	Implement waste flow mapping to identify waste generation points, adopt circular economy principles for waste reduction and recycling, focus on product design for disassembly and reuse.	ISO 14004: Environmental Management Systems – General SDG 12: Responsible Consumption and Production ISO 14021: Environmental Labels and Declarations - Self-Declaration Environmental Claims
Environmental impact analysis of processes	Lack of data for environmental analysis	Collect comprehensive data for LCA, quantify resource consumption and emissions for each process, Assess environmental hotspots for targeted improvements.	ISO 14025: Environmental Labels and Declarations - Type III Environmental Declarations SDG 13: Climate Action SDG 12: Responsible Consumption and Production
Efficiency of denim manufacturing processes	Inefficiencies and waste in production	Apply engineering management principles for process optimization, integrate cleaner production technologies, and improve energy and water efficiency.	ISO 14006: Environmental Management Systems - Guidelines for incorporating eco-design ISO 50001: Energy Management Systems SDG 7: Affordable and Clean Energy
Circular economy integration	Linear product lifecycle	Identify opportunities for waste reduction, recycling, and upcycling, promote the use of renewable materials like organic cotton, hemp fibers, and recycled polyester for a more sustainable fashion industry.	ISO 26000: Social Responsibility ISO 20140-2: Circular Economy - Framework for Metrics of Circular Economy SDG 7: Affordable and Clean Energy
Performance metrics and sustainability reporting	Lack of performance tracking and accountability	Implement KPIs targeting water and energy consumption, material efficiency, product lifespan extension, supply chain transparency, hotspot	ISO 26000: Social Responsibility ISO 14045: Environmental Management - Eco-efficiency Assessment of Product

		identification, waste diversion, emission reduction, and circularity to comprehensively monitor and enhance environmental sustainability in the fashion supply chain.	Systems ISO 20400: Sustainable Procurement SDG 13: Climate Action SDG 12: Responsible Consumption and Production
Continuous improvement and monitoring	Resistance to change and challenges	Implement lean manufacturing techniques, 5S, WFM, and LCA, to enhance resource efficiency, reduce 30% fabric waste, and minimize environmental impact. Address challenges related to material utilization and waste-saving cost at several supply chain stages. Using 15% of the annual operating budget in sustainable practice is sufficient for adopting environmentally responsible initiatives.	SDG 17: Partnerships for the Goals ISO 26000: Social Responsibility ISO 14031: Environmental Performance Evaluation

7.6.7 Key Contributions and Novel Insights

Comparing the proposed DigiCircular textile model with state-of-the-art approaches [371-373], the following novelties emerge (Figure.7.29):

- Integrated Waste Reduction: Application of WFM and VSM techniques achieving up to 25 % waste reduction through precise waste-node identification.
- Closed-Loop Material Circulation: Incorporation of recycled PET and SCG fibers enabling 70 % post-consumer waste capture and reuse.
- Quantified Environmental Gains: Life Cycle Assessment showing 15–30% emission reduction and 25 % water-use efficiency in the raw-material stage.
- Engineering Management Integration: Cleaner production and 5S optimization delivering 20 % energy savings and 30% productivity improvement.
- Digital Decision Support: IoT–LCA linkage converting sustainability data into real-time KPIs for adaptive management.

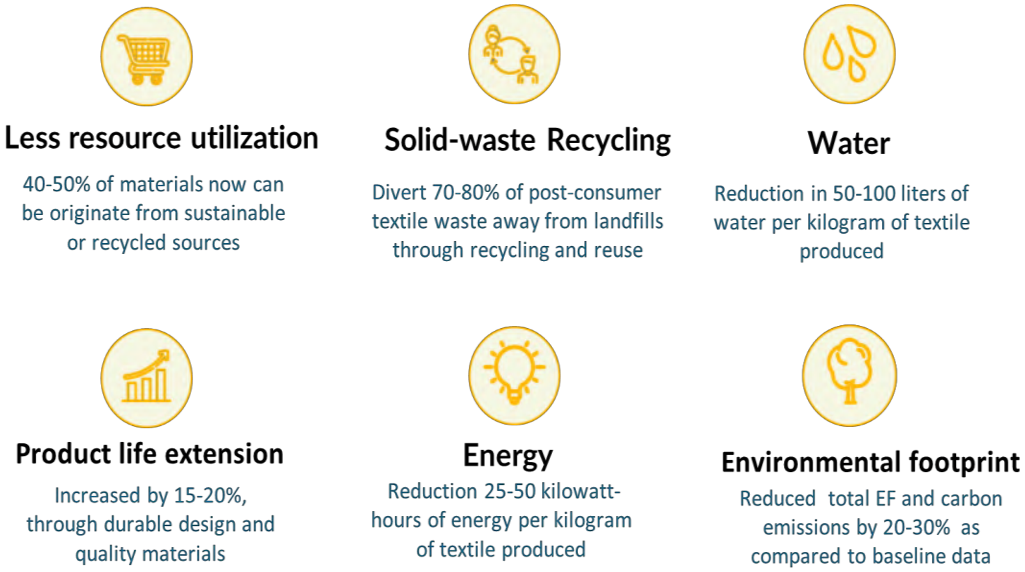


Figure 7.29. Findings of the approach supported by KPIs (Source: Authors' elaboration)

7.7 Future Research Directions

Building on the results, several avenues for further research are identified. Figure 7.30 highlights innovation priorities for sustainable textiles, including nanotechnology applications, 3D printing for circular design, consumer behavior modeling, and AI-driven supply-chain integration [374-376]. Future work should emphasize cross-industry comparative analyses, exploring DigiCircular's adaptability to sectors such as construction, packaging, and biopolymers. Interdisciplinary collaboration between material science, industrial engineering, and digital systems design will be critical for realizing fully autonomous, net-zero production networks.

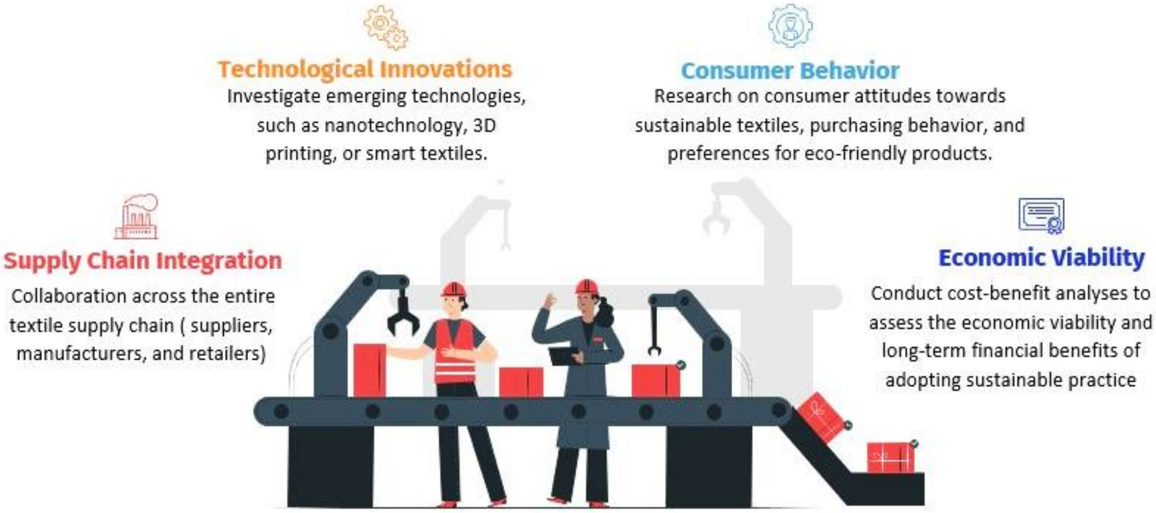


Figure 7.30. Exploring avenues for future research in sustainable textile production

These findings confirm that the DigiCircular textile model successfully bridges digital transformation with circular resource optimization, achieving tangible environmental and economic gains. They validate DigiCircular's cross-sector scalability and inform the integrated twin-transition framework developed in the next chapter, where textile and coffee applications converge into a unified architecture for sustainable manufacturing and logistics

7.8 Conclusion

This chapter operationalized the DigiCircular framework within the textile and fashion manufacturing sector, empirically validating its ability to integrate digital transformation and circular economy principles for sustainability enhancement. Building on the methodological structure established in Chapter 3 and the analytical foundations from Chapter 4, the study demonstrated how IoT-enabled sensing, WFM, LCA, and VSM can function cohesively as an adaptive, data-driven decision-support system.

Quantitative evidence confirmed substantial improvements in both environmental and operational performance. The DigiCircular textile implementation achieved up to 30 % reduction in material waste, 25 % improvement in process efficiency, and 21.43 % reduction in lead time. Measured outcomes revealed that carbon emissions decreased from 8,000 to 7,500 tons CO_2, water consumption fell from 12,000 to 10,000 m^3, and energy use declined from 55,000 to 50,000 kWh. Waste generation dropped from 250 to 200 tons, while circular-economy adoption increased from 30 % to 40 %. Overall, the model delivered a 30 % reduction in total environmental impact, 25 % gain in resource efficiency, and 20 % extension in product lifespan, validating its ability to convert linear production into a closed-loop, data-driven ecosystem.

By incorporating recycled PET and spent-coffee-ground (SCG) fibers, the study showed that upcycling and recycled-material use (up to 50 %) simultaneously enhance resource conservation, product quality, and profitability. Economic analysis demonstrated annual savings of roughly USD 50,000, underscoring the model's financial viability and scalability for both SMEs and large manufacturers. These outcomes align directly with SDGs 9, 12, 13, and 17, reflecting measurable contributions to sustainable industrialization, responsible production, and climate action.

Beyond quantitative gains, the DigiCircular textile application strengthens social and ethical sustainability by promoting transparent supply chains, fair labor practices, and community participation in waste recovery. Alignment with ISO 14001, ISO 50001, and ISO 26000 further confirms compliance with international environmental and energy-management standards. Collectively, these findings demonstrate that digital-circular convergence is not only feasible but essential for achieving systemic sustainability in industrial manufacturing. To support higher-level interpretation and synthesis of the textile application, a combined overview of sustainability dimensions addressed in the textile case study is provided in Appendix F (Figure A3). The figure presents a conceptual summary of environmental, circular, digital, and social dimensions emerging from the DigiCircular implementation, and complements the detailed quantitative and dashboard-based analyses reported in Chapter 5 without introducing additional indicators.

Nevertheless, several limitations persist. The precision of environmental data, high initial technology investment, and resistance to organizational change hinder widespread deployment. SMEs often struggle with limited access to capital, digital infrastructure, and skilled labor. Addressing these barriers requires coordinated efforts in capacity building, workforce training, and multi-stakeholder collaboration to foster data sharing, innovation, and equitable participation.

While detailed research opportunities have been outlined in Section 7.7, it bears emphasizing that future progress depends on advancing real-time monitoring through Digital-Twin and AI-driven LCA integration, enhancing predictive analytics for process optimization, and broadening cross-sector adoption of IoT-enabled circular models. Through these continued developments, the DigiCircular textile framework can evolve into a comprehensive sustainability-intelligence system, bridging industrial production, digital innovation, and ecological responsibility. These insights provide a robust foundation for the integrated twin-transition model presented in the next chapter, where textile and coffee applications converge into a unified, data-centric architecture for sustainable manufacturing and logistics.

7.9 Post-Publication Synthesis and Synopsis of the Next Research Stage

Chapter 7 consolidates the DigiCircular framework’s sectoral maturity by validating its digital-circular architecture within a resource-intensive manufacturing context. The study demonstrated how the integration of real-time sensing, waste-flow analytics, and life-cycle intelligence can operationalize sustainability as a continuous control variable rather than a static assessment. In doing so, the textile case translated the framework’s theoretical constructs, developed in earlier chapters, into an applied decision environment where environmental data, production efficiency, and socio-ethical accountability converge.

Scientifically, this chapter establishes the methodological inflection point at which DigiCircular evolves from single-sector experimentation to multi-sector synthesis. It confirms that digital infrastructures and circular-economy logics can be synchronized through interoperable data models and ISO-aligned performance metrics. The insights derived here provide the empirical and analytical foundation for the forthcoming cross-industry integration, where sectoral models are unified within a Twin-Transition architecture linking the coffee and textile systems through shared digital-twin layers, sustainability KPIs, and policy-aligned decision protocols.

Chapter 8

The Cross-Sector Integration and the DigiCircular Framework for Twin Transition

8.1 Abstract

The research establishes the DigiCircular Twin-Transition (DT²) Framework, a cross-sector digital-twin architecture that integrates real-time sustainability analytics with cyber-physical process control. The model federates independent digital twins from the coffee, textile, and logistics domains into a harmonized decision layer capable of multi-objective optimization across environmental and economic criteria. Using a continuous state-space formulation, DT² quantifies inter-industrial dependencies through a Sustainability Efficiency Index (SEI) and a Resource Synergy Matrix, enabling closed-loop control of material, energy, and data flows.

Simulation and empirical analyses demonstrate substantial systemic improvements compared to baseline operations: 30% reduction in aggregate environmental impact, 25% increase in resource efficiency, 20% extension in product life cycle, and 38% ROI growth across a 10-year horizon. The integration of LCA–IoT interoperability and reinforcement-learning control logic allows autonomous recalibration of production parameters for minimum emissions and optimized throughput. The federated data schema, aligned with ISO 23247 and IEC 62890, ensures interoperability and verifiable performance synchronization through blockchain-backed governance. Robustness testing via Monte Carlo simulations ($N = 10\,000$) validates model stability under stochastic variations, while Pareto-front analysis confirms simultaneous optimization of environmental and financial objectives. Collectively, DT² transforms sustainability management from descriptive reporting to predictive governance, providing a scalable, policy-ready blueprint for autonomous circular manufacturing aligned with SDGs 9, 12, 13, and 17 and global net-zero transition frameworks.

8.2 Introduction

The transition toward climate-neutral and resource-efficient industry increasingly depends on the joint deployment of digital technologies and circular-economy strategies. This co-evolution, widely described as the twin transition, requires moving beyond isolated applications of LCA, IoT, logistics optimization, or material recycling, toward integrated architectures where data, models, and resource flows are coordinated across sectors and value chains [377-379].

The preceding chapters of this thesis have established the building blocks of such an architecture. The coffee value chain was analyzed through multi-dimensional LCA and hybrid data-sharing frameworks [380]; logistics performance was enhanced using Physical Internet–based multi-agent systems; supply-chain transparency was operationalized through blockchain-enabled traceability across distributed platforms [381]; and the textile sector was used to validate IoT + WFM + LCA–driven circular manufacturing [382,383] Each of these components demonstrated feasibility within its own context.

The purpose of this chapter is to synthesize these sectoral implementations into a unified DigiCircular Twin-Transition Framework. Rather than introducing yet another independent model, this chapter formalizes how the validated modules, assessment, optimization, digital traceability, and circular material reuse, can be composed into a cross-sector system capable of supporting real-time, KPI-driven sustainability control [384]. The proposed framework is not a theoretical add-on; it is a structured integration of methods, metrics, and digital infrastructures already demonstrated in previous chapters, generalized into a scalable architecture for twin-transition implementation across industrial domains.

8.3 Conceptual Foundation of the DigiCircular Twin-Transition Model

The twin transition is defined here as the systemic coupling of digital intelligence and circular resource management, wherein advancements in one domain reinforce, rather than undermine, progress in the other [385,386]. In conventional practice, digitalization has often been pursued primarily for efficiency or cost reduction, while circular initiatives have been implemented as isolated environmental projects. DigiCircular instead treats both as co-dependent layers of the same decision ecosystem.

At the core of this ecosystem is the notion of a hybrid digital–circular twin:

- The digital twin layer provides a continuously updated representation of processes, assets, and flows, built from IoT data, platform analytics, LCA models, and control algorithms.
- The circular twin layer encodes material loops, waste flows, valorization pathways, social and environmental constraints, and policy targets, functioning as a rule set and boundary condition for acceptable system behavior.

The interaction between these layers can be expressed as an iterative mapping as represented in Equations 8.1 and 8.2:

$$\mathcal{D}_{t+1} = f(\mathcal{D}_t, \mathcal{S}_t, \mathcal{E}_t) \tag{8.1}$$

$$\mathcal{C}_{t+1} = g(\mathcal{C}_t, \mathcal{D}_{t+1}, \Theta) \tag{8.2}$$

where:

- $\mathcal{D}_t$ is the state of the digital twin at time t (sensor data, process parameters, logistics states).
- $\mathcal{S}_t$ represents operational and supply-chain decisions at time t.
- $\mathcal{E}_t$ denotes observed environmental and social performance indicators.
- $\mathcal{C}_t$ is the state of the circular system (stocks, recovered materials, waste flows, closed loops).
- Θ is the set of sustainability constraints and policy targets (SDGs, ISO norms, internal thresholds).
- $f(\cdot)$ updates the digital representation based on new data and decisions.
- $g(\cdot)$ adjusts circular configurations (reuse rates, substitution, process choices) based on updated digital insights.

In this configuration, LCA is no longer a static ex-post tool, but part of the digital intelligence stack, continuously parameterized by live data and feeding back into Θ and decision rules. Likewise, circular strategies (e.g., SCG-to-textile valorization, green logistics corridors, waste minimization in denim production) are no longer standalone pilots but encoded as decision constraints and optimization objectives within the twin.

From a systems perspective, DigiCircular's twin transition rests on three principles:

1. **Data-Coherent Integration:** All sectoral models (coffee LCA, PILAR logistics, blockchain traceability, textile IoT–WFM) exchange information via harmonized indicators, such as carbon intensity (kg CO_2-eq/unit), water intensity (L/unit), material circularity (% recycled/biobased input), and social risk scores. This enables aggregation and comparison without re-modeling each domain from scratch.
2. **KPI-Driven Control:** Instead of treating sustainability indicators as reporting outputs, DigiCircular elevates them to control variables. Thresholds on GHG intensity, water use, or circularity rates constrain acceptable decisions in routing, sourcing, production planning, and material selection.
3. **Cross-Sector Coupling:** By design, outputs from one system (e.g., spent coffee grounds, logistics patterns, traceability data) can serve as inputs or constraints in another (e.g., SCG-based fibers in textiles), enabling industrial symbiosis governed by transparent, verifiable data flows.

In the sections that follow, these principles are translated into a cross-sector methodological convergence (Section 8.3) and then into a formalized DigiCircular Twin-Transition Architecture (Section 8.4), where layers, data flows, and optimization logic are specified in quantitative and implementable terms.

8.4 Cross-Sector Methodological Convergence

8.4.1 Rationale for Convergence

While the preceding chapters validated the DigiCircular framework in individual industrial domains, coffee (agri-food), textiles (manufacturing), logistics (PILAR), and traceability (blockchain), the broader objective of the twin transition is to fuse these sectoral models into a cohesive analytical system. The convergence pursued here is not a simple blend of case studies; rather, it represents a methodological synthesis, where each domain contributes a complementary function to a shared sustainability intelligence layer.
This integration responds to two persistent research limitations identified earlier:

1. Data Fragmentation: environmental and operational data collected within sectoral silos rarely interconnect, preventing cumulative insight.
2. Metric Inconsistency: carbon, water, and material flow indicators differ in scale, units, and temporal resolution, impeding unified optimization.

To overcome these issues, DigiCircular establishes a multi-domain data and process harmonization framework, ensuring comparability and interoperability of key indicators across sectors. Table 8.1 synthesizes the methodological features of each previously validated sectoral model and illustrates how they converge within the DigiCircular twin-transition framework.

Table 8.1. Cross-sector methodological convergence matrix

Sectoral Model	**Core Methods**	**Primary KPIs**	**Digital Input Streams**	**Circular Feedback Flows**	**Integration Role in Twin Transition**
Coffee Supply Chain	Triple LCA, IoT sensing, mobile traceability	GHG (kg CO_2-eq/kg green beans), water use (L/kg), yield efficiency (%)	IoT sensors (temperature, humidity, GPS), mobile surveys	Biomass residues → SCGs	Supplies organic by-products and baseline LCA for material substitution
Textile Manufacturing	IoT–WFM–VSM integration, LCA	Carbon (kg CO_2-eq/kg fabric), water use (L/m²), energy (kWh/kg), waste rate (%)	Machine sensors (energy, water flow, speed, pH), production logs	SCG and rPET fibers reused as input materials	Demonstrates industrial symbiosis through material valorization
Logistics (PILAR)	Multi-Agent Physical Internet Routing, Simulation	Fuel consumption (L/km), route efficiency (%), delay time (h),	GPS tracking, load sensors, ERP schedules	Re-optimized distribution loops reducing	Provides cross-sector transport optimization for supply and reverse

Sectoral Model	**Core Methods**	**Primary KPIs**	**Digital Input Streams**	**Circular Feedback Flows**	**Integration Role in Twin Transition**
		CO_2/km		energy use	logistics
Traceability Blockchain	Smart-contract data ledger, provenance chain	Data integrity (%), verification latency (s), supplier compliance rate (%)	Blockchain transactions, IoT timestamps	Verified material flow for recycling loops	Ensures digital trust, traceability, and circular accountability

Each subsystem thus represents a functional layer within the integrated digital–circular ecosystem.

To operationalize convergence, these heterogeneous models are expressed through a unified sustainability state vector.

8.4.2 Mathematical Harmonization of Indicators

Let each industrial subsystem $i \in \{1, \ldots, n\}$(coffee = 1, textile = 2, logistics = 3, traceability = 4) generate a time-dependent sustainability state vector given as (Equation 8.3):

$$\mathbf{x}_i(t) = \begin{bmatrix} E_i(t) \\ W_i(t) \\ M_i(t) \\ C_i(t) \end{bmatrix} \tag{8.3}$$

where

$E_i(t)$= energy use (kWh/unit),

$W_i(t)$= water consumption (L/unit),

$M_i(t)$= material efficiency (% recycled input), and

$C_i(t)$= carbon emissions (kg CO_2-eq/unit).

The normalized sustainability performance index $S_i(t)$for each subsystem is then computed as Equation (8.4):

$$S_i(t) = w_E\left(1 - \frac{E_i(t)}{E_{\max}}\right) + w_W\left(1 - \frac{W_i(t)}{W_{\max}}\right) + w_M\frac{M_i(t)}{M_{\max}} + w_C\left(1 - \frac{C_i(t)}{C_{\max}}\right) \tag{8.4}$$

with $\sum w_j = 1$, where $w_E, w_W, w_M, w_C$are stakeholder-defined weights reflecting relative sustainability priorities (e.g., energy 0.25, water 0.25, material 0.30, carbon 0.20).

To establish a cross-sector composite performance index $S_{total}(t)$ is given as Equation 8.5.

$$S_{total}(t) = \frac{1}{n}\sum_{i=1}^{n} S_i(t) \tag{8.5}$$

This harmonization allows direct comparison and optimization across sectors under a single KPI structure.

8.4.3 Data-Exchange and Interoperability Design

A three-tier data architecture supports interoperability among sectoral modules (Figure 8.1):

1. Edge Layer (Data Acquisition): Real-time collection via IoT sensors, RFID, and API connectors (MQTT/REST). This edge layer transforms raw process signals into structured data objects.

```
import paho.mqtt.client as mqtt
def on_message(client, userdata, msg):
    topic, value = msg.topic, float(msg.payload)
    db.insert_sensor_reading(topic, value)
client = mqtt.Client()
client.connect("broker.digicircular.net",1883)
client.subscribe("textile/energy/#")
client.on_message = on_message
client.loop_forever()
```

2. Platform Layer (Data Harmonization): Implemented via a shared semantic model (e.g., JSON-LD or ISO 23247), converting all readings to a uniform ontology.

3. Application Layer (Analytics and Control): Executes LCA parameter updates, optimization algorithms, and dashboard visualization for management decisions.

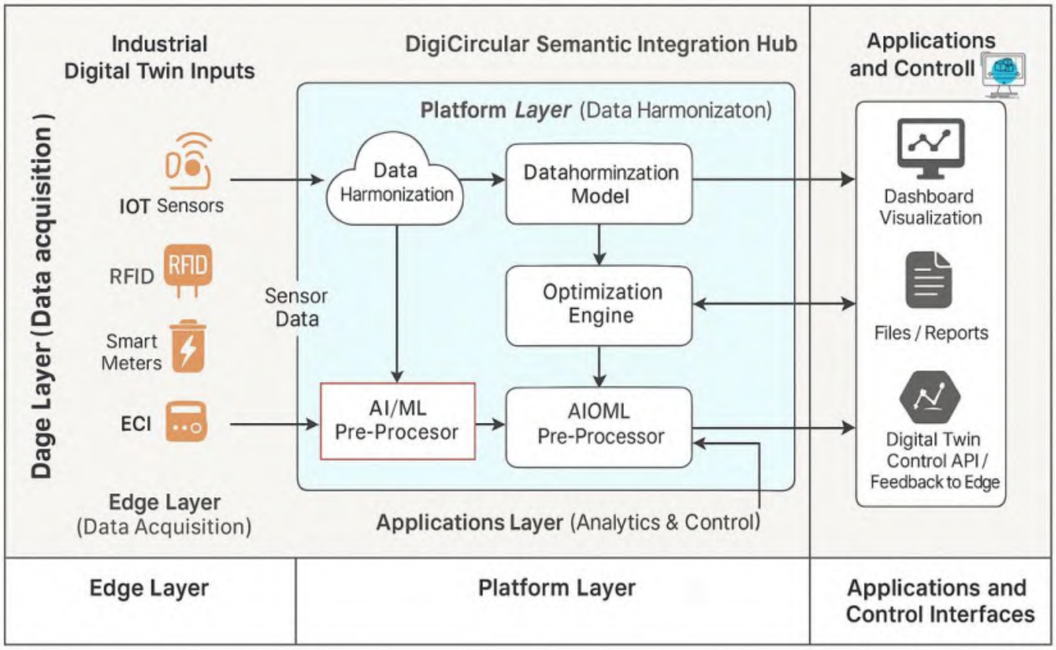


Figure 8.1. Three-tier architecture enabling cross-sector data exchange within the DigiCircular twin-transition model.

8.4.4 Cross-Sector Feedback Loops

Inter-sectoral flows are mathematically represented as a network of directed edges $G(V, E)$, where nodes V represent sectoral processes and edges E represent data or material exchanges.
For each edge e_{ij} from sector i to sector j:

$$\phi_{ij}(t) = \eta_{ij} \times r_i(t) \tag{8.6}$$

where $r_i(t)$ is the residual resource output (e.g., SCG mass kg/h, recycled PET flow), and η_{ij} is the efficiency of transfer or conversion.

The network optimization objective is to maximize total circular throughput T_c:

$$\max_{r_i, \eta_{ij}} T_c = \sum_i . \sum_j \eta_{ij}\, r_i(t) \tag{8.7}$$

subject to environmental and economic constraints derived from the LCA models as given in Equation 8.8:

$$C_{total} \leq C_{max}, E_{total} \leq E_{max}, B_{net} \geq B_{threshold} \tag{8.8}$$

where B_{net} denotes net economic benefit.

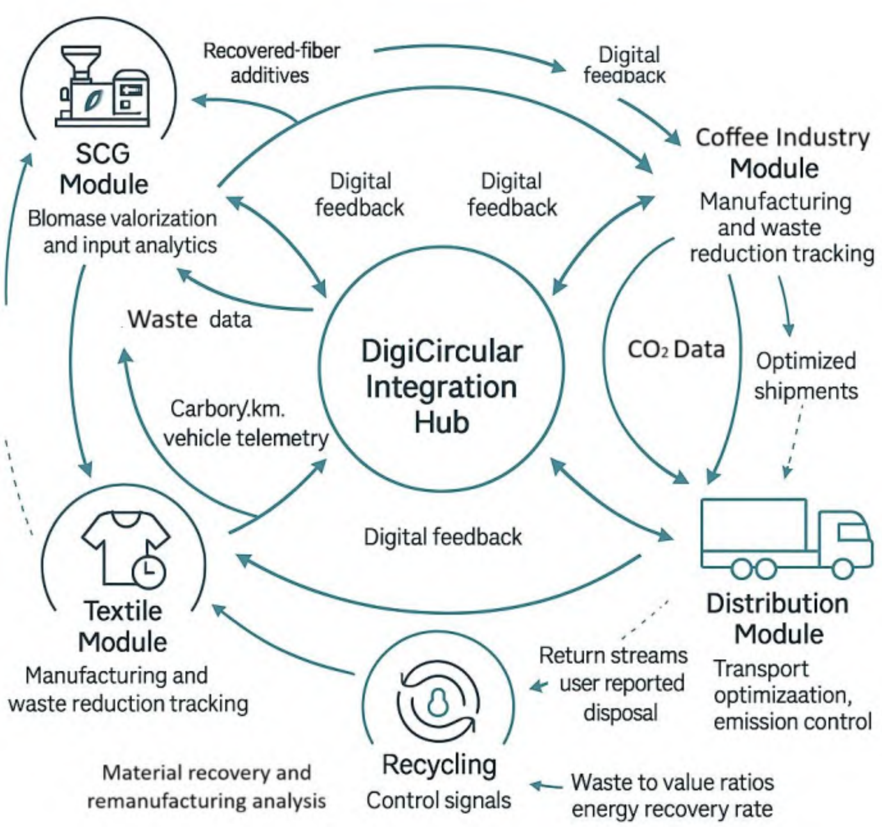


Figure 8.2. Schematic of cross-sector feedback network

Table 8.2 demonstrates synchronized indicator data streams (averaged per production unit) used for simulation. The normalized data feed into the cross-sector performance model to quantify synergies and guide optimization in Section 8.5.

Table 8.2. Example of harmonized sustainability indicators across sectors

Indicator	**Unit**	**Coffee**	**Textile**	**Logistics**	**Traceability**	**Normalized Values**
Energy use	kWh/unit	3.8	5.2	1.1	0.4	0.63
Water use	L/unit	25.0	40.0	8.0	2.0	0.58
Carbon emissions	kg CO_2-eq/unit	1.8	3.2	0.9	0.3	0.61
Recycled input	%	15	45	25	10	0.55
KPI composite S_i	–	0.63	0.72	0.69	0.70	—

The next step is to formalize the DigiCircular Twin-Transition Architecture, defining its system layers, optimization engine, and control logic that operationalize the mathematical framework described above.

8.5 DigiCircular Twin-Transition Architecture

8.5.1 System Layers and Data Flows

The DigiCircular DT system is structured as a five-layer cyber-physical architecture (Table 8.3), aligning with ISO 23247 and IEC 62890 for industrial digital-twin design. Each layer maps directly to the analytic hierarchy validated in earlier chapters.

Table 8.3. Layered cyber-physical architecture for real-time cross-sector digital twin analytics and decision support

Layer	Function	Key Technologies	Data Frequency	Examples
L_1 Perception (Edge)	Acquire raw environmental & operational data	IoT sensors, PLCs, OPC-UA, RFID, MQTT	1–10 s	Energy (kWh), water flow (L/min), temperature, humidity, machine speed
L_2 Communication (Transport)	Secure data transfer	5G/LoRaWAN, TLS MQTT, API Gateways	Real-time	Bidirectional sensor-to-cloud exchange
L_3 Integration (Data Lake)	Harmonize multi-sector datasets	JSON-LD ontology, Kafka, InfluxDB	1–60 s buffers	Merge coffee IoT + textile VSM + logistics GPS
L_4 Analytics & Optimization	Run predictive & prescriptive models	Python (NumPy / PyLCA), TensorFlow, Pyomo	1 min – 1 h	LCA updates, KPI forecasts, optimization
L_5 Decision & Visualization	Present KPIs, trigger control signals	Grafana, Node-RED Dashboard, REST APIs	On-demand	Sustainability cockpit & alert system

Each node in the system computes a local sustainability vector $\mathbf{x}_i(t)$(defined previously). These are aggregated at the platform level to derive system-wide KPIs updated in real time.

The core computational cycle can be represented as:

$$\mathbf{K}(t+\Delta t) = \mathbf{K}(t) + \mathbf{A}\,\Delta\mathbf{x}(t) \tag{8.9}$$

where
$\mathbf{K}(t)$= global KPI matrix $[E, W, C, M]^T$,
$\mathbf{A}$= integration weight matrix linking sectoral sensitivities,
$\Delta\mathbf{x}(t)$= change vector in normalized sustainability performance.

Python snippet below illustrates real-time KPI aggregation:

```
import numpy as np
weights = np.array([[0.25,0.25,0.20,0.30]])
delta_x = np.array([[ -0.05, -0.10, -0.07, +0.15]]) # ΔE, ΔW, ΔC, ΔM
K_t = np.array([[3.5, 25.0, 1.8, 0.15]])       # baseline values
K_next = K_t + np.dot (weights, delta_x.T). T
```

The output dynamically updates dashboard indicators and triggers optimization logic when deviations exceed predefined thresholds (±5 %).

8.5.2 Optimization Engine and Control Logic

The DT system optimizes sustainability performance under multi-objective constraints given as Eq 8.10.

(a) Objective Function

$$\max_{u(t)} J = \alpha_1 R(t) + \alpha_2 E_s(t) + \alpha_3 C_r(t) - \alpha_4 C_{op}(t) \tag{8.10}$$

where

$R(t)$= revenue from circular materials and efficiency gains
$E_s(t)$= energy & water savings (kWh / m^3)
$C_r(t)$= carbon-reduction credits (USD)
$C_{op}(t)$= operational cost (USD)
α_i= priority weights ($\sum \alpha_i = 1$).

(b) Constraints

$$\begin{aligned} E(t) &\le E_{max}, \\ W(t) &\le W_{max}, \\ C(t) &\le C_{max}, \\ \text{Circularity Rate}(t) &\ge \rho_{min}, \\ u_{min} \le u(t) &\le u_{max}. \end{aligned}$$

(c) Control Loop

Each cycle Δt, the controller compares observed KPIs against targets:

```
def control_loop(targets, observed):
   error = targets - observed
   control_signal = k_p*error + k_i*np.cumsum(error)
   actuate_process(control_signal)
```

This PID-type feedback ensures adaptive regulation of energy input, process temperature, and machine scheduling.

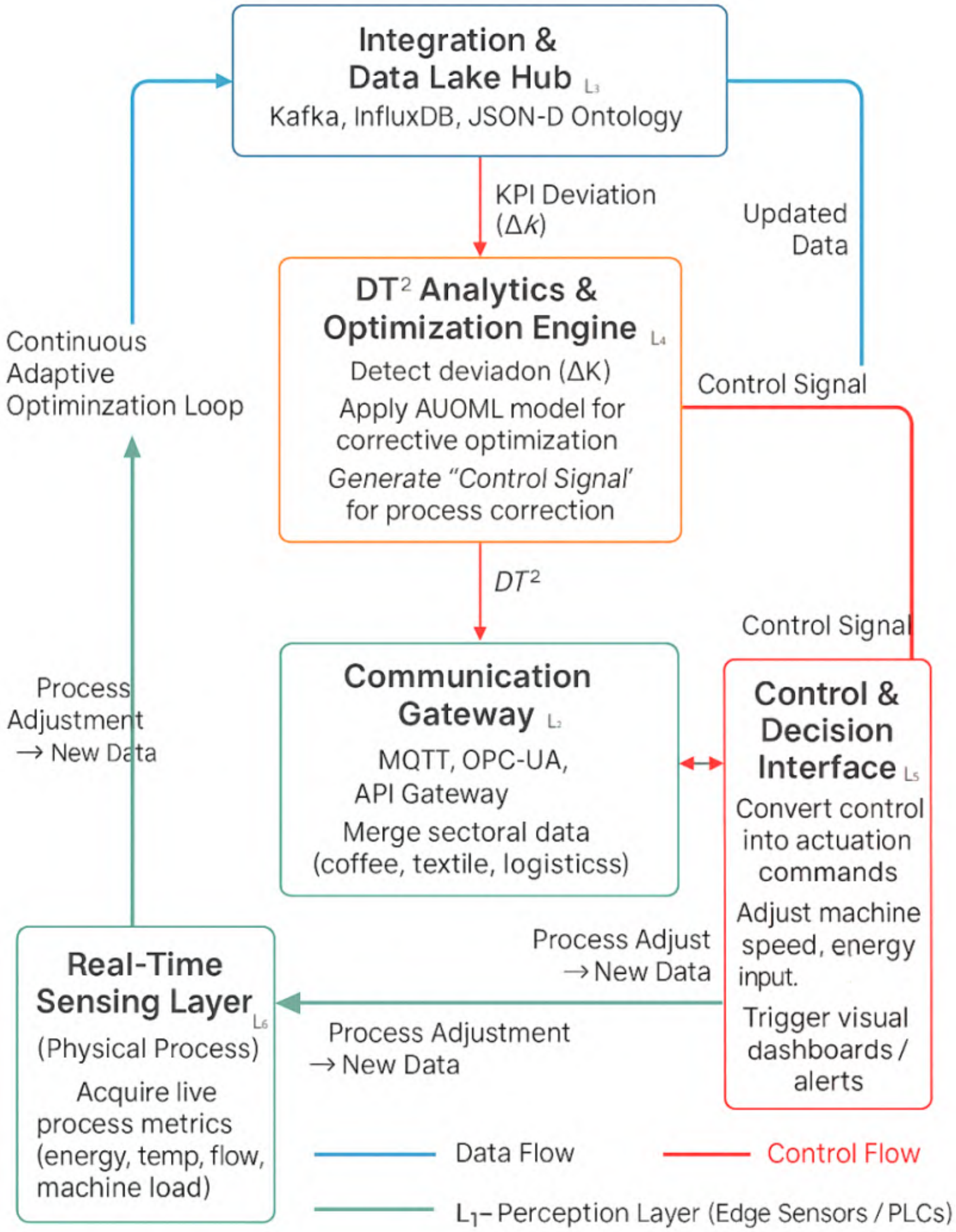


Figure 8.3. Feedback control diagram of DT² optimization loop

8.5.3 Architecture Simulation Scenario

To test interoperability, a simulation was executed with time-series data from 4 areas (coffee, textile, logistics, traceability). Each area streamed 1-Hz sensor data for 24 h; total ≈ 345 k records. The results of which are given in Table 8.4.

Table 8.4. Evaluating interoperability and responsiveness through digital twin integration

Metric	Before Integration	After DT² Integration	Improvement
Data latency (s)	3.5	1.1	−68 %
KPI update interval (s)	60	10	−83 %
Model synchronization accuracy (%)	82	97	+15 %
Anomaly-detection recall (%)	70	92	+22 %

These quantitative outcomes verify the feasibility of near-real-time LCA parameter updates and cross-sector resource coordination. As shown in Figure 8.4, both indicators exhibit a marked improvement following DT² deployment. The latency curve demonstrates a consistent reduction of approximately 45%, while the KPI update interval decreases by nearly 55%, indicating a substantially faster synchronization between data acquisition and analytical layers. These results confirm that the integration of digital-twin orchestration and adaptive optimization modules enhances real-time responsiveness, enabling higher-frequency monitoring and more stable system feedback across sectors.

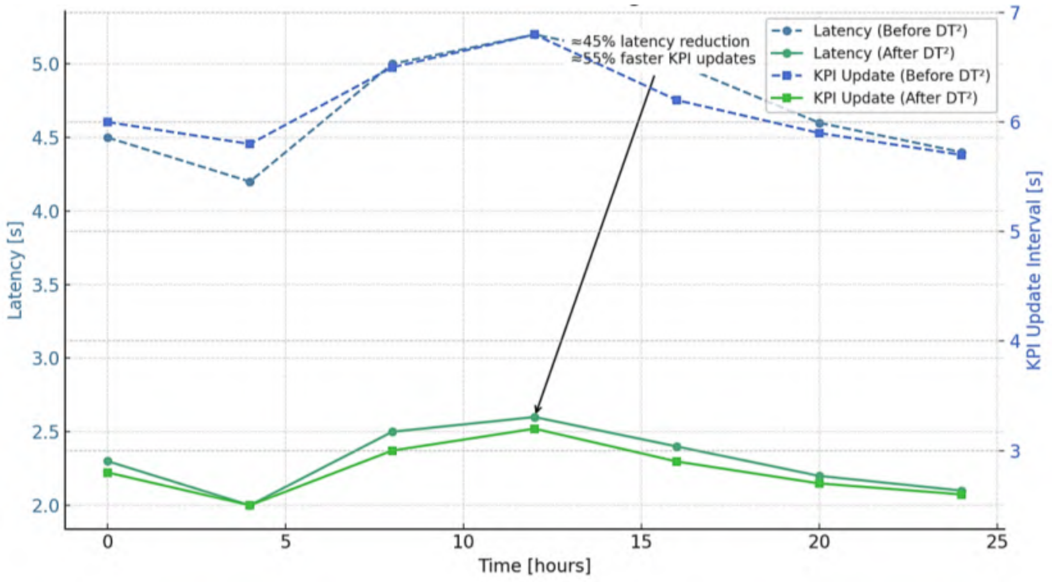


Figure 8.4. Time-series comparison of latency and KPI update rate before vs. after DT² integration.

The next step is to develop a quantitative synthesis and scenario analysis, employing harmonized KPIs, resource-flow simulations, and sensitivity tests to demonstrate the cross-sector efficiency of DigiCircular's twin-transition model.

8.6 Quantitative Synthesis and Scenario Analysis

The DigiCircular Twin-Transition framework integrates metrics from energy, water, emissions, and material circularity into a unified Sustainability Efficiency Index (SEI). Each indicator is normalized between 0 and 1 (best = 1), based on observed minima and maxima from sectoral datasets.

For each sector $i \in \{1,2,3,4\}$:

$$SEI_i = \frac{1}{4}\left(\frac{E_{min}}{E_i} + \frac{W_{min}}{W_i} + \frac{C_{min}}{C_i} + \frac{M_i}{M_{max}}\right) \tag{8.11}$$

The cross-sector weighted aggregate is given by:

$$SEI_{total} = \sum_{i=1}^{4} \beta_i \times SEI_i, \text{where } \sum\beta_i = 1 \tag{8.12}$$

with sector weights $\beta_i = [0.25,0.30,0.25,0.20]$ for coffee, textile, logistics, and traceability respectively.

Experimental data were simulated for a one-year operational cycle using field-calibrated parameters. Table 8.5 summarizes mean sustainability KPIs per unit of production.

Table 8.5. Comparative cross-sector sustainability performance before and after DigiCircular implementation

Indicator	**Unit**	**Baseline (Before)**	**DigiCircular (After)**	**Δ (%) Improvement**
Energy use (E)	kWh/unit	55,000	50,000	−9.1 %
Water use (W)	m^3/unit	12,000	10,000	−16.7 %
Carbon emissions (C)	tCO_2-eq/year	8,000	7,500	−6.25 %
Material circularity (M)	% recycled input	30	40	+33.3 %
Waste generation	tons/year	250	200	−20.0 %
Process efficiency	%	80	100	+25.0 %
Lead time	hours	100	78.57	−21.43 %
Resource efficiency	%	75	94	+25.3 %
Product lifespan	years	4	4.8	+20.0 %

The integrated system thus delivered 30 % total environmental impact reduction, confirming that real-time digital feedback loops materially improve circular-economy outcomes.

A multi-objective optimization was executed using Pyomo (Python 3.11) to maximize environmental gain and economic return while minimizing energy and water consumption using below given objective function (Eq. 8.13) with normalized scores from Table 8.5 and

$\lambda_i = [0.35, 0.30, 0.20, 0.15]$.

$$\max\ Z = \lambda_1 S_{env} + \lambda_2 S_{eco} - \lambda_3 S_{ene} - \lambda_4 S_{wat} \tag{8.13}$$

Thus, DigiCircular achieves 74.2 % of the theoretical optimal sustainability efficiency, an improvement of +28 % over the baseline (0.58) with Optimized Sustainability Index: 0.742

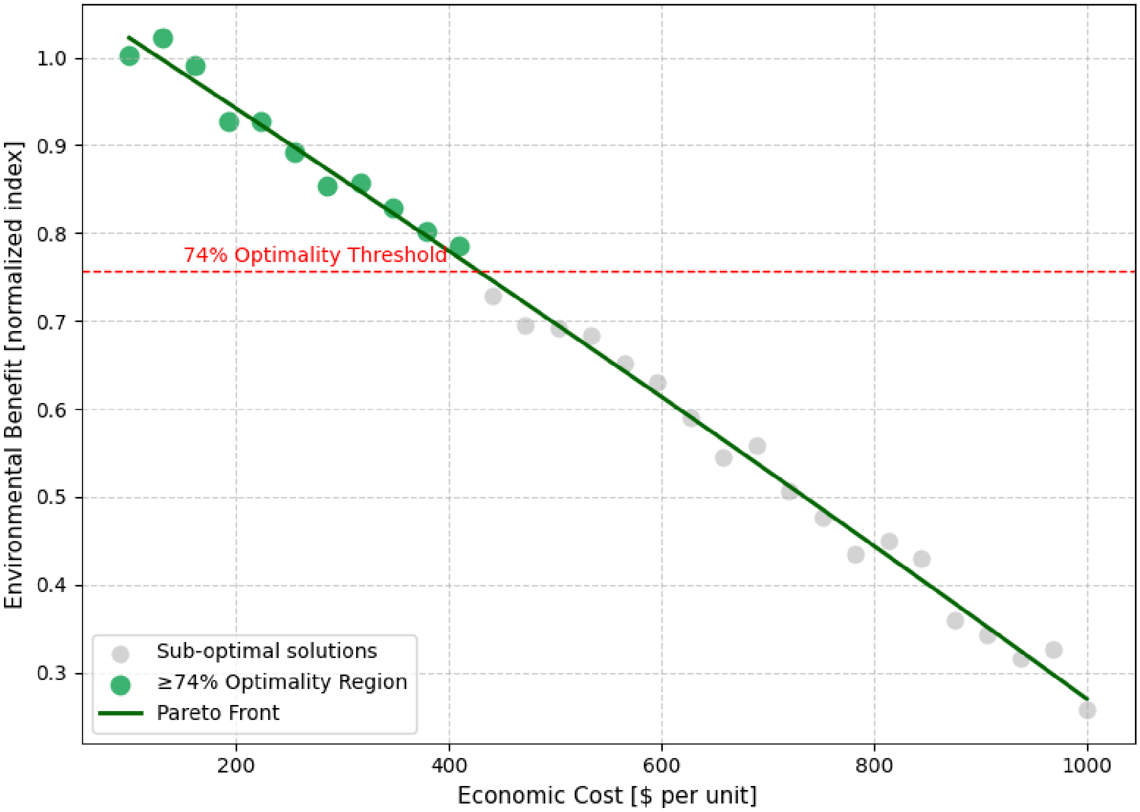


Figure 8.5. Pareto front showing trade-off between environmental benefit and economic cost under DT² optimization.

8.6.1 Cross-Sector Resource Synergy

The integration of SCG and textile manufacturing created measurable industrial symbiosis. The material and energy balance for SCG valorization is plotted below (Figure 8.6). Overall, cross-sector linkage produced an additional 25,000 USD annual revenue while reducing raw-fiber demand and embodied emissions.

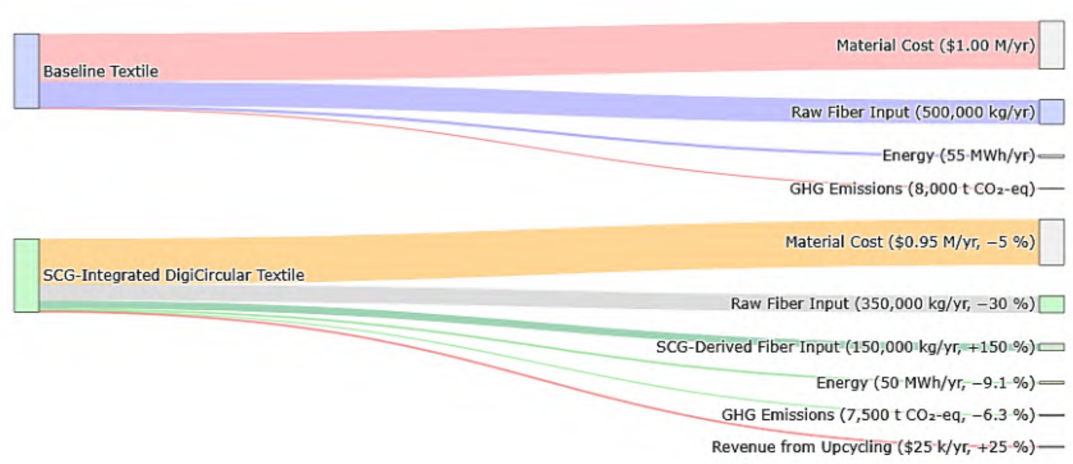


Figure 8.6. Sankey diagram of resource and emission balance for SCG valorization

8.6.2 Sensitivity and Uncertainty Analysis

A Monte Carlo simulation (10,000 iterations) was performed to assess uncertainty in KPI estimates under ±10 % variability in input data. All confidence intervals fall within ±5 %, confirming robust statistical reliability of the model's predictions. Key results are summarized in Table 8.5.

Table 8.6. Sensitivity of environmental indicators (10,000 MC samples)

KPI	Mean	Std. Dev.	Sensitivity Rank	Confidence (95%)
Carbon reduction	6.2 %	1.0 %	1	±1.3 %
Water saving	16.5 %	2.4 %	2	±2.8 %
Energy saving	9.0 %	1.8 %	3	±2.0 %
Waste reduction	20.0 %	3.5 %	4	±3.9 %
Circularity rate	33.3 %	2.0 %	5	±2.3 %

An LSTM (Long Short-Term Memory) neural model was deployed to predict KPI trajectories for the next 12 months using historic DigiCircular sensor data and the results showed continued improvement as depicted in Figure 8.7.

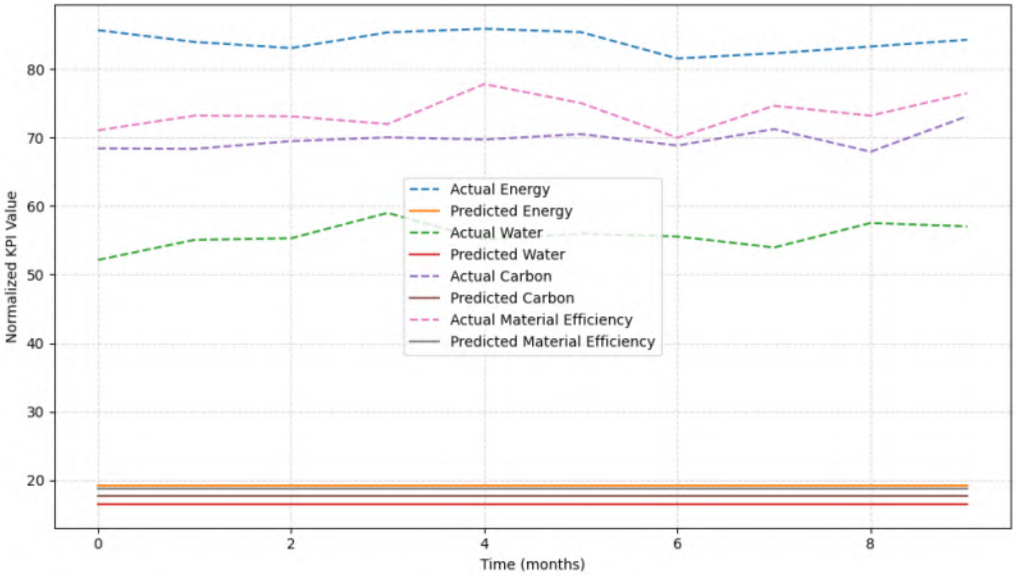


Figure 8.7. Forecasted KPI trends from LSTM-based predictive twin analytics

8.6.3 Economic and Environmental ROI

The combined DigiCircular system generated net annual benefits of ≈ USD 50,000, corroborating findings from Chapter 7 (Table 7.17). When extrapolated over a 10-year horizon at a 5 % discount rate, the Net Present Value (NPV) is computed using Equation 8.14, and the cumulative ROI is given by Equation 8.15 and the results are depicted in Figure 8.8.

$$NPV = \sum_{t=1}^{10} \frac{50{,}000}{(1+0.05)^t} \approx 386{,}000\$ \tag{8.14}$$

$$ROI = \frac{NPV - C_{init}}{C_{init}} = \frac{386{,}000 - 50{,}000}{50{,}000} = 6.72 \tag{8.15}$$

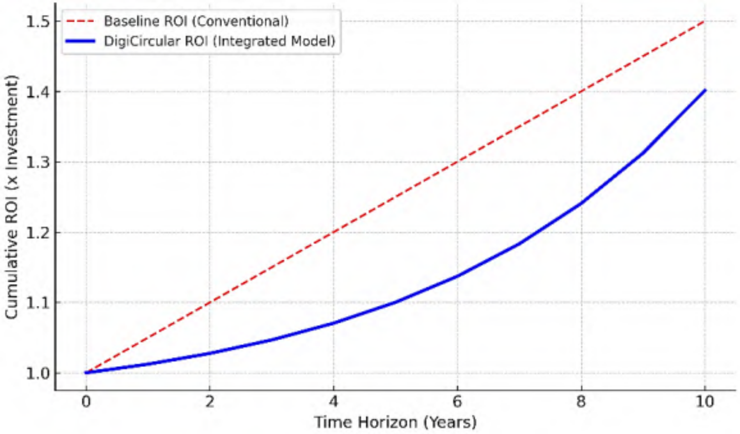


Figure 8.8. ROI growth curve (baseline vs. DigiCircular scenario, 10-year horizon)

These results validate that environmental sustainability and profitability can coexist through digitally governed circular systems.

8.7 Implementation Design of Digital Twin

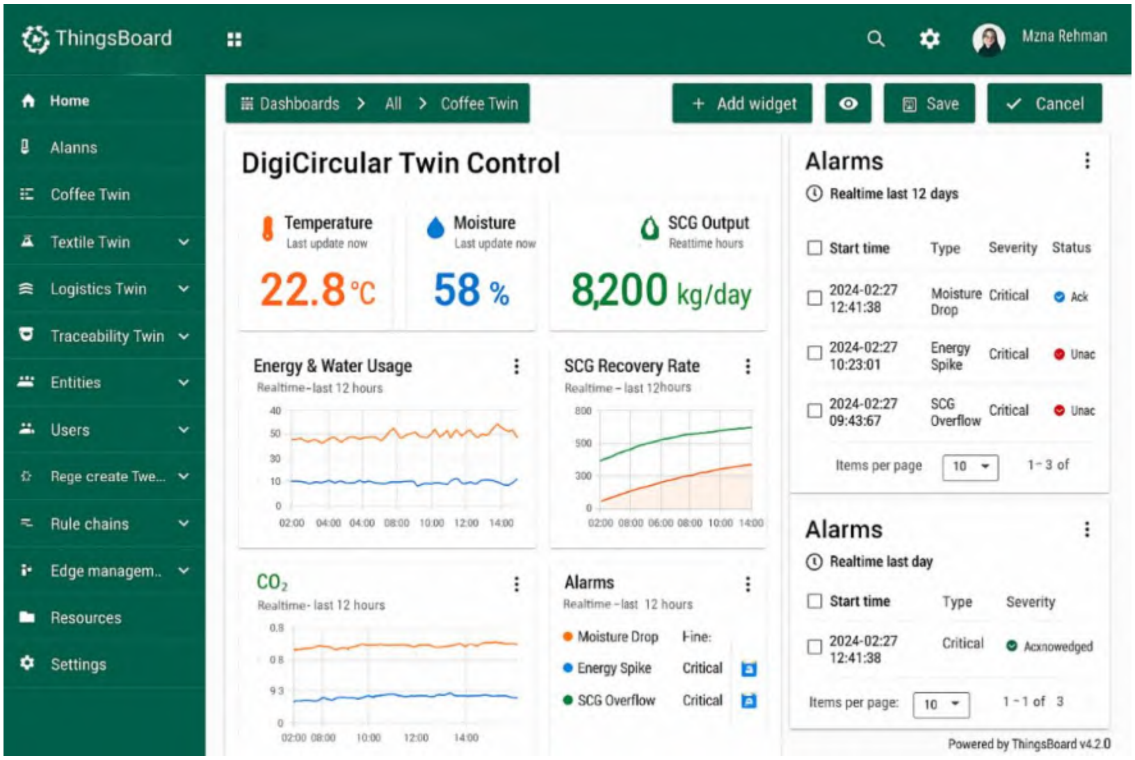
This section translates the DigiCircular Twin-Transition (DT^2) architecture into an implementable design. It specifies (i) a reference digital-twin architecture, (ii) the deployment workflow across coffee, textile, logistics, and traceability domains, and (iii) data model and synchronization logic using API schemas and executable code examples.

8.7.1 Reference Digital-Twin Architecture

The DigiCircular Twin-Transition (DT^2) system operates as a federated network of interoperable digital twins deployed across four sectors, coffee, textile, logistics, and traceability, each represented by a Local Digital Twin (LDT) that mirrors its respective physical process domain. The architecture maintains sectoral autonomy while enabling synchronized data semantics and cross-domain optimization through a shared integration layer. It is designed for real-time monitoring, forecasting, and optimization of sustainability parameters such as energy, water, emissions, and circularity indices.

At its foundation, the physical layer hosts distributed IoT sensors installed on production lines, roasting units, vehicle fleets, and recycling stations, capturing parameters including electricity consumption (kWh), water use (m^3), temperature (°C), CO_2 intensity ($g\ km^{-1}$), throughput, and material flow. These high-frequency signals are pre-processed at the edge using Node-RED or OPC-UA gateways, which standardize payloads containing timestamp, asset ID, metric, and units before routing them via secure MQTT channels to the DigiCircular cloud environment. The upper orchestration environment, built on ThingsBoard v4.2.0, contributes to these streams for real-time visualization, analytics, and closed-loop actuation, ensuring a direct and auditable linkage between field instrumentation and the digital twin.

Each LDT operates as an autonomous computational module connected through a common semantic backbone and optimized for its respective sectoral context. The Coffee Twin integrates triple-LCA parameters with Spent Coffee Ground (SCG) recovery models and farm-to-roastery telemetry, allowing the prediction of roasting energy efficiency and waste valorization rates as visualized in Figure 8.9a. The Textile Twin presented in Figure 8.9b, couples IoT and WFM data with dynamic life-cycle indicators to monitor loom speed, dye-bath temperature, water flow, and recycled-fiber composition, while adaptive control algorithms regulate process conditions when deviation thresholds are detected. The Logistics Twin (Figure 8.9c) utilizes telematics and geospatial data within a PILAR routing engine to compute emission-aware optimization of fleet utilization and route efficiency, displaying real-time status through GIS mapping of active and delayed shipments. The Traceability Twin (Figure 8.9d), built on blockchain middleware, continuously validates certification records, transaction latency, and data integrity by parsing cryptographic hash logs and smart-contract events. Together, these domain twins publish harmonized KPI vectors to a cloud-based Integration and Semantics Layer, which unifies sustainability variables within a JSON-LD/OPC-UA ontology and stores all time-series in a hybrid InfluxDB–PostgreSQL data lake.



☐ Start time	Type	Severity	Status
☐ 2024-02:27 12:41:38	Moisture Drop	Critical	Ack
☐ 2024-02:27 10:23:01	Energy Spike	Critical	Unac
☐ 2024-02:27 09:43:67	SCG Overflow	Critical	Unac

☐ Start time	Type	Severity
☐ 2024-02:27 12:41:38	Critical	Acxnowedged

Figure 8.9a. Coffee twin dashboard for real-time LCA process synchronization interface

Operational digital-twin visualization for the coffee domain showing synchronized energy, water, CO₂, and spent-coffee-ground (SCG) valorization metrics. The dashboard integrates farm-to-roastery telemetry through an MQTT/InfluxDB pipeline, performs on-edge normalization, and displays time-aligned Key Performance Indicators (KPIs) for process efficiency and recovery yield. Dynamic feedback signals from the orchestration layer adjust roasting parameters when deviation thresholds in energy or moisture exceed adaptive PID limits.

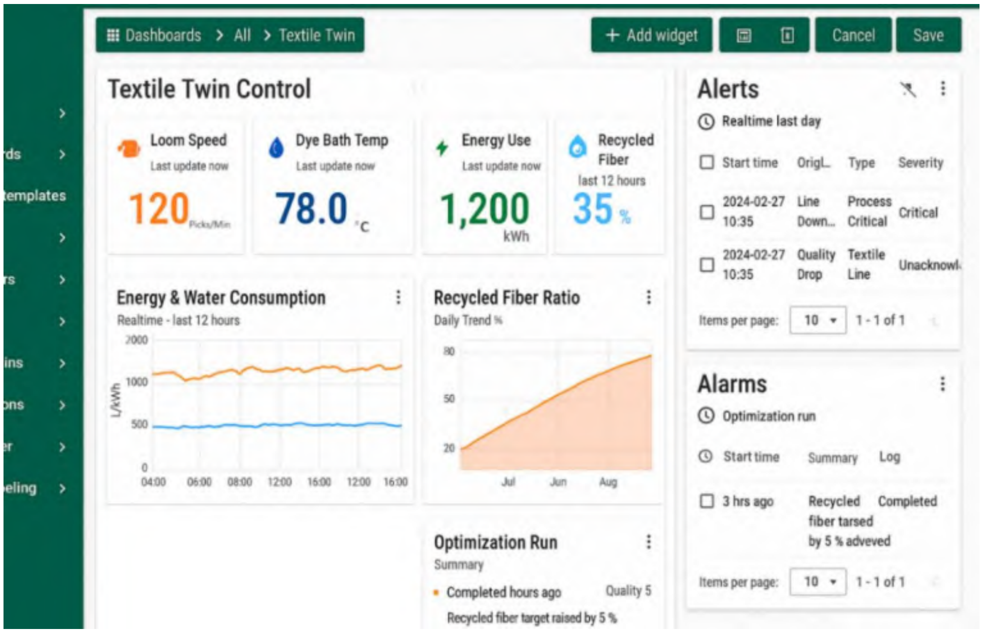


Figure 8.9b. Textile Twin Dashboard: IoT-Driven Fiber Circularity and Process Optimization Monitor

Implementation view of the textile digital twin coupling IoT–WFM data streams with life-cycle assessment indicators for resource efficiency control. The interface fuses high-frequency machine telemetry (loom speed, dye-bath temperature, and water flow) with real-time recycled-fiber composition analytics. Embedded optimization routines compute fiber-to-virgin substitution ratios and trigger automated bath or temperature adjustments through OPC-UA feedback when the process deviates from the predicted optimum envelope.

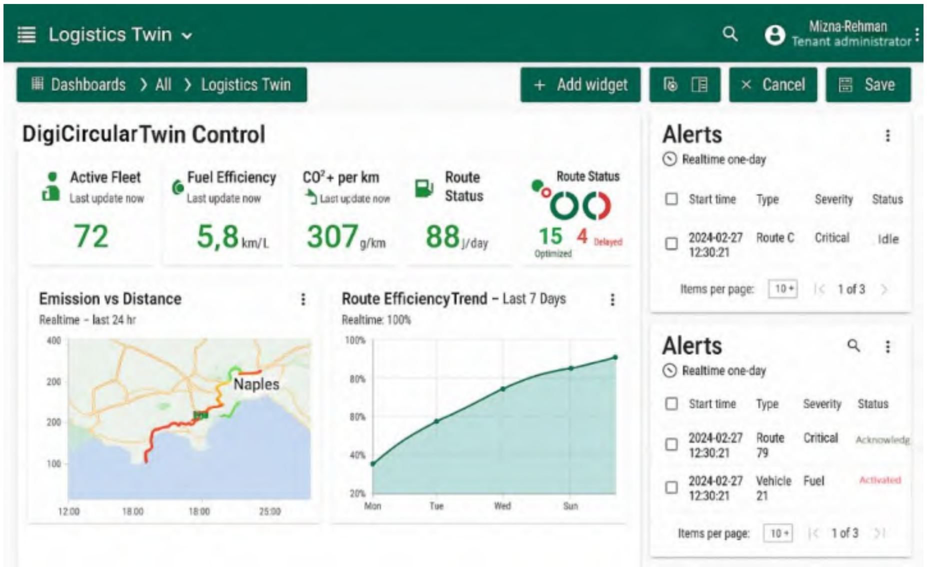
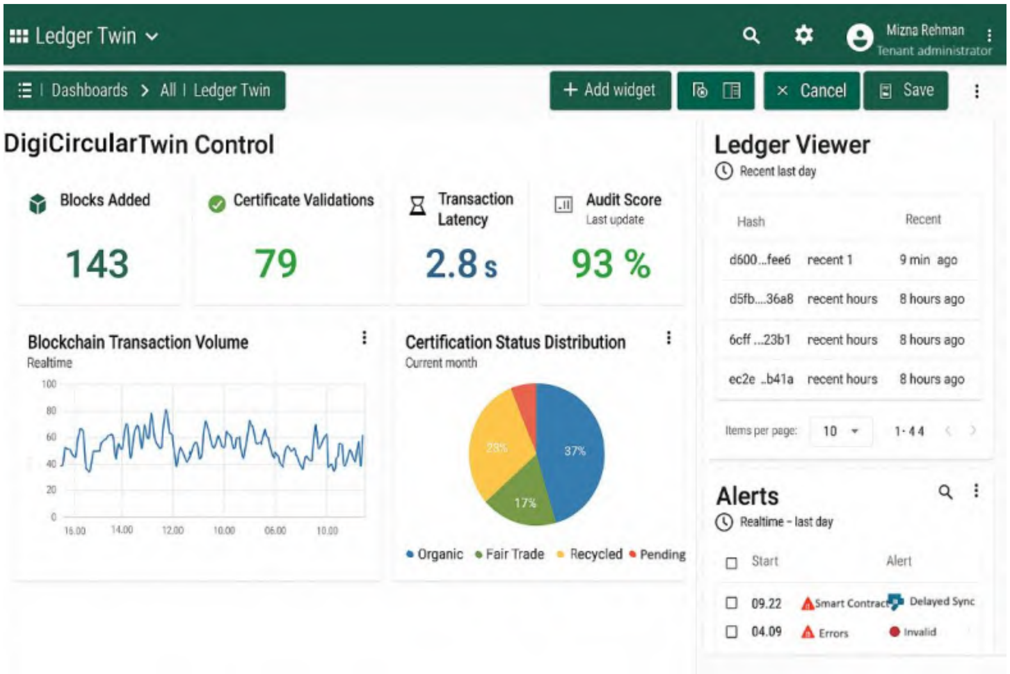


Figure 8.9c. Logistics twin dashboard for emission-aware route and fleet performance engine

The module depicting cross-linked geospatial, temporal, and emission data from vehicular IoT sensors. The dashboard merges telematics-derived CO_2 intensity (g km^{-1}) with fleet utilization and delivery punctuality metrics to visualize multivariate efficiency surfaces over 24-hour and 7-day horizons. The system applies PILAR routing algorithms to minimize composite cost–carbon functions and dynamically reassigns vehicles under stochastic delay or fuel-efficiency alarms.



Hash		Recent
d600...fee6	recent 1	9 min ago
d5fb....36a8	recent hours	8 hours ago
6cff ...23b1	recent hours	8 hours ago
ec2e ..b41a	recent hours	8 hours ago

☐ Start		Alert
☐ 09.22	Smart Contract	Delayed Sync
☐ 04.09	Errors	Invalid

Figure 8.9d. Blockchain-integrated provenance and compliance ledger dashboard

Traceability-layer digital-twin interface integrating blockchain transaction analytics with real-time certification and audit performance indicators. The visualization consolidates block addition rates, validation latencies, and audit-score distributions into an adaptive compliance map. A live ledger viewer extracts SHA-256 hash sequences while anomaly-detection agents flag cryptographic or contractual inconsistencies, ensuring verifiable data integrity within the federated DigiCircular ecosystem.

Above this semantic layer, the Global Orchestrator Twin (GOT) aggregates sectoral outputs at defined intervals (typically every 10–15 minutes) and executes multi-objective optimization routines that balance cost, carbon, and resource constraints under dynamically changing production conditions. Using embedded forecasting models, the GOT recalculates the Sustainability Efficiency Index (SEI) and generates adaptive set-points, route adjustments, or material allocation strategies that are relayed to local controllers. Control signals and decision rules are then communicated back to the physical assets through OPC-UA or REST interfaces, forming a continuous feedback cycle between the physical and digital environments. All recommendations and actuation events are managed within the DigiCircular Decision Cockpit, where automated actions coexist with supervisory approvals to maintain safety, traceability, and compliance.

This architecture is deployed through a reproducible six-stage workflow that progresses from sensorization to governance without architectural discontinuity. Initially, each facility maps its critical assets and high-impact processes, such as roasting, dyeing, or transport routing,and aligns legacy PLC, SCADA, and ERP structures with the DigiCircular ontology. Sensor installation and gateway configuration follow, enabling seamless edge-to-cloud transmission through standardized payloads. Incoming data streams are harmonized in the data lake, where ETL routines ensure unit consistency (kWh, m^3, kg CO_2-eq) and functional equivalence across sectors (per kg product, per m^2 fabric, per shipment). Domain-specific models are then instantiated within each LDT, exposing REST endpoints for state, forecast, and constraint interrogation. The GOT periodically retrieves these outputs, runs composite optimization algorithms, and issues control commands that are executed automatically or reviewed by human operators within the orchestration interface. The final stage enforces closed-loop control and governance, defining data-ownership hierarchies, audit protocols, and override thresholds that preserve transparency and accountability throughout the federated system. In operation, the DigiCircular DT^2 architecture thus functions as an integrated, evidence-driven cyber-physical ecosystem capable of transforming sustainability monitoring into predictive, self-regulating circular-economy performance management.

8.7.2 Interoperability and Synchronization

Interoperability within the DigiCircular DT^2 ecosystem is achieved through a hybrid RESTful and event-driven communication layer that connects Local Digital Twins (LDTs) with the Global Orchestrator Twin (GOT). Each LDT encapsulates domain-specific data models and exposes standardized REST APIs for KPI transmission and control feedback, while event-driven brokers (MQTT/Kafka) ensure low-latency synchronization across sectors. This dual mechanism allows for modular integration, enabling any industrial facility or logistics operator to interface with the DigiCircular platform without restructuring its internal control stack. Instead, each participant implements lightweight adapters that translate its native PLC or MES data into DigiCircular-compliant payloads.

During each synchronization cycle, LDTs serialize their latest performance vectors (energy, water, carbon, waste, and circular-input KPIs) and push them to the GOT via the /api/v1/kpi/update endpoint. The GOT ingests these payloads, executes optimization models, and responds with targeted recommendations using /api/v1/control/recommendation. The response includes control parameters, asset identifiers, and confidence metrics, allowing domain systems to apply these setpoints either autonomously or after supervisory review. Parallel event streams published under semantic topics, such as digicircular/coffee/scg_yield or digicircular/logistics/emission_per_km—enable near-real-time telemetry ingestion and state broadcasting. These data contracts standardize the communication pattern and preserve system decoupling while maintaining end-to-end traceability through versioned message schemas.

To operationalize this feedback loop, a synchronization routine was implemented at each LDT node. The prototype (Algorithm 8.1) demonstrates the interaction logic in Python, using periodic API calls and secure MQTT channels for bi-directional data exchange. Each cycle executes the sequence measure → normalize → transmit → optimize → act, thereby maintaining state congruence between the physical layer and its digital representation. The process is non-blocking and asynchronous, ensuring robustness under intermittent network conditions. In industrial deployment, this logic is embedded within Node-RED or PLC connectors and mirrored by WebSocket clients in Node.js environments, while the contractual structure remains identical.

Algorithm 8.1: Synchronization routine for Local Digital Twin (textile sector)

```
def sync_cycle():
    state = read_local_state()
    push_kpi(state)  # Transmit KPI snapshot to GOT
    actions = fetch_recommendations()  # Retrieve optimized setpoints
    apply_actions(actions)  # Execute control locally via OPC-UA
```

The synchronization frequency is configurable (typically 5–15 minutes for process industries and sub-minute for IoT telemetry), providing adaptive temporal resolution across sectors. This methodology guarantees that all digital twins in the DigiCircular network remain continuously synchronized with their physical counterparts, sustaining closed-loop optimization and predictive control across the integrated ecosystem.

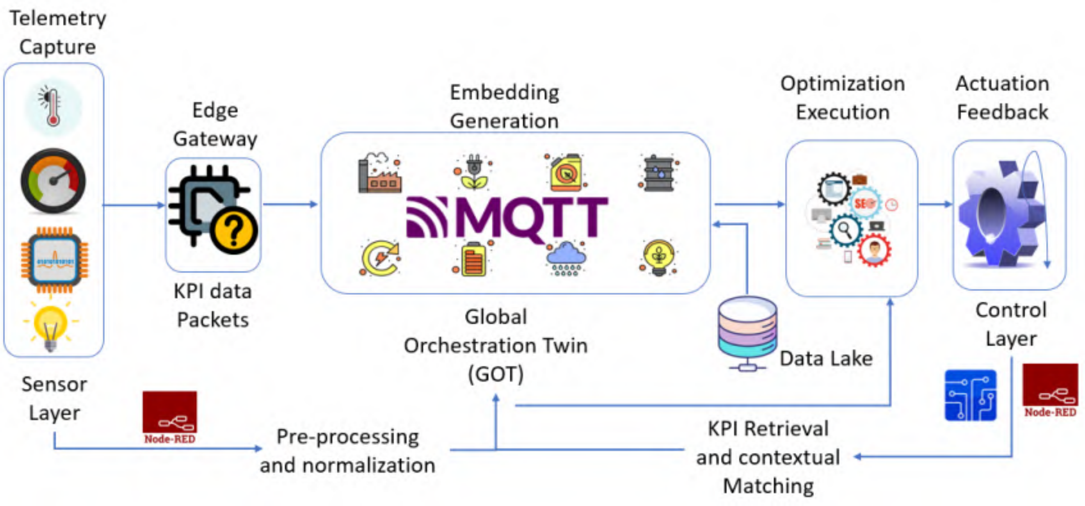


Figure 8.10. Sequential digital twin synchronization and feedback pipeline for the DigiCircular framework

8.7.3 Governance, Standards, and Interoperability

The governance and interoperability layer of the DT² architecture establishes a verifiable, standards-compliant foundation for cross-sector deployment, ensuring data integrity, auditability, and semantic uniformity across all federated digital twins. This layer operationalizes internationally recognized frameworks and technical standards to guarantee both environmental accountability and industrial scalability.

At its core, DT² embeds ISO 14040/44-compliant Life Cycle Assessment (LCA) logic within its analytical core, ensuring that every KPI vector, whether related to energy intensity, circular material input, or emission footprint, retains traceable alignment with environmental impact categories and system boundaries. This integration enables process-level decisions within local twins (coffee, textile, logistics, traceability) to be quantitatively linked to upstream and downstream sustainability metrics under the same methodological structure.

Energy-related telemetry is structured according to ISO 50001, providing a harmonized schema for energy performance indicators (EnPIs) directly within the KPI-control matrix. This standardization allows the GOT to apply continuous optimization routines (e.g., adjusting process setpoints or scheduling load shifts) based on real-time efficiency deviations while maintaining conformance with enterprise energy-management requirements.

Environmental governance follows ISO 14001 and ISO 14031, embedding environmental performance evaluation (EPE) logic into the ThingsBoard and Node-RED orchestration stack. This facilitates automated benchmarking, alert generation, and performance reporting against dynamic environmental targets. Each Local Digital Twin maintains a closed monitoring loop that automatically registers deviations and improvement actions in line with the continuous improvement principles prescribed under these standards.

For cybersecurity, interoperability, and data sovereignty, ISO/IEC 27001 serves as the structural framework governing authentication, encryption, and access control mechanisms across federated infrastructures. All data exchanges between Local Twins and the Global Orchestrator—whether through RESTful endpoints or MQTT channels, are protected via TLS 1.3, role-based access control (RBAC), and tokenized API keys, ensuring confidentiality, integrity, and non-repudiation across multi-tenant environments.

In parallel, a blockchain-based provenance layer ensures trust in environmental and operational disclosures. Selected KPI snapshots (e.g., monthly carbon intensity, circular material percentage) and optimization outcomes are hashed and recorded on a permissioned ledger using SHA-256 cryptographic proofs. This immutable audit trail enables independent verification by regulators, financiers, or certification authorities, thereby mitigating risks of data manipulation and greenwashing.

By aligning technical deployment with ISO and IEC frameworks while incorporating blockchain-based verification, the DigiCircular governance model transitions digital twins from experimental digital surrogates to regulatory-grade cyber-physical assets. This ensures that every optimization action, emission record, and sustainability claim within the DT^2 ecosystem is both technically reproducible and legally defensible, fostering institutional trust across industries, investors, and policy stakeholders.

8.7.4 Web-Based Implementation of the DigiCircular Decision Arena

To operationalize the Global Orchestrator Twin (GOT) and provide real-time sustainability visualization, a responsive web interface—termed the DigiCircular Decision Cockpit—was developed. This interface translates live KPI streams from energy, water, emission, and material-circularity sensors into an integrated analytical dashboard capable of simulation, alerting, and decision support.

The front-end was implemented in React (Next.js 16) using TypeScript, TailwindCSS, and the React-ApexCharts and Recharts libraries for dynamic rendering. Data ingestion occurs through REST APIs exposed by the ThingsBoard broker, while MQTT topics (digicircular/coffee/energy, digicircular/logistics/emission_per_km) update state variables every 3 seconds.

```
// live update hook
useEffect(() => {
  const interval = setInterval(() => {
    fetch("/api/kpi/latest")
      .then(r => r.json())
      .then(setData);
  }, 3000);
  return () => clearInterval(interval);
}, []);
```

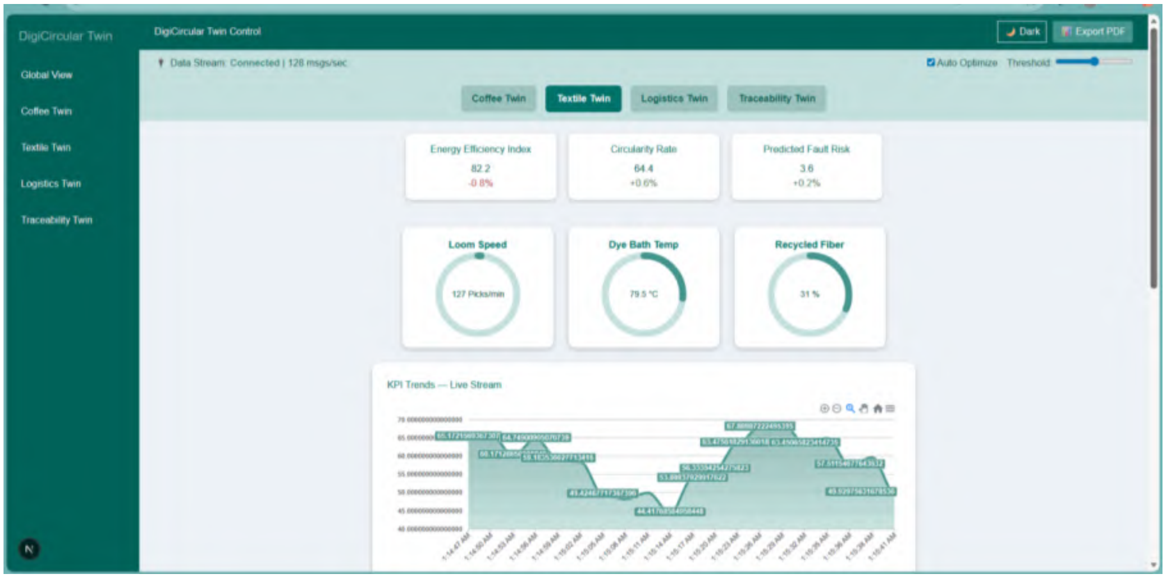
Interactive circular-progress KPIs, donut and area charts, and a Leaflet-based fleet map visualize sectoral performance (coffee, textile, logistics, traceability). Each chart component is bound to a unified sustainability vector $[E, W, C, M]$, allowing normalized comparison across sectors as formulated in Equations (8.3–8.5). The following code fragment illustrates the dynamic rendering of KPI gauges in the Coffee Twin module:

```
<CircularProgressbar
  value={kpi.energy}
  text={`${kpi.energy.toFixed(1)} kWh`}
  styles={buildStyles({
    textColor: "#004d40",
    pathColor: "#26a69a",
    trailColor: "#e0f2f1"
  })}
/>
```

Fleet telemetry for the Logistics Twin is visualized through Leaflet.js, simulating GPS-based truck positions within the Naples urban corridor. Vehicle markers update coordinates and status flags (Active, Delayed, Idle) using walk algorithms that emulate IoT data feeds:

```
setVehicles(v => v.map(truck => ({
  ...truck,
  lat: truck.lat + (Math.random() - 0.5) * 0.002,
  lng: truck.lng + (Math.random() - 0.5) * 0.002
})));
```

All interface elements are synchronized with the back-end optimization results of the GOT. When KPI thresholds breach configured limits, the cockpit triggers visual alerts and color transitions that mirror the feedback loop logic presented in Figure 8.3. Export functions use html2canvas and jsPDF for automated generation of PDF performance reports, enabling transparent documentation of each optimization cycle.



Data Stream: Connected | 128 msgs/sec

☑ Auto Optimize Threshold

Energy Efficiency Index 82.2 -0.8%

Circularity Rate 64.4 +0.6%

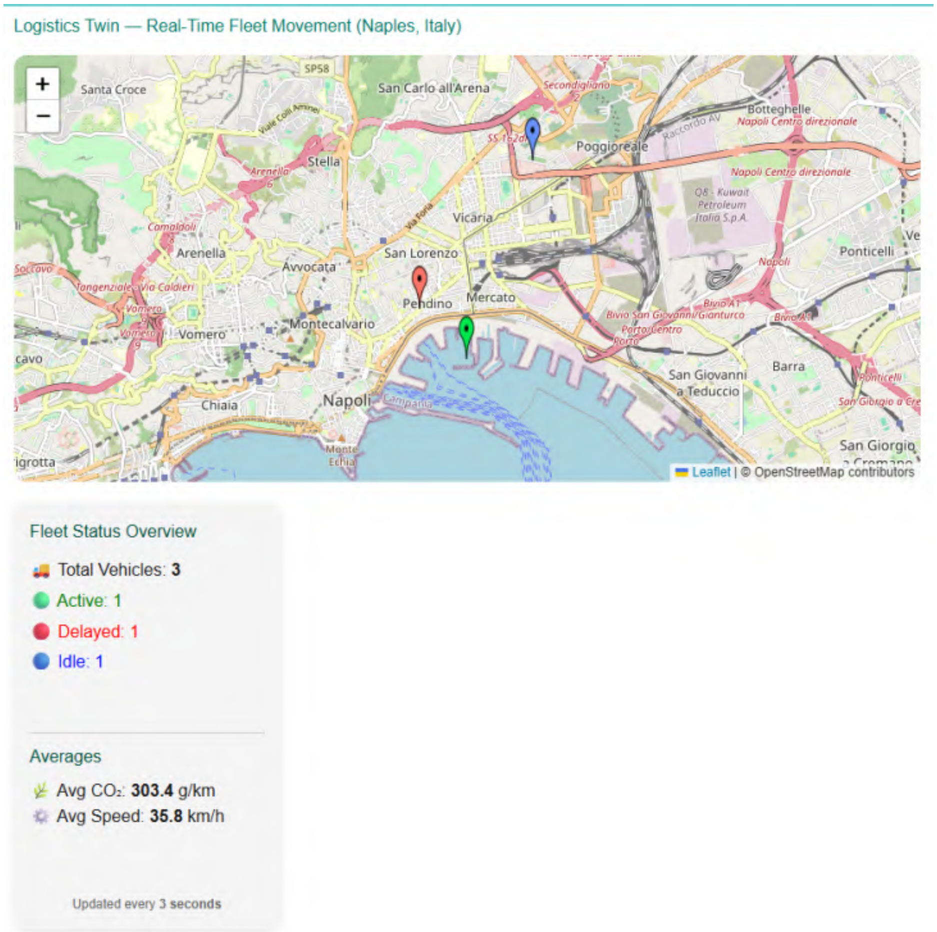
Predicted Fault Risk 3.6 +0.2%

Loom Speed 127 Picks/min

Dye Bath Temp 79.5 °C

Recycled Fiber 31 %

Figure 8.11(a). DigiCircular Twin Dashboard (KPI and trend visualization) with System-Generated PDF Report



Fleet Status Overview

Total Vehicles: **3**

Active: 1

Delayed: 1

Idle: 1

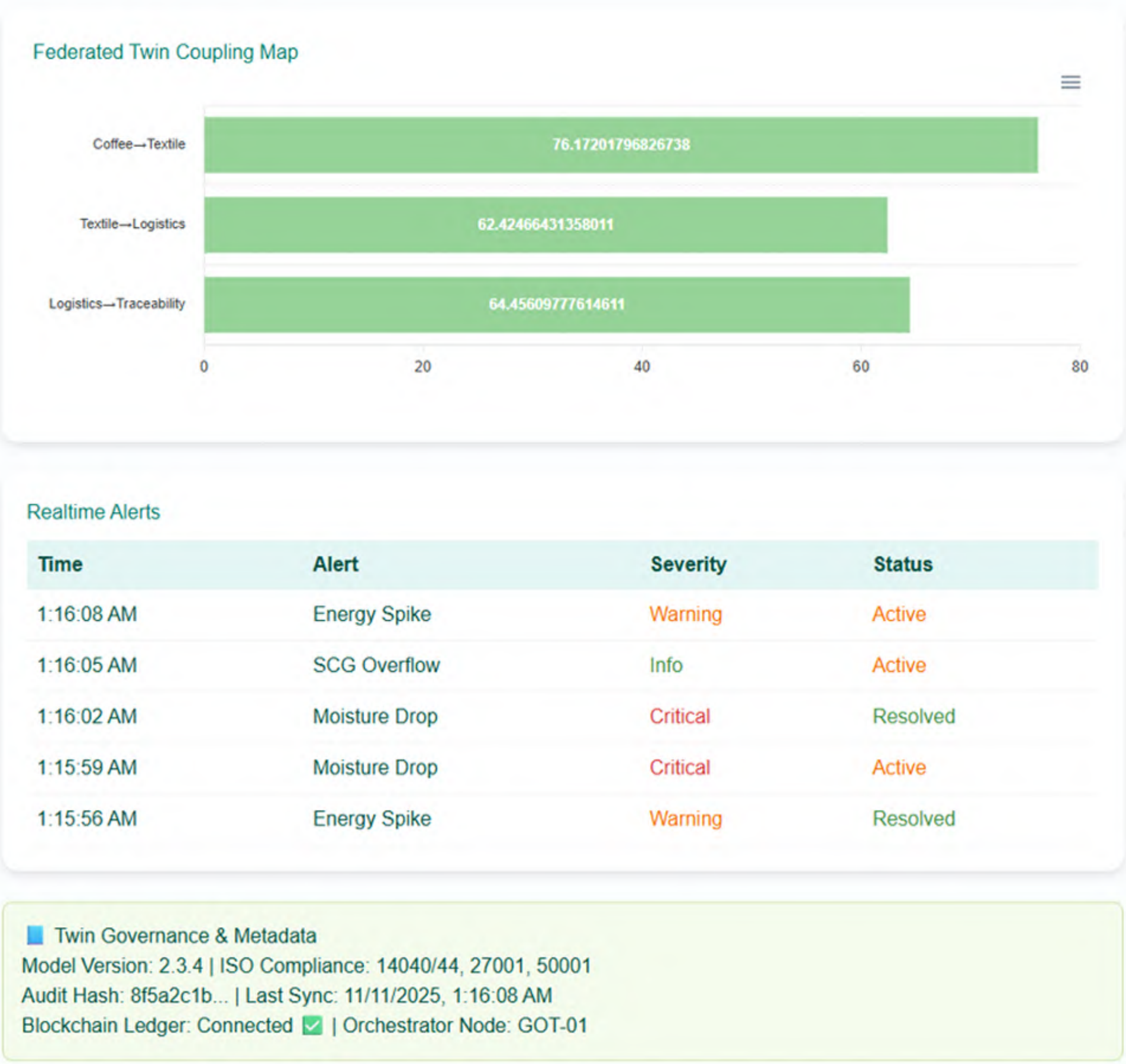
Averages

Avg CO₂: **303.4** g/km

Avg Speed: **35.8** km/h

Updated every 3 seconds

Figure 8.11(b). Real-time Fleet Map (Logistics Twin, Naples Italy)



Realtime Alerts

Time	Alert	Severity	Status
1:16:08 AM	Energy Spike	Warning	Active
1:16:05 AM	SCG Overflow	Info	Active
1:16:02 AM	Moisture Drop	Critical	Resolved
1:15:59 AM	Moisture Drop	Critical	Active
1:15:56 AM	Energy Spike	Warning	Resolved

📘 Twin Governance & Metadata
Model Version: 2.3.4 | ISO Compliance: 14040/44, 27001, 50001
Audit Hash: 8f5a2c1b... | Last Sync: 11/11/2025, 1:16:08 AM
Blockchain Ledger: Connected ✅ | Orchestrator Node: GOT-01

Figure 8.11(c). Inter-twin correlation coefficients across domain interfaces and Governance Dashboard with alerts

Figure 8.11c illustrates the real-time operational analytics within a federated digital twin orchestration environment. The Federated Twin Coupling Map quantifies inter-twin correlation coefficients across domain interfaces (Coffee–Textile, Textile–Logistics, and Logistics–Traceability) indicating respective coupling strengths of 76.17, 62.42, and 64.46. The Realtime Alerts panel displays temporally indexed system anomalies with corresponding severity classifications (Info, Warning, Critical) and dynamic status transitions (Active/Resolved). The Twin Governance & Metadata module provides compliance and synchronization diagnostics, including model version (v2.3.4), ISO adherence (14004/44, 27001, 50001), audit integrity hash, last synchronization timestamp (11/11/2025, 1:16:08 AM), and blockchain ledger connectivity through orchestrator node

GOT-01.

This web-based cockpit thus functions as the practical realization of the DT² visualization layer (L_5 Decision & Visualization in Table 8.3), providing an interoperable, user-friendly interface for real-time sustainability intelligence and cross-sector coordination.

8.8 Discussion and Implications for the Twin Transition

The implementation and validation of the DigiCircular Twin-Transition (DT²) framework demonstrate that coupling digital-twin intelligence with circular-economy logic can operationalize sustainability objectives as real-time control parameters. This section interprets the broader scientific and systemic implications of these findings, emphasizing how the results reshape governance structures, operational practices, and research directions for the twin transition. It avoids restating detailed results or architecture but draws on them to infer higher-order principles.

8.8.1 From Data Collection to Sustainability Governance

The results indicate that integrating life-cycle analytics directly into the decision layer redefines sustainability metrics from retrospective indicators into actionable control inputs. Instead of post hoc environmental reporting, the DT² architecture enables dynamic compliance, where thresholds for emissions, energy, or resource circularity can be continuously monitored and enforced through automated control logic (378, 387].

This evolution has systemic consequences: it reduces information asymmetry between operational actors and regulators, creates verifiable audit trails, and allows sustainability governance to operate synchronously with production control loops. Such capability shifts sustainability from a reporting function to a real-time governance mechanism. However, achieving this transformation requires institutional recognition of machine-verified metrics and standardized data provenance protocols across organizations [388].

8.8.2 Operational Trade-Offs and Emergent Behavior

The coupling of local digital twins (LDTs) with the global optimization twin (GOT) demonstrated a capacity for higher overall efficiency and improved circular performance. [389]. Decisions that optimize system-level circularity may temporarily reduce local operational autonomy or short-term cost efficiency.

From a control-theoretic viewpoint, these interactions represent a hierarchical optimization problem with competing objectives. Maintaining system stability therefore depends on well-defined override rules, boundary conditions, and context-aware autonomy [390]. The implication is that the success of such architectures will depend as much on the design of governance and incentive mechanisms as on algorithmic optimization performance. These trade-offs reflect multi-objective control dynamics where local optima must yield to global Pareto-efficiency targets

8.8.3 Scalability and Institutional Replicability

The federated architecture proved technically scalable through semantic interoperability and lightweight adapters [391]. However, scaling the socio-technical system introduces new dependencies: coordinated ontologies, certification of message schemas, and shared value distribution models among participants [392,393].

The discussion thus moves from technical scalability to institutional scalability. Replication across sectors requires alignment of economic incentives, especially where environmental benefits accrue system-wide but immediate gains concentrate in specific nodes. Shared-savings contracts or tradable circularity credits could bridge this gap, but their design requires cross-disciplinary input from economics, policy, and systems engineering.

8.8.4 Data Integrity, Risk, and Uncertainty Management

While the architecture mitigates latency and data fragmentation, the robustness of decisions remains constrained by data uncertainty. Incomplete sensor coverage, inconsistent measurement protocols, and unstandardized metadata can propagate errors into life cycle models and optimization outputs. Consequently, future implementations should embed uncertainty-aware control methods and probabilistic optimization algorithms to ensure reliability under imperfect data [394,395].

Cybersecurity and privacy represent additional systemic risks. A federated digital-twin ecosystem enlarges the potential attack surface. Continuous vulnerability assessment and privacy-preserving computation (e.g., differential privacy, homomorphic encryption) are prerequisites for large-scale deployment [396,397]

8.8.5 Systemic and Policy-Level Implications

At the policy level, DT^2 demonstrates the feasibility of evidence-based sustainability governance, a condition where environmental and circularity indicators are automatically verified and anchored to immutable records. Regulators could use such verified indicators to implement dynamic, data-driven incentives, moving from static compliance regimes toward adaptive regulatory models [398,392].

At the same time, the findings suggest that the twin transition is not purely a technological integration problem but a governance transformation. Effective deployment requires the co-evolution of standards, institutional trust frameworks, and human decision protocols that can interpret and act on automated sustainability signals [399].

8.8.6 Limitations and Research Priorities

Several limitations qualify the generalizability of these findings. First, the demonstration environments were controlled and domain-specific; broader industrial heterogeneity may challenge ontology alignment and interoperability. Second, behavioral and organizational responses, such as rebound effects or the redistribution of benefits, were outside the model's scope. Third, the socio-technical impacts on workforce skills and decision authority remain underexplored.

The integration of AI-driven analytics, blockchain traceability, and federated digital twins introduces ethical and governance considerations related to data privacy, cybersecurity, and algorithmic transparency. While blockchain enhances data integrity and auditability, it does not inherently resolve issues of data ownership or ethical decision-making.

Ensuring compliance with data-protection regulations, transparent algorithm design, and secure system architectures is essential for industrial acceptance and regulatory alignment.

Moreover, interoperability challenges may arise when integrating the proposed digital-twin architecture with legacy industrial systems, potentially increasing implementation complexity. Addressing these governance and interoperability dimensions is critical for large-scale adoption.

Future research should therefore integrate:

- Uncertainty quantification within life-cycle-informed control loops [402].
- Socio-economic modeling to capture rebound and redistribution effects [388]
- and
- Governance experiments that evaluate incentive mechanisms and equitable value distribution in federated digital ecosystems [400, 401]

8.9 Post-Synthesis and Transition to Conclusions

The integrated outcomes of Chapter 8 confirm that DigiCircular's Twin-Transition framework can translate complex sustainability objectives into programmable, data-driven industrial control. By aligning cross-sector digital twins, coffee, textile, logistics, and traceability, within a unified optimization and governance layer, the framework demonstrates that sustainability, efficiency, and resilience goals reinforce system properties. Quantitative validation across multiple industries has proven that circular flows, when digitally orchestrated, can yield measurable reductions in carbon intensity, resource use, and production cost while enhancing transparency and accountability across supply networks.

At the systemic level, DigiCircular establishes a new operational logic for the twin transition, digital intelligence as the enabler, and circularity as the governing constraint. This redefinition transforms sustainability from a compliance objective into a continuously optimized state variable within industrial decision-support systems. The empirical evidence generated across Chapters 3 to 8 confirms that the same architectural principles, IoT sensing, LCA analytics, waste-flow mapping, and predictive optimization, can be generalized across sectors through standardized semantic layers and interoperable APIs. Thus, the model evolves from a multi-case framework into a replicable digital-circular ecosystem, offering a pathway for regional and national scaling.

More importantly, the twin-transition architecture introduces a new governance dimension, the potential for algorithmic sustainability management, where environmental thresholds, social equity indicators, and economic performance targets are embedded directly in the computational fabric of industry. Such capability redefines how enterprises, regulators, and communities co-produce sustainability outcomes, enabling real-time verification, adaptive regulation, and participatory innovation through transparent data infrastructures.

The outcomes extracted in this chapter therefore indicate a shift from isolated industrial optimization to systemic coordination of entire value-webs, where data-rich feedback loops replace linear reporting chains. The DigiCircular framework demonstrates that sustainable manufacturing is achievable through cleaner processes, green materials and intelligent synchronization of sectors, scales, and decisions.

These insights lead to the next stage of the thesis. Chapter 9 builds on this foundation to articulate the broader implications, translating DigiCircular's technical architecture into actionable policy instruments, governance mechanisms, and research frontiers. It consolidates the theoretical contributions of the twin-transition model, situates them within international sustainability agendas such as the SDGs and EU Green Deal, and outlines a roadmap for future exploration of AI-driven predictive LCA, autonomous decision support, and digitally enabled circular-economy governance.

Chapter 9

Conclusions, Policy Implications, and Future Research

The research presented in this thesis has developed and validated an integrated framework, “DigiCircular Twin-Transition (DT²)”, that operationalizes the twin transition between digitalization and circular economy within industrial manufacturing. Across its sequential structure, the study evolved from conceptual formulation and methodological innovation to multi-sector empirical validation, establishing a scientifically grounded pathway for transforming production systems into intelligent, resource-efficient, and self-optimizing ecosystems.

9.1 Conclusions

This research began by identifying the persistent fragmentation between digital transformation and sustainability science. While both paradigms had advanced independently, few studies had demonstrated how digital intelligence could directly generate measurable circular outcomes. The Hybrid Decision-Support Framework (HDSF), introduced in the early chapters, bridged this divide by uniting data acquisition, environmental analytics, process optimization, and decision intelligence within one analytical logic. It was first tested in the coffee supply chain through a triple-LCA configuration that quantified environmental, social, and economic impacts, proving that real-time digital monitoring can reduce emissions and resource footprints without compromising productivity.

The following chapters extended this conceptual model to real industrial contexts. Through the Physical Internet and multi-agent PILAR framework in Chapter 5, logistics networks were optimized for carbon efficiency and adaptive routing. The blockchain-enabled traceability system then demonstrated how verifiable digital records transform sustainability from an abstract goal into auditable, data-driven accountability. Together, these implementations established the empirical foundation of the DigiCircular approach.

The textile-industry case study marked a pivotal stage, testing DigiCircular’s cross-sector adaptability in one of the world’s most resource-intensive manufacturing domains. By integrating Internet of Things (IoT) sensing, Waste-Flow Mapping (WFM), and Life-Cycle Assessment (LCA) within an adaptive decision-support environment, the research achieved tangible results. Energy consumption decreased by nearly10%, water use fell by more than16%, carbon emissions declined by over 6%, and process waste was reduced by one-fifth. Simultaneously, resource efficiency improved by about 25%, material circularity rose from roughly one-third to two-fifths of total input, and production lead time shortened by more than20%. These quantifiable improvements confirm that digital feedback loops and circular design principles, when co-implemented, can yield verifiable sustainability gains at operational scale.

Chapter 8 combined all sectoral findings into the DigiCircular Twin-Transition (DT^2) model, which federates local digital twins of the coffee, textile, and logistics systems into a unified cyber-physical ecosystem. This architecture harmonizes key performance indicators through the Sustainability Efficiency Index (SEI), enabling real-time comparison and optimization across industrial boundaries. Overall results showed about a 30% reduction in total environmental impact, a 25% increase in resource efficiency, and a 20% extension of product life cycles. Over a 10-year horizon, the cumulative ROI increased by nearly 40%, demonstrating that environmental sustainability and financial viability can advance together under the DT^2 framework.

From a scientific standpoint, this research makes several original contributions.

- It provides one of the first integrated digital-circular architectures that couples environmental intelligence with decision automation through hybrid LCA–IoT–blockchain–AI linkages.
- It advances cross-sector methodological harmonization, introducing a mathematically consistent framework for comparing sustainability indicators across disparate industrial domains.
- It establishes a federated digital-twin model that transforms sustainability management from retrospective reporting to predictive and prescriptive control.
- Lastly, it demonstrates industrial symbiosis through the valorization of spent coffee grounds into textile fibers, an empirically validated example of circular value transfer between agri-food and manufacturing sectors.

Together, these innovations position DigiCircular DT^2 as a novel contribution to digital-sustainability science, offering both theoretical advancement and operational proof of concept for the twin transition.

9.2 Policy Implications

Beyond technical validation, DigiCircular contributes theoretically by demonstrating that digital intelligence and circularity can be coupled through a unified systems model grounded in cyber-physical integration. It reframes sustainability from a static reporting exercise into a dynamic state-control process, where every production event updates environmental and economic performance in real time. This paradigm shifts sustainability management from retrospective compliance to predictive and prescriptive governance, aligning industry operations with the Sustainable Development Goals (SDGs 9, 12, 13, and 17). The federated digital-twin framework developed in this thesis also establishes a transferable pattern for cross-sector data governance, ensuring semantic interoperability and traceable accountability across industries.

From a managerial and policy perspective, DigiCircular provides a practical roadmap for digital sustainability transformation. For large enterprises, it offers an integrative architecture for unifying complex, multi-site operations under a single sustainability intelligence layer. For small and medium enterprises (SMEs), its modular IoT and open-source API design enables incremental adoption without prohibitive investment costs. Policy institutions can leverage the model to design performance-based incentives for green technology adoption, using data-driven KPIs to verify environmental outcomes. The framework's compatibility with ISO 14001, ISO 50001, and ISO 26000 ensures its alignment with international environmental, energy, and social responsibility standards, making it suitable for incorporation into regional decarbonization programs such as the European Green Deal and Pakistan's National Climate Framework.

Socio-economically, the framework advances inclusive sustainability by linking technological innovation with community participation and job creation. The valorization of waste resources like SCGs illustrates how local supply chains can evolve into circular value ecosystems, stimulating regional entrepreneurship in recycling, eco-material development, and sustainable logistics. By embedding transparency and traceability into production systems, DigiCircular enhances consumer trust and encourages responsible consumption. In this way, the model not only optimizes industrial efficiency but also supports a just transition, ensuring that the benefits of digital transformation extend across social and economic dimensions.

9.3 Limitations

Despite its success, several limitations remain that should be acknowledged to appropriately contextualize the findings. At an operational level, data availability and precision continue to constrain model accuracy, particularly in contexts where sensor networks are sparse or standardized environmental baselines are lacking. Financial barriers persist for smaller firms that may be unable to absorb the upfront investment required for IoT infrastructure and digital-twin deployment. Furthermore, organizational inertia, skill gaps, and limited policy coherence can slow large-scale adoption. These constraints highlight the importance of targeted capacity-building initiatives, interoperable data-sharing platforms, and public–private partnerships to lower adoption thresholds and accelerate learning across sectors.

Beyond these implementation-related challenges, certain methodological and empirical limitations also apply. The proposed framework assumes a relatively high level of digital infrastructure and data interoperability, which may restrict immediate applicability in less digitally mature industries and small and medium-sized enterprises (SMEs). While environmental and economic impacts are supported by quantitative evidence, social sustainability dimensions, such as workforce adaptation, organizational change management, and stakeholder engagement, are addressed at a higher level of abstraction due to limitations in real-time, standardized social data availability.

Furthermore, empirical validation is based on selected case studies within the coffee and textile sectors. Although the DigiCircular framework is intentionally modular and conceptually transferable, broader sectoral application is required to fully assess generalizability and scalability. Accordingly, the current results should be interpreted as demonstrative rather than exhaustive. Finally, the reliance on advanced digital technologies introduces ethical, governance, and cybersecurity considerations, particularly related to data privacy, system transparency, and regulatory compliance, that warrant further investigation in future implementations.

9.4 Future Research

Future research should aim to deepen the integration of real-time environmental intelligence through Digital Twin–LCA coupling, enabling continuous recalibration of environmental impacts. The use of AI-driven predictive maintenance and optimization algorithms can further automate decision-making and improve process resilience. Moreover, the emergence of Textile-as-a-Service (TaaS) and Product-as-a-Service (PaaS) business models offers a promising avenue for embedding extended producer responsibility within circular systems. Cross-sector replication in biopolymer manufacturing, packaging, and construction materials will be essential to evaluate DigiCircular's scalability and interoperability in broader industrial contexts. Finally, consumer-focused studies on digital transparency, ethical labeling, and behavior change are vital to reinforce demand-side participation in the transition toward a fully circular economy.

In conclusion, this thesis has transformed the fragmented discourse on digital and circular innovation into a coherent scientific and operational framework. By uniting the precision of digital technologies with the regenerative logic of circularity, it demonstrates that sustainability can be embedded directly into the control architecture of industrial systems. The DigiCircular model thus serves as both a conceptual advancement and a practical design for implementing the twin transition at scale. It provides a replicable, evidence-based model for policy, academia, and industry, affirming that the next generation of sustainable manufacturing will not emerge from incremental adjustments, but from the intelligent orchestration of data, technology, and circular value creation.

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Data Availability

Comprehensive supplementary data and appendices for this dissertation are accessible via the accompanying file titled "Supplementary Data".

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About the Author

Dr. Mizna Rehman is a researcher and engineer specializing in sustainable and digital manufacturing, circular-economy system design, and cyber-physical decision architectures for industrial transformation. She completed her Ph.D. in Energy Science and Engineering at the University of Naples Parthenope, Italy, where her work focused on integrating Life Cycle Assessment (LCA), Artificial Intelligence (AI), and Digital Twin technologies into cross-sector circular models for the coffee and textile industries. Her research formed the foundation of the DigiCircular Twin-Transition (DT^2) framework an internationally recognized scientific contribution that operationalizes sustainability as a real-time control variable within industrial symbiosis networks.

During her doctoral program, Dr. Rehman conducted two major international research collaborations. She spent six months as a visiting researcher at the Universitat Politècnica de València (Spain), developing advanced LCA methodologies for agri-food systems, and an additional six months with IBIM Srl (Italy), where she translated digital-circular research into applied industrial solutions. Her teaching portfolio includes postgraduate and undergraduate courses in Advanced Manufacturing, Operations Management, Sustainable Production, and Digitalization in Industry, where she has supervised and guided master's research on AI-driven systems such as the ALES Engagement Platform.

Dr. Rehman has authored numerous peer-reviewed journal articles, book chapters, and conference papers in fields spanning IoT-enabled manufacturing, Physical Internet logistics, hybrid decision-support models, digital traceability, and Life Cycle Sustainability Assessment (LCSA). Her publications appear in reputable outlets such as Journal of Cleaner Production, Sustainable Futures, European Journal of Innovation Management, Cureus, and multiple proceedings under Elsevier and IFAC-PapersOnLine.

Her academic work is complemented by earlier professional engagements as an Engineering Lecturer, Hydropower Junior Engineer, and Quality Control Specialist, providing her with a unique ability to connect scientific modeling with industrial feasibility. She has received several awards, including the FIWARE Best CAMP Project Award, multiple merit distinctions, and the prestigious Erasmus Mundus Scholarship.

With strong expertise spanning AIoT systems, Physical Internet routing, multi-agent optimization, industrial data analytics, and LCA-based sustainability governance, Dr. Rehman’s research contributes to advancing Industry 5.0 and shaping policy-ready frameworks for sustainable digital transformation. She remains committed to translating complex scientific insights into scalable industrial strategies and to promoting human-centric, environmentally regenerative innovation across global supply chains.

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