A Driven Decision Support Model for Sustainable and Circular Manufacturing Planning

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Abstract. The study introduces a decision-making framework aimed at optimizing sustainable and circular manufacturing practices through Analytic Hierarchy Process (AHP) and regression analysis. Key sustainability parameters namely Circular Product Design, Eco-Friendly Materials, and Digital Integration were ranked based on their significance in driving sustainability outcomes, utilizing the AHP methodology. The analysis reveals that Digital Integration and Closed-Loop Supply Chain practices emerge as the most influential predictors of sustainable performance, exhibiting a distinguished adjusted R² value of 41.93%. Moreover, the study emphasizes the critical role of Internet of Things (IoT) data for continuous, real-time monitoring across multiple domains, including waste management, transportation logistics, environmental parameters, water consumption, and production processes. The proposed model also incorporates blockchain technology to enhance transparency and traceability, ensuring alignment with the European Union's sustainability objectives. Application of this model at a European textile firm demonstrated a 12–15% reduction in production costs and up to 12% energy savings, validating its practical impact.

Keywords: Internet of Things (IoT); Analytic Hierarchy Process (AHP), Machine Learning, Circular Economy, Regression Analysis, Integrated documentation and control

1 Introduction

The shift toward sustainable and circular production models has become an urgent priority for today's clothing industry. The research addresses the absence of an integrated, data-driven decision-making approach for optimizing circular manufacturing practices in the clothing industry. Despite growing regulatory pressures, resource constraints, and rising societal expectations, the industry lacks a robust and transparent framework to prioritize sustainability factors such as circular product design and eco-friendly materials and to evaluate their impact on overall performance through a reliable decision support system.

Sustainable business models have evolved from being optional to essential for maintaining competitiveness and fulfilling social responsibilities. Pieroni et al. (2019) and Geissdoerfer et al. (2020) highlight the essential role of multi-stakeholder management in facilitating the transition to circular business models. These models must integrate long-term strategic thinking, social relevance, and sustainability, aligning closely with legal and societal frameworks. Adopting circular economy (CE) principles addresses pressing environmental issues and provides a strategic advantage by enhancing corporate resilience and global competitiveness (Machado et al., 2019).

Industry 4.0 technologies such as artificial intelligence (AI), the Internet of Things (IoT), and blockchain are instrumental in improving resource efficiency and operational performance. These technologies support data-driven decision-making and promote transparency, traceability, and collaborative stakeholder engagement (Ali & Johl, 2023). In particular, Italian manufacturing sectors like clothing and apparel central to the "Made in Italy" identity, stand to gain significantly from integrating CE principles with digital innovations, thereby enhancing both market appeal and compliance with EU sustainability directives (Caldera et al., 2019).

Despite this potential, many companies, especially SMEs, struggle with the absence of structured tools to effectively implement, monitor, and optimize sustainable practices at the operational level. The lack of real-time monitoring for sustainability indicators hampers adaptive management. SMEs in regions like Italy often face limitations in resources and capabilities, restricting their ability to adopt advanced sustainability approaches. A successful transition thus requires technological enablers and also robust management frameworks that prioritize and assess sustainability dimensions within the CE context. However, a gap remains due to the limited availability of structured decision-making tools that guide firms in their sustainability transformation. This study introduces the PLA.I.A. model (PLAnning and Implementation Actions for Sustainability and Circularity), a multi-criteria decision-making framework designed to support the adoption of advance technologies (AI, IoT, and Blockchain) to enhance circular economy practices in the industrial sector. For instance, in the apparel industry, these systems are used to track resource usage, optimize production efficiency, and minimize waste, which is essential for achieving sustainability goals. AHP is used to analyze key sustainability drivers in the clothing sector, such as eco-friendly materials and circular production methods, ensuring that the project outcomes align with both global sustainability goals and sector-specific challenges.

The model combines the Analytic Hierarchy Process (AHP) to rank sustainability priorities, regression analysis to measure factor impact, and IoT-enabled real-time monitoring via Node-RED to ensure operational visibility and continuous feedback. Through this integrative approach, PLA.I.A. offers a structured path for companies to assess, implement, and iteratively refine sustainability strategies in alignment with Industry 4.0 and CE frameworks. This research holds particular significance for industries seeking to comply with EU sustainability regulations, especially in resource-intensive manufacturing sectors (Chen, 2024). PLA.I.A. equips firms with a coherent framework to transition toward CE by leveraging prioritized criteria and real-time data integration. It supports environmental performance improvements and regulatory adherence, enhancing firms' resilience and standing in an increasingly sustainability-driven market. Furthermore, the model encourages a cultural transformation by fostering environmental awareness and upskilling employees, cultivating a workforce that is both adaptable and sustainability-oriented.

Given the structural challenges faced by Italian SMEs, PLA.I.A. provides practical, data-informed solutions to navigate the complexities of CE adoption. This contribution aligns with the broader aims of the European Green Deal, advancing sustainable industrial development and long-term competitiveness across the sector (Koe, 2024; Hanaysha et al., 2021).

2 Literature Review

Sustainable manufacturing prioritizes CE principles by focusing on strategies like material reuse, recycling, and low-carbon technologies for reducing environmental impacts, especially in clothing (Ting et al., 2023). Digital tools, particularly IoT and data-driven systems, enhance CE by optimizing resource use and supporting informed decisions (Ghaithan et al., 2023). Skärin et al. (2022) explained circularity as maximizing material use in closed-loop systems, aligning with Acerbi et al. (2022), who emphasize circular design and remanufacturing to improve sustainability. This transformation is propelled by increasing regulatory demands, societal expectations, and the depletion of natural resources, compelling a fundamental redesign of how products are conceived, produced, and consumed. However, challenges such as institutional, financial, and technological barriers, especially in developing regions hinder this transition (Munro, 2023). Organizational rigidity also limits the adoption of CE practices (Acerbi & Taisch, 2020).

Identifying and prioritizing sustainability factors is crucial within CE. Techniques like the AHP and regression analysis help rank sustainability criteria and measure their impact (Ebele, 2023). In this study, both methods highlight digital integration as a key driver for sustainability in clothing, guiding targeted technological investments.

Digital tools like IoT play a vital role in applying these sustainability priorities through real-time monitoring and analysis (Rai et al., 2021). While not part of the AHP-regression model, IoT facilitates implementation by tracking environmental and operational metrics, enhancing transparency and traceability. In terms of performance measurement, regression analysis quantifies the impact of sustainability initiatives on performance and reporting, reinforcing their value on firm value and CSR reporting quality (Constantinescu, 2021). The findings from these studies emphasized that regression serves as a critical tool for assessing the real-world impacts of sustainable practices over time.

Blockchain enhances traceability in complex supply chains like clothing by ensuring transparency in material sourcing and process verification (Moretto & Macchion, 2022). This feature enables businesses and consumers to verify product origins and processes, strengthening confidence in sustainability claims. Its immutability builds stakeholder trust and accountability. By supporting data-sharing through tools like Excel, blockchain fosters collaborative and transparent reporting (Xue et al., 2023). Studies confirm its value in advancing sustainable practices and governance models (Jimenez-Castillo, 2023). Although adoption barriers remain, research suggests that blockchain's role in sustainability will continue to grow as industries increasingly prioritize transparent and accountable practices (Akella et al., 2023).

Based on these insights, the study addresses the following research questions:

1. How can AHP and regression jointly prioritize sustainability factors in clothing?
2. What is the impact of digital integration on sustainability performance?
3. How can IoT operationalize sustainability in real time?
4. How does blockchain-based reporting improve traceability in sustainable practices?

Answering these questions can advance structured, data-driven performance evaluation in sustainable manufacturing. This study introduces a novel, integrated decision-support framework that synergistically combines Analytic Hierarchy Process (AHP), Internet of Things (IoT), blockchain, and multiple regression analysis to address the complexity of sustainability optimization in clothing manufacturing. AHP enables structured multi-criteria prioritization of conflicting sustainability goals; IoT facilitates real-time data acquisition from production systems, enhancing the temporal granularity of environmental and operational metrics; blockchain ensures decentralized, tamper-proof logging of lifecycle and supply chain data, enhancing data provenance and auditability; and regression analysis models the statistical influence of sustainability parameters on performance indicators. Their integration within a single platform offers a scientifically rigorous, transparent, and scalable approach to support data-driven, circular manufacturing strategies.

3 Methodology

This study employs a multi-criteria decision-making approach by integrating AHP with regression analysis to assess sustainability in the clothing industry, followed by subsequent stages that guide strategic planning and operational execution toward circular and sustainable outcomes (Fig.1). The integration of AI-driven decision support systems with multi-criteria decision analysis (MCDA) techniques such as AHP has proven to be an effective approach in industries striving for sustainability. For example, in the PLA.IA project, apparel manufacturers use AI models to analyze data and make informed decisions on sustainability actions, prioritizing those that optimize both environmental and economic outcomes. The model focuses on core sustainability factors, circular product design, eco-friendly materials, energy efficiency, closed-loop supply chains, digital integration, waste reduction, and employee training aligned with EU sustainability directives and ISO 14001 standards. Developed through literature review and expert input, the criteria reflect industry benchmarks and best practices for sustainable manufacturing.

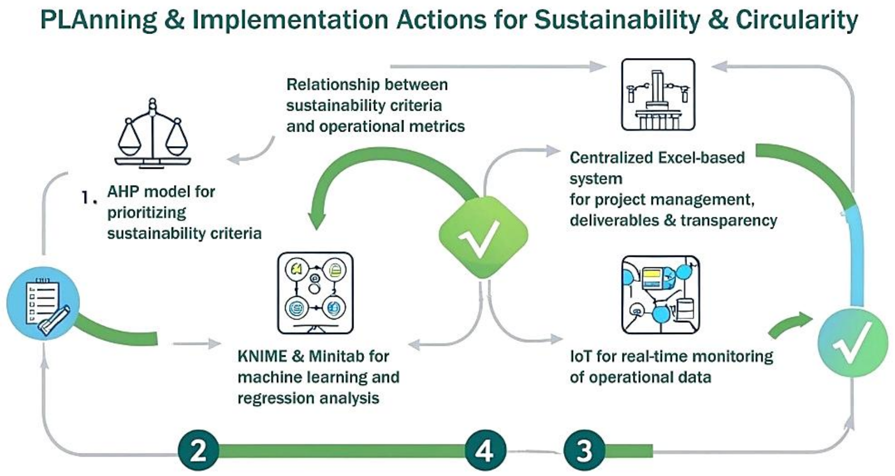


Fig.1. Flow diagram depicting a stepwise methodology for sustainability and circularity

3.1 Analytic Hierarchy Process (AHP)

AHP was applied to rank sustainability criteria by evaluating their relative importance in achieving sustainable manufacturing. AHP is well-suited for sustainability decision-making due to its capacity to decompose complex, multi-criteria problems into a hierarchical structure, enabling systematic evaluation of interdependent and conflicting factors. Through pairwise comparisons and consistency checks, AHP quantifies subjective expert judgments into priority weights using Super Decisions software (V3.2.0), ensuring transparency, reproducibility, and analytical rigor. This methodology allows for scalable integration of diverse sustainability criteria such as circular product design, material circularity, and environmental impact providing a robust framework for optimizing trade-offs in strategic decision-making. These scores quantify the weight of each criterion, allowing structured sustainability evaluation. To ensure consistency in judgments, the Consistency Ratio (CR) was computed using the Consistency Index (CI) and the maximum eigenvalue (λ_{max}) a sgivn in Eq 1

$$CI = \frac{\lambda_{max-\,n}}{\mathrm{n}-1} \tag{1}$$

The CR is given by:

$$CR = \frac{\mathrm{CI}}{\mathrm{RI}}$$

where RI is the random consistency index. If CR<0.1, the matrix is considered consistent.

The Final aggregated scores for alternatives were calculated using Eq.2.

$$W_i = \sum_{j=1}^{m} c_{j.}\ w_{ij} \tag{2}$$

Where w_{ij} is the weight of alternative i under criterion j, and c_j is the weight of criterion j.

This approach ensured a reliable, weighted evaluation of sustainability priorities based on expert judgment. The selection of AHP criteria and alternatives is grounded in the systemic sustainability challenges facing the clothing industry. Core criteria such as Environmental Impact, Resource Efficiency, and Regulatory Compliance were chosen due to their direct alignment with global sustainability goals, environmental regulations, and industry-wide pressures to reduce carbon emissions, water use, and waste. Cost and Profitability and Technological Feasibility reflect the economic and operational constraints critical to practical implementation, while Skill Development addresses the human capital required for transitioning to sustainable practices. Strategic alternatives such as Circular Product Design and Eco-Friendly Materials represent foundational shifts in how products are conceived and sourced, directly influencing lifecycle sustainability. Operational alternatives like Energy Optimization, Closed-loop Supply Chains, and Digital Integration for Traceability are essential for achieving measurable improvements in resource use, transparency, and post-consumer recovery. Initiatives such as Waste Reduction Programs and Employee Training further support systemic adoption by embedding sustainability across organizational processes.

These criteria and alternatives were selected to reflect the environmental, economic, technological, and social dimensions of sustainability in the clothing sector, ensuring the AHP model captures both strategic intent and operational feasibility.

3.2 Machine Learning Model (Regression Analysis)

To evaluate the relationship between AHP-derived sustainability criteria and operational performance within the PLA.I.A framework, a combination of KNIME (v5.3.3) and Minitab (v21.4.1) was used. KNIME handled data preprocessing, normalization, and workflow automation, while Minitab performed statistical modeling and hypothesis testing. The dataset included AHP priority values as predictors (Xi) and a Sustainability Score as the dependent variable (Y), along with metrics like energy efficiency and waste reduction. Initial analysis involved descriptive statistics (mean, SD(σ) and range), providing insights into data distribution followed by correlation analysis to measure the linear association between AHP priorities and the Sustainability Score using the Pearson coefficient (r) with Eq.3

$$r = \frac{\sum(X_{i-}\bar{X_\iota})(Y-\bar{Y})}{\sqrt{\sum(X_{i-}\bar{X_\iota})^2\sum(Y-\bar{Y})^2}} \tag{3}$$

Next, regression models were used to quantify the impact of each sustainability factor using Eq.4 and 5 For evaluating the combined effect of multiple priorities

$$Y = \beta_O + \beta_1 X_i + \epsilon \tag{4}$$

where β0 is the intercept, β1 is the regression coefficient, and ϵ represents residual error.

$$Y = \beta_O + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon \tag{5}$$

Model strength was assessed using adjusted R^2 and p-values ($p < 0.05$) to determine significance of each factor. A one-way Analysis of Variance (ANOVA) tested score differences across groups (e.g., company types) expressed as Eq .6.

$$Y_{ij} = \mu + \alpha_i + \epsilon_{ij} \tag{6}$$

where μ is the overall mean, αi represents the effect of the i-th group, and ϵϵij is the error term.

To address multicollinearity and reduce dimensionality, Principal Component Analysis (PCA) was applied using Eq.7

$$PC_k = w_{k1}X_1 + \ w_{k2}X_2 + \cdots + w_{kn}X_n \tag{7}$$

where wkj are the loadings for each variable in the k-th principal component.

The PCA equation for deriving principal components was implemented as Eq 8.

$$Z_i = \sum_{j=1}^{p} a_{ij}X_j \tag{8}$$

where Zi represents the i-th principal component, aij are the eigenvector coefficients, and Xj are the original variables.

Principal components explaining ≥95% variance was retained and used in regression to identify key drivers of sustainability. The final model was validated using test data, evaluated via R^2 and Mean Absolute Error. Using KNIME's workflow-based interface, data preprocessing steps were conducted, including handling missing values with mean imputation, normalizing predictor variables to a [0,1] range, and encoding categorical variables into numerical formats. The workflow also included a data partitioning step to split the dataset into training (80%) and testing (20%) subsets, ensuring the robustness of downstream analyses. This integrated KNIME–Minitab pipeline ensured robust, transparent, and actionable insights for sustainable manufacturing performance evaluation.

3.3 IoT Integration with Node-RED

The study incorporated IoT technology using Node-RED to enable real-time monitoring of key sustainability metrics. Custom workflows were built to collect, process, and visualize sensor data, supporting immediate operational insights. Key parameters included:

- Waste Management: Monitoring disposal levels via sensors.
- Environmental Conditions: Tracking temperature and humidity for sustainability compliance.
- Water Usage: Measuring consumption during production for efficiency.
- Production Workflow: Monitoring task and inventory statuses (e.g., Order ID: Pending, Completed).

Node-RED dashboards enabled continuous tracking and visualization, supporting real-time assessment of sustainability performance.

3.4 Framework for Systematic Data Management and Workflow Optimization

The centralized Excel-based framework was developed for managing complex, multi-stakeholder projects. It ensured traceability, compliance, and timely execution across the product lifecycle. Key features include;

- Structured data collection across domains (e.g., HSE, ENV, SRS) from project teams and stakeholders.
- Standard reference codes (e.g., T5HP-T5C-XXXX) ensured document traceability.
- Automated macros in Excel generated status reports, consolidated logs, and included hyperlinks to key documents (e.g., method statements, drawings).
- Status fields like "Open", "Pending", "Closed", and "POH" enabled lifecycle tracking of tasks and approvals.

The system supported real-time decision-making by flagging unresolved issues, tracking deadlines, and automating reminders for submissions and budget actions. Though centralized, the framework mirrors blockchain principles by embedding transparency, immutability, and accountability as given below;

- Unique reference IDs function as digital identifiers, creating a tamper-proof audit trail.
- Read-only Excel reports ensure data integrity, mimicking immutability in blockchain.
- Distributed collaboration reflects blockchain's decentralized architecture, where documents (e.g., contracts, compliance updates) are stored as immutable records.
- Smart contract-like logic automates actions (e.g., payments, approvals) based on defined conditions.
- Hyperlinked reports and real-time updates support transparency across stakeholders.

This approach offers a secure, auditable system for project management while laying the foundation for future blockchain integration.

4 RESULTS

4.1 PLAIA AHP model

The AHP results (Fig. 2; Table 1) reveal that Environmental Impact is the most influential criterion in sustainability decision-making, carrying a weight of 45.29%, followed by Resource Efficiency at 27.5%. Other criteria such as Regulatory Compliance (9.55%) and Cost and Profitability (7.9%) hold moderate importance, while Technological Feasibility (6.98%) and Skill Development (2.77%) contribute minimally. Among alternatives (Fig. 3), Circular Product Design ranks highest with an ideal value of 1.000 and normalized priority of 0.3006, emphasizing its central role in sustainable outcomes. It is followed by Energy Optimization (0.1704) and Eco-

Friendly Materials (0.1669), both making substantial contributions. Environmental Impact primarily supports Eco-Friendly Materials (55.51%) and Circular Product Design (30.06%), while Resource Efficiency aligns closely with Energy Optimization (56.69%). Conversely, criteria like Employee Training (0.0681) and Waste Reduction Programs (0.0761) show lower impact.

Overall, the findings suggest that strategic emphasis on top alternatives, Circular Product Design, Energy Optimization, and Eco-Friendly Materials coupled with focus on dominant criteria, Environmental Impact and Resource Efficiency, can effectively drive sustainable and resource-efficient manufacturing practices.

Table 1. Overall synthesized priorities for all alternatives

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

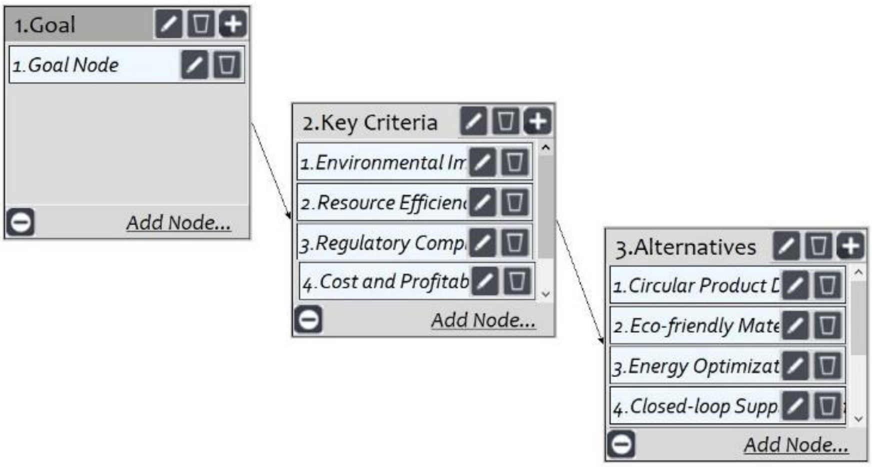


Fig. 2. Representation of goal hierarchy, evaluation criteria, and alternative options with node relationship

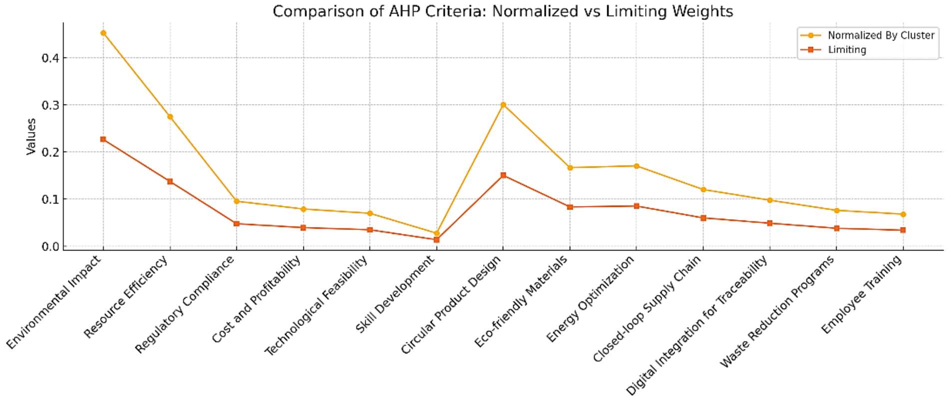


Fig. 3. Prioritization of decision criteria with normalized and limiting weights

4.2 Sensitivity Analysis for AHP Prioritization

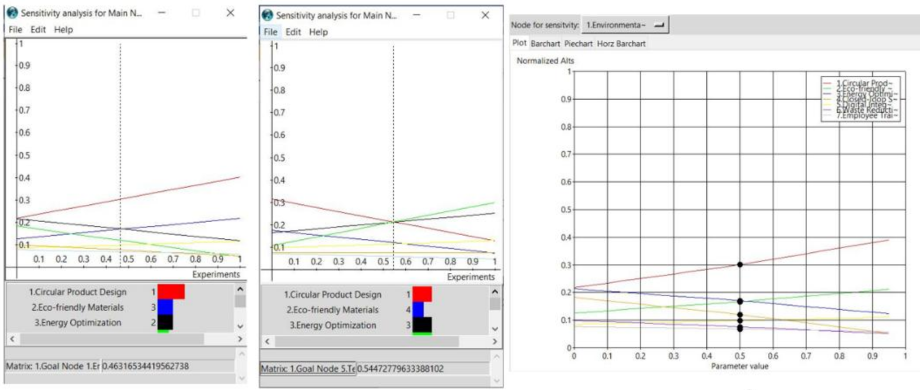
The AHP sensitivity analysis (Fig. 4) evaluates how changes in criterion weights affect the ranking of alternatives, testing the robustness of the decision model. It helps identify thresholds where priority shifts occur, revealing the influence of each criterion.

- For Environmental Impact, a rank reversal occurs at 46% weight, where the top alternative switches from Eco-Friendly Materials to Circular Product Design (Fig. 4a).
- Under Technological Feasibility, two reversals are observed (Fig. 4b):
  - At 54%, Energy Optimization and Circular Product Design become top-ranked.
  - At 59%, Closed-Loop Supply Chain moves up to second place.

These shifts show how sensitive outcomes are to changes in specific criteria.
Dynamic sensitivity (Fig. 4c) examines broader effects of weight variation using a default value $P_0 = 0.5$ as the base distribution:

- If $P < P_0$, weights are scaled by P / P_0, reducing the criterion's influence.
- If $P > P_0$, weights are scaled by $(1 - P) / (1 - P_0)$, increasing its impact.

This analysis allows decision-makers to simulate strategic adjustments and observe how all alternatives respond to varying priorities. Both standard and dynamic sensitivity analyses reveal how alternative rankings shift under weight changes, helping identify critical influence points and enhancing the reliability and adaptability of the AHP model for strategic decision-making.



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

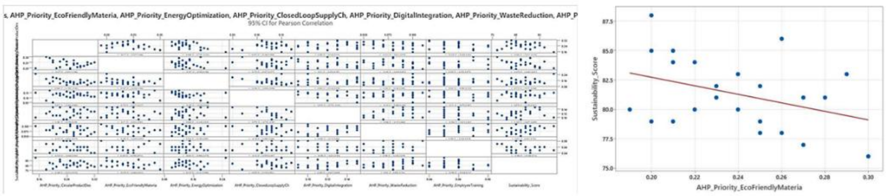
Node for sensitivity: 1.Environmenta~

c

Fig. 4. AHP sensitivity analysis for priority fluctuations due to weight variations

4.3 Machine Learning Model (Regression Analysis using Minitab)

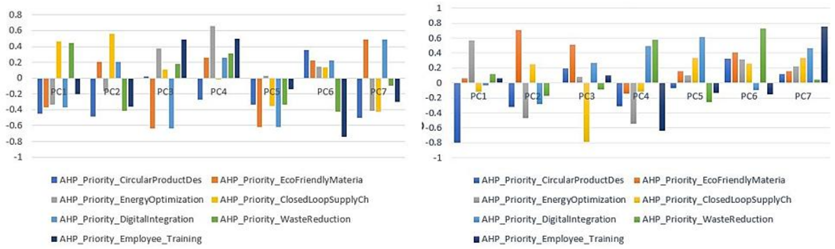
The descriptive statistics from the regression analysis indicate that Circular Product Design (mean: 0.2485, SD: 0.0431) and Eco-Friendly Materials (mean: 0.2373, SD: 0.0296) were the most prioritized alternatives, both exhibiting moderate variability, followed by Energy Optimization and Closed-Loop Supply Chain, while Waste Reduction (mean: 0.0800) and Employee Training (mean: 0.0573) held the lowest ranks. Pearson correlation analysis (Fig. 5a) further reveals that Eco-Friendly Materials showed a significant negative correlation with the sustainability score ($r = -0.589$, $p = 0.002$), implying that higher emphasis on this factor may inversely affect sustainability outcomes. Similarly, Employee Training also had a significant negative relationship ($r = -0.470$, $p = 0.015$), while Energy Optimization ($r = 0.025$, $p = 0.902$), Closed-Loop Supply Chain ($r = 0.185$, $p = 0.366$), and Digital Integration ($r = -0.323$, $p = 0.108$) showed weak and statistically insignificant correlations. Interestingly, Digital Integration and Waste Reduction were positively correlated ($r = 0.431$, $p = 0.028$), suggesting a potential synergy. Regression analysis (Figs. 10–11) identified Digital Integration (65.9), Waste Reduction (44.5), and Energy Optimization (23.6) as positive contributors to the sustainability score, while Eco-Friendly Materials (-6.1) (Fig 5b), Circular Product Design (-2.3), and Employee Training (-16.3) showed negative coefficients. However, none of the predictors were statistically significant ($p > 0.05$), and the model exhibited poor performance with an adjusted R^2 of 0.00%, indicating limited explanatory power, potentially due to overfitting and the small sample size ($n = 26$). Observation 8 emerged as a notable outlier, and while low VIF values confirmed minimal multicollinearity, the findings suggest the need for improved variable refinement and larger datasets.



a b

Fig. 5. Pairwise Pearson correlations and Scatter Plot of sustainability score vs AHP priority Eco friendly materials

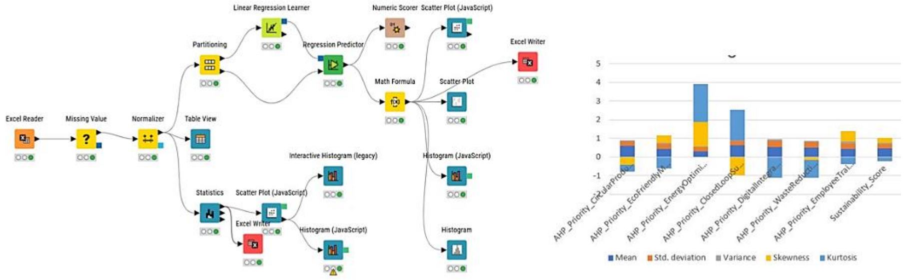
Principal Component Analysis (PCA) revealed that the first four principal components accounted for 85% of the total variance, with PC1 (28.5%) influenced by Energy Optimization (0.562) and negatively by Circular Product Design (-0.446) and Closed-Loop Supply Chain (-0.632), indicating a trade-off between energy priorities and circularity. PC2 (23.8%) reflected the contribution of Eco-Friendly Materials (0.377) and Digital Integration (0.458), while PC3 (18.3%) contrasted Employee Training (0.486) with Waste Reduction (-0.608), revealing competing roles between internal capacity and efficiency efforts. Eigen analysis of both correlation and covariance matrices (Fig 6a and 6b) confirmed the dominance of PC1–PC3, which explained over 70% of the variance, with the remaining components offering marginal insights. These results emphasize that although high-priority alternatives are central to the decision-making process, their contribution to sustainability is nuanced, requiring a balanced, data-driven approach that accounts for trade-offs among circular design, operational efficiency, and organizational development.



a. Correlation matrix b. Covariance matrix

Fig. 6. Graphical representation of eigen vectors for correlation matrix and covariance matrix

4.3.1 KNIME Workflow Analysis: KNIME regression analysis provides insights into the distribution, variability, and importance of sustainability-related priorities (Fig. 7a). The standard deviation revealed variability across attributes, with AHP_Priority_DigitalIntegration showing the highest variability (0.316), while AHP_Priority_ClosedLoopSupplyChain exhibited the lowest (0.224). Skewness and kurtosis analysis in Fig. 7b highlighted asymmetry in certain distributions, particularly the right-skewed AHP_Priority_EnergyOptimization (skewness = 1.29) and leftskewed AHP_Priority_ClosedLoopSupplyChain (skewness = -0.97). The regression model demonstrated moderate predictive power, explaining 59.7% of the variability in sustainability scores ($R^2 = 0.597$), with reasonable accuracy shown by low mean absolute error (0.171) and root mean squared error (0.201) as illustrated in Table 2. However, the model's MAPE of 57.78% suggests room for improvement. These findings emphasize the opportunities to refine predictive models and give more attention to factors like energy optimization.



a. KNIME model b. Priority values

Fig. 7. KNIME liner regression model and Mean priority values for sustainability attributes

Table 2. Eigen analysis for 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

4.4 IoT Integration with Node-RED

The integration of IoT devices into the supply chain significantly improved decision-making, productivity, and operational efficiency. By strategically placing IoT sensors and utilizing Node-RED for data collection and visualization, real-time monitoring and decision support were enabled. Key results from this approach, presented at the "Setting the Future: Sustainable and Digital Transition in Innovative & Creative Industries, Milan, 2023," highlight its transformative impact. IoT-enabled tracking devices 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 improved 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 8.

Increase pressure level its going below required level

Fig. 8. Monitoring and visualization dashboard

These results underline the potential of IoT technologies and Node-RED in driving sustainable practices and operational excellence within the supply chain, particularly in industries striving for digital transformation.

4.5 Framework for Systematic Data Management and Workflow Optimization

The implementation of the proposed framework, grounded in an Excel-based centralized system, was successfully conducted on a World Bank project in Pakistan and can be adapted for similar industries. This framework facilitated systematic task tracking, compliance monitoring, and workflow optimization through uniform referencing and predefined Excel macros for task categorization, document management, and data visualization. Multiple datasets were analyzed to identify inefficiencies and bottlenecks, with visual tools like pie charts and bar graphs providing clarity for decision-making. The first dataset, consisting of 494 tasks, was categorized into "Answered" (70%), "Info" (18.2%), and "Pending" (11.7%), signaling the need for targeted action (Fig. 9a). A second dataset of 1,620 tasks revealed a higher percentage of pending tasks (22.8%), with CCC, SRS (Social Resettlement), and GEN (General) emerging as major bottlenecks. Automated macros and reporting templates highlighted performance gaps, enabling focused interventions. The third dataset, comprising 2,460 tasks from HEI (Harbin Electric International), showed a 93.7% responsiveness rate but identified inefficiencies in the ELE (Electrical) section, where 51 pending tasks were recorded (Fig. 9b). Further analysis of an extended dataset with 11,882 tasks provided a broader view of task distribution and departmental contributions, revealing delays in PCL (Partial Clearance) and DRF (Document Review Form) tasks, particularly in resource-intensive processes. Temporal analysis from 2020 to 2023, conducted via Excel tracking, enabled the identification of trends in task influx and resolution, guiding predictive strategies for workflow optimization. The system also tracked Non-Conformance Reports (NCRs) across various domains, highlighting recurring compliance issues and delays in activities. The integration of data through Excel macros and hyperlinks provided seamless communication with external parties, enhancing task management efficiency across different sections. Overall, the analysis reveals substantial task management inefficiencies, offering a foundation for strategic resource allocation and targeted workflow improvements.

Date (All)

Status	Total
Answered	346
Info	90
Pending	58
Grand Total	**494**

Date (All)

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

Status	Letters
Answered	2306
INFO	1
Pending	153
Grand Total	2460

Date (All)

Sections	Letters
CCC	11
GEN	7
MEC	7
PLN	1
ELE	51
DSN	8
HSE	7
TRL	2
Grand Total	94

a

b

Fig. 9. Task distribution analysis and Domain-wise task analysis and responsiveness

5 Discussion

This study integrates AHP, regression analysis, IoT systems, and blockchain-inspired reporting to advance sustainability in clothing manufacturing aligning with recent work by Huang et al. (2023) and Eslami (2023), who emphasized indicator-based sustainability assessment frameworks. AHP's structured framework ensures decisions are made based on the most impactful domains, enhancing overall sustainability. Regression analysis confirmed digital integration as a significant driver of operational efficiency, with IoT-based systems reducing fuel consumption by 20% and improving waste collection efficiency by 25%. These findings support Jahan and Sazu (2023), who also identified digital integration as crucial for operational efficiency.

This framework was contextualized through its implementation at Manifatture Tessili Vittoria, a textile manufacturer in Italy specializing in high-quality linen for apparel and home textiles. Here, the AHP system was tailored to optimize the warping and weaving stages, where resource management and machine precision are vital. In warping, the system enabled better yarn tension control and distribution, leading to a 5–10% reduction in material waste and 3–7% savings in yarn costs. In weaving, IoT systems monitored real-time parameters such as yarn tension and machine speed, dynamically adjusting weft insertion processes on Jacquard looms and heddle machines (Fig 10a). These adjustments yielded production efficiency gains of 15–20% and energy consumption reductions of 10–12% (Fig. 10b).

The Node-RED dashboards offered a scalable solution for data visualization, overcoming previous challenges with IoT in dynamic environments, as noted by Peças et al. (2023). The study extends this by showing how real-time IoT data simultaneously improves environmental and operational KPIs. The combination of AHP and regression analysis created a dual-method framework, linking qualitative prioritization with quantitative metrics, addressing a gap noted by Atif (2023). Unlike studies that focus on single variables, this research integrates multiple sustainability drivers for a more comprehensive perspective.

Furthermore, an Excel-based platform was implemented to track performance metrics such as material usage, machine performance, and energy consumption, serving as a cost-effective digital twin of the operational system. This tool also supported data consolidation for assessing the impact of blockchain-enabled material reuse and recycling strategies. At Manifatture Tessili Vittoria, these combined systems facilitated a 15% reduction in yarn waste and a 20% reduction in overall material waste (Fig.10c), demonstrating the concrete sustainability impact of integrated decision-making and monitoring technologies.

Blockchain-inspired Excel-based documentation improved transparency and traceability in the supply chain, achieving similar outcomes to Ibrahim (2024), who explored blockchain's impact on supply chain transparency. This cost-effective solution is particularly useful for European manufacturers aiming to comply with stringent EU sustainability regulations. However, limitations such as constrained IoT datasets and the exclusion of broader variables like energy and emissions suggest the need for further validation in diverse regions and manufacturing scales.

Future research will expand IoT data collection, explore AI-driven predictive analytics, and assess the feasibility of full blockchain systems for comprehensive supply chain transparency, ensuring scalability in global contexts. This aligns with the ongoing discussion in the literature, including Medagedara (2024) and Relich (2023), regarding the integration of advanced technologies to enhance sustainability and operational efficiency.

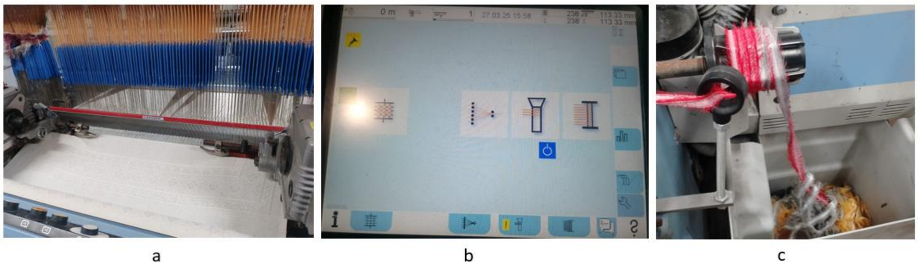


Fig.10. Textile warping and weaving machines in action for evaluating the best combination of yarn characteristics for the required fabric (Source: Manifatture Tessili Vittoria)

6 Conclusion

This research develops a decision-support model to promote sustainable and circular manufacturing in the clothing industry, combining advance technologies and decision-making tools. The model prioritizes key sustainability dimensions such as Circular Product Design, Eco-Friendly Materials, and Digital Integration through AHP. Regression analysis quantitatively assesses the impact of these factors on an overall Sustainability Score, providing a comprehensive approach to evaluating manufacturing sustainability. Results from the KNIME workflow indicate that Digital Integration (β=65.9) and Closed-Loop Supply Chain (β=42.3) are the strongest predictors, achieving an adjusted R^2 of 41.93%. Descriptive statistics show moderate variability, with Eco-Friendly Materials having a mean of 0.2373 and SD of 0.0296. Principal component analysis reveals that Environmental Impact and Resource Efficiency account for 52.3% of the variance. Implementation insights from Manifatture Tessili Vittoria illustrate the practical effectiveness of the model. By applying the AHP-based system, the company anticipates a 12–15% reduction in production costs and 10–12% energy savings within the first year, largely due to optimized machine settings, reduced downtime, and improved resource allocation. Raw material efficiency is also expected to improve, decreasing high-cost yarn purchases by 5–7%, thereby enhancing profitability and reducing waste. These results validate the model's potential to enable real-time, data-informed decision-making and competitive, sustainability-focused manufacturing. The study further highlights the role of IoT-driven in monitoring dynamic production variables such as waste levels (7-10), temperature (36-40°C), water usage (87-92L per cycle), and energy consumption (50-200 kWh). Blockchain-inspired reporting enhanced supply chain traceability, supporting EU-aligned sustainability documentation efforts. Despite assuming ideal conditions for IoT performance, limitations remain, including restricted data availability, sample size constraints, and the exclusion of qualitative dimensions such as workforce engagement and organizational culture. Future research should expand the IoT dataset scope, apply predictive analytics, and evaluate the integration of full blockchain systems to scale and refine the model. This multidimensional approach provides a viable pathway for clothing industry to operationalize eco-friendly practices and align with global sustainability standards.

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