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Green Costing: Using AI in SAP for Sustainable Product Costing Models

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Abstract: With rising environmental issues and regulatory pressures, it is becoming increasingly incumbent on manufacturers to include their environmental effects, such as carbon emissions, into the financial system. In the traditional sense, product costing methods in SAP Controlling-Product Costing (CO-PC) mostly offer only partial integration of environmental factors and would rarely meet the challenges in providing genuine accounting for sustainability. This paper discusses green costing as a new approach that espouses charging product prices and cost structures with environmental and carbon-related costs. By integrating AI into SAP environments, especially through SAP S/4HANA and SAP Analytics Cloud, sustainability accounting is made dynamic and data driven. AI models include forecasting and allocating various environmental costs including carbon emissions, energy consumption, and waste disposal by collecting real-time data from IoT-enabled devices, supply chain, and production systems. Integrating AI into SAP CO-PC will shift the paradigm from traditional, static costing to smart, green decision-making. This paper addresses key methodologies, case studies, and operational benefits of installing green costing machinery in SAP through AI, thereby rendering a programmatic path for those firms that want to have sustainability objectives as a complementary metric with profitability.

Keywords: *Green Costing, SAP CO-PC, Artificial Intelligence, Sustainability Accounting, Carbon Costing, AI in SAP, Product Costing, Environmental Impact, Predictive Analytics, Sustainable Manufacturing.*

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I. INTRODUCTION

A. Introduction to Green Costing and Sustainability in Manufacturing

Green costing is a very strategic method wherein environmental considerations or factors like carbon emissions, energy consumption, and waste management are used in addition to product costing procedure. As the global regulatory bodies, EU and UNFCCC continues with the implementation of carbon disclosure laws, industries would be required to properly measure and manage environmental costs just as they do for financial costs (Carbon Disclosure Project, 2023).

Even though traditional cost accounting methods, perhaps under the label SAP's Controlling-Product Costing (CO-PC), also consider operational costs such as materials, labor, and overhead, they rarely consider indirect environmental costs related to Scope 1, 2, and 3 carbon emissions or energy inputs during the lifecycle (Schaltegger & Burritt, 2017). This creates an environment where the true environmental footprint and product positioning become disguised, which on the flip side warned manufacturers of reputational and compliance risk in carbon-conscious markets.Green costing aims to address this gap by internalizing environmental externalities into cost structures, thereby aligning cost management practices with sustainability objectives (Epstein & Buhovac, 2014). This is especially critical for organizations pursuing Environmental, Social, and Governance (ESG) integration into their core strategies. Through green costing, firms can assess trade-offs between product design, material choices, and environmental performance, fostering innovation toward more sustainable production processes (Kumar et al., 2022).

This integration of alternative apprehensions arises into the domain to amplify the potential transformation of green costing. AI-based algorithms are crafted to extract, process, and predict environmental data from several sources such as IoT-enabled machinery, environmental product declarations (EPDs), and supplier databases. Combining these with an ERP platform such as SAP S/4HANA paves the way for real-time sustainability analytics and automated cost attribution (Rosenberg et al., 2020). Machine learning algorithms can thus automatically come up with estimations of carbon emissions per unit of product output or the cost implications of switching to renewable energy sources, thereby giving manufacturers well-conceived insights toward making ecological decisions (McKinsey & Company, 2023).

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In addition to this, sustainability-oriented organizations are shifting to a more transparent and traceable system of costing. Regulatory tools such as the EU Taxonomy and the Corporate Sustainability Reporting Directive (CSRD) require disclosure of information regarding environmental performance in great detail, which reinforces the business case for carbon-inclusive costing (European Commission, 2022). The embedding of AI into SAP CO-PC enables businesses to meet these regulations while retaining their efficiency in operations and competitiveness in costs.

In closing, green costing, being a very recent development in the ambit of cost accounting, facilitates the corporate world for environmental responsibility without profit compromise. Coupling of AI technologies with SAP platforms unveils new pathways for integrating sustainability within financial systems, thus aiding the switch toward low-carbon and resource-efficient economies.

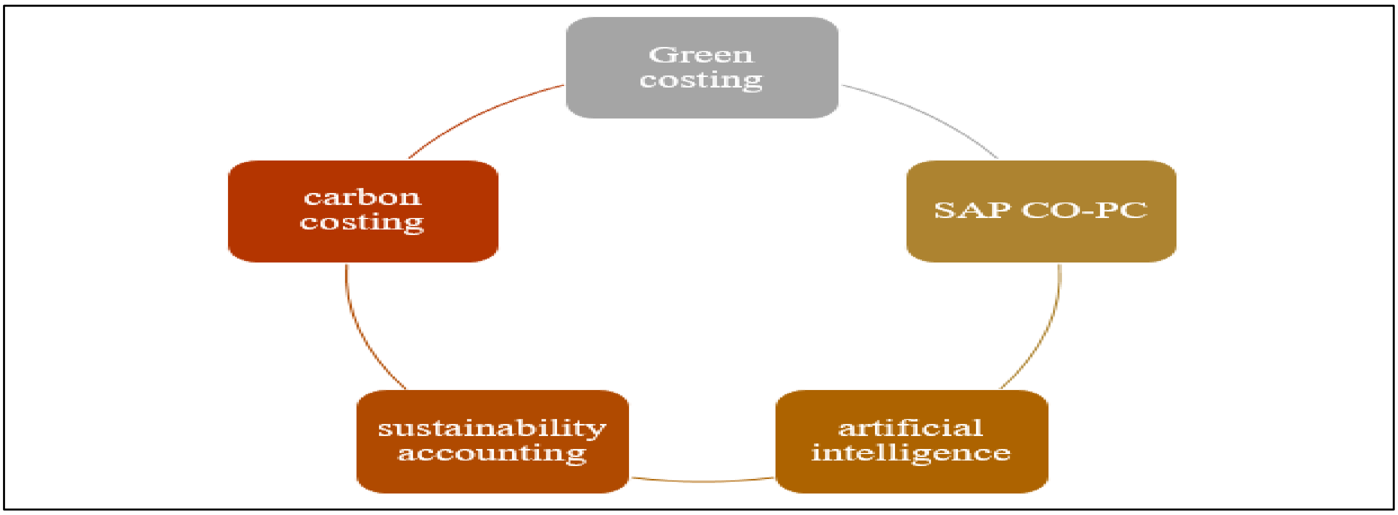

Fig 1 The lifecycle of Green Costing with AI revolution

II. LIMITATIONS OF TRADITIONAL COSTING MODELS IN SAP CO-PC

The Controlling-Product Costing (CO-PC) system in SAP has been traditionally used as an essential system for manufacturing enterprises to ensure that production costs of a product are accurately calculated based on predefined structures for materials, labor, overheads, and cost centers. While these activities promote financial and operational planning, there is very little that they can do to include environmental costs or carbon data—parameters that would matter for sustainability-centric industries (Hansen & Mowen, 2021).

A typical SAP CO-PC cost flow follows a deterministic pattern: the standard costs are computed with reference to historical consumption patterns, static material master data, and infrequent updates. Such models do not factor in environmental changes such as carbon price fluctuations, shifts in energy mix, or waste levels—matters that have become increasingly pertinent to cost assessment (Pritchard et al., 2020). Furthermore, overhead allocations tend to be fairly coarse and do not very well distinguish between environmentally intensive and sustainable processes.

The other important hurdle is the inability of the software to deal with Scope 3 emissions, i.e., indirect upstream and downstream emissions from the suppliers, transport, or end-of-life disposal. These emissions are often attributed as the largest share of the environmental impact of a product and are invisible in standard costing reports of SAP, unless supplemented by external tools or manual calculations (Weidema et al., 2016). In the absence of dynamic sustainability-related metrics, the actor will be limited to identifying cost-effective low-emission alternatives for procurement or production.

Another problem that leverages SAP CO-PC is its inability to integrate with carbon pricing models or environmental product declarations (EPDs) naturally. This becomes an issue for manufacturers that operate in jurisdictions in which carbon taxes, emission trading schemes, or environmental labels are enforced. The cost estimates become distanced from the actual financial risk if these elements are left out and pose further challenges in meeting ever-tightening regulations, such as the EU Corporate Sustainability Reporting Directive (European Commission, 2022).

This lack of environmental integration also creates a challenge for product lifecycle management. If there is no way to trace energy usage or waste generation throughout the production chain, lifecycle costing cannot incorporate the entire ecological impact of the product. This, in turn, weakens the aspiration of a company to target the net-zero gig, circular economy initiatives, or climate-aligned innovation (Stewart & Raman, 2021).

The below table illustrates the gaps between the traditional and sustainability-enhanced costing system capabilities in SAP: The below table illustrates the gaps between the traditional and sustainability-enhanced costing system capabilities in SAP:

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Table 1 Comparison of Traditional vs. Green Costing in SAP CO-PC

Feature	Traditional SAP CO-PC	Green Costing with AI Integration
Environmental Data Capture	Not supported	Real-time input from IoT, EPDs, external databases
Carbon Emissions Tracking	Manual, partial	Automated Scope 1, 2, and 3 estimation
Overhead Allocation	Standard, volume-based	AI-based with environmental sensitivity
Regulatory Compliance (e.g., CSRD)	Indirect, requires customization	Built-in support via AI-enhanced analytics
Lifecycle Costing Support	Limited	End-to-end visibility of environmental impact
Forecasting & Scenario Modeling	Periodic & static	Dynamic, predictive simulations
Integration with Carbon Pricing	Not native	AI-linked carbon cost estimation and tracking

This identifies the need for more advanced solutions that move beyond the static, finance-oriented costing methods of traditional ERP systems. With AI embedded in its product costing modules, SAP allows manufacturers to develop financial systems that are more robust, transparent, and aligned with sustainability.

III. LEVERAGING AI FOR GREEN COSTING IN SAP

With ever-expanding applications for artificial intelligence and machine learning in interface and experience development, the software industry uses them for more process simulation and design application in aiming for green costing inside ERP systems such as SAP. With the technologies of artificial intelligence like ML, NLP, information pertaining to environmental administration, and predictive analysis, manufacturers can clean, process, and act on huge volumes of environmental and operational data. When embedded within SAP CO-PC workflows, AI can help integrate sustainability metrics into cost structures, enabling a dynamic and forward-looking approach to cost management (Kiron & Unruh, 2018).

A. AI-Powered Cost Prediction Models

One of the greatest contributions AI makes towards green costing is the forecasting of environmental costs with great precision. Machine learning algorithms can use historical consumption data, supplier records of emissions, and real-time production data to estimate present and future carbon emissions, energy use, and waste levels. It further permits cost assignment at a more detailed level, beyond the ordinary overheads, to the emission and environmental impact per product, batch, or production line (Rosenberg et al., 2020).

Such models may be used to estimate the carbon cost of producing a new product configuration from historical emissions data and trends in carbon price. The predictive outputs are then directly fed into costing run simulation software from SAP, which would allow financial planners and engineers to assess low-emission design alternatives at a very early design stage. Furthermore, SAP AI-assisted tools, such as SAP Predictive Analytics and SAP AI Core, offer a means to develop bespoke models interacting in real time with SAP HANA databases (SAP, 2023).

B. Real-Time Data from IoT Devices and Sensors

Another noteworthy aspect in green costing with AI is data acquisition. IoT sensors installed in production equipment and infrastructure in the facilities continuously log parameters such as emissions, temperature, water use, and energy consumption. AI sorts through this data to associate the use of resources with cost centers or bill of-materials (BOM) items, thus getting real-time visibility into environmental costs (Gupta et al., 2021).

Feeding into SAP Digital Manufacturing Cloud or SAP Asset Intelligence Network, these IoT feeds keep the cost estimates updated with the changes in production. These real-time capabilities become ever so important to manufacturers with dynamic environments such as the batch-production or make-to-order system, in which environmental effects vary with the level of enumeration.

C. Enhanced Cost Allocation and Variance Analysis

Typically, cost allocation charges environmental fees based on various chargeable prices or production-volume-based formulas, thus obscuring the true environmental burden to specific processes. AI facilitates precision and contextual cost allocation analysis, factoring in usage pattern, process efficiency, and real-time resource consumption along the way. For instance, AI can discover that, unlike its counterpart which is energy efficient, that an assembly line being equally voluminous emits more CO_2 credits and subsequently imposes a heavier carbon burden (Schaltegger & Zvezdov, 2015).

In addition, AI provides the possibility for advanced variance analysis. Any time environmental costs vary against forecast, AI immediately diagnoses the variance' source, whether it is an inefficient machine, a change in supplier carbon intensity, or a production process deviation—and notifies stakeholders down the line through SAP analytics interface (SAP, 2023). This root-cause analysis then equips the organization with quick maneuvering abilities to curb inefficiencies and optimise resource utilisation.

D. Integration with Sustainability Standards and External Data

An AI is also making SAP systems proficient in interfacing with third-party sustainability data. For example, one can scrape supplier environmental disclosures; extract emissions data from environmental product declarations (EPDs); and cross-reference this with internal procurement data for the calculation of Scope 3 emissions. NLP models have an ability to scour the unstructured format of reports and automatically categorize these into SAP sustainability performance management dashboards (Lützkendorf & Balouktsi, 2017).

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This integration helps the fulfillment of frameworks such as the Global Reporting Initiative (GRI), the EU Taxonomy, and the Science-Based Targets initiative (SBTi). AI aggregates and augments the internal ERP data with external sustainability data sets to present a holistic and audit-ready view of environmental performance inside cost accounting.

E. AI in Action: SAP and Industry Use Cases

The incorporation of AI for sustainability in SAP has already begun, mainly through tools such as SAP Sustainability Control Tower, which aggregates ESG metrics along supply chains, and SAP Business Technology Platform, which helps custom AI apps to interact with real-time business data. Some big manufacturers have been trying out green costing methodologies integrated with AI to support their carbon-reduction goals and product-development decisions (BASF, 2023).

An example illustrates a European automotive supplier that used AI to track and predict emissions throughout its complex supply network. These predictions were fed into their SAP CO-PC configurations to allow the firm to adjust cost drivers and select low-emission suppliers, thereby lowering carbon-adjusted unit costs by 14% while being better aligned with regulatory requirements (McKinsey & Company, 2023).

Table 2 Examples of AI Use Cases in Green Costing within SAP

Use Case	AI Functionality	SAP Integration	Impact
Predicting carbon cost per product	ML regression on historical & supplier data	SAP Predictive Analytics + CO-PC	Improved design and pricing strategies
Dynamic cost updates based on energy input	IoT sensors with real-time AI analysis	SAP DMC + HANA Cloud	Real-time cost accuracy and responsiveness
Automated Scope 3 estimation	NLP + web scraping for supplier emissions	SAP Sustainability Control Tower	Regulatory compliance and audit-readiness
Carbon-adjusted variance reporting	Root-cause analysis using anomaly detection	SAP Analytics Cloud	Early identification of environmental inefficiencies
AI-enabled cost simulation for renewables	Scenario modeling	SAP S/4HANA + BTP	Informed investment in low-carbon strategies

Artificial intelligence dramatically extends the traditional scopes of an SAP CO-PC framework in aspects of environmental data processing, dynamic costing, predictive analytics, and automated sustainability integration. These tools allow organizations to lift their cost models from static, backward-looking assessments to intelligent, forward-looking tools, which constitute support for both profit and environmental responsibility.

IV. AI INTEGRATION IN SAP: TECHNICAL ARCHITECTURE AND WORKFLOW

During the successful implementation of green costing into SAP, it becomes essential to understand how artificial intelligence can be technically embedded into already existing SAP architecture. This section delineates the system components, data flows, and integration layers that allow AI to effectively operate within the SAP ecosystem, especially when it comes to sustainable product costing.

A. Architecture Overview

The integration of AI into SAP systems typically involves three layers:

➢ *Data Layer (The Foundation):*

SAP S/4HANA databases, SAP Master Data Governance (MDG), and external sources like IoT sensor feeds, supplier ESG disclosures, and emissions databases are engulfed in this layer of data resources. These data assets act as the training and inference grounds for AI.

➢ *Processing Layer (AI & Analytics):*

The systems here comprise SAP AI Core, SAP AI Launchpad, and external machine learning platforms such as TensorFlow, PyTorch, or SAP BTP AI Foundation without intermittent layers. Models emerge here to pattern recognition, to predict outcomes, and to assign environmental costs.

➢ *Application Layer (Business Processes):*

The AI output comes into SAP CO-PC, SAP Product Lifecycle Costing, or SAP Analytics Cloud to make real-time decisions for costing, budgeting, and forecasting (SAP, 2023).

This multiple tiered configuration of the architecture assures that AI tools will be used for support and enhancement while not replacing existing costing functionalities and instead be embedded with considerable intelligence in their everyday workflow.

B. Data Sources and Preprocessing

On AI-driven analysis, costing is highly data-dependent in the quality and comprehensiveness of information ingested. The data sources are classified under the following four heads:

➢ *SAP internal data:*

Includes BOMs, routing sheets, cost center records, and past costing runs.

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- *Real-time/random operational data:*

Data acquisition through SAP Plant Connectivity (PCo) from shop-floor machinery and energy meters.

- *Sustainability external data:*

Sustainability emission factors, Environmental Product Declarations, and carbon prices via API to public and private databases (e.g., ecoinvent, DEFRA).

- *Supplier Data:*

Through SAP Ariba or upon other supplier networks, increasingly includes results of third-party certifications or audits.

Before passing these datasets on to AI models, preprocessing steps- normalization, outlier detection, data enrichment, and missing value imputation-must be considered (Chatterjee et al., 2021). These tasks are often orchestrated in an efficient manner with the help of SAP Data Intelligence.

C. AI Modeling Workflow

A typical development cycle for costing AI models generally follows:

- *Problem Definition:*

For example, product-wise prediction of carbon-adjusted cost.

- *Feature Engineering:*

Variables can include material type, supplier emissions, or energy sources, among others.

- *Model Training:*

For instance, employing supervised learning models such as gradient boosting or random forest algorithms to forecast carbon impact or cost-related variances.

- *Validation:*

This involves testing for determines the accuracy of the forecast alongside historical carbon-adjusted costing results and sustainability outcomes.

- *Deployment:*

Models trained and deployed to SAP AI Core, where they are called using REST APIs, or directly integrated into Fiori apps.

Such AI models can be retrained constantly by SAP integrated MLOps pipelines to keep them aligned with changes in data (e.g., newer carbon tax, updated production methods) (SAP AI Foundation, 2023).

D. Integration with SAP CO-PC

Once the AI models are developed and validated, integration with SAP CO-PC is undertaken in one of two ways:

- *Inline Integration:*

The outputs of models are written back to costing master data fields via BAPIs or IDOCs. For instance, an AI-estimated carbon cost per unit would be inserted into a costing variant for further simulation.

- *Decision Support Layer:*

Results are shown via dashboards in SAP Analytics Cloud, where users may consider scenarios prior to actually updating the cost structures.

During costing, the AI models also provide dynamic values for activity rates, scrap rates, and emission coefficients, in lieu of the usual static assumptions in SAP.

E. Automation and Workflow Orchestration

For accurate AI-driven green costing, the entire landscape demands firm orchestration across SAP and non-SAP systems. SAP Intelligent Robotic Process Automation (SAP iRPA) can thus automate:

- Data collection from non-integrated supplier systems
- Report generation and sustainability compliance documents
- Alert triggering whenever carbon cost thresholds are exceeded

These alerts may include acts such as alerts issued to sustainability managers if a batch exceeds the carbon footprint target by 10%. Then the SAP iRPA would trigger an automatic root cause analysis in SAP Analytics Cloud, notify sustainability managers via SAP Business Workflow, and log a corrective action task in SAP Fiori (SAP, 2022).

F. Security, Compliance, and Governance

When it is AI touching sensitive financial and ESG data, well-honed governance becomes a must. SAP provides tools like:

- SAP Data Custodian to ensure data residency and privacy
- SAP Governance, Risk and Compliance (GRC) for audit trails and model approvals
- Model Monitoring Dashboards for bias detection and drift analysis

Given these tools, any AI models deployed for green costing must be explainable and auditable as well as being compliant with regulations such as the EU AI Act and CSRD (European Commission, 2022).

In conclusion, integrating AI into SAP for green costing is a technically feasible and strategically valuable initiative. It requires careful alignment of data pipelines, modeling workflows, and business logic, all supported by SAP's expanding suite of AI and sustainability tools.

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V. BENEFITS OF AI-DRIVEN SUSTAINABLE COSTING FOR MANUFACTURERS

The integration of AI into SAP for green costing is not an upgrade of financial calculations; it mechanizes the strategic worth of costing itself. Manufacturers are increasingly being pressured into decarbonizing their operations across all sectors, complying with environmental laws, and meeting stakeholder expectations. There are some key benefits sustainable costing gives using AI that could tie up financial performance with environmental accountability.

A. Enhanced Cost Accuracy with Environmental Components

Conventional product costing methods tend to overlook or at best superficially take into account environmental costs-and hence, the pricing of the product and profit margin assessment are largely distorted. AI models require an added dimension of real-time carbon emissions, energy consumption, and waste metrics into the cost estimate while properly accounting for the environmental impact.

By means of regression models trained on historical data of productions and energy, AI predicts the carbon-adjusted unit cost of a product with finer granularity (Moghaddam et al., 2021). Such predictions can consider some factors, such as the location of production, time of the day, machine efficiency, and source of raw materials, thereby accounting more accurately for environmental costs.

B. Improved Decision-Making in Product and Process Design

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C. Proactive Compliance and Risk Mitigation

With the impending enforceability of environmental regulations such as the EU's Corporate Sustainability Reporting Directive (CSRD), the Carbon Border Adjustment Mechanism (CBAM), and climate risk disclosure rules by the U.S. SEC, companies will then have to disclose carbon cost information on their financial and ESG reports. Through this type of automated mechanism, the AI-integrated SAP systems undertake the processes of accrual, calculation, and reporting of emissions-related costs. The systems even have the foresight to alert the user if operations are headed towards surpassing a regulatory threshold so that an intervention can be made beforehand (Rajapakse & Gunaratne, 2020).

Cross-checking costing data with taxonomy-aligned activities can be done with SAP's embedded compliance tools, ensuring the reported data is defensible during an audit or disclosure.

D. Strategic Supplier and Procurement Optimization

The concept of AI-driven costing allows manufacturers to determine not only the price of inputs but also their ecological performance. Through integration with SAP Ariba or Supplier Lifecycle Management, AI models can assign scores to suppliers for their carbon footprint, water consumption, and circularity practices. Procurement managers, with such a complete perspective, can then accord priority to vendors who can deliver both cost and sustainability benefits. For instance, it may recommend sourcing steel from a supplier with electric arc furnaces powered by renewables, even though the unit price might be a little higher-because savings down the road-from avoidance of carbon taxes or good brand reputation-may far outweigh the immediate cost (Kumar et al., 2021).

E. Competitive Advantage and Brand Value

Green costing backed by AI contributes to a company's competitive differentiation. Consumers and investors are increasingly favoring companies that transparently disclose their environmental impact and demonstrate credible reduction strategies.

Once computed on-the-fly by the SAP AI-enhanced solutions versus verifiable carbon cost data, companies can take this data to eco-labeling, B2B sustainability scoring, and ESG investor communications. Green costing also allows manufacturers to charge premium prices for better products environmentally, thus recovering their sustainability investments (Accenture 2023).

F. Operational Efficiency and Continuous Improvement

SAP systems with AI capabilities bring into solution erstwhile hidden inefficiencies by correlating cost variance with energy intensity, process deviations, or material wastage. One such example consists of a predictive model disclosing increased scrap rates in certain shifts, thus contributing both to the rise of costs and emissions.

Based on such insights, managers can trigger Lean or Six Sigma actions in specific areas that enhance both environmental and financial KPIs. Therefore, AI aids the continuous improvement loops in production, logistics, and finance (Zhou et al., 2020).

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Table 3 Comparison of Traditional vs AI-Driven Green Costing

Feature	**Traditional Costing (SAP CO-PC)**	**AI-Driven Green Costing with SAP**
Carbon Cost Inclusion	Rarely included or manual estimates	Real-time AI-based estimation
Scenario Simulation	Limited and static	Dynamic, multi-variable simulations
Supplier Evaluation	Price-focused	Includes ESG performance
Compliance Support	Manual and reactive	Automated and predictive
Data Sources	Internal, structured	Multi-source, including IoT/ESG APIs
Decision Intelligence	Descriptive	Predictive and prescriptive
Sustainability Integration	Weak	Fully embedded into costing logic

G. Summary of Benefits

The convergence of AI, SAP, and sustainability presents a transformative shift, moving legacy costing from a reactive, compliance-driven methodology to a green costing philosophy that proactively enables strategy. These benefits disperse from the front line to the finance departments, from design to investor relations, enhancing the competitiveness of organizations and their climate accountabilities.

VI. CHALLENGES AND LIMITATIONS OF IMPLEMENTING AI-ENHANCED GREEN COSTING

AI-driven green costing, when implemented in SAP, can be revolutionary if but under a shared perception of being difficult to accomplish. From data restrictions to infrastructure complications and organizational resentments to regulatory complexities, manufacturers are kept away from fully benefiting from it. This section discusses the primary challenges in the implementation of AI sustainable costing models.

A. Data Quality, Integration, and Granularity

Large volumes of fine data are generally required by AI models. However, in manufacturing environments, environmental data related to energy, emissions, and waste are usually confined away in silos across different departments or stored in different incompatible formats. Integration with the traditional version of cost components in the SAP CO-PC or Product Lifecycle Costing (PLC) gets much more complex (Lee et al., 2022).

On the other hand is the problem of nonstandard carbon accounting for suppliers, which stands in the way of integrating scope 3 emissions. Small and medium suppliers may not collect, educate, or disclose carbon data at all, thus leaving a gap filled with estimated inputs. The predictions of AI can be undermined in terms of confidence, and indeed sustainability reporting may suffer.)

B. High Implementation and Maintenance Costs

Infrastructure-wise, talents-wise, and change management-wise, implementing AI-based costing solutions in SAP tends to rack up enormous costs. Firms have to upgrade to cloud-based versions of SAP (e.g., SAP S/4HANA), implement data lakes, and interface with third-party sustainability APIs. All these technical upgrades require huge upfront and ongoing maintenance expenses (PwC, 2021).

Furthermore, the training and upkeep of AI models require skilled professionals like data scientists, environmental engineers, and SAP integration specialists- these roles are generally quite expensive and difficult to fill, especially for SMEs.

C. Organizational Resistance and Skill Gaps

Infrastructure-wise, talents-wise, and change management-wise, implementing AI-based costing solutions in SAP tends to rack up enormous costs. Firms have to upgrade to cloud-based versions of SAP (e.g., SAP S/4HANA), implement data lakes, and interface with third-party sustainability APIs. All these technical upgrades require huge upfront and ongoing maintenance expenses (PwC, 2021).

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D. Regulatory Uncertainty and Standardization Challenges

While regulations such as the CSRD and the SEC climate disclosure rules are coming into the spotlight, global standards for carbon accounting and environmental cost reporting are still evolving. Companies that pursue green costing will usually encounter uncertainty with decisions to be made with respect to which emission data are to be included, how to allocate environmental costs among SKUs, or how to reconcile carbon pricing with a local tax structure.

This ambiguity, in turn, creates compliance risk. For example, the use of an AI tool in which carbon costs are estimated on the basis of averages for a region could very well go against jurisdictional standards for reporting. Regulators could ask how these approximated values may be considered valid unless methods are fully disclosed and validated (IFRS Foundation, 2023).

Table 4 Summary of Implementation Challenges

Challenge	Description	Impact on AI Green Costing
Data Fragmentation	Siloed and inconsistent environmental data	Reduces prediction accuracy
Model Opacity	Lack of interpretability in advanced models	Low user trust, audit difficulties
High Deployment Cost	Infrastructure upgrades, cloud migration, hiring specialists	Limits accessibility, especially for SMEs
Cultural Resistance	Inertia among finance and procurement teams	Slows adoption, undermines value
Regulatory Ambiguity	Inconsistent or evolving standards for carbon accounting	Creates compliance risks, deters investment
Weak External Ecosystems	Limited availability of supplier- or region-specific emissions data	Restricts model precision and actionability

E. Overcoming the Barriers

Despite these hurdles, a swarm of mitigation solutions is slowly emerging. For instance, companies can start small by deploying pilot AI models on high-impact product lines and gradually scale up. Also, leveraging explainable AI (XAI) methods can improve user trust as they make model logic more transparent (Arrieta et al., 2020).

Meanwhile, SAP continutes expanding the functionalities of its Sustainability Control Tower and Green Ledger to provide more standardized frameworks for carbon accounting and integration with costing modules. To improve in these areas, industry alliances also work together, with the Partnership for Carbon Transparency (PACT) working to advance cooperation on emissions data sharing across supply chains.

F. Summary

Organizations need to horse before they can ride in this regard. With technical, cultural, and regulatory hurdles to overcome, successful integration requires more than just investment in software. It mandates transformation in data governance, talent management, and cross-silo collaboration.

VII. FUTURE DIRECTIONS: AI, BLOCKCHAIN, AND PREDICTIVE ESG COSTING IN SAP

The integration of environmental, social, and governance (ESG) considerations into enterprise systems such as SAP reaches a new phase. As sustainability is placing toward the very core of the business and not as an afterthought of various compliance requirements, some future-oriented manufacturers are asking how emerging technologies — specifically, AI, blockchain, and digital twins — could be molded to increase the sophistication, transparency, and predictability of green costing systems. This section outlines some promising avenues leading into the future for research and industrial deployment.

A. AI for Scenario-Based Cost Modeling

One of the most transforming evolutions of AI in SAP costing is that of scenario-based modeling for trade-offs between environment and finance. Traditionally, costing relies on historical averages; however, AI models simulate several futures by means of variable inputs, varying from changes in carbon tax policy, changes in energy prices, or changes in emissions intensity at the supplier level.

According to these "what-if" scenarios, the decision-maker can look into the cost implications under certain strategic options, such as whether to shift production, switch to low-emission suppliers, or pursue circular economy interventions. On the other hand, a model may forecast the carbon-adjusted cost of a product in 2030, given assumptions about regulatory shifts, to support improved capital allocation (Bocken et al., 2014).

B. Blockchain for Emissions Traceability

Today, one major constraint in green costing is the lack of verifiable, real-time emissions data coming from partners situated upstream or downstream. With blockchain technology, one may argue that an immutable, decentralized tracking of carbon footprints at the product level could be facilitated.

Several pilots are underway, such as SAP with the Climate Chain Coalition, to figure out how blockchain might be used to tag and trace emissions across the supply chain. Integrating this traceability with AI further improves the modeling of scope 3 emissions, hence enhancing ESG compliance and cost allocation accuracy (Saberi et al., 2019).

C. Digital Twins for Real-Time Environmental Costing

Digital twin technology — that is, a virtual copy of physical assets, processes, or systems — is increasingly being applied toward manufacturing sustainability. A digital twin deployed along with SAP and AI-based models can simulate both operational performance and environmental impact, basing the simulations on cost.

For example, considering the digital twin of a product line, it could consider how replacing a machine impacts water consumption, energy consumption, and CO2 emissions and transfer these insights directly into product cost estimates, thereby dynamically adjusting costing in a fast and fine-grained manner. (Grieves & Vickers, 2017).

D. ESG-Integrated Vendor and Product Scoring

A growing application is that of ESG scoring, driven by an AI system, at the supplier or product level. These scores can then be fed into SAP procurement or materials management modules for sourcing decisions based on sustainability. AI models utilize structured and unstructured ESG data-which includes supplier audits, news reports, and emission disclosures-to rank sustainability performance ratings.

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With the forefront of global development of carbon pricing mechanisms, one can expect these ESG scores to be included in predictive cost models so that the expected product cost would be automatically adjusted according to supplier risk levels; thereby, for instance, a supplier being flagged for high methane emission would trigger an automatic costing premium by SAP CO-PC.

Table 5 Future Directions and Applications

Future Technology	Application in Green Costing	Benefits
Scenario-Based AI	Forecast cost under future regulatory or resource scenarios	Informed long-term strategic planning
Blockchain	Immutable carbon tracking across supply chains	Improves trust and traceability of emissions data
SAP Green Ledger	Dual carbon-financial accounting inside ERP	Unified view of cost and sustainability
Digital Twins	Real-time simulation of environmental impact and cost	Dynamic costing, higher operational visibility
ESG Scoring Engines	AI-based supplier and product risk profiling	Promotes responsible sourcing and cost adjustment

A. Policy and Standardization Support

The development of predictive ESG costing must be supported by clearer policy frameworks and international standards. Efforts by the International Sustainability Standards Board (ISSB), the Global Reporting Initiative (GRI), and the EU's Green Taxonomy will help define the metrics and thresholds that SAP systems must measure.

Furthermore, AI regulation — such as the EU AI Act — must ensure that sustainability algorithms in enterprise software are transparent, fair, and explainable, especially when used in automated procurement or resource allocation decisions.

B. Summary

The AI-issued ESG scores at the supplier or product levels are an emerging application. Subsequently, the integration of those scores in SAP procurement or materials management modules enables sourcing decisions based on sustainability. AI models then would rank sustainability performance scores based on structured and unstructured ESG data, which includes supplier audits, news reports, supplier disclosures for emissions, and so on.

With respect to the global landscape surrounding carbon pricing mechanisms, the intention is that these ESG scores get plugged into predictive cost models so that the cost projection of a product would automatically be adjusted based on the level of supplier risk; for example, a supplier being flagged for high methane emissions would trigger an automatic costing premium through SAP CO-PC.

VIII. CONCLUSION AND RECOMMENDATIONS

If we were looking historically, the integration of AI into SAP pricing engineering would be a shift toward sustainable production. As we see in this article, traditional cost mechanisms are less and less able to speak to the complex, dynamic, and often intangible costs linked with environmental impact and carbon emission. AI costing methods coupled with SAP's new green tools present organizations with the ability to place environmental considerations at the heart of financial transactions, thus charting the course of responsible profitability.

Machine learning can take cost predictions to a new level: greater in accuracy, dynamic enough to integrate changing factors, and able to handle large datasets from across supply chains. These models foresee the changes in costs of materials and energy; simulate hypothetical changes in environmental regulations; and suggest greener alternatives proactively — thus enabling transparent and ethical resolution of cost conflicts. When made part of SAP's CO-PC standard system and integrated with sustainability-oriented modules such as the SAP Sustainability Control Tower and Product Footprint Management, these tools ensure an uninterrupted data flow of both financial and environmental aspects.

A. Recommendations:

- *An investment in AI capability-building:*

  Organizations should develop AI literacy for costing professionals and have data scientists embedded within their finance and sustainability teams.

- *Leverage SAP's Green Tools:*

  Enterprises utilizing SAP should take full advantage of the modules such as Green Ledger, Sustainability Control Tower, and Product Footprint Management in the tracking of emissions together with financial metrics.

In brief, AI-enabled green cost management through SAP offers solutions toward balancing cost efficiency with environmental responsibility for manufacturers. With ever-tightening environmental regulations and the maturing of stakeholder expectations, these capabilities will no longer be a plus, but will rather be a key factor in ensuring long-term sustainability in the global marketplace.

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