Applied Science, Computing and Energy, 2025, 3(3), 431-444

A Review on Sustainable Procurement in the Age of AI: Leveraging Intelligent Systems to Advance U.S. Climate and Economic Resilience

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Received : 12 July 2025/Accepted : 17 October 2025/Published 25 October 2025

Abstract: *This study explores the transformative role of Artificial Intelligence (AI) and intelligent systems in advancing sustainable procurement with a particular focus on U.S. climate and economic resilience objectives. It examines how AI capabilities such as predictive analytics, natural language processing, and machine learning are being applied to improve supplier risk profiling, automate lifecycle emissions tracking, enhance demand forecasting, and enable real-time disruption management. The findings reveal that AI significantly strengthens procurement functions by increasing transparency, optimizing green sourcing, and embedding Environmental, Social, and Governance (ESG) criteria into supplier networks. Furthermore, AI enables the practical implementation of federal initiatives such as "Buy Clean" standards, supports renewable energy and sustainable infrastructure procurement, and enhances supply chain agility in the face of disruptions. Furthermore, the study identifies persistent challenges, including fragmented data, limited supplier disclosure, and the need for coherent policy and governance frameworks to fully harness AI's potential. Ultimately, AI emerges as a critical enabler of sustainable procurement, aligning public purchasing power, decarbonization goals, and long-term economic resilience with national climate policy.*

Keywords: *Sustainable procurement, AI, climate change, supply chain management, ESG, IoT public policy*

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1.0 Introduction

Machine Learning (ML) and Artificial Intelligence (AI) are transforming interdisciplinary fields through efficient systems for accurate data interpretation, predictive analytics, and autonomous operations (Ademilua, 2021; Adeyemi, 2023). Their integration facilitates innovative methods for real-time analysis and automated decision-making across sectors (Adeyemi, 2025). AI and ML reshape research by processing large datasets and enhancing autonomous performance (Ajiboye et ., 2025). The widespread adoption of these tools supports intelligent frameworks that strengthen analytical precision and operational efficiency (Ademilua & Areghan, 2022). By enabling intelligent automation and data-driven reasoning, they offer transformative solutions to modern challenges (Dada *et al*., 2024; Isichei, 2025). Their applications improve data modeling, decision-makin and smart navigation (Okolo, 2023; Adeyemi, 2025). Advanced techniques enhance computational intelligence and predictive modeling (Abolade, 2023; Areghan, 2025), while their convergence optimizes real-time operations and dataset management (Utomi *et al*., 2024; Adeyemi, 2024). Overall, AI and ML redefine automation, analytical accuracy, and intelligent system design (Omefe *et al*., 2021; Umoren *et al*., 2025).

Sustainable procurement involves the consideration of environmental, social and economic aspects in purchasing practices so that purchasing decisions are made in ways that minimize detrimental environmental impacts, contribute to social outcomes, and deliver long term value to the public (Brammer and Walker, 2011; Lawal & Isiyak, 2025a; 2025b). Historically defined as "green public procurement" in many national policies, sustainable procurement has been researched as both a demand-side environmental policy instrument and as what is termed managerial practices that shape supplier behavior and life-cycles of products (Testa *et al*., 2016; Neves *et al*., 2018). In the United States, recent federal policy has brought procurement to the forefront as a direct tool for climate and industrial policy: Executive Order 14057 and accompanying implementation instructions make explicit the federal government's ambition-to harness federal government's portfolio (and some two-half trillion dollars of annual purchasing power) to decarbonize the economy through lowering greenhouse gas emissions, increasing the purchase of sustainable goods and services, and stimulus for domestic clean energy industries (White House / CEQ, 2021). These directives call for agencies to consider lifecycle emissions, increase disclosure of emissions by suppliers, and to seek "Buy Clean" and “Buy American” standards for high-emissions materials - to couple procurement decisions with emissions reduction and domestic industrial objectives.

The United Nations Sustainable Development Goals (SDG 12 on sustainable consumption and production in particular), national climate policy priorities that prioritize decarbonization and resiliency, and Environmental, Social, and Governance (ESG) criteria adopted by investors and firms are all at the intersection of sustainable procurement (UN SDG 12; Seuring & Muller, 2008). By integrating lifecycle impacts, social performance from suppliers, and circularity criteria into sourcing, tiering, and contracting, procurement operationalizes these high goals. Finally, from the standpoint of supply chain resilience, incorporating ESG performance into procurement operations helps firms measure and control Scope 3 emissions that are present in the products and services they buy, reducing exposure to supply disruptions, regulatory risk, and reputational harm (Koberg and Longoni, 2019; Walker and Brammer, 2012). Therefore, by encouraging demand for low-carbon technologies and delivering a set of market signals to providers to decarbonize, integrating sustainability helps with risk management and long-term competitiveness.

Two lenses are used in this review: (a) environmental sustainability, which includes decarbonization, circular inputs, and lifecycle effects in purchased goods and services; and (b) economic competitiveness and resilience, which includes factors like cost effectiveness, industrial development, and supply chain continuity. Markets for sustainable goods and technology can be shaped via public procurement, which is particularly catalytic since it aggregates demand at scale. In many nations, public purchasing scales amount to a sizeable portion of GDP (Testa *et al*., 2016; Brammer & Walker, 2011). According to Neves *et al*. (2018) and Sonnichen *et al*. (2020), there are still ongoing implementation gaps, including data fragmentation, procurement organizations' capacity limitations, and disincentives that hinder adoption. However, careful lifecycle costing, performance-based procurement contracts, and supplier engagement can yield both sustainability and value-for-money. Integrating iniscuspitability without paying close attention to procurement processes can also result in short-term cost increases or compliance burdens.

Despite growing scholarly and policy interest in sustainable procurement, limited attention has been given to how Artificial Intelligence (AI) can be systematically integrated into procurement systems to achieve measurable sustainability and resilience outcomes. Existing studies have largely examined green procurement policies, supplier sustainability criteria, and lifecycle costing frameworks (Testa *et al*., 2016; Neves *et al*., 2018; Walker and Brammer, 2012), but few have explored the specific mechanisms through which AI-driven analytics, predictive models, and intelligent automation can enhance procurement transparency, supplier performance monitoring, and emissions reduction tracking. Moreover, the intersection of AI innovation with U.S. federal climate directives, such as Executive Order 14057 and "Buy Clean" standards, remains under-researched. This gap underscores the need for a systematic review that connects technological capabilities with policy-driven procurement reforms to support national decarbonization and economic resilience goals.

The aim of this paper is to review evidence on how Artificial Intelligence (AI) and related intelligent systems (machine learning, automated recommendation systems, natural language processing, and analytics) are changing procurement capabilities - improving visibility of spend, automating tedious tasks, surfacing supplier risk and emissions data, improving demand forecasting, and enabling lifecycle and scenario analysis that can support climate-informed sourcing decisions. The roles that AI plays in procurement can be typically summarised as (i) automation (addressing transactional costs by reducing manual effort) and (ii) augmentation/smartness (adding predictive insights and recommendations to change the outcome of a decision).

This study is significant because it bridges the emerging technological domain of Artificial Intelligence with the strategic objectives of sustainable procurement and national climate resilience. By synthesizing evidence on how AI-enabled systems—such as predictive analytics, natural language processing, and machine learning—can optimize green sourcing, emissions monitoring, and supplier risk management, the review provides actionable insights for policymakers, procurement officers, and sustainability practitioners. It contributes to the evolving discourse on **how digital transformation can operationalize the United States' climate commitments**, strengthen domestic industrial competitiveness, and advance Environmental, Social, and Governance (ESG) performance across supply chains. Furthermore, the findings are expected to guide the design of data governance frameworks, inform future research, and promote intelligent public procurement practices that align sustainability imperatives with long-term economic resilience.

2. 0 Role of AI and Intelligent Systems in Procurement

2.1 Overview of Intelligent Systems

Artificial Intelligence (AI) is reshaping procurement processes by introducing advanced computational techniques that enhance decision-making in key domains such as supplier selection, contract management, demand forecasting, and spend analytics, thereby improving efficiency, transparency, and sustainability outcomes as demonstrated by Fig, 1. Predictive analytics enables organizations to predict demand, vendor performance, and cost fluctuations from the big data of historical and real-time data (Chopra & Meindl, 2016). Natural Language Processing (NLP) provides an additional benefit in proc acquisition through automating analysis of contracts, supplier communication and also processing of documents leading to less administration load and errors (Kumar *et al.*, 2022). Optimization algorithms are used for optimizing the supply chain for different material suppliers, bidding processes, and inventory management, ensuring cost-effectiveness and sustainability (Ferreira, 2023). Additionally, blockchain and AI integration bolsters procurement ecosystems through a convergence of decentralised trust mechanisms and predictive intelligence, and boosts transparency, accountability, and auditability across global supply chains (Queiroz and Wamba, 2019).

2.2 Applications in Procurement Functions

AI applications in procurement covers many functions ranging from the assessment of suppliers to lifecycle analysis (Fig 2). Machine learning (ML) algorithms support the risk analysis tailored for the supplier by figuring out potential disruption points such as the company's financial instability, geopolitical risks or sustainability non-compliance (Ben-Diya *et al*., 2019). The AI-based cost management solutions are helping companies to identify cost drivers, optimize investments, and find inefficiencies in financial dealings (Choi *et al*., 2018). Another important of introducing environmental considerations into procurement operations is lifecycle assessment (LCA), which may be able to measure the energy, water, and carbon footprint of the provided products (Kumar Dadsena & Pant, 2023). Besides the financial goals of the organization in terms of cost and efficiency, the environmental, social and governance (ESG) goals might be continuously improved during the work of the procurement decisions with the assistance of AI-controlled solutions.

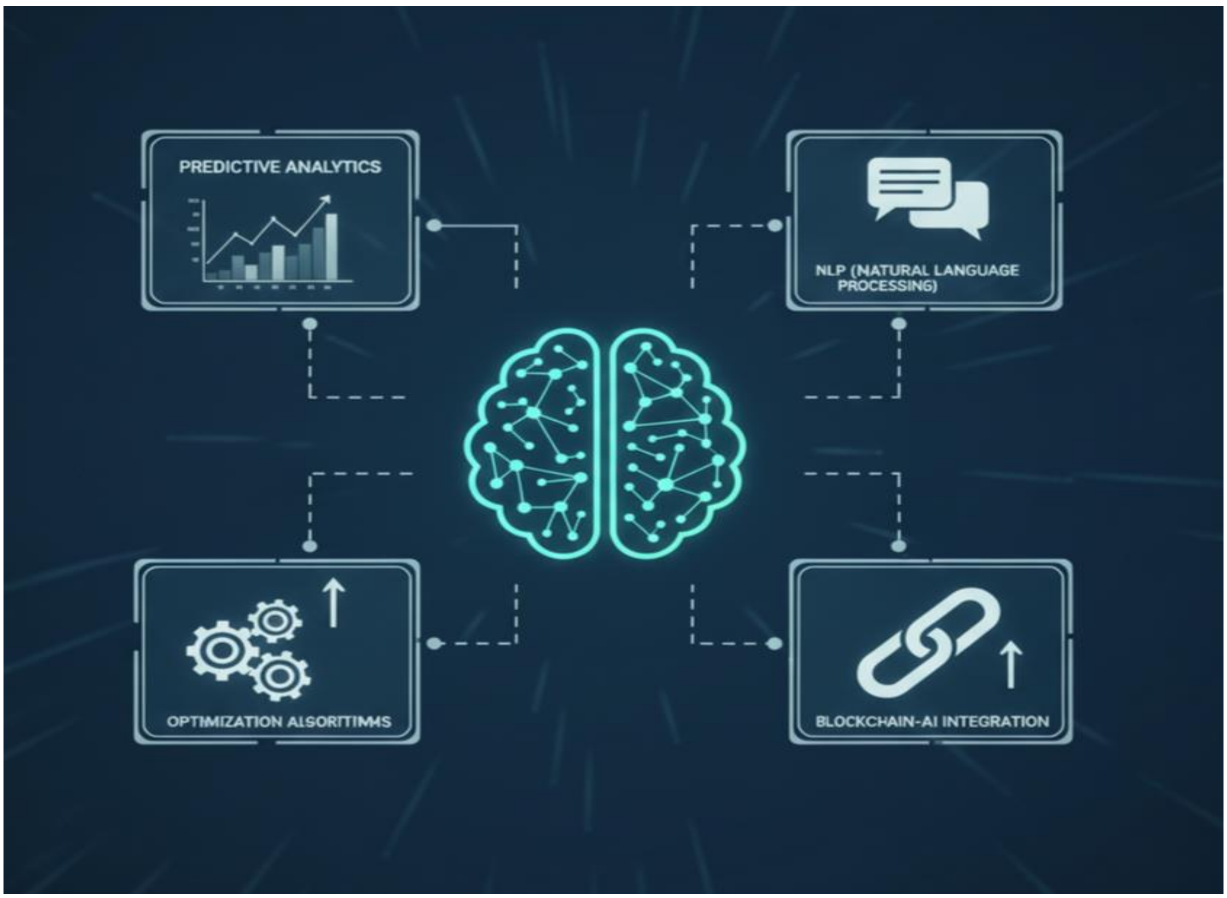

Fig 1: AI and predictive analytics for incorporating advanced methods of computation into the process of making decisions.

2.3 AI in Enhancing Traceability and Transparency across Supply Chains

Transparency and traceability are the pillars of sustainable procurement. The technology of artificial intelligence (AI) minimizes supply chain visibility, unethical actions, and compliance with multiple regulations, including the international trade standards and the U.S. Federal sustainability plan (Queiroz & Wamba, 2019; Sanni, 2024). This makes organizations more resilient and reliable since organizational bottlenecks and vulnerabilities are investigated in real-time using predictive models (Ben-Daya *et al*., 2019). In combination with blockchain, AI potential to establish immutable procurement transaction underpinnings helps companies to confirm that their suppliers are authentic, possess sustainability qualifications, and adhere to ethical sourcing standards (Ferreira, 2023). This integration is especially important in such spheres as energy, defense and pharmaceutical sector where the integrity of supply chains has a direct influence on the welfare of the people and on national security (Fig 3).

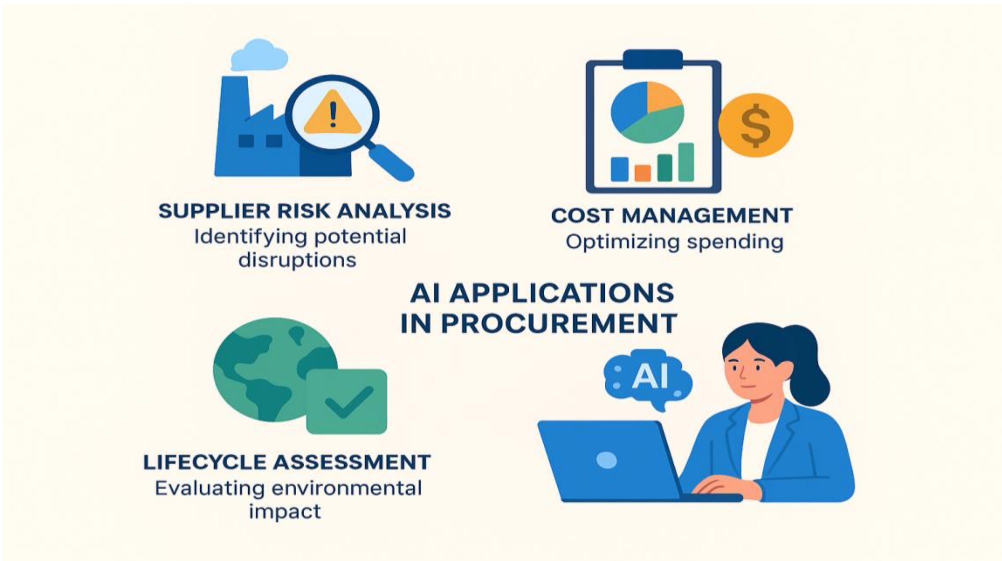

Fig 2: AI applications in procurement functions

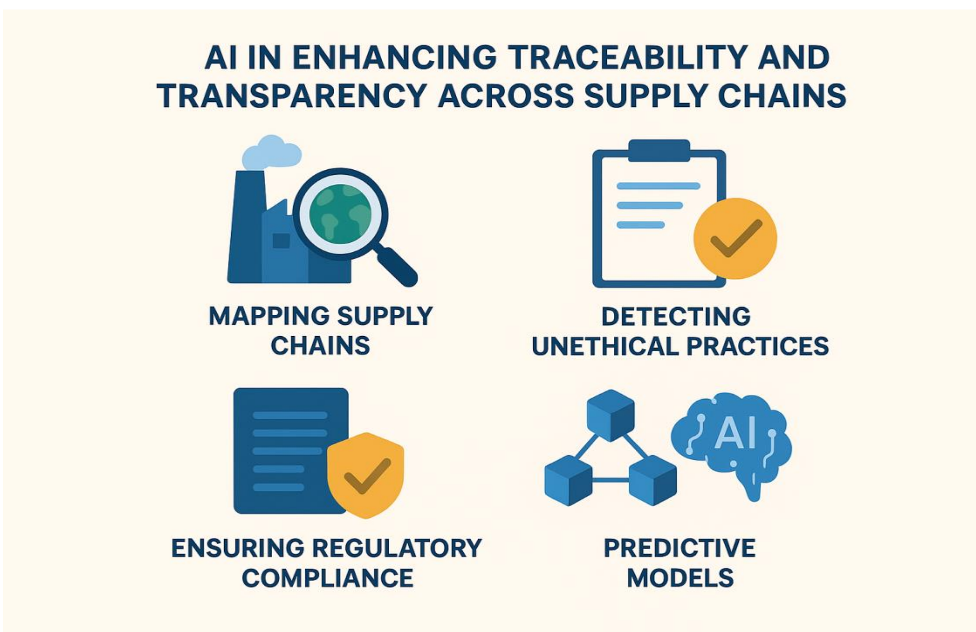

Fig 3: AI in supply chain traceability and transparency

2.4 AI for Real-Time Monitoring and Decision-Making during Disruptions

The recent international supply chain crises caused by trade and the coronavirus pandemic supported the necessity of transparent and open decision making in treaty-based procurement. The companies have also been able to respond to the constantly evolving requirements of the market, supplier constraints, and bottlenecks in the logistics due to AI (Choi *et al*., 2030). Automated processes that harness IoT-enabled sensors and automated analytics with their result enable real-time monitoring of transit routes, inventory, and supplier performance. This helps in the mitigation and identification of risks (Ben-Daya *et al*., 2019). Artificial intelligence-driven control towers such as the one proposed by Kumar Dadsena and Pant (2023) give the purchasing managers real-time information, to enable them to make timely and correct decisions by assessing multiple data points in the event of an emergency. The above-presented functions lead to organizational resilience, lower costs, and strengthen the strategic role of procurement to improve economic sustainability and climate change adaptation.

3.0 AI Models and Approaches Applied to Sustainable Procurement

The procurement process has undergone transformation as well with the use of AI which has allowed decisions to be made smarter, more flexible and data driven. The choice and application of various artificial intelligence models, including classic supervised or unsupervised approaches to learning, as well as reinforcement learning models, deep learning models, and social enterprise hybrid models, determine how far organizations can go in reaching the goals of a circular economy and sustainable procurement (Table 1). The increasing level of AI may be integrated into the procurement operations to fulfill economic and environmental objectives, which are evident in the following methods.

3.1 Supervised and Unsupervised Learning Models for Supplier Risk Profiling and Demand Forecasting

The most common type of supervised machine learning models is used in procurement. Categorizing suppliers and identifying patterns related to non-compliance, financial instability, or disruptions, the algorithms can include logistic regression, support vectors machines (SVMs), random forests, and gradient-boosted decision trees, based on previously labeled datasets (Yang *et al*., 2023). To illustrate, the random forest algorithm that was trained on such data points as supplier delivery times, financial ratios, and ESG ratings can be used by procurement managers to get an early warning about a supply chain risk and take action to diversify their sourcing. Such practices are highly beneficial in structured decision-making environments in which labeled information is easily accessible. Conversely, the procurement requirements are often demanded of dynamic situations where the data density is low in terms of labeling. Unsupervised learning strategies (principal component analysis (PCA), k-means clustering, and anomaly detection models, in this case) can help to detect outliers that signal the risk and reveal concealing patterns in data of the supplier (Akbari & Do, 2021). To determine the areas of their supply chains that require sustainability interventions to be implemented, organizations may use clustering algorithms to categorize suppliers based on the intensity of their carbon footprint, e.g., according to the extent of their negative environmental impact. A mixture of both supervised and unsupervised learning has shown quantifiable improvement in the demand forecasting studies. Cluster-first forecasting approaches, in which products or SKUs are clustered based on unsupervised algorithms and then subjected to a supervised time-series (e.g., definitive: ARIMA, gradient boosting, LSTM-patterns), can be used to improve forecast accuracy and minimize procurement inefficiencies (Akbari & Do, 2021). This specifically applies to the sustainable procurement in that we can reduce waste, restrict the unnecessary use of resources and destroy overproduction when we can better estimate our demand.

3.2 Reinforcement Learning Models and Optimization Models for Dynamic Procurement Decisions

The dynamic character of procurement allows us to make judgments when the demands, trust in the suppliers and swings in the market are uncertain. The interaction between an AI agent and the environment, along with the feedback, i.e., either rewards or even penalties, according to the new paradigm of reinforcement learning (RL), leads to the learning of the best policies adopted by the agent. The successful application of RL has been used to determine dynamic pricing, contract allocation, and inventory management scenarios that entail sequential, adaptive judgments (Quanz *et al*., 2022). Onotole *et al*. (2023) used the vendor-managed inventories in a scenario related to perishable supply chain management, i.e., to apply a deep RL model to shopper marketing. Their results showed that waste was reduced tremendously and there was a better degree of service compared to the rule-based systems. Besides boosting the bottom lines, the improvements also contribute directly to sustainability by reducing resource wastage and greenhouse gases emissions, which have direct correlations with excessive production and disposal. The use of optimization models in procurement remains highly significant in situations where the subject matter is large and the problem has many constraints that could be budget, capacity of suppliers and emission limits. Multi-objective procurement allocation problems are usually solved by using heuristic methods as well as mixed-efficient programming techniques. Hybrid systems, which combine the methods of RL and optimization, gain popularity due to the possibility not only to achieve the flexibility of learning agents but also due to the guarantees of feasibility offered by optimization frameworks (Quanz *et al*., 2022). The models play a critical role in making sure that procurement systems remain operational and efficient in the event of a crisis such as a pandemic, geopolitical unrest or disruption by climate-related shock.

3.3 Deep Learning for Natural Language Contract Analysis and Sustainability Compliance Checks

Contracts are central to procurement, but with their unstructured and complex nature, these documents become time-consuming and error-prone to analyze manually. Deep learning models - and in particular transformers like BERT - are increasingly adopted for the analysis of contracts and compliance with agreements. These models are able to automatically extract clauses, derive sustainability-related obligations, and flag anomalies or missing obligations (Qureshi, 2023). In the case of construction procurement, where sustainability clauses are often very significant, deep learning with natural language processing (NLP) performed surprisingly accurately, resulting in over 93% accuracy in classifying the clauses used in a contract and 83% accuracy in clause similarity analysis (Kang *et al*., 2020). Such applications help to ensure that sustainability commitments are not ignored when negotiating and therefore introduce environmental accountability into the procurement process.

4.0 Implications for Climate and Economic Resilience

This section draws together the academic evidence of how AI-enabled procurement can align through roles in climate mitigation and adaptation goals with economic resilience. The areas being discussed are four interconnected areas: (1) decarbonization and green sourcing; (2) procurement for renewable energy and sustainable infrastructure; (3) economic resilience (costs, agility, and capacity shock response); and (4) policy alignment to U.S. climate and trade priorities.

Table 1: AI Models and Approaches in Sustainable Procurement

AI Model/Approach	Procurement Application	Sustainability/Resilience Outcome	Key References
Supervised Learning (e.g., regression, classification)	Supplier risk profiling (financial stability, ESG compliance), demand forecasting	Anticipates disruptions, optimizes demand planning, reduces waste and excess emissions	Yang *et al*., (2023)
Unsupervised Learning (e.g., clustering, anomaly detection)	Supplier segmentation, fraud detection in procurement transactions, hidden risk discovery	Identifies high-impact suppliers, prevents unethical sourcing, increases transparency	Akbari & Do, (2021)
Reinforcement Learning (RL)	Dynamic supplier selection, real-time logistics rerouting, adaptive sourcing	Enhances agility during disruptions, balances cost and emissions trade-offs	Quanz *et al*., 2022; Onotole *et al*. (2023)
Optimization Algorithms (linear, nonlinear, metaheuristics)	Multi-objective sourcing (cost vs. carbon), inventory optimization	Achieves cost efficiency while reducing lifecycle emissions and energy use	Qureshi, (2023)
Deep Learning (NLP, neural networks)	Contract analysis (sustainability clauses, compliance checks), unstructured data mining	Improves ESG compliance, ensures adherence to green procurement policies	Kang *et al*., (2020)

4.1 AI enabled procurement, reducing carbon emissions and focusing on green sourcing

AI systems can have a material impact on organizations capabilities to measure, manage and reduce greenhouse gas (GHG) emissions in their procurement practices - specifically Scope 3 emissions embodied in purchased goods and services. At the most fundamental level, AI enables better use of data: natural language processing (NLP) and entity resolution algorithms pull out supplier information from invoices, contracts and product specifications, while ML models patch disparate supplier information together to build more comprehensive spend and emissions inventory (Pournader *et al*., 2021; Guida *et al*., 2023). With richer data, organizations can prioritize high-impact categories (construction materials, transportation, manufactured inputs) and target interventions (e.g. supplier engagement, low carbon investigative tenders or material substitutions) that have the highest impact of lowering lifecycle emissions. Predictive models allow upstream interventions, as well as the creation of an inventory. To illustrate, supervised models might be used to identify suppliers with high emissions risk (e.g., centered delays that often happen during logistics or reliance on energy that is more likely to be low carbon) by guiding procurement teams to select low carbon alternatives, to aggregate demands on green supplier anchors, or to require decarbonization plans as part of tendering (Wu *et al*., 2023). Carbon-related externalities can be internalized in sourcing decisions through procurement decision-support Systems that integrate optimization engines with lifecycle assessment (LCA) databases to design procurement portfolios minimizing costs, but still within a given emissions limit (Pournader *et al*., 2021). These pathways can scale, say empirical and modelling studies. Theoretical and simulation work shows machine learning upgrades in supply chains have potential to, in equilibrium, reduce carbon emission intensity and provide competitive incentives for low-carbon suppliers, especially when paired with policy or financial assistance (Wu *et al*., 2023). In practice, the effectiveness of AI is conditioned by data quality, downstream willingness of suppliers to disclose it, and ability to convert insights into contractual requirements and incentives (Guida *et al*., 2023).

4.2 Intelligent systems to aid renewable energy, sustainable infrastructure procurement

Procurement for renewable energy and sustainable infrastructure - two priority domains for national climate policy - are benefiting from the use of AI in the planning and operational phase processes. Machine-learning models are being extensively adopted for renewable generation forecasting (solar and wind), providing greater accuracy on the short-term and day-ahead forecasts that are at the core of power-purchase agreements (PPAs), microgrids procurement, and flexibility services procurement (Benti *et al*., 2023). Improved forecasting helps make balancing more cost-efficient for buyers and utilities, so that renewable contracts become more bankable, leading to a lower effective renewable energy procurement cost. At the infrastructure level, AI-driven digital twins, optimization and scenario modeling allow procurement teams to assess their whole-life performance - energy consumption, resilience to climate extremes, and embodied carbon - across competing design and supplier options. These tools facilitate "Buy Clean" like specifications (embodied emissions thresholds for construction materials) by enabling agencies and firms to compare lifecycle outcomes in bids and identify low-carbon procurement bundles (Pournader *et al*., 2021; Benti *et al*., 2023). When paired with sensor networks and IoT, AI can also be used to enable performance-based contracts (e.g., payford performance for a road or for building contracts) thereby aligning suppliers' incentives with long-term sustainability and resilience outcomes.

4.3 Economic resilience

Artificial intelligence increases the resilience of the economy on several levels. First, by enhancing forecasting, anomaly detection and supplier risk scoring capabilities, it also minimizes inventory wastage and emergency expedited shipping costs - delivering direct procurement savings. (Pournader *et al*., 2021). Secondly, AI can drive agility by real-time monitoring and optimization (control towers, reinforcement learning re-routing) for rapid order reallocation, alternate sourcing, or dynamic pricing responses during disruptions (Ivanov, 2020). Also, AI supports strategies for diversification by mapping multi-tier supplier networks more completely, organizations will be able to identify critical single source outages, and design multi-sourcing/near-shoring strategies that reduce exposure to geopolitical or climate shocks. From the literature on pandemic and disruption response, data-driven models have been shown to reduce recovery time and improve the quality of decision making in the face of pandemic and supply chain shocks that resulted from the Covid-19 pandemic (Ivanov 2020), and these types of capabilities are also relevant in the face of climate-induced events. The economic benefits include therefore avoided disruption costs, increased service levels and the possibility of competitive advantage when firms proceed with procurement to lock in stable supply of low-carbon inputs. Yet the benefits are not automatic, successful outcomes depend upon integration of AI outputs in procurement processes, training of procurement staff and governance mechanisms to validate model recommendations (Guida *et al*. 2023; Pournader *et al*. 2021).

4.4 Policy alignment- AI-driven procurement policies in U.S. climate and trade policy

For AI-enabled procurement to feed into national-scale climate and economic ambitions, coherence with current and legacy policy frameworks is critical. In the United States, Executive Order 14057 (Dec. 8, 2021) and related sets of implementing instructions prioritize buying net-zero; standards on Buy Clean and resiliency in federal procurement; these directives set mandates, and a market pull for low carbon goods and services (Executive Office of the President, 2021; CEQ Implementing Instructions, 2022). Thus, AI systems that generate detailed and auditable emissions Scrutinies and lifecycle comparisons, in turn, enable compliance with these federal directives and permit agencies to put into practice the supplier disclosure duties and limits on emissions. Policy tools are not needed to increase the effects of AI. The narrowing of the information gap and encouraging smaller suppliers to provide the data necessary to run AI systems can be achieved with public procurement rules (OECD; national procurement reforms) and incentive schemes (technical assistance, supplier decarbonization awards) (OECD, 2019). Moreover, in terms of a tradeoff between short-term cost factors and long-term reliability and objectives in climate change, the public acquisition assets might be redeployed to create a strong local supply chain and achieve sustainability objectives by connecting procurement AI to trade and industrial strategy (e.g. local content requirements, renewable energy generation supports).

5.0 Conclusion

The use of artificial intelligence (AI) and intelligent systems can bring immense advantages to transform the sustainability of procurement since it is strategic in dealing with climate change and promoting economic backup vis-a-vis the study. Artificial intelligence (AI) is transforming procurement significantly by enabling more data-driven, transparent, and decarbonization-aligned procurement, through its ability to predict supplier risk profiles, monitor emissions automatically through the lifecycle, and respond to issues in real time. The combination of these technologies advances the possibility that supply chain visibility will be elevated, green sourcing decisions will be maximized, and Environmental, Social and Governance (ESG) requirements of supplier networks will be operationalized. AI will have to steal information providers, address the old issues of data fragmentation, and can integrate the output of algorithms, in turn, into incentive and contract programs. Even though AI is providing us with tools to develop strong supply chains and implement our Buy Clean policies, their practical implementation still requires highly elaborated data governance and cross-functional capacity building, as well as policy frameworks to ensure that they are able to establish a sustainable fair future.

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Declaration

Competing interests

There are no known financial competing interests to disclose

Ethical Consideration

Ethical consideration is not applicable to this study because it is a conceptua paper

Funding:

There was no external financial sponsorship for this study

Availability of data and materials:

The data supporting the findings of this study can be obtained from the corresponding author upon request

Authors' Contributions

Both authors contributed equally in all aspect of the work