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Artificial Intelligence and the Institutional Efficiency of Environmental Policy: A Transaction Cost Perspective

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Abstract: Environmental policy effectiveness is often constrained not by instrument design itself, but by implementation frictions, information asymmetry, high monitoring and enforcement costs, and slow policy adjustment under rapidly changing climate and market conditions. This conceptual article develops a transaction cost perspective on how artificial intelligence (AI) can function as a governance infrastructure that strengthens environmental regulation. It highlights three channels: (1) intelligent monitoring that upgrades Monitoring, Reporting, and Verification (MRV) from periodic reporting to continuous data-driven oversight; (2) predictive modeling that supports adaptive recalibration of policy parameters through a policy feedback loop; and (3) improved integrity of carbon pricing and emissions trading systems (ETS) via anomaly detection and cross-validation of emissions claims. The analysis outlines expected economic effects, such as lower administrative and compliance costs, more reliable price signals, and stronger incentives for green investment, while emphasizing that benefits depend on institutional safeguards. A governance risk framework is proposed to address algorithmic bias, digital inequality, AI energy use, and technological dependency through measurable KPIs. Overall, AI complements rather than replaces environmental policy by expanding institutional capacity for effective regulation.

Keywords: Green AI; Environmental governance; Transaction costs; MRV; Policy feedback loop; ETS; Carbon pricing; Regulatory compliance; Algorithmic governance

1. Introduction

Environmental policy is traditionally understood as an institutional response to market failures, particularly negative externalities associated with pollution and climate change [1,2]. Classical economic instruments, such as Pigouvian taxation, emissions trading systems (ETS), and regulatory standards, are designed to internalize social costs and align private incentives with ecological objectives [3,4]. However, the effectiveness of these instruments depends not only on their formal design but also on the institutional conditions under which they are implemented.

Under accelerating climate dynamics and rapid digital transformation, environmental regulation faces three interrelated structural constraints as follows:

(1) Persistent information asymmetry between regulators and regulated entities undermines the accurate calibration of policy instruments. Firms typically possess more detailed knowledge of their emissions profiles and technological capabilities than public authorities, which rely on periodic reporting and selective inspections [5,6];

(2) Environmental governance entails substantial transaction and administrative costs, including data collection, verification, auditing, and enforcement [7]. In large-scale economies, comprehensive oversight of all pollution sources is infeasible, leading to selective monitoring and weakened compliance incentives [8];

(3) Regulatory systems often exhibit limited adaptability: legislative and administrative adjustments evolve more slowly than technological change, market volatility, and climate risks, generating regulatory lag and reducing dynamic efficiency [9].

These constraints suggest that environmental policy effectiveness is frequently limited not by deficiencies in economic theory, but by institutional implementation frictions. In this context, artificial intelligence (AI) can be conceptualized not merely as a technological tool, but as a governance infrastructure capable of expanding informational capacity, lowering compliance costs, and improving adaptive regulation.

This article develops a transaction cost perspective on AI-enabled environmental governance. It argues that the principal institutional contribution of AI lies in strengthening Monitoring, Reporting, and Verification (MRV) systems, transforming them from periodic reporting mechanisms into continuous data-driven oversight structures [10]. By reducing information asymmetry and automating verification processes, AI lowers transaction costs and enables the formation of a policy feedback loop in which regulatory parameters can be recalibrated based on real-time data.

Unlike much of the AI-for-climate literature, which focuses primarily on technological performance and predictive accuracy, this study shifts attention to institutional efficiency and governance design [11–13]. It examines how AI integration reshapes compliance mechanisms, carbon pricing systems, and policy adaptability, while also identifying the governance risks, such as algorithmic bias, digital inequality, energy consumption, and technological dependency, that may condition these efficiency gains. By linking AI applications to transaction cost theory and new institutional economics, the article provides a conceptual framework for evaluating AI as an institutional capacity rather than a substitute for environmental policy.

2. Theoretical foundations

2.1. Institutional effectiveness and artificial intelligence in environmental governance

Environmental policy, traditionally grounded in market failure theory, seeks to internalize negative externalities through regulatory and market-based instruments [7,8]. However, the effectiveness of such instruments depends not only on their economic design but also on the institutional conditions under which they operate [14]. Regulatory systems frequently encounter implementation constraints related to data reliability, monitoring capacity, and enforcement coordination, which may limit policy credibility and performance [13,15].

Within the framework of new institutional economics, institutional effectiveness is associated with the ability of governance structures to manage uncertainty and coordinate complex interactions among actors [16]. From this perspective, AI can be conceptualized as a technological infrastructure that expands the informational and analytical capacities of environmental governance systems [14].

AI enhances regulatory systems by expanding real-time monitoring capacity, automating verification processes, and supporting predictive policy calibration [6,11].

Rather than replacing existing policy instruments, AI operates as a data-driven governance layer that integrates monitoring, analytical, and decision-support functions within environmental regulatory frameworks.

3. AI integration in environmental policy

3.1. Intelligent monitoring and the strengthening of MRV systems

One of the central directions of AI integration into environmental policy is the digital enhancement of MRV systems [17]. The traditional compliance model relies on periodic reporting and selective inspections. AI transforms this framework into a continuous monitoring system supported by automated analytics [18].

AI integrates satellite remote sensing and sensor networks into a real-time environmental monitoring architecture [10]. Practical applications include the detection of illegal deforestation and anomaly identification in emissions data. From an institutional perspective, AI strengthens MRV by increasing data reliability and detection probability, thereby enhancing regulatory effectiveness and improving the strategic allocation of enforcement resources.

3.2. Predictive modeling and the formation of a policy feedback loop

A second area of integration concerns the use of AI for scenario analysis and dynamic modeling of environmental policy [10]. Unlike static regulatory models, AI enables dynamic scenario analysis by capturing nonlinear system interactions.

AI is applied to evaluate alternative policy trajectories, including adjustments to carbon tax parameters, accelerated energy decarbonization, scaling of renewable energy deployment, and the implementation of circular economy mechanisms. This approach facilitates the development of a closed policy feedback loop, in which regulatory outcomes are continuously analyzed and used to recalibrate policy parameters [19].

As a result, regulation acquires a proactive character: decisions are informed by probabilistic forecasting and sensitivity analysis of system responses to parameter changes. The economic significance of this approach lies in enhanced dynamic efficiency, reducing policy errors, minimizing the risk of miscalibrated instruments, and lowering the costs associated with subsequent institutional adjustments [20].

3.3. Optimization of carbon markets and compliance mechanisms

A third dimension of AI integration concerns carbon pricing systems and emissions trading schemes (ETS), where transparency, reporting accuracy, and price signal stability are central determinants of effectiveness [21].

Machine learning algorithms are employed to detect anomalies in transaction data, analyze speculative trading patterns, forecast quota price volatility, and cross-validate corporate emissions reports with independent data sources [6]. These applications strengthen compliance mechanisms, reduce the likelihood of market manipulation, and enhance the overall transparency of carbon markets [11].

From an economic perspective, AI contributes to the stabilization of price signals, reduction of investor uncertainty, and increased credibility of green financial instruments [12,13]. A more predictable and transparent market environment, in turn, stimulates investment in low-carbon technologies and improves capital allocation efficiency within the broader climate transition process.

4. Economic effects of AI integration

The integration of AI into environmental regulation generates not only institutional but also systemic economic effects. These impacts manifest at the level of transaction costs, innovation dynamics, and structural transformations in the labor market [12]. Collectively, they determine how digitalization influences both the static and dynamic efficiency of environmental policy.

4.1. Reduction of transaction costs and enhancement of allocative efficiency

From the perspective of transaction cost theory, any regulatory framework entails costs related to information gathering, enforcement, and dispute resolution [22,23]. In environmental governance, these costs are substantial due to data verification requirements and compliance oversight. AI integration reduces these burdens through automated data processing, digital verification, and algorithmic anomaly detection [5]. By streamlining monitoring and reporting procedures, AI lowers reliance on resource-intensive inspection mechanisms. For governments, this translates into reduced administrative expenditures; for firms, into lower compliance costs and shorter reporting cycles. At the macroeconomic level, declining transaction costs enhance allocative efficiency, redirecting resources from administrative routines toward investments in environmental modernization.

4.2. Stimulation of green innovation and strengthening of investment incentives

AI exerts a direct influence on the innovation dynamics of the economy [12,13]. Its integration into production and management processes contributes to improved energy efficiency, optimization of logistics networks, reduction of material intensity, and minimization of waste generation. Optimization algorithms enable firms to lower resource-use costs while simultaneously reducing environmental pressure [16].

Beyond technological improvements, AI strengthens institutional incentives for innovation. Increased transparency in environmental performance indicators and more precise ESG assessment mechanisms intensify scrutiny from investors and financial institutions [15,17]. Firms integrating AI into sustainability management systems tend to demonstrate more predictable environmental performance and lower regulatory risk exposure, thereby improving access to green finance.

In this sense, AI functions as a catalyst for green innovation, simultaneously reducing informational uncertainty and reinforcing market incentives for environmental modernization. Over the long term, this process enhances dynamic efficiency by accelerating the structural transition toward a low-carbon growth model.

4.3. Structural transformation of the labor market

The economic implications of AI integration also extend to labor market restructuring. Demand is increasing for specialists in environmental data analytics, digital governance, algorithm development for monitoring systems, as well as AI ethics and sustainable regulation [14]. An interdisciplinary segment of professionals is emerging, combining competencies in economics, environmental science, and digital technologies.

At the same time, the automation of compliance and reporting procedures reduces the need for routine administrative functions. This creates potential risks of structural unemployment in certain segments and necessitates active reskilling policies and investments in human capital.

From a macroeconomic perspective, this transformation represents a form of technological shift accompanying the broader ecological transition [8,15]. When adaptive mechanisms function effectively, the reallocation of labor resources enhances overall productivity and contributes to the emergence of new sectors within the digital sustainability economy.

5. Governance risks and constraints

The integration of AI into environmental policy is associated with technological and institutional risks that may affect both the legitimacy and effectiveness of regulatory systems. The following section presents a risk prioritization matrix and a corresponding set of governance measures supported by measurable key performance indicators (KPIs) for monitoring purposes (**Table 1**).

Table 1. Governance risk matrix for AI integration in environmental policy

Risk	Probability (P)	Impact (I)	Risk level (P×I)	Key policy consequences
Algorithmic bias	H	H	H	Distorted prioritization of policy measures, uneven allocation of resources, erosion of institutional trust
Digital inequality	H	H	H	Increased global and regional asymmetries in access to “smart” governance tools
AI energy consumption	M	M	M	Growth of indirect emissions and reduction of net climate benefits
Technological dependence and cybersecurity risks	M	H	H	Dependence on private vendors, vulnerability of critical infrastructure, risks of environmental data leakage

Scale: H: High; M: Medium; L: Low

The matrix demonstrates that the most significant systemic risks are not primarily technological in nature, but institutional, particularly algorithmic bias, digital inequality, and technological dependence. This underscores the necessity of embedding AI integration within a clearly defined regulatory and infrastructural strategy.

Table 2 operationalizes governance risks as measurable oversight requirements, which is essential for preserving efficiency gains from AI-enabled regulation under institutional constraints.

Table 2. Risks → Consequences → Governance measures → KPIs

Risk	Key governance consequence	Governance measures	KPI / reporting metrics
AI energy consumption	Reduction of net climate benefits due to indirect emissions	Energy-efficient model design; use of low-carbon electricity; “Green AI” standards in public procurement	kWh per model/task; tCO_2e per computation cycle; share of renewable energy in data center consumption
Algorithmic bias	Misallocation of environmental measures; underrepresentation of vulnerable regions	Data audits; bias testing; explainability requirements; human-in-the-loop oversight; mandatory verification	Share of audited AI decisions; error rates across groups/regions; number of detected anomalies; percentage of decisions reviewed by experts
Digital inequality	Unequal access to governance tools and data, widening the green transition gap	Capacity building; infrastructure financing; open data standards; international partnerships	MRV infrastructure coverage; data accessibility (coverage rate); number of trained specialists; data readiness index; participation in interoperable standards
Technological dependence & cybersecurity risks	Institutional vulnerability due to vendor lock-in, system failures, or data breaches	Cybersecurity and data governance standards (encryption, access control, incident response plans); third-party security audits; interoperability requirements; multi-vendor procurement strategy; model validation and stress testing	Number of security incidents (per year); mean time to detect/respond (MTTD/MTTR); mean time to patch critical vulnerabilities; percentage of systems covered by independent security audits; vendor concentration ratio; number of reported data breaches

6. Conceptual framework

Figure 1 shows the conceptual framework of AI-enabled environmental policy in details.

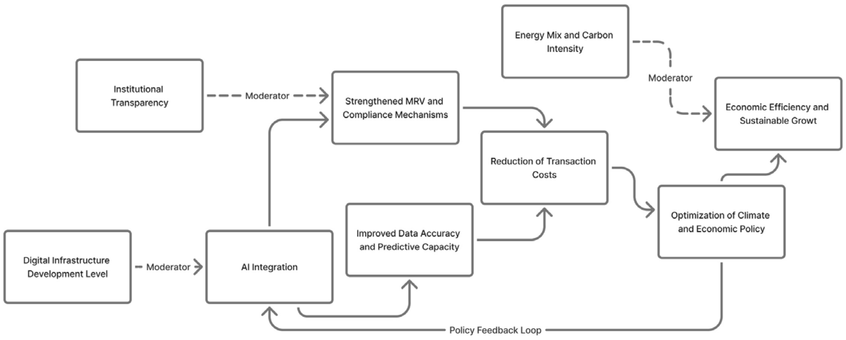

Figure 1. Conceptual framework of AI-enabled environmental policy: MRV, transaction costs, and policy feedback.

7. Practical recommendations

To translate the conceptual findings into actionable governance strategies, a set of practical measures is proposed to ensure the scalable and accountable integration of artificial intelligence into environmental regulation. **Table 3** links each recommended action to its corresponding institutional objective, expected outcome, and KPIs for evaluating effectiveness.

Table 3. Practical recommendations for AI integration in environmental policy

Policy area	Recommended action	Institutional focus	Expected outcome	Key performance indicators (KPIs)
Pilot Implementation and Scaling	Launch AI pilot projects within environmental agencies (monitoring, MRV, carbon regulation) followed by structured evaluation and scaling	Institutional learning and risk mitigation	Improved enforcement efficiency; reduced transaction costs	Reduction in inspection costs (%), detection rate of violations, time required for compliance verification
Green AI Standards	Establish energy-efficiency and carbon accounting standards for AI systems, including sustainability criteria in public procurement	Control of indirect emissions from digital infrastructure	Increased net climate benefits of digitalization	kWh per model/task, tCO_2e per computation cycle, share of renewable energy in data centers
Human Capital Development	Develop interdisciplinary education and training programs at the intersection of economics, environmental policy, and AI (including capacity-building for regulators)	Strengthening digital governance capabilities	Reduced policy errors; improved decision quality	Number of trained specialists, adoption rate of AI tools in agencies, policy revision frequency based on AI analytics
Algorithmic Transparency and Oversight	Introduce regulatory requirements for data auditing, model explainability, and human-in-the-loop procedures in high-impact decisions	Risk mitigation and accountability	Increased institutional trust and equitable resource allocation	Share of audited AI decisions, bias/error rates across regions/groups, percentage of decisions subject to expert review
International Data Cooperation	Expand cross-border environmental data exchange and interoperable MRV standards	Global coordination and comparability	Enhanced effectiveness of transnational climate governance	MRV coverage rate, data interoperability index, number of international data-sharing agreements

8. Conclusion

The integration of artificial intelligence into environmental policy represents a structural transformation of governance rather than a mere technological upgrade. By strengthening MRV systems, enhancing predictive modeling, and improving regulatory coordination, AI increases the effectiveness of environmental policy implementation and supports sustainable economic outcomes. Its impact, however, depends on institutional transparency, digital infrastructure capacity, and the carbon intensity of the underlying energy system. At the same time, AI-driven governance introduces systemic risks, including algorithmic bias, digital inequality, energy consumption, and technological dependency, that require proactive regulatory safeguards and measurable oversight mechanisms. Ultimately, AI should be viewed as a governance-enhancing infrastructure capable of improving environmental policy performance when embedded within accountable and energy-conscious institutional frameworks.

Disclosure statement

The author declares no conflict of interest.

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