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A Critical Systems Heuristics Perspective on AI-Assisted Policy Making for Sustainable Energy Equity and Innovation

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Abstract

The accelerating integration of artificial intelligence (AI) into sustainable energy policy presents both transformative opportunities and complex challenges for achieving equity and innovation in the global energy transition. While AI-driven frameworks promise enhanced efficiency, predictive analytics, and optimized resource allocation across renewable energy systems, prevailing policy approaches often overlook the underlying boundary judgments, stakeholder inclusivity, and socio-technical complexities inherent in these transitions. This study applies Critical Systems Heuristics (CSH) to systematically examine the assumptions, values, and power dynamics embedded within AI-assisted policy making for sustainable energy. Employing a qualitative research design that combines a systematic literature review with expert interviews from policy, technology, and community sectors, the analysis utilizes the twelve CSH boundary questions to contrast current “is” framings with normative “ought” expectations for just and innovative energy governance. Findings reveal that dominant AI-enabled policies frequently prioritize technical optimization and economic growth, with limited mechanisms for participatory decision-making, transparency, or recognition of marginalized communities. In contrast, stakeholders advocate for policy frameworks that explicitly address distributive and procedural justice, foster adaptive learning, ensure algorithmic transparency, and embed equity as a core design principle. The study proposes a CSH-informed conceptual framework to bridge these gaps highlighting pathways for inclusive stakeholder engagement, ethical AI deployment, and systemic innovation in sustainable energy governance. The results underscore the necessity of integrating critical systems thinking with digital innovation to advance socially legitimate and resilient energy transitions.

Keywords: Artificial Intelligence; Sustainable Energy Policy; Critical Systems Heuristics; Socio-Technical Systems; Energy Equity; Innovation; Boundary Judgments; Participatory Governance.

1. Introduction

Artificial intelligence (AI) is increasingly positioned as a pivotal enabler of sustainable energy transitions, promising gains in efficiency, reliability, and system flexibility across generation, transmission, and consumption domains [7,43]. In renewable-rich, decentralized energy systems, AI and machine learning (ML) techniques support forecasting, system modeling, demand response, and real-time control, thereby addressing variability and uncertainty in wind, solar, and distributed resources [10,28]. Recent reviews demonstrate that AI routinely outperforms traditional optimization and control approaches in tasks such as load prediction, fault detection, and resource scheduling, suggesting a transformative potential for cleaner and more resilient energy infrastructures [31,36,40]. Beyond technical performance, AI is increasingly framed as a strategic instrument for achieving broader sustainability and Sustainable Development Goals (SDGs), including climate action, affordable and clean energy, and sustainable cities [13,33]. However, scholarship on AI for sustainability highlights profound socio-technical and governance challenges: algorithmic opacity, data biases, unequal access to digital capabilities, rebound effects, and difficult-to-measure systemic impacts [17,35]. These concerns intersect with longstanding insights from socio-technical transitions research, which emphasizes that energy transitions are not merely technological substitutions but involve contested changes in institutions, power relations, and social practices [8,18,32].

In energy policy, the language of "systems" and "transitions" is now commonplace, yet policy mixes often lack conceptual clarity regarding intervention points, distributional effects, and the role of emerging digital technologies such as AI [24,32]. Studies of hydrogen, waste-to-energy, and other low-carbon options further illustrate that socio-technical, political, and equity dimensions frequently condition technological feasibility and public legitimacy [1,20,21]. AI-assisted policy making in sustainable energy thus emerges within a complex assemblage of actors, infrastructures, narratives, and governance regimes, where optimization logics risk crowding out concerns of justice, participation, and long-term resilience [17,33,35].

Critical Systems Heuristics (CSH) provides a structured approach to interrogate such socio-technical policy configurations by making explicit the boundary judgments that define purposes, beneficiaries, decision-makers, expertise, and sources of legitimation in complex systems. Although CSH has been applied to multi-actor energy and water–energy nexus projects to map stakeholders, conflicts, and legitimacy claims [37], its potential has not been systematically explored for AI-assisted energy policy. At the same time, AI governance debates increasingly call for frameworks that foreground trustworthiness, equity, and collaborative adaptation, rather than narrowly technical risk management [17,33,35]. Against this backdrop, the present study applies a CSH perspective to AI-assisted policy making for sustainable energy, with a particular focus on equity and innovation. Building on insights from AI in energy systems, AI-for-sustainability research, and socio-technical transition and policy-mix literatures, the study critically examines how AI-driven tools are framed, whose interests they serve, what counts as relevant expertise and evidence, and how trade-offs between efficiency, equity, and innovation are governed [7,18,24,43]. By systematically contrasting "is" and "ought" boundary judgments, the study seeks to develop a conceptual framework for more socially legitimate and reflexive AI-assisted energy governance, capable of aligning digital innovation with just and resilient sustainable energy futures. Building on scenario-based studies of the futures of AI in climate-responsive energy systems, which highlight divergent trajectories depending on policy, institutional design, and technological choices, as well as futures research that uses scenario planning and Soft Systems Methodology to formulate exploratory scenarios of operations research and sectoral systems [14].

Accordingly, this study is structured around the boundary critique logic of Critical Systems Heuristics (CSH). The research is guided by six questions. First, how are the purposes, intended beneficiaries, and measures of success of AI-assisted sustainable energy policy currently defined, and how should they be redefined to better support energy equity and innovation? Second, who currently controls AI-assisted energy policy decisions, resources, and implementation conditions, and how should decision-making authority and resource allocation be redistributed to enable more inclusive and resilient energy governance? Third, what forms of knowledge and expertise are currently recognized in AI-assisted energy policy-making, and what additional technical, social, ethical, and community-based knowledge should be included to improve policy legitimacy and innovation capacity? Fourth, whose voices, concerns, and worldviews are currently marginalized or excluded in AI-assisted sustainable energy governance, and how should affected stakeholders be empowered to challenge, revise, and co-shape AI-supported policy decisions? Fifth, what are the main gaps between existing "is" boundary judgments and desirable "ought" boundary judgments across the four CSH dimensions of motivation, control, expertise, and legitimacy? Finally, how can a CSH-informed conceptual framework be developed to support more equitable, transparent, participatory, and innovation-oriented AI-assisted policy-making for sustainable energy transitions?

2. Literature Review

2-1. Artificial Intelligence in Sustainable Energy Systems

AI and machine learning have become central to optimizing modern sustainable energy systems, enhancing forecasting, control, and planning across multiple energy domains. In a comprehensive review of AI applications in smart grids and renewable energy integration, Ahmad et al. (2021) show that machine learning and deep learning techniques significantly improve load forecasting, renewable generation prediction, and fault detection compared with conventional statistical and rule-based methods, thereby supporting higher penetration of variable renewables and more flexible operation of grids. Similarly, Kwon and Lee (2022) highlight that AI-driven demand response, distributed energy resource management, and building energy management systems can reduce peak loads and improve overall energy efficiency in urban systems, particularly when integrated with Internet of Things (IoT) infrastructures. These advances, however, are predominantly framed through a techno-economic lens emphasizing efficiency, reliability, and cost minimization. As noted in recent work on AI-enabled energy planning, optimization models and learning algorithms are often designed around narrowly defined performance indicators such as loss reduction, reliability indices, and operational cost, with limited attention to distributional consequences or social legitimacy. This creates a tension between the technical potential of AI and broader sustainability objectives related to equity, participation, and long-term resilience.

2-2. AI, Sustainability, and Governance Challenges

Beyond sector-specific applications, a growing body of scholarship interrogates AI as a socio-technical phenomenon implicated in sustainability governance. Galaz et al. (2021) argue that AI systems interact with complex global risks through feedbacks that can amplify inequalities, erode accountability, and introduce opaque forms of power, warning that "AI may reinforce existing power asymmetries and lock-in unsustainable practices" if deployed without robust governance. In a related analysis, Vinuesa et al. (2020) assess AI's interactions with the Sustainable Development Goals (SDGs) and conclude that while AI can positively influence many goals, it also risks undermining others, particularly those linked to inequality, decent work, and inclusive institutions, if ethical and political dimensions are neglected. In the energy domain, similar concerns emerge around algorithmic opacity, data biases, and the governance of AI-based decision-support tools. An empirical study of AI adoption in electricity utilities by Wamba et al. [42] finds that organizational and regulatory contexts strongly shape how AI tools are used, including whether they reinforce centralized control or enable more participatory and transparent forms of decision-making. These findings underscore that AI-assisted policy making in sustainable energy cannot be treated as a neutral, purely technical enhancement; it is embedded in power relations, institutional logics, and normative assumptions about what constitutes "good" policy.

2-3. Energy Equity and Socio-Technical Transitions

Research on energy justice and socio-technical transitions provides an essential lens for assessing AI-assisted policy making. Sovacool et al. [39] synthesize three core dimensions of energy justice distributional, procedural, and recognition justice and demonstrate that low-carbon transitions often reproduce or deepen inequities when policies prioritize aggregate efficiency or carbon metrics over the lived experiences and capabilities of affected communities. Similarly, Jenkins et al. [23] propose an integrated conceptualization of energy justice, calling for policy frameworks that explicitly embed justice criteria into the design, implementation, and evaluation of energy interventions. Socio-technical transitions research, particularly the multi-level perspective (MLP), further highlights and transitions are shaped by interactions between niches, regimes, and landscapes, involving struggles over visions, rules, and resources rather than linear technology substitution [18]. Within this perspective, digitalization and AI are understood as cross-cutting "general-purpose technologies" that can either destabilize incumbent fossil-fuel regimes or reinforce them, depending on how policy mixes and governance arrangements are configured. Yet, empirical analyses of transition policy mixes often show a dominance of technology-push and market-based instruments, with limited mechanisms for participation, learning, and justice-oriented evaluation [25]. The convergence of AI, energy policy, and justice therefore raises critical questions: whose interests are prioritized in AI-supported optimization and forecasting; which communities bear the risks of data-driven experimentation; and how are trade-offs between efficiency, innovation, and equity rendered visible and contestable within policy processes?

2-4. Critical Systems Heuristics and Boundary Judgments in Energy Policy

Critical Systems Heuristics, developed by Ulrich, offers a normative systems thinking approach designed to surface and critically examine the boundary judgments that underpin system designs and evaluations. CSH has been applied in various infrastructure and environmental contexts to identify stakeholders, clarify value conflicts, and interrogate claims to expertise and legitimacy. For example, Midgley and Pinzon [30] show how CSH can reveal hidden assumptions and power asymmetries in multi-stakeholder environmental planning, enabling more reflexive and inclusive dialogue about system boundaries and purposes. In the energy field, CSH-inspired analyses have been used to assess large infrastructure projects and multi-actor governance arrangements, particularly at the water–energy–food nexus. Sianipar et al. [37], for instance, employ a multi-actor systems lens to identify critical stakeholders and legitimacy issues in floating photovoltaic projects, demonstrating how different actors construct divergent system boundaries and success criteria. Despite its suitability for examining contested socio-technical systems, CSH has rarely been applied to AI-assisted policy making. Existing AI governance frameworks tend to focus on principles such as transparency, accountability, and fairness, but do not systematically interrogate who defines system purposes, which knowledge counts as relevant, and how affected groups can challenge or re-negotiate AI-supported decisions. As a result, there is a gap in the literature regarding structured, boundary-critical approaches to AI-enabled sustainable energy governance that explicitly center equity and innovation. Recent research has highlighted the usefulness of Critical Systems Heuristics (CSH) for examining complex socio-technical systems. For example, Etemadi et al. [12] adopted a systems thinking perspective by integrating TSI, CSH, and DEMATEL-ANP within a Society 5.0 framework to investigate stakeholder engagement in the energy sector, with particular attention to participatory governance and long-term sustainability. Ebrahimi et al. [11] employed CSH to assess Iran's Water-Energy-Food nexus, identifying fragmented decision-making, short-term policy orientation, and limited interdisciplinary cooperation as major obstacles to sustainable development. Likewise, Fathi et al. [15] explored stakeholder boundary judgments in Iran's gas company and revealed discrepancies between existing and desired practices, emphasizing the importance of clean energy adoption, advanced technologies, and multidisciplinary knowledge. Collectively, these studies demonstrate that CSH is a suitable approach for uncovering systemic inconsistencies and supporting governance and design decisions in complex socio-technical contexts.

2-5. Synthesis and Research Gap

Taken together, the literatures on AI in sustainable energy systems, AI and sustainability governance, energy justice, socio-technical transitions, and critical systems thinking reveal complementary yet largely disconnected strands. AI-energy research offers sophisticated technical tools but often under-theorizes questions of justice and legitimacy. Energy justice and transition studies articulate rich normative frameworks but rarely engage with the specificities of AI-driven decision-support. CSH provides a robust methodology for making boundary judgments explicit, but its application to AI-assisted energy policy remains limited. This fragmentation underscores the need for integrative work that uses CSH to bridge technical AI-energy optimization with critical, equity-oriented perspectives on policy making and socio-technical innovation.

3. Research Methodology

3-1. Research Design

This study adopts a qualitative–interpretive, multi-stage research design grounded in Critical Systems Heuristics (CSH) to examine AI-assisted policy making in sustainable energy.

Qualitative and mixed-method approaches are widely recommended for capturing complex, socio-technical–ecological entanglements and power relations in sustainability and transitions research, rather than relying solely on formal quantitative modelling or single-method design [26]. In energy social science, methodologically plural, multi-method, and theoretically informed designs are explicitly promoted to enhance rigor, creativity, and impact [38].

Table 1. Literature review mapping table.

Authors	Main Objective	Domain	Methodology	Key Insights
Ahmad et al. [3]	Review AI in sustainable energy	Power systems, renewables	Systematic review	AI enhances forecasting and control but focuses on efficiency
Kwon & Lee [27]	Assess AI-based demand response	Buildings, smart grids	Review of applications	AI supports demand response and urban efficiency
Galaz et al. [17]	Analyze AI & systemic risks	Global sustainability	Conceptual analysis	AI may reinforce power asymmetries, needs governance
Vinuesa et al. [41]	AI and SDGs interactions	Global SDGs	Mixed-method assessment	AI supports some SDGs but can harm equity goals
Sovacool et al. [39]	Develop energy justice framework	Energy transitions	Conceptual synthesis	Defines distributional, procedural, recognition justice
Jenkins et al. [23]	Integrate energy justice & transitions	Global energy systems	Theoretical framework	Advocates embedding justice in policy design
Geels [18]	Review socio-technical transitions	Sustainability transitions	Literature review	Highlights the role of regimes, power, and digitalization
Kivimaa & Kern [25]	Analyze policy mixes	Innovation & transitions	Conceptual & empirical	Finds policy mixes often neglect participation and justice
Midgley & Pinzon [30]	Explore boundary critique	Environmental planning	Critical systems thinking	CSH reveals hidden assumptions and power
Sianipar et al. [37]	Map stakeholders in floatovoltaics	Water–energy nexus	Multi-actor systems analysis	Shows divergent system boundaries and legitimacy issues

The design combines: (i) a systematic scoping of literature and policy documents; (ii) semi-structured expert interviews; and (iii) CSH-based boundary analysis of the empirical material. Methodological guides for transitions and energy social science emphasize such multi-stage research designs, mixing document analysis, qualitative data, and conceptual work to address nested, composite systems and governance dilemmas [22].

CSH is a critical systems thinking approach focusing on boundary critique, coercion, emancipation, and explicit contrasts between “is” and “ought to be” framings. It operationalizes boundary judgments through twelve questions grouped into motivation, control, expertise, and legitimacy, and has been used to address power asymmetries and advocacy for marginalized groups across varied problem contexts [22].

The study applies these twelve questions in dual analytical modes: an “is” perspective (current AI-assisted energy governance arrangements) and an “ought” perspective (desirable conditions aligned with equity, participation, and innovation). The “is/ought” contrast is central to CSH and underpins its emancipatory orientation [22].

Stage 1: Literature and Document Review

A systematic, narrative-oriented review is conducted across peer-reviewed literature and grey documents. Energy social science guidelines stress the importance of explicit research design, transparent search and selection strategies, and alignment between research questions and answers [38].

- The review focuses on:

1. AI in sustainable energy and smart energy systems
2. Energy justice and socio-technical (ecological) systems
3. AI and digital governance
4. methodological debates in transitions and qualitative research

Transitions research specifically calls for methodological pluralism, careful handling of complexity, and qualitative–quantitative “bridging” approaches to understand multi-level, co-evolutionary processes [26]. Social-ecological and socio-technical-ecological systems work highlights the need to attend symmetrically to technology, society, and environment, often using iterative, snowball-type literature strategies [2].

Policy documents, regulatory texts, and technical guidelines on AI in energy are collected and pre-coded against the twelve CSH questions, reconstructing formal system boundaries and normative assumptions. This aligns with recommended practice in critical systems and systems-of-systems work, where document analysis complements modelling or case studies to surface implicit framings [22].

Stage 2: Sampling Strategy and Data Collection

The study uses purposive sampling to recruit a heterogeneous panel of experts involved in AI-assisted energy decision-making (system operators, utilities, technology providers, regulators, policy-makers, NGOs, consumer representatives). In complex infrastructure and interdependent critical infrastructure research, purposive sampling of domain-diverse experts is standard for capturing cross-domain dependencies and governance issues. Targeted participants must have substantial experience (≈10 years) in sustainable energy systems, AI/digitalization, or energy/AI governance. Methodological work in energy social science and sustainability transitions explicitly endorses such theoretical and experiential heterogeneity, with an emphasis on appropriateness over statistical representativeness [26,38]. A sample of roughly 15–20 experts is sought, consistent with qualitative CSH and systems work, where diversity and depth of boundary judgments are prioritized over large-N statistical inference. Recruitment continues until theoretical saturation, a standard criterion in qualitative research design [26,38].

Data collection centers on semi-structured interviews structured around the twelve CSH questions, enabling respondents to articulate both descriptive ("what is") and normative ("what ought to be") perspectives. Semi-structured designs are recommended for exploring complex transitions, digitalization, and socio-technical-ecological systems because they allow probing of assumptions, values, and experiences while maintaining comparability across cases [26,38].

- Interview guides elicit reflections on:

1. system purposes and success criteria for AI in energy;
2. beneficiaries and those potentially burdened;
3. decision-making structures and control;
4. recognized expertise and knowledge hierarchies;
5. legitimacy, accountability, and representation of marginalized actors. Interviews are audio-recorded (with informed consent), transcribed verbatim, and imported into qualitative analysis software. Contemporary qualitative research in the digital era recommends leveraging computer-assisted tools for organizing large text corpora while retaining interpretive rigor and reflexivity [4,5].

To enhance validity and robustness, interview findings are triangulated with Stage-1 literature and policy documents, as well as available technical/operational reports, modelling studies, and impact assessments. Triangulation across qualitative and documentary sources is widely advocated in systems, transitions, and energy social science to strengthen claims and address complexity [4,5,38].

Stage 3: Data Analysis

Data analysis follows a CSH-guided thematic and boundary analysis in three steps:

Deductive Coding by CSH Dimensions

Transcripts and documents are coded against the four CSH dimensions and their associated boundary questions, distinguishing "is" and "ought" statements. Deductive use of established conceptual frameworks is standard for theory-driven qualitative analysis in energy and transitions research [2,5,26], and aligns with systematic CSH applications [22].

For each boundary question, coded "is" positions are contrasted with corresponding "ought" positions, identifying gaps that signal policy fragility, power asymmetries, exclusion, or misaligned innovation priorities. CSH is particularly used to expose such coercive structures and advocate for marginalized groups [22].

Patterns across actors and documents are synthesized into a conceptual framework for equitable and innovative AI-assisted energy governance, resonating with methodological recommendations to move from case-specific insights to higher-level, theoretically relevant constructs in transitions and energy social science [26,38].

Throughout, methodological rigor is pursued via:

- Transparent documentation of sampling, data collection, and coding procedures;
- Iterative memoing (note taking) and peer debriefing;
- Reflexive consideration of researcher positionality and digital tools.

The methodological references used in the study are summarized in Table 2.

4. Research Analysis

The empirical findings articulate a rich, multi-dimensional critique of existing governance arrangements for AI-assisted policy making in sustainable energy systems, using Critical Systems Heuristics (CSH) to contrast "what is" with "what ought to be" across motivation, control, expertise, and legitimacy.

4-1. Overall Pattern of Boundary Judgments

The experts' perspectives make clear that boundary judgments are neither uniform nor benign; they are shaped by role, responsibility, and institutional logic, leading to divergent framings of risk, responsibility, and success.

Table 2. Summary of methodological references.

Methodological Aspect	Key Contribution/Use in current Study	Citations
Research design & rigor in energy social science	Justifies multi-method theory-driven qualitative design	[26,38]
Critical Systems Heuristics (CSH)	Boundary critique; is/ought framing power and emancipation	[22]
Handling complexity & interdependence	Multi-domain expert sampling document triangulation	[16,26]
Qualitative vs quantitative modelling	Legitimizes qualitative/systemic approaches alongside models	[9,26]
Interview-based, thematic qualitative analysis	Supports semi-structured framework-guided analysis and saturation	[4,5,38]
Digital/AI-supported qualitative methods	Underpins use of CAQDAS and awareness of AI in analysis	[4,5]
Socio-technical-ecological framing	Justifies focus on technology–society–environment interfaces	[2,16,26]

Rather than treating such divergence as noise, the CSH lens repositions disagreement as analytical value, enabling systematic identification of hidden assumptions and structural vulnerabilities.

Table 3 synthesizes these boundary judgments. It shows that across all four CSH dimensions, the status quo is characterized by instrumental, technocentric, and compliance-oriented framings, while experts' normative expectations consistently call for resilience, prevention, learning, stakeholder inclusion, and socio-technical awareness.

4-2. Thematic Analysis by CSH Dimension

4-2-1. Motivation: From Instrumental Operation to Resilience and Public Value

In current AI-enabled sustainable energy policy, motivation is predominantly framed in narrowly operational and technical terms such as system reliability, efficiency, and compliance with regulatory standards rather than broader societal or environmental objectives. Success metrics are typically lagging indicators (e.g., outage duration, failure rates, downtime), with limited attention to proactive measures like resilience, equity of access, or institutional learning capacity. This instrumental focus risks marginalizing vulnerable stakeholders and discourages adaptive learning necessary for long-term legitimacy. Normative perspectives in the literature advocate for a shift toward resilience-oriented and public value-driven motivation, explicitly integrating social equity, environmental protection, prevention, and transparent governance of trade-offs. Beneficiaries should extend beyond utilities and large consumers to include local communities, frontline staff, emergency services, and future generations. Critical boundary reflections highlight that the prevailing operational focus can erode legitimacy by excluding those most affected by failures and by failing to foster a culture of continuous improvement.

4-2-2. Control: Resource Allocation and Decision-Making Asymmetries

Control in AI-assisted energy systems is characterized by centralized decision-making structures - typically vested in operational managers - with regulators acting as external enforcers rather than collaborative partners. There is limited structured inclusion of frontline workers or community perspectives in governance processes. Resource allocation is often shaped by short-term cost pressures and continuity demands; environmental dependencies are treated as exogenous constraints managed reactively rather than proactively. The "ought" perspective calls for adaptive governance: flexible investment in preventive measures; authority for safety-driven interventions; enhanced diagnostic capabilities; and responsive adaptation to regulatory shifts, supply chain disruptions, or environmental variability. Centralized control combined with resource constraints fosters reactive management practices - deferred maintenance and increased vulnerability to cascading failures - rather than anticipatory resilience-building.

4-2-3. Expertise: From Technocratic Dominance to Socio-Technical Knowledge Integration

Definitions of expertise remain dominated by engineering credentials and compliance with technical standards; experiential knowledge from operators or communities is undervalued and rarely. Current competence guarantees are heavily compliance-based (certifications, absence of major incidents), which may mask capability gaps under abnormal conditions or normalize deviance from best practices. Scholarly consensus increasingly supports expanding epistemic boundaries to include human factors engineering, organizational safety culture, tacit frontline knowledge, risk communication skills, and recognition of cross-functional teams as legitimate experts. The "ought" framing emphasizes continuous scenario-based training, performance-in-use validation, robust learning loops, and independent review mechanisms to ensure adaptive expertise in complex socio-technical environments.

Table 3. CSH-style synthesis for AI-assisted sustainable energy equity policy.

CSH Dimension	Boundary focus	"What is" in current AI–energy policy practice	"What ought to be" for Equity-Centered AI-assisted Policy	Relevance to energy equity & innovation
Motivation	System Purpose	AI used mainly to optimize efficiency, grid stability, and cost in energy systems, with sustainability and equity often secondary or implicit goals (e.g., net-zero, reliability benchmarks).	Explicit policy purpose to co-optimize decarbonization, system innovation, and distributive, procedural, and recognition-based energy equity, using AI as a socio-technical policy instrument rather than a purely technical optimizer.	Narrow efficiency-first goals can exacerbate spatial, social, and digital inequities; re-specifying purpose anchors AI tools in justice-oriented transitions.
Motivation	Beneficiaries	Primary beneficiaries are system operators, large utilities, and national policymakers; vulnerable groups and communities in the Global South are rarely explicit addressees of AI-enabled policy designs.	Beneficiary set expanded to low-income users, rural and off-grid communities, future generations, and workers affected by transition, with AI used to identify and correct inequitable burdens and benefits.	Without explicit attention to marginalized groups, AI-driven optimization can deepen access gaps and affordability problems.
Motivation	Measures of Success	Success measured via predictive accuracy (e.g., forecasts), system efficiency, cost reduction, and headline climate targets; equity, participation quality, and fairness rarely operationalized as indicators.	Multi-criteria evaluation incorporating equity metrics (e.g., affordability, access, distribution of outages/emissions), innovation diversity, and community participation quality, alongside technical and economic KPIs.	Equity-blind metrics risk "green but unjust" transitions; AI-assisted dashboards could embed social and equity indicators.
Control	Decision-Makers	AI deployment decisions concentrated in ministries, regulators, and large utilities; AI models often designed by private vendors or technical experts with limited public oversight.	Plural, co-governed decision structures where regulators, communities, civil society, and independent experts jointly shape AI policy tools, mandates, and acceptable trade-offs.	Centralized control over AI models may hard-code biases and prioritize incumbent interests over vulnerable users.
Control	Resources & Infrastructure	Data, compute, and modelling capacity are clustered in high-income organizations and countries; many developing contexts lack the infrastructure for advanced AI-assisted policy analysis.	Targeted investment in public AI infrastructures (open data, shared models, capacity building) to enable equitable AI capabilities for low-resource regulators and communities.	Unequal AI capacity risks reproducing global energy inequities and policy dependency.

CSH Dimension	Boundary focus	"What is" in current AI–energy policy practice	"What ought to be" for Equity-Centered AI-assisted Policy	Relevance to energy equity & innovation
Control	External Conditions	AI policy tools typically assume given market structures, regulatory regimes, and geopolitics; circular economy and energy poverty dynamics are weakly integrated.	Scenario-based AI-assisted policy design that explicitly models circular economy pathways, global supply chains, and shocks (e.g., price spikes), with attention to distributional effects.	Ignoring structural drivers (markets, trade, minerals) can make AI-assisted policy blind to upstream and downstream injustices.
Expertise	Relevant Knowledge	Policy models prioritize data science, engineering, and economics; social science, ethics, and community knowledge rarely treated as co-equal in AI design.	Transdisciplinary knowledge base where domain science, social science, justice studies, and lay expertise jointly define model scope, variables, and constraints.	Technocratic knowledge boundaries can misrepresent lived energy hardship and social acceptance constraints.
Expertise	Who counts as expert	Experts are AI developers, system engineers, and academic modellers; communities and civil society appear mainly as data sources or consultation targets.	Broader expert community including community organizations, NGOs, indigenous groups, and practitioners, with structured roles in validating and interpreting AI-assisted policy outputs.	Narrow expert sets risk legitimizing biased models and undermining trust in AI-assisted decisions.
Legitimacy	Stakeholder Voice & Challenge	Limited transparency over models, datasets, and assumptions; few institutionalized mechanisms for affected groups to contest AI-supported policy choices.	Strong contestability and redress mechanisms, explainable AI for policy, and participatory audits where stakeholders can challenge data, objectives, and distributional outcomes.	Lack of challenge channels can entrench opaque, inequitable energy policies under a veneer of "algorithmic objectivity."
Legitimacy	Normative Framing & SDGs	AI-enabled energy policy is often framed as a technical enabler of SDG 7 and climate targets, with weaker articulation of links to SDG 9, SDG 10, and SDG 16.	Integrated framing where AI-assisted policy is evaluated against equity, innovation, and strong-institutions goals (SDG 7, 9, 10, 13, 16) within a coherent sustainability and justice narrative.	A fragmented SDG framing underestimates institutional reforms and justice safeguards needed for legitimate AI-enabled transitions.

4-2-4. Legitimacy: Stakeholder Voice, Representation, and Worldview

Current legitimacy boundaries in AI-assisted sustainable energy policy are narrow and procedural. Stakeholder engagement is often limited to formal compliance processes or post-hoc consultation after controversies arise; marginalized communities have little direct representation or opportunity to challenge underlying assumptions. Legitimacy is frequently reduced to regulatory approval or ethical checklists rather than substantive accountability for distributive impacts or social equity outcomes. Normative scholarship calls for protected challenge mechanisms, structured stakeholder engagement throughout the policy lifecycle (including explicit inclusion of vulnerable groups), and a socio-technical worldview that recognizes the interdependence among technology, humans, organizations, regulation, and society. Narrow legitimacy boundaries suppress weak-signal learning (early warnings), reduce accountability for those bearing risk (e.g., frontline staff or marginalized communities), and undermine trust in both technology and institutions over time.

4-3. Integrated Synthesis: Boundary Gaps and Policy Vulnerabilities

Synthesizing across the twelve boundary questions, the analysis reveals systematic "is/ought" gaps that translate into policy vulnerabilities: instrumental purposes, narrow beneficiaries, lagging metrics, constrained resources, centralized decision-making, technocratic expertise, and thin legitimacy each contribute to reactive, compliance-driven safety governance.

5. Discussion and Conclusion

This study applied Critical Systems Heuristics (CSH) to explore how AI-assisted policymaking can contribute to sustainable energy equity and innovation. By systematically interrogating boundary judgments who is included or excluded as a stakeholder, what is recognized as legitimate knowledge, whose risks and burdens are considered acceptable, and which futures are treated as desirable or realistic the analysis demonstrates that AI tools in energy governance are not neutral decision aids. Instead, they embody implicit assumptions about justice, responsibility, technological progress, and the distribution of costs and benefits across social groups and generations. The findings underscore three overarching implications. First, AI-enabled energy policy must be explicitly oriented toward both distributive and procedural equity. This involves more than adding fairness constraints to models; it requires that marginalized and vulnerable communities are meaningfully involved in defining problem framings, influencing data collection and curation practices, and co-shaping evaluation criteria for policy success. Without such participation, AI risks reinforcing existing inequalities in energy access, affordability, and exposure to environmental harms. Second, the study highlights the central importance of transparency and contestability. For AI to legitimately support democratic energy governance, both the technical workings of models and the value choices embedded in their design need to be open to scrutiny, challenge, and revision. This includes clarifying which indicators are prioritized, how uncertainties are handled, and what trade-offs are deemed acceptable. Mechanisms for ongoing stakeholder oversight and critical questioning are essential to prevent the quiet stabilization of biased or narrow policy logics.

Third, integrating CSH into AI governance processes can foster more reflexive, participatory, and learning-oriented policy cycles. Rather than treating models as fixed optimization engines, a CSH-informed approach treats them as provisional, revisable tools that are continuously adjusted in light of new empirical evidence, shifting sustainability targets, and stakeholder feedback. This orientation can help align AI deployments with long-term ecological limits and social justice commitments, rather than short-term efficiency or growth metrics alone. Overall, the analysis suggests that AI can play a constructive role in sustainable energy transitions only when embedded within ethically informed and inclusive institutions. Technological sophistication alone is insufficient; what matters is how AI is integrated into broader arrangements of accountability, deliberation, and shared responsibility. Future research should operationalize CSH-based boundary critique in real policy settings, test it in concrete AI-supported planning and regulatory processes, and develop practical tools and metrics for monitoring energy equity impacts. Further work is also needed on co-design approaches that bring together policymakers, technologists, and affected communities to jointly shape AI systems that support just, resilient, and low-carbon energy futures.

5-1. Practical Insights for AI-Assisted Energy Policy Implementation

While this study has examined the theoretical implications of AI in sustainable energy governance through the Critical Systems Heuristics (CSH) lens, it is crucial to translate these insights into actionable policy recommendations. The following practical four steps can be integrated into AI-assisted energy policy development to ensure that digital innovations are aligned with justice, equity, and long-term sustainability:

5-1-1. Actionable AI-Policy Framework

- Integrating Equity into AI Design: It is essential for energy policymakers to establish frameworks that prioritize distributive and procedural justice in AI policies. This involves ensuring that AI tools do not just optimize for efficiency but also consider the impact on marginalized communities. For example, using AI to identify and rectify energy access disparities across socio-economic groups could lead to more equitable policy outcomes.
- Balancing Technical and Ethical Goals: Policymakers should frame AI as a sociotechnical tool rather than just a technical optimizer. A policy framework that co-optimizes decarbonization and system innovation with equity-focused goals should be the baseline. AI models should be assessed not only on performance indicators (e.g., energy

efficiency, reliability) but also on their ability to address equity and community participation in decision-making.

5-1-2. Transparency and Inclusivity Mechanisms

- Transparency in Algorithmic Decisions: For AI to be a legitimate tool in governance, stakeholders must be able to scrutinize the decision-making process. This could include public-facing dashboards where the workings of AI systems are explained, making the trade-offs and assumptions explicit. Decision models must be open for public feedback, especially in communities that might be directly impacted by AI-driven policies.
- Community and Stakeholder Involvement: Policymakers should implement mechanisms that actively involve marginalized and vulnerable communities in shaping AI policies. This could be achieved through regular public consultations, participatory workshops, or involving community representatives in decision-making boards.

5-1-3. Co-Designing AI Systems for Equity and Innovation

- Pilot Projects Using CSH: To operationalize CSH-informed thinking, it is advisable to start with pilot projects where AI systems are tested with a specific focus on equity and participatory governance. For example, energy optimization projects could involve diverse community stakeholders, using CSH to critically assess which communities benefit most and which are excluded from the benefits of AI-driven policies.
- Stakeholder Engagement: Develop frameworks where all relevant stakeholders, from system operators to affected communities, jointly shape the AI systems. Collaborative partnerships should be the norm, ensuring that AI tools are continuously adapted to real-world needs and realities.

5-1-4. Linking AI Policy to Sustainable Development Goals (SDGs)

- Embedding SDG Principles: The application of AI in energy policy must be directly aligned with the broader SDG agenda, particularly SDG 7 (Affordable and Clean Energy), SDG 10 (Reduced Inequalities), and SDG 13 (Climate Action). An inclusive AI governance approach can help bridge the gap between technological innovation and social justice, ensuring that no group is left behind in the transition to a low-carbon economy.
- Equity Indicators in Policy Evaluation: A set of equity-focused metrics should be included in AI-assisted policy evaluations. These metrics can include accessibility to energy resources, affordability of services, and distributional equity in energy generation and consumption. By incorporating these measures into policy design, AI systems can be steered toward equitable, just, and inclusive energy transitions.

5-2. Research Limitations

Like all qualitative and interpretive studies, this research has several limitations that should be acknowledged. First, the study is primarily based on a CSH-informed qualitative design, combining literature review, policy document analysis, and expert interviews. While this approach is appropriate for uncovering boundary judgments, normative assumptions, and power relations in AI-assisted energy governance, the findings are not intended to be statistically generalizable across all national or institutional contexts. Instead, the value of the study lies in its analytical depth and its ability to reveal hidden assumptions in policy framing.

Second, the study depends on the perspectives of selected experts from policy, technology, energy, and civil society domains. Although purposive sampling was used to capture diverse viewpoints, the sample may not fully represent all affected groups, particularly marginalized communities, low-income energy users, rural populations, Indigenous groups, and actors from the Global South. Since energy equity is highly context-specific, future studies should include more direct engagement with communities affected by AI-assisted energy policies.

Third, the analysis is shaped by the interpretive nature of Critical Systems Heuristics. CSH is useful for exposing boundary judgments and contrasting “is” and “ought” perspectives, but the interpretation of these judgments inevitably involves researcher reflexivity. Different researchers or stakeholder groups may define system boundaries, legitimacy claims, and desirable futures differently. Therefore, future research should apply participatory validation methods, such as stakeholder workshops, Delphi panels, or community-based review sessions, to strengthen the credibility and practical relevance of CSH-based findings.

Finally, AI technologies, energy markets, and sustainability regulations are evolving rapidly. As a result, the governance challenges identified in this study may change as new forms of generative AI, automated decision support, data infrastructures, and regulatory standards emerge. Longitudinal studies are therefore needed to examine how AI-assisted energy governance evolves over time and whether equity-oriented safeguards remain effective under changing technological and institutional conditions.

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