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AI-Induced Energy Inequality: Digital Exclusion, Algorithmic Bias, and Unequal Access to Smart Energy Benefits

Muhammad Islam[1*], Nasrin Akhter[1], Shamsul Alam[2]

Abstract

AI is increasingly embedded in smart energy systems, from smart meters and automated demand response to digital platforms for energy management. Although these systems are often presented as efficient and empowering, they can also generate new forms of exclusion. The literature has not sufficiently conceptualised how AI specifically induces energy inequality through interacting mechanisms. Digital exclusion, algorithmic bias, and unequal access to smart energy benefits are often discussed separately rather than as connected pathways of disadvantage. This article critically analyses AI-induced energy inequality by developing a framework that links digital exclusion, algorithmic bias, and unequal access to smart energy benefits. It identifies feedback loops through which these mechanisms may compound vulnerability over time. A conceptual synthesis of energy justice, digital divide, algorithmic fairness, and smart grid literature is conducted. No empirical research, modelling exercise, survey, experiment, or quantitative analysis is performed. The framework identifies three primary inequality pathways: digital exclusion that blocks participation, algorithmic bias that discriminates in energy decisions, and the concentration of smart energy benefits among already-privileged groups. Three analytical tables provide taxonomies of exclusion mechanisms, bias-outcome mappings, and intersectional vulnerability matrices. AI-driven energy systems risk becoming engines of inequality unless proactive justice-oriented design and regulation are implemented. The critical framework offers a diagnostic tool for policymakers and a research agenda for scholars.

Keywords Energy justice, AI, Energy inequality, Digital exclusion, Algorithmic bias, Smart energy benefits

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Introduction

AI is becoming central to the smart energy transition, shaping how households are monitored, priced, incentivised, and enrolled into flexibility services. In optimistic accounts, AI-enabled energy systems promise efficiency, decarbonisation, real-time responsiveness, and consumer empowerment, particularly through digitalised smart grids and data-driven services [1]. Yet the same systems also redistribute power, because the ability to benefit from smart energy increasingly depends on access to digital infrastructures, data visibility, and platform participation. This means that AI in energy should not be treated as a neutral technical layer but as a socio-technical force that reorganises participation, responsibility, and advantage.

The efficiency narrative becomes unstable when viewed through energy justice and digital inequality perspectives. Digitalised energy systems can systematically exclude households without reliable internet access, digital literacy, smart

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appliances, secure housing tenure, or the financial capacity to invest in enabling technologies [2]. Algorithmic systems may also reinforce discrimination when historical data, market assumptions, or optimisation rules encode unequal patterns of consumption, payment, infrastructure access, or vulnerability [3]. As a result, AI-enabled energy transitions may deepen rather than resolve inequalities if their benefits are captured primarily by digitally connected, affluent, and flexible consumers.

This article argues that AI can magnify existing energy inequalities when it is deployed within unequal social, infrastructural, and market conditions. Energy justice scholarship has shown that low-carbon transitions can create new divides when vulnerable communities are asked to bear risks while better-resourced groups capture benefits [4]. In AI-driven energy systems, these divides may be intensified because algorithms convert unequal data visibility into unequal service eligibility, risk classification, and benefit allocation. A focused critical analysis is therefore needed to identify how AI-induced inequality emerges through mechanisms that are technical, economic, and institutional at the same time.

The objective of this article is to develop a critical framework for analysing AI-induced energy inequality through three interlocking mechanisms: digital exclusion, algorithmic bias, and unequal access to smart energy benefits. The framework builds on energy justice, smart energy inclusion, and digitalisation research that warns against treating participation as automatic in technologically mediated energy systems [5].

Background

Energy justice and inequality in the digital age

Energy justice provides a critical vocabulary for examining how energy systems distribute benefits, burdens, recognition, and decision-making power. In digitalised energy systems, these justice concerns become more complex because access to energy benefits increasingly depends on data infrastructures, automated decisions, and platform-mediated participation [6]. Plural energy justice perspectives also show that inequality is not only economic but racialised, gendered, colonial, spatial, and institutional [7]. AI-induced energy inequality should therefore be understood as a justice problem rather than a narrow issue of consumer adoption or technological diffusion.

The digital divide in energy

The digital divide in energy refers to unequal access to the devices, connectivity, skills, trust, and institutional support required to participate in smart energy systems. Research on smart energy transitions shows that digitalisation can marginalise household users when technical designs assume stable connectivity, rational engagement, and continuous consumer responsiveness [8]. Vulnerable consumers may be expected to manage complex interfaces, interpret automated feedback, or respond to dynamic tariffs without the resources required to do so safely [9]. Digital exclusion is therefore not simply the absence of technology but a structured barrier to participation in AI-enabled energy services.

Algorithmic fairness and bias in critical infrastructure

Algorithmic fairness becomes especially important in energy because AI systems increasingly influence access, pricing, reliability, and service prioritisation in critical infrastructure. Bias in energy AI may emerge from unrepresentative datasets, proxy variables for income or geography, optimisation objectives that privilege aggregate efficiency, or deployment contexts that ignore vulnerability [3]. Because energy is a basic service, biased AI decisions can have consequences beyond inconvenience, affecting affordability, comfort, safety, and exposure to disconnection or curtailment. Fairness in energy AI therefore requires more than technical debiasing; it requires normative attention to who bears the risks of automation.

Smart energy benefits and their distribution

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Smart energy benefits include energy savings, flexibility payments, improved service quality, peer-to-peer trading opportunities, and access to low-carbon technologies. However, flexibility capital is unevenly distributed because households with smart appliances, flexible routines, home ownership, electric vehicles, batteries, or solar panels are better positioned to respond to market signals [10]. Peer-to-peer energy trading may appear democratising, but participation often depends on trust, platform access, technical knowledge, and the ability to invest in distributed resources [11]. The distribution of benefits therefore tends to privilege consumers already positioned to act as flexible, data-rich, and investment-capable market participants.

Existing frameworks and their gaps

Existing frameworks in energy justice, smart city inclusion, and digital energy governance identify important risks, but they often do not fully connect digital exclusion, algorithmic bias, and unequal benefit distribution as mutually reinforcing mechanisms. Inclusion frameworks for smart energy city development highlight participation and governance challenges, yet they may not sufficiently theorise how AI models translate exclusion into automated disadvantage [12]. Energy justice analyses of smart grids identify procedural and distributive concerns, but algorithmic decision-making adds new layers of opacity and classification that require closer attention [5]. This article addresses that gap by conceptualising AI-induced energy inequality as a feedback-driven process rather than a set of isolated harms.

Conceptual Framework For AI-Induced Inequality

Defining AI-induced energy inequality

AI-induced energy inequality can be defined as the additional or amplified inequality produced when AI systems shape energy access, pricing, participation, and benefit allocation in ways that disadvantage already vulnerable groups. This concept does not imply that AI alone creates energy injustice; rather, AI may intensify pre-existing inequalities by embedding them into automated classifications, digital interfaces, and market mechanisms [13]. A justice-oriented definition must therefore distinguish between background inequality and the specific contribution of AI to exclusion, discrimination, and unequal benefit capture. AI-induced inequality is most visible when energy systems become more efficient overall while specific groups become less able to access security, affordability, or participation.

The three interlocking mechanisms

The framework identifies three interlocking mechanisms: digital exclusion, algorithmic bias, and unequal access to smart energy benefits. Digital exclusion prevents some households from entering AI-enabled systems, while algorithmic bias may misclassify or disadvantage those who are included but poorly represented in data [14]. Unequal benefit distribution then channels savings, flexibility revenues, and service improvements toward households already able to participate in digital and market-based energy arrangements. Together, these mechanisms show why AI-driven energy inequality is not simply a problem of missing access but a layered process of selective inclusion, unequal classification, and asymmetric reward.

Feedback loops and cumulative disadvantage

The most serious risk is that these mechanisms form feedback loops that deepen inequality over time. When vulnerable households are excluded from smart services, they generate less usable data, which may make them less visible to AI systems and less likely to be targeted for beneficial innovations [15]. If biased models then treat low data availability, payment instability, or limited responsiveness as risk signals, disadvantaged households may face worse tariffs, fewer incentives, or more restrictive service conditions. Cumulative disadvantage emerges when digital invisibility becomes algorithmic disadvantage and algorithmic disadvantage becomes economic exclusion.

Figure 1 presents the Archetype AI Sustainability Life-Cycle Framework, illustrating how AI-enabled energy systems can generate cumulative inequality through a life-cycle sequence of digital access, data visibility, algorithmic decision-making,

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benefit allocation, and feedback effects.

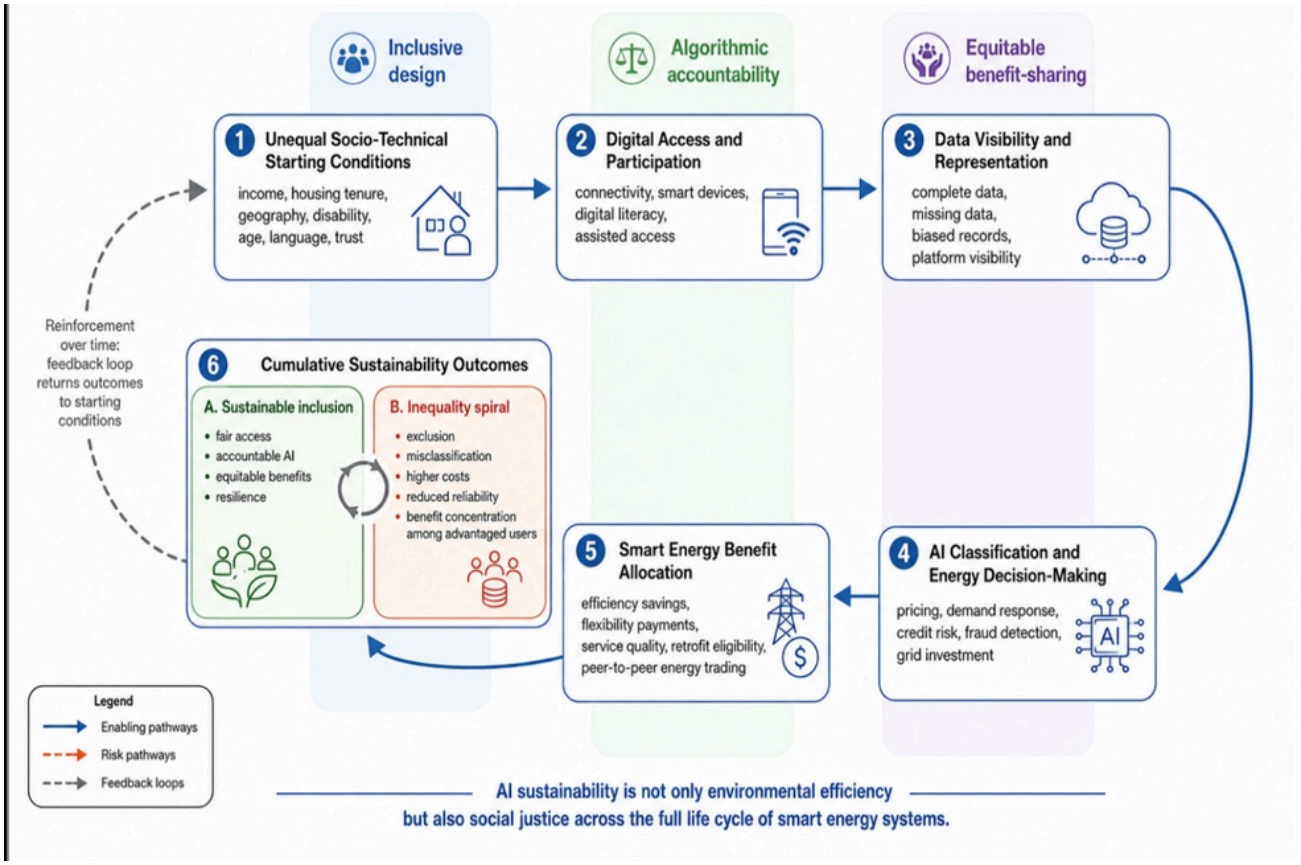


Figure 1. Archetype AI Sustainability Life-Cycle Framework for AI-Induced Energy Inequality

Digital Exclusion From Smart Energy Systems

Forms of digital exclusion

Digital exclusion in smart energy systems includes access exclusion, skills exclusion, economic exclusion, trust exclusion, and institutional exclusion. Access exclusion occurs when households lack broadband, smartphones, smart meters, or interoperable devices, while skills exclusion arises when interfaces demand literacy, confidence, or constant engagement that not all users possess [2]. Economic exclusion appears when participation requires upfront investment in appliances, batteries, electric vehicles, or home energy management systems. Trust and institutional exclusion also matter because households that have experienced poor service, surveillance, or punitive billing may avoid digital energy systems even when nominal access exists.

Energy services gated by digital access

Many AI-enabled energy services are gated by digital access because they require continuous data flows, app-based enrolment, automated control, or algorithmic profiling. Dynamic tariffs, demand response, smart meter feedback, home energy management systems, and automated flexibility services often assume that users can interpret signals and adjust consumption patterns [16]. Digitalisation research shows that social inclusion in smart energy transitions cannot be assumed simply because technologies are technically available [1]. The more energy services become mediated through platforms and AI, the more digital access becomes a condition for energy participation itself.

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Consequences of exclusion

The consequences of digital exclusion are tangible and cumulative, not merely symbolic. Excluded households may miss tariff savings, efficiency recommendations, demand response payments, automated fault detection, or targeted support, while still facing system-wide costs associated with smart infrastructure deployment [17]. In this sense, digitalisation without safeguards can systematically exclude vulnerable consumers from the benefits used to justify the transition. **Table 1** presents a taxonomy of digital exclusion mechanisms in AI-enabled energy services, linking exclusion types to affected services, populations, and inequality outcomes.

Table 1. Taxonomy of Digital Exclusion Mechanisms in AI-Enabled Energy Services

Exclusion Type	Affected Service	Population Affected	Inequality Outcome
Connectivity exclusion	App-based smart meter feedback and real-time consumption alerts	Rural households, low-income households, and households with unstable internet access	Reduced ability to monitor consumption, respond to price signals, or detect avoidable energy waste
Device exclusion	Home energy management systems and automated demand response	Renters, elderly consumers, and households without smart appliances	Inability to participate in automation-based flexibility programs and loss of potential compensation
Skills exclusion	Dynamic tariff comparison tools and AI-generated energy advice	Consumers with limited digital literacy, language barriers, or cognitive accessibility needs	Higher exposure to unsuitable tariffs, confusion around automated recommendations, and reduced consumer agency
Economic exclusion	Battery optimisation, rooftop solar management, and electric vehicle charging algorithms	Households without capital, secure tenure, or access to credit	Concentration of optimisation benefits among homeowners and wealthier consumers
Data visibility exclusion	AI-based eligibility screening for efficiency upgrades or support programs	Informal households, prepayment users, and consumers with incomplete digital records	Under-recognition of need and reduced access to targeted assistance
Trust exclusion	Platform-mediated peer-to-peer trading and third-party flexibility aggregation	Communities with prior experience of exploitative billing, surveillance, or poor service	Voluntary non-participation that becomes structurally penalising as benefits shift to digital platforms
Institutional exclusion	Online-only enrolment for smart tariffs, rebates, and demand response schemes	Disabled consumers, elderly consumers, migrants, and households requiring assisted access	Administrative barriers to participation and reduced procedural fairness

Algorithmic Bias and Discriminatory Energy Decisions

Sources of bias in energy AI

Bias in energy AI can arise from data, model design, optimisation objectives, and deployment contexts. Data bias occurs when training data underrepresent vulnerable households or encode historical inequalities in consumption, arrears,

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infrastructure quality, or service access [3]. Model bias emerges when variables such as postcode, payment method, housing type, or load profile function as proxies for income, race, disability, or geography. Deployment bias occurs when technically accurate models are implemented in contexts where vulnerable households have fewer resources to respond to automated decisions.

Energy decisions affected by bias

AI systems may influence energy decisions such as demand response selection, dynamic pricing, load curtailment, fraud detection, credit scoring, and grid investment prioritisation. In demand response, algorithms may favour households that can reliably reduce or shift load, thereby excluding those with inflexible routines, medical needs, or poor housing conditions [18]. In grid congestion management, automated allocation of constraints could be perceived as unjust when communities experience unequal restrictions without meaningful explanation or participation [19]. These decisions matter because algorithmic classification can determine who is rewarded, who is penalised, and who is treated as a risk to system optimisation.

Inequality outcomes from bias

The inequality outcomes of algorithmic bias include higher costs, reduced reliability, exclusion from incentives, increased surveillance, and misrecognition of vulnerability. AI systems that optimise for system efficiency may reinforce disadvantage when they classify vulnerable households as low-value, high-risk, or insufficiently flexible participants [20]. Bias can also operate through apparently neutral market rules that reward predictable flexibility while penalising those whose energy use reflects care work, illness, overcrowding, or inefficient housing. **Table 2** maps selected AI applications in energy to potential bias mechanisms, affected populations, and inequality outcomes.

Table 2. Algorithmic Bias in Energy AI: Applications, Biases, and Inequality Outcomes

AI Application	Type of Bias	Affected Population	Inequality Outcome
Demand response enrolment algorithms	Selection bias toward households with predictable, shiftable loads	Shift workers, households with care responsibilities, medically vulnerable consumers	Exclusion from flexibility payments and portrayal as less valuable system participants
Dynamic pricing recommendation systems	Affordability-blind optimisation that assumes users can shift demand	Low-income households, elderly consumers, and families with fixed routines	Exposure to unsuitable tariffs and increased risk of higher bills
Automated load shedding or curtailment prioritisation	Infrastructure and geography bias embedded in grid data	Rural communities, peripheral neighbourhoods, and areas with weaker networks	Disproportionate exposure to service disruption and reduced energy security
AI-based credit scoring for energy supply or prepayment risk	Proxy discrimination through postcode, payment history, or housing tenure	Renters, prepayment users, migrants, and households with unstable income	More restrictive payment terms, punitive monitoring, or exclusion from favourable contracts
Smart meter anomaly and fraud detection	Behavioural bias against non-standard consumption patterns	Multi-generational households, overcrowded housing, disabled consumers using medical devices	Heightened surveillance, false suspicion, and procedural burden
Grid investment optimisation	Data visibility bias favouring high-value	Low-data communities, informal settlements, and digitally	Underinvestment in vulnerable areas and reinforcement of

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	digital users and visible flexibility resources	excluded households	infrastructure inequality
AI-targeted energy efficiency programs	Eligibility bias based on incomplete or platform-generated data	Households without digital records, private renters, and fuel-poor consumers	Failure to identify need and exclusion from retrofit or support interventions

Unequal Access to Smart Energy Benefits

The concentration of efficiency gains

AI-enabled efficiency gains tend to accrue most readily to households that can afford smart appliances, high-quality insulation, rooftop solar, batteries, electric vehicles, and home energy management systems. This concentration reflects what smart energy research describes as unequal capacity to participate in digitalised services, where connected and resourced users are better able to translate information into savings [21]. AI may therefore reinforce inequality by converting investment capacity into recurring optimisation benefits. In justice terms, the problem is not only that some households save more, but that vulnerable households may subsidise system transformation while receiving fewer direct benefits.

Flexibility markets and compensation disparities

Flexibility markets often reward consumers who can shift demand, export stored energy, automate appliance use, or participate through aggregators. The concept of flexibility justice is useful here because it shows that flexibility is not evenly distributed; it depends on housing quality, household routines, appliance ownership, and the ability to tolerate changes in comfort or timing [10]. AI-enabled aggregation may intensify this disparity by identifying and rewarding the most profitable flexibility providers while leaving inflexible households outside compensation streams. As peer-to-peer and platform-mediated energy trading expand, participation may appear open while practically privileging technically confident, asset-owning, and digitally connected consumers [11].

Table 3 summarises how different smart energy assets influence participation capacity and compensation opportunities in AI-mediated flexibility markets.

Table 3. Distribution of Smart Energy Assets and Flexibility Participation Capacity

Household Characteristic	Smart Energy Asset Availability	AI-Mediated Flexibility Capacity	Likely Economic Outcome
Affluent homeowners	Solar panels, batteries, electric vehicles, smart appliances, home automation systems	High capacity for automated load shifting and market participation	Repeated access to flexibility payments, tariff optimisation, and energy savings
Middle-income digitally connected households	Partial smart appliance ownership and stable internet access	Moderate ability to respond to dynamic pricing and demand response signals	Selective participation benefits with moderate optimisation gains
Private renters	Limited authority to install smart technologies or retrofit properties	Restricted participation in automated flexibility schemes	Lower access to compensation and continued exposure to residual system costs
Fuel-poor households	Minimal smart infrastructure and reliance on basic	Low flexibility due to constrained consumption	Exclusion from premium smart energy benefits and

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	appliances	patterns	limited savings potential
Elderly or digitally excluded consumers	Limited use of app-based or automated systems	Reduced responsiveness to AI-generated energy signals	Under-participation in smart tariffs and flexibility incentives
Rural households with weak connectivity	Inconsistent access to digital infrastructure and aggregators	Reduced integration into real-time flexibility platforms	Lower inclusion in platform-mediated energy markets

Innovation and investment bias

AI-driven energy innovation often follows commercial incentives that target profitable customers rather than vulnerable consumers. Digital energy services may be designed around users who generate valuable data, own compatible devices, and can pay for premium optimisation, which can marginalise households most in need of affordability support [22]. This investment bias means that vulnerability is not simply overlooked but structurally deprioritised by platform business models and market design. A justice-oriented approach would require AI innovation to be evaluated not only by technical performance but by whether it expands or narrows access to energy security.

Geographic and spatial inequality

AI-induced energy inequality also has a spatial dimension because smart energy infrastructures are unevenly distributed across urban, rural, affluent, peripheral, and historically underserved areas. Research on smart energy inclusion shows that local governance, infrastructure quality, and urban development strategies shape who can participate in digital energy systems [12]. Rural and lower-income areas may face weaker connectivity, less grid hosting capacity, fewer smart service providers, and lower visibility in data-driven investment planning. These spatial inequalities can turn AI-enabled optimisation into a mechanism that improves already attractive locations while leaving disadvantaged areas with poorer service and fewer opportunities.

Intersectional Vulnerabilities and Feedback Loops

Intersecting dimensions of disadvantage

AI-induced energy inequality is intersectional because income, race, age, disability, housing tenure, geography, language, and digital literacy can combine to shape exposure to exclusion and bias. Plural energy justice scholarship emphasises that energy injustice cannot be reduced to a single axis of disadvantage because different forms of social marginalisation interact within energy systems [7]. For example, an elderly renter in inefficient housing may face digital skills barriers, limited control over appliances, and reduced ability to respond to dynamic prices. AI systems that treat such households only as data points may misrecognise structural vulnerability as poor responsiveness or low market value.

Feedback loops that deepen inequality

The framework identifies a feedback loop in which digital exclusion produces poor data visibility, poor data visibility increases algorithmic misclassification, and algorithmic misclassification reduces access to benefits. Studies of smart energy governance warn that energy justice is often not sufficiently safeguarded in local smart energy systems, especially when inclusion is treated as secondary to innovation [23]. Once vulnerable households are excluded from smart services, AI systems may learn from a skewed population of participants and then reproduce that skew in future targeting, pricing, and investment decisions. Inequality thus becomes cumulative because the excluded are not merely left behind once; they are repeatedly rendered less visible, less profitable, and less governable within AI-mediated systems.

Visualising the inequality spiral

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The inequality spiral begins when a household lacks digital access, compatible technology, or trust in automated systems, which limits participation in smart energy services. Limited participation then reduces the household's data visibility, and AI systems may interpret this absence as low flexibility, low value, or high risk rather than as evidence of structural exclusion [15]. Over time, benefit allocation shifts toward households that already have better data profiles, stronger assets, and greater digital capacity. **Table 4** illustrates how digital exclusion, algorithmic bias, and unequal benefit distribution intersect across different vulnerable groups.

Table 4. Intersectional Vulnerability Matrix for AI-Induced Energy Inequality

Vulnerable Group	Digital Exclusion Mechanism	Algorithmic Bias Mechanism	Unequal Benefit Distribution	Compounding Inequality Pattern
Low-income households	Limited access to smart devices, broadband, and upfront investment capital	Payment history or postcode may be used as risk proxies	Reduced access to dynamic tariff savings, automation benefits, and flexibility payments	Affordability pressure increases while eligibility for beneficial services declines
Elderly consumers	Lower digital confidence and greater difficulty navigating app-based services	Non-standard or stable consumption may be misread as low flexibility	Fewer rewards from automated demand response or tariff optimisation	Procedural exclusion combines with higher exposure to unsuitable digital choices
Rural households	Weak connectivity and fewer smart service providers	Grid location may be treated as a constraint or cost risk	Lower access to peer-to-peer markets, aggregation, and smart infrastructure upgrades	Spatial exclusion becomes reinforced through data-poor investment decisions
Disabled consumers	Accessibility barriers in digital interfaces and dependence on energy-intensive care devices	Medical or assistive energy use may be flagged as anomalous or inflexible	Reduced ability to shift demand without compromising safety or dignity	Essential consumption is misrecognised as inefficient or commercially unattractive
Renters	Limited control over appliances, insulation, solar, batteries, and smart upgrades	Housing tenure may correlate with lower modelled investment value	Landlords or asset owners capture efficiency gains while tenants face residual costs	Split incentives prevent participation while AI services privilege property owners
Migrant or language-minority households	Language barriers and unfamiliarity with digital energy contracts	Thin credit files or administrative gaps may be treated as risk indicators	Lower access to rebates, advice tools, and tailored support programs	Administrative invisibility becomes algorithmic disadvantage
Fuel-poor households	Prepayment dependence and limited ability to engage with digital platforms	High consumption from inefficient housing may be misclassified as behavioural inefficiency	Exclusion from premium optimisation and lower participation in reward schemes	Structural deprivation is reframed as consumer inefficiency

The role of institutional and regulatory failures

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Institutional and regulatory failures enable inequality spirals when AI energy systems are deployed before fairness safeguards, accessibility duties, and accountability mechanisms are established. Research on frontlining energy justice shows that community-based perspectives are essential for identifying harms that top-down transition strategies often miss [24]. If regulators treat AI as a technical efficiency tool rather than a distributive governance instrument, they may fail to detect how automated pricing, targeting, and service allocation affect vulnerable consumers. Mitigation therefore requires normative commitment, not only better data, because the central issue is whose security and participation the system is designed to protect.

Figure 2 illustrates how institutional and regulatory failures allow AI-enabled energy systems to convert technical deployment choices into distributive harms when fairness safeguards, accessibility duties, community participation, and accountability mechanisms are weak or absent.

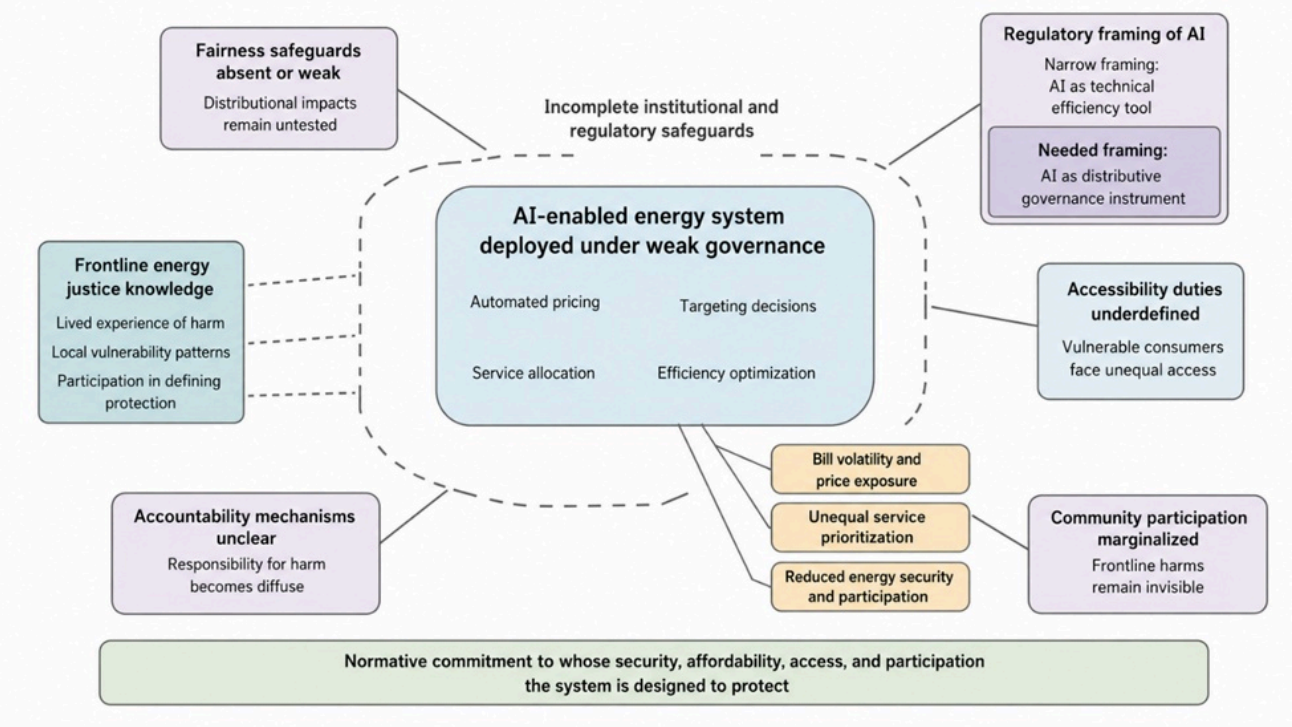


Figure 2. Institutional Failure Pathways in AI-Enabled Energy Inequality Spirals

Policy Responses and Mitigation Strategies

Inclusive AI design and universal access

Inclusive AI design should begin from universal access, assisted participation, and non-digital alternatives rather than assuming that all consumers can or should become digitally optimised energy users. Digital-energy divide research suggests that internet connectivity and knowledge infrastructures shape whether AI-enabled energy systems can become socially inclusive rather than exclusionary [25]. Energy providers should therefore design smart services with accessible interfaces, multilingual support, assisted enrolment, opt-out protections, and safeguards for households unable to automate or shift consumption. Inclusive design should be treated as a core reliability and justice requirement, not as an optional consumer engagement feature.

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Table 5 outlines governance strategies that can mitigate AI-induced energy inequality across different stages of smart energy system deployment.

Table 5. Governance Strategies for Mitigating AI-Induced Energy Inequality

Governance Area	Recommended Intervention	Inequality Risk Addressed	Expected Justice Outcome
Digital accessibility	Provide assisted enrolment, multilingual interfaces, and offline participation options	Digital exclusion from smart energy services	Improved procedural inclusion and broader participation
Algorithmic accountability	Require explainability audits and independent fairness assessments	Hidden bias in automated decision-making	Greater transparency and reduced discriminatory outcomes
Consumer protection	Establish safeguards against punitive automated pricing and disconnection	Disproportionate burden on vulnerable households	Enhanced affordability and protection of essential energy access
Inclusive infrastructure investment	Prioritise underserved and low-connectivity communities in smart grid upgrades	Spatial and geographic inequality	More equitable access to smart energy opportunities
Benefit-sharing regulation	Mandate equitable access to flexibility payments and smart tariff benefits	Concentration of optimisation gains among affluent users	Fairer distribution of economic benefits
Data governance	Limit exploitative data practices and improve consumer control over energy data	Surveillance and unequal data visibility	Increased trust and recognition of vulnerable consumers
Community participation	Incorporate civil society and community organisations into AI governance processes	Lack of procedural justice and local accountability	More democratic and socially responsive energy governance

Regulation for equitable smart energy outcomes

Regulation should address AI-induced energy inequality through fairness audits, consumer protection, transparency duties, benefit-sharing mechanisms, and accountability for automated decisions. Critical reviews of energy justice research show that frameworks must move beyond abstract principles toward operational tools that can identify who benefits, who bears risk, and who has voice in transition governance [26]. Regulators could require energy AI systems to test for exclusionary effects, explain differential treatment, and ensure that smart energy benefits do not concentrate only among affluent participants. Equitable market design should also protect consumers who cannot provide flexibility, because essential energy rights should not be conditional on algorithmic usefulness.

Recent scholarship further emphasises that AI governance in energy systems must address transparency, accountability, and structural power imbalances rather than focusing only on technical optimisation. Research on AI and energy justice argues that automated electricity governance can undermine fairness when algorithmic systems operate without meaningful procedural safeguards, explainability, or public oversight [27]. Studies of ethical AI risk assessment similarly demonstrate that justice-oriented governance requires attention to relational power asymmetries, especially where vulnerable communities are subject to opaque automated classifications [28]. In addition, lifecycle-oriented approaches to AI ethics in energy systems suggest that fairness and accountability should be embedded throughout the full design, deployment, and evaluation process rather than treated as post-deployment corrections [29].

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Evaluation of the Critical Framework

Conceptual rigour and justice orientation

The framework is conceptually rigorous because it links distributive, recognitional, and procedural justice to specific AI-enabled mechanisms of exclusion, bias, and benefit capture. It also aligns with energy justice index research by treating inequality as multidimensional rather than as a single affordability problem [30]. Its contribution is to clarify how AI adds a new layer of automated classification and platform mediation to existing energy vulnerabilities. This justice orientation challenges techno-centric narratives by asking whether smart energy systems expand democratic access or merely optimise participation for the already advantaged.

Practical utility for policy and advocacy

The framework has practical utility because it offers policymakers, regulators, utilities, and civil society groups a diagnostic structure for identifying inequality pathways before they become normalised. Digitalisation-oriented energy transition research stresses that resilience and sustainability require attention to social inclusion, not only technological sophistication [31]. The three mechanisms can be used to examine whether a smart energy program excludes users at the point of access, disadvantages them through algorithmic classification, or denies them a fair share of benefits. For advocacy groups, the framework provides language for contesting automated energy governance that appears neutral while producing unequal outcomes.

Limitations and need for empirical testing

The framework remains conceptual and requires empirical testing across different regulatory systems, market designs, data environments, and social contexts. Research on energy justice in demand response demonstrates the value of examining distributional consequences using real residential energy data, but this article does not conduct such analysis or report quantitative findings [18]. Future research should investigate whether the proposed mechanisms appear in particular AI-enabled services, how affected communities experience them, and which regulatory interventions reduce harm. The framework should therefore be read as a diagnostic and theoretical contribution rather than as an empirical measurement instrument.

Figure 3 illustrates the article's evaluative claim that the proposed framework is strongest when read as a justice-oriented diagnostic tool: it connects AI-enabled exclusion, algorithmic bias, and unequal benefit capture to distributive, recognitional, and procedural energy justice, while also marking the need for empirical testing across real smart-energy contexts.

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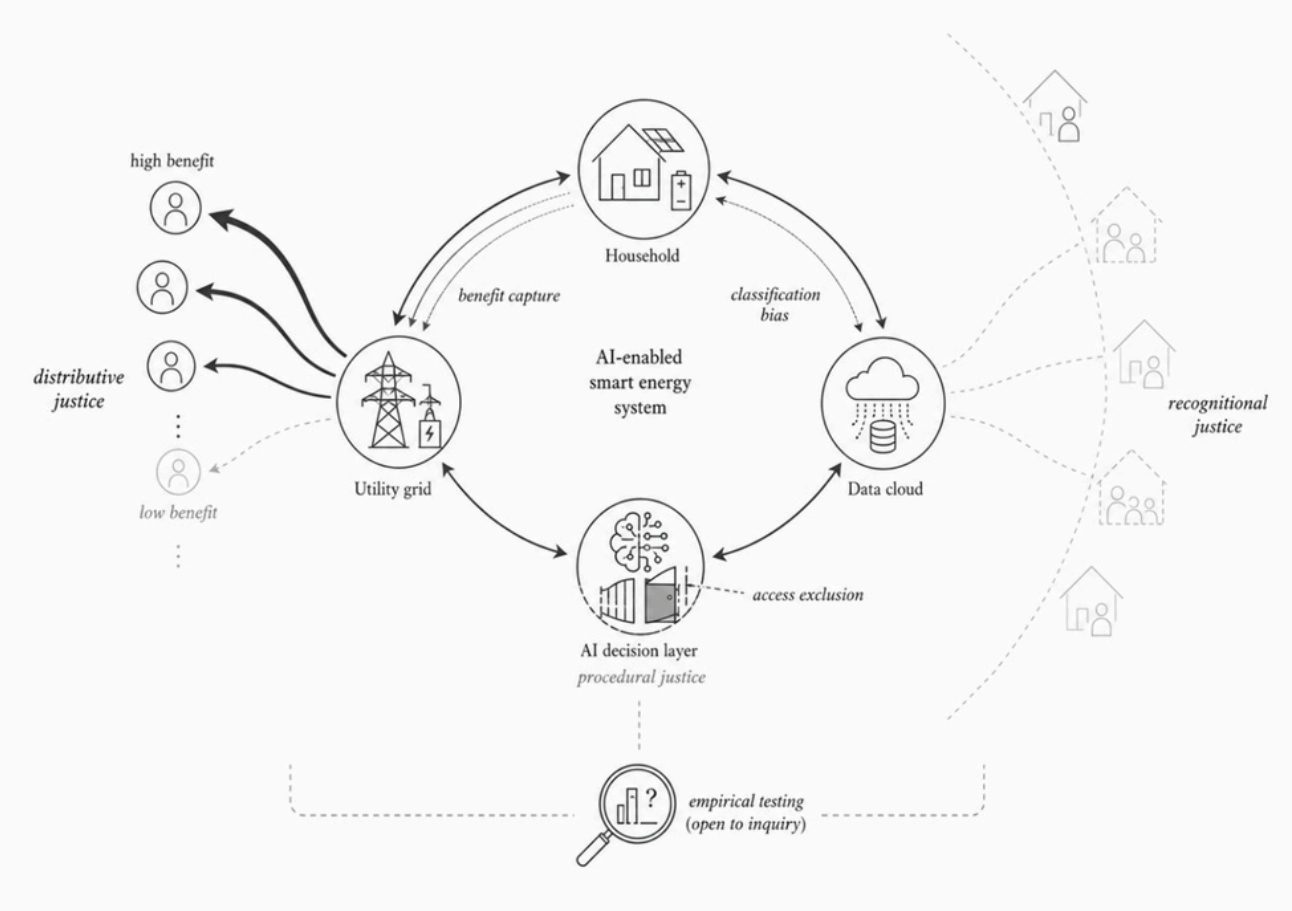


Figure 3. Justice-Oriented Evaluation of AI-Enabled Smart Energy Governance

Limitations

Scope and generalizability

The scope of this article is limited to conceptual analysis of AI-induced energy inequality rather than empirical comparison across countries, technologies, or consumer groups. Smart energy inclusion varies across institutional settings, and the mechanisms identified here may appear differently in liberalised markets, public utility systems, rural electrification contexts, and community energy initiatives [32]. The framework also focuses on household and consumer-facing inequality, although AI may create additional inequities in labour, supply chains, infrastructure siting, and transnational energy governance. Its generalizability therefore depends on further contextual adaptation and empirical validation.

The evolving AI and inequality landscape

The AI and energy inequality landscape is rapidly evolving as smart meters, automated flexibility markets, digital twins, predictive analytics, and generative AI tools become more embedded in energy governance. Recent work on AI and energy justice suggests that AI could support vulnerable communities if designed around justice, but it may also reinforce inequality when deployed through exclusionary platforms and market logics [13]. This creates a moving target for analysis because technologies, regulations, and business models are changing faster than many justice safeguards. The framework should therefore be updated as new AI applications reshape energy access, decision-making, and benefit distribution.

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Conclusion

AI-induced energy inequality emerges through three connected mechanisms: digital exclusion, algorithmic bias, and unequal access to smart energy benefits. Digital exclusion blocks participation, algorithmic bias shapes discriminatory decisions, and benefit maldistribution concentrates rewards among those already positioned to participate in smart energy systems. Together, these mechanisms form a critical framework for understanding how AI can deepen inequality in the energy transition.

The central argument is that AI-induced energy inequality is systemic rather than incidental. It is produced when techno-centric energy transitions treat efficiency, automation, and optimisation as inherently beneficial while ignoring unequal capacities to participate. Without justice-oriented governance, AI may make energy systems smarter for some while making them more opaque, conditional, and punitive for others.

A justice-centred approach to AI in energy requires inclusive design, universal access protections, algorithmic accountability, and equitable benefit-sharing. It also requires sustained research on the intersection of energy inequality, digital exclusion, and automated decision-making. Smart energy systems should not be judged only by how efficiently they optimise grids, but by whether they expand dignity, security, participation, and fairness for those most at risk of being left behind.

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References

1. Sareen S. Digitalisation and social inclusion in multi-scalar smart energy transitions. Energy Res Soc Sci. 2021;81:102251.

2. Chambers J, Robinson C, Scott M. Digitalisation without detriment: A research agenda for digital inclusion in the future energy system. People Place Policy Online. 2023;16:177-92.

3. Eze C, Ezema A, Roth L, Pan Z, Ponci F, Monti A. AI Bias in Power Systems Domain—Exemplary Cases and Approaches. Energies. 2025;18(18):4819.

4. Sovacool BK, Hook A, Martiskainen M, Brock A, Turnheim B. The decarbonisation divide: Contextualizing landscapes of low-carbon exploitation and toxicity in Africa. Glob Environ Change. 2020;60:102028.

5. Milchram C, Hillerbrand R, van de Kaa G, Doorn N, Künneke R. Energy justice and smart grid systems: evidence from the Netherlands and the United Kingdom. Appl Energy. 2018;229:1244-59.

6. Ciplet D. From energy privilege to energy justice: A framework for embedded sustainable development. Energy Res Soc Sci. 2021;75:101996.

7. Sovacool BK, Bell SE, Daggett C, Labuski C, Lennon M, Klinger J, et al. Pluralizing energy justice: Incorporating feminist, anti-racist, Indigenous, and postcolonial perspectives. Energy Res Soc Sci. 2023;97:102996.

8. Tarasova E, Rohracher H. Marginalising household users in smart grids. Technol Soc. 2023;72:102185.

9. Shirani F, Groves C, Henwood K, Pidgeon N, Roberts E. 'I'm the smart meter': Perceptions of smart technology amongst vulnerable consumers. Energy Policy. 2020;144:111637.

10. Powells G, Fell MJ. Flexibility capital and flexibility justice in smart energy systems. Energy Res Soc Sci. 2019;54:56-9.

11. Pumphrey K, Walker SL, Andoni M, Robu V. Green hope or red herring? Examining consumer perceptions of peer-to-peer energy trading in the United Kingdom. Energy Res Soc Sci. 2020;68:101603.

12. Noori N, Hoppe T, van der Werf I, Janssen M. A framework to analyze inclusion in smart energy city development: The case of Smart City Amsterdam. Cities. 2025;158:105710.

13. Delina LL, Tung YS. Towards a just AI-assisted energy transitions for vulnerable communities. Energy Res Soc Sci. 2024;118:103752.

14. Guder M, Balta-Ozkan N. An integrated agent-based modelling and artificial intelligence framework for enhancing the experience of minority ethnic communities in digital energy services. Energy AI. 2025;22:100624.

15. Thunshirn P, Ettwein F, Höferl KM. Assessing the digital divide in the energy transition: Surveying the social factors influencing home energy management systems in Austria. Energy Res Soc Sci. 2025;120:103941.

16. Calver P, Simcock N. Demand response and energy justice: A critical overview of ethical risks and opportunities within digital, decentralised, and decarbonised futures. Energy Policy. 2021;151:112198.

17. Fawcett T, Palmer J, Terry N, Boardman B, Narayan U. Using smart energy meter data to design better policy: Prepayment meter customers, fuel poverty and policy targeting in Great Britain. Energy Res Soc Sci. 2024;116:103666.

18. Gao Y, Liu M, Hu Z, Yamate S, Otomo J, Chen WA, et al. Quantitative analysis of energy justice in demand response: Insights from real residential data in Texas, USA. Renew Energy. 2025;242:122477.

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19. de Winkel E, Lukszo Z, Neerincx M, Dobbe R. Adapting to limited grid capacity: Perceptions of injustice emerging from grid congestion in the Netherlands. Energy Res Soc Sci. 2025;122:103962.

20. Chen L, Jiang N, Wang S. An impossible driver for energy justice? Exploring the impact of artificial intelligence on China's energy transition. Energy Policy. 2025;207:114839.

21. Ye X, Zhang Z, Qiu Y. Review of application of high frequency smart meter data in energy economics and policy research. Front Sustain Energy Policy. 2023;2:1171093.

22. Farhangi M, Rohracher H, Magnusson D. More than wires and screens: Assumptions about agency of devices in smart energy projects. Energy Res Soc Sci. 2024;114:103592.

23. van der Wel K, Akerboom S. Overlooked, misunderstood, or sidelined?: Explaining why energy justice is not safeguarded in smart local energy systems. Energy Res Soc Sci. 2024;118:103785.

24. Elmallah S, Reames TG, Spurlock CA. Frontlining energy justice: Visioning principles for energy transitions from community-based organizations in the United States. Energy Res Soc Sci. 2022;94:102855.

25. Moftah N, Alzubi AB. Bridging the Digital–Energy Divide: Artificial Intelligence, Internet Connectivity, and Knowledge Management. Sustainability. 2025;17(19):8912.

26. Iwińska K, Lis A, Mączka K. From framework to boundary object? Reviewing gaps and critical trends in global energy justice research. Energy Res Soc Sci. 2021;79:102191.

27. Noorman M, Espinosa Apráez B, Lavrijssen S. AI and energy justice. Energies. 2023;16(5):2110.

28. Krijger J. What about justice and power imbalances? A relational approach to ethical risk assessments for AI. Digit Soc. 2024;3(3):56.

29. El-Haber N, Burnett D, Halford A, Stamp K, De Silva D, Manic M, et al. A lifecycle approach for artificial intelligence ethics in energy systems. Energies. 2024;17(14):3572.

30. Apergi M, Eicke L, Goldthau A, Hashem M, Huneeus S, de Oliveira RL, et al. An energy justice index for the energy transition in the global South. Renew Sustain Energy Rev. 2024;192:114238.

31. Zakeri B. Digitalization for Resilient and Sustainable Energy Transitions. Energies. 2024;17(21):5434.

32. Hargreaves N, Hargreaves T, Chilvers J. Socially smart grids? A multi-criteria mapping of diverse stakeholder perspectives on smart energy futures in the United Kingdom. Energy Res Soc Sci. 2022;90:102610.

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